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Impact of high-quality agricultural development on agricultural carbon efficiency

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Abstract: *Realizing carbon peak carbon neutrality is an inherent requirement for implementing the new development concept, constructing a new development pattern and promoting high-quality development. In this paper, based on the relevant data of 31 provinces in China from 2012 to 2022, the super-efficiency data envelopment model (Super-SBM) with non-expected outputs is used to measure the efficiency of agricultural carbon emissions, and the comprehensive indicators of agricultural high-quality development and digital economy are constructed through the entropy weight method. Based on the mediating effect, it can be seen that high-quality development of agriculture can improve the efficiency of agricultural carbon emissions by promoting the use of digital economy.*

Keywords: *Agricultural carbon emission efficiency, Super-SBM, entropy weight method, mediating effect*

1. Introduction

Since 2020, China clearly put forward the “dual carbon” goal of carbon peak and carbon neutrality, this landmark strategic decision has rapidly become the focus of global attention, and has also outlined a clear path for China's economic and social green transformation, which demonstrates the role of a great country in the process of addressing global climate change. With the continuous development of the economy and society, the traditional mode of agricultural development is facing many bottlenecks, and it is difficult to meet the strict requirements of the “dual-carbon” goal. Traditional agricultural production methods often rely on a large number of resource inputs and sloppy management, inefficient resource utilization, resulting in high carbon emissions. At the same time, the traditional means of agricultural emission reduction are mostly localized and temporary measures, lacking systematic and long-term effectiveness, making it difficult to fundamentally solve the contradiction between agricultural development and carbon emissions[1]. At this critical juncture, the booming development of digital economy has brought new opportunities for the agricultural sector. Therefore, studying the mediating effect of digital economy between agricultural high-quality development and agricultural carbon emission efficiency is of great theoretical and practical significance for revealing the intrinsic relationship between agricultural high-quality development and agricultural carbon emission efficiency, as well as exploring the effective path of agricultural low-carbon development.

2. Theoretical analysis and research hypothesis

2.1. The direct impact of high-quality agricultural development on the efficiency of agricultural carbon emissions

High-quality development of agriculture is the core way to realize the modernization and sustainable development of agriculture, and the key lies in achieving efficient, green and sustainable development of agriculture through technological innovation, industrial upgrading and optimal allocation of resources. In the field of technological innovation and application, the high-quality development of agriculture has significantly improved the precision and intelligence of the agricultural production process through the introduction of modern biotechnology, information technology and intelligent equipment[2]. At the same time, high-quality development of agriculture has promoted the optimization and upgrading of industrial structure, and reduced the reliance on traditional agricultural models with high carbon emissions. Through the development of emerging industries such as leisure agriculture and ecological agriculture,

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the deep integration of traditional agriculture and service industry has been realized, the economic and social benefits of agriculture have been enhanced, and the rural ecological environment has been effectively protected and improved, which reduces the negative impact of agricultural production on the environment to a certain extent. Accordingly, the following hypotheses are proposed:

Hypothesis H1:High-quality development of agriculture can significantly improve the efficiency of agricultural carbon emissions.

2.2. Analysis of the mediating mechanism of high-quality agricultural development to enhance the efficiency of agricultural carbon emissions

In the context of the new era, the high-quality development of agriculture represents the transformation and upgrading of agriculture. In this transformation process, the digital economy serves as the core driving force, and its in-depth integration and application in agricultural production plays a key role in optimizing resource allocation and enhancing carbon emission efficiency.

The high-quality development of agriculture has significantly enhanced agricultural productivity through technological innovation, eco-friendly development and intelligent management tools, and has provided a strong impetus for the advancement of the digital economy. In a high-quality agricultural system, the efficient use of resources, ecologically friendly production modes, and the enhancement of added value of agricultural products are emphasized, and the realization of these goals relies on the support of the digital economy. At the same time, the high-quality development of agriculture promotes the optimization of the agricultural structure and the upgrading of the industrial chain, which lays a solid foundation for the popularization and innovation of digital technology in the field of agriculture.

