Study on the Impact of China's Digital Economy on Agricultural Carbon Emissions

Linjie Tong[1], Chaoyang Wang[1]*, Qinghua Qi[1], Shenglin Ma[2], Jie Mei[2]

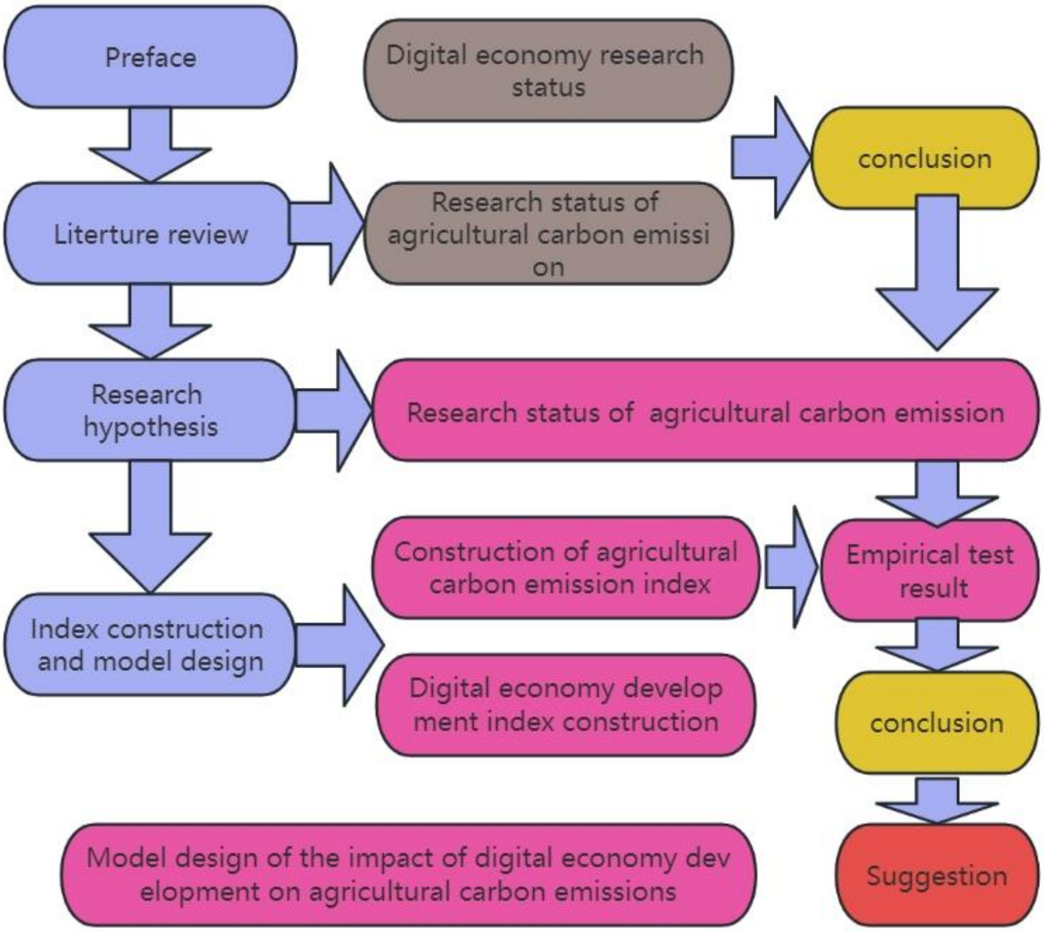
[1] School of Humanities and Law, Yanshan University, Qinhuangdao, China.

[2] School of Economics and Management, North University of China, Taiyuan, China.

*Corresponding author: Chaoyang Wang

E-mail: 3463660933@qq.com, tel: +8619862131590

GRAPHICAL ABSTRACT



ABSTRACT: Under the background of China's “double carbon” goal, digital economy has become an important way to reduce carbon emissions in China. This paper utilizes the provincial panel data of China from 2012 to 2022, introduces the perspective of agricultural science and technology innovation, empirically examines the impact mechanism of regional digital economy development on agricultural carbon emission through regression analysis model, and portrays the dynamic effect and spillover effect of digital economy development on agricultural carbon emission from both time and space dimensions. The empirical results show that: digital economic development will have a significant inhibitory effect on the intensity of agricultural carbon emissions, and the inhibitory effect will be indirectly affected through the path of agricultural scientific and technological innovation; the impact of digital economic development on the intensity of agricultural carbon emissions there is a time lag effect, the current stage of the digital economic development will still have a strong inhibitory effect on the intensity of agricultural carbon emissions in the future; Digital economic development has a spatial spillover effect, i.e., the development of the regional digital economy will have an inhibitory effect on the intensity of agricultural carbon emissions in neighboring provinces. Based on this, it is proposed to strengthen the construction of digital infrastructure, promote the coordinated development of the digital economy in the region, and formulate policies to reduce carbon emissions in agriculture.

Keywords: digital economy; agricultural carbon emissions; agricultural carbon reduction

1. Introduction

The realization of green, low-carbon and sustainable development has become an international consensus. In order to effectively address the adverse impacts on human society and the natural world caused by global warming, drought and air pollution resulting from the emission of greenhouse gases, such as carbon dioxide, the United Nations Framework Convention on Climate Change adopted by the General Assembly of the United Nations in May 1992 proposes that in order to jointly combat climate change, all countries of the globe should take action to limit the emission of greenhouse gases and stabilize the concentration of greenhouse gases in the atmosphere at a level that prevents dangerous anthropogenic interference with the climate system. dangerous anthropogenic interference with the climate system, and that this level should be achieved within a timeframe sufficient to enable ecosystems to proceed sustainably. Against this international backdrop, the Chinese government has clearly proposed a two-step strategic goal of low-carbon emission reduction; carbon dioxide emissions strive to peak by 2030 and neutralize by 2060. As the basic industry of national economic development, the greenhouse gas emissions generated by China's agriculture account for about 17% of the total national carbon emissions, which is much higher than the United Nations Intergovernmental Panel on Climate Change concluded that agricultural greenhouse gas emissions account for about 13.5% of the total greenhouse gas. with the excessive use of pesticides, chemical fertilizers and other chemicals and land burning and other characteristics of the crude agricultural production model will produce more agricultural carbon emissions and higher intensity of agricultural carbon emissions, a serious constraint on the low-carbon development of agriculture, and China's low carbon development concept is contrary to. In order to implement the major decision-making and deployment of carbon peak carbon neutral, we should take the green and low-carbon development of agriculture and rural areas as the purpose, take agricultural pollution reduction and carbon reduction as the starting point, accelerate the formation of an overall layout that matches the carrying capacity of the resources and the environment, and coordinates with the conditions of production and living, and push forward the improvement of the quality of agriculture and increase its efficiency, as well as promote the construction of agricultural modernization.

