Global NEST Journal, Vol 26, No 9, 06424

Driving effects and spatial spillover of technological innovation on the carbon balance of agriculture

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Received: 10/07/2024, Accepted: 20/08/2024, Available online: 08/010/2024
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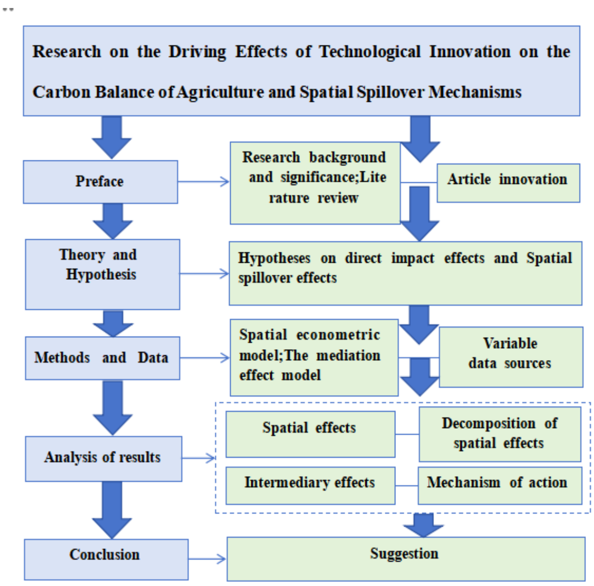
https://doi.org/10.30955/gnj.06424

Graphical abstract



Abstract

There is significant controversy over the overall effects of technological innovation on carbon balance. Based on panel data of agriculture from 28 provinces in China from 2009 to 2021, utilizing ArcGIS and spatial Durbin model, the spatial-temporal patterns of agricultural technological innovation and carbon balance are analyzed, and furtherly the spatial effects of technological innovation on carbon balance are examined. The results indicate: (1) the overall agricultural carbon surplus in Chinese provinces has been continuously increasing from 2009 to 2021; (2) the direct effect of technological innovation on the carbon surplus in agriculture is significantly positive, while the spatial spillover effect is significantly negative; (3) the mediating effect results show that technological innovation affects the output of the agricultural sector and thereby influences agricultural carbon balance; (4) the impact of technological innovation on agricultural carbon balance exhibits an asymmetric spatial spillover effect. Advantageous regions suffer from the positive effects of spatial spillover, while non-advantageous regions benefit from the negative impacts of spillover, resulting in an overall negative effect. This study's findings play an important role in addressing the existing controversy over the overall effects of technological innovation on carbon balance and provide important insights for formulating policies on low-carbon technological innovation in agriculture.

Keywords: Technological innovation effects, agricultural carbon balance, spatial spillover effects, direct effects, indirect effects

1. Introduction

In the context of actively promoting the dual-carbon strategy goals in China, research on agricultural carbon emissions has gradually become a hot topic. Technological innovation is considered one of the key means to address the issue of carbon emissions. However, there has long been controversy in economics regarding the role of technological innovation in solving environmental problems, with the earliest debates tracing back to the British economist Jevons, who proposed the famous "Jevons Paradox". This paradox points out that technological progress can improve resource utilization efficiency, thereby saving energy usage, but at the same time, it also reduces the relative prices of resource, inversely leading to the risk of excessive resource consumption and environmental degradation.

For the calculation of carbon emissions and carbon sinks, China currently lacks direct monitoring data. Existing assessments of carbon balance are based on "top-down" inventory methods, model evaluation methods, or flux methods. Developed countries have already conducted research on atmospheric observation, inversion monitoring, and verification and support methods. The monitoring and evaluation of carbon emissions/sinks in China remains a key focus of current research. Current studies indicate that China's carbon balance over the past 20 years has shown a trend of increasing firstly and then slowing down, with a spatial distribution pattern of "higher in the north, lower in the south, more in the east, and less in the west" (Yan L., Zong L., 2024). In terms of the Jevons paradox effect associated with technological innovation, while it aids in lowering carbon source emissions and boosting carbon sinks, demand and price effects can potentially reverse the overall impact, resulting in a negative influence on carbon balance. In agriculture and animal husbandry, existing literature examines the controversy surrounding the impact of technological innovation on environmental carbon balance. Some studies suggest that technological innovation can enhance agricultural carbon surplus, while others argue that it diminishes agricultural carbon surplus.

