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Exploring the "Double-Edged Sword" effect of the digital economy on sustainable agricultural development: Evidence from China

Qingning Lin [a,1], Yuqing Jian [b,1], Deshuo Zhang [a,1], Jingdong Li [c,d,*], Shiping Mao [a,*]

[a] Institute of Agricultural Economics and Development, Chinese Academy of Agricultural Sciences, Beijing, 100081, China
[b] College of Urban and Environmental Sciences, Peking University, Beijing, 100091, China
[c] Center of High-quality Development Research, Beijing Academy of Science and Technology, Beijing 100009, China
[d] Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

A R T I C L E I N F O

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A B S T R A C T

The prolonged reliance on excessive resource utilization and unsustainable production methods has resulted in significant environmental issues in China, posing serious challenges to the sustainable development of agriculture. While the digital economy offers new opportunities for enhancing agricultural sustainability, its rapid and unregulated growth could also lead to negative effects. Therefore, exploring the relationship between the digital economy and sustainable agriculture development (SAD), along with clarifying the mechanisms involved, is of paramount importance. This study uses the EBM-GML index to calculate AGTFP as a representation of SAD and empirically tests the impact and mechanism of the digital economy on SAD. Additionally, it explores the moderating role of government behavior, specifically Agricultural fiscal support and digital policies. The main findings are as follows: (1) During the observation period, SAD showed a steady upward trend, but regional disparities widened, forming a contiguous agglomeration pattern. The decentralization of the digital economy weakened, trending towards unipolarization and homogenization, with a north-to-south diffusion. (2) The impact of the digital economy on SAD presents an inverted "U" shape, indicating a "double-edged sword" effect. This relationship remains significant after robustness and endogeneity tests. Additionally, the digital economy exhibits significant spatial effects, maintaining an inverted U-shaped relationship with SAD in neighboring areas. (3) Regional heterogeneity shows that coastal provinces are in digital economy suppression or alert areas, while inland regions are in enhancement areas. During the study period, the number of suppression and alert areas did not significantly increase, but there was a trend of shifting from coastal to inland regions. (4) When below the threshold, the digital economy promotes agricultural green technology innovation, optimizes resource allocation, and fosters synergetic agglomeration of agriculture with the secondary and tertiary industries, enhancing SAD. However, surpassing the threshold negatively impacts these mechanisms. (5) Fiscal support for agriculture smooths the inverted "U" curve, mitigating the negative impact of excessive digital economy growth on SAD. Conversely, digital policies steepen the inverted "U" curve, exacerbating these negative effects. The findings highlight the need for balanced digital economic development to support sustainable agricultural growth.

1. Introduction

Since the reform and opening up, China's agricultural sector has achieved remarkable progress, effectively ensuring food security for nearly 18 % of the world's population (Li and Lin, 2023). However, the longstanding "extractive" agricultural production model has resulted in inefficient utilization of water and land resources, excessive use of chemical fertilizers and pesticides, and significant emissions from livestock and poultry manure, leading to serious carbon emissions and agricultural non-point source pollution (Liu et al., 2020; Chen et al., 2021). Additionally, China's agricultural development faces challenges such as increased external risk factors, growing pressure to ensure supply and income, and a shrinking rural labor force. It is urgent to shift from traditional production methods to green and sustainable practices. Agricultural Green Total Factor Productivity (AGTFP), defined as the production efficiency that maximizes agricultural output while

* Corresponding authors.
E-mail addresses: lijingdong@bjast.ac.cn (J. Li), maoshiping@caas.cn (S. Mao).
[1] These authors contributed equally to this work and jointly share the first authorship.

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minimizing pollution emissions under given input factors, reveals sustainable growth beyond input factors under environmental pressures and serves as an objective indicator of agricultural sustainability (Liu et al., 2021; Yu et al., 2022b). Therefore, improving AGTFP has become a topic of widespread concern in academia. Current research has examined the impact of agricultural technology, digital inclusive finance, insurance, fiscal expenditure, carbon emissions trading pilots, environmental regulation and other factors on AGTFP from the perspectives of technology, resources, organization, and policy (Liu et al., 2021; Fang et al., 2021; Gao et al., 2022; Song et al., 2022; Yuan and Xiang, 2018; Xiong et al., 2023). In this context, China's digital economy is highly developed and constantly penetrating into various economic sectors. In 2023, the scale of China's digital economy exceeded 50 trillion yuan, accounting for 44 % of GDP. It has gradually become an important variable in China's scientific and technological innovation and a crucial force in industrial transformation. Exploring the impact of the digital economy on sustainable agricultural development is, therefore, of great significance.

The digital economy represents a new economic paradigm centered on data resources and digital technology innovation, leveraging technologies such as ABCD (Artificial Intelligence, Blockchain, Cloud Computing, and Big Data). With the advent of the digital economy era, its impact has garnered significant attention. Tapscott (1996) first introduced the concept of the digital economy, describing it as an integrative carrier of machines, knowledge, and wisdom that fosters economic development and promotes social progress. Subsequent studies have generally agreed that the digital economy,driven by shifts in development paradigms and economic and social structures due to digital technology, can transform and upgrade production methods by optimizing resource allocation, innovating organizational business models, and reducing transaction costs, thereby empowering traditional economic development. At the macro level, Xu and Li (2023) found that the digital economy enhances China's innovation output. Zhu et al. (2023) found that the digital economy significantly improves urban resilience in China and has a notable spatial spillover effect. Shahbaz (2022) concluded that the development of the digital economy can improve governmental governance capacity and facilitate energy transformation. Additionally, other studies suggest that the digital economy plays an important role in improving government fiscal health, alleviating resource mismatches, and narrowing the urban-rural income gap (Zhang et al., 2023a; Lyu et al., 2023a,b). At the micro level, research indicates that the digital economy promotes the digital transformation of enterprises, enhances corporate social responsibility, and boosts corporate performance and innovation capabilities (Wu et al., 2023; Liu et al., 2024a; Li et al., 2022; Sun et al., 2024).

In recent years, extreme climate events have occurred frequently, and the adverse effects of climate change have become increasingly prominent. Achieving the sustainable development goals outlined in the Paris Agreement and the United Nations Framework Convention on Climate Change is urgent (Dwivedi et al., 2022). The energy conservation and emission reduction effects of the digital economy have begun to attract significant academic attention (Wang et al., 2022), mainly focusing on national, provincial, urban, and other macro levels. At the national level, Chen (2022a) found that the digital economy significantly inhibits carbon emissions in BRICs countries such as Brazil and China. At the provincial level, research indicates that the digital economy can promote technological innovation and the development of the tertiary industry, thereby reducing carbon emissions (Wang et al., 2022b; Li et al., 2023; Chang et al., 2023; Chen et al., 2023a; Liu et al., 2022). At the urban level, research suggests that the digital economy helps to modernize industrial structures and enhance technological innovation, leading to green development (Liu et al., 2024b; Li and Zhou, 2024; Chen, 2022b; Ren, 2022). Focusing on the topic of the digital economy and green total factor productivity, current scholars have confirmed the positive impact of the digital economy on green total factor productivity mainly from the macro level, as well as in forestry, manufacturing, mining, and other industries (Rehman and Nunziante, 2023; Chen et al., 2023b; Liu et al., 2023; Fang et al., 2024; Deng et al., 2022). In the agricultural sector studied in this paper, some scholars have also affirmed the role of the digital economy in improving AGTFP (Chen et al., 2023c; Zhang et al., 2023b).

While existing research has highlighted the positive impact of the digital economy on green total factor productivity at the macro level and within specific industries like forestry, manufacturing, and mining, its influence on the agricultural sector remains underexplored. Additionally, although some scholars have acknowledged the digital economy's positive role in reducing carbon emissions, there is limited focus on its impact on sustainable agriculture development and the potential nonlinear relationship. Furthermore, research on the pathways through which the digital economy affects SAD, as well as the moderating effects of government intervention, is still insufficient. This study aims to address these gaps by measuring AGTFP as a representation of Sustainable Agricultural Development (SAD), investigating the impact mechanisms of the digital economy on SAD, and exploring the external moderating effects of government actions. The subsequent sections of this paper are structured as follows: Chapter 2 elaborates on the theoretical analysis and presents the research hypotheses regarding the potential impacts of the digital economy on SAD. Chapter 3 details the research design and methodology employed in the study. Chapter 4 conducts empirical tests and discusses the mechanisms and the role of government intervention. Chapter 5 offers a comprehensive discussion of the findings. Finally, Chapter 6 presents policy recommendations and outlines directions for future research.

