frontiers | Frontiers in Sustainable Food Systems

TYPE Original Research
PUBLISHED 31 July 2025
DOI 10.3389/fsufs.2025.1607567

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OPEN ACCESS

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RECEIVED 07 April 2025
ACCEPTED 20 June 2025
PUBLISHED 31 July 2025

CITATION
Wang L and Cai Y (2025) The impact of digital economy on agricultural green total factor productivity: evidence from the quasi-natural experiment of the "Broadband China" Strategy.
Front. Sustain. Food Syst. 9:1607567.
doi: 10.3389/fsufs.2025.1607567

The impact of digital economy on agricultural green total factor productivity: evidence from the quasi-natural experiment of the "Broadband China" Strategy

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Introduction: The empowerment of agricultural green transformation through the digital economy has emerged as a critical pathway toward sustainable development.

Methods: Utilizing panel data from 286 Chinese cities spanning from 2011 to 2023, this study employs the "Broadband China" Strategy as a quasi-natural experiment to construct a multi-period difference-in-differences (DID) model. We examine the impact of the digital economy (DE) on agricultural green total factor productivity (AGTFP), while also exploring its underlying mechanisms, heterogeneous characteristics, and spatial spillover effects.

Results: The findings reveal the following: (1) The DE significantly enhances AGTFP. (2) This enhancement is driven by green technology innovation, environmental regulation, and financial development. (3) The impact of DE on AGTFP varies across natural geographical factors and socio-economic factors. (4) Positive spatial spillover effects are observed in the impact of DE on AGTFP.

Discussion: This study highlights that to achieve sustainable agricultural growth, it is crucial to continuously promote rural digital economy development, leverage financial instruments to support agricultural green transformation, implement region-specific development strategies, and strengthen inter-regional cooperation and communication.

KEYWORDS

digital economy, agricultural green total factor productivity, "Broadband China" Strategy, difference-in-differences model, financial development

1 Introduction

Agriculture, as the most fundamental sector in the national economic system, not only provides significant social benefits but also contains profound economic value. However, under the traditional agricultural model, the issue of low capital return rate has long restricted the realization of its economic potential. This reality has prompted industrialized countries worldwide to systematically integrate modern production factors into the agricultural field, with the aim of enhancing agricultural profitability and ensuring sectoral stability. For China, a country with vast agricultural resources, the post-1978 reform and opening-up period has witnessed remarkable agricultural advancements. Historical records indicate that the gross output value of the primary industry has grown at an average annual rate of 5.5% at constant prices over the past 45 years. Concurrently, national grain production has risen from 304.76 million to 695.41 million metric tons, and exceeded 700 million tons for the first time in 2024.

When reviewing China's agricultural development trajectory, a historical prioritization of quantitative growth over sustainable frameworks has brought forth a series of environmental challenges that require careful consideration, including the intensive utilization of agrochemicals driven by yield maximization, soil salinization risks associated with suboptimal irrigation practices, and farmland quality management issues linked to agricultural waste disposal mechanisms (Zhou and Zhang, 2024). Since the early 21st century, China's agricultural sector has emitted approximately 1 billion tons of CO2 equivalent annually (Tian and Yin, 2022). Notably, recent findings indicate that agricultural non-point source pollution has become a non-negligible contributor. In terms of pollutant emissions, it has exhibited a trend of exceeding industrial and domestic sources in certain indicators, accounting for 64.2% of chemical oxygen demand (COD), 52.7% of total nitrogen (TN), and 70.6% of total phosphorus (TP) emissions (Ministry of Ecology and Environment of the People's Republic of China, 2024). Such pollution incurs economic costs equivalent to 6% of agricultural GDP (Tang et al., 2016), with broader implications for ecological quality, food security, and public well-being.

The persistent ecological deficit will gradually materialize its adverse impacts on the growth potential of agriculture, suggesting that a transformative shift is worth consideration. To achieve sustainability, it is crucial to advance strategies for the green transition of agriculture to harmonize economic benefits with ecological preservation (Khan and Ali, 2022). China has consistently maintained an exploratory stance in eco-governance, deepening its insight and innovation concerning the development pathways of green agriculture through systematic methodologies. As early as 2008, the Chinese government proposed establishing a "resource-efficient and environmentally friendly agricultural production system" to modernize practices. Since the second decade of the 21st century, China has been progressively shifting its national economic paradigm from "quantity-oriented growth" to "quality-driven improvement" (Hao et al., 2021). The transition was supported by top-level strategies, with multiple Central No.1 Documents explicitly emphasizing improving agricultural quality through green development. During this period, a series of policy frameworks—including the National Agricultural Sustainable Development Plan (2015-2030), Opinions on Innovating the System and Mechanism to Promote Green Agricultural Development, and the 14th Five-Year Plan for National Green Agricultural Development—have systematically outlined the pathway for green agricultural progress. The 20th National Congress Report of the Communist Party of China further elevated agricultural green development as a key component of national rejuvenation. In contrast to conventional total factor productivity (TFP), green total factor productivity (GTFP) incorporates environmental factors into its analytical framework (Weitzman, 1976; Kumar and Khanna, 2009). This indicator effectively evaluates the level of high-quality economic development under environmental constraints, emphasizing the principles of environmental sustainability, efficiency, and green growth. Research confirms that improving agricultural green total factor productivity (AGTFP) is a viable strategy for green agricultural development (Wu et al., 2020).

The digital economy, developing at an unprecedented pace, has become the cornerstone of modern industry and a primary driver of global business innovation. This paradigm has exerted and will continue to exert a profound impact on socio-economic development and global governance evolution. According to official reports, China's digital economy has gained significant prominence within its national economic structure. By 2023, its scale had expanded 3.8 times over the past 11 years, accounting for 42.8% of the annual GDP and contributing 66.45% to overall economic growth (China Academy of Information and Communications Technology, 2024). Notably, industrial digitalization reached 43.84 trillion CNY, accounting for 81.27% of the total digital economy, thereby highlighting its pivotal role in upgrading traditional industries. Although the digital penetration rate in China's primary sector stood at 10.78% in 2023—relatively modest in comparison to the secondary and tertiary sectors—the agricultural sector is actively pursuing digital transformation to achieve leapfrog development along green growth pathways. The enhancement of AGTFP, a critical metric evaluating the dual objectives of production efficiency and environmental sustainability, fundamentally relies on the extensive application and deep integration of digital technologies. Since the implementation of the "Broadband China" Strategy in 2013, the Chinese government has progressively designated 117 pilot cities (urban clusters), fostering substantial progress in national informatization and digital economic development. This raises several critical research questions: Has this pilot policy effectively promoted improvements in AGTFP? What are the underlying mechanisms driving this effect? What distinctive characteristics do the policy effects exhibit? Addressing these questions bears significant practical implications for achieving green and high-quality agricultural development in the digital era.

The structure of this study is as follows: Following the introduction, Section 2 provides a review of relevant literature. Section 3 outlines the policy context and presents a theoretical analysis. Section 4 details the variables, models, and data employed in the study. Section 5 examines empirical results, which have been subjected to a series of robustness tests. In Section 6, we further analyze the mechanisms, heterogeneous characteristics, and spatial spillover effects. Section 7 is the discussion. Finally, Section 8 summarizes the research conclusions and offers policy recommendations.

2 Literature review

In studies examining the impact of the digital economy (DE) on AGTFP, scholars have employed both qualitative and quantitative approaches. From a theoretical perspective, Le Clech and Fillat-Castejon (2020) argued that agricultural systems have been undergoing a digital revolution, particularly through the global proliferation of Internet of Things (IoT) technologies. These innovations facilitate intelligent resource management, critical for enhancing agricultural productivity and sustainable development. Rijswijk et al. (2019) applied the concept of "disruptive forces" to characterize digitalization's transformative effects on agriculture. Through a case study of Sub-Saharan Africa, Mapiye et al. (2021) demonstrated that digitalization significantly improves accessibility to information and services, thereby enhancing agricultural productivity and farmer livelihoods. Chen (2021) identified that DE-driven rural industries leverage the multiplier effect of information technology to optimize agricultural input–output efficiency. Synthesizing these insights, Luo et al. (2022) systematically analyzed the efficiency-enhancing mechanisms and positive externalities of the DE through three dimensions—agricultural production systems, operational systems, and industrial systems. Their work further established the foundational role of digital technologies in facilitating agricultural functional expansion.

Extensive empirical research supports that the DE serves as a catalyst for TFP growth (Pfeiffer et al., 2020; Naqeeb and Giulia, 2023). The integration of digital technologies into agricultural industries has reshaped resource management paradigms, reduced allocation disparities, and led to greener practices (Sharma et al., 2020; de Obade and Gaya, 2021), with EU data validating these effects (Bocean, 2024). In Denmark, precision farming technologies and controlled traffic systems alleviate ecological pressures while generating sustained economic benefits (Jensen et al., 2012). Canadian farmers widely recognized the advantages of digitalization in enhancing work quality, advancing farm productivity, and improving agricultural profitability, particularly strong among early adopters (Abdul-Rahim et al., 2024). Although innovative technologies (e.g., GPS-based fertilization) emerge in high-income countries, they have a substantial impact on the improvement of agricultural output in underdeveloped economies (Li T. et al., 2024). In Brazil, the digital agricultural technology paradigm is oriented towards better land use and lower socio-environmental impacts, promoting the growth of ATFP in a green manner (Souza et al., 2020). In Bangladesh, the modest rate of agricultural productivity growth primarily benefits from technological progress, and this transformation is the result of the diffusion of green technologies (Bagchi et al., 2019). Evidence from six Southeast Asian countries also indicates that the sustainable path of agricultural green development is driven by technological innovation rather than technological efficiency promotion. In brief, the higher the level of green technology, the greater the likelihood of improving AGTFP (Hamid et al., 2023). A micro-survey in Tanzania reveals that digital technologies, represented by radio and SMS, have improved smallholder farmers' awareness and adoption of sustainable agricultural practices through cost-effective information dissemination (Silvestri et al., 2021). Through case studies of developing countries, Deichmann et al. (2016) demonstrated that digital technologies help mitigate information asymmetries in agricultural supply chains, unlocking potential digital dividends for rural areas. Nevertheless, they warned that multidimensional digital divides could exacerbate developmental inequalities. Krishna and Naik (2020) emphasized that limited channels for information dissemination in India contribute to gaps in crop production practices, potentially resulting in higher production costs, lower yields, and worsening environmental degradation. However, emerging evidence suggests nonlinear U-shaped or inverted U-shaped relationships between digital investments and agricultural green development (Wang et al., 2023; Fu et al., 2024; Zhou et al., 2023), whereas Dutch dairy farm case studies have demonstrated statistically insignificant effects of digital equipment adoption on productivity growth and technological advancement (Steeneveld et al., 2015).

