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Original Research

Research on the Carbon Reduction Effect of Digital Transformation of Agriculture in China

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Abstract

In the context of global warming, advanced digital technologies such as 5G, IoT, artificial intelligence, and blockchain are driving the digital transformation of agriculture and contributing to the reduction of agricultural carbon emissions as a new driver of green and sustainable growth and global warming mitigation. In this study, we measured digital agriculture and agricultural carbon emission indicators using entropy and IPCC methods based on panel data for 31 provinces in China from 2013 to 2020, and explored the factors of digital transformation of agriculture and their impact on agricultural carbon emissions. According to our findings, the digital transformation of agriculture decreases carbon emissions and has significant spatial spillover benefits. It significantly contributes to green technological advances, agricultural scale operations, optimization of agricultural cropping structures, and decreased agricultural carbon emissions. Notably, digital agricultural infrastructure and industrialization increased the rise of green agriculture, while the influence on digital agricultural subject quality was small. Increasing the application of advanced digital technologies in agriculture and encouraging the reduction of carbon emissions greatly supports the response to abrupt climate change and the achievement of green and sustainability.

Keywords: climate change, carbon reduction effect, digital transformation of agriculture, green technological advancement

Introduction

Since the reform and opening up of China, significant achievements have been made under the practical guidance of the government, and the total agricultural output value of China has grown at an average annual rate of 11.62% [1]. The agricultural sector's contribution has gradually become an essential pillar of China's economic and social development. However, with accelerated urbanization, rural labor migration, and the widespread use of agricultural machinery, this rough agricultural development has resulted in various environmental problems, such as ecological degradation and environmental pollution, the most prominent of which is greenhouse gas emissions. The increased greenhouse effect has, in turn, led to environmental and ecological problems such as earthquakes, heavy rains, floods, and desert storms. The World Resources Institute (WRI) has released data on global CO_2 emissions over the past 30 years. From 1990 to 2018, the five largest

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economies in terms of CO2 emissions were China, the United States, the European Union, India and Brazil. China surpassed the United States as the world's largest carbon emitter around 2004. China topped the list by emitting 778 million tons of carbon dioxide over the past 30 years [2]. Specifically, agricultural carbon emissions account for 17% of total emissions in China, but only 7% in the U.S. and 11% globally [3]. Compared to other sectors, agriculture is one of the most vulnerable to external adverse climate change and one of the most significant sources of carbon emissions [4]. Therefore, carbon emission reduction in agriculture is becoming increasingly necessary [5]. The Chinese government is committed to implementing carbon emission reductions to fulfill its obligation to reduce emissions effectively. It pledged to the world at the 75th UN General Assembly in September 2020 that carbon emissions will peak by 2030 and be carbon neutral by 2060[6].

Digital transformation of agriculture is based on a large amount of data from modern agriculture [7]. It is realized through advanced digital technologies such as cloud computing and the Internet of Things [8], effectively improving agricultural production efficiency by monitoring, controlling, and optimizing activities [9]. Digital transformation of agriculture is based on advanced digital technology and uses water-saving irrigation technology and straw return technology to effectively decrease environmental pollution effectively. By replacing chemical fertilizers with organic fertilizers [10], farmers effectively decrease the use of chemical fertilizers and lower carbon emissions of agriculture. Agricultural robots have increased yields and productivity, replacing heavy machinery to effectively decrease problems associated with topsoil compaction in agriculture [11] and preventing soil degradation. Remote sensing technology detects and maps many crop diseases [12], and blockchain provides an effective solution to effectively improve the security and transparency of food traceability [13]. Digital transformation of agriculture transforms market supply, business processes, and models, providing new solutions for connecting "small farmers" to "big markets" [8], alleviating information asymmetries, and reducing agricultural waste. According to FAO, digital agriculture is the "fourth agricultural revolution".It can address harsh climate change concerns by enhancing the efficiency, equality, and environmental sustainability of agricultural value chains [14]. The digital transformation of agriculture will greatly support sustainable green change and play a key role in supporting the development of green agriculture and promoting carbon reduction in agriculture. Therefore, it is necessary to include the digital transformation of agriculture in the study of agricultural carbon reduction.

This paper contributes to the existing literature in several ways. First, although the digital transformation of agriculture and agricultural carbon emission reduction has received extensive attention from researchers and policymakers, there are only a few academic studies on agricultural carbon emission reduction from the perspective of the digital transformation of agriculture. This paper attempts to fill this research gap by focusing on the research question of the impact of digital transformation of agriculture on agricultural carbon emissions and how it affects them. Few studies have directly discussed these two concepts in an explanatory framework. And spatial econometric techniques are used to verify the spatial spillover effect of digital transformation's carbon emission reduction effect in agriculture and the innovative use of instrumental variables to address the endogeneity issue. Secondly, most studies explain the digital changes in agriculture as digital agriculture indicators in rural infrastructure, digital governance, agricultural digital expenditures, etc. However, the digital transformation of agriculture also needs to be supported by the digital industry. This paper includes rural e-commerce represented by Taobao villages in the study to measure digital agriculture more comprehensively. Thirdly, three impact mechanisms of digital agricultural transformation on agricultural carbon emissions are theoretically explained, including green technology progress, agricultural scale operation, and agricultural planting structure adjustment. Unlike previous studies examining the relationship from one specific aspect, we put all relevant factors in a comprehensive explanatory framework. Finally, this paper considers the specificity of Chinese grain production considering heterogeneity analysis in conjunction with China's functional agricultural production zones, which is more in line with the actual situation of Chinese agricultural production.

The rest of the paper is organized as follows: the second section presents the literature review of the paper; the third section presents the theoretical analysis and formulates the research hypothesis; the fourth section presents the material and methods; the fifth section is results and discussion; and the last section gives the conclusion and policy recommendations.

Literature Review

This study is based on two main branches of literature. One is discussing methods for measuring agriculture carbon emissions and measures to reduce them. The other is the area of research on the environmental effects of the digital transformation of agriculture, especially regarding agricultural carbon emission reduction.

The discussion of agricultural carbon emissions has been going on for a long time.Regarding the measurement and exploration of carbon emissions of agriculture, Khanali et al. (2021) [15] used a life cycle approach to assess agricultural carbon emissions to explore their environmental impact on agricultural products.Yun et al. (2014) [4] calculated carbon emissions of agriculture for the first time in 31 Chinese provinces and cities from 1995-2010 based on 23 huge sources of carbon emissions, such as agricultural inputs, rice fields, soils, and livestock farming. Most studies used the IPCC method to measure carbon emissions of agriculture [5, 16], which was obtained based on the cumulative multiplication of carbon sources from relevant agricultural activities. By measuring agricultural carbon emissions through the IPCC method, the contribution of various carbon sources can be examined more precisely and carbon reduction can be implemented in a targeted manner. After constructing the agricultural carbon emission index system and measurement, scholars focus on the specific measures to effectively decrease carbon emissions of agriculture. Agricultural scale operation can promote the rational use of water and soil resources [17]. Farmers can realize the substitution effect of chemical fertilizers in agricultural activities through no-till planting and straw return to the field to effectively decrease the intensity of carbon emissions of agriculture [5]. Abnormal responses such as extreme weather and pests caused by harsh climate change can effectively decrease agricultural production efficiency. Therefore, developing low-carbon agriculture to adapt to regional harsh climate changes [18] and allocating carbon revenue to crops and broader non-energy areas for R&D inputs can control agricultural resource inputs while balancing agricultural and economic development to achieve win-win goals [19]. Although the above literature does not directly discuss the impact of the digital transformation of agriculture on agricultural carbon emission reduction, it provides essential implications for the digital transformation of agriculture to achieve emission reduction measures because the environmental effect of the digital transformation of agriculture is to consider the reduction of pollution emissions.