2. Theoretical analysis and research hypothesis

2.1. Direct impact of the digital economy on sustainable agriculture development

The digital economy represents a new economic paradigm centered on data resources and digital technology innovation. Current studies generally affirm the positive role of the digital economy in energy conservation and emission reduction. However, for the agricultural sector in China, this article posits that the impact of the digital economy on sustainable agriculture development(SAD) follows an inverted "U" shape. The main reasons are as follows: (1) The digital economy can improve SAD when it does not exceed a certain threshold. Firstly, the development of the digital economy helps achieve economies of scale in agricultural production, thereby enhancing SAD. The costs associated with agricultural production include fixed costs, such as agricultural materials, and transaction costs, such as management expenses. While fixed costs are inevitable sunk costs, the development of the digital economy facilitates the platformization of information, materials, and other elements (Hukal et al., 2020), reducing transaction costs for agricultural producers and enabling economies of scale (Goldfarb and Tucker, 2019), thus promoting the improvement of SAD. Secondly, the development of the digital economy optimizes the agricultural production process, thereby improving the efficiency of green agricultural production.

Technological advancements in the digital economy (such as the Internet and big data) can effectively alleviate information asymmetry between agricultural production and market demand (Gouveia et al., 2004; Bajari et al., 2015). Additionally, derivative tools like digital finance can alleviate financing constraints in agricultural production (Li et al., 2023), contributing to improvements in SAD. The application of technologies such as the Internet of Things, e-commerce, and big data has led to the comprehensive digitization of agricultural production process, high digitization of agricultural resource management, full digitization of the agricultural supply chain, and precise digitization of agricultural services (Liu, 2022; Chen et al., 2023b; Lyu et al., 2023b), thereby improving SAD.

(2) When the digital economy exceeds the threshold, it negatively

affects SAD. Firstly, the excessive development of the digital economy increases environmental pressure. For example, the construction and use of data centers, digital infrastructure, and digital agricultural equipment leads to higher energy consumption and carbon emissions (Saidi et al., 2017), which are detrimental to the improvement of SAD. Secondly, China's agriculture is a typical traditional industry, so the adjustment speed of the agricultural development model may struggle to keep pace with the rapid development of the digital economy. Consequently, an overdeveloped digital economy may face challenges in deeply integrating with the agricultural real economy, leading to significant resource waste (Chen et al., 2023b), which is not conducive to the improvement of SAD.

Based on the above analysis, this paper proposes the research hypothesis H1:

H1: The impact of the digital economy on SAD follows an inverted "U" shape, showing a "double-edged sword" effect.

2.2. Effect mechanism of the digital economy on sustainable agriculture development

2.2.1. Green innovation effect

When the digital economy does not exceed the threshold, it can promote agricultural green technology innovation, thus improving SAD. Firstly, according to Schumpeter's innovation theory, innovation is a process of rearranging and combining production factors (Schumpeter, 2008). The development of the digital economy introduces data as a new production factor in agricultural technology innovation, transforming the traditional production function Y=AF(L,K) into Y=AF(D,L,K). This coupling and rearrangement of data elements with traditional elements (Kohli and Melville, 2019) lead to green technology progress and improvements in SAD. Secondly, the digital economy improves the circulation speed of innovation resources, the exchange speed of R&D information, and the operation efficiency of the innovation process, thereby promoting green technology progress (Wang et al., 2024; Lyu et al., 2023a) and improving SAD. Thirdly, due to the unique attributes of agricultural science and technology, such as natural constraints and life attributes, agricultural technology innovation carries greater risks compared to other industries. Open innovation and the acquisition of heterogeneous knowledge and technology are crucial. The digital economy fosters collaborative innovation among agricultural enterprises, research institutes, and universities (Lyu et al., 2023b), thus enhancing SAD.

However, When the digital economy surpasses the threshold, its initial benefits for agricultural green technology innovation begin to diminish. This shift occurs as resources become disproportionately allocated towards the digital economy at the expense of agriculture. Critical inputs such as policy attention, government funding, industrial resources, innovation inputs, human capital, and financial investments are diverted from agricultural development to support the burgeoning digital sector. This imbalance creates a crowding-out effect, leaving agriculture without the necessary resources to sustain green technological advancements (Hong et al., 2016; Yuan and Xiang, 2018). The focus on the digital economy can lead to a neglect of agricultural needs, resulting in stagnation or even regression in green technology innovation within the agricultural sector. As a result, the potential for SAD is undermined. Based on the above analysis, this paper proposes the research hypothesis H2:

H2: The digital economy affects SAD through agricultural green technology innovation.

2.2.2. Allocation effect

Resource allocation refers to the rational distribution and use of production factors such as labor, capital, land, and technology among different economic activities and regions to maximize output and efficiency (Kogan et al., 2017). Proper resource allocation helps improve agricultural productivity, reduce resource waste, and promote sustainable agricultural development.

When the digital economy does not exceed the threshold, it can improve resource misallocation, thereby increasing SAD. Firstly, the development of the digital economy enables the monitoring, analysis, and simulation of production factors, climate change, market fluctuations, and other data in the agricultural production process, thus enhancing resource allocation and achieving refinement and efficiency in the production process (Akaev et al., 2018). Secondly, agricultural production has distinct regional, natural constraints, and life attributes, and the transaction cost between supply and demand within the agricultural industry chain is high. The digital economy can link various resources such as agricultural producers and consumers through digital technologies like the Internet, promoting the orderly flow of agricultural resources (Pee, 2016), and achieving the supply and demand matching of agricultural products (Li et al., 2023), thus improving resource misallocation and increase the marginal output of agricultural resources. Thirdly, the development of the digital economy can strengthen the networking between agricultural extension personnel and agricultural producers, providing precise services for agricultural production decision-making and improving factor allocation efficiency (Lin and Mao, 2022).

However, once the digital economy exceeds a certain threshold, it can have negative effects on resource allocation, detrimental to the improvement of SAD. Firstly, the excessive development of the digital economy may exacerbate the "digital divide" between regions (Lyu et al., 2023b), resulting in a more pronounced Matthew effect. This makes it difficult for agricultural production in some regions to benefit from the digital economy, hindering optimal resource allocation. Secondly, China's agricultural production is characterized by a "large country with small farmers", where the digital literacy of agricultural producers is relatively low (Zhang et al., 2024). This mismatch in the application of digital technology in the agricultural sector can lead to resource waste and misallocation.

Based on the above analysis, this paper proposes the research hypothesis H3:

H3: The digital economy affects SAD through resource allocation.

2.2.3. Agglomeration effect

Industrial synergetic agglomeration refers to the interdependence, interconnection, and mutual reinforcement between different industries, enhancing overall production efficiency through geographic concentration and economic collaboration (Ellison et al., 2010). When the digital economy remains below a certain threshold, it can foster synergetic agglomeration between agriculture and the secondary and tertiary industries, thereby improving SAD.

When the digital economy is within limits, it can facilitate the synergetic agglomeration of agriculture with the secondary and tertiary sectors, thus enhancing SAD. Firstly, the development of the digital economy enables more efficient mobilization of heterogeneous resources across agriculture and other industries (Irene et al., 2011), creating a networked development pattern (Chen et al., 2023b). Digital technologies such as blockchain also help address moral hazard issues in the cooperation between agriculture and the secondary and tertiary industries (Jesse et al., 2016), thereby stabilizing the cooperation network and promoting synergistic agglomeration. Secondly, the digital economy enhances the connection and interaction between agriculture and the secondary and tertiary industries, reduces information asymmetry, increases trust in cooperation, and significantly boosts the frequency of technical collaboration and talent exchange. This leads to scale and agglomeration effects (Liu, 2022), and spawns new forms of synergy among agriculture and the secondary and tertiary industries.

However, when the digital economy exceeds a certain threshold, it can negatively impact the synergetic agglomeration of these industries, which is detrimental to SAD. Despite policies encouraging the return of talent to agriculture, the sector continues to face significant talent loss. (Ma et al., 2024). Additionally, financial investment in agricultural science and technology has been declining, from 4.02 % in 2015 to 3.76 % in 2020. This marginalization trend in agriculture is exacerbated by excessive digital economy development, which diverts agricultural talent to tertiary industries like the digital sector, thereby crowding out resources essential for agricultural development and hindering the formation of a synergetic agglomeration of the three industries.

Based on this analysis, this paper proposes the research hypothesis H4:

H4: The digital economy affects SAD through the synergetic agglomeration of agriculture with the secondary and tertiary industries.

2.3. The moderation effect of government behavior

The government generally exerts moderating effects through subsidies and the introduction of relevant policies. Therefore, this article focuses on exploring the moderating effects of fiscal support for agriculture and digital policies. (1) The moderating effect of fiscal support for agriculture. Fiscal support for agriculture has both resource attributes and signal attributes (Kleer, 2010; Wu, 2017), providing financial and industrial chain support for agricultural and rural development. This support helps improve the quality of agricultural producers and facilitates the transformation and upgrading of agricultural production. It alleviates the "crowding out effect" caused by the excessive development of the digital economy and the challenges agricultural development faces in matching digital technology changes. Consequently, fiscal support for agriculture can smooth the inverted "U" curve of the digital economy's impact on SAD. (2) The moderating effect of digital policies. In the context of China's developing market economy, policies significantly impact the development of the digital economy through support and guidance (Besharov and Smith, 2014). Digital policies provide multi-dimensional support and a conducive development environment for the development of the digital economy through supply-oriented, demand-oriented, and environment-oriented policy tools. This positively moderates the impact of the digital economy on SAD when it does not exceed the threshold. However, China's digital policies often face issues such as over-reliance on "target planning" tools and an emphasis on construction over utilization (Zhang et al., 2021; Liu, 2022; Li and Lin, 2022). Therefore, when the digital economy exceeds the threshold, these policies may exacerbate its overdevelopment, leading to more severe problems like the "crowding out effect", thus worsening the negative impact on SAD. Consequently, digital policies make the inverted "U" curve of the digital economy's impact on SAD steeper.