Recent scholarly investigations have provided significant empirical insights into China's digital agricultural transformation. Based on provincial panel data from 30 Chinese mainland provinces (excluding Tibet), Hong et al. (2023) and Zeng et al. (2024) demonstrated measurable enhancements in AGTFP driven by DE. Zhang Q. et al. (2024) further elucidated that technical efficiency improvements constitute the primary mechanism underlying this productivity boost. Using the forestry sector as a case study, Chen C. et al. (2023) identified regional heterogeneity in this effect, with eastern and northeastern regions outperforming central and western. Wen et al. (2024) emphasized a critical mismatch between China's agricultural trajectory and green productivity needs. Their findings position digitization as a mediator capable of bridging this gap, thereby facilitating the development of sustainable agricultural frameworks. Moreover, several studies have covered the Yangtze River Economic Belt (Wu and Song, 2018), the Yangtze River Delta region (Bao et al., 2023) and the Dongting Lake region (Du and Dai, 2020), while others have utilized city-level data from provinces such as Jiangsu (Ma and Lv, 2024), Zhejiang (Jin and Zhong, 2024), and Shandong (Peng et al., 2024a). County-level analysis reveals that a one-percentage-point increase in rural digitalization corresponds to a 1.78% increase in AGTFP (Lu S. et al., 2024). Additionally, a survey conducted among Chinese melon farmers provides micro-level empirical support for the role of the DE in promoting the green transformation (Musajan et al., 2024). Hua et al. (2024) further argued that digital monitoring has promoted environmentally friendly practices in swine breeding.

Scholars have also adopted multidimensional analytical frameworks to examine the impact of DE on AGTFP, generating a range of interpretations and findings. Industrial evolution studies identify underlying mechanisms including industrial structure upgrading (Chen C. et al., 2023; Gao et al., 2022), rural industrial integration (Zeng et al., 2024), and agricultural industrial agglomeration (Liu, 2024). Production factor analyses emphasize the mediating roles of large-scale farmland operation (Hu et al., 2023), labor transfer (Song et al., 2025), agricultural capital deepening (Wu et al., 2025), green technological innovation (Chen C. et al., 2023; Gao et al., 2022), and production management skills (Cai and Han, 2024). Notably, Guo and Liu (2023) empirically validated a resource allocation mechanism in which digital village construction promotes AGTFP by mitigating factor mismatches in labor, land, and capital. As an optimized capital allocation mechanism, digital inclusive finance—representing the financial dimension of the DE—has a positive effect on AGTFP improvement (Gao et al., 2022), with digital logistics serving as a critical implementation channel (Xu et al., 2025). Liu et al. (2024), utilizing provincial panel data, evaluated the effectiveness of financial agglomeration in driving carbon emission reduction in the agricultural sector. Furthermore, Lu S. et al. (2024) demonstrated that rural digitization stimulates entrepreneurial activities in rural areas, thereby enhancing AGTFP—with the mediating effect accounting for 3.34% of the total effect. Threshold analyses revealed diminishing AGTFP marginal returns from digital village construction when environmental regulation exceeds optimal intensity (Cai and Han, 2024). Spatial econometric modeling has further confirmed positive spatial autocorrelation in DE, revealing significant AGTFP spillover effects through spatial weight matrices (Lu S. et al., 2024).

The reviews of existing literature reveal substantial scholarly achievements alongside three limitations: first, most studies rely on provincial-level data or use such data as a sample for regional analyzes, with scarce research conducted on larger-scale datasets. Compared to city-level data, the former is more prone to aggregation bias, which affects the accuracy of regression analysis. Second, although causal effects between DE and AGTFP have been extensively explored, the prior studies predominantly treat quantitative assessments of policy effects as part of robustness tests rather than core analytical objectives. Third, existing literature has primarily explored mechanisms through perspectives such as industrial evolution and production factors, whereas the perspective of financial development—despite finance's centrality in modern economies—remains underexplored.

Accordingly, we utilize panel data from 286 Chinese cities spanning from 2011 to 2023 and employ the "Broadband China" Strategy as a quasi-natural experiment within a multi-period difference-in-differences (DID) model to examine the impact of DE on AGTFP. We further explore the underlying mechanisms, heterogeneous characteristics, and spatial spillover effects. Compared with existing literature, the potential marginal contributions of this study are as follows: First, we use nationwide city-level panel data and a DID model to quantitatively assess the policy effects of the "Broadband China" Strategy, identifying the causal relationship between DE and AGTFP. Furthermore, we examine heterogeneity across natural geographical factors (e.g., natural geographical locations, precipitation distributions, and terrain relief degrees) and socio-economic factors (e.g., agricultural functional zones, digitalization levels, and financial literacy levels), while testing for spatial spillover effects to enhance interpretability and generalizability. Second, in constructing an evaluation index system for AGTFP, we innovatively incorporate "agricultural ecological value" as a desired output indicator—measured by the actual ecological value—thereby enhancing the scientific rigor and comprehensiveness of the evaluation framework. This approach considers not only agricultural economic value but also its ecological performance. Third, using financial development as the entry point, we constructed a comprehensive indicator system composed of financial scale, financial structure, and financial efficiency. We analyzed the role of financial development in the impact of the DE on AGTFP, highlighted the core position of finance in the modern economy, and provided new empirical evidence and policy insights for understanding how the DE promotes agricultural green transformation through financial channels.

3 Policy background, theoretical analysis, and research hypotheses

3.1 Policy background

For a prolonged period, China's digital transformation faced systemic constraints due to underdeveloped broadband infrastructure, limited network coverage, and suboptimal stability in performance. According to data from the International Telecommunication Union (ITU), in 2011, Chinese mainland ICT Development Index was recorded at 3.88, ranking 78th among 155 global economies—a significant gap relative to developed nations in Europe and North America. In response to these challenges, the Chinese government instituted the "Broadband China" Strategy and Implementation Plan in 2013, outlining five strategic priorities, including coordinated regional broadband development, accelerated network modernization, and enhanced broadband applications. In the subsequent 3 years, 117 cities (city clusters) at different levels covering the eastern, central and western regions were selected in phases as pilot zones for the "Broadband China" Strategy. The primary objective was to bolster network supply capacity and service quality through improved digital infrastructure, which laid a foundation for integrating digital elements into agricultural practices and driving green transformation.

The implementation of the strategy has yielded significant outcomes with particular relevance to fields of agriculture and rural areas. According to data from the Ministry of Industry and Information Technology (MIIT), by the end of 2024, China had 670 million fixed broadband subscriptions, with rural users comprising 29.9% of this total. This rural broadband penetration has been pivotal in enabling the adoption of digital technologies aligned with green agricultural principles. The advancement of fiber-optic networks has enabled 207 gigabit-capable cities to provide ultra-high-speed connectivity to over 500 million households, and has supported the deployment of smart agricultural systems in rural areas. For instance, precision agricultural technologies, such as GPS autosteering tractors, depend on high-speed broadband to collect and analyze real-time data (Chancellor, 2023). This process, by minimizing resource waste and environmental impact, embodies the fundamental principles of green agriculture.

Furthermore, the nation has deployed 4.251 million 5G base stations, ensuring comprehensive urban coverage at prefecture and county levels, with 5G adoption rates surging to 70%, which has enabled the development of remote monitoring and management solutions for agricultural production. In the realm of green agriculture, 5G-based technologies enable real-time environmental monitoring, automatic pest and disease identification, and carbon footprint measurement, among other functions. These capabilities enable data-driven decision-making, which helps decrease dependence on intensive farming methods, encourages sustainable land utilization, and improves the traceability of green agricultural products. These applications exemplify how improved broadband connectivity enables the adoption of green agricultural practices, aligning with China's dual objectives of digital economy advancement and ecological civilization construction.

The "Broadband China" Strategy has not only catalyzed the rapid growth of digital infrastructure but has also accelerated the pervasive integration of digital applications across various industries, thereby accelerating the convergence between the digital and real economies. Fundamentally, the DE, as a novel economic paradigm, is highly dependent on a well-developed digital infrastructure, particularly broadband networks. As the primary conduit for digital information transmission, broadband infrastructure establishes the physical foundation for digitalization. Its enhancement is manifested in multiple dimensions, such as network coverage expansion, transmission velocity optimization, and service accessibility improvement, all of which are critical indicators reflecting regional digital maturity.

Research by Zhao et al. (2020) and Tian and Zhang (2022) further confirms the strong correlation between digital infrastructure advancement and digital economic growth, highlighting the proactive role of the "Broadband China" Strategy. The highly correlation between broadband infrastructure enhancement and digitalization progression stems from the fact that advanced broadband networks not only enhance data transmission efficiency but also reduce adoption barriers for digital technology. This, in turn, promotes the widespread application of digital solutions across different industries, including agriculture. The strategic implementation creates synergistic interaction between digital infrastructure development and industrial green transformation, establishing an enabling ecosystem for digital-green integration in agricultural practices. Therefore, our study posits that the "Broadband China" Strategy serves as an institutional embodiment of digital economy evolution. Meanwhile, the strategy adopts a phased and gradual promotion model. This design meets the exogeneity requirement of policy shocks and reduces its correlation with concurrent local agricultural policies, which can be regarded as an ideal quasi-natural experiment. We employ this national pilot policy as a proxy variable to measure DE, thereby constructing a novel analytical framework to examine policy-driven digitalization impacts on agricultural sustainability.

3.2 Theoretical analysis and research hypotheses

3.2.1 The direct impact of DE on AGTFP

Departing from traditional economic paradigms, the DE, characterized by its distinctive advantages in processing massive data, reducing search costs, and improving matching quality and transaction efficiency between the supply and demand sides, is profoundly transforming conventional agricultural production methods and management practices (Borenstein and Saloner, 2001). This transformation stems from the integration of digital technologies into physical industries and their role in driving agricultural digital-intelligent transformation and green transition.

At the macro level, the sustained implementation of the "Broadband China" Strategy has invigorated the development of digital infrastructure, thereby promoting the optimization of agricultural systems. First, the strategy facilitates intelligent allocation and efficient utilization of agricultural resources. By expanding rural broadband coverage and boosting network transmission speeds, it provides essential support for digital management of agricultural production factors. Through high-speed connectivity, agricultural producers can employ IoT and big data technologies to gather real-time information on soil moisture, meteorological data, and crop growth. Such practices allow for the precise and dynamic adjustment of water, fertilizers, and pesticides, reducing resource waste and environmental pollution, and advancing the green transformation of the "input side" in AGTFP (Radoglou-Grammatikis et al., 2020; Barros et al., 2020). Second, the strategy assists in establishing a data-driven environmental monitoring and green technology dissemination system. High-speed broadband networks enable real-time tracking and quantification of environmental indicators (e.g., carbon emissions and non-point source pollution), which is achieved via remote sensing and drone technologies. Agricultural ecological data platforms facilitate dynamic ecological benefit assessments (Sun, 2022), supporting targeted green subsidy policies. Digital technologies also accelerate the diffusion of sustainable agricultural innovations, reducing technology adoption costs and driving the shift to low-emission, high-efficiency production models (Li, 2024). Third, the strategy promotes the deep integration of agricultural value chains with the DE. Emerging models such as agricultural e-commerce and smart logistics, catalyzed by broadband development, have reconfigured agricultural product supply-demand mechanisms. Rural e-commerce streamlines supply chains, reducing costs and promoting high-value-added products to optimize the "desired output" in AGTFP (Song et al., 2021). Meanwhile, broadband-supported cold chain logistics monitoring ensures product quality and reduces post-harvest waste, enhancing the overall efficiency and sustainability of the agricultural sector.

