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Empowering sustainable development: revolutionizing agricultural green total factor productivity through rural digitalization

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Introduction: The rapid advancement of digital technology has catalyzed the emergence of “digital villages,” presenting both new opportunities and challenges for the digital transformation of agriculture. This transformation has become a core driving force behind sustainable agricultural development. This paper utilizes panel data from 30 provincial-level administrative regions of mainland China (excluding Tibet) for the period 2011 to 2020 to explore how digital rural development (DRD) impacts agricultural green total factor productivity (AGTFP) and examines its underlying mechanisms.

Methods: Regarding variable measurement, the study employs the entropy weighting method to quantify the DRD and uses an extended Data Envelopment Analysis-Malmquist model to assess AGTFP. For the research approach, the study constructs a two-way fixed effects model to evaluate the impact of DRD on AGTFP and explores the underlying mechanisms. Specifically, the study conducts benchmark regression analysis, endogeneity tests, robustness tests, mechanism examinations, and heterogeneity tests.

Results: (1) DRD significantly enhances AGTFP, a conclusion that remains robust following the province-year clustering robust standard error estimates, winsorization tests, and excluding COVID-19-affected years. (2) Mechanistic analysis indicates that DRD primarily boosts AGTFP by promoting the development of digital inclusive finance (DIF) and facilitating the integration of primary, secondary, and tertiary industries (IPST). (3) Heterogeneity tests show that the positive impact of DRD on AGTFP is more pronounced in regions with higher levels of informatization and central regions of China.

Discussion: To harness DRD's potential more effectively in fostering sustainable agricultural development, policymakers should concentrate on DIF and the IPST. Additionally, the government should pay close attention to disparities in informatization levels and resource allocation across regions and develop targeted strategies accordingly. Fundamentally, this study aims to elucidate China's efficacy in rural digitalization and the green transformation of agriculture to an international audience. It seeks to provide insights and guidance on formulating more scientific, efficient, and sustainable strategies for agricultural development worldwide, thereby promoting green agricultural growth and supporting rural revitalization.

KEYWORDS

digital rural development, agricultural green total factor productivity, sustainable development, fixed effects analysis, green transformation of agriculture, high-quality development

1 Introduction

The global climate crisis, characterized mainly by climate warming and the frequent occurrence of extreme weather, is one of the significant contributors to food shortages. The food crisis has forced some countries to adopt a low-quality, energy-intensive, and crude model of agricultural development. In this cycle of cumulative causality, environmental degradation, and food shortages have become two of the century's most significant challenges to global sustainable development (Sakariyahu et al., 2024). Concurrently, advanced information technologies catalyze the emergence of innovative models, technologies, and products worldwide, facilitating the digital transformation of rural locales (Maroušek, 2014; Kliestik et al., 2023). Digital rural development (DRD) exemplifies the pivotal role contemporary technologies play in bolstering global food security and enhancing environmental stewardship, thereby serving as a dynamic impetus for the high-quality economic advancement of rural regions (Jiang et al., 2024).

Considering the projected increase in the global population and the food crisis, advancements in agricultural technology to enhance production efficiency are evolving rapidly (Maroušek et al., 2023a,b,c). Consequently, the digital transformation in agriculture has become a focal point of concern for nations worldwide (Zscheischler et al., 2022). In 2015, the Indian government initiated the "Digital India" strategy to enhance rural network connectivity and enable access to e-governance and telemedicine services in rural areas. Following this, in 2016, Japan proposed the "Next Generation Agriculture, Forestry, and Fisheries Technology" program, which integrates intelligent machinery with sophisticated information technology to enhance the effectiveness of agricultural resource management and develop smart agriculture. A year later, in 2017, the European Union's "Smart Villages" initiative focused on enhancing network infrastructure in rural areas and promoting innovative agricultural technologies to improve the agricultural production process. Concurrently, responding to emerging trends in rural transformation, China has prioritized accelerating the DRD to boost informatization in agriculture and rural regions. This initiative aims to facilitate the transition of agriculture towards greener production methods, thereby promoting sustainable and high-quality advancement of Chinese agriculture (Liu et al., 2024).

According to the National Bureau of Statistics of China (n.d.), the gross output value of agriculture, forestry, animal husbandry, and fisheries in China increased from 437.2 billion dollars in 2004 to 2.32 trillion dollars in 2022. This demonstrates a robust development trend in the agricultural economy. Nevertheless, the rapid expansion of agriculture has placed continuous pressure on resources and the environment, revealing the vulnerability of China's agrarian development (Luo et al., 2022). Environmental pollution and the irrational use of resources, including carbon dioxide emissions, soil degradation, and excessive application of chemical fertilizers and pesticides, have exerted significant pressure on the ecological environment. This has led many rural economic regions into a quandary of "growth without development" (Wu, 2024) and has even triggered the "resource curse" phenomenon (Yang C. et al., 2024). Faced with these challenges, constructing digital villages to achieve a green transformation of the agricultural economy becomes particularly important. The DRD in China encompasses the application of a range of modern technologies, from intelligent agricultural equipment to big data analytics, cloud computing, the Internet of Things, and artificial intelligence, ensuring optimal resource allocation and environmental protection in agrarian production (Sharma et al., 2020; Papadopoulos et al., 2024). By implementing smart agriculture and digital financial

services, the DRD enables the recombination of agricultural production factors, enhances resource utilization efficiency in rural areas, and optimizes agricultural management (Hong et al., 2024).

In this process, it is essential to effectively assess the impact of the DRD on the development of agriculture and rural areas. The agricultural green total factor productivity (AGTFP) provides an integrated approach to evaluating the efficiency of agriculture and its environmental impacts. By assessing the input and output efficiency of various resources such as land, labor, capital, and technology in agricultural production and emphasizing the production process's impact on the environment, the AGTFP has become a crucial tool for evaluating the influence of digitalization on agricultural sustainability (Ge et al., 2018; Tang et al., 2023). Nevertheless, research is scarce on the correlation between digital villages and the overall efficiency of agricultural production in terms of environmental sustainability. Therefore, this study constructs a comprehensive evaluation system based on the concept of digital villages and employs a two-way fixed effects model to analyze the relationship between the DRD and AGTFP across 30 provincial-level administrative regions of mainland China (excluding Tibet) from 2011 to 2020. The study is guided by three specific objectives: (1) Assess the influence of DRD on AGTFP and enhance the scholarly discourse in this field; (2) Examine the underlying mechanisms linking them, thereby guiding the strategic development of digital rural infrastructure; (3) Investigate the regional disparities in the impacts of DRD on AGTFP and identify the factors contributing to these variations to promote balanced development across different regions. This study aims to provide fresh perspectives and empirical evidence for evaluating the impact of the DRD on achieving green transformations in agriculture. Furthermore, it seeks to offer decision-making support to policymakers striving to balance efficiency in agricultural production with environmental protection, thereby better facilitating global sustainable agricultural development.

This study presents the following marginal contributions: firstly, compared to traditional research on AGTFP, which focuses on established influencing factors, this study highlights the significance of digital villages as a critical enabler in the new era. Specifically, regarding the research object, this study has created a unique indicator system encompassing five dimensions of agricultural and rural digitalization: infrastructure, production, operation, circulation, and life services. This system enables an all-round and comprehensive assessment and analysis of the DRD. Secondly, this study enhanced the measurement of AGTFP by incorporating the afforestation area as an input indicator, building on existing metrics. This expansion improves the comprehensiveness of the AGTFP assessment and integrates the environmental contributions of forestry activities, which have frequently been overlooked in previous research. Thirdly, to address the limitations of the traditional Data Envelopment Analysis (DEA)-Malmquist model, the study employed the Super-Efficiency Epsilon-Based Measure-Malmquist (SE-EBM-Malmquist) model and the Super-Efficiency Slacks-Based Measure-Malmquist (SE-SBM-Malmquist) model to assess AGTFP accurately. These approaches were chosen to improve the credibility and scientific rigor of the study. Lastly, countries worldwide are exploring effective strategies to promote digital rural communities' development and enhance agricultural ecological environmental construction. This study extensively investigates the mechanisms behind the DRD's role in AGTFP, particularly from digital inclusive finance (DIF) perspectives and the integration of primary, secondary, and tertiary industries (IPST). This approach significantly enriches the research framework concerning their interrelationship. In addition, this study examines

the impact of the DRD on AGTFP by analyzing the differences in informatization levels and geographic locations among provinces. This study provides empirical evidence for the targeted implementation of digital rural strategies and the comprehensive promotion of green transformation in agriculture worldwide. It also offers insights into DRD for countries experiencing regional development imbalances.

The structure of this paper is presented as follows. Section 2 focuses on literature review. Section 3 introduces research hypotheses. Section 4 presents the models and data used in the analysis. Section 5 discusses benchmark regression, endogeneity tests, robustness tests, and studies of mechanisms and heterogeneity. Section 6 concludes with a summary and discussion.

2 Literature review

2.1 Research background

Digital transformation in rural areas is increasingly recognized as a critical driver of environmental sustainability and enhanced production efficiency, attracting significant global interest. Developed nations have been at the forefront of incorporating digital economy strategies into their agricultural sectors. Examples include large-scale smart agriculture in America, intelligent livestock farming in Germany, innovative greenhouse production in the Netherlands, and compact intelligent equipment in Japan, significantly boosting agricultural productivity and facilitating rural modernization (Dvorsky et al., 2023). The United Nations Food and Agriculture Organization promotes the “Digital Villages” initiative worldwide to foster broader participation in digital agriculture governance. This strategic effort is designed to drive the transformation of agricultural and food systems and to enhance the sustainability of agricultural practices globally. Globalization presents many opportunities for China’s digital villages, aligning them with international standards in technology application and facilitating collaboration and exchange. Moreover, it has enabled China to share its experiences and case studies of DRD globally, thereby contributing to the sustainable development of rural economies worldwide (Balsa-Barreiro et al., 2019).

Weak infrastructure and inadequate public services have long impeded the development of China’s rural areas (Liu D. et al., 2023). In response, China has initiated and is actively advancing digital village initiatives aimed at digitally transforming and upgrading traditional infrastructure in rural regions. These initiatives also foster deep integration between the Internet and specialized agricultural practices, gradually enhancing the socio-economic development of agricultural and rural communities. Moreover, the fundamental conditions in China differ significantly from those in developed nations, with notable disparities in development levels, economic structures, resource allocation, and urbanization between China’s eastern and inland regions (Liu W. W. et al., 2022). Through its strategy of promoting DRD, China is actively working to diminish the economic and social disparities between urban and rural areas and between the eastern, central, and western regions, aiming to achieve balanced regional development and harmonious national progress. Consequently, these disparities provide an ideal platform for examining the effectiveness of DRD in areas with uneven development. Thus, this study offers valuable insights for other nations grappling with similar challenges of regional development imbalance.

