Journal of Innovation and Development
ISSN: 2958-4752 | Vol. 4, No. 1, 2023

The Impact of China's Digital Agriculture on Carbon Emissions under the Dual Carbon Target

-- Empirical Research based on Quantile Regression and Spatial Durbin Model

Yinghui Liu [1,*], Zejiong Zhou [2]

[1] School of International Trade and Economics, Anhui University of Finance and Economics, Bengbu, Anhui, 233030, China
[2] School of Economics, Anhui University of Finance and Economics, Bengbu, Anhui, 233030, China

*** Corresponding author:** Yinghui Liu (Email: 2898733574@qq.com)

Abstract: This article measures carbon emissions and digital agriculture in 30 provinces and cities in China from 2011 to 2020, and empirically analyzes their influencing factors. The results indicate that the total carbon emissions and the overall level of digital agriculture development in China are showing an increasing trend; Under different quantiles, the impact of population size and digital agriculture development level on inter provincial carbon emissions decreases, the impact of industrial upgrading level first decreases and then increases, and the impact of economic development level and greening level increases; The population size will promote the rise of carbon emissions in the local area and suppress carbon emissions in neighboring areas, the level of economic development will promote the rise of carbon emissions in the local and neighboring areas, the level of digital agriculture development will suppress the rise of carbon emissions in the local area, and the level of industrial upgrading and greening will suppress the rise of carbon emissions in the local and neighboring areas. Therefore, it is recommended to promote China's accelerated progress towards carbon neutrality goals through rational allocation of energy elements, enhancement of ecosystem carbon absorption capacity, and vigorous development of digital agriculture.

Keywords: Digital Agriculture; Carbon Emissions; Quantile Regression; Spatial Durbin Model.

1. Introduction

The practice of digital agriculture began in the 1960s with the application of computer technology in agricultural production in developed countries. However, there is currently no consensus on the concept of digital agriculture, and commonly used terms include smart agriculture, information agriculture, etc. The essence of digital agriculture lies in utilizing digital technology to improve the production and circulation of agricultural products in the agricultural production process, ultimately enabling the entire agricultural industry chain to create more economic value in an environmentally friendly manner. China's digital agriculture started relatively late and mainly relies on policy guidance. Since 2019, relevant departments have intensively issued relevant policy opinions to promote the application of agricultural and rural big data, Internet of Things and remote sensing technology, Internet plus agriculture and other digital technologies in the agricultural field. Under the guidance of policies, digital technology is gradually being promoted and applied in the vast rural areas of China. According to data from the Ministry of Agriculture and Rural Affairs, in 2020, the overall level of digital agriculture and rural development in counties in China reached 37.9%, and the digital level of agricultural production exceeded 23%. The digital transformation of agricultural production is accelerating.

As early as the 1980s, the United Nations established the IPCC to address global climate change. As the world's second largest economy, China has a relatively high carbon emission intensity in agriculture, and should shoulder the responsibility and obligation of transitioning to low-carbon development goals. Therefore, achieving carbon peaking and carbon neutrality is of great significance. At the 2020 United Nations General Assembly, Xi Jinping proposed the goal of achieving carbon peak by 2030, striving to achieve carbon neutrality by 2060, and setting an example for leading the global low-carbon transformation and development. The "Opinions of the Central Committee of the Communist Party of China and the State Council on Completely, Accurately and Comprehensively Implementing the New Development Concept and Doing a Good Job of Carbon Peak and Carbon Neutrality" released in 2021 pointed out that the key to achieving carbon peak and carbon neutrality lies in technological innovation. China is currently continuously developing a green and low-carbon technological revolution, and has already reached the forefront of the world in fields such as power batteries and indirect liquefaction technology. However, China still faces severe challenges in industries with high carbon emissions and low-carbon technologies, and efforts are needed to achieve the "dual carbon" goal. Therefore, the development of digital agriculture and the realization of the "dual carbon" goals in agriculture are mutually supportive, and the digital transformation and upgrading of agriculture and the achievement of the "dual carbon" goals are still the primary issues in China at this stage.

This article selects indicators related to digital agriculture and uses the entropy weight method to measure the development level of the digital economy, obtaining the relative level of digital agriculture in each province. In terms of carbon emissions measurement, surface energy estimation method is used to measure, and then panel regression model is used to further analyze the mechanism of digital agriculture and related control variables on carbon emissions. Finally, spatial spillover effect analysis is used, Determine the impact of the development level of digital agriculture on carbon emissions.

This article refers to a large number of literature when measuring the development level and carbon emissions level

of digital agriculture, making the selected indicators more reasonable and the results more objective. When conducting panel model analysis, the spatial correlation of the explained variables is considered.