With the growing environmental and ecological problems brought about by severe climate change, some scholars have begun to focus on the environmental benefits of digital transformation of agriculture, especially on the issue of the impact on carbon emissions. Digital transformation of agriculture enables green sustainable agricultural development through a range of advanced digital technologies that effectively decrease chemical use [20], use of agricultural robots can help reduce agricultural carbon emissions by effectively reducing pesticide use and water waste through manual substitution, increased use of clean energy, additional end-of-pipe treatment facilities, and increased sewage treatment capacity [11]. Yet the use of robots also raises social and security issues. The use of agricultural robots will reduce some employment opportunities, and farms and production facilities that rely heavily on automation and robots will become correspondingly more vulnerable to hacking and attacks. Digital transformation of agriculture effectively decreases the consumption of chemical fertilizers by replacing them with organic matter in organic fertilizers. Reducing fertilizer use can effectively decrease carbon emissions of agriculture as a huge source of carbon emissions of agriculture [10]. Remote sensing can obtain the spatial distribution and change characteristics of global agricultural carbon sources rapidly and continuously. It can broadly apply to carbon sink estimation and management and global carbon emission monitoring. Aerial and satellite imagery has been successfully used to detect and map many crop diseases, and mapping crop diseases can hugely effectively decrease the area affected by crops, ensure food security, and effectively decrease carbon emissions, such as citrus greening disease, flowering hedgehog disease, and alfalfa root rot [12]. With advances in imaging sensor technology and image-processing techniques, it is necessary to evaluate advanced imaging sensors and analytical methodologies for differentiating diseases from other confounding factors.IoT technologies apply new technologies such as artificial intelligence, robotics, and sensors to farm production systems [21], which can be implemented to monitor crop growth. Blockchain is used to track the safety and transparency of food by building an early warning system for carbon emission monitoring. This information makes it visible to the public, which is crucial for producers and policymakers on how to produce green food sustainably. Through the distributed storage of valid information recorded at each stage of the supply chain, carbon emissions are thus guaranteed to decline at each stage of production of agricultural products, ultimately achieving carbon reduction targets [13]. However, SMEs have difficulties in adopting the technology.Moreover, drones and satellite technology in daily farming operations can provide more accurate weather data [22] giving farmers forecasts and sound advice for intervening in crop planting. This technology dramatically effectively improves the efficiency of green production and effectively decreases greenhouse gas emissions from crops.

The above studies show that digital transformation of agriculture has contributed hugely to green agricultural production and effectively decreased carbon emissions. Although their studies support the digital transformation of agriculture to achieve carbon emission reduction, most of them are case studies, and the findings need to be measured according to each country's economic and technological development of each country. Some of the literature has explored the spatial spillover effects of digital agricultural transformation on agricultural carbon emissions [4, 16, 23]. However, they have not considered the degree of industrialization of digital transformation of agriculture, and the literature has shown that rural e-commerce, represented by Taobao villages, exhibits vital spatial agglomeration phenomena and environmental values [24], which are essential for achieving agricultural carbon emission reduction. This is a significant contribution to achieving carbon emission reduction in agriculture.

In summary, this paper provides a more comprehensive view of the relationship between the digital transformation of agriculture and agricultural carbon emissions in the face of insufficient research in related fields. The findings of this paper draw on some preliminary research results, existing databases, and improved econometric methods to provide new perspectives for academics and policymakers.

Theoretical Analysis and Research Hypothesis

Digital transformation of agriculture is crucial to effectively decrease farmers' information asymmetry and market transaction costs. Li et al. (2022) [25] state that the platform economy has an essential regulatory function in reducing carbon emissions. It was found that rural e-commerce can promote green supply chains and accelerate green recovery [26]. Rural e-commerce brings green technological advances and diversified market demand, facilitating grassroots entrepreneurship in rural areas [27]. Rural e-commerce sells products directly to consumers, bypassing intermediary platforms and effectively reducing the cost of sales. Since agricultural products are perishable and have high storage costs, e-commerce can effectively decrease the risk of sales and lower agricultural costs. At the same time, rural e-commerce redefines standardized production in terms of agricultural variety, quality, and brand unification [24], which is conducive to regulating chemical fertilizer reduction and converting it into green inputs such as organic fertilizers and soil-measured fertilizers [1]. Knowledge spillover from rural e-commerce agglomeration can facilitate the diffusion and creation of green technologies, effectively improve the efficiency of green production in agriculture, and facilitate farmers to effectively decrease production costs by sharing rural digital Infrastructure in the region [27, 28], and other industries with industry-specific skills will exhibit higher geographic concentration to achieve labor sharing and realize labor benign development of market supply and demand.

Digital transformation of agriculture optimizes the allocation of resource factors. Due to the replicability, updatability, non-consumability, and shareability of data, digital production factors can be replicated almost infinitely without cost. By sharing production materials and accelerating the circulation of information elements, digital transformation of agriculture overcomes the scarcity and exclusivity of traditional agricultural resources, effectively decreases energy consumption, and achieves optimal resource allocation [9]. Advanced digital technologies such as 5G, artificial intelligence, blockchain, and remote sensing are used to effectively improve agricultural production efficiency, effectively decrease labor costs, and effectively decrease input factor waste, which can form economies of scale and long-tail effects in a favorable economic environment and suppress carbon emissions of agriculture.

Accordingly, this article proposes.

Hypothesis 1: Digital transformation of agriculture has a huge inhibitory effect on carbon emissions of agriculture.

Digital transformation of agriculture is open and inter-temporal [6]. It has a spatial spillover effect on carbon emissions of agriculture, mainly reflected in the following three aspects. The first is the agglomeration effect. Agro-industrial agglomeration plays a crucial role in agricultural carbon emission reduction. Along with industrial agglomeration, agricultural production gradually tends to be standardized, which facilitates the optimization of the allocation of various resources and facilitates the promotion of agricultural technology, thus reducing energy consumption and improving the efficiency of agricultural materials, and achieving the purpose of agricultural carbon emission reduction. More importantly, the economies of scale brought by the agglomeration of agricultural industries can effectively optimize the agricultural and industrial structure and form an excellent driving effect on the development of agriculture in the surrounding areas, thus generating the overflow of agricultural technology and management experience. The positive influence on agricultural machinery factor agglomeration on agricultural carbon emission reduction is also relatively noticeable. Agri-machinery factor agglomeration effectively decreases the cost of cross-regional operation of agricultural machinery in the region through input sharing, labor pooling, and knowledge spillover." The second is the diffusion effect. According to the "center-periphery" theory, the demonstration effect of green low-carbon agricultural development formed by digital transformation of agriculture can lead to imitation and learning in the "peripheral areas," further forming a diffusion effect [24]. The experience of green, low-carbon agricultural development driven by digital transformation of agriculture diffuses spatially through competitive imitation and learning among regions, agricultural sectors, and farmer groups. Administrative boundaries do not limit this diffusion effect. Thus regions that are the first to achieve green, low-carbon agricultural development are more likely to become targets of imitation and learning. Third, the upstream and downstream pull effects. When market demand is robust and rural e-commerce will drive the development of upstream and downstream industries in the surrounding areas [16], and online businesses will not only cooperate with local farmers and enterprises on green production technologies but also further promote the production of low-carbon agricultural products in the surrounding areas.