2.2 Literature on AGTFP

2.2.1 Measurement methods

Given the urgent need for sustainable development, scientifically and effectively evaluating the performance of AGTFP has become a vital issue. Currently, the primary methods for measuring AGTFP include Stochastic Frontier Analysis and DEA. Compared to Stochastic Frontier Analysis, DEA can handle decision units with multiple input and output indicators simultaneously without requiring a specific production function to be set (Liu D. et al., 2021). These advantages make DEA more widely used. The traditional DEA model does not account for the slack in input–output variables, making it unable to calculate efficiency values that include undesirable outputs accurately. In recent years, incorporating undesirable outputs, such as environmental pollution, into the AGTFP measurement framework has become an essential aspect of productivity research. Furthermore, although a range of models within the DEA framework are prevalently utilized for assessing static efficiency, they do not capture the temporal dynamics of efficiency trends among decision-making units (DMUs).

The Malmquist productivity index method allows dynamic panel data analysis from a time series perspective (Diewert et al., 1982). Integrating it with DEA can be utilized to calculate changes in productivity (Fare et al., 1994). Hence, Zhou and Zhang have attempted to use extended DEA-Malmquist models that consider undesirable outputs to measure AGTFP, aiming for more accurate results (Zhou and Zhang, 2024). To further ensure more accurate efficiency evaluations, researchers have applied extended DEA models to assess AGTFP, building on the studies by Tone (2002). For instance, Jiang et al. (2024) employed the SE-SBM-Global Malmquist-Luenberger index model to evaluate AGTFP across various Chinese agricultural provinces. Similarly, Lu F. et al. (2024) used the SE-SBM-Global Malmquist index to assess AGTFP in agricultural regions of China. Notably, the EBM, which combines radial and non-radial features, effectively addresses the challenges of calculating efficiency values inherent in traditional DEA and SBM models. This model merits further investigation for its potential to improve productivity assessments in AGTFP (Jin and Ren, 2022).

2.2.2 Measurement indicators

Input variables, desirable and undesirable output are integral to evaluating AGTFP within the DEA model. Yet, the academic field has not agreed on the specific inputs and outputs crucial for accurately measuring AGTFP. Existing research predominantly identifies key inputs in agricultural production as capital, labor, land resources, machinery, chemical fertilizers, diesel, agricultural water, and agricultural plastic film (Ge et al., 2018; Yang and Tong, 2023; Jiang et al., 2024). Future research needs to incorporate additional input factors into the analysis framework to more comprehensively assess the impact of resource utilization efficiency on AGTFP. Additionally, as resources become scarcer and the prices of resource factors rise, it is increasingly crucial to achieve greater output with minimal investment (Maroušek et al., 2020; Vochozka et al., 2020a; Vochozka et al., 2020b). Existing studies generally use metrics such as total agricultural output (Liu Y. et al., 2021) or agricultural value-added (Ge et al., 2018) when assessing desired agricultural outputs. The former quantifies the overall production scale, whereas the latter evaluates the net economic contribution of agricultural activities. The selection of traditional indicators in terms of undesirable output indicators was based on research by Lai et al. (2004) and Chen et al. (2006). These studies conclude that agricultural pollution measurements

primarily stem from chemical oxygen demand, total nitrogen, and total phosphorus generated collectively by chemical fertilizers used on farmland, livestock and poultry farming, organic solid wastes from farmland, and rural living. However, the choice of these indicators has been contentious. For instance, manure from livestock has long been used as organic fertilizer in crop production, and its role as a pollutant is debatable (Maroušek and Maroušková, 2021). Given these issues, the academic community has revisited undesirable agricultural outputs in light of the Intergovernmental Panel on Climate Change reports and the realities of climate change. An increasing number of studies consider carbon emissions during agricultural production as a metric for assessing the AGTFP, such as those by Liu D. et al. (2021), Huang et al. (2022), Song et al. (2022), Luo et al. (2023) and Zhou and Zhang (2024), and this perspective is gaining increasing recognition. Simultaneously, achieving maximum efficiency in carbon emissions reduction and fostering the development of a circular economy has become a topic of intense discussion (Stávková and Maroušek, 2021; Maroušek et al., 2023a,b,c).

2.2.3 Influencing factors

Using the DEA model as a foundation for evaluating AGTFP, researchers also examine the effects of environmental financing, fiscal expenditures, environmental legislation, technical advancements, and other variables on AGTFP. Regarding environmental finance, Li et al. (2023) employed moderating and mediation effects on panel data from 30 Chinese provinces (2015–2019) to verify that the growth of green finance can considerably raise the AGTFP, with an apparent regional heterogeneity and an inverted U effect. Liu S. Y. et al. (2023) verified that green trade restrictions favorably increased the nation's AGTFP, using panel data for China and the Organization for Economic Co-operation and Development nations from 2005 to 2019. Regarding fiscal expenditures, Deng et al. (2023) confirmed that agricultural fiscal expenditures significantly increased the AGTFP of maize, and this effect was mainly realized through the enhancement of rural infrastructure. Concerning environmental regulation, the research by Sun and Zhang (2021) indicates that stricter environmental regulations are positively correlated with higher levels of AGTFP. Furthermore, by validating the “Porter Hypothesis,” they highlight the pivotal role of green innovation technologies in linking environmental regulation with AGTFP. In addition, Xiong et al. (2023) conducted a relevant investigation. In the field of technological advancement, Wang et al. (2024) utilized panel data from the China Family Panel Studies for the years 2016, 2018, and 2020 as their sample. Their research confirmed that farmers' use of the internet significantly enhances AGTFP.

2.3 Literature on the DRD

In the digital wave, the rapid emergence of modern digital information technologies, epitomized by the internet, is increasingly becoming a crucial driver in implementing digital rural strategies worldwide (Kliestik et al., 2024; Valaskova et al., 2024). Although digital technologies have significantly transformed rural areas, there is a scarcity of studies on the digitalization of rural settings (Cowie et al., 2020; Wang H. et al., 2022). Rural areas are characterized by their unique and diverse nature, and their challenges and technological contexts vary between countries. Consequently, there are different interpretations of the understanding of digital villages. Concerning the DRD's conceptual clarity, the majority of studies have theorized the digital phenomenon considering regional experiences with rural living; hence, for instance,

various researchers have given it different names, such as “Platform Ruralism” (Wang W. et al., 2022), “Smart Villages” (Bokun and Nazarko, 2023), “Rural Broadband” (Ali and Duemmel, 2019; Schmit and Severson, 2021), and “Digital Villages” (Irwansyah, 2020), etc. Simultaneously, the existing assessments of DRD encompass both multidimensional comprehensive indicators (Zhu and Chen, 2022) and single-dimension evaluation metrics (Wang et al., 2021). Nevertheless, research on accurately gauging the level of DRD remains scarce, and a mature indicator evaluation system still needs to be developed.

Previous studies on DRD have mainly concentrated on the urban–rural digital divide (Salemink et al., 2017). As digital technologies increasingly permeate rural areas, it is essential to shift our research focus from solely examining disparities in digital access to exploring the specific impacts of DRD on rural socio-economic development, quality of life enhancements, and the promotion of sustainable agricultural practices. Xia et al. (2019) believe that the DRD, supported by digital technology, may stimulate the high-quality growth of agriculture, contributing to economic development. Galperin et al. (2022) verified the beneficial effects of broadband deployment on labor income and employment in rural Ecuador to enhance quality of life. Additionally, DRD demonstrates significant potential for environmental protection and sustainable agricultural development. Demonstrated in their study that green growth in agriculture is driven by DRD, employing methods such as fixed effects models and mediated effects models. In their critical analysis of the research on intelligent agriculture's efficacy, Zul Azlan et al. (2024) clarified how innovative agricultural technology can curb environmental hazards, spur green economic development, and advance social inclusion. Moreover, comparable research on the DRD and their ecological effects include those by Shen et al. (2022) and Fu et al. (2023).

2.4 Literature review of the DRD on AGTFP

As DRD progressively evolves, the academic community has comprehensively evaluated its environmental impacts. Current research primarily focuses on specific aspects of the DRD, such as the effects of digital applications on AGTFP, including areas like DIF (Gao et al., 2022; Shen et al., 2024), internet use (Wang et al., 2024), digital technology (Sun et al., 2023; Du et al., 2024), rural broadband (Li, 2024) and agricultural mechanization (Lu S. et al., 2024). However, comprehensive measurements of DRD to delve deeper into their relationship with AGTFP are scarce. Among the few studies, Du et al. (2023) have shown that DRD boosts AGTFP by promoting scaled agricultural operations and agricultural informatization. Additionally, the DRD indirectly enhances AGTFP by promoting green technological advancements and improving resource allocation efficiency (Guo, 2024). Similarly, Lu F. et al. (2024) found that DRD enhances AGTFP by stimulating entrepreneurial activities in rural areas, with the mediating effect of these activities accounting for 3% of the total effect. Nevertheless, more potential mechanisms remain to explore further to affirm the relationship between these factors.

2.5 Literature gaps and improvements

In summary, the studies provide strong literature support for this paper's research direction, indicator selection, and measurement methods. However, it should be noted that there are still some

deficiencies in the current research. Regarding the indicators, on the one hand, a mature evaluation system for measuring DRD has not yet been established, necessitating a more multidimensional assessment. On the other hand, the indicators for AGTFP need further refinement. Additionally, more input factors should be included in the calculations to comprehensively reflect the resource use in the production process and its impact on AGTFP. Regarding research methodologies, while the conventional DEA-Malmquist model is widely used for productivity measurement, it has some limitations. More innovative methods are available for measuring AGTFP, ensuring greater accuracy in research findings. Regarding research content, most existing studies begin by examining the application of digital technologies in specific rural aspects to assess their impact on AGTFP. Literature that comprehensively measures DRD across multiple dimensions and explores its effects on AGTFP is rare. Furthermore, more potential mechanisms await discovery to further confirm the relationship between these two areas.

Given this, the paper expands and improves the existing research in four ways: initially, the study develops a comprehensive assessment framework for DRD, covering five critical dimensions: infrastructure, production, operation, circulation, and life services, which enriches the research on the evaluation system of DRD indicators. Secondly, in addition to traditional measures of AGTFP, the study incorporates afforestation area as an input indicator. This inclusion reflects the recognition that afforestation activities enhance the ecological value of land and are integral to sustainable agricultural strategies (Hou et al., 2020). Factoring in afforestation areas enables a more holistic assessment of agricultural activities' environmental impacts and contributions. Thirdly, to mitigate the inherent shortcomings of conventional DEA models, this study initially applies the SE-SBM-Malmquist model for assessing AGTFP. This model moderates the strict proportional assumption between inputs and outputs by incorporating slack variables, enabling more accurate efficiency evaluations for DMUs. Following this, the EBM model, which includes both radial and non-radial characteristics, is utilized to resolve the issues encountered in the efficiency calculations of the radial DEA and SBM models. Consequently, the SE-EBM-Malmquist model is applied to re-assess AGTFP, enhancing the credibility and scientific rigor of the study. This approach yields two sets of AGTFP values, facilitating further analysis. Finally, this study comprehensively explores the impact of DRD on AGTFP from the perspectives of DIF and the IPST, thereby expanding the research framework between them. Previous literature typically considered DIF and IPST as independent variables, examining their relationship with AGTFP. This study treats these factors as mechanism variables, further deepening our understanding of how DRD influences AGTFP. Additionally, the paper conducts a heterogeneity analysis across provinces with different levels of informatization and geographic locations, revealing the asymmetric effects of DRD on AGTFP, thus providing more nuanced insights for policymakers.