2. Literature Review

With global warming, the issue of greenhouse gas emissions reduction has been highly valued, and countries around the world are working towards it. On the other hand, as a major agricultural country, the development of digital agriculture in China can reduce carbon emissions in various ways, which helps to achieve the beautiful vision of "carbon peaking and carbon neutrality" in China. Therefore, a large number of scholars have conducted research on digital agriculture and carbon emissions.

Zhang Hong et al. (2021) used the AHP entropy weight method and comprehensive evaluation model to empirically measure and evaluate the development of digital agriculture in 31 provinces of China from 2015 to 2019; Ma Xiaoni and Li Qiang [2] (2023) identified the influencing factors of digital agriculture in terms of development environment, digital basic resources, government support, green development, and digitalization of management services, and measured them using grey correlation analysis and entropy method; Wang Wenshu [3] (2022) starts from three dimensions of development environment, industrial development, and green development, uses the Thiel index and Gini coefficient to calculate the degree of regional differences, and uses obstacle factor diagnosis models and geographic detector models to study the development characteristics of digital agriculture; Xie Yonghao and Liu Zheng [4] (2022) used the grey prediction method GM (1,1) to predict the carbon emissions of 31 provinces in China over the next 5 years, and analyzed their spatiotemporal differentiation characteristics in depth; Chen Jiang and Xiong Ligui [5] (2022) analyzed and defined the connotation of digital agriculture, and analyzed the development status, opportunities, and challenges. Zhao Yuxiang and Liu Jun [6] (2023) used the super efficiency SBM model to calculate carbon emission efficiency data and analyze its spatiotemporal evolution process. Cao Ze et al. (2023) constructed benchmark regression and spatial econometric models to explore the impact and spillover effects of industrial intelligence on carbon emission intensity.

Through research, it has been found that there is currently a lot of research on carbon emissions and digital agriculture in the academic community. However, most studies focus on digital agriculture and carbon emissions separately, and few scholars have studied the impact of digital agriculture on carbon emissions. On the basis of accurately grasping the "dual carbon" goal, this article measures digital agriculture and carbon emissions, and selects multiple explanatory variables to study the impact of digital agriculture on carbon emissions.

3. Measurement of Relevant Indicators

3.1. Carbon Emission Measurement

In terms of carbon emission measurement methods, the theoretical community generally adopts the surface energy consumption estimation method published by the IPCC [8]. This method directly utilizes the total energy consumption data of each unit, and the calculation results are more accurate and widely used compared to other methods. The measurement step is to first multiply the carbon emission coefficient with the consumption of a certain type of fossil energy to obtain the carbon emissions generated by that type of energy in a certain region, and then add up the carbon emissions generated by various energy sources to calculate the carbon emissions of energy consumption in that region. The calculation formula is as follows:

$$CE = \sum_{i=1}^{m} \sum_{j=1}^{n} CF_{ij} w_j$$

Where, CE is the total carbon emissions generated by fossil energy consumption, w_j is the carbon emission coefficient of the third energy source, and CF_{ij} is the consumption of the j fossil energy source in the i province.

Considering the diverse characteristics of energy consumption in China, data such as coal consumption, gasoline consumption, natural gas consumption, kerosene consumption, electricity consumption, crude oil consumption, fuel oil consumption, diesel consumption, and coke consumption are selected at the provincial level for actual calculations. Given the serious lack of data in the Tibet region of China, we measure the carbon emissions of 30 provinces and cities in China from 2011 to 2020, except for Tibet. The measurement data is sourced from the "2006 IPCC Guidelines for National Greenhouse Gas Inventories" and the "China Energy Statistical Yearbook".

The calculation results of carbon emissions show that from 2011 to 2020, the carbon dioxide emissions of 30 provinces and cities in China showed an increasing trend year by year, with the total amount increasing from 1995.55662 million tons in 2011 to 25.02309 million tons in 2020. 2011 was a turning year for China's carbon emissions growth rate to slow down from fast to slow. The reason may be that before 2011, China's economic development relied more on fossil fuels, and the utilization efficiency of fossil fuels was relatively low. Local environmental awareness was also relatively weak, leading to the prevalence of extensive development methods, resulting in an annual increase in the growth rate of total carbon emissions. After 2011, China began to attach importance to carbon emission reduction issues. With the strong promotion of national top-level design, local environmental awareness and capacity have been enhanced, and the development mode has also accelerated the transition to low-carbon, driving the growth rate of China's carbon emissions to decrease year by year.

