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ARTICLE

Coupling Coordination Analysis between Total Factor Productivity and Digital Economy in China's Agriculture

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ABSTRACT

This study aims to systematically analyze the coupling and coordinated development between the digital economy (DE) and total factor productivity (TFP) in China's agricultural sector, focusing on their impact on regional agricultural advancement. Using a comprehensive dataset from 31 Chinese provinces covering the period from 2014 to 2021, we apply the EBM model, entropy weight method, and coupling coordination degree model to assess TFP-DE interactions. To capture spatial-temporal dynamics and regional disparities, we employ kernel density estimation, Moran's I index, the Dagum Gini coefficient, and an obstacle degree model. The findings reveal an initial phase of "multipolarization" in TFP-DE coordination, which gradually stabilizes towards preliminary coordination levels. Despite this progress, significant regional imbalances persist, particularly in central and western provinces where "low-low" clusters dominate, in contrast to the "high-high" clusters in eastern regions. While disparities in coordination have narrowed in eastern areas, they continue to widen across central and western regions. The primary obstacles have shifted from foundational infrastructure to challenges directly associated with DE and TFP. This study underscores the necessity of region-specific policies to address these disparities, particularly in underdeveloped areas, to enhance agricultural productivity through digital integration. The findings provide a strategic foundation for policymakers to foster balanced and sustainable growth, contributing to China's broader goals for

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agricultural modernization.

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1. Introduction

The Central Government of China's "2023 Work Plan for Digital Rural Development" proposes multiple measures to develop the digital economy in county-level regions, further deepening the strategies of "digital revitalization of agriculture" and "e-commerce empowerment of agriculture". The digital economy represents a new economic model formed by the integration of digital technologies into traditional economic sectors. In China, digital technologies are already applied to the production and sale of agricultural products. Agricultural production is significantly affected by external factors, including climate, temperature, pests, and diseases, which can reduce agricultural productivity and pose significant risks to agricultural productivity and sustainability. To address these challenges, technology is used to predict potential crises, enabling early prevention and reducing the area of agricultural damage. Recently, the rise of the digital economy has emerged as a potential solution for these challenges. Digital technologies enable the real-time monitoring of climate data. For example, meteorological knowledge and services can be maximally connected to thousands of households through apps and other platforms. Agricultural meteorological data differs from general meteorological data in terms of content, indicators, real-time requirements, and other aspects. In other words, general meteorological data cannot replace agricultural-specific data. More complete and agriculture-specific meteorological data output and services will greatly benefit the improvement of digital agriculture algorithms and production management, allowing farmers to dynamically adjust input structures according to changing environmental conditions [1]. This transformation is pivotal for enhancing agricultural efficiency and productivity. Using digital technology to bridge the "last mile" of agricultural technology extension has become a new approach. By leveraging big data technology, a standardized production model can be developed that integrates local land resources, climate conditions, pest and disease data, and real-time monitoring of adverse conditions. Additionally, with the continuous development of the digital economy, agricultural products now have access to online sales channels, which accelerates the efficiency of agricultural product circulation. Information technology also facilitates the rapid transmission of consumer demand to the supply side, reducing the production of low-end agricultural products with limited market demand and promoting the upgrading and transformation of agriculture. As agriculture continues to develop, technological advancements, such as scientific planting methods, are crucial for improving agricultural productivity. With China's ongoing urbanization, developing agriculture on limited land while ensuring food security has become a critical issue. Therefore, the need to improve agricultural productivity will drive the application of the digital economy in agriculture. The development of the digital economy and agriculture is interdependent, and analyzing their synergistic effects is key to promoting the sustainable development of agriculture.

Economic activities supported by digital technology began in the 1950s, while China connected to the internet in 1994. Although scholars have not yet reached a clear, unified definition of the digital economy, there is consensus that digital technology and big data are fundamental components. The digital economy is generally defined as an economy driven by digital technologies [2]. Moreover, the digital economy aims to boost economic activity by leveraging digital data and utilizing information and communication technologies. Various internet-based platforms, developed with digital computing technology, have driven the expansion of the digital economy [3, 4]. At the G20 Hangzhou Summit, China defined the digital economy as an economic activity that relies on digital knowledge and information as key production factors, uses modern information networks as an important medium, and effectively employs information and communication technologies as a key driver for improving efficiency and optimizing economic structure (G20, 2016). The Organization for Economic Cooperation and Development (OECD) has referenced the digital economy in its reports for several consecutive years. In the era of the digital economy, trends such as big data analysis and cloud computing are among the most important drivers, making the future "intelligent era" possible and providing greater convenience for businesses, consumers, and society as a whole [5]. Developed economies in Europe and the United States have played a leading role in formulating data laws and policies, driving business development, and improving market structures. In contrast, China has promoted the digital economy across various aspects of economic and social development through a series of strategic goals. These efforts have driven the scale of digital industrialization, promoted the transformation of traditional industries, fostered innovation in regional digital economies, and improved people's livelihoods [6]. The development of the digital economy breaks the limitations of time and geography on the demand side, emphasizing personalized consumer needs and creating a "demand-driven" market. On the supply side, information dissemination and data analysis push companies to expand the boundaries of production possibilities [7]. In other words, the development of the digital economy contributes to changes in production structure. After China's economy entered the "new normal", rural and agricultural development also entered a new phase, with the main challenges in agriculture shifting to structural issues, such as an oversupply of low-end, ineffective agricultural products and a shortage of mid- to high-end, personalized agricultural products. The development of the digital economy can drive the shift in agriculture from a production-oriented to a demand-oriented model, improving agricultural productivity and economic growth [8]. The emergence of the digital economy appears to break the constraints of agricultural development, which are often affected by factors like weather and funding. It can leverage cutting-edge digital technologies to monitor climate change data and adjust the input structure of agricultural factors, offering a new path for agricultural development [1]. Previous studies have emphasized the significant role of the digital economy (DE) in improving agricultural productivity by enhancing access to digital tools and facilitating the efficient allocation of production factors [9, 10]. Additionally, unified data platforms and the exploration of endogenous dynamics in agriculture provide dual benefits for both the data economy and agricultural economy [11, 12]. In China, modernization strategies focus on optimizing the allocation of physical capital within and across farms, with digital technologies, particularly information and communication technologies (ICT), playing a key role in this optimization and improving resilience and productivity in agriculture [13, 14]. Furthermore, digital solutions such as precision farming and smart agriculture have been shown to enhance efficiency, even during crises, such as food supply chain disruptions [15–17].