As a brand new economic form, the digital economy has shown great potential for development. In 2022, the scale of China's digital economy will reach 50.2 trillion yuan, ranking second in the world in terms of total volume, with a year-on-year nominal growth of 10.3% and accounting for 41.5% of GDP. With its advantages of high scale, high value-addedness, high participation and high convenience, has shown certain environmental effect while promoting the high-quality development of China's economy, and continues to contribute to the green transformation and low-carbon development of agriculture by promoting the combination of digital technology and green development of agriculture. In September 2021, the "Digital Space Green Low-carbon Action Proposal" issued by the first China Digital Carbon Neutral Summit Forum proposed to explore the path of digital carbon neutrality, vigorously promote the coordinated transformation and development of digital green, and point out the direction for the digital economy to enable low-carbon agricultural development. The digital economy can rely on big data, cloud computing, artificial intelligence and other underlying science and technology to combine digital technology with agricultural low-carbon development strategies, promote the deep integration of digital elements and traditional production factors. By embedding digital technology into agricultural production, deeply implementing the concept of green development, testing and controlling the whole process of agricultural production, reducing resource waste and reducing the input of "high-carbon" production factors such as fertilizers and pesticides, and then establish a new agricultural production model.

2. Literature review

Agricultural carbon emission is a general term for greenhouse gases produced during agricultural production, but in the early stage of related research, the concept of agricultural greenhouse gases was recognized by more scholars, such as Dong et al (2008), who defined agricultural greenhouse gas emissions as carbon emissions triggered by rice cultivation and livestock and poultry farming. It was not until Li et al (2011) measured carbon emissions based on six types of carbon sources such as fertilizers, pesticides, and agricultural films that the concept of agricultural carbon emissions was formally formed. The so-called agricultural carbon emission refers to the carbon emission caused by human activities in the process of agricultural production (including inputs of agricultural production materials, agricultural machinery operation, etc.). On this basis, Tian et al (2014) reconstructed the measurement system of agricultural carbon emissions based on four dimensions: agricultural energy use, agricultural inputs, rice cultivation, and livestock and poultry breeding, which greatly expanded its theoretical boundary. At present, most Chinese scholars measure agricultural carbon emissions at different administrative levels, such as national, provincial and county, with the help of kaya constant equation (Dai et al.,2015), LMDI model (Ning et al.,2024) and STIRPAT model (Li et al.,2018). Generally speaking, in terms of absolute quantity, the total agricultural carbon emission is led by the central region, centered in the eastern region, and last in the western region, showing a “center-periphery” structure, with a tendency of spreading to the “periphery”, and its positive spatial correlation has become weakened, and the spatial difference has gradually widened. The positive spatial correlation is weakening, and the spatial difference is gradually expanding, which is characterized by path dependence or spatial locking to a certain extent. From the perspective of emission efficiency, China's inter-provincial presents a more obvious “east high, west low” characteristics, with Beijing, Zhejiang, Shandong, etc. as the representative of the eastern and central regions of the agricultural carbon emission efficiency value is in the optimal frontier, with Xinjiang, Qinghai and other western and northwestern regions of the agricultural carbon emission efficiency value is relatively low, there is a greater overall room for improvement (Tian et al.,2024).

Digital economy, as a new economic form with data resources as the key elements, modern information network as the main carrier, and the integration of information and communication technology application and digital transformation of all elements as the important driving force, is both a new engine to promote national economic growth and an important part of fueling social development. Kapoor (2014), Bauer (2018) found through their research that digital economy is a new type of driving force to promote the high-quality development of the economy in the new era, which not only helps to reduce the cost of searching, copying, transporting, tracking and verifying in the economic activities (Goldfarb et al.,2019), establishes a business innovation model centered on the service of consumers and users (Vargo et al.,2004), significantly promotes the improvement of the country's economic innovation capacity, but also realizes the expansion of the scale of import and export trade in emerging markets (Liu et al.,2012), and increases the total amount of market transactions. In addition, Ma (2020) and Jiao et al (2020)point out that the digital economy includes artificial intelligence, 5G and other emerging technologies to help realize the optimal allocation and regeneration of resources, and is of great significance in promoting industrial upgrading and transformation, technological innovation, etc., and is a key factor in triggering the change of residents' consumption, adjusting the industrial structure of the region and promoting the optimization and upgrading of the industrial structure of the various regions.

Since then, with the rapid development of the digital economy, academics have begun to notice its important role in energy conservation and emission reduction, optimization of industrial structure, and the formation of sustainable development ecosystems, and have introduced the digital economy into the framework of agricultural development to explore the role of the digital economy in promoting low-carbon agriculture. Low-carbon agriculture is to realize low-carbon production in all dimensions of agricultural production, consumption and agricultural economy on the basis of comprehensive calculation of total agricultural carbon emissions. Research shows that the digital economy has the potential to transform agricultural production factors. The application of emerging technologies such as big data and the Internet of Things included in the development of the digital economy not only provides optimization strategies for promoting the standardization and high-quality production of agricultural products (Obade et al., 2021), but also reduces the overuse of fertilizers and pesticides in agricultural production, so the digital economy is an important driving force for achieving the green transformation of agricultural production （Wen et al.,2024）. In addition, Liu (2019), from the perspective of precision agriculture, argues that the application of modern spatial information technology guarantees the timely, localized and balanced crop growth demand and input of agricultural production factors, and it is an important way to build a green agricultural production system. Cheng et al (2022), based on the perspective of digital inclusive finance, found that the breadth of coverage, depth of use and degree of digitalization of digital inclusive finance all contribute to the carbon emission reduction effect in agriculture. Liu et al (2023), by constructing a comprehensive evaluation index system for rural digital economy, found that the development of rural digital economy helps to broaden financing channels, introduce efficient and low-carbon agricultural technologies, and form green business models, thus significantly reducing the intensity of agricultural carbon emissions. However, through combing through the articles, it is found that there are still shortcomings in the existing literature: firstly, from the perspective of research objects, most of the inhibitory effects of the digital economy on carbon emissions are concentrated in the industrial field, and less attention is paid to the agricultural field; secondly, from the perspective of research, there is a lack of intermediary influence mechanism of the digital economy to reduce carbon emissions in agriculture; thirdly, from the perspective of research dimension, there is a lack of a systematic and dynamic description of the impact of digital economy development on agriculture in the temporal and spatial dimension. Based on this, the possible contributions of this paper are as follows: (1) Using the panel data of 31 provinces in China from 2012 to 2022, this paper constructs an indicator system for digital economy development and agricultural carbon emissions, and verifies the impact mechanism of digital economy on agricultural carbon emissions. (2) Introduce agricultural science and technology innovation into the influence mechanism, and explore whether agricultural science and technology innovation plays an intermediary effect in the influence mechanism. (3) Construct a time lag model and a spatial Durbin model to explore the temporal dynamic effect and spatial spillover effect of digital economy on agricultural carbon emissions from two dimensions of time and space.