Research on the impact of technological innovation on carbon balance mainly focuses on carbon emissions. Mojority ofliterature studies indicate that green technology innovation aids in reduceinge carbon emissions. Qin (2023) constructed a spatial Durbin model to empirically test the external spillover effects of green technology innovation on industrial carbon emissions. Cheng *et al*. (2023) used ArcGIS spatial analysis and spatial Durbin model to examine the spatial effects of green technology innovation on industrial carbon dioxide emissions. Shen *et al*. (2023) constructed static and panel models to investigate the impact of green technology innovation on carbon emission intensity and the pathways of action. Duan and Jin (2021) applied the spatial Durbin model to empirically test the direct effects and spatial spillover effects of green technology innovation on low-carbon productivity. Wang *et al*. (2021) established a spatial Durbin model (SDM) to study the relationship between green innovation and low-carbon productivity. Shi and Tang (2019) utilized panel data models to study the impact of low-carbon technology innovation on carbon emissions and the response of energy consumption to low-carbon technology. Tian and Wu (2023) used a panel data Tobit model to test the independent and synergistic effects of urbanization, technological innovation, and regional carbon emission performance in three rural regions. Pei and Chen (2023) used a panel vector auto-regressive model to study the relationship between technological innovation and low-carbon productivity. Some studies have found that technological innovation has a negative or insignificant effect on low-carbon productivity. Some literature suggests that technological innovation reduces low-carbon productivity, such as Fang and Xue (2024) who constructed a spatial econometric model to study the negative effects of economic growth and technological innovation on carbon emissions. Lu *et al*. (2019) empirically tested the direct impact and spatial spillover effects of breakthrough low-carbon technology on carbon emissions using a dynamic spatial Durbin model (SDM). Some literature suggests that technological innovation has no significant effect on carbon productivity, such as Xu *et al*. (2020) who used a panel quantile model to compare the impact of energy use technology, carbon emission technology, and general technological innovation on regional carbon emissions. Chen (2019) analyzed the threshold effects and correlations between technological innovation, carbon emissions, and economic growth in China based on a nonlinear panel threshold model.

Some literature has assessed the effects of carbon balance. Ding *et al*. (2024) measured the driving factors and spatiotemporal heterogeneity of carbon balance in rural of Shaanxi Province. Zhou *et al*. (2023) assessed the spatiotemporal distribution and influencing factors of carbon sources/sinks and carbon balance in the three northeastern provinces of China. Chen *et al*. (2023) combined carbon sources/carbon sinks with GDP data to explore the spatiotemporal variation characteristics of carbon emission intensity and carbon sink intensity at the provincial level in China from 2005 to 2020. Based on this, they analyzed the spatiotemporal changes in carbon balance over 15 years and used a geographical detector to identify the driving factors influencing carbon balance at different periods. Wang *et al*. (2016) calculated the spatiotemporal changes in carbon sources and carbon sinks in Henan Province. Wang *et al*. (2024). selected driving factors from both Shanxi and national levels to construct an open STIRPAT model, and applied scenario analysis to predict the carbon emissions in Shanxi Province from 2021 to 2040, providing strategic solutions for energy conservation and emission reduction.

Some studies have explored the relationship between technological innovation and agricultural carbon sequestration. Cao *et al*. (2022) introduced agricultural carbon sequestration and carbon emissions as desirable and undesirable outputs, respectively, into the framework of agricultural production performance analysis. Using panel data from 31 provinces (including autonomous regions and central-controlled municipalities) from 2007 to 2020 as samples, they evaluated the carbon sequestration effect and agricultural production performance using carbon measurement models, revealing their spatiotemporal characteristics. Shen and Zhou (2022) measured agricultural green TFP from the perspectives of carbon sequestration and carbon emissions based on provincial panel data in China from 2000 to 2019, and conducted spatial convergence analysis. Combining panel data from 42 low-carbon pilot provinces and cities in China from 2007 to 2015, Chen and Jiang (2017) analyzed the spatiotemporal trends of the development performance of low-carbon agriculture in China using carbon measurement models, super-efficiency SBM models, and ML efficiency indices, and then evaluated the effects of low-carbon agricultural policies in different regions.