In the context of the digital economy, agricultural production can obtain accurate decision support through the use of advanced technologies such as big data analysis, cloud computing and artificial intelligence. Specifically, the digital economy promotes the low-carbon development of agriculture through the following ways: first, realize accurate monitoring and resource optimization. With the help of remote sensing satellites and Internet of Things technology, the digital economy carries out real-time monitoring of key indicators such as land humidity, soil fertility and meteorological conditions, so as to realize precise fertilization and irrigation, scientifically regulate the frequency and dosage of pesticides and fertilizers, improve the accuracy of resource inputs, reduce the unnecessary consumption of chemical fertilizers and water resources, and thus reduce greenhouse gas emissions; secondly, build an electronic traceability supervision system for agricultural inputs. Secondly, build an electronic traceability supervision system for agricultural inputs[3]. The digital economy uses blockchain technology to enhance the transparency and traceability of the agricultural supply chain, which not only helps consumers and regulators ensure the safety compliance of agricultural products, but also enhances trust between producers and the market and promotes the reduced use of fertilizers and pesticides. These measures not only significantly improve the efficiency of agricultural production, but also promote the transition of agriculture towards green and low-carbon, providing solid technical support and management strategies to improve the efficiency of agricultural carbon emissions. Based on the above analysis, hypotheses are proposed:

Hypothesis H2: High-quality development of agriculture can improve the efficiency of agricultural carbon emissions through the digital economy

3. Design Research

3.1. Description of variables and data sources

3.1.1. Explanatory variable

First of all, based on the scope of plantation agriculture to examine the agricultural carbon emissions, mainly from three aspects of measurement of agricultural carbon emissions, one is the use of agricultural energy, mainly agricultural diesel use of agricultural carbon emissions and the use of electricity in the irrigation process of carbon emissions; the second is the amount of agricultural material inputs, specifically examining the most widely used pesticides, agricultural films and fertilizers produced by the carbon emissions; the third is the planting of crops generated by methane and other crop carbon emissions, mainly through the sowing area of crops to measure. The total agricultural carbon emissions measured in this paper are equal to the sum of the product of the sown area of crops, effective irrigated area, agricultural diesel fuel consumption, pesticide and agricultural film application, and agricultural fertilizer

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purification and agricultural carbon emission coefficients, which are shown in Table 1.

Table 1 Carbon emission factors for various carbon sources

Carbon Source	Carbon Emission Factor	Reference Source
Diesel	0.59kg/kg	IPCC United Nations Intergovernmental Panel on Climate Change
Pesticides	4.93kg/kg	Oak Ridge National Laboratory, USA
Agricultural film	5.18kg/kg	Nanjing Agricultural University, Institute of Agricultural Resources and Ecological Environment
Fertilizer	0.89kg/kg	Oak Ridge National Laboratory, USA
Tillage	312.60kg/km2	Fenlin Wu et al.
Irrigation	266.48kg/hm2	Duan Huaping et al.

Secondly, in order to overcome the problem of slackness in the traditional DEA model measurement method that does not consider input and output variables, this paper chooses the super-efficient SBM model that includes non-expected outputs to measure the efficiency of agricultural carbon emissions, and the super-efficient SBM model is constructed as follows:

$$\rho = \min \frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^x}{x_{i0}}}{1-\frac{1}{s_1+s_2}\left(\sum_{k=1}^{s_1}\frac{s_k^y}{y_{k0}}+\sum_{l=1}^{s_2}\frac{s_l^z}{z_{l0}}\right)}$$

$$s.t.\begin{cases} x_{i0} \ge \sum_{j=1,\ne 0}^{n}\lambda_j x_j - s_i^x, \forall i \\ y_{k0} \ge \sum_{j=1,\ne 0}^{n}\lambda_j y_j + s_k^y, \forall k \\ z_{i0} \ge \sum_{j=1,\ne 0}^{n}\lambda_j z_j - s_i^z, \forall l \\ 1-\frac{1}{s_1+s_2}\left(\sum_{k=1}^{s_1}\frac{s_k^y}{y_{k0}}+\sum_{l=1}^{s_2}\frac{s_l^z}{z_{l0}}\right) > 0 \\ s_i^x \ge 0, s_i^y \ge 0, \lambda_j \ge 0, \forall i,j,k,l \end{cases} \tag{1}$$

