The impact of rural digitization on agricultural carbon emissions and its mechanism pathways

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Abstract

This paper utilizes provincial macro data from 2011 to 2020 to thoroughly investigate the impact of rural digitization on agricultural carbon emissions. The research findings reveal that rural digitization significantly reduces agricultural carbon emissions, a conclusion confirmed through robustness and endogeneity tests. Using a "technology effect-knowledge effect" logical framework, it is found that agricultural technological advancements and rural human capital act as intermediary pathways. These advancements indirectly achieve carbon reduction by promoting agricultural technological progress and enhancing rural human capital levels. Heterogeneity tests indicate that the "carbon reduction effect" is most significant in eastern regions, while it is weakest in the western regions due to disparities in rural digitization levels. Additionally, the study uncovers a significant spatial correlation and spillover effect between rural digitization and agricultural carbon emissions, implying that rural digitization in one region can notably reduce carbon emissions in surrounding areas. Consequently, it is recommended to further improve rural digitization development levels, fully leverage the benefits of digital advancements, and provide impetus for sustainable agricultural development.

Keywords: Rural Digitization; Agricultural Carbon Emissions; Sustainable Development; Carbon Reduction Effect

Introduction

With the continuous growth of the population and the rapid development of the global economy, the importance of agricultural production activities for maintaining social development and improving the quality of life has been widely recognized. However, greenhouse gas emissions from agricultural production have also significantly increased, becoming a major obstacle to sustainable agricultural development. [0]Under the "dual carbon" strategic goals, the central government has placed great emphasis on sustainable agricultural development. With the implementation of policies such as the "No. 1 Central Document," the "14th Five-Year Plan for National Agricultural Green Development," and the "National Plan for Sustainable Agricultural Development (2015-2030)," China's agricultural carbon emissions have been effectively mitigated. According to the "2023 China Low Carbon Development Report for Agriculture and Rural Areas" published by the Chinese Academy of Agricultural Sciences on March 1, 2023, China's efforts in carbon sequestration and emission reduction in agriculture have shown continuous improvement. The decoupling trend between agricultural food security and carbon emissions has become evident. For example, in rice cultivation, there has been an 8.8% increase in yield, a more than 30% improvement in nitrogen fertilizer utilization efficiency, a cost reduction of 8.3%-9.7%, and a methane reduction of 31.5%-71.7%, demonstrating significant carbon reduction effects. However, challenges and problems persist in achieving agricultural carbon reduction. The input of production factors is fundamental to ensuring agricultural output, but the distortion in the structure of input factors leads to low resource utilization efficiency,[Error! Reference source not found.] hindering sustainable agricultural development in the long term. Furthermore, as agriculture is a fundamental industry of the national economy, its high interconnectivity with other industries increases the difficulty of implementing carbon reduction solutions. Therefore, exploring new pathways for carbon reduction is of great practical significance.

Currently, digital technology is bringing significant transformations to rural development. Digital infrastructure and services are continuously extending to rural areas, [Error! Reference source not found.]with emerging models such as "Internet + rural public services," "Internet + grassroots social governance," and "Internet + agricultural emergency management." The penetration of digital technology is deepening, enhancing the level of digital governance in rural areas and effectively promoting agricultural transformation and upgrading. According to the "2022 China Broadband Development White Paper" published by the China Academy of Information and Communications Technology, China's rural digital infrastructure has further improved. By the end of 2021, broadband coverage had reached all 510,000 village-level units nationwide, with the coverage rates of broadband in administrative villages and poverty-stricken villages both reaching 100%, and the dynamic elimination of non-broadband administrative villages. The "2023 H1 China Online Retail Market Development Report" released by the Ministry of Commerce on July 31, 2023, shows that China's rural online retail sales reached 1.12 trillion yuan, a year-on-year increase of 12.5%, with rapid growth in rural online retail sales across eastern, central, western, and northeastern regions, highlighting the empowering role of rural digitalization. Based on this, exploring the impact of rural digitalization on agricultural carbon emissions at a critical time for the transition to high-quality agricultural development, and clarifying its inherent mechanisms, provides important reference value for guiding subsequent agricultural production and operations and continuously promoting agricultural transformation and upgrading.

1 Literature review

In recent years, agricultural carbon emissions have not only garnered significant attention from the central government but have also become a focal point of academic research. Scholars have conducted extensive studies on agricultural carbon emissions, providing valuable references for carbon sequestration and emission reduction in agriculture. Summarizing these studies, scholars have mainly focused on the measurement of agricultural carbon emissions and their interactive effects. In terms of measuring agricultural carbon emissions, scholars have employed various methods, such as the emission coefficient method, model simulation, and field measurements[Error! Reference source not found.], to calculate the extent of agricultural carbon emissions in China. They have also analyzed the status and spatiotemporal evolution of agricultural carbon emissions[Error! Reference source not found.]. On the other hand, based on accurate measurements of China's agricultural carbon emissions, researchers have explored the characteristics and influencing factors of these emissions from multiple perspectives, including economic growth[Error! Reference source not found.], the digital economy[Error! Reference source not found.], digital rural areas[Error! Reference source not found.], digital inclusive finance[Error! Reference source not found.], urban-rural integration[Error! Reference source not found.], agricultural mechanization[Error! Reference source not found.], agricultural industrial agglomeration[Error! Reference source not found.], rural industrial integration[Error! Reference source not found.], land productivity[Error! Reference source not found.], farmland transfer[Error! Reference source not found.], agricultural trade[Error! Reference source not found.], technological advancement[Error! Reference source not found.], extreme temperatures[Error! Reference source not found.], and agricultural services[Error! Reference source not found.]. These studies have provided solid scientific guidance for agricultural carbon reduction actions.

The development of rural digitization is a strategic priority for rural revitalization and an essential component of building a digital China[Error! Reference source not found.]. Rural digital development is increasingly becoming a hot topic in practical fields[Error! Reference source not found.], and academia has also gained a deep understanding of this issue from different perspectives. Scholars have primarily focused on empowering rural industrial revitalization, improving farmers' well-being, and enhancing rural governance. In terms of rural industrial revitalization, scholars believe that rural digitization can help alleviate the misallocation of agricultural production factors[Error! Reference source not found.], thereby enhancing agricultural green total factor productivity[Error! Reference source not found.] and strengthening agricultural economic resilience[Error! Reference source not found.]. Some researchers also argue that rural digital development promotes urban-rural integration[Error! Reference source not found.], transforms rural development modes and growth drivers[Error! Reference source not found.], accelerates agricultural transformation and upgrading[Error! Reference source not found.], and ultimately achieves rural revitalization[Error! Reference source not found.]. Regarding farmers' well-being, scholars suggest that rural digitization can facilitate information utilization, alleviate credit constraints[Error! Reference source not found.], promote farmers' entrepreneurship, increase farmers' income[Error! Reference source not found.], narrow the urban-rural income gap[Error! Reference source not found.], and contribute to poverty reduction[Error! Reference source not found.], ultimately achieving common prosperity[Error! Reference source not found.]. In the area of rural governance, researchers have found that rural digitization enhances the educational literacy of rural households[Error! Reference source not found.], thereby improving farmers' environmental awareness, stimulating their willingness to participate in waste sorting, and enhancing the rural ecological living environment[Error! Reference source not found.]. Additionally, some scholars argue that improving rural governance efficiency driven by digital technology is an urgent requirement for achieving good rural governance in the digital era[Error! Reference source not found.]. Therefore, the organic integration of digital technology with rural public health service systems helps overcome information silos and promotes the development of rural public health services[Error! Reference source not found.].