At the meso-level, the implementation of the "Broadband China" Strategy significantly promotes the integration of digital technologies into agricultural sector, thereby reshaping industrial organization and structural framework. First, the strategy enhances digital collaboration and efficiency across agricultural industry chains. The proliferation of broadband networks breaks down information barriers among production, processing, and distribution segments (Ma and Lv, 2024). Industrial internet platforms enable end-to-end data integration, from pre-production procurement to post-harvest marketing. For example, processing enterprises utilize real-time crop data to meet green product demands and guide crop structure optimization. Logistics firms optimize routes using network data, reducing agricultural product loss. Such digital coordination mitigates information asymmetry and resource misallocation, improves input–output efficiency, and boosts the technical efficiency in AGTFP. Second, the strategy accelerates greening and specialization in agricultural industrial clusters. Network platforms facilitate technology sharing, resource complementarity, and market coordination, speeding up digital transformation. In digital-developed regions, agricultural clusters establish shared laboratories and remote technical service centers via broadband, promoting green technology applications and reducing individual enterprises' R&D costs. Concurrently, cluster enterprises jointly build green brands, creating advantages of scale and environmental sustainability, thus elevating regional AGTFP (Zhang et al., 2022; Ding et al., 2024). Third, the strategy optimizes spatial allocation and structural adjustment of agricultural production factors. By reducing information search and transaction costs, it guides production factors towards greener and more efficient applications (Xu et al., 2023). This "green orientation" of factor allocation drives agricultural industries towards resource-efficient and eco-friendly models, structurally enhancing AGTFP. Moreover, digital technologies have spurred the deep integration of agriculture with the secondary and tertiary sectors (Huang et al., 2023). The integration has birthed diverse business models that expand the scope of traditional agriculture, enhancing its comprehensive benefits and market competitiveness. Broadband networks, as the linchpin of these changes, provide technological support for inter-industry integration, further optimizing resource allocation and strengthening the sustainability of agricultural growth.

At the micro-level, the robust digital infrastructure constructed through the "Broadband China" Strategy has fully unleashed the potential of digital tools, profoundly empowering behavioral shifts among agricultural production entities. First, the strategy bolsters farmers' digital literacy and willingness to adopt green production technologies. For instance, farmers can obtain green cultivation techniques (e.g., eco-friendly pest control methods) through short videos and livestreaming (Aker, 2011; Ren et al., 2023). Meanwhile, e-commerce platforms provide real-time insights into consumer preferences for green agricultural products, thereby guiding production decisions. This digital enablement decreases dependence on traditional high-pollution practices, increases the acceptance of environmentally friendly technologies, and optimizes the pure technical efficiency in AGTFP. Second, the strategy propels digital transformation and managerial modernization in agricultural enterprises. Agribusinesses leverage broadband networks to deploy IoT-based monitoring systems and intelligent equipment, facilitating precision-controlled and automated production processes. For example, sensor-based real-time soil moisture monitoring enables automated irrigation adjustments to minimize water wastage, and big data analytics refines fertilization strategies to reduce chemical inputs

(Parra-López et al., 2024). Concurrently, digital traceability systems allow enterprises to conduct full-chain environmental impact assessments from field to table, meeting consumer demand for product transparency and enhancing product added value. Such digital transformation reduces production costs while increasing the potential for green premiums (Parida and Örtqvist, 2015; Goldfarb and Tucker, 2019), creating dual impetus for AGTFP growth. Third, the strategy intensifies consumer-driven market incentives for green production. The digital ecosystem fosters a transparent market information environment, enhancing the transmission of consumer preferences. Through e-commerce platforms and social media, consumers increasingly access product-specific environmental data, showing marked preference for low-carbon and organic products that command price premiums (Peng et al., 2024b; Huang and Dou, 2024). These demand-side signals, rapidly transmitted via broadband networks to producers, compel farmers and enterprises to adopt green standards. Consequently, a "demand-driven" green transition mechanism emerges at the micro-level, achieving dual optimization of "desirable outputs" and "undesirable outputs" in AGTFP.

Based on the foregoing analysis, we propose the following hypothesis:

> *H1*: Under the "Broadband China" Strategy, DE has a significant positive effect on AGTFP.

3.2.2 The indirect effects of DE on AGTFP

3.2.2.1 Green technological innovation

As a critical integration point between the DE and green agricultural development, what theoretical logic underlies green technological innovation? The following analysis will be conducted from the dimensions of accelerated knowledge flow, transformed innovation models, and promotion and application of achievements.

First, the "Broadband China" Strategy has consolidated the infrastructure for the DE and opened up a "high-speed channel" for knowledge flow in the agricultural sector. The high-speed and wide-coverage broadband network it constructs, relying on its data integration capabilities, breaks down the barriers to knowledge flow in the traditional innovation system (Tang et al., 2021). On the one hand, it promotes the deep integration of knowledge from different disciplines and fields in green technological innovation, providing interdisciplinary support for the research and development of environmentally friendly agricultural technologies (Ning et al., 2023). On the other hand, it reduces the information exchange costs among scientific research institutions, enterprises, and farmers through digital innovation platforms, facilitating the rapid dissemination and sharing of cutting-edge theories and practical experience required for green technological innovation. The acceleration of knowledge accumulation lays a theoretical foundation for green technological innovation, enhances the quality and efficiency of innovation, and reserves technological strength for AGTFP improvement.

Second, the development of the DE has driven shifts in innovation models, particularly in the R&D phase, where its data-driven characteristics have played a crucial role. The "Broadband China" Strategy has achieved high-speed network coverage, creating conditions for the real-time collection and efficient analysis of agricultural production data. Through this, innovation entities can accurately identify the technical bottlenecks and demand pain points in agricultural green development, enhance the targeting of green technology R&D, and avoid resource waste and blind R&D efforts. Meanwhile, the application of technologies such as digital simulation and artificial intelligence in R&D has significantly shortened the technology development cycle. The high-speed data transmission channels facilitate the instant sharing of R&D data among scientific research teams in different regions, forming an efficient model of cross-regional collaborative R&D (Chen Y. et al., 2023). The improvement in R&D efficiency enables faster introduction of new technologies that meet the needs of agricultural green development. When applied to crop production, these technologies will promote the improvement of AGTFP.

Third, the application of green technological innovation achievements in agricultural production is essential to improve AGTFP, and the "Broadband China" Strategy provides critical infrastructure support for this process. Digital platforms based on high-speed broadband networks break through spatial and temporal limitations, enabling rapid dissemination of green technological innovation achievements to farmers in remote areas. Farmers can obtain green technology information through mobile terminals and solve application challenges through online video guidance, remote expert consultations, and other means (Aker, 2011; Kansiime et al., 2019). Furthermore, the DE drives transformations in agricultural production organization. Large-scale and intelligent agricultural operators, leveraging stable networks and efficient data processing capabilities, are more inclined to adopt and apply green technologies and can also drive surrounding farmers to collectively adopt new technologies. As green technological innovation achievements are widely popularized in crop cultivation, the production efficiency and sustainable development capabilities of the agricultural industry are enhanced, ultimately achieving a comprehensive improvement in AGTFP.

Based on the foregoing analysis, we propose the following hypothesis:

> *H2*: Under the "Broadband China" Strategy, DE exerts a significant positive effect on AGTFP through green technological innovation.

3.2.2.2 Environmental regulation

Environmental regulation serves as a vital means to promote the green transformation of agriculture, while the digital economy development provides momentum for environmental regulation. Taking environmental regulation as the entry point, the following theoretical discussion will be conducted from the dimensions of precise decision-making, efficient supervision, and collaborative cooperation.

First, in traditional agriculture development, the goals of environmental regulation are often constrained by issues such as incomplete information collection and lagging data updates, resulting in insufficient pertinence. However, the implementation of the "Broadband China" Strategy enables the government to rely on an information network covering all aspects of agricultural production to obtain real-time multi-dimensional data on resource utilization and pollutant emissions. Through the analysis and mining of massive data, the government can accurately identify environmental issues in different regions, and then formulate environmental standards and regulatory policies that are suitable for the actual situation of agriculture (Wang and Fu, 2022). This kind of precision-oriented approach avoids the efficiency loss of the "one-size-fits-all" model. It motivates farmers to proactively adjust production methods, increase investment in green technologies, optimize resource allocation, and improve environmental quality, providing support for the improvement of AGTFP from the institutional level.

Second, the effective implementation of environmental regulations depends on strict supervision. Technologies such as the IoT and big data promoted by the "Broadband China" Strategy have helped the government establish a full-fledged and real-time supervision system, which can accurately capture whether farmers' production behaviors comply with environmental requirements. Such efficient supervision significantly reduces regulatory costs, enhances the precision and deterrence of supervision (Hampton et al., 2013), and compels agricultural producers to abandon the traditional high-pollution and high-energy-consumption model and shift to green and low-carbon production technologies and management methods (Wang and Fu, 2022). To meet regulatory requirements, farmers will take the initiative to adopt green technologies. While reducing agricultural non-point source pollution, these technologies can improve the quality and yield of agricultural products, achieve the coordinated improvement of production efficiency and ecological benefits, and directly promote AGTFP growth (Lu H. et al., 2024).

Third, the "Broadband China" Strategy enhances information sharing and collaborative cooperation among government departments, between governments and enterprises, and between farmers. This enables the government to use digital platforms to integrate resource data from multiple departments, and to deeply integrate environmental regulation with agricultural industry policies. Based on the agricultural production data provided by the DE, the government can formulate precise industrial support policies that align with environmental regulation objectives, guiding enterprises to increase investment in green technology R&D and farmers to adopt new technologies (Song et al., 2022). Meanwhile, relying on real-time data monitoring, the government can dynamically evaluate policy effects and adjust policy directions to ensure that environmental regulations match the needs of agricultural green development. This collaborative policy system optimizes the allocation of agricultural production factors, improves resource utilization efficiency, reduces environmental costs, and creates systematic support conditions for the sustained improvement of AGTFP.

Based on the foregoing analysis, we propose the following hypothesis:

> *H3*: Under the "Broadband China" Strategy, DE exerts a significant positive effect on AGTFP through environmental regulation.

3.2.2.3 Financial development

As the cornerstone of modern economy, the financial sector also plays an indispensable role in the process of the DE promoting the improvement of AGTFP. Therefore, from the perspective of financial development, we aim to analyze this indirect impact through three dimensions: financial scale, financial structure, and financial efficiency.

In terms of financial scale, the "Broadband China" Strategy utilizes digital technologies to break through the geographical limitations of rural financial services, promoting the extension of financial services to county-level rural areas. It activates the enthusiasm of farmers and agricultural SMEs for financial participation, thereby expanding rural green financial demand (Liang et al., 2022). In response, financial institutions allocate more resources to green technology fields such as smart irrigation and precision fertilization to support the green transformation of high-standard farmland (Zhang Y. et al., 2024). Meanwhile, broadband networks help improve farmers' financial literacy and foster new business entities like agricultural cooperatives. The large-scale financing needs of these entities prompt financial institutions to expand the supply of green agricultural credit (Zhang and Wang, 2022; Ye et al., 2023). Additionally, the strategy accelerates the digitalization of agricultural industry chains, enhances production transparency, and drives financial institutions to design green financial products around industry chains. This promotes green transformation across the entire chain, forming a virtuous cycle between scale effects and green development.