In equation (1), m, s_1 and s_2 represent the number of inputs, desired outputs and non-desired outputs, and s_i^x, s_k^y, s_l^z represent the slack variables of inputs, desired outputs and non-desired outputs, x_{i0}, y_{k0} and z_{l0} represent the values of inputs, desired outputs and non-desired outputs in the same time period, respectively, n is the number of decision-making units, λ is the vector of their weights, and ρ is the value of the efficiency of decision-making units. Agricultural Carbon Emission Efficiency (ACEE) input indicators are determined from the three dimensions of land, labor, and agricultural resources, and output indicators consider the total agricultural output value of desired output, and the total agricultural carbon emissions of non-desired output, and the specific indicators are shown in Table 2.

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Table 2 Agricultural Carbon Emission Efficiency Evaluation Indicator System

Category	Dimension	Specific Indicator	Unit
Agricultural Input Variables	Labor Input	Primary Employment	10,000 persons
	Land input	Total sown area of crops	Thousand hectares
		Effective irrigated area	Thousand hectares
	Agricultural inputs	Fertilizer use	10,000 tons
		Agricultural diesel fuel use	10,000 tons
		Pesticide use	10,000 tons
		Total power of agricultural machinery	10,000 kilowatts
Agricultural output variables	Desired output	Gross agricultural output value	100 million yuan
	Non-desired output	Total agricultural carbon emissions	10,000 tons

3.1.2. Explanatory variable

Agricultural high-quality development (AHQD) is the core driving force to promote the modernization and sustainable development of agriculture, covering multiple key dimensions such as technological innovation, industrial upgrading, and optimization of resource allocation. Drawing on relevant research and combining with the actual situation of agricultural development, the evaluation index system of agricultural high-quality development is constructed. Starting from the five first-level indicators of innovation, coordination, greenness, openness and sharing, multiple representative second-level indicators are selected for measurement[4].

3.1.3. Intermediary variable

The deep penetration and wide application of digital economy (DIG) in agriculture has had a profound impact on the change of agricultural development mode, efficiency improvement and carbon emission optimization, which is the key mediating variable in this study. The indicator system is constructed from three aspects: digital facilities construction, digital industrialization and industrial digitization to comprehensively measure the level of digital economy development[5].

3.1.4. Control variable

In order to comprehensively analyze the impact of high-quality agricultural development on the efficiency of agricultural carbon emissions, and to avoid the bias of the empirical results caused by omitted variables, the following control variables are chosen[6] :the level of tax burden (TAX), measured by the ratio of tax revenues to GDP; the degree of government intervention (GOV), measured by the ratio of local government general public budget expenditures to GDP; and the level of social consumption (SOC),taking the ratio of total retail sales of consumer goods to GDP; the level of transportation infrastructure (TRA), which is expressed by means of the logarithm of the combined freight volume; and the level of human capital (PEO), which is referred to by means of the ratio of the number of students enrolled in tertiary institutions to the total population.

3.1.5. Data sources and processing

Considering the comprehensiveness and availability of the indicators and the accuracy of the empirical results, the panel data of 31 provinces (excluding Hong Kong, Macao and Taiwan) in China for a total of 11 years from 2012 to 2022 are selected for the empirical test. The main core variables are from China Statistical Yearbook, China Rural Statistical Yearbook, and Digital Inclusive Finance Index released by Digital Inclusive Finance Research Center of Peking University. Some missing data are filled in using the mean value method and linear interpolation method[7].

3.2. Model setup

3.2.1. Basic regression model

In order to accurately test the efficiency of the impact of Agricultural High Quality Development (AHQD) on Agricultural Carbon Emission Efficiency (ACEE), this study constructs a fixed effects model. The model fully considers individual heterogeneity and time trend, and can effectively control the influence of regional characteristics that do not change over time as well as macro-factors that change over time on the explanatory variables, with the following formula:

$$ACEE_{\mathrm{it}} = \alpha_0 + \alpha_1 AHQD_{\mathrm{it}} + \alpha_2 X_{\mathrm{it}} + \mu_i + \varphi_t + \varepsilon_{it} \tag{2}$$

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In equation (2), $ACEE_{it}$ denotes the agricultural carbon emission efficiency of province i in year t, and $AHQD_{it}$ denotes the high quality development of agriculture in province i in year t; α_0 is the intercept term,, α_1 and α_2 are the impact coefficients of the explanatory variables and control variables, respectively; μ_i denotes a province fixed effect, φ_t denotes a time fixed effect, and ε_{it} is a randomized perturbation term.