3 Research hypotheses

3.1 The direct influence of the DRD on AGTFP

The neoclassical theory of economic growth posits that continual increases in input factors and sustained enhancements in productivity are the fundamental drivers of long-term growth (Solow, 1999). Concurrently, endogenous growth theory points out that as inputs of

material resources such as labor, capital, and land reach saturation, their marginal returns begin to decline, whereas the marginal returns on knowledge and technology tend to increase (Helpman, 1992; Kopf, 2007). Similarly, the significance of technological advancements in enhancing the quality and efficiency of production factors is underscored both in economic development theory (Becker, 1962) and innovation systems theory (Markard et al., 2015). Therefore, knowledge and technology are essential endogenous drivers of total factor productivity increase due to their positive externalities (Vu, 2013; Chou et al., 2014). Combined with the above theoretical analysis, we believe that in the current digital information era, integrating digital technology with the traditional agricultural economy and society significantly contributes to the growth of the AGTFP.

Specifically, the DRD encompasses five dimensions: digital infrastructure, digital production, digital operation, digital circulation, and life service digitalization. Each plays a significant role in driving AGTFP, so our hypothesis is structured around these five dimensions.

- (1) Digital infrastructure: The DRD is epitomized by digital infrastructure. This foundational development in digital infrastructure has catalyzed the digitization of agricultural production, operations, circulation, and living services for rural residents. It has provided essential technical and informational support to enhance AGTFP. Furthermore, it has fostered the efficient utilization of resources and the sustainable development of rural environments.
- (2) Digital production: The DRD is reflected in the digitization of agricultural production. Adopting digital technologies has facilitated a shift from labor-intensive agricultural practices to technology-driven methods (Klerkx et al., 2019). Various digital tools, including the Internet of Things, big data, and artificial intelligence, provide precise guidance for optimizing crop structures and irrigation systems. These technologies offer comprehensive technical support across all stages of agriculture—from seeding and nursery to planting, harvesting, and storage—effectively reducing production costs and enhancing agricultural efficiency (Papadopoulos et al., 2024).
- (3) Digital operation: The DRD enables market entities to adapt to complex external environments through continuous production and operational strategy improvements. On the one hand, digital management via e-commerce platforms directly connects agricultural products with consumers, reducing intermediary steps and lowering transaction costs. This allows agricultural producers to better adjust their production strategies based on market demand, thereby avoiding overproduction and resource waste. On the other hand, more precise market positioning and product distribution contribute to reducing carbon footprints and environmental pressure (Ji et al., 2024).
- (4) Digital circulation: Utilizing network media and the platform economy, DRD has expanded the functionality of integrated agricultural production and sales systems, establishing a deeply interconnected agricultural economic ecosystem. This cohesive technological strategy not only bolsters the efficiency of the entire agricultural supply chain but also mitigates carbon footprints through streamlined transportation logistics (Falter et al., 2023). Consequently, agricultural circulation becomes more eco-friendly, fostering the evolution of a sustainable agricultural model attuned to ecological preservation (Bosworth et al., 2023).

- (5) Life service digitalization: DRD can leverage digital technologies to revitalize rural resource elements, enhance the application and conversion of knowledge and technology within the agricultural economy, and foster innovative services for rural living. These initiatives stimulate the growth of rural digital markets, effectively addressing disparities in resource allocation and spatial constraints typical in rural development. This not only ensures fairness in development but also significantly improves the quality of life of rural residents, thereby providing strong support for the sustainable development of the rural economy.

From the above analysis, the DRD enhances agricultural production's technical efficiency and improves agriculture's environmental sustainability and economic benefits (see Figure 1). Based on this, the following hypothesis 1 is proposed:

H1. The DRD can significantly promote AGTFP.

3.2 Mechanisms for the impact of the DRD on AGTFP

3.2.1 Mechanical effects of the DIF

The DRD offers the opportunity to achieve financial inclusion and sharing for all by enhancing the accessibility and convenience of financial services. This can effectively facilitate the redistribution of social resources and contribute to the advancement of high-quality rural development (Pang and Wang, 2023). In traditional setups, rural areas often face difficulties accessing financial services due to their remote locations and a lack of adequate banking infrastructure. Within the framework of the DRD, digital finance empowers farmers in these remote areas by providing access to financial services and credit resources through mobile payment platforms and online banking. Furthermore, DRD can effectively improve rural financial services' coverage breadth and depth.

The DIF significantly contributes to the enhancement of AGTFP. By integrating digital financial services, agricultural practices can more effectively utilize financial resources and alleviate financing constraints enterprises face. On the one hand, regarding risk prevention and control, DIF provides farmers with a more flexible and broad coverage of agricultural insurance products. Banking financial institutions can automatically approve crop conditions based on technologies such as the Internet, satellite remote sensing, and remote video, conduct online insurance coverage for agriculture insurance, and improve the efficiency of credit services, thereby helping farmers cope with income instability caused by natural disasters or market volatility. On the other hand, in promoting the green transition to agricultural investment by providing startup funds, entrepreneurial loans, and subsidies specifically for sustainable farm projects, the DIF can encourage farmers to invest in water-saving irrigation systems, bio-fertilizers, and other environmentally friendly technologies. Adopting these technologies directly increases ecological sustainability, thereby boosting the AGTFP.

In summary, DIF boosts financial inclusion in rural areas, directly supporting agriculture's modernization and green transformation. This transformation not only enhances the efficiency and environmental sustainability of agricultural production but also strengthens the overall competitiveness of rural economies. Hence, the study proposes the following hypothesis 2 (see Figure 1):

H2. The DRD can promote AGTFP through the effect of the DIF.

3.2.2 Mechanical effects of the IPST

Rural industrial integration refers to agriculture-based, through industrial penetration, industrial linkage, etc., to complementarity and synergy between industries and the integration of the entire agricultural industry chain development model. Industry agglomeration theory posits that the IPST strengthens inter-industry connections and facilitates the sharing of technology, resources, and information (Fan and Scott, 2003). The DRD leverages digital technologies to integrate agriculture, manufacturing, and services seamlessly. This integration fosters the development of an industrial ecosystem that enhances the efficiency and sustainability of the agricultural economy (Yang et al., 2023). Significantly, it boosts AGTFP.

Specifically, the IPST influences the green development of agriculture primarily through three aspects: (1) Improving agricultural productivity: The DRD can enhance the efficiency and quality of agricultural production by integrating intelligent agricultural technologies. These smart systems improve resource efficiency and enable continuous environmental monitoring and management, advancing agriculture's green development. (2) Promoting deep processing and value-added agricultural products: The DRD can merge agriculture and manufacturing through digital technologies, enhancing agricultural products' deep processing and branding. This approach increases the market value of products and boosts farmers' incomes. (3) Integrating agriculture and services through digital construction: Digital platforms, mainly e-commerce, enable agricultural products to move directly from producers to consumers. This shortens the supply chain, reduces resource consumption, and cuts carbon emissions in intermediate stages.

As the integration of the three industries in rural areas progresses, the increasing specialization and intensification of agricultural production not only enhance the efficiency of resource use and reduce waste but also lower the environmental costs associated with agriculture. This shift drives the greening of the agrarian output, establishing it as a trend for long-term and effective rural development. Therefore, hypothesis 3 is as follows (see Figure 1):

H3. The DRD can enhance AGTFP by promoting the IPST.

4 Research design and data sources

4.1 Model construction

The core issue of this study is to identify the relationship between the DRD and the growth of AGTFP. Based on panel data, the empirical analysis employs a two-way fixed effects model for the benchmark regression model. The model is set as follows:

$$\ln AGTFP_{it} = \alpha_0 + \alpha_1 DRD_{it} + Controls_{it} + Year FE_t + Province FE_i + \varepsilon_{it} \quad (1)$$

In Equation 1, i, t respectively indicate the province and the year; The study defines the value of green total factor productivity in agriculture measured by the SE-SBM-Malmquist model as AGTFP1 and by the SE-EBM-Malmquist model as AGTFP2; DRD_{it} represents the digital rural development status in province i during year t ; $Controls_{it}$ indicates the set of control variables; $Year FE_t$ denotes year fixed effects, for which the study employed interaction terms between control variables and year fixed effects; The term $Province FE_i$

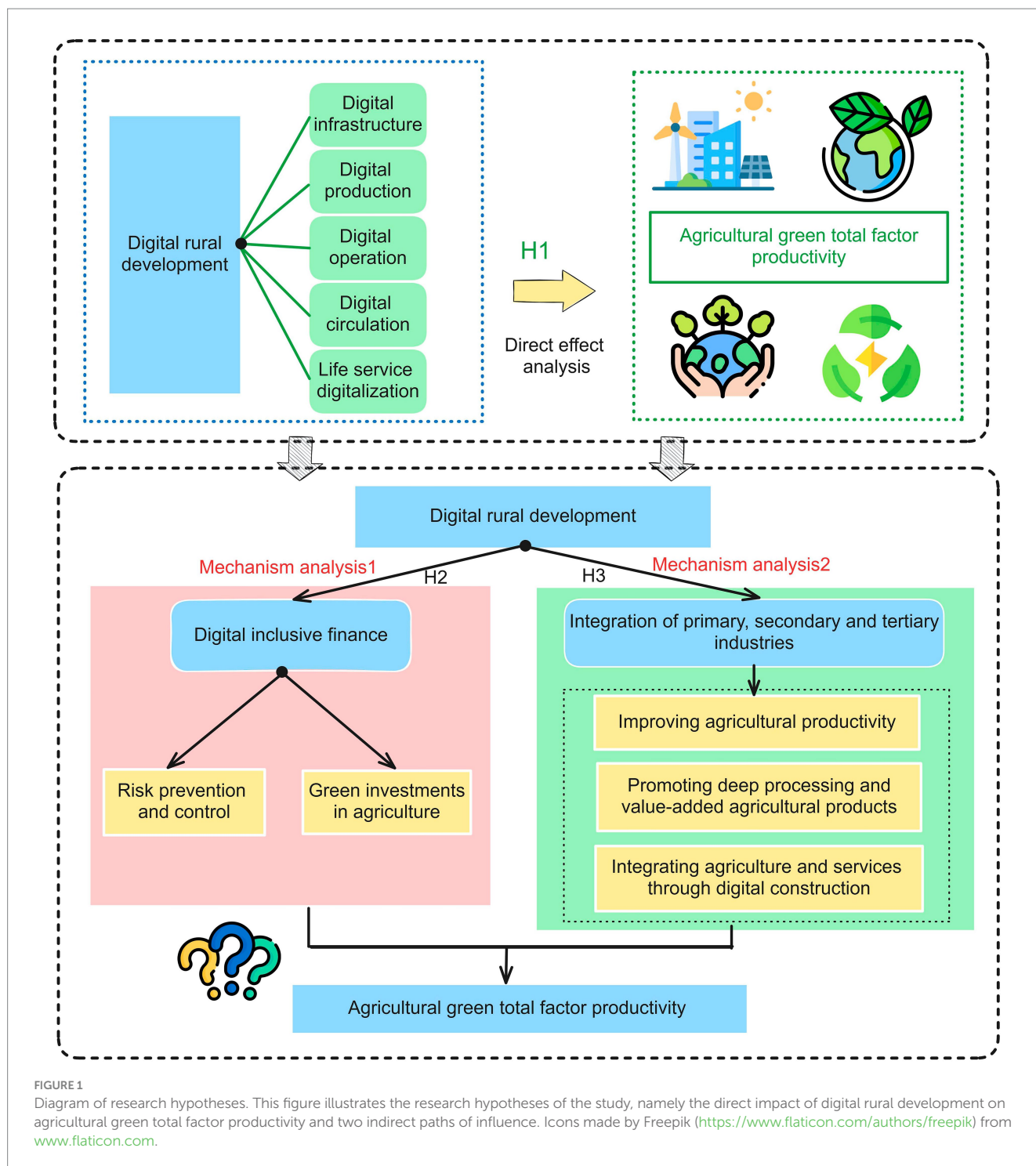


FIGURE 1 Diagram of research hypotheses. This figure illustrates the research hypotheses of the study, namely the direct impact of digital rural development on agricultural green total factor productivity and two indirect paths of influence. Icons made by Freepik (<https://www.flaticon.com/authors/freepik>) from www.flaticon.com.

denotes province fixed effects, which were addressed by using interaction terms between control variables and provincial fixed effects; ε_{it} represents the random error term; α_0 is the constant.