Limited research exists on the holistic effects of technological innovation on carbon balance in agriculture. Current studies have not thoroughly investigated the mediating effects of changes in agricultural product demand on the relationship between technological innovation and carbon balance, which is linked to the Jevons paradox. This impact is more pronounced in agricultural output than in industrial output. Hu *et al*. (2018) used panel data of 30 provinces in China from 2003 to 2014 to study the influence of agricultural policies on agricultural technological innovation in the context of increasing environmental protection constraints, as well as the pathway through which technological innovation affects agricultural carbon emissions. Zhang and Wang (2020) studied the moderating effects of environmental regulations on the impact of agricultural technological innovation on agricultural carbon emissions using the System GMM method. Liu *et al*. (2022) constructed a spatial Durbin model and used a multiple mediation effects model to analyze the transmission mechanism of the impact of green technological innovation on carbon productivity through three intermediate variables: industrial structure upgrading, development of circular agriculture, and substitution of transportation. He *et al*. (2021) combined traditional Durbin models and partitioned Durbin models to analyze the correlation of agricultural carbon emission, cooperation modes arrangement, and agricultural technology spillovers effect.

In conclusion, existing empirical studies consistently demonstrate the positive impact of green technology innovation on carbon emissions. However, there is limited research on the overall impact of technological innovation on carbon balance, leading to significant controversy among these studies. It is crucial to provide a unified explanation for these discrepancies and to uncover the pathways and mechanisms through which technological innovation affects carbon balance. This study's key contribution lies in analyzing the direct effects of technological innovation on agricultural carbon balance using data on Chinese agricultural technological innovation and carbon balance. Additionally, spatial econometric methods are utilized to investigate the spatial spillover effects of technological innovation on agricultural carbon balance. Subsequently, an intermediate effect model is developed to examine the asymmetric impact of technological innovation on carbon surplus in agricultural sectors (provinces), thus resolving the discrepancy of the opposite signs of direct and indirect effects and offering new insights into the empirical results on the effects of technological innovation on carbon balance. The findings of this study will serve as a scientific foundation for the comprehensive development of agricultural low-carbon policies at both national and regional levels.

2. Theoretical analysis and research hypotheses

The close economic ties between regions lead to the impact of regional technological innovation not only on the carbon balance of the local agriculture, but also on that of the adjacent areas. Based on existing research (Jin and Li, 2023) this paper analyzes the effects of technological innovation on the carbon balance of agriculture from two dimensions: direct effects and spatial spillover effects (see Figure 1).

2.1. Direct impact effects

The impact of technological innovation on carbon balance is initiated through two processes. The first process is manifested as the growth of quantity and quality of agricultural production factors, which is directly driven by technological innovation. There are two main direct effects:

Positive effects of technological innovation on carbon balance: By adopting innovative techniques, tools, and facilities that reduce carbon emissions and increase carbon sequestration, the carbon surplus in the area can be directly enhanced.

Effect of increased planting scale: Through technological innovation that saves land, the same area of farmland can achieve more output, equivalent to increasing the cultivated area Similarly, technological innovations that save labor and capital can boost overall agricultural output in the same area by achieving greater productivity with the same input of labor and capital. Scaling up the planting operations can elevate the carbon surplus level in the local area, leading to a reduction in carbon emissions and an increase in carbon sequestration. Therefore, we have the following research hypothesis:

Hypothesis 1: Technological innovation has a positive direct effect on the carbon balance of agriculture.

2.2. Spatial spillover effects

The second process that influences the carbon balance of technological innovation is the spatial diffusion process resulting from the impact and dissemination of the initial process, known as the spatial spillover effect. This effect primarily arises from the demand-increasing effect triggered by the quantity and quality impacts. The positive quantity or quality effects induced by the initial technological innovation lead to alterations in the relative prices of agricultural production factors in the region and neighboring areas, thereby influencing the demand and supply of production factors. This process will impact the carbon balance of agriculture. The environmental consequences brought about by demand growth align with the Jevons paradox, wherein an increase in demand will lead to a negative spatial spillover effect on the carbon balance of the region.

Spatial spillover effects induced by changes in planting: Variations in demand will result in disparities in the adoption scale of technological innovations across different regions, causing the spatial spillover effects to diverge from the direct effects. For instance, regions with a significant original planting area may exhibit a relatively muted response to land-saving technological innovations, whereas regions with a smaller planting area may respond positively to the same type of technological innovation. This leads to a marginal shift in the direction of planting area contrary to the initial relative scale proportion, thereby generating effects on the carbon balance that are diametrically opposed to the direct effects, resulting in negative spatial spillover effects.