Based on the above analysis, this paper proposes research hypotheses H5 and H6:

H5: Fiscal support for agriculture makes the inverted "U" curve of the digital economy's impact on SAD smoother.

H6: Digital policies make the inverted "U" curve of the digital economy's impact on SAD steeper.

3. Research design

3.1. Variable selection

3.1.1. Dependent variable

The dependent variable in this paper is sustainable agricultural development (SAD), represented by Agricultural Green Total Factor Productivity (AGTFP). Based on previous research (Wei et al., 2018; Shen et al., 2021; West and Marland, 2002; Anjali and Rattan, 2009; Yu et al., 2022a), AGTFP is deemed a suitable and objective indicator for measuring sustainable agriculture development. AGTFP assesses the efficiency of agricultural production while accounting for environmental constraints and aiming to minimize pollution emissions. Consequently, AGTFP reflects sustainable growth beyond input factors in the face of environmental pressures, making it a reliable proxy for SAD. The input-output indicator system used to measure AGTFP is detailed in Table 1.

After establishing the measurement index system, this study adopts the EBM-GML index within the Data Envelopment Analysis (DEA) framework, following the approach of Tone and Tsutsui (2010), to assess Agricultural Green Total Factor Productivity (AGTFP) across Chinese provinces. AGTFP serves as an indicator for sustainable agriculture development (SAD). This method is selected for several reasons: The EBM model is non-radial and non-angular, allowing it to account for both input and output slack variables, which results in more accurate measurements compared to traditional radial DEA models. The GML index offers a consistent efficiency measurement standard and addresses the non-circularity issue inherent in the traditional Malmquist-Luenberger (ML) index, thereby ensuring more coherent results. By combining the precision of the EBM model with the dynamic nature of the GML index, the EBM-GML index provides robust overall performance. The definitions of the EBM model and GML index are as following Eq. (1):

$$\widetilde{E} = \min\left[\frac{\theta - \varepsilon_x \sum_{i=1}^{m} \frac{w_i^- s_i^-}{x_{ik}}}{\phi + \varepsilon_y \sum_{r=1}^{q} \frac{w_r^{g+} s_r^{g+}}{y_{rk}} + \varepsilon_v \sum_{t=1}^{p} \frac{w_t^{b-} s_t^{b-}}{v_{tk}}}\right] \tag{1}$$

$$s.t\begin{cases} \sum_{j=1,j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq \theta \cdot x_{ik}, \ i = 1,\ldots,m \\ \sum_{j=1,j\neq k}^{n} y_{rj}\lambda_j - s_r^{g+} \geq \phi \cdot y_{rk}, \ r = 1,\ldots,q \\ \sum_{j=1,\,j\neq k}^{n} v_{tj}\lambda_j - s_t^{b-} \leq v_{tk}, \ t = 1,\ldots,p \\ \lambda \geq 0, \quad s^- \geq 0, \quad s^{g+} \geq 0, \quad S^{b-} \geq 0 \end{cases}$$

where, $\widetilde{E}$ represents the value of green productivity of agriculture; x_{ij} represents the set of input variables; y_{rj} represents the desirable output, which is expressed in total agricultural output value; v_{tj} represents the undesirable output, which is the carbon emissions during agricultural production; s_i^-, s_r^{g+} and s_t^{b-} are slacks of inputs and outputs; w_i^-, w_r^{g+} and w_t^{b-} represent the relative importance of various input indicators and

Table 1
Input - output indicators of AGTFP.

Index	Element	Definition	Explain
Input indicators	Labor input	Number of agricultural employees	Ten thousand people
	Fertilizer input	Application amount of agricultural chemical fertilizer	10,000 tons
	Mechanical investment	Total power of agricultural machinery	10,000 kW
	Land investment	Sown area of crops	Hectares
	Irrigation input	Agricultural water consumption	Billion cubic meters
Output indicators	Expected output	Total agricultural output value	CNY100 Million yuan
	Undesired output	Carbon emissions in agricultural production	10,000 tons, calculation method: *pesticide* * 4.934 kg kg^{-1} + *fertilizer* * 0.896 kg kg^{-1} + *diesel* * 0.593 kg kg^{-1} + *agricultural film* * 5.18 kg kg^{-1} + *ploughing* * 312.6 kg/km^2 + *irrigation* * 20.476 kg/hm^2

outputs, with $\sum_{i=1}^{m} w_i^- = 1(w_i^- \geq 0)$, $\sum_{i=1}^{m} w_r^{g+} = 1(w_r^{g+} \geq 0)$ and $\sum_{i=1}^{m} w_t^{b-} = 1(w_t^{b-} \geq 0)$; θ represents the efficiency value under input orientation; ϕ represents the efficiency value under output orientation; ε is the importance of the non-radial part, $\varepsilon \in [0, 1]$.

On this basis, referring to existing studies (Oh, 2010), the Global Malmquist Luenberger (GML) index is used to measure the growth rate of AGTFP, following Eq. (2).

$$\begin{aligned}\mathrm{GML}_i(X_{t+1}, Y_{t+1}, b_{t+1}; X_t, Y_t, b_t) &= \frac{1 + D_G^t(X_t, Y_t, b_t)}{1 + D_G^{t+1}(X_{t+1}, Y_{t+1}, b_{t+1})} \\ &= \frac{1 + D_C^t(X_t, Y_t, b_t)}{1 + D_C^{t+1}(X_{t+1}, Y_{t+1}, b_{t+1})} \times \left[\frac{(1 + D_G^t(X_t, Y_t, b_t))/(1 + D_C^t(X_t, Y_t, b_t))}{(1 + D_G^{t+1}(X_{t+1}, Y_{t+1}, b_{t+1}))/(1 + D_C^{t+1}(X_{t+1}, Y_{t+1}, b_{t+1}))}\right] \\ &= \frac{\mathrm{GTE}^{t+1}}{\mathrm{GTE}^{T}} \times \left[\frac{\mathrm{PG}_{t+1}^{t,t+1}}{\mathrm{PG}_{t}^{t,t+1}}\right] \\ &= \mathrm{GTEC}^{t,t+1} \times \mathrm{GTC}^{t,t+1}\end{aligned} \tag{2}$$

Where, $D_G^t(x, y, b) = \max\{\beta | (y + \beta y, b - \beta b) \in P_G(x)\}$, P_G represents the production possibility set for Global; GTEC represents the change in agricultural green technology efficiency, and GTC represents the advancement of green technology in agriculture.

3.1.2. Main explanation variable

The main explanation variable in this paper is the digital economy index for various provinces in China. In line with existing research (Chen, 2022; Wang et al., 2024), the digital economy is measured using several indicators: the digital inclusive finance index, the number of Internet users per 100 people, the proportion of urban employees engaged in information transmission, computer services, and software industries, the per capita total value of telecommunications business (in 10,000 yuan), and the number of mobile phone users per 100 people. To ensure precision and account for temporal variations, this study employs the entropy method with time-varying dynamic weights to compute the digital economy index for each province in China.The calculation process is detailed as follows:

To make the indicators comparable, the original data is first standardized as Eq. (3):

$$Z_{ij}(t) = \frac{x_{ij}(t) - \min(x_j(t))}{\max(x_j(t)) - \min(x_j(t))} \tag{3}$$

where $Z_{ij}(t)$ is the standardized value of indicator j for province i at time t.

Next, the entropy value for each indicator is calculated as Eq. (4):

$$E_j(t) = -k\sum_{i=1}^{n} P_{ij}(t) ln\, P_{ij}(t) \tag{4}$$

Where $P_{ij}(t) = \frac{z_{ij}(t)}{\sum_{i=1}^{n} z_{ij}(t)}$. The weight for each indicator is then determined as Eq. (5):

$$w_j(t) = \frac{1 - E_j(t)}{\sum_{j=1}^{m}(1 - E_j(t))} \tag{5}$$

Finally, the digital economy index for each province is computed as Eq. (6):

$$S_i(t) = \sum_{j=1}^{m} w_j(t) \cdot Z_{ij}(t) \tag{6}$$

This method allows the weights to adjust dynamically over time, ensuring the index reflects the changing importance of each indicator.

3.1.3. Mediating variables

This study examines several mediating variables: agricultural green technology innovation (green innovation effect), resource allocation (allocation effect), and the synergetic agglomeration of agriculture with the secondary and tertiary industries (agglomeration effect).