The rest of the paper is set up as follows: section 3 briefly describes the research hypotheses. Section 4 explains the research methodology, model and correlation. Section 5 picks up the empirical results and discussion. Section 6 provides over the conclusions and policy recommendations of the paper.

3. Research hypotheses

3.1 Direct influence mechanism

The inhibitory effect of the digital economy on agricultural carbon emissions is mainly reflected in the following aspects: First, the digital economy takes data resources as the key production factors, and breaks through the time and space limitations by virtue of the data's own reproducibility, shareability and other characteristics, which can alleviate the degree of mismatch of agricultural resource factors, effectively eliminate the information asymmetry problem in agricultural production, and reduce agricultural carbon emissions while improving agricultural production efficiency. Secondly, the Internet platform is the carrier of the digital economy, the booming development of the digital economy will promote the popularization of the Internet platform, so that high-quality agricultural knowledge, agricultural technology and other resources can be widely disseminated, and agricultural laborers can improve their own agricultural literacy through learning so as to use a new type of agricultural production methods (Gao et al.,2020). Thirdly, with the improvement of the national digital infrastructure, the digital economy will continue to penetrate and apply in the field of agriculture, establish a closer connection system in the agricultural production end and sales end, change the existing social-network-physical structure of agriculture, optimize the agricultural value chain, promote the integrated development of the agricultural industry, and improve the efficiency of agricultural development. In summary, this paper puts forward the following hypotheses:

Hypothesis 1 (H1): The digital economy contributes to the reduction of carbon intensity in agriculture.

3.2 Indirect influence mechanism

The impact of the digital economy on agricultural carbon emissions can be realized indirectly through agricultural science and technology innovation. Specifically, digital technology, as the core power of the digital economy enabling green development, has its own environmental and green attributes, and realizes agricultural carbon emission reduction through the formation of a large-scale technology reservoir effect. Relying on advanced science and technology such as blockchain and sensing technology, it effectively improves the level of science and technology in agricultural production, promotes the precise management of agricultural production, and creates a new type of agricultural production industry. The wide application of digital technology helps to monitor the whole process of agricultural production, regulate the crop growth environment based on implementation of sensing and intelligent learning, accurately grasp all kinds of growth factor inputs, and fundamentally get rid of the agricultural production mode of crude factor inputs, directly reducing carbon emissions. For example, through cloud computing and data analysis, it provides real-time crop growth data for agricultural laborers, and combines digital equipment such as agricultural drones and intelligent fertilization systems to rationally utilize agricultural production materials such as fertilizers and nutrient solutions, and to reduce the over-reliance on chemicals. Based on this, the article proposes the following hypothesis:

Hypothesis 2 (H2): The digital economy can effectively reduce the intensity of agricultural carbon emissions through agricultural science and technology innovation.

3.3 Time-dynamic effects

The impact mechanism of digital economy on agricultural carbon emissions is a long-term dynamic process, the reason is that the development of digital economy requires the participation of digital infrastructure, technological innovation and research and development, industrial support capacity and other factors, and these factors from the initial establishment to play a role in the existence of a long period of cyclicality (Wang et al., 2022), so the analysis of the mechanism of the role of the digital economy on agricultural carbon emissions needs to be placed in a long-term time dimension Examination. In the early stage of the development of digital economy, due to the influence of imperfect digital infrastructure, insufficient investment in digital technology, and low degree of industrial digitization (Hu et al., 2022), it is difficult for digital economy to give full play to the inhibition of agricultural carbon emissions in a short time. However, with the deepening of social digitization, the digital economy can promote the optimization of agricultural industrial structure, develop green agriculture, eco-agriculture and organic agriculture, and gradually play a role in suppressing agricultural carbon emissions under the joint action of many factors. Therefore, when analyzing the low-carbon development of agriculture empowered by the digital economy, the possible time lag effect should be considered. Based on this, the article puts forward the following hypotheses:

Hypothesis 3 (H3): there is a time lag in the dampening effect of the digital economy on agricultural carbon emissions.

3.4 Spatial spillover effects

Yilmaz et al (2002) utilized the panel data of 48 states in the United States from 1970 to 1997 to test the spatial spillover effect of state-level telecommunication infrastructure investment on national output, and became the earliest scholars to focus on the spatial spillover effect of the digital economy. Since then Academic community has gradually combined the spatial spillover effect of the digital economy with the carbon emission, urban development and other elements, such as Xu et al (2024) conducted empirical tests on the carbon emission performance of the digital economy network, and found that in the spatial network of digital economy, cities form a high-level and sustainable economic system together, which has a significant "network effect" on the carbon reduction target of cities. Han et al (2017) used city data to empirically analyze the spatial spillover effect of productive service industry agglomeration on carbon emissions, and found that specialized and diversified agglomeration has a significant effect on the carbon emission level of the neighboring cities, and the spatial spillover effect of diversified agglomeration on carbon emissions is significantly larger than that of specialized agglomeration. In addition, the empirical studies of Wang et al (2022) and Cheng et al (2022) proved that the development of digital technology also has a spatial effect on agricultural carbon emissions. The spatial spillover effect of the digital economy stems from the fact that it breaks the traditional spatial and temporal limitations of information transmission, promotes the flow of inter-regional factors to be more frequent, and the dynamic relationship between competition and cooperation to change more. In addition, the development of the digital economy has phased characteristics, so that the digital economy will have an impact on agricultural carbon emissions through the group effect, learning effect and diffusion effect, resulting in spillover effect (Tian et al.,2024), so that the advanced green technology, knowledge and experience in this region are more likely to spill over to neighboring regions, and improve the level of low-carbon agricultural development in neighboring regions. Based on this, this paper puts forward the following hypotheses:

Hypothesis 4 (H4): the dampening effect of the digital economy on agricultural carbon emissions has spatial spillover effects.