In summary, scholars have conducted in-depth studies on rural digitization and agricultural carbon emissions, providing useful references for this research. However, despite the attention given to the impact of rural digitization on agricultural carbon emissions, several gaps remain. First, most studies on agricultural carbon emissions only consider emissions from agricultural input factors and overlook emissions from rice cultivation (CH_4) and livestock management (CH_4/N_2O). Second, while some researchers include multiple indicators to measure agricultural digitization, they often ignore the axiomatic principles of monotonicity, consistency, and additivity among variables, potentially leading to unrealistic conclusions. Third, existing studies have not considered the spatial spillover effects due to the fluidity of data elements. Additionally, measuring agricultural carbon emissions using total emission volumes is still a subject of considerable debate. Given these gaps, this study aims to make the following marginal contributions: (1) based on the current state of rural digital development, it measures the degree of agricultural digitization and comprehensively calculates the intensity of agricultural carbon emissions, analyzing the impact of rural digitization on agricultural carbon emissions and its specific pathways; (2) it further introduces spatial factors to explore the spatial impact relationship between rural digitization and agricultural carbon emissions.

2 Theoretical analysis and research hypotheses

Integrating digital technology with agricultural development optimizes the allocation of input factors, helps reduce circulation costs and intermediate losses, thereby improving resource utilization efficiency and reducing agricultural carbon emissions. Based on the "technology benefit-knowledge effect" logical framework, rural digitization may indirectly curb agricultural carbon emissions by promoting agricultural technological advancement and enhancing rural human capital. Additionally, the high mobility of data elements determines the formation of multidimensional spatial linkages between digitization development and surrounding areas, potentially creating a "carbon reduction effect" on neighboring regions. Based on this, the following hypothesis is proposed:

H1: Rural digitization has a significant "carbon reduction effect" on agricultural carbon emissions.

2.1 Analysis of the mediating effect of agricultural technological advancement

With the continuous improvement of rural digital infrastructure, the enabling role of digital technology in agricultural production will be further enhanced, significantly promoting carbon sequestration and emission reduction in agriculture. This is reflected in several aspects: From the perspective of factor allocation, the application of digital technology in agriculture promotes continuous progress in traditional agricultural productivity, reducing agricultural production costs, improving the efficiency of agricultural factor allocation, expanding the agricultural production possibility frontier, and achieving low-carbon agricultural development[Error! Reference source not found.]. From the perspective of production behavior, digital technology mainly provides information services for agricultural production. The diffusion of digital technology into non-informational industries can enhance the informatization and intelligence levels of the sector[Error! Reference source not found.], effectively addressing the information asymmetry between farmers and the market, reducing the cost of information searching, and alleviating resource wastage caused by market failures. Farmers can obtain the latest market information in a timely manner and adjust their production decisions accordingly, thereby reducing dependence on chemical inputs. From the perspective of production management, rural digitization strengthens the management efficiency of agricultural business entities. The input of digital technology facilitates the collection, organization, and analysis of data from various stages of agricultural production by agricultural enterprises and research units, thereby enhancing the specificity of agricultural science and technology research and development, promoting continuous innovation and application of biotechnology (seeds, fertilizers, pesticides), and achieving reduced agricultural carbon emissions[39]. Based on this analysis, the following hypothesis is proposed:

H2: Agricultural technological advancement plays a mediating role; whereby rural digitization effectively promotes agricultural technological advancement and indirectly achieves a "carbon reduction effect" in agriculture.

2.2 Analysis of the mediating effect of rural human capital

Thodore W. Schultz posits that the cause of poverty and backwardness in rural areas is the lack of updated production technology, and the key to updating production technology lies in improving the quality of human resources[Error! Reference source not found.]. Rural digitization provides various digital information services and talent support for rural development[Error! Reference source not found.], thereby helping to improve rural human capital levels. On one hand, rural digitization provides social infrastructure conditions for rural elites to participate in grassroots urban-rural governance[Error! Reference source not found.], building bridges for urban-rural communication and laying the groundwork for urban elites to participate in village governance or even serve as village officials. This helps overcome the shortage of rural labor and the lack of skilled labor[Error! Reference source not found.]. On the other hand, rural digitization helps bridge the digital divide and inequality in educational resources between urban and rural areas[Error! Reference source not found.], breaking through traditional education and training methods. Farmers can enrich training and learning content through various learning platforms, which helps solidify green production awareness and reduce rigid dependence on chemical products. Based on this, the enhancement of rural human capital levels strengthens the application of advanced technology, facilitating the effective replacement of traditional factors with advanced ones. This shift promotes agricultural technological progress towards energy-efficient agricultural practices, improves agricultural energy utilization efficiency[Error! Reference source not found.], and ultimately achieves a carbon reduction effect in agriculture. Based on this, the following hypothesis is proposed:

H3: Rural human capital plays a mediating role; whereby rural digitization effectively enhances rural human capital levels and indirectly achieves a "carbon reduction effect" in agriculture.

2.3 Analysis of the spatial spillover effects of rural digitization

Based on the viewpoint of the "first law of geography," everything is related to everything else, but near things are more related than distant things[47]. Digital technology breaks the spatial limitations of technological flow and significantly reduces the cost of cross-regional data flow, forming spatial technological spillovers[Error! Reference source not found.]. These spillovers can be divided into positive and negative effects. Positive spillovers have positive externalities, promoting economic and social development and bringing economic benefits, while negative spillovers have negative externalities, hindering economic and social development. First, rural digitization weakens the decay rule of technological spillover effects brought by geographical distance, breaking spatial distance constraints, significantly enhancing the inclusiveness of knowledge and information, and strengthening the learning and imitation efficiency of market entities in surrounding areas[Error! Reference source not found.], forming "learning by doing."

Second, rural digitization enhances the flow of data elements, helping to break traditional information barriers and data silos between upstream and downstream agricultural industry chains, stimulating collaborative innovation among agricultural business entities, and increasing competitive strength. Under market competition, a "forcing mechanism" is formed, prompting business entities in surrounding areas to continuously broaden the depth and breadth of innovation through imitation[Error! Reference source not found.], forming "reverse engineering."

Additionally, rural digitization also carries economic spillover effects. Albert Otto Hirschman pointed out that economic activities between industries have obvious linkage effects and promote the development of other industries through diffusion influence and gradient transfer. Therefore, the development of rural digitization in this area gives rise to new industrial forms or models, creating a large demand for labor, promoting the cross-regional flow of rural labor by providing employment opportunities and increasing expected income[Error! Reference source not found.], helping to alleviate resource constraints and labor redundancy in surrounding areas. Furthermore, rural digitization spawns various platform economies, forming platform effects[Error! Reference source not found.] and network externalities[Error! Reference source not found.]. Under platform effects, agricultural product sales channels are expanded, market demand is increased, and neighboring areas are helped to "hitch a ride."(fig 1)

Based on this analysis, the following hypotheses are proposed:

H4: Rural digitization and agricultural carbon emissions have significant spatial correlations and exhibit obvious spatial clustering characteristics.

H5: Rural digitization, through spatial spillover effects, also has a significant "carbon reduction effect" on agriculture in surrounding areas.

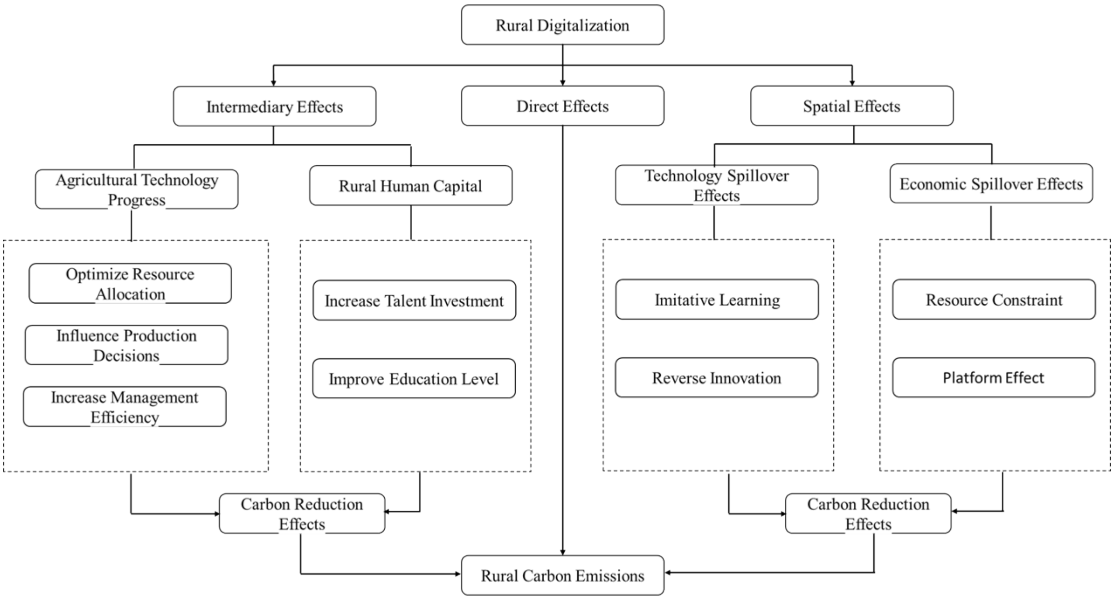

Fig 1. Mechanism pathway diagram of rural digitization's impact on agricultural carbon emissions