(1) Agricultural Green Technology Innovation (Green Innovation Effect). Following Li and Lin (2023), agricultural green technology innovation is assessed by the ratio of the area dedicated to green technologies (including mechanized deep tillage and scarification, precision and semi-precision sowing, no-tillage sowing, mechanized straw return, mechanized deep fertilization, and water-saving irrigation) to the total crop planting area in each province.

(2) Resource Allocation (Allocation Effect). Based on Hsieh and Peter (2009) and Li et al. (2023), the factor misallocation index is first calculated as Eq. (7):

$$\tau_{Ki} = 1/\gamma_{Ki} - 1,\ \tau_{Li} = 1/\gamma_{Li} - 1 \tag{7}$$

Where, τ_{Ki}, τ_{Li} refer to the mismatch index of capital and labor input respectively, and γ refers to the absolute distortion index of production factors. Since the absolute distortion index cannot be calculated directly, the relative distortion coefficient is usually used in the calculation process, denoted by $\widehat{\gamma}$, that is Eq. (8):

$$\widehat{\gamma}_{Ki} = \left(\frac{K_i}{K}\right) \Big/ \left(\frac{s_i\beta_{Ki}}{\beta_K}\right),\ \widehat{\gamma}_{Li} = \left(\frac{L_i}{L}\right) \Big/ \left(\frac{s_i\beta_{Li}}{\beta_L}\right) \tag{8}$$

Where, s_i, β_K, β_L respectively represent the ratio of the total output value of each province to the total output value of the economy, the output weighted capital contribution rate and the output weighted labor contribution rate.

On this basis, referring to the processing method of Bai and Liu (2018), the resource allocation index is expressed as Eq. (9):

$$Mis = -|\widehat{\gamma}_{Ki} / \widehat{\gamma}_{Li}| \tag{9}$$

(3) Synergetic Agglomeration of Agriculture and the Secondary and Tertiary Industries (Agglomeration Effect). Industrial collaborative agglomeration refers to the spatial clustering characterized by interdependence, correlation, and collaborative development among different industries (Ellison and Glaeser, 1997). To measure this synergy, this study calculates the coupling coordination degree between agriculture and the secondary and tertiary industries, using location entropy for each sector within provinces. First, the system coupling degree between agriculture and the secondary and tertiary industries is computed. The formula for this calculation is as following Eq. (10):

$$\mathrm{C} = \left\{(agri_{it} + indus_{it} + ser_{it}) \Big/ [(agri_{it} + indus_{it} + ser_{it})/3]^3\right\}^{1/3} \tag{10}$$

Where, C represents the system coupling degree of agriculture and the secondary and tertiary industries, and $agri_{it}$, $indus_{it}$, ser_{it} represent the location entropy of agriculture, industry, and service industries respectively. The coupling degree of the system reflects the strength of the interaction between agriculture and the secondary and tertiary industries. To assess the quality of this interaction and the extent of mutual development, it is crucial to evaluate the coupling coordination between these sectors. Therefore, the overall level of the system encompassing agriculture and the secondary and tertiary industries is calculated as following Eq. (11):

$$T = \alpha_{agri}agri_{it} + \alpha_{indus}indus_{it} + \alpha_{ser}ser_{it} \tag{11}$$

Where, T represents the comprehensive score of the system of agriculture and the secondary and tertiary industries, and α_{agri}, α_{indus}, α_{ser} respectively represent the importance of agriculture, industry, and service industries. To achieve the coupling and coordinated development of the three, they are considered equally important, so their weights are each assigned as 1/3. Based on the system coupling degree C and the system comprehensive score T, the coupling coordination scheduling of agriculture and the secondary and tertiary industries is calculated. The Eq. (12) is as follows:

$$\text{agglo} = \sqrt{C \times T} \tag{12}$$

Where, *agglo* represents the coupling and coordination of agriculture with the secondary and tertiary industries, indicating the degree of synergetic agglomeration between them. The value of *agglo* ranges from 0 to 1. The higher the value, the greater the degree of interdependence, correlation, and collaborative development between agriculture and the secondary and tertiary industries.

3.1.4. Moderator variables

This paper explores whether the government's "visible hand" effectively moderates the impact of the digital economy on sustainable agricultural development, focusing on two key areas: (1) Fiscal support for agriculture is measured as the ratio of fiscal expenditure on agriculture, forestry, and water affairs to total fiscal expenditure. (2) Digital policies are evaluated using a dummy variable coded as 0 for periods before 2018 and 1 for periods from 2018 onward, reflecting the introduction of the digital village strategy outlined in the No. 1 document of the CPC Central Committee in 2018.

3.1.5. Control variables

Referring to existing studies (Li et al., 2023; Li and Lin, 2023), the control variables in this article include: (1) Agricultural Human Capital. Measured by the formula "(non - urban population of each province/total population of each province) * Per capita years of education in each province ". (2) Degree of Marketization. Represented by the marketization index for each province. (3) Agricultural Market Demand. Indicated by the growth rate of the total agricultural output value in each province. (4) Non-Agricultural Income. Measured by the logarithm of per capita non-agricultural income in each province. (5) Infrastructure. Represented by the logarithm of traffic road mileage in each province. (6) Investment in Environmental Governance. Expressed as the logarithm of investment in environmental pollution control in each province. (7) Sunshine Conditions. Measured by the logarithm of crop sunshine duration in each province (hours). (8) Affected Sown Area. Indicated by the ratio of affected crop area to the total sown area in each province. (9) Income Gap. Represented by the ratio of per capita disposable income of rural residents to per capita disposable income of urban residents.

3.2. Data sources and descriptive analysis of variables

Given that the development of China's digital economy has been most pronounced since 2010, the research period is set from 2011 to 2020. Due to significant data gaps for some indicators in the Xinjiang Uygur Autonomous Region and the Tibet Autonomous Region, the research sample comprises the remaining 29 provinces, autonomous regions, and municipalities directly under the Central Government of China (excluding Hong Kong, Macao, and Taiwan). The data for this study are sourced from official statistical publications, including the China Statistical Yearbook, the China Rural Statistical Yearbook, the China Urban Statistical Yearbook, the National Compilation of Agricultural Product Cost-Benefit Data, and the China Agricultural Machinery Industry Yearbook, as well as from official institutions such as the National Bureau of Statistics and data platforms like the China Research Data Service Platform (CNRDS) and the Digital Finance Research Center of Peking University. Descriptive statistical analysis of all variables used in this study is presented in Table 2.

Table 2
Descriptive analysis results of each variable.

Variable	Symble	Mean	Std. Dev.	Min	Max
Sustainable agriculture development	SAD	1.076	0.109	0.765	2.362
Digital economy	DE	0.242	0.184	0.049	1.000
Agricultural green technology innovation	AGTI	1.145	0.780	0.077	3.639
Resource allocation	RA	−1.983	2.158	−7.381	−0.209
Synergetic agglomeration of three industries	SATI	1.422	0.160	1.004	1.876
Fiscal support for agriculture	FSA	0.113	0.032	0.041	0.190
Digital policies	DP	0.300	0.459	0.000	1.000
Agricultural human capital	AHC	3.818	1.102	0.994	7.206
Degree of Marketization	DM	3.643	0.599	1.222	4.498
Agricultural market demand	AMD	0.230	0.055	0.078	0.308
Non-agricultural income	NAI	5.366	0.799	3.336	7.620
Infrastructure	INF	4.647	1.184	2.413	6.974
Investment in environmental governance	IEG	5.438	1.067	0.698	7.296
Sunshine conditions	SG	7.552	0.298	6.394	8.009
Affected sown area	ASA	0.153	0.121	0.000	0.696
Income gap	IG	0.390	0.061	0.251	0.547

3.3. Model construction

First, we constructed a fixed-effect model to empirically test the impact of the digital economy on SAD, and the benchmark model is as follows:

$$SAD_{it} = \alpha + \beta_1 DE_{it} + \beta_2 DE_{it}^2 + \gamma x_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{13}$$

Where, SAD_{it} refers to SAD, and DE_{it}, DE_{it}^2 refer to the digital economy and the squared term of the digital economy respectively. By incorporating higher-order terms of the independent variable, polynomial regression can capture more complex nonlinear relationships. Further, taking the first and second derivatives of the model reveals its mathematical properties: the first derivative, $dy/dx = \beta_1 + 2\beta_2 x$, represents the rate of change of y with respect to x . The sign and magnitude of the derivative indicate the direction and speed at which y increases or decreases as x changes. The second derivative, $d^2y/dx^2 = 2\beta_2$, represents the acceleration of y with respect to x, or the curvature of the relationship. If $\beta_2 \neq 0$, this confirms that the relationship between y and x is nonlinear. Then, x_{it} represents control variables, and μ_i, φ_t, ε_{it} refer to individual fixed effect, time fixed effect, and random disturbance term respectively.