4.2 Variable selection and data description

4.2.1 Explained variables

The explained variable in this study is the AGTFP. To address the comparability issues of AGTFP across different periods, this study

employs the MAXDEA9 software, utilizing both the E-SBM-Malmquist and SE-EBM-Malmquist models. These models were applied to evaluate the AGTFP of 30 provincial-level administrative regions of mainland China (excluding Tibet) from 2011 to 2020, designated as AGTFP1 and AGTFP2, respectively (SE-SBM-Malmquist: AGTFP1; SE-EBM-Malmquist: AGTFP2). Additionally, the raw scale productivity data may exhibit heteroscedasticity. To mitigate this issue, data were logarithmically transformed to conform more closely to statistical models' assumptions and enhance the analysis's interpretive power. The specific computational methods and indicators selected are detailed below.

4.2.1.1 Methods of measurement

4.2.1.1.1 SE-SBM

The DEA model is a widely used method for measuring the efficiency of inputs and outputs. The efficiency value calculated by the traditional DEA model can only be kept in the interval (0,1], with efficient DMUs all assigned a value of 1, which makes it impossible to compare the effective DMUs further. Additionally, issues related to slack and undesirable outputs may introduce biases into the calculated efficiency scores. [Tone \(2001\)](#) formulated the SBM model to address the limitations, which adopts a non-radial and non-angular methodology. This model significantly enhances accuracy by overcoming weaknesses inherent in conventional DEA methodologies. Further advancing this approach, [Tone \(2002\)](#) integrated the advantages of super-efficiency models with the SBM model to create the SE-SBM model. This innovative model effectively handles undesirable output issues and comprehensively evaluates DMUs at the efficiency frontier. Drawing on the approach of [Song et al. \(2022\)](#), this study initially implemented the SE-SBM model to assess the AGTFP statically. Assuming a set of n DMUs, denoted as $DMU_j (j=1,2,\dots,n)$, each DMUs is characterized by m inputs, represented by $x_i (i=1,2,\dots,q_1)$. Desired output is recorded as $y_r (r=1,2,\dots,q_2)$, and undesirable output as $b_t (t=1,2,\dots,q_3)$. The model is configured as stated in [Equation 2](#):

$$\rho = \min \frac{1 + \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{ik}}}{1 - \frac{1}{q_1 + q_2} \left(\sum_{r=1}^{q_1} \frac{s_r^+}{y_{rk}} + \sum_{t=1}^{q_3} \frac{s_t^{b-}}{b_{rk}} \right)}$$

$$\begin{cases} \sum_{j=1, j \neq k}^n x_{ij} \lambda_j - s_i^- \leq x_{ik} \\ \sum_{j=1, j \neq k}^n y_{rj} \lambda_j + s_r^+ \geq y_{rk} \\ \sum_{j=1, j \neq k}^n b_{tj} \lambda_j - s_t^{b-} \leq b_{tk} \\ 1 - \frac{1}{q_1 + q_2} \left(\sum_{r=1}^{q_1} \frac{s_r^+}{y_{rk}} + \sum_{t=1}^{q_3} \frac{s_t^{b-}}{b_{rk}} \right) > 0 \\ \lambda \geq 0, s^- \geq 0, s^+ \geq 0 \end{cases} \quad (2)$$

where ρ is the efficiency evaluation index; s_i^- , s_r^+ , and s_t^{b-} are the input slack variable, desirable output slack variable, and undesirable output slack variable, respectively; and the λ_j is the weight of the DMU. If the efficiency value ρ exceeds 1, the efficiency for that year is in an optimal state.

4.2.1.1.2 SE-EBM

To ensure the robustness of the results, the SE-EBM model is employed for static measurement of AGTFP once again. The model is an improvement on the SE-SBM model. It facilitates the effective integration of both radial and non-radial approaches by relaxing the assumption of proportional reduction in radial function inputs. Additionally, it accommodates the radial ratios between the input frontier and actual values and the non-radial slack based on input differentiation. Consequently, this model

effectively addresses the limitations of both radial and non-radial models and overcomes the deficiencies of the SE-SBM model ([Tone and Tsutsui, 2010](#)). The specific model configuration is as follows:

$$\gamma^* = \min \frac{\theta - \varepsilon_x \sum_{i=1}^m \frac{\omega_i^- s_i^-}{x_{ik}}}{\varphi + \varepsilon_y \sum_{r=1}^s \frac{\omega_r^+ s_r^+}{y_{rk}} + \varepsilon_b \sum_{p=1}^q \frac{\omega_p^{b-} s_p^{b-}}{b_{pk}^b}$$

$$\begin{cases} \sum_{j=1}^n \lambda_j x_{ij} + s_i^- = \theta x_{0i}, i = 1, 2, \dots, m \\ \sum_{j=1}^n \lambda_j y_{rj} + s_r^+ = \varphi y_{rk}, r = 1, 2, \dots, s \\ \sum_{p=1}^n \lambda_j b_{pj} + s_p^{b-} = \varphi b_{pk}, p = 1, 2, \dots, q \\ \lambda_j \geq 0, s_r^+ \geq 0, s_i^- \geq 0, s_p^{b-} \geq 0 \end{cases} \quad (3)$$

in the above [Equation 3](#), s_i^- is the slack variable for the desired output of class r , s_p^{b-} is the slack variable for the class p non-desired output; ω_p^{b-} are the weighting indicators of each of the above, respectively; b_{pj} is the class p non-desired output of decision cell j ; b_{pk} is the class p non-desired output of decision cell k .

4.2.1.1.3 Malmquist index

Various models under the DEA framework are extensively utilized for static efficiency assessments. However, these models fail to capture the dynamic trends in efficiency changes over time among DMUs. To address the limitations of DEA's discontinuous description, this paper introduces the Malmquist index to evaluate the dynamic changes in AGTFP across provinces over time. This index measures changes in productivity by assessing the distance between DMUs and the production frontier ([Malmquist, 1953](#)). Consequently, this study integrates DEA with the Malmquist index, employing the SE-SBM-Malmquist and SE-EBM-Malmquist methods to analyze the dynamic changes in AGTFP across provinces over multiple periods. The change rate of AGTFP from period t to $t+1$ can be measured by the Malmquist index between periods t and $t+1$. The model is set up as follows in [Equation 4](#):

$$AGTFP^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \sqrt{\frac{D^t(x^{t+1}, y^{t+1}) D^{t+1}(x^t, y^t)}{D^t(x^t, y^t) D^{t+1}(x^{t+1}, y^{t+1})}} \quad (4)$$

4.2.1.2 Indicator selections

Input variables, desirable and undesirable outputs are essential for assessing AGTFP using the DEA model. In selecting input indicators, this study draws on the research of [Jiang et al. \(2024\)](#), [Ge et al. \(2018\)](#), and [Yang and Tong \(2023\)](#), selecting capital, labor, land resources, irrigation, pesticides, chemical fertilizers, agricultural plastic film, agricultural machinery, and diesel as input factors. Additionally, this study introduces afforestation area as a novel input indicator. An increase in afforestation area reflects investments in sustainable land management and environmental protection, which enhance the

ecological value of the land, boost carbon sequestration, and increase vegetation productivity (Xiao et al., 2015). By including this input indicator, a more comprehensive assessment of AGTFP can be achieved. Moreover, agricultural carbon emissions exacerbate global climate change, leading to rising temperatures, altered precipitation patterns, and increased extreme weather events, accurately reflecting the negative environmental impacts of agricultural activities (IPCC, 2007). Hence, this paper follows Ding et al. (2022) in using calculated values of agricultural carbon emissions as a definition for undesired outputs, with sources including chemical fertilizers, pesticides, plastic film, diesel, plowing, and irrigation. Finally, inspired by the research of Guo and Liu (2020), this study selects the total agricultural output value as the desired output. The specific inputs and outputs selected are shown in Figure 2.