Regional convergence effect of farming scale: According to the law of diminishing marginal returns, regions with different planting scales have divergent demands for technological innovation. In relatively land-abundant regions with large land scales, there will be less use of land-saving technological innovations, while in relatively land-scarce regions, the use of the same technology will increase. Under the influence of this marginal effect of technology use, the farming scales of regions will tend to converge. Specifically, regions with larger farming scales will relatively decrease their farming scale, while regions with smaller land scales will relatively increase their farming scale. In contrast to the direct effects, this influence leads to negative spatial spillover effects of technological innovation on the carbon balance. Based on this, this article proposes research hypothesis 2:

Hypothesis 2: Technological innovation has a significant negative spatial spillover effect on the carbon balance of agriculture.

Negative spatial spillover effects occur through two channels: one is through the impact of technological innovation on the demand for agricultural products, which in turn affects the carbon balance, and the other is through the bias effect on the regional planting scale. Therefore, hypotheses 3 and 4 can be proposed:

Hypothesis 3: The mediating effect of agricultural product demand is negative, that is, technological innovation will reduce the carbon surplus level by influencing the level of demand for agricultural products. This hypothesis will confirm the existence of the Jevons paradox.

The carbon balance effects of technological innovation will have heterogeneous impacts on regions with different planting scales. By testing this hypothesis, the sign of the indirect effects and total effects on the carbon balance can be determined.

Hypothesis 4: The proportion of planting scale has a negative mediating effect on the carbon balance of technological innovation.

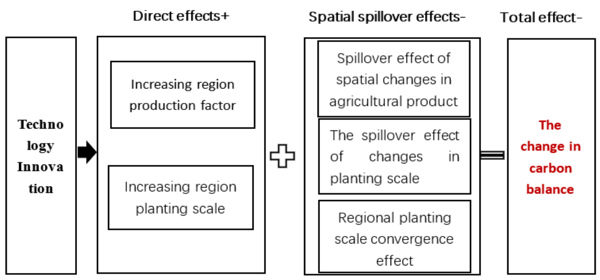


Figure 1. The Impact of technological innovation on agricultural Carbon balance

3. Methods and data

3.1. Research methods

3.1.1. Spatial econometric model

Introduction to a spatial econometric model analyzing the impact of technological innovation, population density, and clustering of agricultural industries on agricultural carbon balance is crucial. Common spatial econometric models include spatial autoregressive (SAR) models, spatial error (SEM) models, and spatial Durbin models (SDM). The specific models are outlined as follows:

$$\mathrm{SAR}: CB = \rho W \times CB + \beta_i X + \mu \quad (1)$$

$$\mathrm{SEM}: CB = \beta_i X + \mu, \mu = \lambda W \mu + \varepsilon \quad (2)$$

$$\mathrm{SDM}: CB = W \times CB + \beta_i X + \delta_i WX + \mu \quad (3)$$

In the equation, CB represents the dependent variable of carbon balance; X denotes all explanatory variables; ρi and δi are spatial autoregressive coefficients; W is the spatial weight matrix; βi represents the coefficients of X; and μ stands for the random error.

3.1.2. The mediation effect model

Construct the following model for testing the mediating effect, the model is as follows:

$$CB = c_0 + c_1 TI + \theta X + \varepsilon_1 \quad (4)$$

$$M = \partial_0 + \partial_1 TI + \theta X + \varepsilon_2 \quad (5)$$

$$CB = \gamma_0 + \gamma_1 TI + \gamma_2 M + \theta X + \varepsilon_3 \quad (6)$$

In the equation，CB represents the dependent variable carbon balance; TI represents the core independent variable technological innovation; X represents other explanatory variables; M represents the mediating variables, including agricultural supply and demand and planting scale; c1 represents the total effect of technological innovation on carbon balance; ∂2 represents the effect of technological innovation on the mediating variable M; γ1 and γ2 respectively represent the effects of the mediating variable M on carbon balance and the direct effect of technological innovation on carbon balance after controlling for the mediating variable M.

3.2. Variable selection

3.2.1. Explained variables

When conducting research and analysis using spatial econometric models, the carbon balance (CB) are selected as the dependent variable, and the measurement method is as follows:

(*1*) *Calculation of agricultural carbon emissions*

Based on the measurement methods in relevant literature, a framework for calculating agricultural carbon emissions in various provinces (including autonomous regions) of China is established from three aspects: paddy cultivation, agricultural land use, and livestock breeding. The calculation formula is as follows:

$$C = \sum C_{it} = \sum T_{it} \cdot \partial_i \quad (7)$$

Where C is the total agricultural carbon emissions, C_{it} is the agricultural carbon emissions of the i-th carbon source in year t, T_{it} is the amount of the i-th carbon source in year t, and ∂_i is the carbon emission coefficient of various carbon sources (see Appendix 1).