3 Data sources, variable description, and model design

3.1 Data sources

This paper uses provincial panel data from 2011 to 2020 as observation samples. Due to data missing from Tibet, Hong Kong, Macao, and Taiwan, considering the effectiveness of panel data connection, these areas are not included in the sample. After sorting, data from 30 provinces (cities/autonomous regions) are effectively retained. Missing data are supplemented using linear interpolation and subjected to 1% winsorization. The data mainly come from the "China Agricultural Yearbook," "China Animal Husbandry Yearbook," "China Statistical Yearbook," "China Population and Employment Statistical Yearbook," "China Rural Statistical Yearbook," "China Information Industry Yearbook," as well as the National Bureau of Statistics and local statistical yearbooks.

3.2 Variable explanation

3.2.1 Explained Variables

The explained variable in this paper is agricultural carbon emission intensity (CO_2). Based on existing literature, researchers mostly use the ratio of agricultural carbon emissions to agricultural gross output value at constant prices to measure agricultural carbon emissions. Agricultural carbon sources mainly come from four aspects (excluding fisheries): (1) carbon emissions from input factors such as fertilizers, pesticides, and plastic films; (2) carbon emissions generated during agricultural operations such as the energy consumption of agricultural machinery, soil tillage, and irrigation; (3) methane (CH_4) emissions from rice planting; and (4) carbon emissions from livestock management, such as CH_4 emissions from enteric fermentation and CH_4 and N_2O emissions from manure management systems. The calculation methods for carbon emissions mainly use factor measurement formulas and the carbon footprint method, with the factor formula method being more widely used at present[Error! Reference source not found.]. Therefore, this paper continues to use this method. The agricultural carbon emission coefficients and sources are shown in Table 1. The calculation method is as follows (table 1):

Table 1. Carbon emission coefficients of agricultural sources and data sources

Carbon Emission Sources of Crop Farming	Carbon Emission Coefficients	Data Sources	Livestock Carbon Emission Sources	Data Sources
Agricultural Fertilizer Usage	0.8956kg/kg	Oak Ridge National Laboratory, USA [Error! Reference source not found.] (2002)	CH_4 Emissions from Enteric Fermentation	IPCC Guidelines (2006)
Agricultural Film	5.18kg/kg	Oak Ridge National Laboratory,	CH_4 Emissions from	IPCC

Usage		USA（2002）	Livestock Manure Management	Guidelines（2006）
Agricultural Machinery (Diesel)	0.5927kg/kg	IPCC Guidelines Error! Reference source not found.（2006）	N2O Emissions from Livestock Manure Management	Hu Xiangdong et al Error! Reference source not found.（2010）
Pesticides	4.934kg/kg	Institute of Agricultural Resources and Environment, Nanjing Agricultural University		
Irrigation	266.48kg/hm^2	Duan Huaping et al Error! Reference source not found.（2011）		
Tillage	312.6kg/hm^2	Wu Fenlin et al Error! Reference source not found.（2007）		
Rice	338 kg/hm^2/year	Wang Xiaoke et al Error! Reference source not found.（2003）		

Note: (1) CH_4 Emissions from Livestock: Dairy Cows: 13 kg/head/year, Water Buffalo: 2 kg/head/year, Yellow Cattle: 1 kg/head/year; Horses: 1.64 kg/head/year, Donkeys and Mules: 0.9 kg/head/year, Camels: 1.92 kg/head/year; Pigs: 3 kg/head/year, Goats: 0.17 kg/head/year, Sheep: 0.15 kg/head/year. CH_4 emissions from livestock manure management are positively correlated with temperature. According to Zhang Guangsheng et al Error! Reference source not found.. (2014), the emission values are based on an average annual temperature of 15°C. (2) N_2O Emissions from Livestock: Dairy Cows: 1 kg/head/year, Water Buffalo: 1.34 kg/head/year, Yellow Cattle: 1.39 kg/head/year; Horses: 1.39 kg/head/year, Donkeys and Mules: 1.39 kg/head/year, Camels: 1.39 kg/head/year; Pigs: 0.53 kg/head/year, Goats and Sheep: 0.33 kg/head/year.

(1) Calculation of Agricultural Carbon Emissions:

$$E_{\mathrm{it}} = \sum E_i = \sum T_i \times \delta_i \qquad (1)$$

In the formula: E_{it} represents the total agricultural carbon emissions for province i in year t; E_i represents the total carbon emissions for the N-th type of carbon source. T_i represents the amount of each carbon source; δ_i represents the carbon emission coefficient for each carbon source.

(2) Calculation of Agricultural Carbon Emission Intensity:

$$CO_{2it} = E_{it} / CP_{it} \qquad (2)$$

In the formula: i represents the province, t represents the time; E_{it} represents the total agricultural carbon emissions; CO_{2it} represents the agricultural carbon emission intensity; CP_{it} represents the total agricultural output value at constant prices (since fisheries are not included in the calculation of agricultural carbon emissions, the total agricultural output value excludes fisheries, and is deflated to the base year 2000).

3.2.2 Explanatory Variables

The core explanatory variable is rural digitization (Digi). Existing literature on the empirical quantification of rural digitization is still limited, and there are no direct indicators that can reflect the development level of rural digitization. Therefore, this paper draws on the approach of Wang Dingxiang et al[Error! Reference source not found.]. (2022), using the ownership of major durable consumer goods (computers and mobile phones) per 100 rural households and the number of broadband internet access points as metrics, and uses the entropy method to measure the development level of rural digitization.

3.2.3 Mediating Variables

(1) Rural Human Capital (Manp): Mainly measured by the average years of education of rural residents[Error! Reference source not found.]. The calculation method is as follows:

Average Years of Education per Rural Resident=(Number of People with Primary Education ×6+Number of People with Junior High Education×9+Number of People with Senior High Education×12+Number of People with College Education and Above×16)/Total Sample Population Aged Six and Above.

(2) Agricultural Technological Progress (Tech): The agricultural technological progress index for each province is calculated using the DEA-Malmquist index method [Error! Reference source not found. The calculated Total Factor Productivity (TFP) index can be decomposed into the agricultural technical efficiency change index and the agricultural technological progress index. Input indicators include labor factors (measured by the number of people employed in the primary sector), land factors (measured by the area of crops sown), and capital factors (calculated using the Goldsmith perpetual inventory method to estimate agricultural capital stock). Output indicators mainly include the total agricultural output value (adjusted for price fluctuations using 2000 constant prices). The method is as follows:

$$TFP = M(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}\right] \times \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} \tag{3}$$

In the formula, X represents inputs, Y represents outputs, t represents time periods, D represents the distance function, and M represents the Total Factor Productivity (TFP) index. When M<1, it indicates a decline in agricultural technological progress from period t to t+1; when M=1, it indicates that agricultural technological progress efficiency remains unchanged from period t to t+1; when M>1, it indicates an improvement in agricultural technological progress efficiency from period t to t+1. Further decomposition of TFP reveals the agricultural technological progress index and agricultural technical efficiency.