Total factor productivity (TFP) is an important reference indicator for measuring the quality of economic growth in a country or region. There are various methods for measuring TFP, which are generally categorized into parametric and non-parametric approaches. Parametric methods include the Solow growth rate equation, the production function approach, and the stochastic frontier approach (SFA). Non-parametric methods mainly rely on the Malmquist productivity index based on Data Envelopment Analysis (DEA). TFP considers the interactions between all input factors, combining capital, labor, and other inputs with energy to measure the relationship between inputs and outputs. Agricultural total factor productivity (ATFP), based on this framework, integrates agricultural production factors with key input variables such as labor, capital, and land, reflecting real trends in agricultural production efficiency. For scenarios involving multiple inputs and outputs, non-parametric methods are generally more suitable for measuring production efficiency than parametric methods [18]. The traditional DEA model has the drawback of neglecting non-radial slack variables [19]. To address this, Tone [20] proposed the non-radial SBM (Slack-Based Measure) model, which considers both radial and non-radial slack variables. However, the SBM model lacks information on the ratio between input or output target values and actual values, resulting in efficiency values that are typically lower than the actual efficiency. To address this issue, Tone and Tsutsui [21] introduced the EBM (Epsilon-Based Measure) model, a hybrid model that incorporates both radial and SBM distance functions, providing a new method for evaluating the efficiency of decision-making units. Therefore, this study uses the EBM model to measure agricultural total factor productivity. In addition to the differences in research methods, scholars also vary in their focus on agricultural total factor productivity. (1) The first aspect is the temporal evolution of agricultural TFP. One study examines the growth of agricultural productivity in 93 countries over the period from 1980 to 2000. These results indicate a degree of catch-up in productivity levels between high-performing and low-performing countries [22]. Regional analysis shows that the growth rates of agricultural total factor productivity in China vary across different regions, and the sources of growth also differ [23]. (2) The second aspect is the factors influencing agricultural TFP. TFP performance is strongly related to technological capital, and technological capital is required for TFP and cost reduction growth [24]. The increase in extension service expenditures may impact the dissemination of the latest innovations among farmers, enabling them to use digital agricultural technologies more precisely and fostering the development of digital talent [25, 26]. (3) The third aspect is total factor productivity under the context of new challenges in agriculture. Rising temperatures have a significantly inhibitory effect on agricultural productivity [27]; extreme weather has a significant negative impact on agricultural green total factor productivity (AGTFP) in severely affected areas [28]. Additionally, the aging of the rural population has a negative inhibitory effect on AGTFP in China, especially in the western region, while the effect was less significant in eastern and central regions [29].

The digital economy facilitates improvements in agricultural TFP by leveraging data, and information and ICT. It provides farmers with accessible and cost-effective information on agricultural practices, markets, and climate conditions, thereby promoting technological advancement and efficiency [30] (**Figure 1**).

Moreover, digital technologies enhance credit channels for agricultural financing and offer a more sustainable financial foundation for agricultural development [31]. The digital economy also supports smart farming through Internet-based agricultural monitoring systems, contributing to the development of precise supply chains and livestock management [32]. Conversely, improvements in agricultural TFP driven by effective climate resource management can stimulate the growth of the digital economy. Enhanced agricultural productivity increases farmers' incomes and promotes urbanization, which, in turn, provides human capital, financial resources, and data necessary for the expansion of digital economy [33]. Additionally, improved agricultural efficiency generates a demand for technological innovation and industry collaboration, expanding the market for digital solutions in agriculture. Through the above analysis, it is evident that existing literature primarily focuses on the impact and role of one direction—either proving the influence of the digital economy on agriculture or the impact of agriculture on the digital economy—without exploring their integrated development. This study posits that the synergistic development of the digital economy and agricultural total factor productivity is a key approach to advancing smart agriculture and promoting sustainable agricultural development. Therefore, this paper will comprehensively assess the synergistic development level of the digital economy and agricultural total factor productivity across 31 provinces in mainland China and explore the regional development disparities in depth.

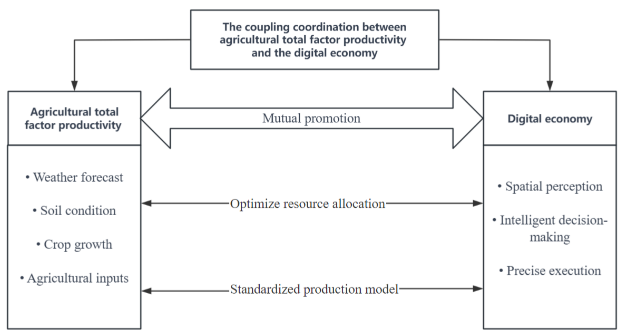

Figure 1. Coordination mechanism of agricultural TFP and DE.

Previous literature provides the theoretical foundation and starting point for the logical framework of this study. However, a review of the literature reveals a lack of clear evidence supporting the stability and balanced interaction between the digital economy and agricultural productivity. In response, this study expands on three key aspects: First, it incorporates climate factors into the input indicator system, recognizing their impact on agriculture, and uses the super-efficiency EBM model to comprehensively measure agricultural total factor productivity. Second, a coupling coordination model is employed to assess the coupling coordination degree between China's digital economy and agricultural total factor productivity during the sample period. At the same time, regional economic development levels and natural geographic factors are considered, dividing China into three regions to provide a comprehensive understanding of the coupling coordination degree. Next, kernel density parameters, Moran's index, and the Gini coefficient are used to measure the dynamic evolution trends, spatial correlations, and sources of differences in coupling coordination degree across China and its regions. Finally, the barrier degree model is applied to explore the factors influencing the development of coupling coordination at different stages. This study aims to provide recommendations for the coordinated development of the digital economy and agricultural total factor productivity, offering insights for digital agriculture initiatives in other countries and promoting sustainable agricultural development.

2. Materials and Methods

This study used data from 31 provinces in China between 2014 and 2021, sourced from the China Statistical Yearbook, China Rural Statistical Yearbook, and other official publications. The research methodology incorporates a super-efficiency EBM model to assess total factor productivity (TFP) in agriculture, along with the entropy weight method for evaluating the development of DE.

2.1. Indicator Evaluation System

Typical climate-related models include the Miami model, the Thornthwaite Memorial model, and the Chikugo model. Some scholars have compared the accuracy of these three models in calculating the climate production potential of China and concluded the following: The Miami model lacks comprehensive consideration of climatic factors and has larger errors; the Chikugo model produces results that align more closely with actual conditions, demonstrating higher accuracy; the Thornthwaite Memorial model, which uses actual evapotranspiration as a variable and integrates various climatic factors, is a strong representative climate indicator. While its precision may be slightly lower in certain areas, its overall results are close to measured values and are similar to those of the Chikugo model.This paper selects the Thornthwaite Memorial model to calculate climate production potential [34–37]. The Thornthwaite Memorial model, also known as the Montreal model, was proposed by H. Lieth and E. Box at the 22nd International Geographical Congress held in Montreal, Canada, in 1972. This model predicts biological productivity using actual annual evapotranspiration [38–40]. Climate production potential refers to the maximum biological yield of plant biomass per unit area during a specific period, determined solely by climatic resources, assuming all other controlling variables are optimal and excluding climatic conditions themselves [41]. This study employs the Thornthwaite Memorial model to calculate regional climate production potential [42]. The calculation formulas are shown as (1–3) below. The EBM (Epsilon-Based Measure) model can address the measurement of total factor productivity (TFP) by incorporating undesirable outputs (such as pollutants and carbon emissions), making it particularly suitable for analyzing areas related to environmental sustainability and resource management. It is also well-suited to handle heterogeneity across different regions or sectors, especially in scenarios with varying economies of scale, such as agricultural productivity in different regions. However, considering the issues of multiple DMUs and comparability over time series, this study measures AGTFP through the super-efficiency EBM window method. Consequently, this study constructs a global super-efficiency EBM window method under the assumption of variable returns to scale to measure agricultural TFP. For the measurement of TFP, there are a total of nine input indicators and one output indicator, including climate resources input, labor input, land investment, fertilizer input, agricultural film investment, irrigation input, mechanical input, energy input and agricultural output value (**Table 1**). The calculation formulas are shown as (4). In multi-criteria comprehensive evaluations, the entropy weight method is more objective than other weighting methods, making it suitable for handling complex evaluation systems with multiple dimensions and indicators. Given that the evaluation of the digital economy involves four primary indicators—infrastructure, rural governance, industrial development, and the level of digital public services—and 24 secondary indicators (**Table 2**), the entropy method was chosen to assign weights to DE evaluation indicators, thereby measuring the development level of DE.