4.2.2 Explanatory variable

The explanatory variable in this study is DRD. Previous literature primarily focused on building indicators for DRD that concerned the digital economy, industry applications, and service innovation (OECD, 2014; Pant and Hambly Odame, 2017). Nevertheless, this paper aligns with Chinese policy documents and incorporates the research findings of Zhang et al. (2020), Yin et al. (2020), and Zhou and Deng (2023) to establish a comprehensive DRD evaluation indicator system. This system, detailed in Table 1, comprises five key dimensions: digital infrastructure, digital production, digital operation, digital circulation, and life service

digitalization. Regarding the measurement approach, the study utilizes the entropy weight method to assess the extent of DRD, drawing on the analysis of Zhu and Chen (2022). The specific procedures involved in this measurement process are outlined as follows:

Step 1: normalization of primary data

In the initial step, the extreme value method is employed for the non-quantitative normalization of primary data. The formulas used to handle the positive and negative indicators are distinct, as outlined in Equation 5 and Equation 6 below:

For positive variables:

$$X_{ijt} = \frac{x_{ijt} - \min(x_{jt})}{\max(x_{jt}) - \min(x_{jt})} \quad (5)$$

For negative variables:

$$X_{ijt} = \frac{\max(x_{jt}) - x_{ijt}}{\max(x_{jt}) - \min(x_{jt})} \quad (6)$$

X_{ijt} represents the normalized value of the j th indicator for the i th province in year t , where $i=1, 2, \dots, m$ (m being the total number of

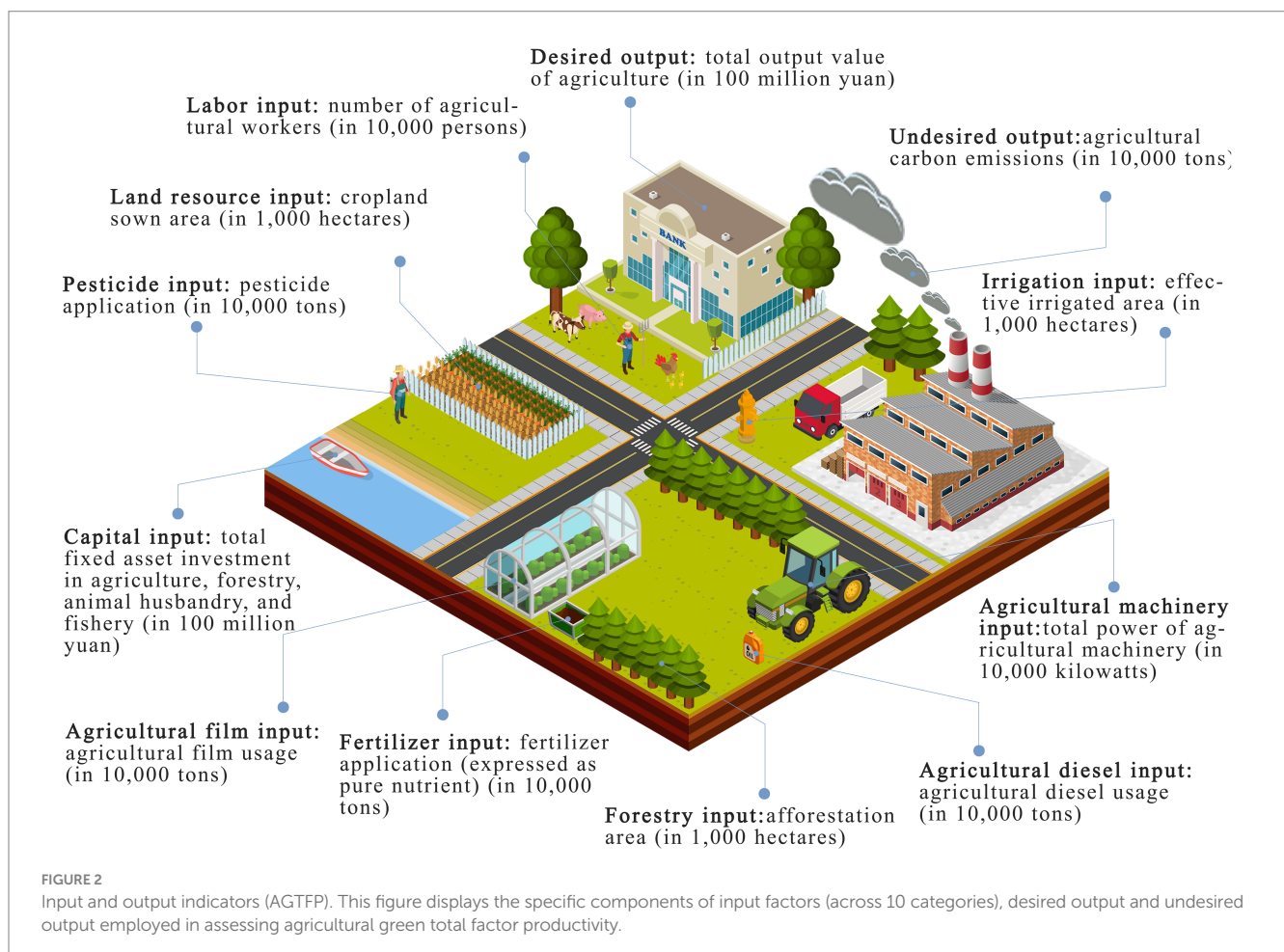


TABLE 1 Digital rural development indicators.

Target layer	Sub-target layers	Criteria layers	Calculating methods	Unit	Weight
DRD	Digital infrastructure	Internet prevalence rate (+)	District Internet users/district population	%	0.0192
		Mobile coverage (+)	Number of mobile phones per 100 households in rural areas	Pieces	0.0123
		Optical cable line coverage (+)	Length of fiber optic lines (China Telecom)	Kilometers	0.0541
		Fixed investment in the social digital industry (+)	Investment in fixed assets in information transmission computer services and software industries	100 million yuan	0.0541
		Fixed investment in social digital services (+)	Investment in fixed assets in the transport, warehousing, and postal sectors	100 million yuan	0.0486
	Digital production	Environmental testing of agricultural output (+)	Number of agrometeorological observation operating sites	Pieces	0.0235
		Electrification of agricultural production (-)	Value added of agricultural and forestry fisheries/total rural electricity consumption	Yuan/kilowatt-hours	0.0041
		Rural digitization base (+)	Number of Taobao villages	Pieces	0.3354
	Digital operation	Number of enterprise websites (+)	Number of websites per 100 enterprises	Pieces	0.0071
		Enterprise participation in e-commerce (+)	The proportion of enterprises participating in e-commerce transaction activities	%	0.0296
		E-commerce sales (+)	Total amount of goods and services sold based on online orders	100 million yuan	0.1173
		E-commerce procurement (+)	The total amount of goods and services purchased based on online orders	100 million yuan	0.1240
	Digital circulation	Level of rural postal communications services (+)	Average rural service population per post office network	Person	0.0423
		Retail sales of rural consumer goods (+)	Retail sales of rural consumer goods (100 million yuan)/ society-wide retail sales of consumption goods (100 million yuan)	%	0.0183
		Rural delivery line (+)	The length of the route submitted to rural users on the delivery section	Kilometers	0.0371
		Proportion of administrative villages with postal service (+)	Postal administrative villages/all administrative villages	%	0.0021
	Life service digitalization	Farmers' transportation spending level (+)	Percentage of transportation and communication expenditures in farmers' spending	%	0.0226
		Effective invention patent rate (+)	The proportion of effective invention patents to total invention patent applications	%	0.0270
		Number and scale of rural networks (+)	Digital inclusive finance mobile payment index (province), calculated from the Center for Digital Inclusion of Peking University	-	0.0213

This table delineates the five constituent dimensions of the DRD: digital infrastructure, digital production, digital operation, digital circulation, and life services digitalization. Each dimension is accompanied by an explanation of its relevant indicators and the methodologies employed for their measurement. Additionally, the table specifies the weight attributed to each dimension in the computation of the DRD index. The symbol “(+)” indicates that the indicator exhibits a positive value; the symbol “(-)” signifies that the indicator shows a negative value.

provinces), and $j=1, 2, \dots, n$ (n being the total number of indicators). $\max(x_{jt})$ denotes the maximum value of the j th indicator across all years, while $\min(x_{jt})$ represents the minimum value. These normalization techniques ensure that all indicators are scaled uniformly between 0 and 1, facilitating a more effective comparative analysis across different variables and periods.

Step 2: calculation of the proportional value

For each indicator j of province i in year t , the proportional value, P_{ijt} is computed as outlined in Equation 7:

$$P_{ijt} = \frac{X_{ijt}}{\sum_{i=1}^m X_{ijt}} \tag{7}$$

Step 3: determination of the entropy threshold

The entropy threshold E_{jt} for indicator j in year t is calculated using the Equation 8:

$$E_{jt} = -\frac{1}{\ln m} \sum_{i=1}^m P_{ijt} \ln P_{ijt} \quad (8)$$

Step 4: calculation of indicator weights

The weight W_{jt} of each indicator j in year t is derived as shown in Equation 9:

$$W_{jt} = \frac{Y_{jt}}{\sum_{j=1}^n Y_{jt}}, Y_{jt} = 1 - E_{jt} \quad (9)$$

Step 5: computation of the DRD index

Finally, the DRD index for each province i in year t is calculated specified in Equation 10:

$$DRD_{it} = \sum_{j=1}^n W_{jt} \times X_{ijt} \quad (10)$$

This index combines the weighted contributions of all indicators to provide a comprehensive measure of the dynamic changes in each province.

4.2.3 Control variables

To mitigate the impact of the missing variable, the study selected five control variables, each characterized by distinct attributes.

- (1) Human capital level (HCL): The HCL captures the variation in educational attainment across provinces in China, significantly influencing labor productivity. This variation in human capital is particularly relevant during the digitization process; agricultural workers with a solid educational background and applicable skills are more adept at mastering and utilizing advanced digital technologies, thus enhancing agricultural productivity. The HCL is quantified by the ratio of students enrolled in higher education to the total population. A logarithmic transformation is applied to this ratio to normalize the data.
- (2) Agricultural financial support (AFS): Adopting agricultural technology and advanced production management models heavily relies on government financial contributions. Increasing the AFS is crucial to promoting the development of high-quality agricultural productivity and fostering the establishment of low-energy agricultural production systems (Hu et al., 2021). Following the research by Tang and Sun (2022), the study selected the ratio of government financial support for agricultural development to total local fiscal expenditure as an indicator and applied a logarithmic transformation to it.

- (3) Impact of natural disasters on agriculture (INDA): The frequent occurrence of severe natural disasters, such as floods, droughts, and hail, significantly reduces the effectiveness and availability of resources, thereby threatening agricultural productivity (Platania et al., 2022). Consequently, the study selected the area of farmland affected by these disasters as the control variable and applied a logarithmic transformation to the data (Data sources: National Bureau of Statistics of China, n.d.).
- (4) Rural electricity level (REL): Modern electrical facilities support the use of environmentally friendly agricultural technologies, such as precision irrigation and low-carbon energy technologies. These advancements reduce dependence on fossil fuels and decrease the negative environmental impacts of agricultural activities. Consequently, the ratio of rural electricity consumption (in ten thousand kilowatt-hours) to the rural population (in ten thousand) is utilized as the control variable. This data is then subjected to logarithmic transformation.
- (5) Innovation level (INL): Innovation plays a crucial role in transforming agricultural production methods, enhancing productive efficiency, and achieving sustainable agricultural development (Ren et al., 2023). Therefore, the study utilized the urban innovation index calculated by Kou and Liu (2017). The study aggregated city panel data according to the provinces in which they were located to obtain the innovation index for each province. This data was then subjected to logarithmic transformation.

4.2.4 Data sources and sample description

This paper is based on sample data from 30 provincial-level administrative regions of mainland China (excluding Tibet) between 2011 and 2020. The relevant data are mainly from the China Statistical Yearbook, the China Rural Statistical Yearbook, the China Environmental Statistical Yearbook, the China Trade and Foreign Economic Statistics Yearbook, the Peking University Digital Comprehensive Financial Index, the Ali Research Institute (n.d.) report, and the monthly statistical report on imports and exports of Chinese agricultural products. Other sources include China's Urban and Industrial Innovation Power Report 2017 and the official website of the National Bureau of Statistics of China (n.d.). The descriptive statistics of the above data are shown in Table 2.