(*2*) *Calculation of agricultural carbon sequestration*

Chen *et al.* (2016) defined agricultural carbon sequestration as the fixation of atmospheric carbon by crops through photosynthesis during the growth process, as well as the amount of carbon absorbed by crops. Referring to the research of Li (2002), the carbon absorption of crops is calculated using the economic coefficients, carbon absorption rates, and moisture content of different crops (see Appendix 2).

(*3*) *Calculation of agricultural carbon balance*

The carbon balance can reflect the relationship between regional carbon emissions and carbon absorption, expressed as the difference between agricultural carbon absorption and agricultural carbon emissions. The calculation formula is:

$$CB = S - C \quad (8)$$

The CB represents the agricultural carbon balance in a certain region in a certain year, where S stands for carbon sequestration and C stands for carbon emissions. When CB > 0, it indicates a carbon surplus in the region; when CB < 0, it indicates a carbon deficit in the region; when CB = 0, it indicates carbon neutrality in the region (see Appendix 3 and 4).

3.2.2. Core explanatory variables

Technological innovation (TI) is represented by the number of agricultural patent applications in various regions. Enterprise technological innovation is mainly measured from the perspective of innovation output, using the number of patent applications to gauge innovation output.

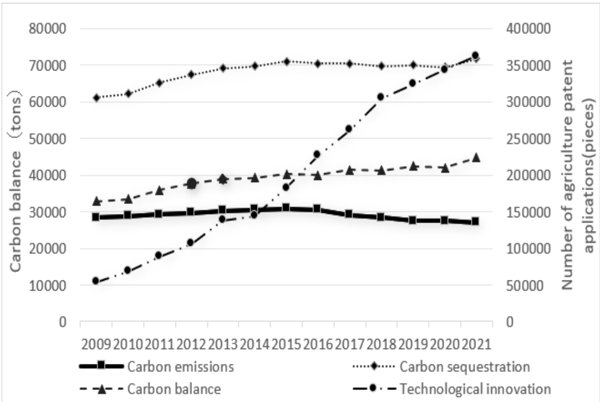


Figure2. Trends and Structure of Carbon Balance and Technological Innovation Changes from 2009 to 2021

3.2.3. Control variables

(1) Population density (DENSITY) is represented by the ratio of the total population to the area of the region. The change in population density will affect various factors such as production, consumption, and others, thereby influencing the carbon balance. (2) Agricultural industry agglomeration (Industry) is measured by location entropy, that is, the ratio of the agricultural, forestry, animal husbandry, and fishery output value of region i in year t to the national agricultural, forestry, animal husbandry, and fishery output value, and the ratio of the total output value of region i in year t to the national total output value. Changes in the agglomeration of the agricultural industry can affect the total carbon emissions. (3) Government intervention (GOV) is represented by the ratio of local fiscal expenditure to GDP.The advancement and implementation of government-related policies can impact the regional carbon balance through adjustments in industrial structure, energy structure, and other aspects. (4) Level of financial development (FINANCIAL) is represented by the ratio of the balance of various loans of financial institutions at the end of the year to GDP.Financial development can influence regional carbon balance through foreign investment, loans, and other means. (5) Level of economic development (GDP_PC) is represented by per capita GDP.The improvement of the economic development level will lead to an increase in energy-intensive products, thereby increasing carbon emissions; furthermore, after the economic development level reaches a certain point, the industrial structure within the region will be optimized and upgraded, leading to a reduction in carbon emissions. (6) Economic growth rate (GROWTH RATE) is represented by the GDP growth rate Changes in the speed of economic growth can drive the optimization and upgrading of industrial structure and technological progress, thereby impacting the regional carbon balance.

3.2.4. Mediating variables

(1) Agricultural supply and demand (using lnGDP_pc as proxy index) – In order to obtain more robust regression results, the total agricultural output value is logarithmically centered, and the total agricultural output value can serve as a proxy variable for changes in agricultural demand;

(2) Planting scale (PS) is represented by the proportion of the total planting area of crops in each province and city to the planting area of crops in various regions.