In terms of financial structure, the "Broadband China" Strategy enables financial institutions to incorporate ESG factors into risk assessment. It optimizes credit structures, guides capital toward resource-saving agricultural projects, and promotes the green upgrading of traditional credit systems (Liu and Ren, 2023). The DE breaks down traditional financing barriers by relying on digital platforms to expand non-credit financing methods such as stocks and bonds, thereby constructing a diversified capital supply structure. This allows agricultural operators to flexibly adjust financing strategies and enhance the financial resilience of green production (Chu et al., 2024). In the insurance sector, digital technologies address the information asymmetry issue in traditional insurance, promoting the popularization of customized products such as climate index insurance and agricultural product price index insurance (Holmstrom, 2021; Hu et al., 2022). This optimizes risk diversification structures, enhances the risk resistance capabilities of agricultural entities, and indirectly strengthens their motivation to adopt green technologies.

In terms of financial efficiency, the "Broadband China" Strategy gives rise to new entities such as internet financial platforms. Through competition, these entities urge traditional institutions to optimize processes, enhance risk control capabilities, and shorten the launch cycle of green financial products. Digital technologies reduce rural financial transaction costs through remote services and utilize big data to precisely assess the creditworthiness and financing needs of business entities, achieving efficient matching of funds with green agricultural projects (Wang and Fu, 2022; Ding et al., 2023). Additionally, agricultural technology enterprises and financial institutions collaborate via technologies like blockchain to transform technological achievements into quantifiable credit assets. This improves the financing efficiency for green technology R&D and commercialization, promotes the large-scale application of green technologies, and achieves dual improvements in agricultural production efficiency and ecological sustainability.

Based on the foregoing analysis, we propose the following hypothesis:

> *H4*: Under the "Broadband China" Strategy, DE exerts a significant positive effect on AGTFP through financial development.

3.2.3 The spatial spillover effects of DE on AGTFP

The DE, characterized by its positive externalities, creates an environment conducive to economies of scale and scope. Through mechanisms—policy demonstration effects, factor mobility effects, and industrial radiation effects—it generates spatial spillover effects on the improvement of AGTFP in neighboring regions.

First, with the support of the "Broadband China" Strategy, the digital economy development has achieved a win-win situation between agricultural production efficiency and environmental sustainability, and established a practical development model. The policy demonstration effect prompts agricultural operators and government administrators in neighboring areas, especially those facing the challenges of high consumption and low efficiency in traditional agricultural practices, to recognize the transformative power of digital solutions. Inspired by the success of pilot zones, they actively adopt and adapt these digital approaches, exploring region-specific paths to develop green agriculture. This emulation process effectively spreads digital innovation, contributing to the overall improvement of AGTFP in surrounding regions (Lu S. et al., 2024).

Second, the "Broadband China" Strategy, with its focus on digital infrastructure development, reduces barriers in accessing green agricultural resources, gradually giving rise to the factor mobility effect (Li R. et al., 2024). Digitalization breaks down geographical constraints, allowing specialized talent to share their expertise across regions and offer valuable insights into green agricultural practices. Advanced technologies spread rapidly through the internet, enabling peripheral regions to benefit from green production innovations. Digital platforms also integrate fragmented information into a unified network, accelerating knowledge sharing and collaborative actions in green agriculture. Through these channels of talent exchange, technology spillover, and information diffusion, the DE promotes the coordinated development of green agriculture, not only locally but also in neighboring areas, thus driving up AGTFP across regions.

Third, the phased implementation of the "Broadband China" Strategy has unlocked various application scenarios for the DE in agriculture. As a critical facet, rural e-commerce bridges gaps in market access, product promotion, and brand building through network technology. By expanding the market reach for green agricultural products, it compels neighboring regions to adopt green standards to meet the growing demand for eco-friendly goods, thereby enhancing AGTFP. Additionally, the DE stimulates cross-regional industrial chain expansion, creating opportunities for the upgrading of supporting industries such as packaging, storage, and logistics. This spatial expansion broadens the influence of green agriculture, fostering extensive cooperation, shared outcomes, and the formation of regional green industrial clusters. Simultaneously, it accelerates the integration of agriculture with non-agricultural sectors like tourism, education, and culture. These emerging business models enhance the resilience and vitality of county-level economies and, through the industrial radiation effect, contribute to the overall improvement of AGTFP across regions.

Based on the foregoing analysis, we propose the following hypothesis:

> *H5*: Under the "Broadband China" Strategy, DE has the spatial spillover effects on AGTFP, and has a significant promoting effect on AGTFP both local and neighboring regions.

4 Research design

4.1 Variable selection

4.1.1 Dependent variable

Considering the significant variations in input, output, and production cycles across different sectors within the generalized agriculture (Ge et al., 2018), this study focuses on the analysis of narrow-sense agriculture (i.e., crop farming). Compared with the DEA model and SBM model, the EBM model can more accurately capture the efficiency of resource allocation through non-radial and non-angle slack variable treatment. Combined with the GML index, it can dynamically evaluate the changes in TFP, which aligns with the evaluation needs of the dual goals of "economy-ecology" in agricultural green transformation. Therefore, we employ the EBM-GML model to evaluate AGTFP. The evaluation index system is presented in Supplementary Table 1, and the relevant calculation formulas are available in the literature (Zhou et al., 2024). It is important to note that we adopt 2011 as the base period and normalize the initial value of AGTFP for each city to capture the cumulative trend in AGTFP, we convert the calculated chain base indices into fixed base indices.

In terms of input indicators, we refer to the research of Ge et al. (2018) and select five indicators to measure agricultural inputs, including land, labor force, agricultural machinery, chemical fertilizer, and water. Among them, labor force input is determined by isolating the number of employees dedicated to the agricultural industry from the total workforce in the primary industry, using the proportion of gross agricultural output value relative to the combined output value of agriculture, forestry, animal husbandry, and fishery as a weighting factor; Agricultural machinery input is calculated following the same methodological principle. Chemical pesticide and agricultural film inputs are excluded due to substantial data gaps at the city-level.

Output indicators comprise both desired and undesired outputs. For the desired output, we use the gross agricultural output value to measure the economic value of agriculture. However, the agricultural value is not only reflected in the economic value created by agricultural production, but also in the ecological value generated by non-economic functions (e.g., climate regulation, water retention, soil stabilization, and biodiversity preservation) (Sun et al., 2011). Specifically, based on the equivalent factor method (Costanza et al., 1997; Xie et al., 2005; Xie et al., 2008), we select seven crops (rice, wheat, corn, soybean, potato, oil crop, and vegetables) to calculate one standard equivalent of agricultural ecosystem services value. Following the methods of relevant literature (Yang et al., 2019), we apply correction coefficients to adjust the total agricultural ecosystem services value in order to reflect the realistic ecological value of agriculture. For the undesired output, we refer to the research of Li et al. (2011) and select four types of carbon emission sources (fertilizer, agricultural diesel, tillage, and irrigation) to estimate agricultural carbon emissions. Additionally, based on the inventory analysis method (Liang, 2011), we select the COD, TN, and TP involved in agricultural chemical fertilizer and farmland solid waste pollution sources to quantify agricultural non-point source pollution, and standardize the pollutant emissions using the equivalent pollution load method for cross-source comparability.

4.1.2 Independent variable

This study employs the "Broadband China" pilot policy as a proxy variable to measure the DE, constructed through the interaction term between city and time dummy variables. To ensure sample comparability, we excluded autonomous prefectures, county-level cities, and city samples with substantial missing data from our analysis. Following the official lists of demonstration cities (city clusters) across different implementation batches, we designate 107 cities as the treatment group (comprising 37 in the first batch, 36 in the second, and 34 in the third), while the remaining 179 cities as the control group.

4.1.3 Mediating variables

In current research, a unified measurement standard for green technological innovation has not yet been established, and there are mainly three methods: First, it is measured by the number of simple technical invention patents. In fact, this approach mainly reflects the total amount of technological innovation but does not distinguish the "green attributes" of patents, thus failing to accurately reflect the core connotation of "green technological innovation." Second, it is measured through green product innovation and green process innovation. However, both require measurement by subdivided indicators (such as product carbon footprint and process pollution emission intensity), which usually rely on survey data or industry standards. This approach is highly subjective and involves high data acquisition costs. Third, considering that environmental regulatory measures can incentivize large-scale green patent R&D, it is measured by the number of green patent authorizations or applications. The former reflects the innovative willingness and investment of R&D entities. The latter represents the substantive innovative achievements approved through official review, which can better reflect the stock of practically applicable green technologies. In summary, we select the number of green patent authorizations to measure green technological innovation (GTI). To address zero values, we process the data by adding 1 and then taking the logarithm.

The environmental regulation system consists of two major categories: formal environmental regulations and informal environmental regulations. The former can be further divided into two forms: command-and-control type and market-incentive type. Currently, China's environmental regulation system is dominated by the command-and-control type (Wang et al., 2015), which is embodied in the government's vigorous promotion of pollution control and related tasks through the introduction of a series of laws and regulations, the scientific formulation of environmental standard systems, and the enforcement of these regulations as the basis. Against this practical backdrop, we refer to the research of Shao et al. (2024), measuring environmental regulation (ER) by the ratio of the word count in sentences containing environmental protection-related vocabulary in city government work reports to the total word count of the entire report. This measurement method not only accords with the institutional characteristics of China's environmental governance, but also provides a quantitative analytical framework for comparative studies on the effects of cross-regional environmental regulations.

Financial development (FD) is a dynamic process that combines quantitative expansion and qualitative improvement, and the construction of its indicators needs to take into account the scale characteristics, structural optimization, and efficiency improvement of the financial system. We construct a comprehensive indicator system composed of financial scale, financial structure, and financial efficiency by synthesizing data availability and the financial needs of agricultural green development, and realize quantitative measurement through the entropy value method. The specific construction logic is as follows: (1) Financial scale, measured as the ratio of the balance of CNY deposits and loans of financial institutions to the regional GDP. This indicator reflects the financial system's potential to support agricultural green development by quantifying regional financial asset agglomeration relative to the total economic volume (Goldsmith, 1969). (2) Financial structure, measured as the ratio of original insurance premium income to the balance of CNY loans of financial institutions. According to the financial function theory (Levine, 1997), non-credit financing tools (such as insurance) can alleviate the risk premium of agricultural green investment through functions such as risk diversification and price discovery, forming functional complementarity with traditional credit. We also considered alternative indicators such as the proportion of direct financing, but were constrained by the small scale of direct financing of agricultural enterprises and the low data availability. Finally, the insurance-credit ratio was selected as a financial structure indicator with more realistic explanatory power. (3) Financial efficiency, measured as the loans-to-deposits ratio of financial institutions in CNY. This indicator focuses on the resource allocation efficiency of the financial system in transforming savings into investment (Stiglitz, 1985). High financial efficiency means that more social funds can flow to the agricultural green production side through credit channels, avoiding capital idling. We also considered alternative indicators such as the non-performing loan ratio, but agricultural loans are greatly affected by natural risks and market fluctuations, and the non-performing loan ratio fluctuates violently, which cannot stably and accurately reflect financial efficiency. Therefore, the loan-deposit ratio was finally adopted as the basic indicator.