5 Empirical analysis

5.1 Benchmark regression analysis

Before executing the benchmark regression analysis, a collinearity assessment was conducted. The findings showed that the Variance Inflation Factors for all variables remained under 10, confirming the absence of significant collinearity within the model. Subsequently, the study utilized Equation 1 for the benchmark regression to explore the interactions among the primary variables of interest. In Table 3, the dependent variables are AGTFP1 and AGTFP2, and the primary explanatory variable is the DRD. Columns (1) and (3) show the estimation results when the control variables are included, with regression coefficients of 0.320 and 0.191, respectively, both significant at the 5% level. Additionally, this study incorporates year

TABLE 2 Descriptive statistics.

Notation	Variable	N	Mean	SD	Min	Max
lnAGTFP1	Agricultural green total factor productivity (SE-SBM-Malmquist)	300	0.110	0.170	-0.280	0.970
lnAGTFP2	Agricultural green total factor productivity (SE-EBM-Malmquist)	300	0.060	0.090	-0.150	0.440
DRD	Digital rural development	300	0.170	0.090	0.060	0.630
lnHCL	The level of human capital	300	-3.950	0.270	-4.820	-3.190
lnAFS	Agricultural financial support	300	-2.220	0.330	-3.190	-1.590
lnINDA	Natural disaster impacts	293	5.260	1.530	-1.610	7.890
lnREL	The level of rural electricity	300	-0.170	1.130	-2.240	3.840
lnINL	Innovation level	300	4.400	1.510	0.200	7.810

This table shows the summary statistics and definitions of the main variables in the empirical analysis. The "ln" denotes the natural logarithm. The "SD" stands for standard deviation.

TABLE 3 Benchmark regression results.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Variable	lnAGTFP1			lnAGTFP2		
DRD	0.320**	0.318**	0.292*	0.191**	0.190**	0.177**
	(2.163)	(2.133)	(1.800)	(2.352)	(2.320)	(2.015)
Control variables	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	N	Y	Y
Province FE	N	N	Y	N	N	Y
N	293	293	293	293	293	293
Adj. R ²	0.022	0.021	0.034	0.023	0.023	0.031

This table presents an estimation of the impact of DRD on the AGTFP. The dependent variables are lnAGTFP1 and lnAGTFP2. The results provide preliminary validation of H1. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. The robust t-values are given in (). The control variables are lnHCL, lnAFS, lnINDA, lnREL, and lnINL. Year FE is incorporated through interaction terms between the control variables and year fixed effects. Province FE is integrated via interaction terms between control variables and province fixed effects.

fixed effects into the model to mitigate the impact of time trends. The results, presented in columns (2) and (5), remain statistically significant. Moreover, recognizing that each province may have distinct cultural, economic, and policy environments that could affect the dependent variables, the study further integrated province fixed effects into our regression analysis to control for potential omitted variable bias due to unobserved provincial attributes. As indicated in columns (3) and (6), the results are significant at the 10% and 5% levels, with the coefficients being 0.292 and 0.177, respectively. These demonstrate that the DRD has significantly enhanced the AGTFP, confirming H1.

Existing research predominantly discusses the impact of DRD on green agricultural growth from singular perspectives, such as digital technological innovations (Yang R. et al., 2024), rural e-commerce (Ji et al., 2023), or digital inclusive finance (Gao et al., 2022; Liu D. et al., 2023). In contrast, our study constructs a multi-dimensional set of DRD indicators, further confirming a positive relationship between DRD and the enhancement of AGTFP. This conclusion aligns with the findings of a few studies, such as those by Jiang et al. (2022), Shen et al. (2022), Du et al. (2023), and Sun et al. (2023). Distinctly, unlike previous studies that often rely on a single dependent variable, our study employs the SE-SBM-Malmquist and SE-EBM-Malmquist models to calculate AGTFP and integrates these measurements into regression analyses, enhancing the reliability and robustness of the research findings.

The empirical analysis highlights that DRD holds significant practical implications for advancing green development in rural areas. On the one hand, by harnessing information technology and upgrading infrastructure, DRD facilitates precise agricultural management. This not only enhances crop yields but also mitigates agricultural carbon emissions and surface pollution (Maroušek, 2023), thus making a substantial contribution to the greening of agricultural production (Maroušek et al., 2023a,b,c). On the other hand, the development of e-commerce platforms and the enhancement of rural logistics networks through DRD have significantly broadened the distribution channels for agricultural products. This enables agricultural producers to align directly with market demands, streamline supply chains, and reduce the consumption of resources and production inputs, thereby playing a pivotal role in fostering the green transition and diversified development of the agricultural economy (Wang H. et al., 2022).

5.2 Endogeneity tests

5.2.1 Propensity score matching tests

To mitigate potential selection bias, this study implements propensity score matching (PSM) to align observable variables between the treatment and control groups, thereby reducing the influence of selection bias on the regression results (Rosenbaum and Rubin, 1983; Shipman et al., 2017).

Provinces with DRD exceeding the yearly average are designated as the treatment group (coded as 1), with the remainder forming the control group (coded as 0). This study employs the widely used nearest-neighbor matching method, which involves pairing units from the treatment and control groups based on the smallest absolute difference in propensity scores. After matching, only control group provinces that closely match the characteristics of those in the treatment group are retained. Subsequently, the study conducted a balance test, with results showing that the standardized biases for most variables were below 10%. This indicates an enhanced balance between the treatment and control groups following the matching, as depicted in Figure 3.

Following variable matching, balance was established between the treatment and control groups, aligning with the balance assumption of PSM. The matched samples obtained through PSM effectively reduced the systematic differences among control variables, providing a solid data foundation for more accurate regression analysis. The regression results are displayed in Table 4. Estimates incorporating control variables are shown in columns (1) and (4), while columns (2) and (5) include additional year fixed effects, and columns (3) and (6) integrate province fixed effects. The analysis revealed that the estimated coefficients consistently achieved significance at the 1% level. Compared to baseline regression analyses, the results after PSM appear more significant. This indicates that the presence of endogeneity may lead to an underestimation of ordinary least squares results, failing to isolate the effects of other factors on AGTFP. The use of PSM effectively circumvents this issue.

5.2.2 Lagged variable estimation

Simultaneity bias might arise between independent and dependent variables, wherein they mutually influence each other, complicating the determination of causality. This paper employs a

lagged variable approach to mitigate this immediate interaction and address potential issues of reverse causality and endogeneity. By regressing the independent variables at a one-period lag, the study examines the delayed impact of DRD on AGTFP. This methodology effectively reduces the immediate feedback loops among variables, as the lagged values are not immediately affected by the current values of the dependent variables. As demonstrated in Table 5, the regression coefficients for the dependent variables lnAGTFP1 and lnAGTFP2 remain significantly positive, confirming that the baseline regression results are robust.

5.3 Robustness tests

5.3.1 Province-year clustering robust standard error estimates

Considering the potential correlations among data points across different years within the same province and provinces within the same year in economic, social, and cultural aspects, this study adopts the methodology from Shen et al. (2023). It incorporates province-year interaction clustered robust standard errors to address potential biases in standard error calculations that may arise from these correlations. The province-year interaction clustering not only enhances the inferential statistics of the model but also increases the reliability of the research findings. As shown in Table 6 columns (1) and (4) present the estimates with control variables, columns (2) and (5) include estimates with year fixed effects, and columns (3) and (6) add province fixed effects to the existing model, with all results proving significant. The findings in Table 6 reinforce those of Table 3, demonstrating that even after accounting for intra-group correlations (within provinces) and

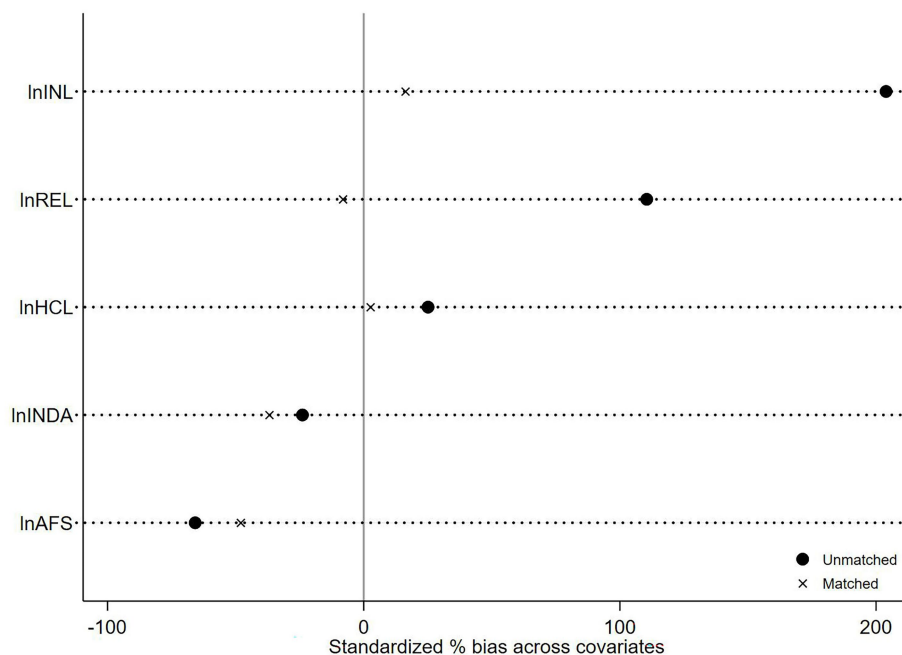


FIGURE 3 Results of the balance test.

TABLE 4 Results of PSM estimation.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Variable	lnAGTFP1			lnAGTFP2		
DRD	1.335***	1.349***	1.387***	0.798***	0.806***	0.855***
	(2.753)	(2.780)	(2.764)	(3.121)	(3.150)	(3.316)
Control variables	Y	Y	Y	Y	Y	Y
Year fixed effects	N	Y	Y	N	Y	Y
Province fixed effects	N	N	Y	N	N	Y
N	147	147	147	147	147	147
Adj. R ²	0.028	0.028	0.005	0.041	0.041	0.026

This table illustrates the estimated impact of DRD on AGTFP after PSM tests. The dependent variables are lnAGTFP1 and lnAGTFP2. These results further confirm the validity of H1. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. The robust t-values are given in (). The control variables are lnHCL, lnAFS, lnINDA, lnREL, and lnINL. Year FE is incorporated through interaction terms between the control variables and year fixed effects. Province FE is integrated via interaction terms between control variables and province fixed effects.

TABLE 5 Results of lagged variable estimation.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Variable	lnAGTFP1			lnAGTFP2		
DRD	0.396**	0.392**	0.374*	0.243**	0.241**	0.234**
	(2.226)	(2.196)	(1.933)	(2.508)	(2.478)	(2.233)
Control variables	Y	Y	Y	Y	Y	Y
Year fixed effects	N	Y	Y	N	Y	Y
Province fixed effects	N	N	Y	N	N	Y
N	263	263	263	263	263	263
Adj. R ²	0.022	0.021	0.035	0.027	0.026	0.038

This table displays the results of lagged estimates from endogeneity tests. The dependent variables are lnAGTFP1 and lnAGTFP2. These findings further support our proposed H1. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. The robust t-values are given in (). The control variables are lnHCL, lnAFS, lnINDA, lnREL, and lnINL. Year FE is incorporated through interaction terms between the control variables and year fixed effects. Province FE is integrated via interaction terms between control variables and province fixed effects.