An analysis of the distribution of annual carbon emissions in 30 provinces and cities in China from 2011 to 2020 found that Shandong, Hebei, and Jiangsu ranked among the top three regions in China in terms of annual carbon emissions, making them the three regions with the highest annual carbon emissions. The reason may be that the economic development of these three regions overly relies on energy intensive industries, coupled with the weak initiative of industrial enterprises in low-carbon transformation in these regions, resulting in a significant amount of carbon dioxide emissions. Qinghai, Hainan, and Beijing are the three regions with the lowest annual carbon emissions. The reason may be that there are fewer industrial enterprises in Qinghai and Hainan, while Beijing's economic development is mainly focused on low-carbon and technological industries, which emit relatively minimal amounts of carbon dioxide. In addition, in terms of spatial distribution, from 2011 to 2020, the average annual

carbon emissions between provinces in China showed an overall trend of increasing from south to north and from west to east, indicating significant regional differences in carbon emissions between provinces.

3.2. Digital Agriculture Measurement

In response to the different characteristics of digital agriculture development in different regions, different dimension indicator systems were selected for measurement in the construction process of measuring the high-quality development of manufacturing industry, as shown in Table 1:

Table 1. Digital Agriculture Indicator System

Target layer	Dimension layer	Indicator layer	Attribute
The level of digital agriculture in various provinces and cities	Industrial scale	Total agricultural output value	+
	Research dimension	Technology Market Turnover	+
		Number of agricultural meteorological observation stations	+
	Government policy	Local financial expenditure on agriculture, forestry, and water affairs	+
		Local fiscal expenditure on science and technology	+
	Degree of industrialization	Chemical pesticide production	+
		Number of industrial enterprises above designated size	+

In the entropy weight TOPSIS model, the weights of various indicators are first obtained through cross-sectional data using the entropy weight method. Then, the TOPSIS method is used to calculate the cross-sectional score of digital agriculture, and the time series score of digital agriculture is calculated. Then, the time series score is used as the year proportion to calculate the score of the entire panel data [9].

The entropy weight TOPSIS model combines the entropy weight method and the TOPSIS comprehensive evaluation model, which can fully utilize the information in the original data. The basic idea is to use the cosine method to identify the optimal and worst solutions from a finite solution based on normalized raw data, and calculate the relative distance of each data object based on the optimal and worst solutions, in order to determine the similarity between the evaluation object and the optimal solution, and evaluate the advantages and disadvantages of each object based on this relative similarity. The basic steps of the entropy weight TOPSIS model are as follows:

(1) Positive normalization of indicators. Due to the fact that all 7 indicators used in this article are benefit-based indicators, there is no need for forward normalization.

(2) Standardized processing. Standardized processing can eliminate differences in different indicator dimensions, and its calculation formula is:

$$z_{ij} = x_{ij} \Big/ \sqrt{\sum_{i=1}^{n} x_{ij}^2}$$

If there are still negative numbers in the Z matrix, a new standardization method needs to be used for the matrix. The standardized formula is:

$$\overline{z}_{ij} = \frac{x_{ij} - \min\{x_{1j}, x_{2j}, ..., x_{nj}\}}{\max\{x_{1j}, x_{2j}, ..., x_{nj}\} - \min\{x_{1j}, x_{2j}, ..., x_{nj}\}}$$

Since negative numbers did not appear in the matrix when we used the first standardized formula, there is no need to use another formula.

(3) Calculate the probability of each data by dividing the individual data values by the sum of the matrices. Due to the presence of 30 evaluation objects and 7 evaluation indicators in the data, the processed non negative matrix is:

$$\overline{Z} = \begin{bmatrix} \overline{z}_{11}, \overline{z}_{12}, \cdots, \overline{z}_{1,j} \\ \overline{z}_{21}, \overline{z}_{22}, \cdots, \overline{z}_{2,j} \\ \cdots \\ \overline{z}_{n2}, \overline{z}_{n2}, \cdots, \overline{z}_{nj} \end{bmatrix}$$

Calculate the probability matrix p, and the calculation formula for each element p_{ij} in the matrix is as follows:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}$$

(4) Calculate the information entropy e_j and information utility value d_j of each indicator, and obtain the normalized entropy weight of each indicator. The calculation formula for its information entropy is:

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln(p_{ij}), j = 1, 2, ..., m$$

The calculation formula for information utility value is:

$$d_j = 1 - e_j$$

(5) Determine the weights of each indicator. The weight of each indicator can be calculated through the results of information entropy, and the calculation formula is as follows:

$$\omega_j = \frac{d_j}{n - \sum_{j=1}^{n} e_j}$$

(6) Establish the optimal vector z^+ and the worst vector z^- for each indicator, where:

$$z^+ = \max_{n\,j} (z_1^+, z_2^+, ..., z_p^+)$$

$$z^- = \min_{n\,j} (z_1^-, z_2^-, ..., z_p^1)$$

Calculate the distance between each evaluation object and the optimal and worst values:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \omega_j (Z_j^+ - z_{ij})^2}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} w_{ij} (Z_j^- - z_{ij})^2}$$

(7) Calculate the relative closeness between the i-th evaluation object and the optimal value, using the formula:

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

This article analyzes and solves the indicator data of digital agriculture in 30 provinces and cities in China from 2011 to 2020 using MATLAB software, obtains the information entropy value e_j and weight of each indicator, and calculates the final score.