4.1.4 Control variables

To mitigate potential estimation biases arising from omitted variables, we select the following control variables: (1) Industrialization (IND), measured as the ratio of secondary industry value-added to regional GDP; (2) Agricultural Fiscal Expenditure (AFE), measured as the ratio of agricultural, forestry, and water-related fiscal expenditures to total local government spending; (3) Foreign Direct Investment (FDI), measured as the ratio of FDI inflows to regional GDP; (4) Human Capital Stock (HCS), measured as the logarithm (after adding one) of the number of college students per 10,000 persons; (5) Productive Infrastructure (PI), measured as the ratio of effectively irrigated area to total crop sown area; (6) Living Infrastructure (LI), measured as the ratio of highway mileage to local land area.

4.2 Modeling

4.2.1 Baseline model

To examine the causal relationship between DE and AGTFP, we employ the "Broadband China" Strategy as a quasi-natural experiment representing exogenous policy shock in digital economy development, utilizing a DID model for identification. Given that the policy was implemented in multiple phases and batches, while a classical DID model is constrained to evaluating the policy effects at a single time point, we construct the following multi-period DID model of Equations (1, 2) to effectively analyze policies spanning multiple time points:

$$AGTFP_{it} = \alpha_0 + \alpha_1 DE_{it} + \alpha_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{1}$$

$$DE_{it} = Treat_i \times Post_t \tag{2}$$

where $AGTFP$ is agricultural green total factor productivity; DE is a policy dummy variable, and its coefficient α_1 reflects the net effect of policy implementation; $Treat$ is a city dummy variable that equals to 1 for pilot cities and 0 otherwise; $Post$ is a time dummy variable that equals to 1 for implementation years and subsequent periods, and 0 otherwise; X is a series of control variables; i is the city; t is the year; μ is the city fixed effect; ν is the time fixed effect; ε is the random perturbation term.

4.2.2 Mediating effect model

Based on the theoretical analysis in the previous section, we posit that DE may have an impact on AGTFP through green technology innovation, environmental regulation, and financial development. To empirically examine the above-mentioned mechanism, we construct the following mediating effect model of Equations (3, 4):

$$Med_{it} = \beta_0 + \beta_1 DE_{it} + \beta_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{3}$$

$$AGTFP_{it} = \gamma_0 + \gamma_1 DE_{it} + \gamma_2 Med_{it} + \gamma_3 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{4}$$

where Med is a series of mediating variables, including green technology innovation (GTI), environmental regulation (ER), and financial development (FD). All other variables retain their definitions consistent with the baseline model.

4.2.3 Spatial effect model

Based on the theoretical analysis in the previous section, we further incorporate spatial factors into the analytical framework to explore the spatial spillover effects of DE on AGTFP, and construct the following spatial difference-in-differences (SDID) model:

$$\begin{aligned} AGTFP_{it} = {} & \rho WAGTFP_{it} + \delta_1 DE_{it} + \delta_2 X_{it} + \theta WDE_{it} \\ & + \eta WX_{it} + \mu_i + \nu_t + (1 - \lambda W)^{-1} \varepsilon_{it} \end{aligned} \tag{5}$$

where W is the spatial weight matrix; ρ, θ, η, and λ are the spatial lag coefficients of the corresponding variables. All other variables retain their definitions consistent with the baseline model. Equation 5 is the general form of the SDID model, which can be divided into three spatial econometric models based on whether a correlation coefficient is zero value: if $\rho = \theta = \eta = 0$, it is a spatial error DID model; If $\theta = \lambda = 0$, it is a spatial lag DID model; If $\lambda = 0$, it is a spatial Durbin DID model. Subsequent empirical tests will determine the optimal model specification.

$$W_1 = \begin{cases} \dfrac{1}{D_{ij}^2}, & i \neq j \\ 0, & i = j \end{cases} \tag{6}$$

$$W_2 = \begin{cases} \dfrac{1}{\left|\overline{GDP_i} - \overline{GDP_j}\right| \times D_{ij}^2}, & i \neq j \\ 0, & i = j \end{cases} \tag{7}$$

$$W_3 = \begin{cases} \dfrac{\overline{GDP_i} \times \overline{GDP_j}}{D_{ij}^2}, & i \neq j \\ 0, & i = j \end{cases} \tag{8}$$

where D is the geographical distance calculated using city coordinates. $\overline{GDP}$ is the average of per capita real GDP from 2011 to 2023. In terms of setting the spatial weight matrices, we selected the geographical distance matrix of Equation (6) constructed based on the geographical coordinates between cities, whose elements are the reciprocals of the geographical distances between any two cities. This matrix assumes that the spatial effect decays with the increase of distance, and is suitable for analyzing the spatial spillover effects caused by geographical proximity. Meanwhile, the economic-geographical distance matrix of Equation (7) is also incorporated into our research. It considers both economic scale and geographical distance, and cities with similar economic characteristics and geographical locations have higher weights. This matrix reflects the interaction between "economic similarity" and "geographical proximity," is appropriate for analyzing spatial spillovers under economic gradient differences, and complements the single-dimensional defect of the W_1. Additionally, the gravity matrix of Equation (8) will be used as part of the robustness test. This matrix simulates the economic attractiveness between cities and places more emphasis on the dominant role of economic scale in spatial spillovers.

4.2.4 Data source and processing

Based on the availability and completeness of data, we take the period from 2011 to 2021 as the temporal scope and select 286 cities in China as research samples. The selection of 2011 as the starting point of the study period is based on the following considerations: First, the "Broadband China" Strategy was implemented in 2013, making the period from 2011 to 2012 a critical pre-policy baseline that provides sufficient pre-treatment data for policy effect evaluation. Second, 2011 marked the commencement of the China's 12th Five-Year Plan, during which agricultural policies explicitly incorporated green transformation objectives, establishing a pivotal observation point for studying agricultural sustainable development. Third, 2011 represents the inaugural year of consistent and complete statistical data at the city level in our research, facilitating the construction of a unified baseline framework. The sample data were primarily sourced from authoritative publications including the China Statistical Yearbook, China City Statistical Yearbook, China Rural Statistical Yearbook, China Financial Yearbook, China Insurance Yearbook, along with regional statistical yearbooks and bulletins. We employ linear interpolation to fill in some missing values, and adjust monetary value indicators to the 2011 base period for temporal comparability. The descriptive statistics of the main variables are reported in Supplementary Table 2.

5 Empirical results and analysis

5.1 Baseline model regression

We utilize the "Broadband China" Strategy as a quasi-natural experiment to examine the causal relationship between DE and AGTFP through a multi-period DID model. The detailed results are reported in Supplementary Table 3. Column (1) indicates that the regression coefficient of DE is positive and statistically significant at the 5% level. Column (2), which adds a series of control variables, shows that the policy net effect of the "Broadband China" Strategy has slightly increased, and still remains highly statistically significant. These results indicate that compared with non-pilot cities, the implementation of pilot policy has a positive effect on improving AGTFP, which can promote an average increase of 0.1075 percentage points in AGTFP in pilot cities. This empirical evidence provides preliminary validation for H1.

During the implementation of the "Broadband China" Strategy, the concurrent economic policies may have generated policy superposition effects that could potentially interfere with our empirical results. To enhance the accuracy and robustness of results, we extend the baseline model by incorporating three additional pilot policies that might impact on AGTFP: (1) National Smart City Pilot Policy (SmartCity), (2) National Big Data Comprehensive Experimental Zones (NBDCEZs), and (3) National Agricultural Science and Technology Parks (NASTPs). Columns (3) to (5) report the results considering only the impact of a single policy, while Column (6) reports the results considering all three policy impacts simultaneously. The results demonstrate that after controlling for these policy-related dummy variables, the regression coefficient of DE remains positive and statistically significant at the 1% level, and the coefficient value is similar to the results in Column (2). This consistency robustly validates our primary research conclusions regarding policy effectiveness.

5.2 Validity test of DID model

5.2.1 Parallel trend test

The validity of the DID model is contingent upon satisfying the parallel trend assumption, which requires that the AGTFP between treatment and control groups maintain comparable developmental trajectories or exhibit no systematic disparities prior to the implementation of the "Broadband China" Strategy. To empirically verify this fundamental assumption, we adopt the methodological framework proposed by Beck et al. (2010), employ the event study methodology for testing, and construct the model specified in Equation (9):

$$AGTFP_{it} = \varphi_0 + \sum_{k=-5,k\neq-1}^{k=5} \varphi_k DE_{ik} + \varphi_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \qquad (9)$$

where DE_{ik} is a series of policy dummy variables, and its coefficient φ_k reflects the differential in AGTFP between treatment and control groups during the kth year following the "Broadband China" Strategy. All other variables retain their definitions consistent with the previous model.

Considering the sample interval, we set the 5 years before and after the implementation of the "Broadband China" Strategy as the window period, with the year preceding policy implementation as the base period. Supplementary Figure 1 reveals that during the pre-implementation phase (when $k \leq 0$), the φ_k consistently encompass zero values in the confidence interval at the 95% level, statistically validating the parallel trend assumption between treatment and control groups. Following policy implementation (when $k > 0$), particularly from the second policy year onward, the φ_k demonstrate statistically significant positive values with an annually increasing trajectory, indicating that DE represented by the "Broadband China" Strategy has a significant marginal increasing effect on AGTFP, but this effect has a latency period of approximately 2 years.

This delayed response can be attributed to multiple factors. First, the deployment of digital infrastructure necessitates substantial temporal investment. Although the "Broadband China" Strategy has been implemented in phases since 2013, the completion of fiber-optic network coverage in rural areas, along with base station construction and terminal equipment popularization, typically requires several years to accomplish (Zhao et al., 2020). Second, agricultural stakeholders' adoption of digital technologies follows a learning curve process. As Aker (2011) observed, farmers' familiarity with and application of digital tools undergo progressive stages of training, trial-and-error experimentation, and adaptive adjustment. For instance, the implementation of precision agriculture technologies demands complementary agronomic knowledge transfer, while the promotion of green production models necessitates modifications to conventional farming practices—both processes being inherently time-intensive. Third, the natural cycles of agricultural production prevent immediate reflection of policy effect in annual statistics. The water-saving efficacy of smart irrigation systems, for example, requires a complete growing season to validate, while carbon emission reduction benefits depend on long-term monitoring. Consequently, initial policy effect primarily manifests as infrastructure development and capacity building, with substantive economic and environmental benefits emerging progressively from the second year onward.

5.2.2 Heterogeneity treatment effect test

A potential issue with the multi-period DID model is the presence of heterogeneous treatment effects, meaning that the same treatment may produce different effects on different individuals. This heterogeneity is mainly reflected in two dimensions. First, in the temporal dimension, the variation of treatment effects over time can lead to negative weights and bias. Second, in the group dimension, differences in group-specific effects at various treatment time points affect the weighted average results. In this case, using the traditional two-way fixed effects model for estimation may introduce potential bias (Goodman-Bacon, 2021). Therefore, we utilize the Goodman-Bacon decomposition method to test for these effects.