4. Research Methodology and Modeling

4.1 Description of variables

4.1.1 Explained Variables

Carbon intensity of agriculture ($\ln \mathrm{TQ}_{it}$). In this paper, the agricultural carbon emission intensity is chosen to measure the level of agricultural carbon emission of each province in China, which is expressed by the ratio of total agricultural carbon emission to agricultural output value, and the specific calculation formula is as follows:

$$\ln \mathrm{TQ}_{it}=\frac{TZ}{ArgGDP} \quad (1)$$

TZ in Equation (1) is the total agricultural carbon emissions and *ArgGDP* is the gross agricultural product based on the value added of the primary sector.

This paper draws on the methodology of Li et al (2011) to measure agricultural carbon emissions from six aspects, including diesel fuel, fertilizer, and pesticides, and the carbon emission calculation formula is as follows:

$$TZ = \Sigma TZ_i = \sum T_i \times \sum \sigma_i \quad (2)$$

In Equation (2): TZ_i denotes the total amount of carbon emissions from carbon sources of category i; T_i denotes the absolute amount of carbon sources of category i; σ_i denotes the carbon emission coefficient of carbon sources in category i . Specific carbon sources and carbon emission coefficients are shown in Table 1.Table 1. Agricultural carbon sources and emission factors

Carbon Source	Carbon Emission Factor	Reference source
Diesel fuel	0.59 kg/kg	IPCC 2013
Fertilizers	0.89 kg/kg	Oak Ridge National Laboratory, USA
Pesticide	4.93 kg/kg	Oak Ridge National Laboratory, USA
Agricultural film	5.18 kg/kg	Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University

Irrigated	266.48 kg/hm^2	Duan et al (2011)
Sowing	312.6 kg/km^2	Li et al (2011)

4.1.2 Core explanatory variables

The level of development of the digital economy (DIG_{it}). Based on the Statistical Classification of the Digital Economy and Its Core Industries (2021) and referring to the research results of Wang et al (2021), this paper establishes digital economy evaluation indexes from five aspects, including digital network infrastructure, logistics and transportation, digital trade capacity, digital technological innovation, and trade potential, and applies entropy method to measure and calculate the level of digital economy development of each province in China. The established digital economy evaluation index system is shown in Table 2.

Table 2. Evaluation index system for the level of comprehensive development of the digital economy.

First-level indicators	Second-level indicators	Unit	Attribute
Digital network infrastructure	Number of domain names	Ten thousand	+
	Number of websites	Ten thousand	+
	Internet broadband access port	Ten thousand	+
	Length of long-distance fiber optic cable lines	Kilometers	+
	broadband access user	Ten thousand people	+
Logistics	Logistics and transportation-related practitioners	People	+
	Ownership of road-operating goods vehicles	ten thousand vehicles	+
	Civilian transportation ship	Vessels	+

	ownership		
Digital trade capacity	E-commerce sales	Hundred million RMB	+
	Revenue from express delivery operations	Hundred million RMB	+
	Total telecommunication services	Hundred million RMB	+
	Revenue from software operations	Ten thousand RMB	+
Digital technology innovation	R&D expenditures of industrial enterprises above designated size	Ten thousand RMB	+
	Total technology contract turnover	Ten thousand RMB	+
	Number of patent applications	Item	+
Trade potential	GDP per capita	RMB	+
	market openness	%	+
	Total exports and imports	billions	+

4.1.3 Other variables

It mainly includes the mediating variable: agricultural science and technology innovation (AST_{it}). Due to the lack of data related to agricultural science and technology innovation index, this paper uses the number of agricultural science and technology patents in each province to represent it. In addition, considering that agricultural carbon emissions are affected by a variety of factors, this paper selects the regional urbanization rate (URB_{it}), regional road mileage ($ROAD_{it}$), the proportion of government support for agriculture (PGS_{it}) and rural electricity consumption (REC_{it}) as control variables. These selected indicators are specifically designed to reflect agricultural development and economic and social conditions.

Table 3. Descriptive statistics results of main variables

Variables	Obs	Average	SD	Max	Min
$\ln TQ_{it}$	341	3. 2535	2. 3099	9. 9572	1. 2723
DIG_{it}	341	0. 1244	0. 1001	0. 5903	0. 0174
AST_{it}	341	3. 0909	3. 1523	16. 6510	0. 0100
URB_{it}	341	0. 5980	0. 1268	0. 8960	0. 2287
$ROAD_{it}$	341	1. 5483	0. 8314	4. 05390	0. 1254
PGS_{it}	341	1. 1568	0. 3453	2. 03840	0. 4040
REC_{it}	341	2. 7755	3. 9524	20. 1100	0. 0102

4.2 Data sources

This paper uses 31 provinces (autonomous regions and municipalities directly under the central government) in mainland China from 2012 to 2022, excluding Hong Kong, Macau and Taiwan. The data come from China Statistical Yearbook, China Agricultural Statistical Yearbook, National Bureau of Statistics, Provincial Statistical Yearbook, EPS data platform, and Peking University Digital Inclusive Finance Index. For some missing data, this paper uses linear interpolation to supplement.

4.3 Model design and spatio-temporal correlation test

First of all, in order to explore the direct impact of the development of digital economy on the intensity of agricultural carbon emissions, this paper constructs the following basic model:

$$\ln TQ_{it} = \partial_0 + \partial_1 DIG_{it} + \partial_2 X_{it} + \delta_i + \tau_t + \mu_{it} \quad (3)$$

In equation (3), $\ln TQ_{it}$ is the explained variable agricultural carbon emission intensity, DIG_{it} is the core explanatory variable digital economy development level, and X_{it} is the set of control variables, δ_i and τ_t denote region and time fixed effects, respectively, and μ_{it} denotes the random perturbation term.

Secondly, in order to verify that the digital economy can have an indirect impact on the intensity of agricultural carbon emissions through agricultural science and technology innovation, this paper constructs the following mediating effect model with reference to the research results of WEN et al:

$$\mathrm{AST}_{it} = \beta_0 + \beta_1 \mathrm{DIG}_{it} + \beta_2 X_{it} + \delta_i + \tau_t + \mu_{it} \tag{4}$$

$$\ln \mathrm{TQ}_{it} = \gamma_0 + \gamma_1 \mathrm{DIG}_{it} + \gamma_2 \mathrm{AST}_{it} + \gamma_3 X_{it} + \delta_i + \tau_t + \mu_{it} \tag{5}$$

In equations (4) (5), AST_{it} represents the mediating variable agricultural science and technology innovation, other symbols and variables are the same as in equation (3).