The measurement results of digital agriculture indicate that the weight of industrial scale and government policy dimensions is relatively high, which is the main factor affecting the development level of digital agriculture. From 2011 to 2020, the overall level of digital agriculture development in China showed an upward trend, possibly due to the widespread application of technologies such as Beidou Navigation, 5G, and blockchain in the agricultural field in recent years. New technologies have been encountered in agricultural development, resulting in a significant improvement in production efficiency. The rapid development in 2014 and 2015 may be due to the fact that China's internet industry was basically mature in 2014, and various departments attached great importance to the development of digital agriculture, thereby promoting the development of digital agriculture.

An analysis of the average annual development level of digital agriculture in 30 provinces and cities in China from 201 to 2020 found that Shandong, Sichuan, and Heilongjiang ranked among the top three regions in the country in terms of average annual development level of digital agriculture, making them the three regions with the highest average annual development level of digital agriculture. Shanghai, Beijing, and Hainan are the three regions with the lowest average annual level of digital agriculture. The reason may be that Shanghai and Beijing have relatively developed economies, and Hainan Province has a subtropical monsoon climate, which is not suitable for the development of digital agriculture. Overall, the development level of digital agriculture in the southeast of China is relatively high, while the development level of digital agriculture in the northwest is relatively low.

4. Research Design

4.1. Establishment of Empirical Models

4.1.1. Quantile Regression

The general form of quantile regression is:

$$Q_\tau(y_i) = \beta_0(\tau) + \beta_1(\tau) x_{i1} + ... + \beta_p(\tau) x_{ip}, i = 1, 2, ..., n$$

The panel quantile regression model under fixed effects is:

$$Q_\tau \ln CE = \beta_1(\tau) \ln SP_{i1} + \beta_2(\tau) \ln ED_{i2} + \beta_3(\tau) DA_{i3} + \beta_4(\tau) ISL_{i4} + \beta_5(\tau) GL_{i5} \ , \ i = 1, 2, ..., n$$

In the formula, i is the number of provinces, cities, and regions; β_1 - β_5 is the quantile regression estimation coefficient.

4.1.2. Space Panel Model

The construction results of the spatial panel model are:

$$Y_{it} = \alpha + \beta X_{it} + \lambda \sum_{j=1}^{n} w_{ij} Y_{jt} + \theta \sum_{j=1}^{n} w_{ij} X_{jt} + u_{it}$$

$$u_{it} = \rho \sum_{j=1}^{n} w_{ij} u_{jt} + \varepsilon_{it}$$

In the equation, w_{ij} is the spatial matrix, Y_{it} is the carbon emissions of province i in year t, X_{it} is the explanatory variable of province i in year t, Y_{jt} and X_{jt} are the carbon emissions and explanatory variables of neighboring province j in year t, and $w_{ij}X_{jt}$、$w_{ij}Y_{jt}$ represents the spatial lag term of the variable. To ensure the robustness of the regression results, spatial adjacency matrix, geographic distance matrix, and economic distance matrix were selected for analysis.

4.2. Variable Selection

The dependent variable is carbon emissions (CE), which was calculated using the surface energy consumption estimation method mentioned earlier.

The core explanatory variable is Digital Agriculture (DA), which is taken from the comprehensive scores of 30 provinces and cities in China's digital agriculture development evaluation from 2011 to 2020 in the second section.

Meanwhile, by reviewing existing literature, it was found that population size, economic development level, advanced industrial structure, and greening level may all be important factors affecting China's carbon emissions. Therefore, they are used as explanatory variables. Among them, the population size (SP) is measured by the year-end permanent population. The level of economic development (ED) is measured by per capita GDP; Advanced Industrial Structure (ISL) is measured by the proportion of the tertiary industry to GDP; Greening level (GL) is measured by the proportion of the total afforestation area to the area of each region.

4.3. Data Description

Considering data availability, this article selects panel data from 30 provinces and cities in China (excluding Tibet) from 2011 to 2020 for empirical analysis. Except for the carbon emissions data calculated in the previous text, all other data are from the "China Statistical Yearbook" (2002-2021) and "China Energy Statistical Yearbook" (2002-2021), and some missing data are supplemented using Lagrangian interpolation method. Descriptive statistics were conducted on variables, and the results are shown in Table 2.

5. Benchmark Regression Results

5.1. Quantile Regression Results

Select three quantiles of 0.3, 0.5, and 0.7 for regression, and report the results of ordinary least squares regression for comparison. (See Table 3).