3.2.4 Control Variables

Based on a review of existing literature, the control variables in this study are as follows. Land: Measured by the ratio of the total area of land transfer to the cultivated land area. Fina: Measured by the proportion of expenditures on agricultural, forestry, and water affairs relative to total general fiscal expenditure. Mach: Measured by the ratio of the total power of agricultural machinery to the total agricultural output value. LnSow: Measured by the natural logarithm of the crop sowing area. Irri: Measured by the ratio of the area of effective agricultural irrigation to the cultivated land area. Gend: Measured by the ratio of the number of rural laborers working outside the village to the total number of rural laborers. Descriptive statistics are detailed in Table 1.

Table 2. Descriptive Statistics of Variables

Variable Name	Variable Symbol	Obs	Mean	SD	Min	Max	VIF
Agricultural Carbon Emissions	CO_2	300	0.197	0.061	0.071	0.350	-
Rural Digitization	Digi	300	0.261	0.157	0.086	0.759	1.790
Agricultural Technological Progress	Tech	300	1.064	0.040	0.970	1.182	1.600
Rural Human Capital	Manp	300	7.755	0.594	6.104	9.476	1.050
Land Transfer	Land	300	0.325	0.417	0.024	2.529	1.240
Fiscal Support for Agriculture	Fina	300	0.114	0.033	0.042	0.187	1.770
Level of Mechanization	Mach	300	0.461	1.080	0.002	4.970	1.330
Crop Sowing Area	LnSow	300	8.177	1.155	4.719	9.606	2.360
Effective Irrigation Area	Irri	300	0.408	0.213	0.029	1.031	2.110
Outflow of Rural Labor Force	Gend	300	0.516	0.010	0.495	0.552	1.290

3.3 Model design

3.3.1 Baseline Regression Model

To test Hypothesis 1, this paper analyzes the impact of rural digitization on agricultural carbon emissions by constructing an ordinary linear regression model. According to the Hausman test, controlling for individual fixed effects is significantly stronger than random effects and time fixed effects. The model is as follows:

$$CO_{2it} = \partial + \beta Digi_{it} + \gamma \sum X_{it} + \mu_i + \varepsilon_{it} \tag{4}$$

In the equation, CO_{2it} represents the intensity of agricultural carbon emissions, $Digi_{it}$ represents rural digitization, X_{it} represents control variables, μ_i represents individual fixed effects, ε_{it} represents random disturbance terms, ∂ represents the intercept term, and β represents the estimated coefficient.

3.3.2 Mediation Effect Model

Building on the baseline regression model, to explore the specific pathways through which rural digitization impacts agricultural carbon emissions, this paper draws on the approach of Wen Zhonglin et al[Error! Reference source not found.]. (2004) and employs stepwise regression to test for mediation effects. The models are as follows:

$$M_{it} = \partial_1 + \beta_1 Digi_{it} + \gamma_1 \sum X_{it} + \mu_i + \varepsilon_{it} \tag{5}$$

$$CO_{2it} = \partial_2 + \beta_2 Digi_{it} + \eta_2 M_{it} + \gamma_2 \sum X_{it} + \mu_i + \varepsilon_{it} \tag{6}$$

In the equation, M_{it} represents the mediating variables, which respectively denote agricultural technological progress and rural human capital. The other variables are explained as in equation (4).

3.3.3 Spatial Effect Model

To further investigate whether rural digitization has a spatial spillover effect on the agricultural carbon emissions of surrounding areas, this paper conducts the following analysis according to the spatial modeling sequence:

(1) Spatial Autocorrelation Test. First, test whether there is a spatial influence relationship among the variables. The model is as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{s^2 \cdot \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{7}$$

In the equation, n represents the total number of spatial units in the region, x_i and x_j respectively represent the attribute values of the random variable x at spatial units i and j, $\bar{x}$ is the mean attribute value of n spatial unit samples, $s^2 = \sum_{i=1}^{n} (x_i - \bar{x})^2/n$ is the sample variance, W_{ij} is the element of the spatial weight matrix (representing the distance between regions i and j), and $\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}$ is the spatial weight sum. The Moran's Index takes values between -1 and 1; a value within [0, 1] indicates positive correlation, meaning regions with similar attributes cluster together; a value between -1 and 0 indicates negative correlation, meaning regions with dissimilar attributes cluster together; a value close to 0 indicates random distribution, or no spatial autocorrelation.

(2) Spatial Weight Matrix. Based on the foundational adjacency weight matrix, this paper incorporates the inverse distance matrix and the economic geography matrix for supplementary analysis. Although the real geographical distance matrix is intuitive and reliable, it is insufficient to describe the complex economic and social relationships between spatial units. Therefore, a distance matrix based on economic relationships is added.

Adjacency Spatial Matrix:

$$W_1 = \begin{cases} 1 & \text{i and j are adjacent} \\ 0 & \text{i and j are not adjacent} \end{cases} \quad (8)$$

In the equation, adjacent regions are assigned a value of 1, while non-adjacent regions are assigned a value of 0.

Inverse Distance Matrix:

$$W_1 = \begin{cases} 1/d^2 & i \neq j \\ 0 & i = j \end{cases} \quad (9)$$

In the equation, d is the distance between regions i and j. This geographical distance matrix is based on the economic gravity index of provincial cities as a measure of distance.

Economic Weight Matrix:

$$W_3 = \begin{cases} 1/\left|\overline{y}_i - \overline{y}_j\right|, i \neq j \\ 0, \quad i{=}j \end{cases} \tag{10}$$

In the equation, $\overline{y}_i$ is the per capita GDP of region i, and $\overline{y}_j$ is the per capita GDP of region j. This economic distance matrix is based on the inverse of the average per capita GDP values from 2011 to 2020 as a measure of economic distance.

(3) Spatial Econometric Model. This mainly includes the Spatial Error Model (SEM), the Spatial Lag Model (SAR), and the Spatial Durbin Model (SDM). Under certain conditions, the Spatial Durbin Model can be transformed into a Spatial Error Model or a Spatial Lag Model, which can better analyze the impact of changes in rural digitization in one region on the agricultural carbon emissions of surrounding regions. Therefore, this paper chooses to establish a Spatial Durbin Model (SDM) for empirical testing. The model is as follows:

$$\begin{cases} CO_{2it} = \rho W_j CO_{2it} + \lambda_1 Digi_{it} + \lambda_2 Con_{it} + \theta_1 W_j Digi_{it} + \theta_2 W_j Con_{it} + \mu_i + \varepsilon_{it} \\ \varepsilon_{it} = \lambda Con_i \varepsilon_t + \tau_{it} \end{cases} \tag{8}$$

In the equation, W_j represents the spatial weight matrices, j=1,2,3 respectively represent the adjacency spatial matrix, the inverse distance matrix, and the economic distance matrix; ρ is the spatial autoregressive coefficient, mainly reflecting the spatial spillover effect; θ is the spatial lag variable coefficient, and when θ>0, it indicates that the explanatory variables of this region have a positive spillover effect on surrounding regions, while θ<0 indicates a negative spillover effect. Other variables are defined the same as in equation (4).

4 Empirical results analysis

4.1 Baseline estimation results analysis

Before model estimation, a collinearity test was conducted, and the Mean VIF value was 1.61, indicating that there is no serious collinearity problem in the model. The estimation results of the random effects and fixed effects were obtained using Stata 16 software, as shown in Table 3.

Firstly, observe the estimation results of the random effects. Without the inclusion of control variables, the regression estimation value of rural digitization on agricultural carbon emissions is -0.129, which passes the 1% significance level. This initially indicates a "carbon reduction effect" of rural digitization on agricultural carbon emissions. Secondly, after adding control variables, the estimation value of rural digitization becomes -0.217, still passing the 1% significance level. This shows that after controlling for interference factors, the "carbon reduction effect" of rural digitization is significantly enhanced. Finally, after controlling for individual and time fixed effects respectively, the estimation values of rural digitization are -0.259 and -0.105, still passing the 1% significance level. The results after controlling for individual differences are significantly higher than the results of random effects and time fixed effects, and the R^2 value also increases significantly, indicating that the model fit is better after choosing individual fixed effects, which is consistent with the conclusion of the Hausman test. After controlling for time trends, the influence decreases significantly. This may be because, with the development of time, technology continuously iterates, and agricultural production methods continue to improve, the impact of rural digitization on agricultural carbon emissions gradually weakens. Therefore, it can be further proven that rural digitization helps to curb agricultural carbon emissions, confirming Hypothesis H1.