Furthermore, the digital economy enhances the connectivity and information mobility between regions, suggesting that the impact of the digital economy on SAD may extend beyond the provincial unit to affect SAD in surrounding adjacent areas. To test this possible spatial effect, the above Eq. (13) is extended into a spatial econometric model for empirical research, and the spatial Durbin model is constructed as follow

Eq. (14):

$$SAD_{it} = \rho W \cdot SAD_{it} + \alpha + \beta_1 (W \cdot DE_{it}) + \beta_2 \left(W \cdot DE_{it}^2\right) + \gamma (W \cdot x_{it}) + \beta_3 DE_{it} + \beta_4 DE_{it}^2 + \gamma x_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{14}$$

Where, The geographic distance weight matrix W is measured using the reciprocal of the spherical distance between the centers of two provinces. The greater the distance, the smaller the weight; the shorter the distance, the greater the weight. $\rho W \cdot SAD_{it}$ is the spatial lag term of SAD, reflecting the interaction of SAD between adjacent regions; $\beta_1(W \cdot DE_{it})$ and $\beta_2\left(W \cdot DE_{it}^2\right)$ are the spatial effects of the digital economy and its square term respectively, indicating the potential impact of the digital economy level of adjacent regions on SAD in this region; $\gamma(W \cdot x_{it})$ represents the spatial effect of each control variable, and the meaning of other variables is the same as that of the benchmark model.

Secondly, we test the mechanism of the digital economy and build models following Eqs. (15)–(17):

$$RD_{it} = \alpha + \alpha + \beta_1 DE_{it} + \beta_2 DE_{it}^2 + \gamma x_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{15}$$

$$ALLOCA_{it} = \alpha + \alpha + \beta_1 DE_{it} + \beta_2 DE_{it}^2 + \gamma x_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{16}$$

$$AGGLO_{it} = \alpha + \alpha + \beta_1 DE_{it} + \beta_2 DE_{it}^2 + \gamma x_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{17}$$

Where, RD_{it}, $ALLOCA_{it}$, $AGGLO_{it}$ respectively refer to agricultural green technology innovation, resource allocation, and synergetic agglomeration of three industries.

Finally, we test the moderation effect of government behavior (fiscal support for agriculture, digital policies) on the impact of the digital economy on SAD, and construct models Eqs. (18) and (19) respectively:

$$SAD_{it} = \alpha + \beta_1 DE_{it} + \beta_2 DE_{it}^2 + \beta_3 FSA_{it} + \beta_4 DE_{it} * FSA_{it} + \beta_5 DE_{it}^2 * FSA_{it} + \gamma x_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{18}$$

$$SAD_{it} = \alpha + \beta_1 DE_{it} + \beta_2 DE_{it}^2 + \beta_3 DP_{it} + \beta_4 DE_{it} * DP_{it} + \beta_5 DE_{it}^2 * DP_{it} + \gamma x_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{19}$$

Where, FSA_{it}, DP_{it} respectively refer to fiscal support for agriculture and digital policies. Eqs. (18) and (19) are used to explore the moderation effect of fiscal support for agriculture and digital policies respectively. When investigating the influence of the adjusting variable on the inverted "U" relationship, we refer to the research of Haans et al. (2016), taking Eq. (18) as an example. If β_5 is greater than 0 and significant, the adjusting variable makes the inverted "U" curve smooth, and if β_5 is <0, the adjusting variable makes the inverted "U" curve steep.

4. Empirical analysis and result discussion

4.1. Calculation results and evaluation

Based on the entropy method and the EBM-GML method, we calculated the development levels of the digital economy and Sustainable Agriculture Development (SAD) for each province in China (Fig. 1). We then analyzed the temporal evolution trends using kernel density plots in MATLAB (see Fig. 2). The curve positions indicate that the density function centers for both the digital economy and SAD shifted significantly to the right over the study period, reflecting an upward trend in their development levels. In terms of peak values, the digital economy and SAD exhibit distinct evolution characteristics. For the digital economy, the density function peak became narrower and higher, evolving from a broad peak to a more concentrated one. This suggests a reduction in the dispersion of digital economy development and an increase in its concentration, indicating a trend towards a more uniform and centralized development. In contrast, the peak shape for SAD widened, and its peak value decreased, resulting in an evident bimodal distribution. This change indicates growing regional disparities in SAD and a trend towards polarization.

To further illustrate the spatial distribution and evolution of the digital economy and Sustainable Agricultural development (SAD), ArcGIS10.7 software was utilized to visualize the levels of digital economy development and SAD for the years 2011 and 2020 (Figs. 3 and 4). Following the methodology of previous studies (Liu et al., 2020; Peng et al., 2024), both the digital economy and SAD were categorized into four levels using the Natural-Break method: Low Level, Lower-Middle Level, Upper-Middle Level, and High Level.

Fig. 3 demonstrates that the spatial development of the digital economy originated in Beijing and its neighboring provinces, subsequently extending to the eastern coastal regions, This has resulted in a continuous agglomeration zone from north to south. This pattern indicates progress in enhancing inter-regional coordination and cooperation in China. Moving forward, increased support in digital technology and capital for the central and western regions is recommended to ensure that the benefits of the digital economy are more widely distributed, while also promoting social equity and inclusiveness (Wang et al., 2023a).

Fig. 4 shows that, over the observation period, SAD in the central and western provinces has improved, suggesting effective progress in enhancing agricultural production efficiency and environmental

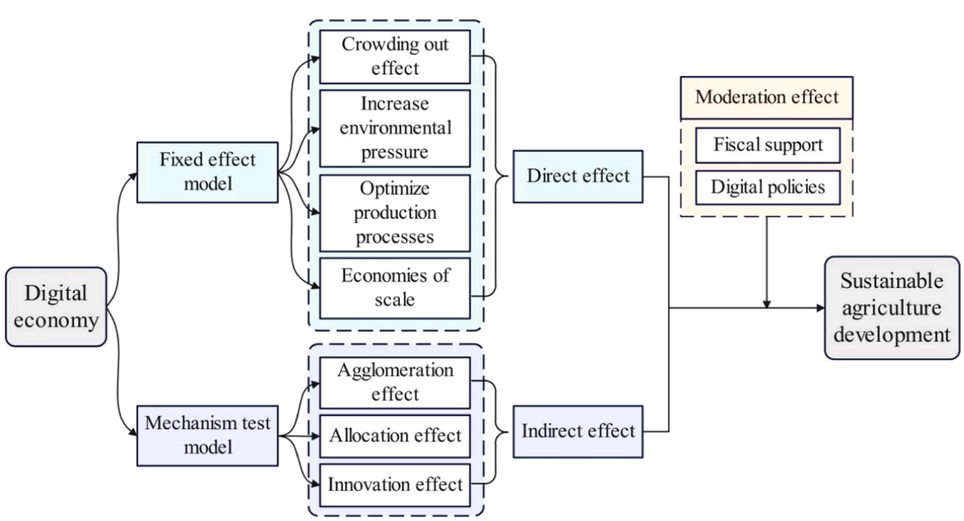

Fig. 1. Theoretical Analysis Framework.

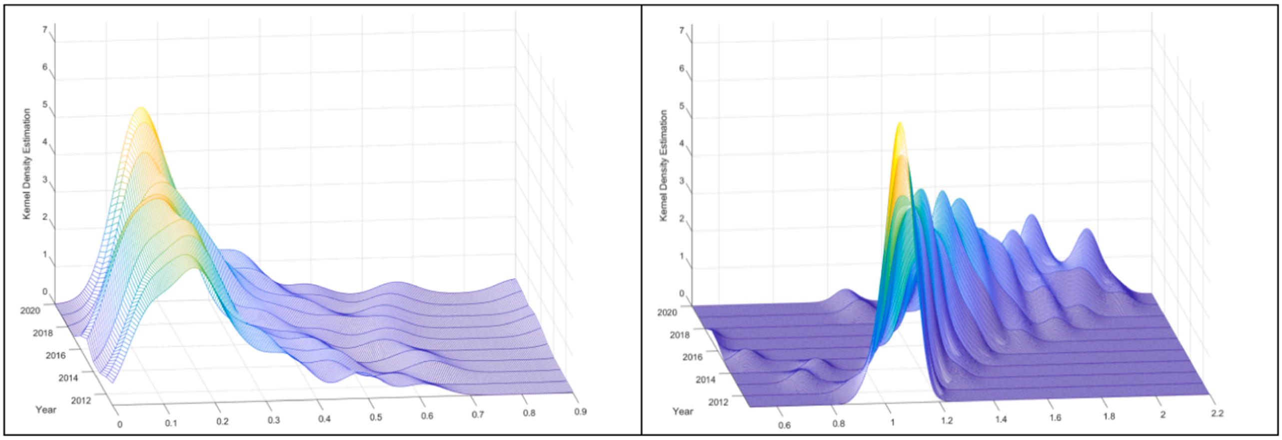

Fig. 2. Kernel density plot of the digital economy and SAD.