As shown in Supplementary Table 4, the results of the multi-period DID are predominantly driven by the "appropriate control group," which uses never treated units as the control group and carries a weight of 92%. In contrast, the "inappropriate control group," which employs earlier treatment units as the control group, accounts for only 5.7% of the weight. This empirical evidence suggests that the heterogeneous treatment effects exert limited impact on our primary results, thus validating the results reported in Supplementary Table 3.

5.2.3 Placebo test

Considering that other unobserved redundant factors might interfere with the baseline regression results, we draw on the approach of Cao and Chen (2022) and adopt the following three placebo test methods.

First, in the temporal placebo test, we advance the implementation timeline of the "Broadband China" Strategy by one to three periods as "pseudo treatment times" and conduct regression using the pre-policy implementation sample. As shown in Supplementary Figure 2, the confidence interval at the 95% level of the placebo effect all contain zero values, indicating that the test does not have statistical significance.

Second, in the spatial placebo test, while maintaining original treatment time and group structures, a subset of observations is randomly selected from the full sample without replacement as "pseudo treatment individuals" for regression. As shown in Supplementary Figure 3, the estimated coefficients of the test are mostly concentrated around zero values and follow a normal distribution, while the estimated value of the policy effect (0.1075) appeared in the right tail of the placebo effect distribution, classifying it as an extreme value.

Third, in the mixed placebo test, we use both "pseudo treatment times" and "pseudo treatment individuals" for regression. As shown in Supplementary Figure 4, the estimated policy effect (0.1075) similarly falls within the extreme value range. This is consistent with the conclusions of the above two placebo tests, jointly demonstrating that the validity of the baseline model results stems from the real policy effects of the "Broadband China" Strategy, rather than accidental factors or model specification biases, thus validating the reliability of H1.

5.3 Robustness test

5.3.1 Instrumental variable test

We use a DID model in the above-mentioned section to evaluate the net effect of the "Broadband China" Strategy on AGTFP. Theoretically, it is believed that the selection mechanism does not have significant endogeneity, that is, the selection of pilot cities is almost random and is basically independent of the model disturbance term. However, in reality, the designation of pilot cities often interacts with urban resource endowments, deviating from the ideal state of completely random allocation. Given the difficulty of fully incorporating such complex factors into the model, the regression results may still contain endogenous bias.

To address this methodological concern, we adopt the idea of Huang et al. (2019), select the interaction term between fixed telephone subscribers per 100 persons (city-level data in 2000) and mobile internet users in the previous year as an instrumental variable (IV), and conduct two-stage least squares (2SLS) estimation. This approach is motivated by two key considerations. First, the fixed telephone subscribers per 100 persons (in 2000) reflects the historical level of telecommunication infrastructure, while the lagged mobile internet user indicator represents the dynamic progression of digital economy development. Their interaction term effectively captures the synergistic effects of communication technology advancement across different stages, which is highly correlated with the DE driven by the "Broadband China" Strategy. Regions with more advanced historical communication infrastructure were more likely to be selected as policy pilot cities and could more readily facilitate agricultural green transformation through digital technology upgrades. Second, the fixed telephone subscribers per 100 persons (in 2000), as a historical indicator, bears no direct relationship with current AGTFP. Its influence operates exclusively through the developmental pathway of DE driven by the "Broadband China" Strategy, rather than through other unobserved factors (e.g., economic development level, educational investment, etc.). Meanwhile, the lagged mobile internet user indicator, as a dynamic measure, eliminates contemporaneous correlation with current policy shocks, thereby ensuring that the instrumental variable affects the outcome variable (AGTFP) solely through the endogenous variable (DE). The detailed results reported in Supplementary Table 5.

In Column (1), Kleiberen-Paap rk LM statistics reject the null hypothesis at the 1% level, satisfying instrumental variable identifiability; Cragg Donald Wald F statistics and Kleiberen-Paap rk Wald F statistics are both greater than the critical value of 16.38 at the 10% level of the Stock Yago weak identification test, rejecting the null hypothesis of weak instrumental variables. These tests collectively validate the instrumental variable appropriateness. In Column (2), after considering endogeneity issues, the regression coefficient of DE remains positive and statistically significant, thus verifying the robustness of the previous conclusion.

5.3.2 PSM-DID

To address potential endogeneity issues arising from the non-randomness of policy implementation and eliminate selection bias caused by systematic errors, we use the Propensity Score Matching Difference-in-Differences (PSM-DID) model for robustness test. Specifically, we select all control variables as covariates and implement three distinct matching methods—nearest neighbor matching, caliper matching, and kernel matching—for propensity score matching. Subsequent DID estimation was performed again based on the matched treatment and control groups.

As shown in Supplementary Table 6, the coefficient of DE remains positive and statistically significant at the 1% level across different matching methods, indicating that DE can still significantly improve AGTFP after controlling for sample selection bias, further confirming the results of the baseline model.

5.3.3 Other robustness tests

As shown in Supplementary Table 7, to further validate the reliability of the results of the baseline model, we conduct additional robustness tests as follows:

(1) Intensity DID. Referring to the research of Zhao et al. (2020), we employ the entropy method to calculate the Digital Economy Advancement Index (DEAI). This index is then interacted with the policy dummy variable (DE) to perform an intensity DID regression. The result shows that the coefficient of the interaction term is positive and statistically significant at the 1% level, indicating that in cities with a highly digitalized environment, the "Broadband China" Strategy has a more remarkable effect in enhancing AGTFP. This finding confirms the synergy between digital infrastructure and policy effects, that is, policies are more likely to play a role in regions with a better digital economic foundation.

(2) Lagged treatment of independent variable. In view of the potential temporal lag effect in the "Broadband China" Strategy, we introduce a two-period lag to independent variable. This adjustment allows for the capture of policy lag effect and mitigates the impact of endogeneity issues on the results. The result shows that the coefficient of the lag term is positive and statistically significant at the 5% level, indicating that the policy effect has persistence. This finding supports the robustness of the conclusion of the baseline model in the time dimension.

(3) Exclude certain city samples. Considering the special status of municipalities directly under the central government, provincial capitals, and municipalities with independent planning status, which are often selected as pilot zones for various economic policies and reform measures, their data may bias the overall result. Therefore, after excluding 35 key cities, we re-conduct the regression using the remaining sample data. The result shows that although the coefficient value of DE has slightly decreased, it remains significant, indicating that the core conclusions still hold after excluding policy-sensitive cities and verifying the universality of the policy effects.

(4) 1% bilateral winsorization. To reduce the interference of extreme values on statistical inference, we winsorize all continuous variables at the 1st and 99th percentiles. The result shows that the regression coefficient remains significantly positive and is highly consistent with that of the baseline model, indicating that the estimation results of the model have strong robustness to the data distribution.

(5) Controlling for province-year fixed effect. While our baseline model already controls for city-specific and year-specific fixed effects, there may still be unobservable factors at the provincial level that vary over time. To address this issue, we further strengthen identification by introducing province-year interactive fixed effect. The result shows that the absolute value of the coefficient increases and remains significant, and the R^2 increases to 0.8170. This indicates that even under strict control conditions, the policy effect remains robust, and the impact of the DE is independent of the traditional provincial policy framework.

6 Further analysis

6.1 Mechanism test

The above-mentioned findings indicate that DE—exemplified by the "Broadband China" Strategy—has a significant positive effect on enhancing AGTFP. However, it remains to be further confirmed whether this effect is achieved through green technology innovation, environmental regulation, and financial development. Therefore, we employ a mediating effect model for empirical testing, with detailed results are reported in Supplementary Table 8.

The regression results for GTI as a mediating variable are shown in Columns (2) to (3) of Supplementary Table 8. In Column (2), the regression coefficient of DE is significant and positive at the 1% level, indicating that DE is conducive to green technology innovation. Column (3) represents the addition of GTI to the baseline regression model. The results reveal that the coefficient of DE remains positive and statistically significant, but the coefficient value has decreased compared to the result reported in Column (1). The coefficient of GTI is positive and statistically significant at the 1% level. This suggests that DE promotes AGTFP through green technology innovation, thus validating H2.

The regression results for ER as a mediating variable are shown in Columns (4) to (5) of Supplementary Table 8. In column (4), the regression coefficient of DE is significant and positive at the 5% level, indicating that DE is conducive to environmental regulation. Column (5) represents the addition of ER to the baseline regression model. The results reveal that the coefficient of DE remains positive and statistically significant, albeit slightly lower than that in the baseline regression. The coefficient of ER is positive and statistically significant at the 5% level. This demonstrates that DE promotes AGTFP through environmental regulation, thus validating H3.

The regression results for FD as a mediating variable are shown in Columns (6) to (7) of Supplementary Table 8. In Column (6), the regression coefficient of DE is significant and positive at the 1% level, indicating that DE is conducive to financial development. Column (7) represents the addition of FD to the baseline regression model. The results reveal that the coefficient value of DE decreased to 0.0516, yet it is not statistically significant. The coefficient of FD is positive and statistically significant at the 10% level, exhibiting a complete mediating effect. This indicates that DE promotes AGTFP through financial development, thus validating H4.

In addition, the results from Sobel test and Bootstrap test confirm the robustness and effectiveness of the above-mentioned mediation mechanisms. Notably, compared with the partial mediating effects of GTI and ER, FD exhibits a complete mediating effect. This finding may reveal a key logic: as the core hub for resource allocation, finance, when deeply integrated with the DE (e.g., digital inclusive finance), can more efficiently impact the green allocation of agricultural production factors (e.g., capital, technology, and labor). In other words, the empowerment of the DE on agricultural green development essentially transforms "data factors" into "capital factors" through the digital transformation of the financial system, thereby driving the greening of production modes. This mechanism not only explains the realistic path of China's agricultural transformation, but also provides a dual-drive paradigm of "digital technology + financial innovation" for developing countries—by enhancing financial accessibility and optimizing capital allocation efficiency, it transforms green development from a policy goal into the spontaneous behavior of market entities.

6.2 Heterogeneity test

6.2.1 Natural geographical factors

China has a vast territory, and differences in natural geographical locations may lead to varied effects of DE on AGTFP. Following the regional classification standards of National Bureau of Statistics of China, we divide the sample into eastern, central, and western regions for comparative analysis. As shown in Columns (1) to (3) of Supplementary Table 9, the promotion effect of DE on AGTFP exhibits a distinct regional gradient, with the strongest in the eastern region, followed by the central, and weaker in the western. However, the regression coefficient for the western region is much lower than those of the eastern and central, failing to reach statistical significance. A possible explanation is that the complex natural geographical conditions in western rural areas have increased the difficulty in broadband network deployment. The remoteness and dispersion of villages has led to extremely high marginal costs for network coverage, and post-maintenance further raises operational costs due to issues such as inconvenient transportation. Additionally, the green transformation of agriculture requires substantial input of resource elements, while the relatively weak economic foundation in western regions restricts such investments. This realistic dilemma of "high-input, low-return" makes it difficult for the enabling effects of the DE to be spontaneously realized through market mechanisms.