Secondly, observe the estimation results of the control variables. After controlling for individual differences, land transfer, fiscal support for agriculture, and the level of mechanization all have a significant inhibitory effect on agricultural carbon emissions, and all pass the 1% significance level, which is consistent with the conclusions of the existing literature.

Table 3. Baseline estimation results

Variable Name	Random Effects		FE	RE
	Agricultural Carbon Emissions (CO_2)	Agricultural Carbon Emissions (CO_2)	Agricultural Carbon Emissions (CO_2)	Agricultural Carbon Emissions (CO_2)
Rural Digitization	-0.129***	-0.217***	-0.259***	-0.105***
(Digi)	(0.017)	(0.019)	(0.017)	(0.021)
Land Transfer		-0.006	-0.046***	-0.011*
(Land)		(0.006)	(0.011)	(0.005)
Fiscal Support for		-0.333**	-0.564***	-0.082
Agriculture (Fina)		(0.115)	(0.146)	(0.099)
Level of Mechanization		-0.018***	-0.010***	-0.015***
(Mach)		(0.002)	(0.003)	(0.002)
Crop Sowing Area		0.020***	0.001	0.015***
(LnSow)		(0.004)	(0.030)	(0.003)
Effective Irrigation		0.069***	-0.023	0.068***
Area (Irri)		(0.015)	(0.071)	(0.013)
Outflow of Rural Labor		-0.982**	-0.335	-0.422
Force (Gend)		(0.311)	(0.221)	(0.309)
_cons	0.231***	0.613***	0.506*	0.335
	(0.007)	(0.178)	(0.222)	(0.174)
R^2	0.113	0.353	0.831	0.493
Obs	300	300	300	300

Note: (1) *, * *, and * * * indicate 10%, 5%, and 1% significance levels, respectively; (2) Robust standard error in parentheses.

4.2 Robustness test results analysis

Through the baseline regression, it can be determined that rural digitization has a "carbon reduction effect" on agricultural carbon emissions. To further verify that the methods and indicators' explanations are not coincidental, robustness tests are necessary. The robustness test methods include variable substitution, sample size reduction, quantile regression, and adding control variables. This paper adopts the variable substitution method and quantile regression method to perform robustness tests respectively.

For measuring the intensity of agricultural carbon emissions, this paper uses the carbon emission per unit area method and the actual carbon emission method to replace the original dependent variable. Quantile regression is mainly conducted at the 25th, 50th, and 75th percentiles. The results show that after replacing the dependent variable, the estimation values of rural digitization are -0.215 and -0.019, both passing the significance level, indicating that the "carbon reduction effect" of rural digitization still holds after variable substitution. The quantile regression results show that the estimation values of rural digitization at each quantile pass the significance level, further verifying robustness.

Table 4. Robustness estimation results

Variable Name	Variable Substitution Method		Quantile Regression: Agricultural Carbon Emissions (CO_2)		
	Agricultural Carbon Emissions (C_1)	Agricultural Carbon Emissions (C_2)	$P_{25\%}$	$P_{50\%}$	$P_{75\%}$
Rural Digitization (digi)	-0.215** (0.075)	-0.019*** (0.003)	-0.236*** (0.026)	-0.237*** (0.030)	-0.231*** (0.038)
Control Variables	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y
Time FE	N	N	N	N	N
_cons	-0.921 (0.610)	0.317*** (0.048)	0.486 (0.384)	0.207 (0.375)	0.599 (0.366)
R^2	0.996	0.980			
Obs	300	300	300	300	300

Note: (1) *, * *, and * * * indicate 10%, 5%, and 1% significance levels, respectively; (2) Robust standard error in parentheses. (3) C_1 represents agricultural carbon emissions per unit area, C_2 represents the natural logarithm of agricultural carbon emissions/crop sowing area.

4.3 Endogeneity test results analysis

Although robustness tests have confirmed the original conclusion, issues of reverse causality and omitted variables might lead to endogeneity problems in the model, thereby affecting the accuracy of the estimation results. Reverse causality refers to the interactive influence between rural digitization and agricultural carbon emissions. For instance, agricultural production losses lead to increased operating costs and reduced profit margins, creating a reverse mechanism that compels business entities to increase the application of digital technology in agricultural production, thereby promoting rural digitization. Moreover, the control variables included in the model are limited and may not fully account for all influencing factors. Therefore, this paper adopts lagged variables and instrumental variable tests to mitigate the endogeneity problem in the model.

Through instrumental variable tests, the Adjusted R-squared value is 0.672, the Partial R-squared value is 0.446, and the F-value is 141.493, significantly exceeding the critical value **Error! Reference source not found.**. Additionally, the over-identification test shows a P-value of 0.159, indicating that the instrumental variables meet the exogeneity test requirements. The estimation results show that the current rural digitization and the one-period lagged rural digitization estimation values are -0.238 and -0.244, respectively, both passing the 1% significance level, indicating the reliability of the carbon reduction conclusion. The first stage results of the two-stage least squares regression show a high correlation between the explanatory variables and the instrumental variables. The second stage regression results show that after adding instrumental variables, the estimation value of rural digitization remains significant, further confirming the original conclusion.

Table 5. Endogeneity estimation results

Variable Name	Variable Lagged Periods	Instrumental Variable Method（2sls）

	L. Agricultural Carbon Emissions (CO_2)	Current Agricultural Carbon Emissions (CO_2)	instrumental variable (1)	instrumental variable (2)	Agricultural Carbon Emissions (CO_2)
Current Rural	-0.238***		0.006***	0.761***	-0.184***
Digitization (Digi)	(0.019)		(0.001)	(0.641)	(0.031)
F. Rural		-0.244***			
Digitization (Digi)		(0.017)			
Control Variables	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y
Time FE	N	N	N	N	N
_cons	0.538	0.159			0.588***
	(0.276)	(0.220)			(0.179)
R^2	0.848	0.849			0.348
Obs	270	270			300

Note: (1) *, * *, and * * * indicate 10%, 5%, and 1% significance levels, respectively; (2) Robust standard error in parentheses.

4.4 Mechanism path estimation results analysis

This paper uses stepwise regression to test the mediation effect of how rural digitization impacts agricultural carbon emissions. Table 6 reports the test results of the mediation mechanism. Firstly, in the total path, after controlling for individual fixed differences, rural digitization has a significant inhibitory effect on agricultural carbon emissions, indicating that the mediation effect hypothesis is valid. Secondly, observe the estimation results of the indirect path. In indirect path (2), the regression estimation value of rural digitization on rural human capital is 0.604, passing the 1% significance level, indicating that rural digitization helps to improve the level of rural human capital. When rural human capital is added to the model, the estimation value for rural human capital is -0.065, passing the 1% significance level, indicating that rural human capital helps to reduce agricultural carbon emissions. Currently, although the estimation value of rural digitization slightly decreases, its sign and significance do not change, indicating that the mediation effect of rural human capital is valid, confirming hypothesis H3. Similarly, observe the estimation results of indirect path (1). The estimation value of rural digitization on agricultural technological progress is 0.039, which is positive but not significant. After adding the mediation variable to the model, the estimation value of the mediation variable is -0.060, but its significance is not evident. This does not negate the mediation effect. According to the research of Wen Zhonglin et al. (2014) **Error! Reference source not found.**, in such cases, a strengthened mediation effect test is needed, that is, a Bootstrap sampling test on agricultural technological progress. After 1000 Bootstrap samples, the estimation value of the mediation effect is -0.013, passing the 10% significance level, while the estimation value of the direct effect is -0.205, passing the 1% significance level, and both reject the null hypothesis of "0" within the 95% confidence interval. This indicates that the model has a partial mediation effect, confirming the mediation effect of agricultural technological progress, and validating hypothesis H2.