Where PET is the climate production potential ($gm^{-2}\ a^{-1}$); ET is the average annual evapotranspiration (mm); E_0 is the annual maximum annual evapotranspiration (mm); R is the annual precipitation (mm); T is the annual average temperature (℃). Equation (2) and Equation (3) hold if and only if R = $0.316E_0$, and E_0 = R when R < $0.316E_0$.

$$R_{ET} = 3000\left[1 - e^{-0.0009695(ET-20)}\right] \tag{1}$$

$$ET = 1.05R/\left[1 + \left(1 + \frac{1.05}{E}\right)^2\right]^{1/2} \tag{2}$$

$$E_0 = 300 + 25T + 0.05T^3 \tag{3}$$

where x and y denote inputs and desirable outputs, respectively; I and H respectively indicate the number of input and output variables. w_i^- denotes the i-th input element's weight, reflecting its importance, satisfying $\sum W_i^- = 1$ plus $\sum W_i^- \geq 0$. w_h^+ denotes the h-th output's weight, satisfyingand $\sum w_h^- = 1$ and $\sum w_h^- \geq 0$. λ represents the adjustment matrix. θ and φ are radial parameters. ε is a data-driven parameter, which indicates the non-radial ratio of inputs and outputs when calculating efficiency, and satisfies 0 ≤ ε ≤ 1. s_i^- and s_h^+ are non-radial slack vectors. ρ^* represents the evaluated efficiency. $\rho^* \geq 1$ indicates the DMU is effective, the larger ρ^*, the higher the efficiency. In particular, the above model can distinguish multiple effective DMUs, thereby avoiding information loss.

$$\rho^* = \min \frac{\theta - \varepsilon_x \sum_{i=1}^{I} \frac{w_i^- s_i^-}{x_{i,k}}}{\varphi + \varepsilon_y \sum_{h=1}^{H} \frac{w_h^+ s_h^+}{y_{h,k}}}$$

$$s.t.\begin{cases} \sum_{n=1}^{N} x_{in}\lambda_n + s_i^- = \theta x_{ik}, i = 1, \ldots, I; \\ \sum_{n=1}^{N} y_{hn}\lambda_n - s_h^+ = \varphi y_{hk}, h = 1, \ldots, H; \\ \lambda_n \geq 0, s_i \geq 0, s_h^+ \geq 0, n = 1, 2 \ldots, N(n \neq k) \end{cases} \tag{4}$$

2.2. Coupling Coordination Model

To scientifically explore the degree of coordination between agricultural TFP and DE in the process of development, this study builds a coupled coordination model between the two. The calculation formulas are shown as Equations (5)–(7).

In the formula, C represents the coupling degree; T represents the comprehensive coordination index; α and β are undetermined coefficients, commonly taken as 0.5 each; D is the coupling coordination, with values ranging from [0,1].

$$C = \sqrt[2]{\eta_1 \times \eta_2}/\eta_1 \times \eta_2 \tag{5}$$

$$T = \alpha\eta_1 + \beta\eta_2 \tag{6}$$

$$D = \sqrt{C \times T} \tag{7}$$

To ensure the reference value of the coupling coordination [43] and combined with practical calculation results, this study classifies the coupling coordination into six levels, as shown in **Table 3**.

2.3. Dynamic Trends

To better understand the dynamic evolution characteristics of agricultural TFP and DE based on climate resource input in China and the three regions, the nuclear density estimation method was used for analysis [44]. Using kernel density estimation plots, one can intuitively discern the areas of data concentration, peaks, outliers, and overall distribution shape. This method helps to understand the development trends of overall and regional coupling coordination.

$$f(x) = \frac{1}{N_h}\sum_{i=1}^{N} K(\frac{X_i - x}{h}) \tag{8}$$

$$k(x) = \frac{1}{\sqrt{2\pi}}\exp(-\frac{x^2}{2}) \tag{9}$$

Where N is the number of observations; X_i is the sample observations; x is the sample average; k(x) is the Kernel density; h is the bandwidth.

2.4. Spatial Correlation

The global Moran's index was introduced to test the spatial correlation of the degree of coupling coordination in China. Owing to the spatial concentration inherent in the development of DE, its growth can facilitate the

Table 1. Agricultural total factor productivity index system.

Indicators	Secondary Indicators	Variable Declaration
Agricultural input	Climate resources input	climatic potential productivity
	Labor input	Total number of employees in agriculture, forestry, animal husbandry and fishery * (agricultural output value/total output value of agriculture, forestry, animal husbandry and fishery) (ten thousand people)
	Land investment	Total sown area of crops (khm^2)
	Fertilizer input	Fertilizer application amount (ten million kWh)
	Pesticide input	Pesticide use (ten thousand kWh)
	Agricultural film investment	Agricultural film used (ten thousand kWh)
	Irrigation input	Effective irrigation area (thousand hm^2)
	Mechanical input	Total power of agricultural machinery (ten thousand kWh)
	Energy input	Agricultural machinery diesel consumption (ten thousand kWh)
Agricultural expectation output	Agricultural output value	Total agricultural output (100 million yuan)

optimization of agricultural production structures and the rational allocation of agricultural production factors. Regions with rapid advancements in the digital economy tend to exhibit improved development in digital agriculture. Therefore, it is hypothesized that, at the provincial level, there may be a spatial clustering effect between agricultural TFP, influenced by climate resources, and the digital economy [45].

W_{ij} represents the spatial weight and $\overline{x}$ represents the mean; x_i and x_j denote the coupling coordination degree scores of research units i and j, respectively, which correspond to the observed values of research units i and j; n is the number of research units. The value of I ranges from [−1, 1].

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(x_i-\overline{x}\right)\left(x_j-\overline{x}\right)}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\right)\sum_{i=1}^{n}\left(x_i-\overline{x}\right)^2} \tag{10}$$

The local Moran's I index was used to investigate local spatial effects in the study area. Compared with the global Moran's I, the local Moran's I provides a more precise analysis of regional differences, including spatial clustering and dispersion phenomena in specific areas. The local Moran's I can reflect whether high-value regions are driving the development of low-value regions or whether high-value regions are monopolizing resources from low-value areas, as well as the spatial heterogeneity across different regions. It also captures spatial heterogeneity across different regions and shows how spatial autocorrelation in certain areas changes over time This information is highly useful for regional analyses and policymaking. The spatial agglomeration types of the local Moran index are usually divided into four types: high–high, low–high, low–low, and high–low

$$I^{*} = \frac{x_i-\overline{x}}{S^2}\sum_{j=1}^{n} W_{ij}\left(x_j-\overline{x}\right)_{,}\ i \neq j \tag{11}$$

$$S^2 = \left[\sum_{i=1}^{n}\left(x_i-\overline{x}\right)^2\right]/n \tag{12}$$

I* is the local Moran's index, with other variables having the same meaning as described above.