TABLE 6 Results of the province-year clustering robust standard error estimation.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Variable	lnAGTFP1			lnAGTFP2		
DRD	0.304**	0.302**	0.279*	0.184**	0.182**	0.171**
	(2.113)	(2.082)	(1.752)	(2.318)	(2.289)	(1.987)
Control variables	Y	Y	Y	Y	Y	Y
Year fixed effects	N	Y	Y	N	Y	Y
Province fixed effects	N	N	Y	N	N	Y
N	293	293	293	293	293	293
Adj. R ²	0.025	0.024	0.038	0.030	0.029	0.041

This table displays the results of robustness checks using province-year clustered robust standard error estimation. The dependent variables are lnAGTFP1 and lnAGTFP2. These findings further substantiate H1. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. The robust t-values are given in (). The control variables are lnHCL, lnAFS, lnINDA, lnREL, and lnINL. Year FE is incorporated through interaction terms between the control variables and year fixed effects. Province FE is integrated via interaction terms between control variables and province fixed effects.

autocorrelations (within years), the main variables of the model still exhibit significant statistical effects.

5.3.2 Winsorization analysis

This study employed a winsorization analysis to assess the robustness of the model results, especially in the presence of potential outliers. Compared to truncation analysis, winsorization is better

suitable for small sample datasets where preserving all data points is crucial (Jose and Winkler, 2008). This approach involves replacing extreme observations: values below the 1st percentile are replaced with the 1st percentile value, and values above the 99th percentile are replaced with the 99th percentile value. After this exclusion, the model parameters were re-estimated, and the results remained robust (see Table 7), enhancing the research findings' reliability.

TABLE 7 Results of the winsorization analysis.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Variable	lnAGTFP1			lnAGTFP2		
DRD	0.304**	0.302**	0.279*	0.184**	0.182**	0.171**
	(2.113)	(2.082)	(1.752)	(2.318)	(2.289)	(1.987)
Control variables	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	N	Y	Y
Province FE	N	N	Y	N	N	Y
N	293	293	293	293	293	293
Adj. R ²	0.025	0.024	0.038	0.030	0.029	0.041

This table presents the results of robustness tests conducted after the winsorization analysis. The dependent variables are lnAGTFP1 and lnAGTFP2. H1 is further confirmed. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. The robust t-values are given in (). The control variables are lnHCL, lnAFS, lnINDA, lnREL, and lnINL. Year FE is incorporated through interaction terms between the control variables and year fixed effects. Province FE is integrated via interaction terms between control variables and province fixed effects.

5.3.3 Tests to exclude the effect of COVID-19

During the COVID-19 pandemic, agriculture faced unconventional operational challenges, such as labor shortages, logistics disruptions, and market demand changes. These challenges may temporarily distort agricultural production efficiency and patterns (Liu Y. et al., 2022), making it difficult to assess the impact of normal-level DRD on AGTFP. Therefore, the study excludes the years during the pandemic and retained the data from 2011 to 2019 to better reflect the true and sustained impact of DRD on AGTFP. Table 8 shows columns (1) and (4), which present the estimation results with control variables included. Columns (2) and (5) show results by adding year fixed effects. Columns (3) and (6) further incorporate provincial fixed effects. The results are significant and consistent with the benchmark regression findings.

5.4 Mechanism tests

The findings discussed earlier demonstrate that DRD can foster the AGTFP. But what mechanisms drive this impact? To address this question, the study develops a mechanism effect model grounded in our research hypotheses:

$$\text{Mechanism}_{it} = \beta_0 + \beta_1 \text{DRD}_{it} + \text{Controls}_{it} + \text{Year FE}_t + \text{Province FE}_i + \varepsilon_{it} \quad (11)$$

In the Equation 11, Mechanism_{it} serve as mechanical variables, for which the study has selected IPST and DIF as the mechanical variables; Year FE_t denotes year fixed effects, for which the study employed interaction terms between control variables and year fixed effects; The term Province FE_i denotes province fixed effects, which were addressed by using interaction terms between control variables and provincial fixed effects. Our study on DIF draws upon the research by Guo et al. (2020), employing the Digital Inclusive Finance Index compiled by the Institute of Digital Finance Peking University (n.d.). This index comprises three dimensions: the breadth of digital finance coverage, depth of usage, and the degree of digitalization in inclusive finance, providing a comprehensive depiction of the development of DIF in China. Financial data frequently exhibit

significant heteroscedasticity due to variations in institutional sizes or transaction volumes. Logarithmic transformation is utilized to stabilize the variance of variables, which is why the study applies logarithmic transformations to DIF. To measure the IPST, our approach builds on the studies by Xiao and Du (2019), developing an evaluation system for integrating rural industries. This system comprises five dimensions: extension of the agricultural industry chain, expansion of agricultural multifunctionality, development of new agricultural business, economic benefits, and social benefits, with 11 criteria layers, detailed in Table 9. Data for all indicators can be downloaded from the website of the National Bureau of Statistics of China (n.d.). Subsequently, the entropy weighting method is employed to calculate the IPST Index, using the methodology described earlier. The results of the mechanical tests are presented in Table 10.

The underlying premise of the DIF mechanism posits that the DRD enhances the accessibility and convenience of financial services in rural areas. Such improvements foster a green transformation in agricultural risk management and investment through digital innovations, thus supporting the growth of AGTFP. Following this rationale, the study further examines the role of DIF within this context. The results, as presented in columns (1) and (2) of Table 10, indicate that after including control variables and year fixed effects in column (1) and further adding province fixed effects in column (2), the estimations are both significantly positive at the 1% level. This demonstrates that DRD significantly enhances DIF, substantially increasing the AGTFP, thereby confirming H2. These findings illustrate the vital role of digital finance in facilitating a transition towards greener and more sustainable agricultural practices. Previous studies (Liu S. Y. et al., 2023; Xie et al., 2023) have examined the direct effects of DIF on AGTFP. In contrast, our research conceptualizes DIF as a mechanistic variable, thus clarifying the relationship between DRD and DIF, and more clearly delineating the pathway through which DRD enhances AGTFP. This approach reveals more intricate mechanisms of influence and helps fill the research gap in the literature on enhancing AGTFP through agricultural digitalization and suggesting strategic directions for promoting DIF within DRD.

The fundamental premise of the industrial integration and development mechanism is that the DRD enhances agricultural production efficiency, facilitates the deep processing and value

TABLE 8 Test results excluding the effect of COVID-19.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Variable	lnAGTFP1			lnAGTFP2		
DRD	0.394**	0.394**	0.380**	0.227**	0.228**	0.218**
	(2.392)	(2.382)	(2.074)	(2.501)	(2.490)	(2.188)
Control variables	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	N	Y	Y
Province FE	N	N	Y	N	N	Y
N	264	264	264	264	264	264
Adj. R ²	0.026	0.026	0.018	0.033	0.033	0.019

This table shows the results of robustness tests that exclude the impact of the COVID-19 pandemic. The dependent variables are lnAGTFP1 and lnAGTFP2. This result further supports our H1. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. The robust t-values are given in (). The control variables are lnHCL, lnAFS, lnINDA, lnREL, and lnINL. Year FE is incorporated through interaction terms between the control variables and year fixed effects. Province FE is integrated via interaction terms between control variables and province fixed effects.

addition of agricultural products, and fosters the growth of rural e-commerce and services. This digital advancement drives the IPST, leading to a more cohesive and efficient economic structure in rural areas. As rural integration of the three industries progresses, the specialization and intensification of agricultural production can enhance the efficiency of agricultural resource use, reduce resource waste, and lower environmental costs in agriculture (Samusevych et al., 2021). Consequently, this contributes to an improvement in the AGTFP. Building on this rationale, the study conducted a mechanical analysis. In column (3) of Table 10, control variables along with year fixed effects were included, and the coefficient is significantly positive at the 1% level, estimated at 0.328. Column (4) extends the model by integrating provincial fixed effects to account for potential biases due to provincial characteristics. The resulting coefficient is positive at the 1% significance level, recorded at 0.406. These confirm that the DRD notably enhances AGTFP by promoting IPST, thereby validating H3.

5.5 Heterogeneity tests

The impact of DRD on AGTFP is likely to be heterogeneous, owing to significant variations in resource endowments, informatization development status, and the baseline levels of rural green development across different regions in China. The study further explores this heterogeneous impact by examining the varying levels of informatization within DRD and by analyzing the specific geographical locations of the provinces. To gauge the informatization level, the study utilizes the total post and telecommunications business ratio to the gross domestic product (Data sources: National Bureau of Statistics of China, n.d.). A province is classified as having a high level of informatization if its value exceeds the median of the sample for that particular year; otherwise, it is considered to have a low level of informatization. The sample includes 146 provinces categorized as high informatization and 147 as low informatization. For regional classification, the study adheres to the standards set by the National Bureau of Statistics of China (n.d.), dividing the sample into eastern, central, and western provinces to conduct heterogeneity analyses.

5.5.1 Heterogeneity of informatization level

The regression results are shown in Figure 4. It is observed that DRD has a significant positive impact on AGTFP in provinces with high informatization levels. However, the coefficients of DRD on AGTFP are not statistically significant in provinces with low informatization levels. The possible reasons for this are: In rural areas with advanced information technology, local farmers are often more capable of adopting new technologies and implementing modern management techniques. This enhances their ability to use digital technologies efficiently, boost agricultural productivity, optimize resource allocation, and reduce waste. Furthermore, areas with high levels of information technology infrastructure—including high-speed internet, data processing centers, and advanced communication facilities—benefit from strong technical support for agricultural production. This infrastructure facilitates the rapid, accurate collection and dissemination of agricultural data. Conversely, regions with limited access to information technology often face economic and technological disadvantages, exhibit low farm digitization and technology adoption levels, and lack the capacity for large-scale agricultural operations. These limitations impede the improvement of AGTFP.

5.5.2 Heterogeneity of geographical location

The regression results in Figure 4 demonstrate that the estimated coefficients of DRD on AGTFP are consistently positive in the central region. This suggests that DRD significantly contributes to enhancing AGTFP in the central region. Nevertheless, the calculated coefficients for DRD on AGTFP in both the eastern and western regions are not statistically significant. The geographical disparities in the success of DRD can be attributed to variations in economic structure and agricultural dependence across different regions (He et al., 2019). Regions vary significantly in terms of economic development. For instance, eastern regions tend to be more economically advanced, boasting well-established agricultural sectors and superior infrastructure. In such settings, the potential enhancements achievable through DRD intervention are relatively minimal, making it challenging to establish statistical significance. Conversely, in the less developed western regions, where infrastructure is deficient, and the economy is relatively weak, DRD holds the potential for significant improvements.

TABLE 9 Evaluation index system of the IPST.