In order to verify the time-dynamic effect of digital economic development to reduce agricultural carbon emissions, this paper lags the core explanatory variables in Equation (3) in order to fully verify the impact of the current time digital economic development on the future intensity of agricultural carbon emissions, the specific model is as follows:

$$\ln \mathrm{TQ}_{it} = \partial_0 + \partial_1 \mathrm{DIG}_{i(t-m)} + \partial_2 X_{it} + \delta_i + \tau_t + \mu_{it} \tag{6}$$

In equation (6), m denotes the number of lags of the core explanatory variables.

Finally, in order to quantitatively examine the spatial effect of digital economic development on agricultural carbon emissions, this paper introduces the spatial interaction terms of digital economic development, agricultural carbon emission intensity and other control variables on the basis of formula (2), and further constructs a spatial measurement model to further explore the study of the impact of digital economic development on agricultural carbon emissions, and the spatial Durbin model (SDM) constructed in this paper is as follows:

$$\ln \mathrm{TQ}_{\mathrm{it}} = \partial_0 + \rho \boldsymbol{W} \ln \mathrm{TQ}_{it} + \varphi_1 \boldsymbol{W} \mathrm{DIG}_{it} + \partial_1 \mathrm{DIG}_{it} + \varphi_2 \boldsymbol{W} X_{it} + \partial_2 X_{it} + \delta_i + \tau_t + \mu_{it} \tag{7}$$

In equation (7), ρ is the spatial autocorrelation coefficient, and $\boldsymbol{W}$ denotes the spatial weight matrix, φ_1、φ_2 denote the elasticity coefficients of the spatial interaction direction of the core explanatory variables and control variables, respectively, and, in order to improve the robustness of the empirical results, this paper adopts the critical matrix and the geographic distance matrix for the regression calculation.

5. Results and discussion

5.1 Baseline regression analysis

As can be seen from (1) (2) in Table 4, the coefficient of digital economic development on agricultural carbon emission intensity is significantly negative, and the addition of control variables does not cause the direction of the coefficient to change, so it proves that the development of digital economy has an inhibitory effect on the intensity of agricultural carbon emissions regardless of the addition of control variables, and hypothesis 1 is established. Specifically, before adding control variables, the coefficient of digital economy is -0.809, indicating that every unit of digital economy can reduce the intensity of agricultural carbon emissions by 0.809 units, and after adding control variables, every unit of digital economy can reduce the intensity of agricultural carbon emissions by 1.026 units. Among them, urbanization rate and road mileage are conducive to reducing the intensity of agricultural carbon emissions, while the proportion of government support to agriculture and rural electricity consumption significantly increase the intensity of agricultural carbon emissions. The reason is that the increase of urbanization rate and road mileage helps to transfer advanced agricultural production knowledge and technology to rural areas, which improves the efficiency of agricultural production and reduces the intensity of agricultural carbon emissions. The increase in the proportion of government support for agriculture expands the input of production factors such as fertilizers and pesticides, which increases the intensity of agricultural carbon emissions. Moreover, rural power generation relies on traditional thermal power generation, and the increase in rural electricity consumption burns more coal and other resources, which also increases the intensity of agricultural carbon emissions.

Table 4. baseline regression and mechanism test results of digital economy affecting carbon intensity in agriculture

Variables	(1) $\ln\ TQ_{it}$	(2) $\ln\ TQ_{it}$	(3) AST_{it}	(4) $\ln\ TQ_{it}$
DIG_{it}	-0.809***	-1.026***	0.141***	-0.749**
	(-2.718)	(-3.236)	(7.909)	(-2.161)
ASTit				-0.196*
				(-1.938)
URBit		-1.972***	0.172***	-1.635***
		(-3.842)	(5.946)	(-3.029)
ROADit		-0.037***	0.046	-0.036***
		(-2.967)	(0.655)	(-2.906)
PGSit		0.705***	-0.0203***	0.665***
		(6.601)	(-3.376)	(6.142)
RECit		0.011	0.000	0.011
		(1.150)	(0.835)	(1.247)
_cons	3.354***	4.29.1***	-0.074***	4.145***
	(87.096)	(19.816)	(-6.099)	(18.153)
Year fixed	YES	YES	YES	YES
Province fixed	YES	YES	YES	YES
N	341	341	341	341
R^2	0.760	0.990	0.837	0.991

Note: *, **, *** denote significant at the 10%, 5%, and 1% statistical levels, respectively. Values in parentheses are test Z-values, same below.

Table (3) (4) shows the results of the mediation test. On the premise that the coefficient of digital economy in Column (2) is significantly negative, the coefficient of digital economy development on agricultural science and technology innovation in Column (3) is significantly positive, and 1 unit increase of digital economy, agricultural scientific and technological innovation will increase by 0.141 units, which indicates that the development of digital economy helps to promote agricultural science and technology innovation. Column (4) shows that the positive and negative regression coefficient of digital economy has not changed, and the regression coefficient of agricultural scientific and technological innovation is significantly negative after adding control variables, and the coefficient of the digital economy in column (4) is lower compared with column (2), which indicates that agricultural science and technology innovation plays a mediating role in the digital economy to reduce the intensity of agricultural carbon emissions.

5.2 Robustness Tests

Considering that there are large differences in the development of digital economy among provinces in China, in order to further enhance the robustness of the conclusions, this paper conducts a robustness test by replacing the variables, shrinking the tail treatment and selecting the sub-sample.

(1) Replacement of core explanatory variables. The digital economy development index is analyzed as the core explanatory variable in the benchmark regression, and in order to further enhance the robustness of the conclusions, the core explanatory variable is replaced from the digital economy index to the digital financial inclusion index (DFI). (2) Tailoring treatment. Under the condition of ensuring that the sample data are not

excluded, the outliers that are less than 1% and greater than 99% are replaced. (3) Selecting sub-samples, after excluding the four municipalities of Beijing, Tianjin, Shanghai and Chongqing, the regression analysis is conducted again for the remaining provinces to test whether the impact of digital economy on agricultural carbon emissions is significant, and the results are shown in the table:

Table 5.Robustness test results

Variables	$\ln TQ_{it}$ (1)	(2)	(3)
DFI	-0.751***		
	(-3.966)		
DIG_{it}		-1.080***	-1.004***
		(-2.988)	(-2.750)
URB_{it}	-0.245***	-0.271***	-0.297**
	(-2.888)	(-3.143)	(-2.037)
$ROAD_{it}$	-0.266***	-0.317**	-0.336***
	(-2.686)	(-2.528)	(-3.069)
PGS_{it}	0.558***	0.600***	0.620***
	(4.806)	(4.708)	(4.802)
REC_{it}	0.868	0.004	0.010
	(1.333)	(0.660)	(1.137)
_cons	5.216***	4.794***	5.227***
	(10.576)	(9.040)	(6.849)
Year fixed	YES	YES	YES
Province fixed	YES	YES	YES
N	341	341	297
R^2	0.991	0.992	0.990

As can be seen from the robustness test results in columns (1) (2) (3) of Table 5, after changing the test method, the impact of the digital economy on agricultural carbon emissions is still significant, all of which are significant at the 1% statistical level, and the sign of the coefficients is consistent with the results of the baseline regression, which indicates that the digital economy has an inhibitory effect on agricultural carbon emissions with strong robustness, and once again verifies the hypothesis (1), that is, the digital economy contributes to the reduction of the intensity of agricultural carbon emission intensity.

5.3 Heterogeneity test

5.3.1 Impact of the development of the digital economy on agricultural carbon emissions in regions with different economic development status

In order to deeply investigate the regional heterogeneity characteristics of the impact of digital economy development on agricultural carbon emission intensity, this paper takes the GDP of each province in China in 2023 as the division criterion, and combines the per capita GDP of each province, geographic location and other factors to divide China's 31 provinces into economically developed regions (Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Chongqing, Hubei), economically developing moderate regions (Inner Mongolia, Liaoning, Anhui, Henan, Sichuan, Jiangxi, Hunan, Hainan, Shaanxi, Ningxia, Xinjiang), and economically backward regions (Hebei, Jilin, Guangxi, Guizhou, Yunnan, Tibet, Shanxi, Gansu, Heilongjiang, Qinghai) at three levels, and regression analyses were conducted using a two-way fixed effects model. The results are shown in Table 5, in economically developed regions and regions with medium economic development, the coefficients of digital economic development on the intensity of agricultural carbon emissions are -1.717 and -0.913, respectively, and are significant at the statistical levels of 5% and 10%, indicating that the digital economic development has a significant inhibitory effect on the intensity of agricultural carbon emissions, and the higher the level of economic development of the region, the more obvious the inhibitory effect. However, the coefficient of digital economic development on agricultural carbon emission intensity is not significant for the economically backward regions, probably because the digital infrastructure of economically backward regions is relatively backward, and the phenomenon of "digital divide" still exists in rural areas, which makes it difficult to give full play to the spillover effect generated by the development of digital economy.

Table 6 Heterogeneity analysis results for different economic development regions

Variables		$\ln \mathrm{TQ}_{it}$	
	(1)	(2)	(3)
DIG_{it}	-1.717**	-0.913*	-0.555
	(-2.534)	(-1.815)	(-1.358)
Controls	YES	YES	YES
_cons	7.679***	5.662***	2.018***
	(6.185)	(5.889)	(4.306)
Year fixed	YES	YES	YES
Province fixed	YES	YES	YES
N	110	121	110
R^2	0.975	0.993	0.995

5.3.2 Impact of the development of the digital economy on agricultural carbon emissions in different food-producing regions

In this paper, with reference to the 2022 national grain data released by the National Bureau of Statistics of China, based on the grain crop yields of each province in China, and combining the regional sowing area, agricultural planting structure, and production methods, China's 31 provinces are categorized into high grain-producing regions (Heilongjiang, Henan, Shandong, Anhui, Jilin, Inner Mongolia, Hebei, Jiangsu, Sichuan, Hunan, and Hubei), medium grain-producing regions (Liaoning, Jiangxi, Yunnan, Xinjiang, Shanxi, Guangxi, Shaanxi, Guangdong, Gansu, Guizhou, Chongqing, and Zhejiang), and low grain producing areas (Fujian, Ningxia, Tianjin, Hainan, Tibet, Qinghai, Shanghai, and Beijing), and utilized the two-way fixed model and conducted regression analysis. As shown in Table 6, the coefficients of the level of digital economy development on agricultural carbon emissions are -0.982 and -1.343 in high grain producing areas and medium grain producing areas, respectively, and both are significant at the statistical level of 10%, indicating that the inhibition of the digital economy on agricultural carbon emissions in medium- and high-grain-producing areas is more significant, whereas the inhibition in low grain-producing areas is not significant, which may be due to the influence of the area of grain cultivation, the level of regional economic development and the level of regional economic development, which is not significant. The reason may be due to the limitation of regional grain cultivation area, regional economic development level and other factors, low-carbon and digital advanced production methods, cultivation methods have not yet been applied on a large scale, the level of agricultural carbon emissions is still maintained at a high level, and the inhibitory effect of the digital economy on the intensity of agricultural carbon emissions has not yet appeared.

Table 7 Heterogeneity analysis results for different food production regions

Variables		$\ln\ \mathrm{TQ}_{it}$	
	(1)	(2)	(3)
DIG_{it}	-0.982*	-1.343*	-0.507
	(-1.907)	(-1.693)	(-1.160)
Controls	YES	YES	YES
_cons	7.070***	4.618***	3.751***
	(5.125)	(4.863)	(8.206)
Year fixed	YES	YES	YES
Province fixed	YES	YES	YES
N	121	132	88
R^2	0.988	0.992	0.996

5.4 Tests for time-dynamic effects

In order to further investigate whether there is a time lag effect of digital economy on agricultural carbon emission intensity, this paper uses time dynamic analysis, i.e., through the lag period of digital economy development variables, to examine the impact of the current period of digital economy development on the intensity of agricultural carbon emission in the future periods. The specific measure is to express the core explanatory variables in terms of the level of digital economic development in the current period, lag 1, and lag 2, respectively, and regress them using fixed effects. The results are shown in Table 8. Columns (1) (3) (5) indicate the impact of the development level of digital economy at the current, lag 1 and lag 2 periods on the intensity of agricultural carbon emissions when controlling for the region fixed effect but not controlling for the time fixed effect, and columns (2) (4) (6) indicate the impact of the development of digital economy at the current, lag 1 and lag 2 periods on the intensity of agricultural carbon emissions when controlling for the region and the time fixed effects, respectively. period, the impact of digital economy development on the intensity of agricultural carbon emissions at the current period, lag 1 period and lag 2 period, respectively. The results show that the level of digital economy development in the current period, lag 1 and lag 2 periods all have a dampening effect on the intensity of agricultural carbon emissions. Specifically, the coefficients of the level of digital economy development on agricultural carbon emissions in Columns (1) (3) (5) and Columns (2) (4) (6) show a decreasing trend regardless of controlling for time fixed effects, indicating that the agricultural emission reduction and carbon reduction role of the digital economy will gradually empower the low-carbon development of agriculture by adjusting the structure of the agricultural industry, popularizing green energy, etc.

over time. Hypothesis (3) is verified.