2.5. Regional Disparity Levels

The Dagum Gini coefficient can not only fully consider the distribution of each sub-sample and the overlap between the samples but also provide a more accurate reflection of the sources of regional differences. By using the Gini coefficient, differences in the coupling coordination of digital agriculture across regions can be compared, allowing for an evaluation of the impact of digital economic policies on the agricultural sector in various areas. This facilitates a deeper understanding of the disparities in digital agriculture development between regions and helps to formulate more effective poli-

Table 2. Evaluation index system of digital economy.

Indicators	Secondary Indicators	Specific Calculation Method
Infrastructure	Radio and television coverage rate	The proportion of rural cable radio and television users is (%)
	Agrometeorological observation station	Number of agrometeorological observation stations
	Smart phone penetration rate	The average mobile phone ownership per 100 households at the end of the year
	Rural electricity consumption	Electricity consumption in rural areas (100 million kWh)
Rural governance	The Internet penetration rate in rural areas	Number of rural Internet broadband access users proportion (%)
	Rural communications expenditure	Transportation and communication consumption expenditure of rural residents (yuan)
	Farm machinery production	Total power of agricultural machinery (ten thousand kilowatts)
Industrial development	Rural per capita income scale	Rural per capita disposable income
	Rural consumption level	Total retail sales of rural consumer goods (100 million yuan)
	Agricultural digital trading	Online retail sales (100 million yuan)
	The proportion of digital product and service consumption	The Engel coefficient of rural residents
Digital public service level	Postal express level	The average number of weekly deliveries in rural areas
	Service scope of information technology applications	Rural delivery route (km)
	Level of digital service input	Expenditure on science and technology (100 million yuan)

Table 3. Type of coupling coordination degree between DE and agricultural TFP.

Coupling Coordination Degree	0 < D ≤ 0.4	0.4 < D ≤ 0.5	0.5 < D ≤ 0.6	0.6 < D ≤0.7	0.7 < D ≤ 0.8	0.8 < D ≤ 1
Coordination type	Completely dysregulated	Imminently dysregulated	Forced coordination	Primary coordination	Intermediate coordination	Advanced coordination
Type code	I	II	III	IV	V	VI

cies to address the imbalances in digital agriculture development[46]. The Dagum Gini coefficient, along with its subgroup decomposition method, is employed to analyze the differences in coupling degrees between regions in China.

$$G=\frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji}-y_{hr}\right|}{2n^2y} \tag{13}$$

$$G_{ij}=\frac{\frac{1}{2Y_j}\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}\left|y_{ij}-y_{jr}\right|}{n_j^2} \tag{14}$$

$$G_w=\sum_{j=1}^{k}G_{jk}p_js_j \tag{15}$$

$$G_{jh}=\frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji}-y_{jr}\right|}{n_jn_h\left(\bar{y}_i+\bar{y}_h\right)} \tag{16}$$

$$G_{nb}=\sum_{j=2}^{k}\sum_{h=1}^{j-1}G_{jh}\left(p_is_h+p_hs_j\right)D_{jh} \tag{17}$$

$$G_t=\sum_{j=2}^{k}\sum_{h=1}^{j-1}G_{jh}\left(p_is_h+p_hs_j\right)\left(1-D_{jh}\right) \tag{18}$$

$$D_{jh}=\frac{d_{jh}-p_{jh}}{d_{jh}+p_{jh}} \tag{19}$$

$$d_{jh}=\int_0^{\infty}dF_j(y)\int_0^{y}(y-x)dFh(x) \tag{20}$$

$$p_{jh}=\int_0^{\infty}dF_h(y)\int_0^{y}(y-x)dFj(x) \tag{21}$$

G_j represents the Gini coefficient of region j; G_{jh} takes part in G_{nb} and represents the Gini coefficient between regions; D_{jh} represents the relative influence of the development level of coupling coordination between regions j, h; d_{jh} is the difference in the development level of coupling coordination between regions; p_{jh} is defined as the hypervariable first-order moment, where $F_h(x)$ is the cumulative density distribution function of the region, and $F_j(x)$ is the cumulative density distribution function in region j.

2.6. Obstacle Degree Model

To explore the main obstacle factors that hinder the coupling coordination level of agricultural TFP and DE under climate change, the barrier degree model was introduced to analyze them. By measuring obstacle factors, the primary barriers to the development of digital agriculture can be identified, helping determine which factors inhibit overall growth. This also provides insight into the relative importance of each factor in terms of hindrance. By formulating policies to prioritize the issues that have the greatest impact on the development of digital agriculture, overall coupling coordination can be improved.

$$O_j = \frac{P_{ij}U_j}{\sum_{i=1}^{n}(P_{ij}U_j)} \tag{22}$$

Where the index contribution U_j represents the weight determined by the entropy method of index j; the index deviation $P_{ij} = 1 - Z_{ij}$, where Z_{ij} is the standardized value of each index; O_j represents the index barrier.

2.7. Data Sources

In order to ensure data consistency and authenticity, the period from 2014–2021 was selected as the research sample period, focusing on 31 provinces in China as the research object. The original data was sourced from the China Statistical Yearbook, China Rural Statistical Yearbook, China's Third Industry Statistical Yearbook, the Provincial National Economic Statistics Announcement and the Chinese Bureau of Statistics website. Considering the dual characteristics of the digital economy and agriculture, the regions are divided into three categories: eastern, central, and western regions. This study explores the coupling coordination degree between DE and agricultural TFP in different regions.

3. Results

According to previous studies and data analysis, the results are discussed in terms of five aspects to analyze China's digital agriculture coupling coordination.

3.1. Analysis of the Coupling Coordination Degree of Agricultural Total Factor Productivity and Digital Economy

Compared with the base year of 2014, the coupling coordination degree of all 31 provinces increased by 2021. The overall coupling coordination of agricultural TFP and DE among the 31 provinces exhibits a spatial distribution and evolution pattern of "high in the southeast, decreasing from coastal to inland areas". This characteristic became more evident in 2018 and was positively correlated with the economic development levels of various provinces in China. The development of the digital economy and agriculture requires financial support; regions with higher levels of economic development tend to have more advanced digital infrastructure [47]. In 2014, only two provinces—Jiangsu and Zhejiang—achieved intermediate coordination, both of which belong to the eastern region. Seventeen provinces, including Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia, were in the primary coordination stage, whereas 11 provinces, including Heilongjiang, Anhui, Shandong, and Henan, were in the barely coordinated stage (**Table 4**). By 2016, there was a significant overall improvement in the coordination coupling of each province. Although Tibet was still on the verge of imbalance, the number of provinces in the barely coordinated stage—such as Xinjiang, Chongqing, Shandong, and Henan—decreased from 11 to 4. Meanwhile, the number of provinces in the primary and intermediate coordination stages increased to 21 and 4, respectively. In 2018, Tibet made a breakthrough by transitioning directly from the verge of imbalance to the primary coordination stage. By this time, all 31 provinces had reached the primary coordination stage or higher. The number of provinces in the intermediate coordination stage increased to five and the number in the primary coordination stage increased to 26.

Table 4. Evaluation results of agricultural TFP and DE.