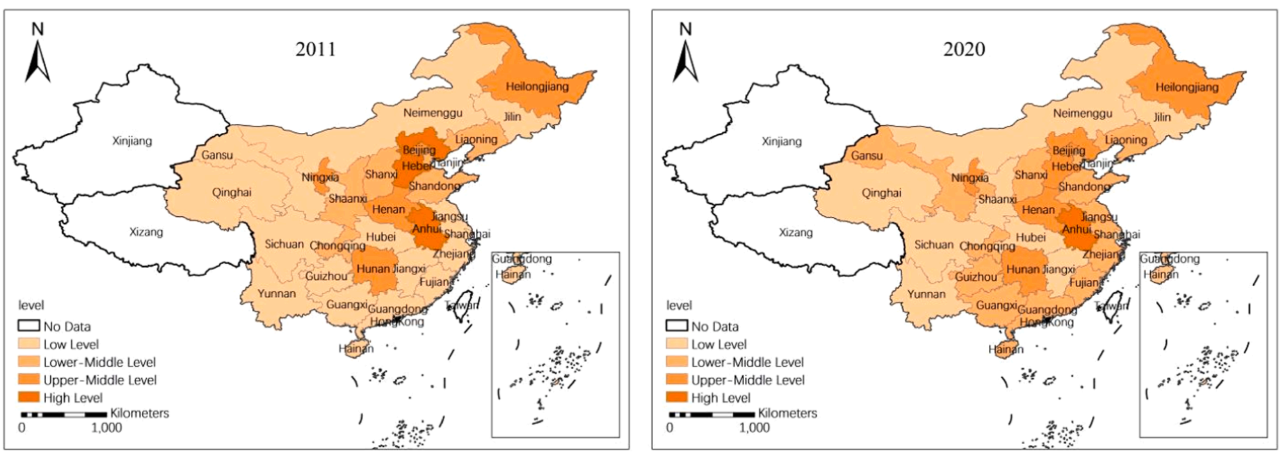

Fig. 3. Spatial distribution of digital economy development level (2011 and 2020). Note: This figure is based on the standard map provided by the Ministry of Natural Resources of China from the Standard Map Service website (GS(2020)4630). The base map boundaries have not been modified, the same below.

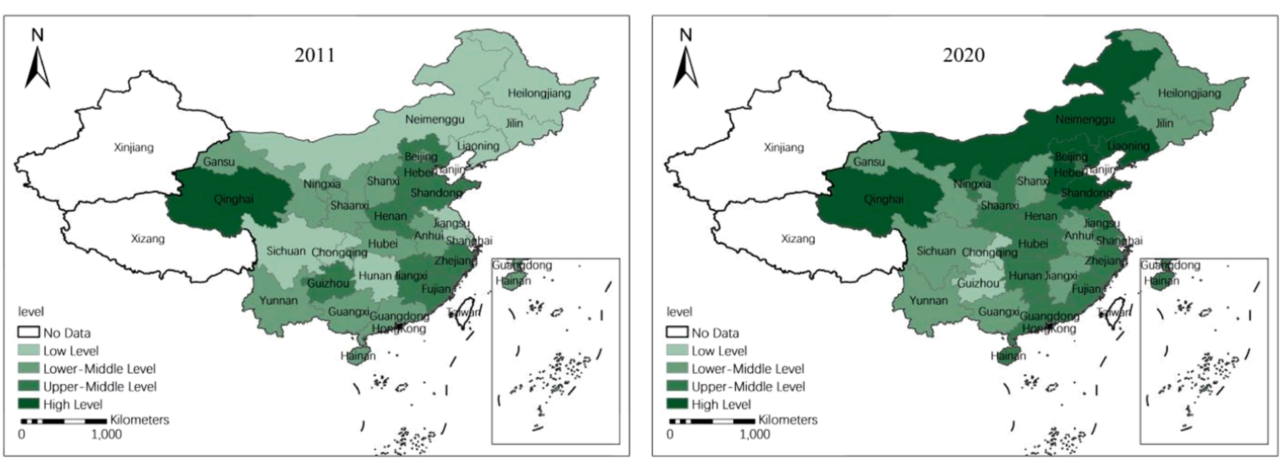

Fig. 4. Spatial distribution of SAD (2011 and 2020).

sustainability. In contrast, SAD in the southeastern coastal provinces has seen only marginal increases. This stagnation may be due to the heavy investment in capital and technology in these developed regions, which has led to increased environmental pressures in agricultural production and hindered the advancement of agricultural green transformation.

Notably, throughout the inspection period, there has been a deepening of both the level of digital economy development and the agglomeration of SAD across regions. This evolution has highlighted the growing spatial correlation among regions, reflecting an increasing mutual influence and dependence.

4.2. Benchmark regression and spatial effect

The fixed effect model is used to empirically test the relationship

Table 3
Baseline Regression, Robustness and endogenous test, and Spatial Regression Results.

Variable	(1) Benchmark regression	(2) Robustness check	(3) Endogenous test1	(4) Endogenous test2	(5) Direct effect	(6) Indirect effect	(7) Total effect
DE	3.759***	0.459	17.550***	11.800***	0.786***	0.203***	0.989***
	(0.620)	(0.577)	(4.030)	(2.570)	(0.03)	(0.03)	(0.03)
DE^2	−34.697***	−1.494*	−21.040***	−14.16***	−0.249***	−0.371***	−0.620***
	(0.923)	(0.859)	(4.924)	(3.165)	(0.04)	(0.03)	(0.04)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Under identification test			19.289***	27.056***			
Weak identification test			19.950***	28.912***			
Spatial Rho					23.57***		
					(0.40)		
R-squared	0.586	0.182	0.348	0.231	0.545		

Note: *,**,* * * respectively indicate that the test has passed the 10 %, 5 % and 1 % significance level tests, with the standard error in parentheses, the same below.

between the digital economy and SAD, as shown in Table 3. The results reveal a significant negative relationship between the squared term of the digital economy and SAD, highlighting a notable inverted "U" relationship and showcasing a significant "double-edged sword" effect. This confirms the research hypothesis H1.To ensure robustness, a robustness test was conducted by replacing the dependent variable. Specifically, the radial DEA-Malmquist method was used to measure SAD, serving as the new dependent variable for empirical testing. The regression results, displayed in the second column of Table 3, affirm the robustness of the inverted "U" relationship (coefficient = −1.494, standard error = 0.859).

To address potential endogenous bias, the Two-Stage Least Squares (2SLS) method was applied. Following Nunn and Qian (2014), the selected instrumental variables include the multiplicative term of the number of fixed telephone lines per 100 people in 1984, the number of post offices per 100 people in 1984, and the national information technology service income from the previous year (IV1 and IV2). These instrumental variables were chosen for their relevance and exogeneity. The regression results, presented in columns 3 and 4 of Table 3, indicate that, even after adjusting for endogeneity, the impact of the digital economy on sustainable agriculture development (SAD) and its inverted "U" relationship remain significant. Furthermore, the results of the under-identification test and weak identification test are positive, underscoring the validity of the instrumental variable selection in this study. These findings confirm that the chosen instrumental variables effectively mitigate endogenous bias, reinforcing the robustness of the study's conclusions.

To verify the spatial effects of the digital economy on SAD, a geographic distance matrix was constructed, and a spatial Durbin model was used based on the previous model for regression estimation. The results, shown in columns 5 to 7 of Table 3, reveal that the primary term of the digital economy has a direct effect of 0.786, signifying a significant positive impact on SAD within the region, consistent with the benchmark regression results. The indirect effect is 0.203, suggesting a positive influence on SAD in adjacent regions through spatial spillovers. Considering the quadratic term of the digital economy, its direct effect is −0.249, indicating a diminishing marginal impact on SAD as the digital economy level increases, thus validating the inverted "U" relationship. The indirect effect of the squared term of the digital economy is −0.371, highlighting a persistent diminishing effect from a spatial perspective. This supports the notion that excessive development of the digital economy may lead to imbalances in resource allocation and a "crowding out effect", thus maintaining the inverted "U" relationship in adjacent areas.

4.3. Re-examination and graphical representation of the inverted "U"

To further validate the inverted "U" relationship between the digital economy and sustainable agriculture development (SAD), this study employed the Utest method in Stata. This method allows for a precise examination of the nonlinear effects of the digital economy on SAD by calculating and comparing extremum points and changes in slope.

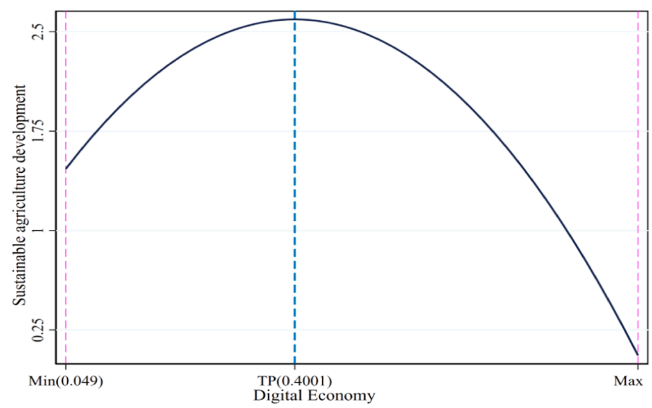

Fig. 5. U sharp test.