Accordingly, this article proposes.

Hypothesis 2: Digital transformation of agriculture has a negative spatial spillover effect on carbon emissions of agriculture.

The continuous integration and development of digital transformation of agriculture with the green technology advancement of higher education institutions and research institutes can stimulate the effective improvement of the green technology degree of enterprises. Digital transformation of agriculture relies on advanced digital technologies such as blockchain, remote sensing, and 5G to drive many new industries. This attracts the influx of high-quality human capital and optimizes the capital structure, providing a good foundation for enterprises' green technology advancement. At the same time, digital platforms provide farmers with a good communication platform. Through knowledge spillover, agricultural producers gain more data, thus breaking down "information silos" [9], which effectively improves production skills and promotes green agricultural production. Thus, digital transformation of agriculture effectively effectively improves green agricultural technology and helps farmers produce green, which is an effective way to effectively improve agricultural green total factor productivity [28]. Green agricultural technology advances enhance the efficiency of conventional energy consumption and change the structure of traditional factor inputs to effectively improve total resource utilisation [29], lowering carbon emissions of agriculture. Drip and sprinkler irrigation, as well as other similar irrigation systems, can help to effectively decrease water and fertiliser usage. Straw return can replace soil organic matter, prevent soil fertility loss, and have a substitution impact on chemical fertilisers, reducing the amount of chemical fertiliser applied [5]. Regions with more advanced green agriculture technologies will disseminate local, high-quality agricultural resources, technologies, and experiences to other regions, resulting in knowledge spillover effects [23], increased agricultural green production efficiency, and carbon emission reduction effects.

In agricultural scale production, mechanized operations brought by digital transformation of agriculture promote rural land transfer [29], which in turn promotes the increase of agricultural production scale. Agricultural scale operation realizes the intensive use of agricultural input factors, which can effectively improve fertilizer utilization efficiency, effectively decrease carbon emissions [30], and promote green agricultural production. In turn, agricultural-scale operation effectively improves agricultural mechanization and effectively decreases the excessive use of energy and environmental pollution of agricultural machinery. This enhances the standardization of agricultural production processes and achieves economies of scale. Production services of agricultural cooperatives effectively decrease the use of chemical fertilizers and pesticides [31]. Studies have also found that family farms with more extensive operations benefit more from adopting advanced digital technologies than smaller farms [32]. Thus achieving agricultural scale can effectively improve technological progress and economic efficiency. In recent years, under the guidance of the Chinese government, farmers have spontaneously formed new agricultural business entities, mainly family farms, agricultural cooperatives, and leading enterprises, to respond to the national requirements of developing green agriculture, promoting the promotion of ecological agricultural technologies [32, 33], and curbing carbon emissions of agriculture.

Frequent trade frictions and international disputes in recent years have led to huge fluctuations in international food prices and highlighted food crises in many countries worldwide. With the advancement of supply-side structural reforms in Chinese agriculture, national policies have guided the production of high-quality, high-yielding food crops to ensure food security [34]. Digital transformation of agriculture has brought about increased mechanization and higher marginal labor input and management costs, leading to a decrease in the proportion of cash crops cultivated [35] and a huge increase in the proportion of food crops cultivated with lower labor requirements, resulting in continuous optimization and adjustment of the agricultural cultivation structure. Food crops generally have lower demand for chemical agrochemicals than non-food crops. The development of food crop production will effectively improve the efficiency of water and fertilizer use. Total chemical and agricultural inputs might be minimized, contributing to green and low-carbon agricultural development and better agricultural green total factor productivity [29]. Food crops sequester the most huge proportion of total carbon, followed by cash crops. Food crops are critical for addressing human food needs and play an essential role in carbon sequestration [18].

Accordingly, this article proposes.

Hypothesis 3: Digital transformation of agriculture hugely inhibits carbon emissions of agriculture through green technology advancement, agricultural scale operation, and agricultural cropping restructuring.

The mechanism of action of digital transformation of agriculture in this article is shown in Fig. 1.

Material and Methods

Econometric Model Construction

As mentioned above, many studies on the determinants of environmental benefits have introduced a discussion of variables [5, 16]. Instead of using cross-sectional data samples, our analysis is based on panel data. For panel data, OLS (ordinary least squares), fixed effects, and random effects models are the most used econometric methods. Due to the need to monitor changes in each province during the course of the time series, the OLS model is not applicable to this investigation. Then, the Hausman test is developed to choose between using a fixed effects model and a random effects model [36]. The p-value for the Hausman test is 0.001. Therefore, the claim that the explanatory factors are unrelated to personal effects is rejected. This study uses a two-way fixed-effects model to empirically assess the influence onthe expansion of digital transformation of agriculture on carbon emissions of agriculture. The starting configuration of the model is as follows:

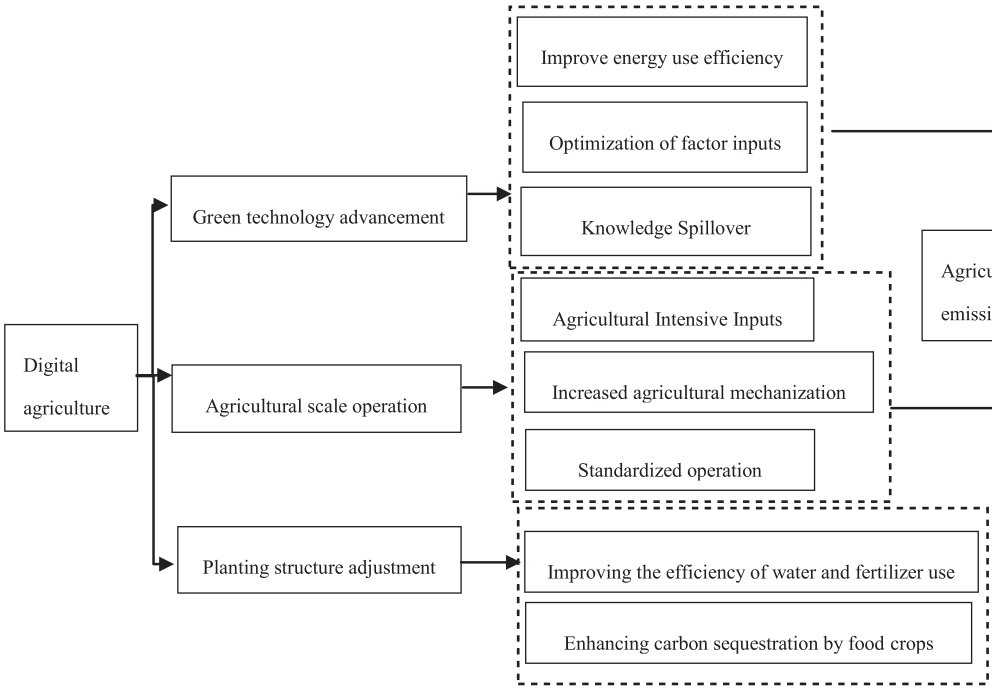

Fig. 1. Mechanisms of digital transformation of agriculture and agricultural carbon emissions.

$$ACE_{it} = \alpha_0 + \alpha_1 Dig\_agri_{it} + \alpha_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