3.2.2. Mediation effects model

From the previous theoretical analysis, it can be seen that high-quality development of agriculture can indirectly promote the efficiency of agricultural carbon emissions by promoting the development of digital economy. In order to rigorously test the transmission mechanism, the following mediation effect model is constructed on the basis of the benchmark regression model:

$$DIG_{it} = \beta_0 + \beta_1 AHQD_{it} + \beta_2 X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{3}$$

$$ACEE_{it} = \lambda_0 + \lambda_1 AHQD_{it} + \lambda_2 DIG_{it} + \lambda_3 X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{4}$$

In equations (3) and (4), DIG_{it} is the mediating variable digital economy, β_0 and λ_0 are the intercept term, λ_1, λ_2 and λ_3 are the variables to be estimated coefficients; the rest of the variables have the same meaning as in equation (2).

4. Empirical results and analysis

4.1. Benchmark regression results

On the basis of the previous theoretical analysis, the impact effect between high-quality agricultural development and agricultural carbon emission efficiency is verified through equation (2), and the specific regression results are shown in Table 3. Among them, column (1) is the regression result without controlling a series of control variables, and this impact coefficient passes the 5% significance test, while in order to prevent inter-individual differences and time trends from masking the real relationship, column (2) adds time and individual fixed effects on the basis of column (1), and its estimated coefficient is 1.5504, which passes the 5% significance test. Columns (3) and (4) are regression results controlling for a series of control variables, and column (4) also controls for time and individual fixed effects, where the impact coefficient of column (3) is 0.9147, which passes the 5% significance test, and the impact coefficient of column (4) is 1.9343, which passes the 5% significance test, suggesting that high-quality development of agriculture can positively affect the efficiency of agricultural carbon emissions, which in turn proves that Hypothesis H1 is established.

Table 3 Benchmark regression results

	(1)	(2)	(3)	(4)
AHQD	-0.8521**	1.5504**	0.9147**	1.9343**
	(0.0125)	(0.0407)	(0.0149)	(0.0208)
TAX			1.0315	-1.5332
			(0.2177)	(0.4457)
GOV			-1.0012***	-0.5805
			(0.0000)	(0.2143)
SOC			0.3415	-0.0528
			(0.1370)	(0.9235)
TRA			-0.3072***	-0.1323
			(0.0000)	(0.3027)
PEO			-9.4576***	14.3325
			(0.0070)	(0.2744)
Time fixed effects	NO	YES	NO	YES
Individual fixed effects	NO	YES	NO	YES
Constant term	1.1073***	0.6148***	4.4720***	2.0938
	(0.0000)	(0.0009)	(0.0000)	(0.2282)
Hausman test			P=0.0462	
N	341	341	341	341
adj. R2	0.0941	0.1680	0.4299	0.2057

** p < 0.1, ** p < 0.05, *** p < 0.01*

4.2. Robustness and endogeneity tests

To further ensure the robustness of the findings, the baseline regression analysis is re-expanded by employing four robustness testing methods. Method 1:Given that municipalities directly under the central government have unique advantages in terms of economy, transportation and culture, which may lead to bias in the regression results of high quality agricultural development on agricultural carbon emission efficiency. In order to effectively avoid the influence of this conclusion on the regression results, it was decided to exclude the sample data of four municipalities directly under the central government in China and re-run the regression analysis on this basis. As shown in column (1) of Table 4, the regression coefficient of high-quality development of agriculture on the efficiency of agricultural carbon emission is significantly positive at 5% statistical level, which confirms the reliability of the research conclusion. Method 2: Shorten the sample years to 2012-2019 and re-expand the analysis, at the same time, it can avoid external shocks due to epidemics and exclude the chance and volatility of the research results. As can be seen from column (2) of Table 4, the value of its regression coefficient is significantly positive, indicating that high-quality development of agriculture has a positive promotion effect on agricultural carbon emission efficiency. Method 3: Taking the logarithm of the total amount of agricultural carbon emissions and replacing the original explanatory variables in the baseline regression analysis, the results are shown in column (3), the regression coefficient is significantly negative at 1% statistical level, indicating that high-quality development in agriculture has a negative correlation with agricultural carbon emissions, which inversely confirms that high-quality development in agriculture has a positive impact on agricultural carbon emission efficiency. Method 4: Considering that high-quality development of agriculture has a time-lag effect on the efficiency of agricultural carbon emissions, and it takes a certain period of time to increase the total output value of agriculture based on the reduction of agricultural carbon emissions, in view of this, the core variable lagged by one period is used as an instrumental variable. As can be seen from column (4), its regression result is significantly positive. All four methods mentioned above have the same significance as that expressed by the benchmark regression results, implying that the above results are robust.