Areas	2014			2021			Change Rate
	Value	Ranking	Type	Value	Ranking	Type	
Beijing	0.696	3	IV	0.777	3	V	11.76%
Tianjin	0.621	12	IV	0.705	10	V	13.49%
Hebei	0.612	15	IV	0.685	17	IV	11.88%
Shanxi	0.636	8	IV	0.704	11	V	10.73%
Inner Mongolia	0.616	14	IV	0.671	25	IV	8.97%
Liaoning	0.638	7	IV	0.676	22	IV	6.10%
Jilin	0.628	10	IV	0.664	26	IV	5.68%
Heilongjiang	0.593	21	III	0.635	30	IV	7.09%
Shanghai	0.674	5	IV	0.727	6	V	7.81%
Jiangsu	0.701	2	V	0.754	4	V	7.59%
Zhejiang	0.702	1	V	0.795	1	V	13.28%
Anhui	0.594	20	III	0.680	19	IV	14.45%
Fujian	0.650	6	IV	0.738	5	V	13.60%
Jiangxi	0.602	19	IV	0.686	16	IV	13.98%
Shandong	0.578	24	III	0.691	15	IV	19.49%
Henan	0.565	29	III	0.648	29	IV	14.82%
Hubei	0.625	11	IV	0.714	8	V	14.26%
Hunan	0.590	22	III	0.692	14	IV	17.22%
Guangdong	0.679	4	IV	0.794	2	V	16.81%
Guangxi	0.602	18	IV	0.693	13	IV	14.98%
Hainan	0.551	30	III	0.655	28	IV	19.01%
Chongqing	0.571	26	III	0.679	20	IV	19.06%
Sichuan	0.619	13	IV	0.714	7	V	15.31%
Guizhou	0.565	28	III	0.706	9	V	24.93%
Yunnan	0.578	25	III	0.673	23	IV	16.44%
Tibet	0.438	31	II	0.633	31	IV	44.42%
Shaanxi	0.628	9	IV	0.696	12	IV	10.67%
Gansu	0.589	23	III	0.672	24	IV	14.10%
Qinghai	0.603	16	IV	0.677	21	IV	12.23%
Ningxia	0.602	17	IV	0.681	18	IV	13.11%
Xinjiang	0.569	27	III	0.658	27	IV	15.69%

By 2021, the number of provinces in the intermediate coordination stage increased to ten, with the remainder in the primary coordination stage.

Overall, by the end of 2021, although no provinces were in a state of imminent dysregulation among the 31 provinces, neither were any provinces at a high level of coordination. Among the provinces in the intermediate coordination stage, 70% belong to the eastern region. In the central region, only Hubei is in the intermediate coordination stage among the eight provinces, while in the western region, only Sichuan and Guizhou are at this stage among the twelve provinces. Additionally, the rate of class transition in some provinces in the central and western regions is low, with many merely maintaining the current level. Therefore, it is crucial to be cautious that these provinces may become the "weakness" hindering the improvement of digital agricultural productivity.

3.2. Dynamic Trend Analysis of the Coupling Coordination Degree: Kernel Density Estimation

Figure 2 illustrates the kernel density estimation maps of the coupling coordination degree between agricultural TFP and the digital economy. **Figure 2a** shows the kernel density estimation map of the coupling coordination degree in China. From the distribution position, the peak of the distribution curve is gradually moving to the right, indicating an overall increase in the coupling coordination degree across the country. The rightward movement from 2017 to 2018 shows a significant increase in the magnitude of the shift. In terms of distribution trends, the kurtosis is steep at first, then gradually levels off, indicating that the coupling coordination degree across provinces develops steadily. Other studies have also demonstrated that the impact of the digital economy on agriculture is gradually becoming more apparent [48]. Looking at the distribution spread, the curve shows a clear right tail phenomenon, suggesting that the growth rate of the coupling coordination degree between agricultural productivity and DE in some provinces is significantly faster than in other regions.

Figure 2b is the kernel density estimation map of the coupling coordination degree in the eastern region. From the distribution position, the peak in the eastern region is constantly moving to the right, indicating a continuous increase in the coupling coordination degree in the eastern region. In terms of distribution trends, the kurtosis has basically not changed, and the curve does not show a clear right tail or a "double peak" phenomenon, indicating that there is no obvious trend of differentiation and polarization in the eastern region.

Figure 2c is the kernel density estimation map of the coupling coordination degree in the central region. From the distribution position, the main peak is moving to the right, indicating an increase in the coupling coordination degree in the central region. In terms of distribution trends, the kurtosis first levels off, then steepens and levels off again, with no tailing phenomenon. This indicates that the development differentiation of the coupling coordination degree between DE and agricultural productivity in the provinces of the central region first increases, then decreases, and then increases again.

Figure 2d is the kernel density estimation map of the coupling coordination degree in the western region. From the distribution position, in the years 2014–2016, the western region showed a clear transition from a "single peak" to a "double peak", indicating a polarization of the coupling coordination degree between agricultural TFP and DE during this period, with significant regional polarization. After 2016, the main peak position shifted to the right, and the distribution shifted from "multi-peak" to "single peak". The kurtosis decreased, and the width gradually increased, with no tailing phenomenon. This indicates an overall increase in the level of coupling coordination in the western region, but with a trend of increasing differentiation in the coupling coordination degree among provinces. The primary reasons for the observed differences are the varying foundational conditions across provinces in the western region, including disparities in agricultural resources, digital talent, and other essential factors [49].

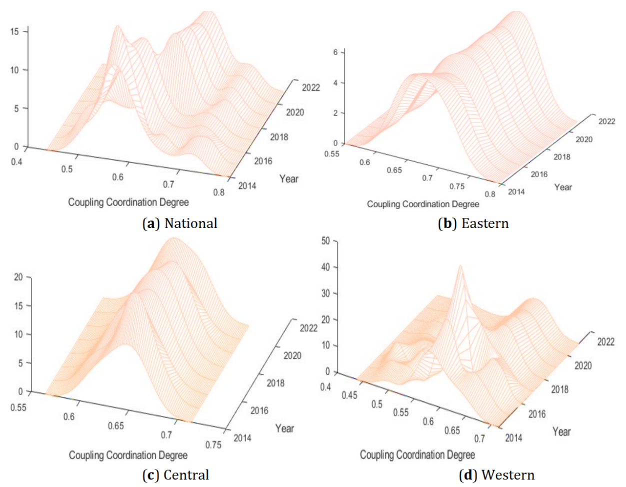

Figure 2. Dynamic evolution of the development level distribution of the coupling coordination degree (2014–2021): (**a**) national kernel density estimation; (**b**) eastern kernel density estimation; (**c**) central kernel density estimation; (**d**) western kernel density estimation.

3.3. Spatial Correlation Analysis of the Coupling Coordination Degree: Moran's I Index

3.3.1. Global Spatial Auto-Correlation

According to **Table 5**, the global Moran's I index of the coupling coordination degree shows some fluctuations over the entire study period but generally exhibits an increasing trend. Significance tests at the 5% level were passed for each year.

Table 5. Global Moran's I index of the coupling coordination degree.