The following sub-tables i and t indicate provinces and years, ACE_{it} is the dependent variable indicating the degree of green growth in agriculture in province i in year t; $Digi\_agri_{it}$ is the independent variable indicating the degree of digital agricultural development in province i in year t. X_{it} indicates a series of control variables that vary over time and affect carbon emissions of agriculture. μ_i denotes individual fixed effects, λ_t denotes time-fixed effects. Jiang et al. (2022) [9] divided digital agriculture at the structural level into digital agricultural infrastructure (Dig_infr), digital agricultural industrialization level (Dig_indu), and digital agricultural subject quality (Dig_enti) and drawing on this literature; this paper constructs a benchmark regression model at the structural level.

$$\begin{aligned} ACE_{it} &= \alpha_0 + \alpha_1 Dig\_infr_{it} + \alpha_2 Dig\_indu_{it} \\ &+ \alpha_3 Dig\_enti_{it} + \alpha_4 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (2)$$

Previous studies have shown that digital agriculture and carbon emissions of agriculture are spatially dependent [1, 4, 16]. Therefore, we constructed the following spatial econometric model to analyze the influence on digital transformation of agriculture on carbon emissions of agriculture

$$\begin{aligned} ACE_{it} &= \rho W ACE_{it} + \theta_1 Dig\_agri_{it} + \beta X_{it} \\ &+ \theta_2 W Dig\_agri_{it} + \delta W X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \\ \varepsilon_{it} &= \rho W ACE_{it} + \tau_{it} \end{aligned} \quad (3)$$

ρ is the spatial correlation coefficient and W is the spatial weight matrix. X_{it} denotes a series of control variables that vary over time and affect carbon emissions of agriculture. θ_1, θ_2, β and δ are coefficients to be estimated.

Many scholars perform spatial econometric regression using adjacency matrix and geographic distance matrix [3, 16, 23]. The fundamental spatial weighting adjacency matrix is chosen in this article, and the geographic distance matrix is compared as a robustness test. Equation (4) in the province i and province j if adjacent to say 1, not adjacent to say 0. Equation (5) of d indicates the geographical distance between the two provinces.

Adjacent space matrix:

$$w_1 = \begin{cases} 1, & \text{i is adjacent to j} \\ 0, & \text{i and j are not adjacent to each other} \end{cases} \quad (4)$$

Geographical distance matrix:

$$w_2 = \begin{cases} \frac{1}{d^2}, & i \neq j \\ 0, & i = j \end{cases} \quad (5)$$

A mediating effect model including green technology advancement, agricultural scale operation, and agricultural cropping structure modification as mediating variables is created to further examine the transmission mechanism of the influence of digital transformation of agriculture on carbon emissions of agriculture. Referring to the study by Ma et al. (2022) [16], we have:

$$Med_{it} = \lambda_0 + \lambda_1 Dig\_agri_{it} + \lambda_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

$$ACE_{it} = \eta_0 + \eta_1 Dig\_agri_{it} + \eta_2 Med_{it} + \eta_3 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (7)$$

Equation (6) reflects the effect of digital transformation of agriculture on mediating variables; Equation (7) reflects the effect of digital transformation of agriculture on carbon emissions of agriculture simultaneously with mediating variables.

Construction of Variables

Dependent Variable

Carbon emissions of agriculture (ACE) is the dependent variable. This article uses the IPCC carbon emission factor approach to calculate carbon emissions of agriculture, based on the method developed by Zhao et al. (2018) [17]. The carbon emissions caused by the six carbon sources involved in the planting industry's production process, such as fertiliser, pesticide, agricultural film, diesel, irrigation, and tillage [1], are primarily investigated, and carbon emissions of agriculture are measured using the relevant carbon emission coefficients with the following equations:

$$E = \sum E_i = \sum T_i * \delta_i \quad (8)$$

In Equation (8), E denotes carbon emissions of agriculture, T_i denotes the input of the ith carbon source, and δ_i denotes the carbon emission coefficient. The main carbon emission sources and carbon emission coefficients of agriculture are shown in Table 1.

To reflect the changes in carbon emissions of agriculture from both dynamic and spatial perspectives, we use arcgis 10.2 to obtain Fig. 2 we take the years 2013 and 2020 as examples. Comparing the two, we found that, one, agricultural carbon emissions are generally on a decreasing trend [16]. This may be related to the fact that China has vigorously promoted green technology inputs and large-scale agricultural operations in recent years to improve resource utilization efficiency and decrease agricultural carbon emissions [5]. Second, there are obvious regional differences in carbon emissions of agriculture, with relatively high agricultural carbon emissions in the central grain-producing regions represented by Henan Province. The possible reason is that the traditional agricultural provinces, especially the main grain-producing areas, are the primary sources of agricultural carbon emissions in China and still mainly adopt the traditional development model, i.e., adhering to the principle of „high input, high yield," with a relatively homogeneous industrial structure [4], which leads to a large number of agricultural carbon emissions.

Key Explanatory Variable

The key explanatory variable in this article is digital transformation of agriculture (dig_agri). This study describes the degree of development of digital transformation of agriculture [9] in terms of digital agricultural infrastructure (dig_infr), digital agricultural industrialization degree (dig_indu), and digital quality of agricultural subjects (dig_enti).

In this article, digital transformation of agriculture infrastructure is represented by the rural Internet penetration rate, precisely measured by the ratio of rural Internet broadband access users to the rural population in the region. The degree of industrialization of digital transformation of agriculture is reflected in the number of "Taobao villages," which, according to the Ali Research Institute, are administrative villages where farmers engaged in e-commerce account for more than 10% of local households and where e-commerce transactions exceed 10 million yuan [24]. To some extent, Taobao villages reflect the concentration of e-commerce in rural China. In addition, the ratio of per capita transportation and communication consumption expenditure of rural residents to per capita consumption expenditure of rural residents is used to assess the digital quality of farmers. The larger the ratio, the better the farmers' mastery and processing of digital information and the smaller the "digital divide" they face [9].

In this article, the measurement of the overall degree of digital transformation of agriculture using the entropy method is divided into four steps.

Table 1. Carbon emission factors for each carbon source.

Carbon Source	Carbon emission factor	Reference Sources
Fertilizer	0.8956 kg C·kg^{-1}	Oak Ridge National Laboratory, USA
Pesticides	4.9341 kg C·kg^{-1}	Oak Ridge National Laboratory, USA
Agricultural film	5.1800 kg C·kg^{-1}	Nanjing Agricultural University
Diesel	0.5927 kg C·kg^{-1}	IPCC
Plowing	312.60 kg C·hm^{-2}	College of Biology and Technology, China Agricultural University
Irrigation	266.48 kg C·hm^{-2}	Dubey and Lal [37]