Table 8. results of the test for time-dynamic effects

Variables	$\ln \text{TQ}_{it}$					
	(1)	(2)	(3)	(4)	(5)	(6)
DIG_{it}	-1.026***	-0.976**				
	(-3.236)	(-2.541)				
$\text{DIG}_{i(t-1)}$			-0.783**	-0.717*		
			(-2.294)	(-1.868)		
$\text{DIG}_{i(t-2)}$					-0.686*	-0.604*
					(-1.819)	(-1.027)
Controls	YES	YES	YES	YES	YES	YES
_cons	4.291***	4.470***	4.971***	4.815***	5.777***	5.657***
	(19.816)	(8.653)	(20.877)	(8.451)	(20.793)	(9.970)
Year fixed	No	YES	No	YES	No	YES
Province fixed	YES	YES	YES	YES	YES	YES
N	341	341	310	310	279	279
R^2	0.348	0.413	0.407	0.448	0.455	0.426

5.5 Testing for spatial spillover effects

In order to examine whether the inhibitory effect of digital economy on agricultural carbon emissions has a spatial spillover effect, this paper adopts a spatial econometric model to test it. First, based on the geographic distance matrix and the adjacency matrix, the intensity of agricultural carbon emissions and the Moran index of digital economy in 31 provinces and cities in China were measured from 2012 to 2022, and the results are shown in Table 9.

It can be found that the Moran'I of digital economy and agricultural carbon emissions from 2012 to 2022, although with certain volatility, are all significantly positive, with obvious spatial clustering trend, indicating that there is a strong spatial autocorrelation of agricultural carbon emissions among provinces.

Table 9. Results of global Moran index of digital economy development and agricultural carbon emissions in 31 provinces and cities in China

YEAR	Geographic distance matrix				adjacency matrix			
	$\ln\ TQ_{it}$		DIG_{it}		$\ln\ TQ_{it}$		DIG_{it}	
	Moran's I	p-Value	Moran's I	p-Value	Moran's I	p-Value	Moran's I	p-Value
2012	0.096	0.050	0.023	0.096	0.251	0.008	0.174	0.041
2013	0.085	0.062	0.039	0.041	0.241	0.010	0.130	0.025
2014	0.061	0.099	0.078	0.023	0.216	0.020	0.198	0.031
2015	0.015	0.018	0.079	0.026	0.204	0.026	0.210	0.023
2016	0.046	0.027	0.085	0.011	0.195	0.033	0.260	0.006
2017	0.042	0.036	0.090	0.018	0.190	0.037	0.296	0.002
2018	0.044	0.035	0.081	0.014	0.188	0.039	0.279	0.003
2019	0.036	0.049	0.077	0.027	0.181	0.045	0.235	0.011
2020	0.043	0.034	0.089	0.032	0.184	0.043	0.223	0.015
2021	0.040	0.042	0.062	0.016	0.178	0.049	0.200	0.026
2022	0.019	0.098	0.065	0.015	0.159	0.074	0.193	0.029

Secondly, in order to further determine the most appropriate model among the three spatial econometric models developed, this paper conducts the LM test, LR test and Hausmann test respectively, and the test results are shown in Table 10. In the LM test to determine the type of spatial effect, the p-value of LM-Lag test, Robust LM-Lag test, LM-Error test and Robust LM-Error test were obtained to be less than 0.1, which significantly rejected the original hypothesis, and the use of the Spatial Durbin Model (SDM) was initially selected. In addition the p-value of Hausman test is 0.000, which supports the use of fixed effect model, due to the possibility of spatial Durbin model degradation into spatial error model and spatial lag model, this paper uses LR test and Wald test to evaluate the model, the results show that spatial Durbin model will not degrade into spatial lag model and spatial error model, therefore, the final use of SDM model of fixed effect is used to conduct the regression analysis.

Table 10.Model selection correlation test

Test items	Statistic	p-Value

LM-lag	44.493	0.000
R-LM-lag	4.104	0.043
LM-error	95.017	0.000
R-LM-error	54.628	0.000
Wald-spatial-lag	16.020	0.003
LR-spatial-lag	12.770	0.000
Wald-spatial-error	17.790	0.001
LR-spatial-error	16.080	0.097

Finally, this paper establishes a fixed-effect SDM model based on spatial geographic distance weight matrix for regression. The results are shown in Table 11, and the data indicate that the development of digital economy has a significant inhibiting effect on agricultural carbon emissions, and the regional urbanization rate and rural electricity consumption have a more significant effect on the intensity of agricultural carbon emissions. In addition the digital economy, urbanization rate has a significant inhibitory effect on the intensity of agricultural carbon emissions in neighboring regions, and rural electricity consumption has a significant effect on the intensity of agricultural carbon emissions in neighboring regions. Given that analyzing the SDM estimates cannot directly draw detailed data conclusions, this paper will discuss the direct and indirect effects of the independent variables.

Table 11.Spatial Durbin model estimation and test results

Variables	SDM	Variables	SDM
DIG_{it}	-0.034**	$WxDIG_{it}$	-0.434***
	(-2.253)		(-3.706)
URB_{it}	-0.497***	Wx URB_{it}	-2.040**
	(4.407)		(2.403)
$ROAD_{it}$	-0.064	Wx $ROAD_{it}$	-0.165
	(-0.945)		(0.314)
PGS_{it}	0.021	Wx PGS_{it}	0.083
	(-0.591)		(0.349)
REC_{it}	0.041***	Wx REC_{it}	0.130***
	(4.879)		(-2.752)
Spatial rho	0.562***	sigma2_e	0.003***
	(5.869)		(13.137)

Table 12 shows the effect of digital economic development on the intensity of agricultural carbon emissions, the direct effect refers to the impact of digital economic development on the intensity of agricultural carbon emissions in the region, the indirect effect is the impact of digital economic development on the intensity of agricultural carbon emissions in neighboring regions, and the sum of the two is the total impact of the digital economy on agricultural carbon emissions.