Year	Moran's I	Z	P
2014	0.221	2.285	0.011
2015	0.185	1.931	0.027
2016	0.198	2.046	0.020
2017	0.237	2.373	0.009
2018	0.214	2.130	0.017
2019	0.248	2.420	0.008
2020	0.217	2.162	0.015
2021	0.224	2.228	0.013

3.3.2. Local Spatial Auto-Correlation

The high-high agglomeration area in 2014 included 10 provinces, including Beijing, Shanghai, and Tianjin, of which eight provinces and municipalities belonged to the eastern region, and the remaining provinces and autonomous regions belonged to the central and western regions (**Figure 3**). In 2021, there were six provinces and municipalities in the high-high agglomeration, all of which belong to the eastern region (**Figure 4**). These provinces, whether in terms of their economic foundation, agricultural modernization level, or abundant human resources, rank among the top in China [50]. It can be observed that provinces in the eastern region have spatial correlations for mutual learning. Regions with well-developed DE infrastructure are better able to learn from advanced development experiences and implement them more quickly [51], ultimately promoting the synergistic development of the digital economy and agriculture. The use of DE in agricultural production in these provinces has had significant effects.

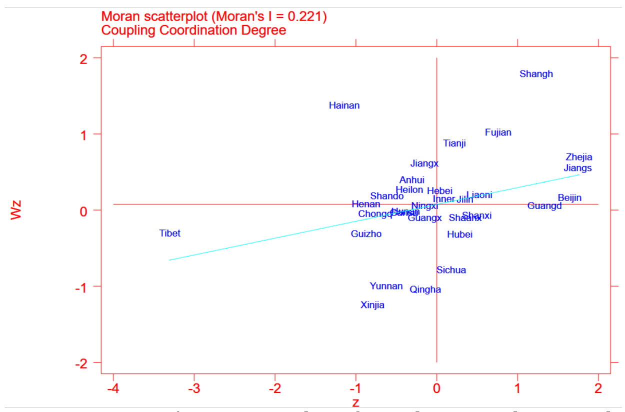

Figure 3. Moran's I scatter plot of coupling coordination degree in 2014.

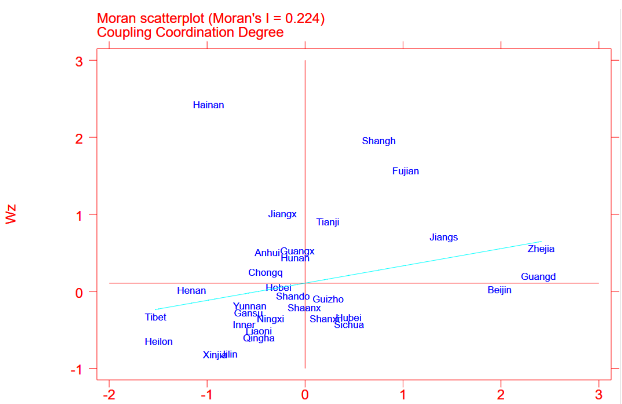

Figure 4. Moran's I scatter plot of coupling coordination degree in 2021.

The number of provinces in the low-high agglomeration area increased from five to six in 2021. Hainan, Jiangxi, and Anhui remained in this category, whereas Guangxi, Hunan, and Chongqing changed from low to high agglomeration. Except for Hainan, these six provinces are all located in the central and western regions with low coupling coordination degrees. Neighboring provinces with better economic development may have exerted a strong suction effect on them, causing the outflow of human, labor, and capital factors, leading to reduced utilization of resources and a clear trend of polarization between provinces [52]. In 2021, the total number of provinces in the low-low agglomeration area increased by two compared with that in 2014. Inner Mongolia, Liaoning, and Hebei changed from high-high agglomerations, while Shandong and Heilongjiang changed from low to high agglomerations. The reasons for these changes may be related to factors such as limited arable land, insufficient manpower, regional culture, and the economic level.

It is worth noting that Guizhou changed from low to low agglomeration, while Hunan and Guangxi changed from low-low agglomeration to low-high agglomeration. Provinces in the high-low agglomeration area have always been rare, indicating that these provinces have a good resource foundation for coordinated development. However, the overall coupling coordination degree of neighboring provinces is relatively low, indicating that these provinces have not been able to drive the development of neighboring provinces and have failed to form "trickle-down" effects [53]. Since the integration of the digital economy and agriculture involves development in both areas, differing development weaknesses among provinces hinder the effective realization of potential spillover benefits.

3.4. Analysis of Regional Differential Contribution of Coupling Coordination Degree: Dagum Gini Coefficient

3.4.1. Overall Differences

According to **Figure 5**, the overall difference in China's coupling coordination between agricultural TFP and DE shows a decreasing trend during the sample observation period. Using 2014 as the base year, the overall difference decreased by an average of 2.1% per year. In other words, regional differences in DE and agricultural TFP have generally shown a reduction trend. The

Gini coefficient between and within different regions showed both increases and decreases. Overall, the economic development policies, digital infrastructure construction, and development of agricultural modernization implemented in China have proven to be effective

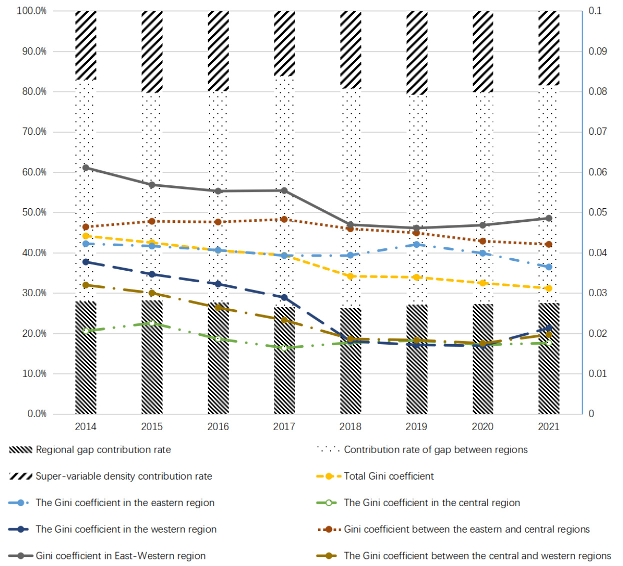

Figure 5. Sources and contributions of regional differences in coupling coordination (2014–2021).

3.4.2. Intra-Regional and Inter-Regional Differences

The regional disparities are significant, with internal differences ranked from large to small as follows: eastern, western, and central. The changes in the disparities between the eastern and central regions exhibited a trend of initially rising and then falling. This may be attributed to the rapid development of some cities in the central region. For example, Hunan Province has established a smart agriculture development demonstration zone [54, 55]. It has set an example for digital agriculture development in the region. The disparities between the eastern and western regions mainly demonstrate a trend of decreasing and continuous increase. It is noteworthy that the Gini coefficient between the central and western regions underwent a stage of initial decline followed by a gradual increase.

3.4.3. Source of Regional Differences and Their Contribution Rates

The contribution rate of the super-variable density was only 18.4%. This indicates that inter-regional differences were the main source of the overall difference. Improving inter-regional disparities will further reduce overall differences and achieve coordinated development.

Overall, contrary to previous literature [56], the differences in coupling coordination within China's central region are gradually expanding, indicating an unbalanced trend in the development of digital-agricultural integration in this region. The observed differences in results may be due to variations in regional classification. Previous studies have primarily examined economic regions, dividing areas into the eastern, central, western, and northeastern regions. In contrast, this study considers both economic factors and grain output, classifying areas into eastern, central, and western regions. The results indicate that the development of the digital economy has not been fully utilized in some major grain-producing provinces. The Gini coefficient reveals that, from 2018 onwards, internal disparities in both the central and western regions are gradually widening, and the differences between the eastern and western regions, as well as between the central and western regions, are also increasing. This trend may be attributed to variations in geographical location, economic development, and agricultural resources among the provinces, leading to regional disparities.