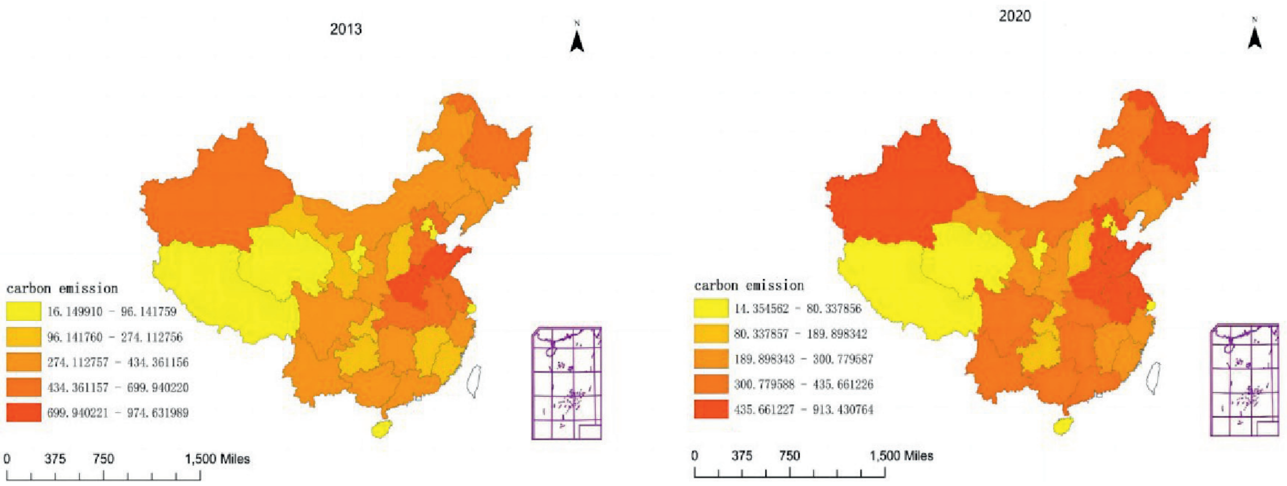

Fig. 2. Spatial distribution of carbon emissions of agriculture in 2013 and 2020.

The first step is to standardize the data in Equation (9)

$$x'_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \tag{9}$$

In the second step, the share of j in year i is calculated as shown in Equation (10)

$$y_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{m} x'_{ij}} \tag{10}$$

The third step calculates the information entropy (e_j) and information entropy redundancy (d_j). The specific calculation formula is shown in Equations (11) and (12), where $y_{ij} = 0$ is defined, then $e_j = 0$. k is a constant, $k = 1/\ln m$, m denotes the year.

$$e_j = -k \sum_{i=1}^{m} (y_{ij} * \ln y_{ij}) \tag{11}$$

$$d_j = 1 - e_j \tag{12}$$

In the fourth step, the indicator weights are calculated using Equation (13), where n is the number of indicators.

Table 2. Digital transformation of agriculture sub-dimension index weights.

Province	Dig_infr	Dig_indu	Dig_enti	Province	Dig_infr	Dig_indu	Dig_enti
Beijing	0.2307	0.6411	0.1282	Hubei	0.3798	0.4953	0.1249
Tianjin	0.3501	0.3497	0.3002	Hunan	0.4200	0.4243	0.1557
Hebei	0.4695	0.4029	0.1276	Guangdong	0.4734	0.2686	0.2580
Shanxi	0.3159	0.4891	0.1950	Guangxi	0.2870	0.6039	0.1090
Neimenggu	0.0832	0.8532	0.0636	Hainan	0.1286	0.7450	0.1264
Liaoning	0.2366	0.5382	0.2251	Chongqing	0.2574	0.6130	0.1296
Jilin	0.3014	0.4698	0.2288	Sichuan	0.3271	0.5010	0.1718
Heilongjiang	0.2379	0.6655	0.0966	Guizhou	0.2484	0.5895	0.1621
Shanghai	0.1000	0.7689	0.1311	Yunnan	0.4804	0.4094	0.1103
Jiangsu	0.3591	0.4269	0.2140	Xizang	0.1984	0.6888	0.1128
Zhejiang	0.3369	0.3658	0.2973	Shaanxi	0.2012	0.6601	0.1387
Anhui	0.3190	0.5729	0.1082	Gansu	0.1773	0.7655	0.0572
Fujian	0.4440	0.3882	0.1677	Qinghai	0.1979	0.7479	0.0542
Jiangxi	0.3488	0.4911	0.1601	Ningxia	0.3895	0.3986	0.2118
Shandong	0.3361	0.4530	0.2109	Xinjiang	0.2959	0.5829	0.1212
Henan	0.3208	0.5360	0.1432				

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{13}$$

Finally, based on the weights calculated, the weights of the assigned structural indicators can be deduced from the overall degree of digital transformation of agriculture development. As illustrated in Equation (14).

$$Dig\_agri = w_1 * Dig\_infr + w_2 * Dig\_indu + w_3 * Dig\_enti \tag{14}$$

Table 2 displays the calculated weights of digital transformation of agriculture structural indicators for each province in China using the entropy value method. It can be seen that within the sample interval, the industrialization degree of digital transformation of agriculture in each province has a more huge weight, with an average value of 0.5454. Furthermore, agricultural entities' digital quality ranks third with an average of 0.1562, while digital transformation of agriculture infrastructure ranks second with an average of 0.2958. From this, we can observe that the digital transformation of agriculture industrialization degree represented by Taobao villages is hugely higher than other measures. The possible reasons are that Taobao villages show a strong agglomeration effect in China, leading to the diffusion of agricultural technology through the knowledge spillover effect, improving agricultural development, and sharing agricultural infrastructure such as logistics and transportation support services to promote the reduction of rural operation costs and green sustainable agricultural development [28].

In order to reflect the changes in digital agriculture from both dynamic and spatial perspectives, we use arcgis 10.2 to obtain Fig. 3. We take 2013 and 2020 as examples. Comparing the two, the degree of digital transformation of agriculture is generally rising. Second, there are obvious regional differences in digital transformation of agriculture. The development degree in the eastern coastal region was relatively high in 2013, while the development degree in the central and western regions was relatively low. This is closely related to the measures taken by the eastern regions (e.g., Zhejiang, Shanghai, and Guangdong) in recent years to pay more attention to the development of the digital economy, strengthen rural digital Infrastructure construction, and promote digital industrialization and digitization of industries [36]. Notably, Alibaba, the largest e-commerce company in China, is located in Hangzhou, the provincial capital of Zhejiang Province, which has become a model of the intelligent digital city in China, promoting the diffusion of advanced production technologies and driving the development of digital agriculture in neighboring cities. In addition, the rapid development of digital agriculture in China's central and western regions in 2020 must be connected to the government's policy inclination and financial investment.

Control Variables

Referring to Fang et al. (2021) [38] and Guo & Zhang (2023) [5], and Xu et al. (2022) [39], this article considers the control variables affecting carbon emissions of agriculture by including the degree of urbanization (urb), the degree of agricultural mechanization (machine), natural disasters (disas), and resource consumption (elect) measured by the proportion of urban population to total population, total power of agricultural machinery, crop affected area, and rural electricity consumption, respectively.

Mechanism Variables

Green technology advancement (GTA). Referring to the method of Wang et al. (2021) [28], this article is expressed by green total factor productivity

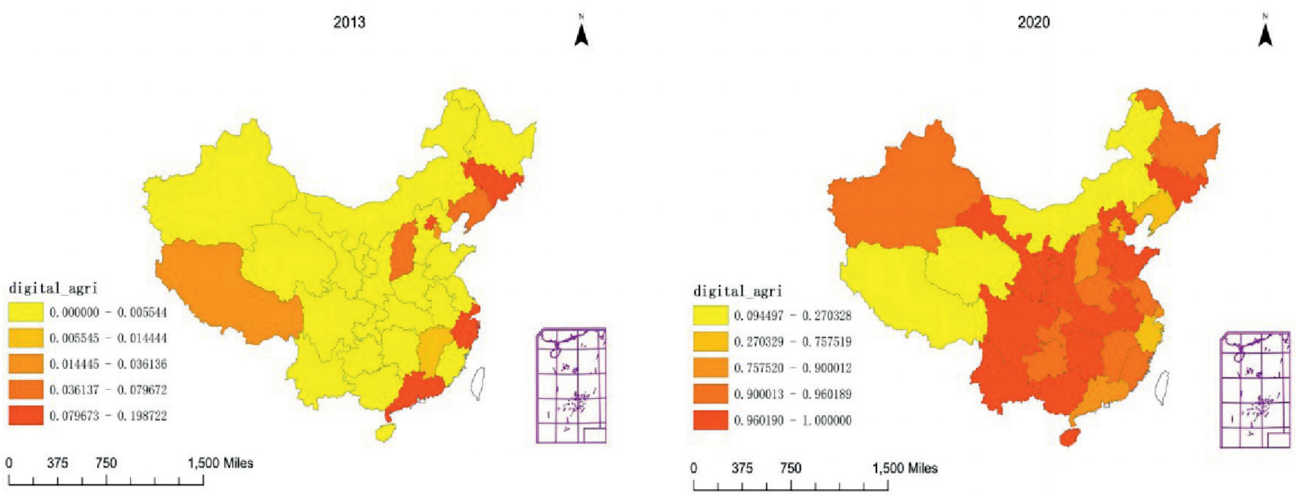

Fig. 3. Spatial distribution of digital transformation of agriculture in China in 2013 and 2020.