Table 6. Mechanism path estimation results

Variable Name	Total Path	Indirect Path (1)	Direct Path (1)	Indirect Path (2)	Direct Path (2)
	Agricultural Carbon Emissions (CO_2)	Agricultural Technological Progress (Tech)	Agricultural Carbon Emissions (CO_2)	Rural Human Capital (Manp)	Agricultural Carbon Emissions (CO_2)
Rural Digitization (Digi)	-0.259***	0.039	-0.257***	0.604***	-0.220***
	(0.017)	(0.026)	(0.017)	(0.110)	(0.019)
Agricultural Technological Progress (Tech)			-0.060		
			(0.035)		
Rural Human Capital (Manp)					-0.065***
					(0.015)
Control	Y	Y	Y	Y	Y

Variables					
Individual FE	Y	Y	Y	Y	Y
Time FE	N	N	N	N	N
_cons	0.506*	1.153**	0.574*	9.131***	1.101***
	(0.222)	(0.370)	(0.228)	(1.572)	(0.246)
R^2	0.831	0.231	0.832	0.922	0.863
Obs	300	300	300	300	300

Note: (1) *, * *, and * * * indicate 10%, 5%, and 1% significance levels, respectively; (2) Robust standard error in parentheses.

Table 7. Agricultural technological progress (bootstrap) estimation results

Test Item	Coefficient Significance	Z Value	[95% Conf. Interval]	
Mediation Effect	-0.013*(0.006)	-2.17	-0.0241	-0.0012
Direct Effect	-0.205***(0.020)	-10.29	-0.2437	-0.1657
Obs	300			

Note: (1) *, * *, and * * * indicate 10%, 5%, and 1% significance levels, respectively; (2) Robust standard error in parentheses.

4.5 Regional heterogeneity estimation results analysis

Due to differences in the development levels of rural digitization between regions, the degree of inhibition on agricultural carbon emissions may vary. To further test the differences in inhibition across regions, an analysis was conducted based on the division of national regions by the National Bureau of Statistics. The results are shown in Table 8. First, let's look at the estimation results for the three major regions. The estimation values of rural digitization on agricultural carbon emissions in the eastern, central, and western regions are -0.191, -0.181, and -0.161, respectively, all passing the significance level. This indicates that rural digitization in each region helps to curb agricultural carbon emissions. By comparing the estimation values, the "carbon reduction effect" of rural digitization in the eastern region is more significant than in the central and western regions, with the weakest impact in the western region. This is mainly because the eastern region has a higher level of economic development, with advanced factors agglomerated and a higher level of rural digitization, thus a higher degree of application in agricultural production and a more significant carbon reduction effect. In contrast, the western region is limited by both natural and economic factors, with a lower degree of rural digitization development, and some areas have only achieved full network coverage in recent years, so the effect is not as significant as in the eastern and central regions.

Next, let's look at the estimation results for the main grain-producing areas and non-grain-producing areas. The estimation value of rural digitization in the main grain-producing areas is -0.169, passing the 1% significance level; the estimation value of rural digitization in non-grain-producing areas is -0.408, also passing the 1% significance level, and the estimation result is significantly higher than in the main grain-producing areas. This may be due to the different provinces included in each area, resulting in different impacts. Non-grain-producing areas include regions like Zhejiang, Beijing, Guangdong, and Shanghai, which are advanced in digitization development, with a high degree of digital application and a significant driving effect on rural areas. In contrast, the main grain-producing areas include traditional agricultural provinces, where traditional agricultural production issues remain, and there are many obstacles in the adaptation of advanced technology to traditional production, hindering the role of digitization.

Table 8. Regional heterogeneity estimation results

Variable Name	Agricultural Carbon Emissions (CO_2)				
	Eastern Region	Central Region	Western Region	Main Grain-Producing Areas	Non-Grain-Producing Areas
Rural Digitization	-0.191***	-0.181**	-0.161***	-0.169***	-0.408***
(Digi)	(0.024)	(0.055)	(0.052)	(0.019)	(0.047)
Control Variables	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y

Time FE	N	N	N	N	N
_cons	0.002	2.958**	1.031	3.031***	0.400
	(0.342)	(1.029)	(0.668)	(0.716)	(0.221)
R^2	0.670	0.925	0.884	0.927	0.806
Obs	110	80	110	130	170

Note: (1) *, * *, and * * * indicate 10%, 5%, and 1% significance levels, respectively; (2) Robust standard error in parentheses.

5 Further discussions

Based on theoretical analysis, the cross-regional mobility of data elements in rural digitization may lead to spatial spillover effects on agricultural carbon emissions in surrounding areas. Additionally, combined with the baseline estimation results and various robustness tests, it is further confirmed that the development of rural digitization indeed has a significant "carbon reduction effect" on agricultural carbon emissions. However, the estimation results of the ordinary panel model cannot separate the impact brought by spatial factors. Therefore, it is necessary to further refine the "carbon reduction effect" of rural digitization. This paper conducts the following tests.

5.1 Spatial correlation test analysis

Before conducting spatial modeling, it is necessary to test the spatial correlation of the core variables, which includes global autocorrelation and local autocorrelation tests. From the global autocorrelation estimation results in Table 9, the global Moran's I value of rural digitization and agricultural carbon emissions from 2011 to 2020 are all positive, indicating that rural digitization and agricultural carbon emissions have significant spatial correlations with surrounding areas. From the local autocorrelation test, the first and third quadrants of the Moran scatter plot represent "high-high" and "low-low" clusters, respectively, while the second and fourth quadrants represent "low-high" and "high-low" clusters. From Figure 2, most of the scatter points of rural digitization fall in the first and third quadrants, with a total of 21 points, while there are 9 points in the second and fourth quadrants. The number of points in the first and third quadrants is significantly higher than in the second and fourth quadrants, indicating an overall positive spatial clustering characteristic. The scatter distribution characteristics of agricultural carbon emissions are roughly the same as those of agricultural ecological efficiency. In summary, the tests indicate that there is a significant spatial correlation and spatial clustering characteristic between agricultural digitization and agricultural carbon emissions, confirming Hypothesis H4, and allowing for spatial modeling analysis.

Table 9. Global Moran's I index estimation results

Time	Rural Digitization（Digi）			Agricultural Carbon Emissions（CO_2）		
	Moran's I	Z-Value	P-Value	Moran's I	Z-Value	P-Value
2011	0.417	3.762	0.000	0.082	0.952	0.170
2012	0.402	3.646	0.000	0.105	1.140	0.127
2013	0.353	3.214	0.001	0.037	0.587	0.279
2014	0.361	3.256	0.001	0.088	0.999	0.159
2015	0.317	2.961	0.002	0.075	0.905	0.183
2016	0.300	2.819	0.002	0.160	1.644	0.050
2017	0.269	2.545	0.005	0.177	1.857	0.032
2018	0.259	2.423	0.008	0.241	2.395	0.008
2019	0.262	2.424	0.008	0.251	2.477	0.007
2020	0.264	2.438	0.007	0.286	2.709	0.003

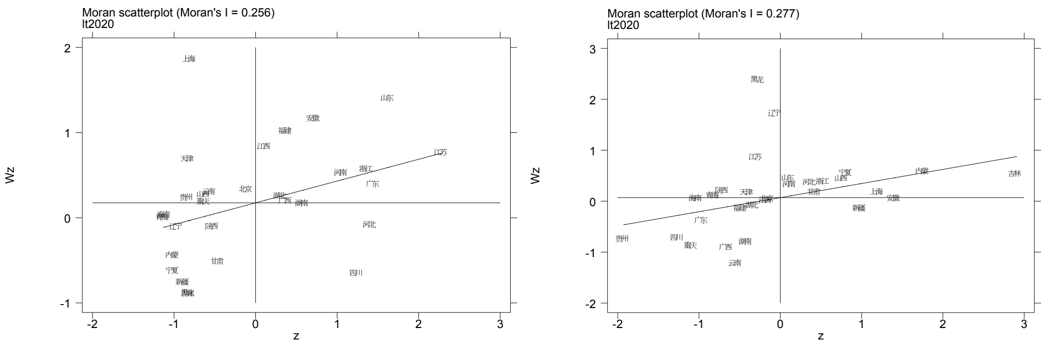

Figure 2 Local Moran scatter plot of rural digitization and agricultural carbon emissions