3.5. Analysis of Obstacles to the Coupling Coordination Degree

From 2014 to 2021, the sum of the obstacle degrees for the top eight ranked factors ranged from a maximum of 71.75% to a minimum of 66.64% (**Table 6**). Among them, rural electricity consumption, online sales, local scientific and technological expenditures, and agricultural output were consistently the top four obstacles during the study period. The sum of obstacle degrees for these four factors in 2014, 2016, 2018, and 2021 was 35.36%, 36.38%, 37.22%, and 37.57%, respectively, indicating an increasing impact of these obstacles on the development of coupling coordination. The degree of obstacles to agricultural electricity consumption and local scientific and technological expenditures has continued to grow.

On the one hand, this may be due to the fact that as

Table 6. Evaluation results of obstacle factors from 2014 to 2021.

Main Obstacle Factors	2014	2016	2018	2021
The Internet penetration rate in rural areas	8.36%	8.23%		
Number of agrometeorological observation stations	8.59%			
Rural electricity consumption	7.89%	8.26%	8.73%	9.92%
Transportation and communication consumption expenditure of rural residents	8.13%	7.73%		
Farm machinery production			7.99%	8.25%
Rural per capita disposable income	8.00%	7.84%	7.58%	
Online sales	9.14%	9.30%	9.37%	9.28%
Retail sales of rural consumer goods			7.69%	7.80%
The average number of weekly deliveries in rural areas		9.00%	6.16%	10.05%
Local spending on science and technology	8.64%	8.81%	8.92%	8.96%
Agricultural output value	9.69%	10.01%	10.20%	9.41%
Climate-based production potential				8.08%
A total of 8 barriers in each year	68.44%	69.18%	66.64%	71.75%

agricultural modernization progresses, practices such as planting, and fertilization increasingly require electricity for machinery. For farmers using digital technology in agricultural production, high electricity consumption and costs may affect the utilization of digital technology in agriculture. On the other hand, the obstacle degree of local scientific and technological expenditure indicates the level of local government support for technological innovation. According to "The China Statistical Yearbook (2022)" from 2013 to the end of 2019, China's arable land area gradually decreased from 1.35 × 108 hm^2 to 1.27 × 108 hm^2, approaching the red line of 1.22 × 108 hm^2 for arable land. This highlights the importance of adhering to the arable-land red line and improving agricultural production efficiency to ensure China's food security. Given limited arable land, promoting technological progress and innovation in agriculture can enhance agricultural production efficiency [57]. Additionally, online sales and agricultural output directly affect farmers' production. The digital economy can leverage the Internet to increase sales of agricultural products [58], and increased agricultural output, in turn, encourages farmers to use the digital economy to enhance agricultural TFP.

During the study period from 2014 to 2016, rural residents' transportation and communication consumption expenditure, agricultural meteorological observation stations, and the internet penetration rate were also significant indicators affecting the degree of coupling coordination. This suggests that investment in agricultural fixed assets can influence the development of digital agriculture [59]. These indicators are more focused on measuring the infrastructure of both the digital economy and agricultural production, indicating that, in the early stages, the adequacy of infrastructure can hinder the development of coupling coordination.

From 2017 to 2021, the agricultural machinery total power, rural retail sales of consumer goods, average weekly delivery frequency in rural areas, and climate-based production potential gradually became the main obstacles affecting the coupling coordination degree of the two. Rural retail sales of consumer goods and local spending on science and technology are related to agricultural technology; other studies also mention that agricultural technology remains a primary barrier to the future development of digital agriculture [60]. With climate change and increasing extreme weather events, the impact of climate factors on agriculture must also be considered [61]. Mitigating the influence of climate factors on the coordinated development of digital agriculture likewise requires innovation in digital technology.

4. Discussion

This study investigates the current state of the coordinated development of the digital economy and agricultural total factor productivity. Although earlier research has explored the impact of the digital economy on agricultural total factor productivity and agricultural development, it has not specifically discussed the synergistic effects, spatiotemporal evolution trends, spatial agglomeration, regional disparities, and obstacles between the two. The measurement results indicate that there is an overall upward trend in the coupling coordination degree between China's digital economy and agricultural total factor productivity. Provinces with a coupling coordination degree above the middle level are all located in the eastern region, supporting research findings that the digital economy has a greater role in promoting high-quality agricultural development in the eastern regions [62]. The western region significantly lags behind the eastern region in terms of digital agriculture development, primarily due to the disadvantaged agricultural resources, human capital, and technology in most western provinces, where the foundational conditions for the development of digital agriculture need to be strengthened. Notably, the growth in the synergistic effect in the central region is modest, which contradicts the conclusion that the digital economy can significantly promote agricultural economic resilience in the central region [63]. In addition to the common measurement indicators, the measurement of agricultural economic resilience also includes the agricultural product price index and research and development expenditure. The development of the digital economy can optimize production, distribution, and exchange processes, while also helping the agricultural product circulation system to mitigate price fluctuations in agricultural products [64, 65]. Additionally, growth in the digital economy stimulates agricultural research and development expenditures, demonstrating that the digital economy can contribute to enhancing agricultural economic resilience in the central region. Compared to agricultural total factor productivity, the digital economy in the central region primarily integrates with agricultural product circulation and technological development, rather than with agricultural production. As a major grain-producing region in China, it is essential to promote the transformation of agricultural science and technology into practical agricultural outcomes in the central region.Strengthening the integration of the digital economy with agricultural total factor productivity is a crucial pathway for achieving sustainable agricultural development.

According to the findings of this study, the kernel density parameters and Gini coefficient show no significant differentiation or polarization trends in the eastern region. In the central region, the development of the coupling coordination degree between the digital economy and agricultural efficiency initially increases, then decreases, and subsequently increases again. In the western region, while the overall level of coupling coordination is rising, there is a trend of increasing differentiation in the coupling coordination degree among provinces. The kernel density curve shifts to the right, displaying a "right tail" phenomenon, indicating that the synergistic effect between the digital economy and agricultural total factor productivity is growing. However, there is no clear trend of decreasing absolute differences between provinces. The main reasons are that some lagging provinces lack robust digital infrastructure, have limited agricultural resources, and lack location advantages, resulting in persistent gaps with higher-coordination provinces in the eastern region. This finding also supports the conclusion that the development of digital agriculture requires a higher level of economic development, digital talent, and technology [66]. In the western region, extreme values were initially evident, but in later stages, the gap between provinces narrowed, primarily due to China's implementation of the "Western Development Strategy", This strategy directed policies toward underdeveloped provinces, improved digital infrastructure, and provided technological assistance, enabling the western region to derive greater benefits from the digital economy [67]. The global Moran's index measurement shows that the synergistic effect between China's digital economy and agricultural total factor productivity exhibits spatial correlation. Provinces with high-high agglomeration are mainly located in the eastern region, aligning with the above measurement results. The agglomeration effect in the central and western regions is constantly evolving, indicating that the development pattern of the synergistic effect across provinces is undergoing constant adjustment. However, some provinces in the western region remain in a low-low agglomeration, suggesting that the current driving forces are insufficient for promoting their synergistic development. To advance digital agriculture, the western region requires external assistance or policy support. Analysis of interregional differences shows that the Gini coefficient in the central region is increasing, indicating that high-value areas, such as Hubei and Hunan provinces, have not exerted a positive spillover effect on neighboring areas. Regional disparities are the primary source of the Gini coefficient, indicating that balanced regional development has not met expectations. The development of the central and western regions faces varying degrees of constraints [68].