in agriculture. In this paper, we use cumulative values.

Agricultural operation scale (AOS). This research refers to the Zhao et al. (2018) [17] study using the number of professional agricultural cooperatives per 10,000 persons in rural areas.

Agricultural cultivation structure (ACS). This article uses the ratio of grain sown area to total crops sown to refer to the method of Liu et al. (2021) [40].

Data Description

This article uses panel data from 2013 to 2020 for 31 Chinese provinces, with data on urbanization degree, agricultural mechanization degree, degree of agricultural disa and resource consumption from previous years' China Statistical Yearbooks; Taobao village data sourced from the Ali Research Institute's 2020 China Taobao Village Research Report; and data on farmers' professional cooperatives sourced from regional governments.

The variable definitions and descriptive statistics of this paper are shown in Table 3 and Table 4.

Results and Discussion

Baseline Model

Column (1) of Table 5 shows that digital transformation of agriculture hugely suppresses carbon emissions of agriculture. Column (5) shows no huge

Table 3. Variable Definition.

	Variable Name	Symbol	Variable definition
Dependent variable	Agricultural carbon emissions	ACE	Provincial Agricultural Carbon Emissions
Independent variable	Digital Agriculture	dig_agri	Provincial digital agriculture development level
Control variables	Urbanization	lnurb	Provincial urban population as a share of total population
	Agricultural mechanization	lnmach	Provincial total power of agricultural machinery
	Natural disasters	disa	Provincial crop damage areas
	Resource consumption	lnelect	Provincial rural electricity consumption
Mechanism Variables	Green technology advancement	gta	Provincial Green Total Factor Productivity in Agriculture
	Agricultural operation scale	aos	Provincial number of rural professional cooperatives
	Agricultural cultivation structure	acs	Provincial share of food crops in crop production

Table 4. Descriptive Statistics.

Variable	Mean	SD	Min	Max
ACE	331.6	234.9	14.35	995.8
dig_agri	0.338	0.310	0	1
dig_infr	0.148	0.124	0	0.763
dig_indu	70.07	218.7	0	1757
dig_enti	0.131	0.0244	0.0751	0.187
lnurb	4.061	0.217	3.175	4.495
lnmach	7.642	1.135	4.543	9.499
disa	737.1	777.9	2	4224
lnelect	4.777	1.519	0.0770	7.606
acs	0.650	0.142	0.355	0.971
aos	59314	42238	2813	208173
gta	1.0929	0.1554	0.8045	1.5859
post_inter	295.0	370.8	0.005	1874
dis_inter	142.7	126.1	0	893.7

Table 5. Baseline regression results.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	ACE	ACE	ACE	ACE	ACE
dig_agri	-32.782***				-28.859 ***
	(8.510)				(8.135)
dig_infr		-10.760**			
		(5.075)			
dig_indu			-18.075***		
			(6.715)		
dig_enti				0.862	
				(5.379)	
lnurb					-74.069 **
					(37.862)
lnmach					24.483 ***
					(9.473)
disa					0.005*
					(0.0024)
lnelect					23.877 ***
					(7.189)
Regional FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
R^2	0.996	0.996	0.996	0.996	0.997

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

change in the impact effect of digital transformation of agriculture by increasing the control variables. Therefore, digital transformation of agriculture has a suppressive effect on carbon emissions of agriculture, and hypothesis 1 is verified. A possible explanation is that digital transformation of agriculture relies on green agricultural technologies to effectively decrease agricultural chemical inputs effectively, adopt low-carbon agricultural production methods [16], and effectively improve green total factor productivity in agriculture, thus effectively reducing carbon emissions of agriculture [40].

From the regression results of the control variables. The effects of most of the control variables are in line with theoretical expectations. Notably, the degree of agricultural mechanization hugely contributes to carbon emissions of agriculture, and it is statistically huge at 1%. The possible reason is that China is still in the period of transformation from traditional to modern agriculture and from rough to intensive development methods, and with the widespread use of agricultural machinery [16], the consumption of agricultural energy, such as diesel, is also increasing, which contributes to a certain extent to the increase of carbon emissions of agriculture [4].

Table 5 (2) (3) (4) columns report the regression findings of digital transformation of agriculture sub-dimensional indicators and carbon emissions of agriculture. With a statistical significance of 1%, the amount of digital farm infrastructure (dig_infr) has a considerable inhibitory effect on carbon emissions of agriculture [25]. The Chinese government may have increased rural infrastructure construction in recent years, effectively improved the rural logistics system at the county-town-village degree, conducted extensive e-commerce demonstrations in rural areas, and the „broadband countryside" pilot policy has been successful [9]. Farmers have the ability to Farmers can effectively decrease carbon emissions of agriculture by sharing rural digital Infrastructure in the region and cutting agricultural production costs and output [24]. The degree of digital transformation of agriculture industrialization (dig_indu) has a huge inhibitory effect on carbon emissions of agriculture and is statistically huge at 1%. Possible explanations are that rural e-commerce, as represented by Taobao villages, effectively decreases transaction costs, avoids blind production [24], promotes green production technologies through knowledge spillover [9], promotes brand building and standardized operation of agricultural products [27], and effectively effectively improves agricultural resource utilization efficiency, which in turn suppresses carbon emissions of agriculture. The quality of digital farming subjects has a minor catalytic influence on carbon emissions of agriculture. Farmers in remote mountainous areas of China may face a huge digital divide due to information and transportation barriers, as well as low degrees of transportation and communication consumption expenditures, making it difficult to access markets and effectively obtain income [41], thereby promoting carbon emissions of agriculture.

Analysis of Spatial Spillover Effects

Moran's index test demonstrates that carbon emissions of agriculture are geographically autocorrelated. Table 6 dispays the test results.

$$Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}+(x_i-\bar{x})+(x_j-\bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{j=1}^{n}(x_i-\bar{x})^2} \quad (15)$$

In this study, tests that were pertinent were conducted using the spatial adjacency weight matrix. The results of the LM, Wald, and LR significance tests were all positive, suggesting that the spatial econometric model should be applied and that the SDM model does not degenerate into a SAR or SEM model [16]. Finally, results from the Hausman test demonstrate that the fixed-effects model beats the random-effects model. The geographical Durbin model with two-way fixed effects is therefore used in this study's empirical research.