3.3. Data source

Panel data from 28 provinces and cities (Guizhou, Xinjiang, and Tibet not includes due to data sparsity issues) from 2009 to 2021 are selected as the research sample. The data comes from the "China Statistical Yearbook" of previous years, the National Bureau of Statistics, and the statistical yearbooks of various regions. In order to meet the requirements of spatial econometrics for data completeness, linear interpolation is used to fill in missing data for the number of agricultural patent applications. Descriptive statistics for each variable are shown in Appendix 5.

4. Analysis of results

4.1. Spatial-temporal pattern and dynamic evolution of carbon balance

(1) Evolution characteristics of carbon balance over time

The above variables were calculated to obtain carbon emissions, carbon sequestration, and carbon balance results, as shown in Figure 2. From 2009 to 2021, agricultural carbon emissions showed a fluctuating downward trend, while agricultural carbon sequestration showed a fluctuating upward trend, increasing from 61,182.08 million tons in 2009 to 71,784.09 million tons in 2021, an increase of approximately 17%. The total carbon balance showed a continuous annual positively increase, rising from 32,826.59 million tons in 2009 to 44,771.42 million tons in 2021, an increase of about 36%. In addition, technological innovation also showed an increasing trend year by year, with the number agricultural patent applications increasing from 53,939 in 2009 to 362,330 in 2021. In terms of growth rate, the growth of technological innovation outpaced the growth of the carbon balance level.

(2) *Spatial evolution characteristics of carbon balance*

The carbon balance of each province and municipality are classified into four levels. Using 2010 as the base year, the rates of carbon balance and technological innovation for 2015 and 2021 were calculated. Rates of Spatial distribution maps of the carbon balance and technological innovation for each province (including autonomous region) in 2010, 2015, and 2021 were drawn using ArcGIS 10.8. Comparing the spatial distribution maps of rates of carbon balance and technological innovation in 2010, 2015, and 2021, it reveals that with time going, the carbon balance in each province continues to increase positively. The carbon balance rates in Northeast China, Inner Mongolia, and Qinghai have significantly increased after 2015. In addition, the overall technological innovation level of each province shows an increasing trend, in which Inner Mongolia, Qinghai, and Anhui have notably increased more. Specifically, after a sharp increase in 2015, the technological innovation rate in Hainan Province declined. (Figure 3)

4.2. The impact of technological innovation on carbon balance: baseline regression results

Table 1 presents the baseline regression results. The Ordinary Least Squares (OLS) regression indicates that technological innovation is significantly positive at the 1% level, regardless of whether control variables are included. This suggests that technological innovation significantly increases regional carbon balance positively. Using the logarithm of the number of graduates from general higher education institutions in the second order lag period as an instrumental variable for technological innovation, the results similarly demonstrate that technological innovation has a significant positive effect on carbon balance at the 1% level. Hypothesis 1 is therefore validated.

Table 1. Benchmark Regression Results

Variant	Model		
	OLS	**OLS**	**IV**
TI	0.0181***	0.0135***	0.184***
	(0.00288)	(0.00491)	(0.0378)
Control Variable	NO	YES	YES
Constant	1,267***	1,159***	1,437***
	(280.3)	(375.4)	(398.0)
R-squared	0.0237	0.0060	0.4901
N	364	364	308

*Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.*

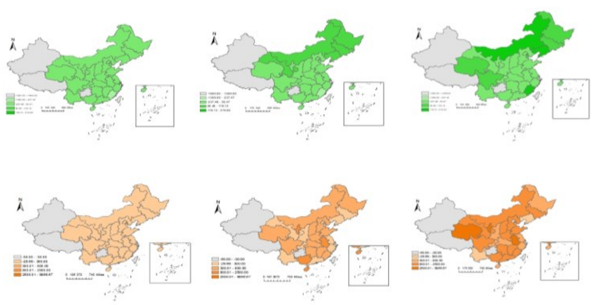


Figure 3. Spatial Evolution of the Rate of Agricultural Carbon Balance and Technological Innovation in different Provinces of China in 2010,2015, and 2021

The direct result of regional technological innovation is an enhancement in the output efficiency of agricultural production factors within the region, meaning that technological innovation enables the same resources and factors to achieve greater output. This relatively intensive production also reduces regional carbon emissions or increases carbon sequestration levels. Due to economies of scale, the impact of technological innovation on carbon balance varies asymmetrically across regions. In regions where agriculture has more advantages (with economies of scale), agricultural technological innovations are more easily promoted and applied, thus exhibiting a greater effect on carbon balance in these regions. Conversely, in regions where agriculture has less advantages, the diffusion and application of technological innovations are more difficult, resulting in a smaller positively effect on carbon balance. Conversely, a decline in economies of scale might lead to a negative effect on carbon balance. This effect will be reported in subsequent mediation effect tests.