From the regression results in Table 12, the coefficients of the results of the direct effect, indirect effect and total effect of the digital economy on the intensity of agricultural carbon emissions have the same sign and are significantly negative, so it can be concluded that hypothesis (4) is valid, the development of digital economy has a spatial spillover effect on agricultural carbon emissions . Through further analysis, it is found that the absolute values of the coefficients of the explanatory variables, the interpreted variables and the control variables in the indirect effect are larger than the absolute values of the coefficients in the direct effect, which indicates that the spatial spillover effect of digital economy is the main factor to restrain agricultural carbon emissions. In the direct effect, the coefficient of the urbanization rate on the intensity of agricultural carbon emissions is -0.544, which is significant at the level of 1%. The increase of the urbanization rate will be conducive to the dissemination of advanced industrial technology, and the workers engaged in agricultural production will be more easily exposed to the more advanced green agricultural production technology, which will significantly reduce the intensity of agricultural carbon emissions. The coefficient of rural electricity consumption on the intensity of agricultural carbon emissions is

0.038 and is significant at the 1% level, probably because electricity in rural areas mainly comes from thermal power generation generated by the combustion of fossil fuels, and with the increase of electricity consumption, the combustion of these fossil fuels will increase accordingly, and thus enhance the intensity of carbon emissions. Among the indirect effects, the impact coefficient of the proportion of agricultural support is 1.263 and is significant at the 1% level, indicating that an increase in the proportion of agricultural support in the region will enhance the intensity of agricultural carbon emissions in neighboring regions, probably because when the proportion of governmental support for agriculture in the province increases, it will increase the inputs of fertilizers, pesticides, and other resources for agricultural production, such as water resources, which will lead to an increase in the price of the production resources, and the neighboring provinces will decrease the amount of agricultural production resources used, but in order to maintain yields and incomes, may choose to use less efficient but more costly agricultural production methods, resulting in a higher carbon emission intensity.

Table 12. Direct, indirect and total effects of factors affecting carbon intensity in agriculture

Variables	direct	Indirect	Total
DIG_{it}	-0.035**	-0.513***	-0.548***
	(-2.177)	(-3.512)	(-3.639)
URB_{it}	-0.544***	-1.095	-1.639
	(4.810)	(1.077)	(1.554)
$ROAD_{it}$	-0.056	-0.192	-0.248
	(-0.830)	(-0.211)	(-0.263)
PGS_{it}	0.036	1.263***	1.299***
	(1.071)	(4.411)	(4.502)
REC_{it}	0.038***	-0.101	-0.062
	(4.614)	(-0.973)	(-0.589)

6. Conclusions and policy recommendations

Based on the panel data of 31 provinces (municipalities and autonomous regions) in China from 2012 to 2022, we construct the time lag model and the spatial Durbin model to empirically test the impact of digital economy on the intensity of agricultural carbon emissions, and this paper also innovatively introduces the agricultural science and technology innovation to explore whether it plays a mediating effect in this effect. The findings are summarized as follows:

(1) The development of China's digital economy has a significant inhibitory effect on agricultural carbon emission intensity, and the conclusion is still valid after the robustness test such as replacing the core explanatory variables. It can be seen from the intermediary test results that agricultural scientific and technological innovation plays a mediating role in the impact of digital economy on agricultural carbon emissions and inhibits agricultural carbon emissions.

(2) The impact of digital economy development on agricultural carbon emission intensity has a time lag effect and a spatial spillover effect, i.e., the inhibitory effect of the digital economy on agricultural carbon emissions will be revealed over time; the development of the digital economy in the region will also have an inhibitory effect on the intensity of agricultural carbon emissions in the neighboring regions.

(3) The impact of digital economy on agricultural carbon emissions shows a certain regional heterogeneity. Specifically, the inhibition effect of digital economy on agricultural carbon emissions is more obvious in regions with medium and high levels of economic development and medium and high grain production, while in regions with

backward economic development and low grain production, the inhibition effect is not significant due to factors such as the acquisition and large-scale application of planting technology.

Based on the conclusions of the above article, this paper makes the following recommendations:

(1)To strengthen the construction of digital infrastructure and create scenarios for the development of digital economy in rural areas. Digital infrastructure construction is both an important support for the development of digital economy and an important guarantee for empowering the low-carbon development of agriculture, so it is necessary to strengthen the construction of digital infrastructure in order to realize the carbon reduction and emission reduction in agriculture. On the one hand, it is necessary to strengthen the basic network construction of gigabit network, mobile Internet of Things and other basic networks in rural areas, especially in economically backward areas such as Guizhou, Guangxi, Tibet, Qinghai and other food real estate areas, to improve the coverage rate of regional broadband network and mobile network, and to lay the network foundation for the improvement of agricultural digitalization level. On the other hand, the integration of digital economy and agriculture should be accelerated, and we should actively introduce agricultural weather stations, soil testing equipment and other digitalized agricultural equipment, rely on the agricultural Internet to build an agricultural production data platform, and explore low-carbon and carbon-free agricultural production modes by digitizing and accurately measuring and controlling agricultural production environments, crop growth conditions and so on.

(2) The government should enhance the overall development level of the digital economy and explore new agricultural development models. First of all, it is necessary to combine the economic development advantages of each province and rely on platforms such as the Internet to vigorously improve the development level of the digital economy in the province. At the same time, it is necessary to further develop digital inclusive finance and use digital service channels to meet the needs of agricultural financing and lay an economic foundation for agricultural carbon emission reduction. Secondly since the suppression of the intensity of agricultural carbon emissions by the digital economy has a spatial spillover effect, neighboring provinces should focus on narrowing the gap in the development of the digital economy, and through breaking down administrative barriers and constructing agricultural partnerships, communicate and exchange information on the development platform of the digital economy, agricultural production technology, and agricultural production concepts, so as to fully unleash the spatial contribution of the digital economy in suppressing agricultural carbon emissions.

(3) Digital economy can reduce agricultural carbon emissions through agricultural technological innovation ,so attention should be paid to the important role played by agricultural science and technology innovation. The government should increase investment in scientific and technological innovation research and development in agriculture and encourage enterprises, scientific research institutes and other organizations to actively carry out scientific and technological innovation, accelerating the transformation of scientific research results, and focusing on the development of

low-carbon energy technologies and green innovation technologies. On the other hand, by joining forces with the Government, universities and local enterprises and other departments, it has organized agricultural technology training bases and regularly held agricultural digital technology training to cultivate agricultural workers' agricultural development concepts of digital production and low-carbon production, develop agricultural workers' digital agricultural production technologies, apply advanced low-carbon technology to the actual agricultural production process and help promote the low-carbon transformation of agriculture.

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