The estimation results in this study are further decomposed into direct and indirect impacts [25], as shown in Table 7. The direct effect of digital transformation of agriculture on carbon emissions of agriculture is expressed as the region's influence on carbon emissions of agriculture. The spatial spillover effect of digital transformation of agriculture on carbon emissions of agriculture in neighbouring regions is the indirect effect.

As shown in columns (1) (2) (3) of Table 7, the direct, indirect, and total effects of digital transformation of agriculture on carbon emissions of agriculture are all negative under the spatial adjacency matrix. They all pass the 1% test, suggesting that digital transformation of agriculture has a considerable regional spillover effect on reducing carbon emissions of agriculture. This suggests that digital transformation of agriculture aids in the reduction of carbon emissions of agriculture in the region and „neighboring regions" [16]; also, the calculated coefficient of spatial autoregression is positive and passes the 5% significance test. As a result, hypothesis 2 is confirmed. It is worth noting that the indirect effects of digital transformation of agriculture on carbon emissions of agriculture are more huge than the direct effects, indicating that the spatial spillover effects of digital transformation of agriculture on carbon emissions of agriculture suppression are becoming more intense, necessitating the development of a regional synergistic emission reduction policy.

Endogeneity and Robustness Tests

Endogeneity is a huge issue that must be addressed in economic research. This research tackles the endogeneity problem caused by mutual causality or omitted variables by using the number of fixed post offices per million people in 1984 (post_inter) and the spherical distance from the province capital city to Hangzhou (dis_inter) as instrumental variables [36]. On the one hand, post offices were primarily utilized for information transfer and communication in early cultures. As a result, the number of post offices may be used to identify the degree of local communication development and is strongly linked to digital transformation of agriculture, which meets the requirements. Furthermore, historical data from 1984 cannot influence contemporary carbon emissions of agriculture, satisfying the exclusivity criteria. As the home of the digital economy symbolized by e-commerce, Hangzhou, on the other hand, leads the growth of digital transformation of agriculture. In theory, the closer you are to Hangzhou, the faster digital transformation of agriculture will develop. Furthermore, as a typical natural geographical feature, geographical distance is unrelated to carbon emissions of agriculture and fits the relevance and exclusivity requirements. Regarding interaction, the number of post offices per million inhabitants in each province in 1984 is multiplied by the rural Internet penetration rate, as is the spherical distance from the provincial capital city to Hangzhou. They serve as instrumental variables for determining the state of digital agricultural development.

Table 6. Results of global autocorrelation test for carbon emissions of agriculture.

Year	Moran I	Z	P	Year	Moran I	Z	P
2013	0.241 ***	2.568	0.005	2017	0.190**	2.087	0.018
2014	0.216***	2.326	0.010	2018	0.188**	2.069	0.019
2015	0.204**	2.219	0.013	2019	0.181**	2.002	0.023
2016	0.195**	2.132	0.017	2020	0.184 **	2.026	0.021

Table 7. Spatial effect analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
dig_agri	-23.627***	-49.386***	-73.013***	-28.471***	-70.88***	-99.352***
	(6.891)	(11.187)	(10.152)	(7.872)	(21.075)	(20.777)
lnurb	-165.78***	231.48***	65.692	-153.35***	361.02**	207.67
	(32.85)	(54.752)	(51.862)	(33.51)	(150.36)	(149.64)
lnmach	35.31***	- 32.61*	2.703	32.704***	7.021	39.725
	(10.78)	(19.21)	(17.133)	(10.995)	(42.66)	(39.085)
disa	0.0042*	-0.0005	0.0036	0.0054***	0.0139	0.0194
	(0.0024)	(0.0045)	(0.0052)	(0.0026)	(0.0153)	(0.0159)
lnelect	27.407***	22.42	49.828***	27.597***	80.995*	108.59**
	(7.536)	(17.67)	(18.983)	(7.876)	(49.841)	(50.61)
ρ			0.217**			0.325*
			(0.085)			(0.147)
sigma2_e			211.14***			229.61***
			(20.58)			(22.45)
Regional FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

First, column (1) (2) of Table 8 reports the estimation results using the number of fixed post offices per million people in 1984 (post_inter) and the spherical distance between the provincial capital city and Hangzhou (dis_inter) as instrumental variables, and finds that the first stage coefficient is hugely positive. The F-statistic score is 30.04 (higher than 10), indicating that the model is free of weak instrumental variable issues. The Sargan result of 22.65 is statistically huge at 1%, showing that there is no difficulty with the over-identification test. After removing the endogeneity problem caused by omitted variables, the results in column (2) reveal that digital transformation of agriculture has a huge inhibitory effect on carbon emissions of agriculture at 1% statistical significance.

Table 8. Endogeneity and robustness tests.

	(1)	(2)	(3)
VARIABLES	Dig_agri	ACE	ACE
Post_inter	0.0002***		
	(0.0000)		
Dis_inter	0.00033**		
	(0.00014)		
Dig_agri		-67.657***	-27.461***
		(24.11)	(8.882)
Control variables	YES	YES	YES
Regional FE	YES	YES	YES
Time FE	YES	YES	YES
R^2	0.836	0.996	0.995
Sargan	22.65***		
First stage F value	30.04		

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Exclusion of the sample. Considering the special administrative status of municipalities in China, this article excludes the sample of municipalities [42], and the regression results are shown in column (3) of Table 8. Compared with the baseline regression, the regression coefficient values, sign direction, and significance degree of digital transformation of agriculture did not change hugely. The robustness of the empirical results is confirmed.

Replacing the weight matrix. The spatial adjacency matrix is substituted with the geographic distance matrix in this study, and the regression results are reported in Table 7 columns (4) (5) (6). The values of digital transformation of agriculture's regression coefficients, sign direction, and significance degree did not vary considerably. The empirical results' robustness is validated.

Mechanism Test

As shown in Table 9, in mechanism I, digital transformation of agriculture hugely positively affects green technological progress, which meets the 1% significance test. Meanwhile, both digital transformation of agriculture and green technological progress have a considerable negative impact on carbon emissions of agriculture, which passed the 1% significance test. The percentage of intermediate impact to the total impact is 19.76%. This is consistent with theoretical predictions. The possible reason is that the development of digital transformation of agriculture may have knowledge spillover effects on agricultural operators to effectively improve the production quality of green agricultural products [16] and effectively decrease carbon emissions of agriculture through the diffusion of green production technologies [28]. Green technology advancement achieves economic growth from technological innovation and alleviates environmental pressure, effectively decreases costs, effectively decreases environmental pollution, and increases the proportion of clean energy, thus reducing carbon emissions of agriculture [5].

In Mechanism II, digital transformation of agriculture hugely positively affects agricultural scale operation, which passed the 5% significance test. Meanwhile, digital transformation of agriculture and n agricultural scale operation have a huge adverse effect on carbon emissions of agriculture, passing the significance tests of 5% and 1%, respectively. The proportion of the total effect of the intermediary effect is 20.34%, which is consistent with the theoretical hypothesis. The possible reason is that digital transformation of agriculture drives the large-scale operation of agriculture, which overcomes the drawbacks of fine-grained and decentralized land management and facilitates the formation of economies of scale. On the other hand, rational resource allocation effectively improves fertilizer utilization, effectively decreases the consumption of agricultural inputs, and effectively decreases pollution to the environment [17, 30], reducing carbon emissions of agriculture.