5.2 Spatial model test results analysis

To determine which spatial model to use for the modeling analysis, targeted tests on spatial models were conducted based on the research approach proposed by Elhorst et al. (2014) [68]. The test results are shown in Table 10. From the estimation results, in the Lagrange Multiplier (LM) test, under three spatial factor conditions, the P-values for the lag model (LM-lag) are 0.000, 0.013, and 0.216, while the robust Lagrange Multiplier (Robust-LM) P-values are 0.179, 0.001, and 0.005, respectively. From these results, it can be considered to use the lag model. Similarly, the P-values for the error model (LM-error) are 0.000, 0.000, and 0.009, while the robust Lagrange Multiplier (Robust-LM-error) P-values are all 0.000, which also indicates that the error model can be considered. Given that both the lag model and the error model are significant, the Durbin model can be considered. Through the Likelihood Ratio (LR) test, the P-values for the lag model (LR-Spatial-lag) and the error model (LR-Spatial-error) are both 0.000, further indicating that the Durbin model can be chosen. The Wald test results, with P-values of 0.005, 0.000, and 0.000, indicate that choosing the Durbin model will not degrade it to an error model or lag model.

Table 10. Spatial SDM Model LM, LR, Wald estimation results

Test Item	Adjacency Weight Matrix		Inverse Distance Weight Matrix		Economic Weight Matrix	
	Statistic	p-value	Statistic	p-value	Statistic	p-value
Lagrange Multiplier （LM-lag）	12.155	0.000	6.217	0.013	1.529	0.216
Robust (LM) -lag	1.805	0.179	10.996	0.001	7.869	0.005
Lagrange Multiplier （LM-error）	42.828	0.000	24.734	0.000	6.901	0.009
Robust (LM)-error	32.478	0.000	29.514	0.000	13.241	0.000
Likelihood Ratio （LR-Spatia-lag）	168.750	0.000	78.840	0.000	119.190	0.000
Likelihood Ratio	441.040	0.000	398.260	0.000	462.040	0.000

(LR-Spatial -error)						
Wald (Wald-lag)	18.360	0.005	43.780	0.000	58.140	0.000

5.3 Spatial effect estimation results analysis

Table 11 reports the estimation results of the spatial effects of rural digitization on agricultural carbon emissions under the influence of three spatial factors. Firstly, observe the coefficients of the lagged dependent variable. From the results, under the influence of the three spatial factors, the estimated values of the lagged term of agricultural carbon emissions are 0.382, 0.359, and 0.360, all passing the 1% significance level. This indicates that agricultural carbon emissions have a significant positive spatial spillover effect, meaning that an increase in agricultural carbon emissions in one region leads to a corresponding change in surrounding areas. At this point, the p coefficient is significant and non-zero. According to the research by LeSage et al. (2009) [69], the partial differentiation method should be used for effect decomposition. The partial differentiation method decomposes the impact of rural digitization on agricultural carbon emissions into direct effects, indirect effects, and total effects. The direct effect can be divided into two parts: the direct impact of the digital economy on the agricultural planting structure within the region and the spillover effect within the region. The indirect effect represents the spatial spillover effect, i.e., the spatial spillover impact of rural digitization on agricultural carbon emissions in surrounding areas. The sum of the direct and indirect effects is the total effect.

Secondly, observe the estimation results of the direct effects. Considering the influence of spatial factors, the estimated values of rural digitization on agricultural carbon emissions within the region are -0.056, -0.030, and -0.077, passing the 10% and 1% significance levels, respectively. This indicates that even after considering spatial factors, rural digitization still has a significant "carbon reduction effect" on agricultural carbon emissions within the region, further confirming Hypothesis H1. Comparing the estimation results of the ordinary linear regression model and the spatial econometric model (i.e., the baseline estimation results and the direct effect estimation results), it is found that the estimation values and significance levels are lower when using the spatial econometric model. This suggests that while the "carbon reduction effect" can be confirmed using an ordinary linear regression model, it may overestimate the effect due to the inability to separate spatial factors and ignore the regional spillover effect, thereby amplifying the "carbon reduction effect" of rural digitization.

Finally, observe the estimation results of the indirect effects (spatial effects). The estimated values of the indirect effects of rural digitization on agricultural carbon emissions are -0.258, -0.269, and -0.172, all passing the 1% significance level, indicating that rural digitization also has a significant "carbon reduction effect" on agricultural carbon emissions in surrounding areas through spatial spillover effects. Therefore, Hypothesis H5 is confirmed.

Table 11. Spatial spillover effect estimation results

Variable Name	Adjacency Weight Matrix		Inverse Distance Weight Matrix		Economic Distance Weight Matrix	
	Direct Effect (Direct)	Indirect Effect (Indirect)	Direct Effect (Direct)	Indirect Effect (Indirect)	Direct Effect (Direct)	Indirect Effect (Indirect)
Rural Digitization (Digi)	-0.056* (0.023)	-0.258*** (0.037)	-0.030* (0.020)	-0.269*** (0.041)	-0.077*** (0.021)	-0.172*** (0.029)
Control Variables	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y
Time FE	N	N	N	N	N	N
Spatial-rho	0.382*** (0.063)		0.359*** (0.070)		0.360*** (0.044)	
sigma2_e	0.000*** (0.000)		0.000*** (0.000)		0.000*** (0.000)	

R^2	0.138	0.079	0.061
Obs	300	300	300

Note: (1) *, * *, and * * * indicate 10%, 5%, and 1% significance levels, respectively; (2) Robust standard error in parentheses.

6 Research conclusions and recommendations

Currently, in the context of digital development, the digital transformation and development of rural areas will undoubtedly become a new driving force for promoting rural revitalization. This paper uses provincial-level macro data from 2011 to 2020 as a sample to deeply study the intrinsic impact of rural digitization on agricultural carbon emissions. The study finds that rural digitization has a significant "carbon reduction effect" on agricultural carbon emissions, and this conclusion is confirmed to be reliable through robustness and endogeneity tests. At the level of specific implementation paths, stepwise regression tests show that agricultural technological progress and rural human capital play a mediating role, meaning that rural digitization indirectly achieves the effect of reducing agricultural carbon emissions by promoting agricultural technological progress and improving rural human capital levels. The heterogeneity test reveals that due to differences in the levels of rural digitization between regions, the "carbon reduction effect" of rural digitization on agricultural carbon emissions is most significant in the eastern region, while the impact is lowest in the western region. Further spatial correlation tests between rural digitization and agricultural carbon emissions show significant spatial correlation and positive spatial clustering characteristics. Using the spatial Durbin model test under three spatial factor conditions, it is found that rural digitization not only has a significant "carbon reduction effect" within the region but also has a significant inhibitory effect on surrounding areas through spillover effects. Based on the above research conclusions, this paper proposes the following policy recommendations:

(1) Accelerate the Construction of Rural Digital Infrastructure: The government should increase investment in digital infrastructure in rural areas, improve broadband networks, mobile communication base stations, and other infrastructure to enhance the level of digitalization in rural areas. Through policy guidance and financial support, encourage enterprises and social capital to participate in the construction of rural digital infrastructure and promote the application of digital technology in agricultural production.

(2) Promote Agricultural Technological Progress: Strengthen agricultural scientific research and promotion efforts, support the innovative application of digital technology in agricultural production, and improve agricultural production efficiency and resource utilization. Promote the deep integration of digital technology with agricultural production, popularize modern agricultural production models such as precision agriculture and smart agriculture, and achieve agricultural emission reduction and efficiency enhancement.

(3) Improve the Level of Rural Human Capital: Increase investment in rural education and vocational training to improve the digital literacy and skills of farmers, enhancing their ability to use digital technology for agricultural production and management. Conduct digital technology training and knowledge dissemination through a combination of online and offline methods to increase farmers' awareness and acceptance of digital technology.