The Utest results indicate that the inflection point of the inverted "U" relationship occurs at 0.4001. This means that SAD reaches its peak when the digital economy index is 0.4001. Specifically, within the range of 0.0491 to 0.4001, the slope is positive, suggesting that SAD increases with the development of the digital economy. However, beyond 0.4001, up to 0.9998, the slope becomes negative, indicating that further increases in the digital economy lead to a decrease in SAD. This change in slope demonstrates that while the digital economy initially boosts SAD, it begins to detract from it once a certain threshold is exceeded.

The statistical test yield a t-value of 4.03 and a P-value of 0.00, confirming the presence of the inverted "U" relationship. These results bolster the model's explanatory power and provides a basis for policy recommendations. Policymakers should be aware of the potential adverse effects of the digital economy on sustainable agricultural development and adjust policies accordingly once the critical threshold is reached. A graphical representation of this relationship is provided to enhance the clarity of the statistical findings (Fig. 5).

4.4. Regional characteristics and trends

To objectively demonstrate the regional characteristics and trends of the digital economy and SAD, this section uses remote sensing data on cultivated and forest land as objective indicators of SAD. These data are combined with maps showing digital economy hot spots and cold spots to form composite maps (Fig. 6), which explore the regional impacts of the digital economy on SAD. Cultivated land data are sourced from the multi-period land use remote sensing monitoring dataset provided by the Resource and Environment Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/DOI:10.12078/2018070201).

In this analysis, provinces are classified based on the previously established inverted U-shaped relationship between digital economy

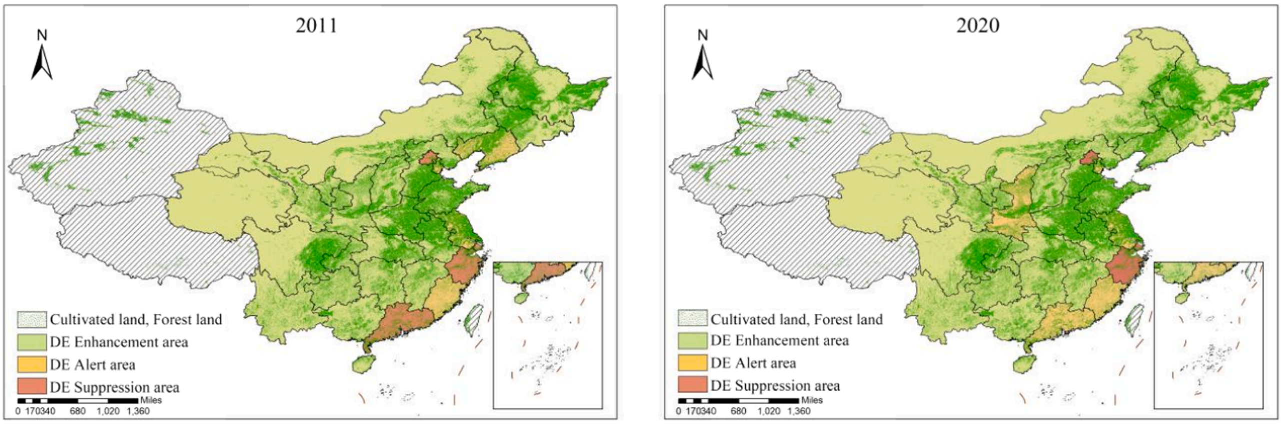

Fig. 6. Regional characteristics and trends (2011 and 2020).

development and SAD. Provinces exceeding the threshold are designated as digital economy suppression areas and are marked in red. Provinces falling within 0.5 standard deviations below the threshold are classified as digital economy alert areas and are shown in yellow. All other areas are designated as digital economy enhancement areas and are depicted in green.

Fig. 6 illustrates the regional differences in the impact of the digital economy on SAD. Digital economy suppression and alert areas are mainly concentrated in economically advanced coastal provinces, which have relatively less cultivated and forest land. This indicates that while the early stages of digital economy development have brought significant technological improvements and efficiency gains to agricultural production in these coastal regions, further development has led to the crowding out of agricultural resources, thereby hindering SAD. In contrast, inland areas, which are at an earlier stage of digital economy development, still experience positive effects on agricultural production, showing a stronger enhancement effect.

From a trend perspective, between 2011 and 2020, the number of provinces classified as suppression or alert areas did not increase significantly. This suggests that government regulations may have been effective in balancing the digital economy with SAD. However, there is a discernible shift of suppression and alert areas from coastal to inland regions. This shift indicates the need for targeted government policies in inland provinces to support SAD effectively and emphasizes the importance of regional differentiation in digital economy policies, avoiding a one-size-fits-all approach to achieve mutually beneficial outcomes for both the digital economy and SAD.

4.5. Mechanism inspection

The fixed-effect model is used to test Eqs. (15)–(17) and explore the mechanism of the digital economy (Table 4). The results show that: (1) The digital economy impacts SAD through agricultural green technology innovation. The coefficient for the squared term of the digital economy's impact on agricultural green technology innovation is −4.421, passing the 1 % significance level test, indicating an inverted "U" shape relationship. This validates research hypothesis 2. When the digital economy is below the threshold, it enables the integration and reorganization of data and traditional elements (Kohli and Melville, 2019; Wang et al., 2024; Lyu et al., 2023a), fostering the deepening of industry-university-research collaborations (Vu and Asongu, 2020; Lyu et al., 2023b), and thus enhancing SAD. However, when the digital economy exceeds the threshold, particularly in the context of China's agriculture, it leads to the excessive development of the digital economy, which diverts funds, talents, and other innovative resources away from agricultural technology innovation, thereby hindering the progress of agricultural green technology. (2) The digital economy influences SAD through resource allocation. The significantly negative impact of the squared term of the digital economy on resource allocation suggests an inverted "U" shape relationship, confirming research hypothesis 3. When the digital economy is below the threshold, it enhances the refinement and efficiency of the agricultural production process (Akaev et al., 2018), promotes the orderly flow of resources (Pee, 2016), and matches agricultural supply and demand (Li et al., 2023), thereby improving SAD. However, when the digital economy exceeds the threshold, it may widen the "digital divide" between regions and create challenges in aligning farmers' information literacy with the rapid pace of digital technology development (Lyu et al., 2023b), thus hindering the improvement of SAD. (3) The digital economy affects SAD through the synergy agglomeration of three industries. The significantly negative impact of the squared term of the digital economy on the synergy agglomeration of three industries indicates an inverted "U" shape relationship, validating research hypothesis 4. When the digital economy is below the threshold, it strengthens the connections and interaction between agriculture and the secondary and tertiary industries (Liu, 2022), forming a networked development pattern (Chen et al., 2023b), thereby improving SAD. However, after the digital economy exceeds the threshold, due to the trend of agricultural "marginalization", the excessive development of the digital economy exacerbates the flow of agricultural talents to the digital industry and other tertiary industries, diverting resources from agricultural development, which negatively affects the synergy agglomeration of three industries and, consequently, SAD.

Table 4
Mechanism of the digital economy.

Variable	Agricultural green technology	Resource allocation	Synergy agglomeration of three industries
DE	1.968***	20.679	0.061
	(0.472)	(17.803)	(0.092)
DE^2	−4.421***	−77.181***	−0.427***
	(0.703)	(26.494)	(0.136)
Control variable	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes
Constant	0.501**	11.601	1.601***
	(0.212)	(7.985)	(0.041)
R-squared	0.337	0.089	0.193

4.6. Moderation effect of government behavior

Using a fixed-effect model to test Eqs. (18) and (19) and explore the moderation effects of government behavior (fiscal support for agriculture and digital policies) (Table 5), the research uncovered the following findings: (1) Moderation Effect of Fiscal Support for Agriculture: The interaction term between the squared term of the digital economy and fiscal support for agriculture is significantly positive. According to the research of Haans et al. (2016), fiscal support for agriculture smooths the inverted "U" curve of the digital economy's impact on SAD, thereby

Table 5
Moderation effect of government behavior.