In Mechanism III, Dig_agri hugely affected agricultural cropping structure, which passed the 5% significance test. Meanwhile, digital transformation of agriculture and agricultural cropping structures hugely adversely affect carbon emissions of agriculture, both of which pass the 1% significance test. The proportion of the intermediate effect to the total effect is 24.02%, consistent with the theoretical prediction. The possible reason is that the Chinese government may have optimized the agricultural cropping structure in recent years to ensure food security [36], directing high-quality food production and increasing the proportion of food crops grown to effectively improve the carbon sequestration effect and effectively decrease carbon emissions of agriculture [34].

Heterogeneity Test

Heterogeneity of Production Structure

This study examines how different agricultural production patterns have different environmental effects and impact carbon emissions of agriculture. This article conducts separate regression analyses on the samples according to the prominent and non-main grain-producing areas classified by Chinese agriculture in 2003. Columns (1) and (2) of Table 10 reveal the results. The regression results for food-producing regions are presented in column (1), while those for non-food-producing regions are presented in column (2). According to the study results, the development of

Table 9. Mechanism Test.

	Mechanism I		Mechanism I I		Mechanism I I I	
	→GTA	→ ACE	→ AOS	→ ACE	→ ACS	→ ACE
Dig_agri	0.1678***	-23.155***	14054.45 **	-17.81**	0.026**	-21.93***
	(0.0387)	(8.409)	(5869.11)	(7.17)	(0.012)	(7.59)
GTA		-33.997***				
		(14.531)				
AOS				-0.000***		
				(0.0000)		
ACS						-268.48***
						(44.48)
RegionalFE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Mediated effect	19.76%		20.34%		24.02%	

Table 10. Heterogeneity test.

	(1)	(2)	(3)	(4)
dig_agri	-35.667***	-7.464	-19.607	-17.701*
	(12.764)	(8.102)	(13.212)	(10.413)
Control variables	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
R^2	0.996	0.996	0.996	0.998

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

digital transformation of agriculture has a more huge suppressive effect on carbon emissions of agriculture in major food-producing regions than in non-food-producing countries. Possible explanations for this result include, on the one hand, the emergence of an apparent "grain-oriented" phenomenon in grain-producing regions of China, where the cultivation of grain crops increases the efficiency of water and fertilizer use and also hugely increases carbon sequestration [18, 29]. On the other hand, adopting green production technologies tends to be higher in food-producing regions than in non-food-producing regions, which has a more pronounced impact on reducing carbon emissions of agriculture. The increasing influence on green production technologies on replacing chemical fertilizers and reducing fertilizer use effectively decreases carbon emissions of agriculture generated by chemical fertilizers [16], thus reducing the intensity of carbon emissions of agriculture. In addition, implementing water-saving irrigation in major grain-producing areas has a more pronounced impact on supplementing chemical fertilizers and improving the overall efficiency of water and fertilizer use [5].

Geographic Heterogeneity

Further, this article considers that different geographical regions affect carbon emissions of agriculture differently. We divide the sample into coastal and inland areas to analysis. The results are shown in columns (3) to (4) of Table 10. Columns (3) and (4) show the regression results for the coastal and inland regions, respectively. The data show that digital transformation of agriculture has a more substantial inhibitory effect on carbon emissions of agriculture in inland areas than in coastal areas. The possible reason is that due to the slower economic development, weak agricultural infrastructure, and lower management degree in inland regions, they have a huge "latecomer advantage" over coastal regions in accelerating the introduction and diffusion of advanced green agricultural technologies, thus hugely increasing agricultural green total factor productivity and reducing carbon emissions of agriculture [40].

Conclusions and Policy Recommendations

Digital transformation of agriculture contributes to the green sustainability of Chinese agriculture. In the face of today's global warming environment and the need for carbon emission reduction, can the current development of digital transformation of agriculture contribute to agricultural carbon emission reduction? On this basis, this article examines the influence of the digital transformation of agriculture on the carbon emissions of agriculture and its spatial spillover utility. In addition, this article investigates how the digital transformation of agriculture ultimately affects carbon emissions through these three mechanisms from the perspectives of agricultural green technology advancement, agricultural scale operation, and agricultural planting structure adjustment. The main conclusions are as follows: (1) Digital transformation of agriculture significantly inhibits agricultural carbon emissions and has a significant negative spatial spillover effect. Digital agricultural infrastructure and industrialization have a substantial inhibitory effect on agricultural carbon emissions at the structural level. However, the carbon emission reduction effect of the leading quality of digital agriculture needs to be insignificant. (2) Heterogeneity analysis shows that the digital transformation of agriculture has a substantial suppressive effect on agricultural carbon emissions in inland areas and food-dominant regions. (3) The mediating effect shows that digital agricultural transformation helps agricultural carbon emission reduction through green technology progress, agricultural scale operation, and agricultural planting structure adjustment.

This paper highlights specific recommendations that further improve the action mechanism of digital agriculture and promote carbon emission reduction.

First of all, promote the application of digital technology in the agricultural field and promote agricultural carbon emission reduction. Develop precision agriculture and smart agriculture, and promote the popularization of 5G, artificial intelligence, blockchain, remote sensing and other technologies in the field of agriculture. Specifically, agricultural carbon emissions can be reduced through water-saving irrigation and straw-returning technology, and organic fertilizers can be adopted to reduce agricultural surface-source pollution. Topsoil compaction problems can be effectively reduced by replacing heavy machinery with agricultural robots to prevent soil desertification. Remote sensing and spectral technologies are used to monitor crop growth and reduce pests and diseases. Blockchain technology improves the transparency of food traceability and records valid information at all stages of the supply chain to ensure good hygiene conditions and guarantee green food safety. In addition drone and satellite technologies provide more accurate weather data to provide sound advice for farmers to intervene in crop cultivation, which in turn promotes agricultural carbon reduction.

Second, the government should implement inter-regional synergistic emission reduction. Since the development of digital agriculture has an obvious negative spatial spillover effect on agricultural carbon emissions, we suggest that provinces with well-developed digital agriculture infrastructure actively drive neighboring provinces to develop digital agriculture while curbing agricultural carbon emissions in neighboring provinces.

Thirdly, the government should promote green technology and invest more in the core technology of digital agriculture. In addition, the government should reasonably guide the land transfer, strengthen agricultural scale operations, cultivate new agricultural business entities such as family farms, agricultural cooperatives, and leading agricultural enterprises, and realize the economic benefits of agricultural scale. Finally, it should optimize the agricultural planting structure, steadily increase the sown area and output of food crops, and promote the high-quality development of the food industry. Promote the transformation of crop planting structure and the structural reform of the agricultural supply side to reduce agricultural carbon emissions effectively.

In this study, the research in this paper has made some progress, but some things could still be improved. On the one hand, this is due to the limitation of data acquisition. The model in this study only includes provincial data for China from 2013 to 2020. A broader sample panel dataset is needed to conduct a complete empirical study on the impact of the digital transformation of agriculture on agricultural carbon emissions. In the future, we plan to expand the panel data. Second, due to the complexity of the internal composition of digital agriculture and the lack of relevant data, this study only measures the degree of digital agriculture development from three perspectives: digital transformation of agricultural infrastructure, digital transformation of agricultural industrialization, and digital transformation of agricultural subject quality, and the measurement results may differ from the current status of agricultural digital transformation development in China. In the future, we must refer to more literature studies to provide a more reliable research method for measuring digital agriculture in China.

Author Contributions

Yumei Lin: Conceptualization, Methodology, funding acquisition; Chenghan Li: Software, investigation, validation, Data curation, Writing – original draft. Yumei Lin. and Chenghan Li.: Writing, proofreading – review & editing. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author.

Conflict of Interest

The authors declare no conflict of interest.

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