Precipitation, a critical component of natural endowments, is directly linked to crop growth, irrigation methods, and ecological stability. Diverse precipitation distributions lead to variations in the demand for and adaptation to digitalization in agricultural production. We use the 800-millimeter isohyet as the criterion to classify samples with an annual average precipitation of 800 millimeters or more as "humid areas," and the others as "non-humid areas." In humid areas with superior water and heat conditions, traditional agriculture has formed a relatively stable pattern, meaning that basic production can be maintained by relying on natural precipitation. In this case, the core role of the DE may be difficult to break through the threshold of the "natural condition dividend," leading to the dilution of its effect on improving AGTFP by natural advantages. Additionally, the areas are mostly major grain-producing areas with obvious characteristics of large-scale planting. Digitalization primarily replaces human labor rather than solving core resource constraints. Therefore, the incremental contribution of the DE fails to pass statistical test (Supplementary Table 9, Column 4). In non-humid areas with scarce water resources and high drought risks, agricultural production relies more on artificial intervention and technological optimization. Technologies brought by the DE, such as intelligent monitoring (e.g., soil moisture sensors) and precision irrigation systems (e.g., IoT-controlled drip irrigation), directly mitigate water bottlenecks. Under resource-constrained conditions, its green effects of "water-saving, yield-increasing, and carbon-reducing" are more likely to emerge. Meanwhile, when confronted with more prominent climatic uncertainties, local farmers may be more inclined to incur technical costs to reduce risks, thus significantly promoting AGTFP (Supplementary Table 9, Column 5).

Terrain factors not only create a diversified spatial layout for agricultural production but may lead to the heterogeneous effect of DE on AGTFP by acting on the application scenarios of digital technology. We use the median of terrain relief degree as the criterion to categorize the sample into higher terrain relief areas (above the median) and lower terrain relief areas (below the median). As shown in Columns (6) to (7) of Supplementary Table 9, the regression coefficients of both exhibit positive effects, but the policy effect intensity and statistical significance of the latter are better. For higher terrain relief areas, although complex terrain increases the cost of digital application, the foundational enabling role of the "Broadband China" Strategy can still optimize resource allocation through information circulation. Moreover, some adaptive technologies (e.g., basic e-commerce and remote guidance) have partially broken through geographical constraints. Meanwhile, agricultural production in these areas is not completely incompatible with digitalization. Under the dual pressures of ecological protection and production efficiency, farmers have a rigid demand for lightweight digital technologies, making the marginal promotion effect of the DE statistically significant. For lower terrain relief areas, the concentrated and contiguous layout of farmland provides a carrier for the standardized and large-scale application of digital technologies, making it easier to quantify and demonstrate policy effects. Furthermore, these areas have more advantages in infrastructure, technological diffusion, and policy implementation, thus better releasing the multiplier effect of policy dividends and exhibiting stronger significance and effect intensity.

6.2.2 Socio-economic factors

The diversity in agricultural production structures is an indispensable consideration in the formulation and implementation of regional agricultural policies, profoundly shaping the evolutionary trajectory of AGTFP. According to the classification criteria of the National Medium- and Long-Term Food Security Outline (2008–2020), we categorize the sample into major grain-producing areas and non-major producing areas. The results are reported in Columns (1) to (2) of Supplementary Table 10. Due to policy attention and resource allocation, major grain-producing areas may have formed a relatively complete agricultural informatization system, and the role of the DE is more reflected in the improvement of marginal efficiency. Meanwhile, these areas face strict ecological assessment, and the DE can achieve green transformation on the premise of ensuring grain production through the integration of green technology. Although the improvement of such technological applications on AGTFP is limited, the policy effect exhibits a long-term mechanism (manifested as high statistical significance), which is consistent with the production logic of "seeking progress while maintaining stability" in major producing areas. In contrast, non-grain major producing areas are dominated by cash crops, with production objectives placing emphasis on economic benefits. Such crops exhibit higher sensitivity to technological innovation and market information. In these areas, the DE represents a "breakthrough from nothing." In the initial stage, the introduction of disruptive technologies through policy-driven measures can rapidly activate the innovative vitality of production entities, leading to a significant increase in AGTFP (characterized by a higher regression coefficient). However, as technological diffusion becomes widespread, the marginal effect may diminish in the later stage.

The penetration and maturity of the DE vary across regions. At different stages of digitization, the impact of the "Broadband China" Strategy on AGTFP may demonstrate heterogeneous characteristics. Using the median of DEAI calculated in the previous as the criterion to divide the sample into highly digitalized regions (above the median) and less digitalized regions (below the median). As shown in Column (3) of Supplementary Table 10, the regression coefficient for highly digitalized regions is positive and statistically significant at the 10% level. A higher level of digitalization implies that these regions have more complete information infrastructure, more advanced digital technologies, and a wider range of digital application scenarios, which contribute to the intelligent, precise, and green transformation of agricultural production. The results in Column (4) of Supplementary Table 10 indicate that in less digitalized regions, the impact of the "Broadband China" Strategy on AGTFP is relatively weak and statistically insignificant. This phenomenon may be attributed to considerable shortcomings in digital infrastructure construction, digital technology application, and digital talent cultivation in these regions, which limit the penetration of digital technology into the agricultural sector and weaken the expected effects of policies.

Financial literacy is defined as individuals' capacity to acquire economic information and achieve rational asset allocation accordingly. Variations in farmers' financial literacy across regions may affect the effectiveness of the "Broadband China" Strategy in improving AGTFP. We use the median of HCS as the criterion to categorize the sample into higher financial literacy regions (above the median) and lower financial literacy regions (below the median). As shown in Columns (5) to (6) of Supplementary Table 10, individuals from higher financial literacy regions usually have stronger skills in information acquisition and interpretation, enabling them to efficiently capture and leverage the opportunities brought by the digital economy development, thereby optimizing agricultural resource allocation and promoting green production transformation. Simultaneously, these regions often have well-developed digital infrastructure and financial service systems, which provide support and guarantee for the transmission of policy measures. Comparatively, individuals from lower financial literacy regions may exhibit deficiencies in policy comprehension, investment decision-making, and risk management, making it challenging to fully convert policy advantages into tangible improvement of AGTFP.

6.3 Spatial effect test

Before incorporating spatial factor into econometric analysis, it is necessary to verify the existence of spatial effects through spatial autocorrelation test on AGTFP. As shown in Supplementary Table 11, under various spatial weight matrix specifications, the Global Moran's I of AGTFP is positive, and the vast majority of years are significant at least at the 1% level, indicating significant positive spatial correlation. Complementary analysis using Local Moran's I scatterplots reveals that the majority of scatter points cluster in Quadrants I (high-high aggregation area) and III (low-low aggregation area), indicating that AGTFP is not independently and randomly distributed in geographical space but rather exhibits significant spatial agglomeration, which confirms the judgment of the Global Moran's I. These findings validate the appropriateness of using spatial econometric model for extended analysis.

To determine the specific estimation form of the spatial econometric model, we sequentially conduct LM test, Hausman test, Wald test, and LR test, ultimately identifying the spatial Durbin DID model with two-way fixed effects as the optimal choice. The detailed results are reported in Supplementary Table 12.

Based on the W_1 and W_2, we use the SDID model to further test the impact of DE on AGTFP, and extend the analysis to the spatial spillover effects of pilot policy on AGTFP. The detailed results are reported in Supplementary Table 13.

First, under various spatial weight matrix specifications, the spatial lag coefficient (Rho) of the dependent variable is positive and statistically significant, indicating that there is spatial autocorrelation in AGTFP, that is, the improvement of AGTFP in a certain region tends to promote similar enhancements in neighboring regions through geographical and economic connections.

Second, when spatial factor is taken into account, the regression coefficient of DE remains positive and statistically significant at least at the 5% level, consistent with the previous findings and reaffirming H1. Meanwhile, coefficient of W*DE is positive and statistically significant, demonstrating that the "Broadband China" Strategy has significant spatial spillover effects on AGTFP. Furthermore, the results of spatial effect decomposition indicate that the direct, indirect, and total effects are all positive and statistically significant, under the "Broadband China" Strategy, there are spatial spillover effects of DE in increasing AGTFP, and the local DE has a positive impact on the improvement of AGTFP in neighboring regions, thus validating H5.

Third, under the W_1, 47.89% of the improvement effect of the "Broadband China" Strategy on AGTFP is achieved through spatial spillover. Conversely, under the W_2, the proportion of indirect effect decreases slightly. In this regard, we make the following analyses: (1) geographical proximity plays a fundamental supporting role in spatial spillover. In the process of the impact of the DE on AGTFP, geographical proximity provides natural convenience for information dissemination, technological diffusion, and resource sharing. Neighboring regions often have similar natural geographical conditions and agricultural production environments. Digital infrastructure upgrades and the application of agricultural digital technologies driven by the "Broadband China" Strategy, among other factors, can rapidly permeate into neighboring regions through direct geographical radiation, forming significant spatial spillover effects. Under the W_2, however, after introducing the factor of economic distance, the pure spatial transmission mechanism of geographical proximity is weakened. When economic similarity and geographical proximity are not fully compatible, the basic spillover effects brought by geographical proximity will be diluted due to the intervention of economic factors. (2) Economic similarity has a complex moderating effect on spatial spillover. Under the W_2, the interaction between geographical distance and economic distance makes the transmission of spatial spillover effects need to cross a dual threshold simultaneously. On the one hand, regions with similar economic development levels may have industrial isomorphism or resource competition, which inhibits the complementary flow of digital economic resources across regions. On the other hand, there is a gap in technological absorption capacity between regions with significant economic disparities. Agricultural green technological innovations in economically developed regions may rely on high-intensity capital investment and high-quality labor, while neighboring regions with weak economic foundations find it difficult to undertake such technological spillovers due to differences in factor endowments. This "screening mechanism" of economic similarity makes the spillover effects based on the W_2 bear higher adaptation costs, ultimately leading to spillover effects slightly lower than those of the W_1, which only relies on geographical proximity.

We report the results of robustness tests in Supplementary Table 14. Three methods are employed to validate the reliability of the above-mentioned research findings. Notably, we replace the spatial weight matrix with W_3, a matrix in which economic scale directly enters the weight calculation in a multiplicative form, thus placing more emphasis on the dominant role of economic factors in spatial spillover effects. In Column (5), the indirect effect of W_3 and its proportion are 0.0848 and 42.58% respectively, both of which are less than those of W_1 (0.0988 and 47.89%) and W_2 (0.0886 and 46.88%). This phenomenon can be interpreted as follows: The W_3 excessively highlights the role of economic factors while underestimating the fundamental support of geographical location. In other words, geographical proximity serves as the primary driver of the spatial spillover effect of DE on AGTFP, whereas economic similarity, as a regulator, can enhance or inhibit the spillover effect, depending on its interaction with geographical factors.

7 Discussion

This study confirms the significant promoting effect of the DE on AGTFP through a multi-period DID model and spatial econometric analysis, which aligns with the conclusions of Hong et al. (2023) and Zeng et al. (2024) at the provincial level. Notably, using city-level panel data and a quasi-natural experiment design, this study for the first time quantifies the causal effect of the "Broadband China" Strategy on AGTFP, mitigating the potential aggregation bias in provincial-level data. Meanwhile, we reveal that the policy effect shows a trend of marginal increase over time, with a two-year latency period. This delayed effect is consistent with the cyclical characteristics of digital infrastructure deployment and agricultural technology adoption (Zhao et al., 2020; Aker, 2011).