Target layer	Sub-target layers	Criteria layers	Calculating methods	Weight
IPST	Extension of the agricultural industry chain	Share of agro-processing industry (+)	Revenue from main operations of the agro-processing industry (100 million yuan)/total output value of agriculture, forestry, animal husbandry, and fishery (100 million yuan)	0.0931
		Number of farmers' professional cooperatives per 10,000 people in rural areas (+)	Number of professional rural farmers' cooperatives/ rural population (10,000 people)	0.0921
		The ratio of the added value of the primary industry to gross regional product (-)	Value added of the primary sector (100 million yuan)/ gross regional product (100 million yuan)	0.0884
	Expansion of agricultural multifunctionality	Level of leisure agriculture (+)	Annual operating income of recreational agriculture (100 million yuan)/gross agricultural product (100 million yuan)	0.0958
		Level of facility-based agriculture (+)	Greenhouse area (millions of square meters)/crop sowing area (thousands of hectares)	0.0987
		Fertilizer application intensity (-)	Amount of agricultural chemical fertilizer (ten thousand tons)/ crop sowing area (thousands of hectares)	0.0884
	Development of new agricultural business	Proportion of rural service sector output (+)	Output value of professional and auxiliary activities in agriculture, forestry, animal husbandry, and fishery (ten thousand yuan)/total output value of agriculture, forestry, animal husbandry, and fishery (100 million yuan)	0.0911
		Mobile phone coverage (+)	Number of mobile phones per 100 rural households	0.0886
	Economic benefits	Engel coefficient for rural households (-)	Total expenditure on food purchase in rural household expenditure (yuan)/total household expenditure (yuan)	0.0853
	Social benefits	The ratio of disposable income of rural residents to urban residents (+)	<i>Per capita</i> disposable income of rural residents (yuan)/ <i>per capita</i> disposable income of urban residents (yuan)	0.0892
Ratio of <i>per capita</i> consumption expenditure of rural and urban residents (+)		<i>Per capita</i> consumption expenditure of rural residents (yuan)/ <i>per capita</i> consumption expenditure of urban residents (yuan)	0.0891	

This table constructs the calculation of the IPST from five dimensions: extension of the agricultural industry chain, expansion of agricultural multifunctionality, development of new agricultural business, economic benefits, and social benefits. Each dimension includes a detailed explanation of its relevant indicators and the methodologies used for their measurement. Additionally, the table outlines the weight assigned to each dimension in the computation of the IPST index. The symbol “(+)” indicates that the indicator exhibits a positive value; the symbol “(-)” signifies that the indicator exhibits a negative value.

TABLE 10 Mechanism analysis results.

Model	(1)	(2)	(3)	(4)
Variable	DIF		IPST	
DRD	1.686*** (3.615)	1.811*** (3.735)	0.328*** (3.088)	0.406*** (3.512)
Control variables	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Province FE	N	Y	N	Y
N	293	293	293	293
Adj. R ²	0.498	0.526	0.467	0.586

The table reveals the results of the mechanism tests, with the dependent variables being digital inclusive finance (DIF) and the integration of primary, secondary, and tertiary industries (IPST). These results confirm the validity of H2 and H3. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively. The robust t-values are given in (). The control variables are lnHCL, lnAFS, lnINDA, lnREL, and lnINL. Year FE is incorporated through interaction terms between the control variables and year fixed effects. Province FE is integrated via interaction terms between control variables and province fixed effects.

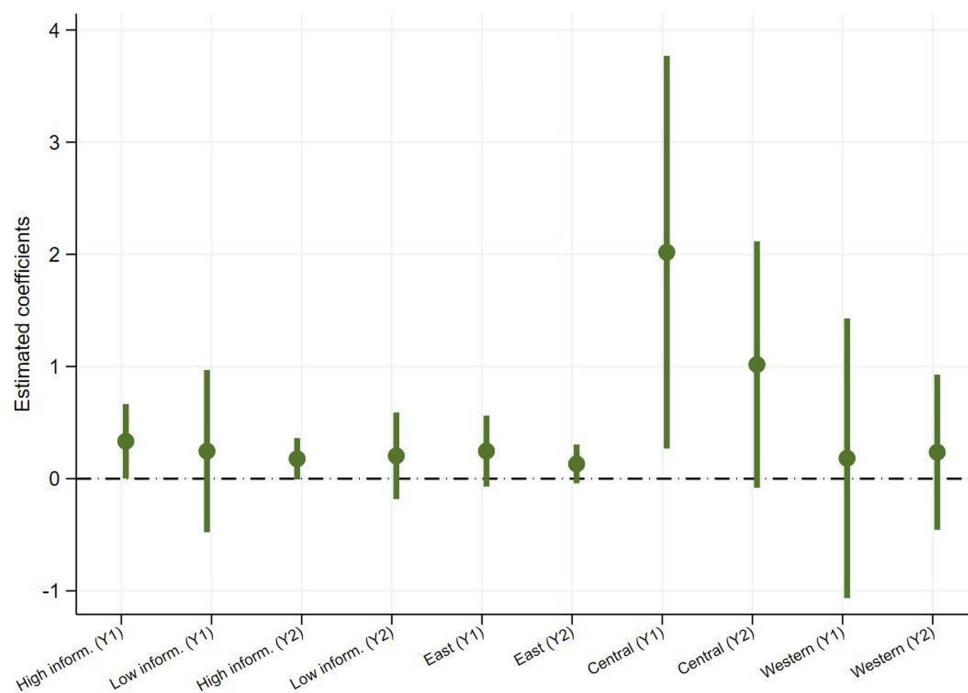


FIGURE 4 Results of heterogeneity tests. Y1 refers to $\ln\text{AGTFP1}$ and Y2 refers to $\ln\text{AGTFP2}$.

However, these improvements may not significantly impact productivity due to the region's weak foundational conditions or other constraints, such as low educational levels and challenging geographic conditions. In contrast, with its greater reliance on agriculture and a higher proportion of its economy attributed to agricultural activities, the central region is likely to experience more noticeable impacts on its economic indicators from enhancements in agricultural productivity. In the heterogeneity analysis, Jin and Ren (2022) argue that the influence of DRD on AGTFP is more marked in the eastern provinces. However, our study observes a more pronounced effect in the central provinces. This discrepancy may be attributed to differences in measurement methods and the selection of indicators. Further research will be necessary to verify these findings.

6 Conclusion and discussion

6.1 Conclusion

Amid the backdrop of rural revitalization and agricultural digital transformation, our study investigates how DRD can leverage modern information technology to enhance agricultural productivity and ecological benefits, aligning with the demands of contemporary development and offering practical guidance. This research initially seeks to evaluate the effects of DRD on AGTFP empirically. We test our hypotheses using a fixed effects model with data from 30 provincial-level administrative regions of mainland China (excluding Tibet) from 2011 to 2020. The findings demonstrate that DRD enhances AGTFP, thereby validating H1.

Furthermore, the research confirms H2 and H3, unveiling the facilitative mechanisms between DIF and IPST in the relationship between DRD and AGTFP. This provides a clear direction for global digital rural initiatives. Additionally, results from heterogeneity tests reveal that DRD significantly enhances AGTFP in regions with higher informatization levels and in the central province of China. The central provinces serve as potential hotspots for the DRD due to their strategic geographic advantages—acting as a bridge between the economically vibrant eastern regions and the developing western areas—rich industrial diversity spanning agriculture, manufacturing, and services, and strong government support. This conclusion can guide policymakers to tailor strategies according to local conditions, implementing region-specific development approaches to promote balanced growth across different areas better. In essence, this study leverages empirical analysis to showcase China's experience and practices in DRD to the global audience. It aims to offer insights and guidance for devising more scientific, efficient, and sustainable agricultural development strategies worldwide, thereby promoting green agricultural growth and facilitating rural revitalization.

6.2 Policy recommendations

Based on the research findings, the study proposes the following policy recommendations.

Firstly, accelerating the development of digital villages is crucial for optimizing green agricultural practices. This study demonstrates that constructing digital villages can significantly enhance the AGTFP. Therefore, the government can advance the

DRD across five strategic dimensions: laying a solid foundation for digital infrastructure in agriculture and rural areas by promoting the widespread adoption of broadband internet and the expansion of 5G networks into rural regions; integrating smart agricultural technologies (Marousek et al., 2012); supporting farmers in leveraging e-commerce platforms to sell their products; enhancing the management of digital supply chains for agricultural products; and improving access to and quality of digital services in education, healthcare, and entertainment. These initiatives form a comprehensive strategy that boosts agricultural efficiency and sustainability and ensures the modernization of rural communities.

Secondly, the government should promote the development of DIF to advance DRD, thereby aiding agriculture's green and high-quality transformation. This initiative starts by supporting and promoting DIF products and services, which provide farmers with more accessible and cost-effective financial resources. For instance, farmers can adopt advanced agricultural equipment and eco-friendly technologies by offering low-interest loans and subsidies tailored to eco-agricultural projects (An et al., 2023). Moreover, the government should promote the integration of DIF with sustainable agricultural practices and encourage financial institutions to develop innovative financial products and tools. These initiatives will guide agricultural enterprises towards adopting green and low-carbon production methods, ensuring the provision of high-quality financial services for advancing green agriculture (Metzker et al., 2021).

Thirdly, the government should drive the deep IPST under the DRD initiative through policy incentives and financial support. This approach begins by promoting the adoption of intelligent agricultural technologies such as precision farming techniques, utilizing big data and artificial intelligence to optimize planting structures and enhance crop yields (Marousek et al., 2013). Additionally, digital technology is used to improve the efficiency and quality of agricultural product processing, such as employing automated food processing and packaging equipment. Finally, developing e-commerce platforms facilitates the direct sale of agricultural products and provides agricultural consultancy and technical services using digital tools. By implementing these specific strategies and actions, the government can effectively promote the integration of the three industries, achieve modernization of agriculture, and enhance both the economic and environmental benefits in rural areas.

Finally, policymakers should focus on the disparities in informatization levels and resource allocation between regions to formulate targeted development strategies accordingly. On the one hand, continuing to enhance digital village infrastructure with a focus on supporting the informatization of agriculture is essential for advancing agricultural technology and optimizing the agricultural industry structure. For areas with lower levels of informatization, governments should increase investment and improve local digital infrastructure, such as enhancing internet coverage and providing more technical support services. On the other hand, digital village construction should be advanced in a manner tailored to the economic development levels of different regions. Implementing an unbalanced development strategy will continually promote the enhancement of the AGTFP, thereby driving the high-quality, green development of global agriculture.

6.3 Limitations and future directions

It should be noted that this study, constrained by data limitations, primarily utilizes data from Chinese provinces to examine the impact of DRD on AGTFP. Future research could gather multi-dimensional data and consider using data from prefecture-level cities and counties, employing various methods to delve deeper into the effects of DRD on AGTFP. Additionally, this research adopts the entropy weighting method to derive the comprehensive development index, paralleling the approach of numerous studies. However, this quantitative method overlooks diverse regions' development needs and objectives. It is recommended that subsequent studies refine evaluative metrics and frameworks to align with the unique developmental contexts and requisites of different geographical areas. Finally, the scope of future studies could expand from focusing solely on China's DRD to encompassing global digital rural initiatives. This broader perspective would enable a more precise analysis of the mechanisms at play.

Data availability statement

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

Author contributions

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

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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