Table 3 shows that the regression results of all explanatory variables are significant. The mean and quantile regression results of population size, economic development level, and advanced industrial structure are significant at the 1% level, while the mean and quantile regression results of greening level are significant at the 10% level. This indicates that population size, economic development level, industrial

structure upgrading, and greening level are all important factors affecting inter provincial carbon emissions in China.

Table 2. Descriptive Statistics of Variables

Variable	Sample	Mean	S.D.	Max.	Min.
LnCE	300	10.658	0.824	7.508	12.445
lnSP	300	8.169	0.755	6.260	9.443
lnED	300	10.195	0.818	8.006	12.013
lnDA	300	-0.675	0.274	-1.395	-0.060
lnISL	300	-0.800	0.181	-1.211	-0.176
lnGL	300	-4.993	0.938	-9.500	-3.221

Note: The data in Table 2 are all natural logarithmic results.

Table 3. OLS and Quantile Regression Results

Variable	OLS	Quantile regression		
	Model	q=0.3	q=0.5	q=0.7
lnSP	0.6181***	0.7146***	0.6714***	0.6417***
	(-21.62)	(-18.88)	(-27.48)	(-14.19)
lnED	0.6499***	0.4791***	0.5454***	0.4561***
	(-14.25)	(-9.62)	(-14.54)	(-8.48)
lnDA	0.4910**	0.4102**	0.5459**	0.6517***
	(-4.45)	(-3.89)	(-5.21)	(-6.45)
lnISL	-4.2565***	-2.8456***	-2.1561***	-2.5458***
	(-8486)	(-5.48)	(-17.56)	(-4.81)
lnGL	0.0654**	-0.0801*	0.0247*	0.1301***
	(-2.24)	(-1.96)	(-1.18)	(-3.46)
_cons	-1.5896***	-2.5462***	-0.8971**	-0.5892
	(-4.86)	(-3.59)	(-2.14)	(-1.34)

Note: *, * *, * * respectively indicate passing the 10%, 5%, and 1% significance tests.

The quantile regression results also revealed significant phased differences in the magnitude of the influencing factors on carbon emissions between provinces in China. Specifically, the mean and quantile regression coefficients of population size are both positive, indicating a positive relationship between population size and carbon emissions. That is, the expansion of population size increases carbon emissions. The quantile regression coefficient of population size shows a decreasing trend overall, indicating that as the quantile increases, the negative impact of population size on carbon emissions reduction is gradually decreasing.

The mean and quantile regression coefficients of economic development level is also positive, indicating that the improvement of economic development level has led to an increase in carbon emissions. Among them, the quantile regression analysis of economic development level shows that at$\tau<0.5$, the quantile regression coefficient is smaller than the average regression coefficient, but there is no significant increase or decrease trend; When the quantile regression parameter shows an increasing trend when it is$\tau<0.5$, indicating that as the quantile increases, the negative impact of economic development level on inter provincial carbon emissions reduction in China is becoming smaller and smaller. Overall, the development level of digital agriculture in China is showing a downward trend. The quantile regression results show that the improvement of the development level of digital agriculture has a limited role in promoting China's inter provincial carbon emission reduction goals. The mean and quantile regression coefficients of the development level of digital agriculture also show a decreasing trend overall. The quantile regression results indicate that the improvement of digital agriculture development level has a "V" shaped trend of change in the impact on fossil energy consumption at the provincial level in China. However, since the regression coefficients of the three quantiles are not significant, the promotion effect on the promotion of carbon emission reduction targets at the provincial level in China is very limited.

The mean and quantile regression coefficients of industrial structure upgrading are both negative and exhibit a "V" shaped trend, indicating that the increase in the proportion of the tertiary industry is conducive to reducing the dependence of China's inter provincial regions on traditional fossil fuels, helping China's industrial enterprises to achieve low-carbon transformation and development, and thus having a positive impact on the promotion of China's inter provincial carbon emission reduction goals. The mean and quantile regression coefficients of greening level show an overall increasing trend, which means that with the improvement of inter provincial greening level in China, the carbon absorption capacity and carbon sink level of the inter provincial ecological environment continue to increase, which can effectively increase the total amount of carbon dioxide gas absorption, help alleviate the pressure of inter provincial carbon emission

reduction in China, and have a positive effect on promoting the achievement of carbon neutrality goals.

5.2. Spatial Panel Regression Results

The global Moran index shows that from 2011 to 2020, the carbon emissions of 30 provinces and cities in China have a strong spatial positive correlation, which can be used for spatial effect analysis. The Hausman test results indicate that a spatial Durbin (SDM) model with individual fixed effects should be selected. For the convenience of comparison, the OLS regression results are also listed (see Table 4).