The baseline regression results failed to reveal spatial correlations between technological innovation and carbon balance. However, spatial spillover effects are crucial in understanding how technological innovation affects carbon balance. For instance, agricultural technological innovations in one region can easily be imitated by its neighbor regions through communication and trade, thereby enhancing and improving agricultural productivity in adjacent areas. When these innovations are widely applied across different regions, they influence supply and demand of agricultural market, which leading to internal differentiation and restructuring of agricultural production within each region. Such changes in agricultural production and supply will cause asymmetric variations in carbon balance across regions. Next, spatial econometric methods will be employed to further explore the spatial relationships between technological innovation and carbon balance.

4.3. Spatial spillover effects of technological innovation on agricultural carbon balance

According to the first law of geography, the carbon balance in each region is influenced not only by internal factors but also by the levels of carbon balance in neighboring regions (He *et al*,2021). Continuing to build spatial econometric models, we investigate the spatial impact of technological innovation on carbon balance. Firstly, introduce the inverse geographical distance weight matrix, which is calculated based on the latitude and longitude to represent the reciprocal of the distance between different regions as the spatial inverse geographical distance weight matrix, examining the spatial correlation of carbon balance (Table 2).we found that, except for the initial two years, the Moran's I for carbon balance in most years is significantly greater than zero, indicating a significant positive spatial autocorrelation in carbon balance.

Table 2. Moran Index of Carbon Surplus

Year	Moran'sI	Year	Moran'sI
2009	-0.001	2016	0.038*
2010	-0.002	2017	0.037*
2011	0.019*	2018	0.025*
2012	0.021*	2019	0.030*
2013	0.028*	2020	0.020*
2014	0.024*	2021	0.035*
2015	0.032*		

*Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.*

Table 3. Spatial econometric regression model results

Variant	Model			
	OLS	SAR	SEM	SDM
TI	0.0135***	0.0143***	0.0156***	0.0194***
	(0.00491)	(0.00426)	(0.00459)	(0.00428)
DENSITY	-0.645***	-0.541*	-0.587*	-0.510
	(0.238)	(0.317)	(0.321)	(0.334)
INDUSTRY	-21.11	763.6***	768.1***	692.7***
	(616.8)	(97.74)	(97.91)	(97.14)
GOV	795.8	616.3	360.9	-14.06
	(630.9)	(579.4)	(675.7)	(670.3)
GDP_PC	0.000535	0.00110	0.000887	-0.00274
	(0.00171)	(0.00163)	(0.00162)	(0.00239)
GROWTH	-115.2	-130.0	-135.1	372.4
	(325.9)	(281.7)	(315.0)	(464.6)
FINANCIAL	179.8	-13.30	23.04	11.23
	(115.3)	(86.80)	(92.09)	(113.8)
Constant	1,159***	374.7	527.7	157.4
	(375.4)	(362.3)	(341.0)	(1,073)
rho		0.0855		-0.446**
		(0.155)		(0.209)
R-squared	0.0060	0.165	0.168	0.167
N	364	364	364	364

*Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.*

For the determination of spatial econometric models, several diagnostic tests were conducted. Firstly, the LM test indicates that the R-LM-error value is not significant (see Appendix 6), which suggesting that the spatial lag model is more suitable for this spatial econometric studies. Secondly, the Hausman test shows a negative value, which means acceptance of the null hypothesis and of a random effects model. Finally, the LR and Wald tests show significant results at the 1% level, which rejecting the null hypothesis that the spatial Durbin model degenerates into a spatial lag model and spatial error model. To mitigate bias, the spatial Durbin model is ultimately chosen.