Table 4 Robustness and endogeneity tests

	(1)	(2)	(3)	(4)	(5)	(6)
	ACEE	ACEE	ln(ACE)	ACEE	Phase I	Phase II
AHQD	2.5251**	3.7160**	-1.5347***			1.8814**
	(0.020)	(0.015)	(0.001)			(0.040)
L.AHQD				1.6031***		
				(2.736)		
Instrumental Variables					0.8521***	
					(0.000)	
Control variables	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES	YES
_cons	0.1360	3.2163	4.9381***	0.4444	0.1607*	-0.2371
	(0.932)	(0.226)	(0.000)	(0.426)	(0.099)	(0.862)
C-D Wald F statistic					258.29***	
N	297	248	341	310	310	310
adj. R2	0.353	0.267	0.624	0.910	0.984	0.919

** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Meanwhile, in order to prevent endogeneity issues from interfering with the research results, for one, the estimation of a two-way fixed-effects model while controlling for multiple control variables may omit important explanatory variables, leading to incorrect parameter estimation and bias. Second, there may be a bidirectional causal relationship between high-quality agricultural development and agricultural carbon emission efficiency. High-quality agricultural development optimizes the structure of factor inputs through technological innovation and factor substitution, and reduces the dependence on fossil energy and chemicals per unit of output. The carbon carrying capacity of the agroecosystem constitutes the natural boundary of high-quality agricultural development, and the improvement of carbon emission efficiency can help mitigate ecological risks such as soil degradation and biodiversity loss, which is the basic guarantee for maintaining agricultural reproduction. Based on the research results of current scholars, the lagged period of the core explanatory variables is used as an instrumental variable, and the two-stage least squares (2SLS) method is selected for estimation.

In choosing instrumental variable method to deal with endogeneity, weak instrumental variable test and unidentifiable test are needed, and there is no over-identification of instrumental variables because the lagged one period of the explanatory variables is used as instrumental variables. From column (5) and column (6) of Table 4 the Wald F-statistic in the weak instrumental variable test is greater than the critical value of 16.38 at the 10% level, indicating that the selected instrumental variables are more reasonable. This indicates that there is a significant positive correlation between high quality agricultural development and agricultural carbon emission efficiency after considering endogeneity, which further validates the reliability of the results of the benchmark regression.

4.3. Mechanism of action analysis

In order to explore the role and influence of agricultural high-quality development on the efficiency of agricultural carbon emissions, an empirical test is carried out based on the role mechanism model, and the results are shown in Table 5. Analyzing column (1) shows that the regression coefficient of agricultural high-quality development is 3.2642, which passes the 1% significance level test, indicating that agricultural high-quality development can improve agricultural carbon emission efficiency. In column (2), the high quality development of agriculture is significant at 1% level for digital economy and the regression coefficient is 1.2944,. Meanwhile, from the data in Column (1) and Column (3), the regression coefficient of high-quality development in agriculture decreases from 3.2642 to 2.4475, which indicates that high-quality development in agriculture can promote the digital economy, and then promote the efficiency of agricultural carbon emissions. It can be seen that the construction H2 is established, at the same time, in the process of Sgmediation command test, Sobel, Goodman1, Goodman2 test, all through the 1% significance level test, this result confirms once again the establishment of the hypothesis H2.