Table 4. OLS and Spatial Durbin Model Regression Results

Variable	OLS	0-1 spatial adjacency matrix	Geographic distance matrix	Economic distance matrix
lnSP	0.3544**	0.5159***	0.3677***	0.4624***
	(2.84)	(3.59)	(4.07)	(3.84)
lnED	0.6451***	0.4832***	0.5981***	0.4083***
	(19.61)	(16.03)	(18.72)	(14.91)
lnDA	-0.8417*	-0.6781*	-0.7941*	-0.7017*
	(-2.53)	(2.66)	(1.97)	(2.04)
lnISL	-0.4796***	-0.4801**	-0.7013***	-0.4066***
	(-6.71)	(-3.41)	(-5.51)	(-4.48)
lnGL	-0.1709***	-0.1055***	-0.8961***	-0.0651***
	(-8.81)	(-7.49)	(-4.65)	(-7.02)
$w \times \ln SP$		-1.4563*	-0.5626	-0.1614
		(-4.16)	(-2.84)	(-2.47)
$w \times \ln ED$		0.5621**	0.02639***	-0.1562*
		(8.45)	(4.48)	(-4.15)
$w \times \ln DA$		0.8134	-0.6560***	-0.5895
		(5.56)	(-4.59)	(-3.21)
$w \times \ln ISL$		-1.0899***	-0.4617**	-0.1603***
		(-5.59)	(-2.25)	(-4.81)
$w \times \ln GL$		-0.0353	-0.2625	0.2562**
		(-0.54)	(-0.15)	(4.85)
Constant	0.4987			
	(0.49)			
rho		0.5256***	0.4568***	0.5659***
		(4.48)	(8.95)	(4.9)
Log-L		389.5671	303.5652	297.5951
N	300	300	300	300
R^2		0.9140	0.8589	0.8514

Note: *, * *, * * respectively indicate passing the 10%, 5%, and 1% significance tests.

Table 4 shows that the regression coefficients of each explanatory variable under different spatial weight matrices have the same direction and are consistent with the OLS regression coefficients, indicating that the regression analysis results are robust and effective. Among them, the spatial regression coefficients of population size, economic development level, industrial structure upgrading, and greening level are all significant at the 5% level, and the spatial regression coefficients of digital agriculture development level are also significant under the economic distance matrix, indicating that these variables are important factors affecting inter provincial carbon emissions in China, and their impact on inter provincial carbon emissions is consistent with the quantile regression results.

At the same time, the rho values are significantly positive at the 1% level, indicating a positive correlation between carbon emissions in different provinces. That is, an increase in carbon emissions in a region will drive an increase in

carbon emissions in its neighboring regions. The reason may be that the increase in carbon emissions caused by fossil energy consumption in a certain province or city region means an increase in its economic production capacity, and drives the corresponding increase in the total economic output of the region, leading to a simultaneous increase in the demand for industrial raw materials by manufacturers in the region and the demand for consumer goods by residents in the region. The supply of industrial raw materials and consumer goods not only comes from the region, but also from neighboring provinces and cities, Therefore, it will promote an increase in fossil energy consumption in adjacent areas, leading to an increase in carbon dioxide emissions in adjacent areas.

5.3. Analysis of Spatial Spillover Effects

The spatial Durbin model regression results cannot reflect the magnitude of indirect forces, so partial differentiation method is used to decompose direct and indirect effects (see Table 5).

Table 5. Decomposition of Spillover Effects

Spatial weight matrix	Variable	Direct effect	Indirect effect	Total effect
0-1 spatial adjacency matrix	lnSP	0.4784***	-0.4982	0.4941*
	lnED	0.4652***	0.0416	0.4864***
	lnDA	0.7484***	-0.5255	0.5464
	lnISL	-0.4798	-1.4940***	-1.4789***
	lnGL	-0.4598***	0.1517	-0.4945
Geographic distance matrix	lnSP	0.4894**	-1.9479*	-1.4984
	lnED	0.8771***	0.4629***	0.7912***
	lnDA	0.4662**	0.1365	0.4864
	lnISL	-0.4644**	-1.4547***	-1.4987***
	lnGL	-0.7897***	-0.4864	-0.7411*
Economic distance matrix	lnSP	0.9527**	-0.7896	-0.0454
	lnED	0.4894***	0.4454***	0.2655***
	lnDA	0.4861***	-0.5454***	-0.8418
	lnISL	-0.4984***	-0.4416***	-0.8488***
	lnGL	-0.0645***	-0.1587	-0.4987*

Note: *, * *, * * respectively indicate passing the 10%, 5%, and 1% significance tests.