The barrier degree model reveals that digital infrastructure, digital technologies, and agricultural production are key factors hindering the coupling coordination development of digital agriculture. Among these, rural electricity consumption, online sales, local science and technology expenditure, and agricultural output have consistently been critical obstacles. These four factors relate to the production and sales processes of agriculture, as well as technological support, indicating that improving the synergy between the digital economy and agricultural total factor productivity requires integration across the entire agricultural industry chain, rather than focusing solely on a single stage of agricultural production. The barrier effects of online sales, scientific, and technological expenditure, and agricultural output on digital agriculture development align with findings in other literature [69–71]. However, the impact of rural electricity consumption on the coordination between the digital economy and agricultural production has received less attention. Low rural electricity consumption may suggest two issues: (1) poor quality of rural power grids [72, 73], and (2) outdated agricultural electric equipment [74]. This implies that advancing digital agriculture coordination requires attention to both digital infrastructure development and rural infrastructure. Enhancing rural infrastructure can improve the efficiency of digital infrastructure, leading to more effective results. From a phased perspective, before 2016, rural infrastructure was the main factor hindering the synergistic development of the digital economy and agricultural productivity, such as rural internet access and agricultural meteorological observation stations. After 2016, specialized facilities related to digital economy and agricultural development became the primary obstacles, with the proportion of technological expenditure gradually increasing. This shift indicates that ongoing technological innovation and financial support can facilitate the coordinated development of the digital economy and agriculture. Climate indicators have appeared as a factor in the later stages, highlighting the importance of considering climate impacts. Future efforts to strengthen synergy between the digital economy and agriculture may need to address challenges posed by climate change.

This study primarily focuses on China. Due to generally low digital literacy among Chinese farmers, underdeveloped digital infrastructure, and the "smallholder" agricultural production model, the findings may differ from those of other countries, limiting their applicability in other regions. However, the integrated development of the digital economy and agriculture is a critical issue that warrants broader attention. Future research will expand to include the development of digital economies and agriculture in other countries within the analytical framework for comparative analysis. Additionally, the scope of influencing factors will be broadened to include the effects of environmental conditions, policies, and other variables, aiming to provide a scientific basis for policymaking in the digital economy and agriculture and to offer valuable insights for agricultural development in other regions.

5. Conclusions

This study uses panel data from 31 provinces in China from 2014 to 2021 to measure the coupling coordination between agricultural TFP and the digital economy (DE). A global EBM model is applied to estimate agricultural TFP, calculating the agricultural productivity for each province. The entropy weight method is then used to construct a DE index. Following this, the coupling coordination model assesses the interaction between DE and agricultural TFP, categorizing each province into specific coupling coordination stages. To explore trends in coupling coordination over time, the Kernel density estimation method is used to analyze dynamic temporal patterns. Spatial distribution is assessed with global and local Moran's I indexes, while the Dagum Gini coefficient investigates regional disparities in coupling coordination among the 31 provinces. Additionally, the obstacle degree model identifies barriers impacting the coordination between the digital economy and agricultural productivity. Based on this comprehensive analysis, the following conclusions are drawn:

During the observation period, the coupling coordination degree between the digital economy (DE) and agricultural total factor productivity (TFP) in China's 31 provinces initially experienced a phase of "multipolarization" before stabilizing, ultimately reaching a preliminary level of coordination or higher. There is evidence of a "regional monopoly" effect, with certain regions dominating. In the short term, the central and western regions may face challenges in achieving significant breakthroughs, potentially becoming "weak links" that hinder improvements in the overall coupling coordination degree.

After incorporating spatial geographical factors, the agglomeration effect among the 31 provinces shows continuous change, yet some western provinces still exhibit a "low-low" agglomeration pattern. All provinces in the "high-high" agglomeration zone are located in the eastern region. Provinces in the intermediate stage of coupling coordination do not show significant positive spillover effects on neighboring provinces, and those in the preliminary coordination stage do not benefit from a learning effect from more advanced provinces. This situation increases the likelihood of the Matthew effect, where strong provinces grow stronger and weaker ones fall further behind.

After incorporating differentiating factors, the disparities in the coupling coordination degree among provinces mainly stem from inter-regional differences, with the ranking of these disparities being "inter-regional > intra-regional > super-variable density". Inter-regional disparities (between the Central-Western and Eastern-Western regions) are widening. At the same time, disparities within the central and western regions are also increasing. Initially, the obstacles affecting the coupling coordination degree were related to infrastructure indicators in both the digital economy and agricultural production. However, in later stages, these obstacles shifted to specific indicators tied to the digital economy and agricultural production.

Based on the above analysis, this paper proposes the following three recommendations: (1) Adopting a systemic approach to coordinated development is crucial to emphasize the synergy between the digital economy and agricultural total factor productivity. As indicated by the analysis, the coupling coordination degree is highest in the eastern region, followed by the central and western regions. To prevent the widening of regional disparities, it is essential to establish a goal of coordinated and balanced development. Policy guidance and support should be leveraged to clarify the development objectives for both the digital economy and agriculture in each province, promote innovation in digital technologies within the agricultural sector, and raise farmers' awareness of the integration of the digital economy with agriculture. Special attention should be given to farmers in the central and western regions by providing digital agriculture technology training and fostering an awareness of sustainable agricultural development. (2) Emphasize spatial agglomeration effects and driving forces, and enhance regional collaboration mechanisms. Provinces should actively seek complementary advantages and areas of cooperation, particularly in the eastern region, where positive spillover effects should be strengthened. Provinces in the central region should focus on implementing collaborative mechanisms such as "inter-provincial alliances" and "cross-provincial cooperation". Despite facing disadvantages in terms of funds and manpower compared to the eastern region, the central region holds relative advantages over the western region. Identifying cooperative bases within the central region can amplify these leading effects. Given the difficulty of transforming agricultural resources into economic value and the high costs of exploitation in the western region, targeted strategic support policies are needed. (3) Continue improving the construction of rural and digital infrastructure. Enhance the quality of electricity supply and narrow the "digital divide". Specifically, in the western region, it is essential to accelerate the deployment of supporting facilities such as internet access and logistics in rural areas, as well as establish digital agricultural management platforms to facilitate faster access to markets for agricultural products. This will strengthen the positive feedback loop for integrating digital agriculture. The government should increase investment in scientific and technological funding, provide more support for agricultural technological innovation, and simultaneously cultivate talent with expertise in both agriculture and digital technologies.

Author Contributions

Conceptualization, S.G., M.Y. and D.G.; methodology, S.G.; validation, S.G. and D.G.; formal analysis, M.Y.; writing—original draft preparation, S.G.; writing—review and editing, S.G. and H.N. All authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement

Ethical review and approval were not applicable as this study did not involve human or animal participants.

Informed Consent Statement

Informed consent is not applicable as this study does not involve human participants.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Conflicts of Interest

The authors declare no conflict of interest.

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