In terms of mechanism analysis, most existing literature focuses on the perspectives of industrial evolution and production factors. This study also emphasizes the key roles of green technological innovation and environmental regulation, while incorporating financial development into the analytical framework represents a significant contribution. It is worth noting that financial development exhibits a complete mediating effect, indicating that the DE does not enhance efficiency in isolation. Instead, it transforms "data factors" into "capital factors" supporting green practices through deep integration into financial system reforms, thereby optimizing the allocation of agricultural production factors. This finding confirms the importance of finance as the core hub for resource allocation, supplements the research of Gao et al. (2022) on digital inclusive finance, and provides a "digital technology + financial innovation" paradigm for developing countries.

The heterogeneity characteristics provide new empirical evidence for targeted policy implementation. For example, in non-humid areas with stronger water resource constraints, the water-saving and efficiency-enhancing effects of digital technology are more significant, which verifies the hypothesis of "resource endowment driving technology adoption" (Schulz and Börner, 2022). In contrast, humid regions are restricted by the "natural condition dividend," reducing the urgency of digital adoption. This finding contrasts with the "resource curse" theory in agricultural production and emphasizes the criticality of technology adapting to local conditions. Higher financial literacy regions have a stronger capability to optimize the green allocation of agricultural resources through digital tools, thereby further amplifying policy effects, echoing the perspective of Abdul-Rahim et al. (2024). These conclusions are consistent with the assertion in existing literature that the effectiveness of the DE depends on regional endowments, but they further refine insights based on natural geographic and socio-economic factors.

This study identifies the positive externality of DE on AGTFP and finds that geographical proximity is more explanatory than economic similarity. We emphasize the dominant role of geographical factors in spatial spillover, with economic factors serving as a regulator, which deepens the spatial econometric research of Lu S. et al. (2024).

Despite some valuable findings, it is essential to recognize the existing limitations: First, this study reveals the relationship between China's DE and AGTFP, but its conclusions are constrained by specific policy environments, agricultural structures, and the level of digital infrastructure. The universality of these conclusions for other developing countries remains to be verified. Second, this study focuses on narrow-sense agriculture (i.e., crop farming), excluding broad-sense agricultural sectors (e.g., forestry, animal husbandry, and fisheries). Significant differences in production cycles, technological applications, and pollution emissions across different agricultural sub-sectors may lead to the conclusions lacking persuasiveness for the overall green development of agriculture. Third, this study employs a comprehensive indicator of FD but does not deeply identify the independent impacts of its secondary indicators. The transmission pathways of various links in the financial system still need to be clarified. Additionally, this study focuses on the command-and-control environmental regulations led by the government, while the mechanisms of market-incentive and voluntary environmental regulations deserve further exploration. Fourth, although this study verifies the spatial spillover effect, analyzing the underlying mechanism from a spatial perspective remains a key direction for future research.

8 Research conclusions and policy recommendations

8.1 Research conclusions

Based on panel data from 286 Chinese cities spanning 2011 to 2023, this study employs the "Broadband China" Strategy as a quasi-natural experiment and utilizes a multi-period DID model to analyze the impact of DE on AGTFP, while revealing its underlying mechanisms, heterogeneous characteristics, and spatial spillover effects. The main findings reveal that: (1) DE has a significant positive effect on AGTFP, with the results remaining robust across a series of robustness tests. (2) The promotion mechanism primarily operates by green technology innovation, environmental regulation, and financial development. (3) The impacts of the DE on AGTFP exhibit heterogeneous characteristics across dimensions. In terms of natural geographical factors, the effects are strongest in the eastern regions, followed by the central, and the weakest and statistically insignificant in the western. The effects are significant in non-humid areas but insignificant in humid areas. Lower terrain relief areas demonstrate better effects than higher relief areas. In terms of socio-economic factors, the effects are more significant in non-major grain-producing areas than in major grain-producing areas. The policy effects are significant in regions with higher levels of digitization and financial literacy. (4) DE exerts positive spatial spillover effects on AGTFP, with the geographical distance matrix captures these spillovers more effectively.

8.2 Policy recommendations

Based on the foregoing conclusions, we propose the following policy recommendations:

(1) Strengthen rural digital infrastructure and technological applications to promote full-chain digital transformation of agriculture. First, relying on the "Broadband China" Strategy, implement the "Rural Digital Infrastructure Tackling Plan," prioritize optical fiber networks, 5G base stations, and agricultural IoT facilities in rural areas of the central and western regions, and explore a diversified investment model of "government subsidies + operator concessions + social capital participation" to narrow the regional digital divide. Second, establish an "Agricultural Digital Technology Innovation Center," collaborate with research institutions and enterprises to develop lightweight tools tailored for smallholder farmers, such as an AI-powered pest and disease identification system based on WeChat mini-program, to lower the threshold for technology adoption. Construct an "integrated space-air-ground" digital monitoring network to collect real-time data through satellite remote sensing, drone patrols, and field sensors, achieving dynamic optimization of resource input. Third, implement the "Farmer Digital Literacy Enhancement Project," cultivate "new agricultural talents" with both agricultural knowledge and digital skills through field schools and practical workshops, and establish an incentive mechanism for "digital demonstration households" to improve farmers' digital adoption rate from point to area. Finally, encourage e-commerce platforms to set up dedicated sections for green agricultural products, improve the blockchain-based traceability system for agricultural products from production to sales, strengthen consumer trust in green agricultural products, and use market demand to drive the green transformation of the production side.

(2) Deepen the "digital + finance" coordination system to unleash the intermediary efficiency of finance. In terms of financial scale, establish a national special fund for agricultural green development, and accelerate the formulation of a unified support catalogue for agricultural green finance. Guide financial institutions to expand green credit issuance through means such as financial discounting and risk compensation. Encourage the inclusion of environmental protection indicators in the assessment of rural financial institutions, and provide tax relief for those that meet the standards. In terms of financial structure, promote the "blockchain + supply chain finance" model. Taking core enterprises as the fulcrum, provide credit loans based on order data for upstream and downstream small and medium-sized farmers. Explore the pledge loan model for agricultural carbon sink income rights. Pilot the "insurance + futures + digitization" combination tool, develop index insurance products for climate-sensitive crops, and use satellite remote sensing data to dynamically adjust premium and claim settlement standards, reducing the impact of natural risks on green production. In terms of financial efficiency, accelerate the digital transformation of rural credit cooperatives, rural banks and other institutions. Improve the "digital finance + credit evaluation" mechanism, establish "digital credit profiles" based on farmers' production data and e-commerce transaction records, simplify the approval process for small loans, and alleviate the financing constraints of agricultural green transformation. According to the characteristics of small farmers, design a repayment mechanism of "quarterly principal repayment and flexible borrowing and repayment," and develop supporting mini-programs for financial knowledge popularization to enhance farmers' ability to use financial tools through gamified interactions.

(3) Implement differentiated strategies for digital agriculture to overcome natural and geographical constraints. In eastern and central regions, promote high-end models such as "Digital Twin Farms" and "vertical agriculture." Leverage the advantages of flat terrain and complete infrastructure to create smart agriculture demonstration belts. In western regions, explore hybrid network solutions combining "low-altitude networking + satellite communication" to improve the coverage of digital services in remote areas. Meanwhile, establish a "digital ecological compensation mechanism" in ecologically fragile areas. Monitor farmers' green production behaviors through remote sensing and provide digital credit rewards. These credits can be redeemed for agricultural input subsidies or financial services to address the real dilemma of "high input, low return" in the western. In humid areas with abundant precipitation, strengthen digital supervision of agricultural non-point source pollution. Establish a linkage model between "agrochemicals input – water quality monitoring" to urge production entities to reduce pollution emissions. In non-humid areas, focus on efficient water resource utilization. Dynamically adjust irrigation volumes based on monitoring data and support digital platforms for agricultural water rights trading to alleviate water resource bottlenecks. For regions with complex terrains, develop lightweight and adaptable digital tools (e.g., portable soil moisture detectors and mountain agricultural robots) to reduce geographical barriers to technological application.

(4) Conduct targeted optimization of the industrial ecology and institutional supply to activate the endogenous momentum of socio-economic factors. In major grain-producing areas, it is necessary to strengthen the dual-goal orientation of stabilizing production and promoting

transformation. Optimize the planting structure through digital technologies and establish a linkage mechanism of "yield forecasting—reserve regulation—price insurance" to ensure farmers' income from grain cultivation. In non-major grain-producing areas, it is essential to support the development of new business forms such as "digital agricultural adoption" and "live-streaming farming experience" in concentrated economic crop areas. Leverage e-commerce platforms and social media to create "digital landmark products" and expand market premium space. In highly digitized regions, encourage exploration of frontier fields such as "artificial intelligence + agricultural breeding" and "metaverse-based agricultural science popularization," and promote the formulation of digital agriculture standards and international cooperation. In regions with lagging digitization, implement the "digital infrastructure gap-filling project," focusing on constructing agricultural IoT demonstration bases and rural e-commerce public service centers to lower the initial threshold for digital applications. In higher financial literacy regions, promote the "e-CNY + green points" consumption model to guide farmers to participate in the carbon inclusive system. In lower financial literacy regions, launch the special initiative of "bringing financial knowledge to rural areas," and popularize green financial products and raise risk prevention awareness through digital financial service stations, mobile publicity vehicles and other forms.

(5) Establish a regional linkage network to share the dividends of digital development. First, develop a "National Agricultural Digital Cloud Platform" to integrate green production technology solutions, agricultural product market information, carbon sink transaction data, etc., from various regions, thereby achieving cross-regional optimal allocation of resources. Second, promote the establishment of a "digital technology benefit-sharing mechanism" between eastern and central-western regions. Specifically, provide ecological compensation or land use index incentives for technology exporters, and offer supporting subsidies for technology adopters, forming a collaborative pattern of "eastern R&D, central-western application" to ultimately achieve the "ripple effect" of AGTFP improvement. Third, rely on regional development strategies such as the Yangtze River Economic Belt and the Yellow River Basin to establish a "Provincial Digital Agriculture Alliance," promoting cooperation among neighboring provinces in technical standards, data sharing, and talent mobility, and jointly formulating regional agricultural green development plans. Fourth, in rural areas around urban agglomerations, develop a "Metropolitan Digital Agriculture Community," and leverage geographical proximity to share intelligent warehousing and cold-chain logistics facilities. Simultaneously, advance the digital upgrading of leisure agriculture, and create an "online adoption + offline experience" model. Finally, build on the "Belt and Road" agricultural cooperation platform and create cross-border digital agriculture demonstration zones. These zones will export China's digital agriculture technologies and experiences to neighboring countries, while introducing international advanced green production standards and management models.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

LW: Funding acquisition, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing. YC: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This study was funded by the National Social Science Fund of China (Grant No. 20BJL142).

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.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2025.1607567/full#supplementary-material

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