Table 5 shows that in terms of population size, the direct effects under different spatial weight matrices are significantly positive, but the indirect effect direction is negative, indicating that the expansion of population size will increase the carbon emissions in the local area and to some extent suppress the growth of carbon emissions in neighboring areas. This may be due to the fact that an increase in population size in a region will promote production and consumption growth, consume more fossil fuels, and generate more carbon emissions. The increase in population size may be affected by the migration of population from surrounding areas, thereby slowing down the growth rate of production and consumption in areas with population loss, and to some extent inhibiting the increase in carbon emissions in surrounding areas.

In terms of economic development level, the regression results of geographical and economic distance matrices indicate that the direct and indirect effects of inter provincial carbon emissions are significantly positive, and the direct effects of spatial adjacency matrix regression are also significantly positive. This indicates that the improvement of economic development level not only causes an increase in carbon emissions in the local area, but also in the surrounding areas. The reason may be that there is a high degree of economic correlation between provinces, cities, and regions in China. As a result of economic development, a region increases fossil energy consumption, while also increasing demand for industrial and consumer goods in the surrounding areas. This will further promote the economic development of the surrounding areas and lead to an increase in fossil energy consumption.

In terms of the development level of digital agriculture, the regression results under the three spatial weight matrices indicate that the direct effect of inter provincial carbon emissions is significantly positive, but the indirect effect is only significantly negative under the economic distance matrix. This indicates that the improvement of the development level of digital agriculture will significantly cause an increase in local carbon emissions and to some extent inhibit the growth of carbon emissions in adjacent regions. The reason may be that with the acceleration of the development process of digital agriculture, an increasing number of people and technological products are gathering together, which will lead to the agglomeration growth of local production and consumption, thereby increasing fossil energy consumption. Moreover, due to the migration of population in surrounding areas, the production and consumption demand in surrounding areas is reduced, thereby suppressing the increase in fossil energy consumption in neighboring areas.

In terms of industrial structure upgrading, the regression results of geographical and economic distance matrices indicate that both direct and indirect effects of inter provincial carbon emissions are significantly negative, and the indirect effects under spatial adjacency matrix regression are also significantly positive. This indicates that as the proportion of the tertiary industry economy increases, the carbon emissions of the local and neighboring regions show a significant downward trend. The reason may be that the tertiary industry is mainly composed of the service industry and has a lower

dependence on fossil energy. A higher proportion of the tertiary industry means that the amount of fossil energy required for economic development is less, and the corresponding carbon emissions are also less. Under the synergistic effect of upgrading the industrial structure with surrounding provinces and cities, it has to some extent suppressed the rise of carbon emissions in neighboring areas.

In terms of greening level, the direct effects of the three spatial weight matrices regression are significantly negative, but the indirect effects are not significant. This indicates that the improvement of greening rate has a significant inhibitory effect on the increase of carbon emissions in the local area. The reason is that the higher the level of greenery in a region, the higher the number of green plants that can absorb carbon dioxide, and the more carbon dioxide can be absorbed through photosynthesis of green plants, which is more conducive to promoting carbon emission reduction goals in China's inter provincial regions.

6. Robustness Testing

By comparing three spatial regression models, the robustness of the regression results has been preliminarily verified in the previous text. In addition, there may be a two-way causal relationship between carbon emissions and economic development, that is, on the one hand, rapid economic development will lead to a large number of fossil energy consumption, leading to an increase in greenhouse gas emissions; On the other hand, due to the substantial increase in carbon emissions, the state will strengthen the supervision of the environment and encourage industrial enterprises to reduce CO2 emissions through the development of low-carbon technologies. On this basis, the two-step least square method proposed by sunhuachen, sunfengkai and others [10] was used to test its endogeneity. The results indicate that the empirical results are basically consistent with the regression results of the spatial Durbin model mentioned earlier, so the empirical analysis results in this article are robust.

7. Conclusion and Suggestions

We used the surface energy consumption estimation method to measure and analyze the carbon emissions of 30 provinces and cities in China from 2011 to 2020, and selected multiple indicator dimensions to measure the development level of digital agriculture through the entropy weight TOPSIS algorithm. We empirically analyzed the factors affecting inter provincial carbon emissions in China. The results indicate that the total carbon emissions in China are showing an overall growth trend; Under different quantiles, the impact of digital agriculture development level and population size on inter provincial carbon emissions decreases, the impact of industrial upgrading level first decreases and then increases, and the impact of economic development level and greening level increases; The population size will promote the rise of carbon emissions in the local area and suppress carbon emissions in neighboring areas, the level of economic development will promote the rise of carbon emissions in the local and neighboring areas, the level of digital agriculture development will suppress the rise of carbon emissions in the local area, and the level of industrial upgrading and greening will suppress the rise of carbon emissions in the local and neighboring areas. Therefore, the following suggestions are proposed:

(1) Reasonably allocate fossil energy element resources and continuously promote the development of digital agriculture. As a major agricultural country, China's digital transformation of agriculture can effectively reduce carbon emissions. In addition, major industries in China are also in a critical period of low-carbon transformation and development. On the basis of ensuring the stability of China's economic fundamentals, it is necessary to better utilize market mechanisms to promote the optimization of energy factor allocation, improve the market exit mechanism for high energy consumption and high emission enterprises, resolutely eliminate industrial enterprises that are unfavorable or lack awareness of low-carbon transformation from the market, and enhance market incentives for the development of low-carbon enterprises. We still need to further promote the optimization and upgrading of China's industrial structure, stimulate the growth and progress of more service-oriented small and medium-sized enterprises, enhance the development momentum of China's tertiary industry, accelerate the process of inter provincial carbon reduction, and help achieve carbon neutrality goals as soon as possible.

(2) Strengthen the supervision of ecological environment protection and enhance the carbon absorption capacity of the ecosystem. Further enhance local governments' awareness of ecological and environmental protection, strengthen supervision and supervision of ecological and environmental protection, and improve long-term mechanisms for ecological and environmental protection. At the same time, measures such as artificial afforestation, forest restoration, wetland protection, natural water ecological environment protection, returning farmland to forests and grasslands will be taken to protect and increase the carbon sequestration capacity of the natural ecology, promote the sustainability of the natural ecology's carbon sequestration and absorption capacity, and enhance the ability of the ecosystem to suppress the growth of inter provincial carbon emissions in China.

(3) Advocate for a low-carbon development model and vigorously develop low-carbon technologies. On the one hand, China should actively advocate the use of low-carbon clean energy to replace fossil energy consumption, reduce carbon emissions from the source, promote the improvement of low-carbon, energy-saving, and environmentally friendly economic development models, and explore the establishment of a low-carbon, energy-saving, and environmentally friendly society; On the other hand, technological progress plays a decisive role in achieving carbon neutrality goals. Therefore, we need to vigorously develop low-carbon technologies, focus on promoting the low-carbon transformation and development process of industrial enterprises, and comprehensively enhance China's industrial enterprises' carbon emission reduction capabilities and support carbon neutrality capabilities.

Acknowledgments

This research is funded by Anhui University of Finance and Economics Provincial College Student Innovation and Entrepreneurship Training Program Project (No.: S202210378247).

References

[1] Zhang Hong, Wang Haoran, Li Zhe. Measurement of the High Quality Development Level of Digital Agriculture in China under the Background of Rural Revitalization: Analysis Based on Data from 31 Provinces and Cities in China from 2015 to

2019 [J]. Journal of Shaanxi Normal University (Philosophy and Social Sciences Edition), 2021,50 (03): 141-154.

[2] Ma Xiaoni, Li Qiang. Evaluation of Digital Agriculture and Rural Development Level and Analysis of Temporal and Spatial Differences [J]. Xinjiang Agricultural Reclamation Economy, 2023, (01): 39-50.

[3] Wang Wenshu. Comprehensive Evaluation and Influencing Factor Analysis of the Development Level of Digital Agriculture in China's Provinces [D]. Inner Mongolia University of Finance and Economics, 2022.

[4] Xie Yonghao, Liu Zheng. A Study on the Spatial and Temporal Differentiation and Equity of Carbon Sink and Carbon Emissions in China's Provincial Planting Industry [J] World Agriculture, 2022, (02): 100-109.

[5] Chen Jiang, Xiong Ligui. Research on the connotation, mechanism, challenges, and promotion path of digital agriculture [J]. Southwest Finance, 2022, (10): 92-102.

[6] Zhao Yuxiang, Liu Jun. The impact of green technology innovation on carbon emission efficiency under the dual carbon target [J]. Operation and Management: 1-15.

[7] Cao Ze, Zhang Hao, Cheng Yi. Research on the Impact of Industrial Intelligence on Carbon Emission Intensity in China under the Background of "Dual Carbon" [J]. Journal of Chongqing University of Technology (Social Sciences): 1-16.

[8] Liu Yiwen, Yang Chao, Cai Hongyu. Inter-provincial differences and factor decomposition of China's total carbon emissions and intensity [J]. Journal of Hunan University of Technology, 2022, 36 (01): 1-9.

[9] Wang Hong, Guo Heng, Wu Jingyun, Zhang Zheqiao. Research on the Evaluation of Low Carbon Transformation Process of Power Generation Enterprises Based on Entropy Weight TOPSIS Method [J]. Thermal power generation, 2023,52 (07): 26-32.

[10] Sun Huachen, Sun Fengkai. Empirical evidence on the impact of urban-rural income gap on carbon emissions - also on how "fairness" can improve "efficiency" [J]. Macroeconomic Research, 2016, (01): 47-58.