Table 5 Mediation effect test results

Variable	ACEE	DIG	ACEE
	(1)	(2)	(3)
AHQD	3.2642***	1.2944***	2.4475***
	(0.000)	(0.000)	(0.000)
DIG			0.6309***
			(0.004)
N	341	341	341
Control variables	YES	YES	YES
Time fixed effects	YES	YES	YES
Individual fixed effects	YES	YES	YES
Constant term	4.0031***	-0.3132***	4.2007***
	(0.000)	(0.007)	(0.000)
adj. R2	0.5210	0.5493	0.5314
Sobel test		0.8166***(Z=2.858)	
Goodman-1 test		0.8166***(Z=2.858)	
Goodman-2 test		0.8166***(Z=2.858)	
Mediating effect		1.2944*0.6309=0.8166	
		Mediation effect/total effect = 1.2944*0.6309/3.2642 = 0.2502	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Policy Recommendations

5.1. Research on strategies to promote the application of green agricultural technology

The deep integration of 'good land, good seeds, good methods, and good opportunities' is the guiding ideology for agricultural modernization, in which green agricultural science and technology innovation plays an indispensable role in this process. Therefore, we need to start from the following aspects to systematically promote the application of green agricultural technology: First, strengthen the innovation and promotion of low-carbon agricultural technology, vigorously promote the development of low-carbon and environmentally friendly agricultural technology such as precision fertilizer application, water-saving irrigation, organic agriculture, biological control, and so on, so as to reduce the impact of agricultural production on the environment[8]. Secondly, a special fund should be set up to encourage colleges and universities, scientific research institutions and agricultural science and technology enterprises to increase their R&D investment in low-carbon agricultural technologies, especially to carry out in-depth research in the fields of biobased fertilizers, crop resistance improvement, and agricultural waste recycling. Through the construction of an integrated cooperation mechanism among industries, universities and research institutes, the rapid transformation and application of scientific research results will be promoted.

5.2. Enhancing Agricultural Carbon Emissions Management and Monitoring

The digital economy provides solid data support for improving the efficiency of agricultural carbon emissions. Through the use of big data and blockchain technology, real-time monitoring of agricultural carbon emissions can be realized, and the contribution of different agricultural activities to carbon emissions can be assessed, so as to formulate more accurate emission reduction strategies. At the same time, farmers are encouraged to adopt intelligent agricultural machinery to provide real-time feedback on carbon emissions during the agricultural production process and assist farmers in optimizing their production behavior. The government should also promote the development of agricultural digitalization standards to ensure the standardization and consistency of technology application.

5.3. Carbon Emission Management Strategies for Regional Differentiation

In the course of agricultural development, the carbon emission efficiency of different regions varies significantly. Therefore, according to the actual situation of each region, a targeted carbon emission management strategy should be formulated. The eastern region, with its solid economic foundation and high level of agricultural technology, should focus on promoting high-quality agricultural development and the application of carbon emission reduction technologies. On the one hand, it should increase the promotion of low-carbon agricultural technologies, and promote green production technologies such as soil testing and formula fertilization, increased application of organic fertilizers, and water-saving dry farming, in order to reduce the intensity of chemical fertilizer and pesticide use. Relying on its economic foundation and technological advantages, the eastern region should focus on promoting high-end low-carbon agricultural technologies such as precision agriculture, intelligent agricultural machinery and biodegradable mulch, as well as strengthening the integration of agriculture and industry and promoting the development of the agricultural product processing industry in a low-carbon direction[9]. On the other hand, agricultural enterprises are encouraged to apply new energy agricultural machinery, energy-saving equipment for primary processing and storage and transportation of agricultural products to enhance agricultural production efficiency while realizing energy saving and emission reduction. The western and northeastern regions are rich in agricultural resources, but the application of digital infrastructure and agricultural technology is relatively lagging behind, and the introduction of digital agricultural equipment and management tools should be increased. Local governments should strengthen the construction of digital agricultural infrastructure, attract social capital participation through financial subsidies, tax breaks and other preferential policies, and promote the digital transformation of agriculture. Combining the digital economy with regional characteristics, they should promote low-carbon agricultural technologies that are suitable for local environments, and avoid a “one-size-fits-all” approach.

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