Variable	The moderating role of fiscal support for agriculture	The moderating role of digital policy
DE	9.581*** (1.839)	2.240*** (0.556)
DE^2	−9.815*** (1.840)	−3.516*** (0.867)
FSA	9.782*** (2.549)	
DE * FSA	−51.382*** (15.332)	
DE^2 * FSA	51.447*** (18.651)	
DP		0.145* (0.077)
DE * DP		0.924** (0.445)
DE^2 * DP		−1.023** (0.484)
Control variable	Yes	Yes
Fixed effect	Yes	Yes
Constant	−2.868*** (0.413)	−0.649** (0.252)
R-squared	0.610	0.724

verifying research hypothesis H5. Specifically, the resource and signal attributes of fiscal support for agriculture provide additional financial and industrial chain support for agricultural and rural development (Kleer, 2010; Wu, 2017), helping to mitigate the "crowding out effect" associated with the excessive development of the digital economy, thus smoothing the inverted "U" curve. (2) Moderation Effect of Digital Policies: The interaction term between the squared term of the digital economy and digital policies is significantly negative. According to Haans et al. (2016), digital policies steepen the inverted "U" curve of the digital economy's impact on SAD, thereby verifying research hypothesis H6. Digital policies provide multi-dimensional support and create a conducive development environment for the digital economy, which helps to positively moderate its impact on SAD when it does not exceed the threshold. However, policies introduced by China often suffer from issues such as overly frequent "target planning" tools and an emphasis on construction over utilization (Zhang et al., 2021; Liu, 2022; Li and Lin, 2022), which may exacerbate the excessive and disorderly development of the digital economy, resulting in a more pronounced "crowding out effect" and other problems, thus steepening the inverted "U" curve.

5. Discussion

This study offers several key discoveries regarding the relationship between the digital economy and sustainable agriculture development (SAD).

Firstly, the analysis reveals a significant inverted "U" shape relationship between the digital economy and SAD, indicating a "double-edged sword" effect. While the digital economy enhances SAD up to a certain point, excessive development beyond this threshold leads to resource misallocation and inefficiencies. The positive initial impact is attributed to the optimization of agricultural production processes, economies of scale, and enhanced efficiency through digital tools (Goldfarb and Tucker, 2019; Gouveia et al., 2004; Bajari et al., 2015; Li et al., 2023). However, beyond the threshold, the digital economy's growth outpaces the agricultural sector's ability to adapt, leading to wastage and decreased productivity (Chen et al., 2023b). This perspective aligns with Solow's productivity paradox (Solow, 1987), highlighting that rapid technological advancements can initially boost productivity but may eventually hinder growth if not managed properly. This study thus contributes to the understanding of the complex, nonlinear impacts of the digital economy on SAD.

Secondly, the study identifies the mechanisms through which the digital economy influences SAD, specifically through technological innovation, resource allocation, and the synergy agglomeration of industries. Technological innovation facilitated by the digital economy drives improvements in agricultural productivity and sustainability. Efficient resource allocation ensures optimal use of inputs, while the synergy agglomeration of agriculture with secondary and tertiary industries promotes holistic development. These findings align with existing research on the positive impacts of the digital economy on green total factor productivity in other sectors such as manufacturing and forestry (Rehman and Nunziante, 2023; Chen et al., 2023b; Liu et al., 2023; Fang et al., 2024; Deng et al., 2022). Unlike current studies that primarily focus on positive impacts, this research highlights potential negative outcomes when the digital economy surpasses the optimal threshold, providing a balanced view of its role in SAD.

Third, this study explores the moderating role of government behavior in the relationship between the digital economy and SAD. The findings support Keynesian theories of the "visible hand," highlighting the crucial role of government regulation in promoting SAD. Fiscal support from the government can smooth the inverted "U" curve and mitigate the negative impacts of excessive digital economy growth by providing necessary resources and stabilizing agricultural development. Specifically, moderate fiscal subsidies and financial guidance, such as direct subsidies, low-interest loans, and funding for sustainable agricultural projects, can effectively alleviate the adverse effects of overdeveloped digital economies. Conversely, coercive administrative interventions and overly frequent policy tools may exacerbate these negative impacts, making the inverted "U" curve steeper. While digital policies aim to promote technological advancements, mismanagement can lead to excessive and disorderly development of the digital economy, further intensifying resource misallocation and pressure on the agricultural sector. Therefore, when formulating and implementing policies related to the digital economy, governments should focus on balance and sustainability (Li et al., 2024), ensuring that policies yield long-term benefits rather than short-term gains (Besharov and Smith, 2014; Zhang et al., 2021; Liu, 2022; Li and Lin, 2022; Wang et al., 2023b). Strategic and balanced policy interventions are essential for promoting sustainable agriculture development.

Future research should further explore these dynamics through regional comparative studies and policy simulation and evaluation. Cross-country comparisons can validate the inverted "U" relationship under different economic, cultural, and institutional contexts, enriching the global perspective on digital economy research. Policy simulations can provide more precise recommendations, enhancing the effectiveness of interventions aimed at fostering sustainable agricultural development.

6. Conclusions and policy implications

6.1. Conclusions

Aiming to address the research question "Can the digital economy improve sustainable agriculture development (SAD), what is the mechanism of action, and can government behavior effectively play a moderating role?" this paper puts forward research hypotheses derived from a literature review and theoretical analysis. Utilizing provincial-level data from China covering the period from 2011 to 2020, the EBM-GML model was employed to calculate AGTFP as a measure of SAD, Kernel density estimation and spatial visualization methods were used to investigate the spatial and temporal evolution characteristics of SAD. The study empirically tests the impact mechanism and effect of the digital economy on SAD and explores the moderating role of government behavior. The main conclusions are as follows:

(1) SAD Trends and Regional Disparities: During the observation period, China's SAD showed a steady upward trend, but regional differences widened, with polarization trends gradually

emerging. The spatial distribution characteristics of SAD showed contiguous agglomeration, and its spatial correlation deepened over time. Meanwhile, the decentralization of the digital economy's development level gradually weakened, trending towards unipolarization and homogenization, with spatial diffusion from north to south.
(2) Inverted "U" Shape Relationship: The impact of the digital economy on SAD presents an inverted "U" shape, showing a significant "double-edged sword" effect. That is, there is an optimal threshold for the digital economy, when it is below this threshold, it positively affects SAD, but when it exceeds the threshold, it negatively impacts SAD. In addition, the digital economy has significant spatial effects and maintains an inverted U-shaped relationship with SAD in neighboring areas.
(3) Regional Variations: Coastal provinces are in digital economy suppression or alert areas, while inland regions are in enhancement areas. From 2011 to 2020, the number of suppression and alert areas did not increase significantly, but there was a trend of shifting from coastal to inland regions..
(4) Mechanisms of Impact: When the digital economy is below the threshold, it promotes agricultural green technology innovation, optimizes resource allocation, and achieves synergetic agglomeration of agriculture with secondary and tertiary industries, thereby improving SAD. However, when the digital economy exceeds the threshold, it negatively impacts agricultural green technology innovation, resource allocation, and the synergetic agglomeration of the three industries, hindering SAD.
(5) Moderating Role of Government: Fiscal support for agriculture can smooth the inverted "U" curve, helping to alleviate the negative impact of the digital economy on SAD when it exceeds the threshold. Conversely, digital policies can steepen the inverted "U" curve, exacerbating the negative impact of the digital economy on SAD beyond the threshold.

6.2. Policy implications

To ensure the dual advancement of the digital economy and sustainable agriculture development (SAD), the following policy recommendations are proposed:

(1) Balanced Investment in Digital Infrastructure: Increase investments in digital infrastructure in rural and underdeveloped regions to bridge the "digital divide." This can include expanding broadband access, supporting digital literacy programs for farmers, and promoting the use of digital tools in agriculture.
(2) Encouraging Green Technology Innovation: Provide subsidies and incentives for research and development in agricultural green technologies. This includes funding for innovations that improve efficiency, reduce emissions, and promote sustainable farming practices.
(3) Optimizing Resource Allocation: Implement policies that promote efficient resource allocation through digital platforms, such as online marketplaces for agricultural products and services. This can help match supply and demand more effectively, reduce waste, and enhance overall productivity.
(4) Strategic Government Interventions: Ensure that fiscal support for agriculture is well-targeted and sufficient to mitigate the "crowding out" effect of excessive digital economic growth. This can involve direct subsidies, low-interest loans, and grants for sustainable agricultural projects.
(5) Sustainable Digital Policies. Formulate digital policies that are carefully balanced to prevent excessive and disorderly development of the digital economy. Policies should focus on sustainable growth, emphasizing long-term benefits over short-term gains.

CRediT authorship contribution statement

Qingning Lin: Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Yuqing Jian:** Writing – review & editing, Validation, Formal analysis. **Deshuo Zhang:** Writing – review & editing, Visualization, Validation, Formal analysis. **Jingdong Li:** Writing – review & editing, Visualization, Validation, Supervision, Software, Formal analysis. **Shiping Mao:** Writing – review & editing, Visualization, Validation, Supervision, Software, Formal analysis.

Declaration of competing interest

The authors declare no conflict of interest.

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Lin Qingning, male, PhD, Associate Research Fellow at the Institute of Agricultural Economics and Development, Chinese Academy of Agricultural Sciences, with a research focus on agricultural technology innovation and sustainable development.

Mao Shiping, male, PhD, is a researcher at the Institute of Agricultural Economics and Development, Chinese Academy of Agricultural Sciences. His research focuses on agricultural technology economy and agricultural science and technology policies.