(4) Promote Regional Collaborative Development: Encourage digital cooperation and exchanges between regions, build cross-regional digital technology sharing platforms, and realize the mutual sharing of resources and information. Through regional cooperation, promote advanced digital agricultural technologies and management models, drive the joint development of surrounding areas, and form a regional collaborative emission reduction effect.

(5) Strengthen Policy Support and Guidance: The government should formulate and improve relevant policies and regulations, encourage and guide rural digital development, and provide policy support such as tax incentives and financial subsidies to reduce the cost of digital transformation. Strengthen the supervision and guidance of digital agricultural development to ensure the standardized application of digital technology in agricultural production and prevent potential risks during digitalization.

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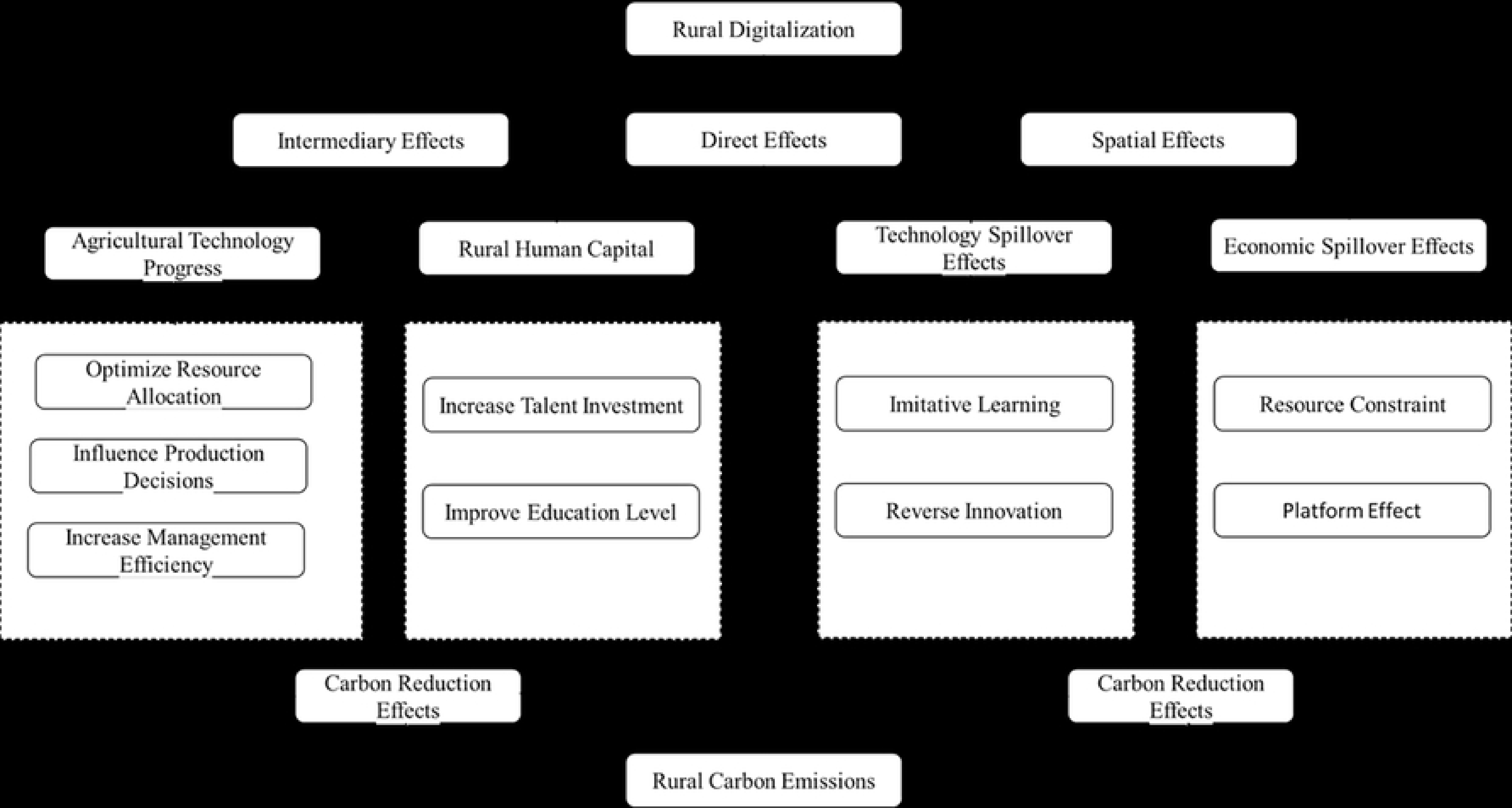
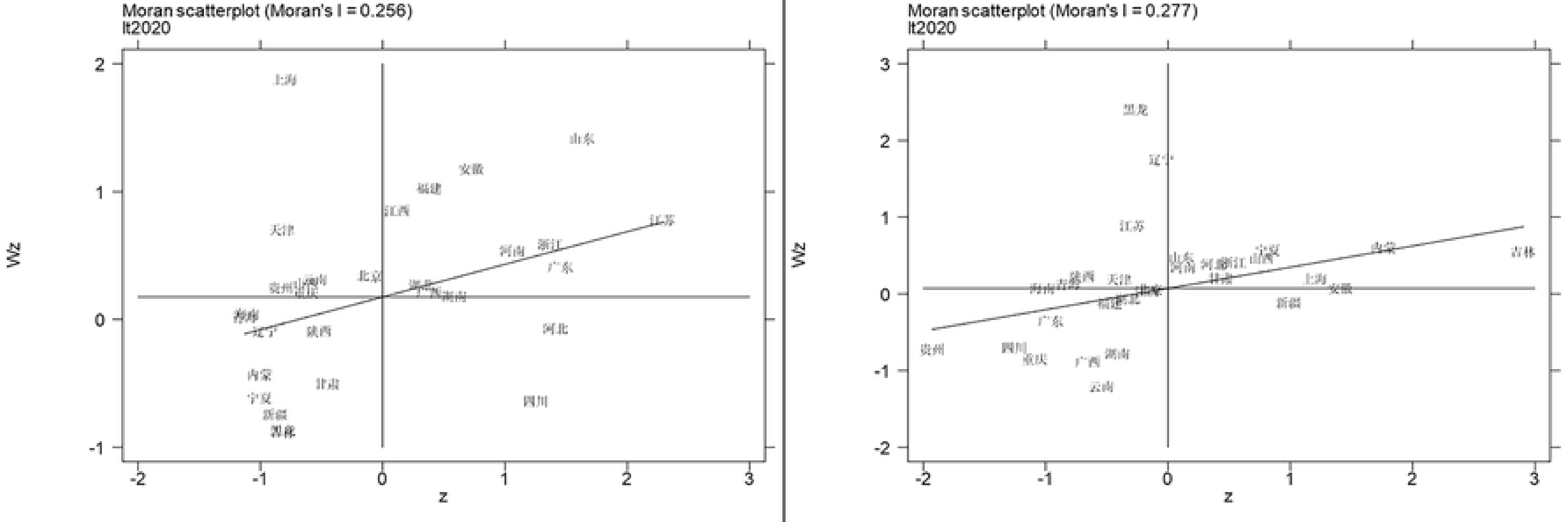

Rural Digitalization
Intermediary Effects
Direct Effects
Spatial Effects
Agricultural Technology Progress
Rural Human Capital
Technology Spillover Effects
Economic Spillover Effects
Optimize Resource Allocation
Influence Production Decisions
Increase Management Efficiency
Increase Talent Investment
Improve Education Level
Imitative Learning
Reverse Innovation
Resource Constraint
Platform Effect
Carbon Reduction Effects
Carbon Reduction Effects
Rural Carbon Emissions


Moran scatterplot (Moran's I = 0.256)
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北京
河北
陕西
内蒙
甘肃
宁夏
新疆
四川
Moran scatterplot (Moran's I = 0.277)
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上海
安徽
新疆
天津
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广东
贵州
四川
重庆
广西
湖南
云南