The spatial econometric regression results are presented in Table 3. The results indicate a spatial correlation coefficient of -0.446, significant at the 5% level, suggesting a negative spatial spillover effect overall for carbon balance. Technological innovation shows a positive significant effect at the 1% level, indicating its promotion to carbon balance in the region. Additionally, agglomeration in the agricultural industry also significantly promotes carbon balance positively. Other control variables show no significance

Decomposing spatial effects results are shown in Table 4. The results show that the direct effect of technological innovation is significantly positive at the 1% level. Which indicates that technological innovation plays a promotional role in the carbon balance for region's agricultural sector, significantly enhancing region carbon balance. Meanwhile, the indirect effect of technological innovation is significantly negative at the 1% level, which suggesting a suppressive effect on the carbon balance of adjacent regions, which confirms Hypothesis 2. The impact of technological innovation on adjacent regions' carbon balance is primarily achieved through its influence on supply and demand of agricultural products. The theoretical analysis is as follows: in the first stage, the direct effect phase, technological innovation enhances the efficiency of agricultural production factors locally, thereby directly increasing the agricultural carbon balance in one region. In the second stage, as technological innovation spills over through exchange and trade, adjacent regions also benefit from the improved efficiency of their production factors. During this process, changes in relative prices of production factors also affect their allocation. Such impacts vary across regions of with different factor proportions. For instance, technological innovations that demands less land will primarily promote the producing of regions of with less land, thereby mainly affecting the carbon balance of these regions positively. Conversely, regions with more agricultural land are less affected by the same technological innovation, which resulting in a less significant increase in spill-over effects.

The results of Table 4 indicate a significant negative spatial spillover effect, suggesting that the changes in supply and demand of agricultural products are substantial enough to result in a dominant negative spatial spillover effect in regions of with larger agricultural land areas. Further decomposition and intermediate effect analysis of the spatial effects are presented below.

Additionally, population density inhibits region carbon balance, indicating that as population density increases in a region, carbon balance will decrease. Agricultural industry agglomeration promotes regions carbon balance positively, indicating that higher levels of agricultural industry agglomeration facilitate an increase in carbon surplus. Government intervention and economic development have a significantly positive impact on the carbon balance of adjacent regions and a negative impact on themselves' carbon balance, albeit not significant.

Table 4. Decomposition o fspatial effects

Variant	Direct effect	Indirect effect	Total effect
TI	0.0212***	-0.0563***	-0.0351***
	(0.00449)	(0.0133)	(0.0123)
DENSITY	-0.535*	0.395	-0.140
	(0.320)	(0.947)	(1.016)
INDUSTRY	711.0***	-264.4	446.6
	(92.89)	(459.3)	(459.5)
GOV	-123.2	2,975***	2,852***
	(656.1)	(1,082)	(919.1)
GDP_PC	-0.00321	0.0189***	0.0157***
	(0.00231)	(0.00390)	(0.00307)
GROWTH RATE	417.7	-586.1	-168.4
	(479.1)	(552.9)	(292.9)
FINANCIAL	21.79	-294.7	-272.9
	(118.7)	(240.2)	(218.6)

*Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.*

4.4. Robustness test

The robustness test is conducted using adjacent spatial weight matrix and geographical distance spatial weight matrix (inverse of squared distance) as spatial weights, and the results are consistent with those in the previous section. Observed that technological innovation has a significant positive effect on regional carbon balance, while its spatial effect is significantly negative (see Table 5). This demonstrates the robustness of the conclusion.

4.5. Examination of the impact pathways of technological innovation on agricultural carbon balance

Further exploration is into the mechanisms through which technological innovation affects the spatial effects of carbon balance. Based on baseline assumptions, further verify how technological innovation in the second phase drives changes in agricultural supply and demand. According to the conclusion of negative spatial spillover effects, two scenarios can be hypothesized: (1) The diffusion and promotion of technological innovation increase the demand for agricultural products, thereby increasing the regional agricultural production value. (2) The increase in agricultural output value results in regions of with more farmland region obtaining negative marginal output values. According to the asymmetric impact on carbon balance, these regions will also experience negative spatial spillover effects. Conversely, regions of with a less farmland will exhibit positive spillover effects. (3) If the proportion of farmland in a region exceeds that of regions with an average farmland proportion, it can be inferred that the overall spatial spillover effect of technological innovation on carbon balance is negative. The mediation effects model can effectively verify the above mechanisms.

4.5.1. Mediation effects of agricultural product demand

Using agricultural production total value as a proxy variable for agricultural product demand, mediation effect tests were conducted. Sobel tests show a Sobel coefficient of -0.003034, indicating an indirect effect of -0.003034 and a direct effect of 0.017783, and show statistically significant. Table 6 presents the results of the mediation effect tests. Column 2 indicates a positive effect of technological innovation on carbon balance. The positive coefficient in column 3 suggests that technological innovation increases regional agricultural GDP, validating the mechanism of the first stage that technological innovation enhances the supply and demand of region agricultural products. The significance of technological innovation and agricultural

GDP ratio at the 1% level in column 4 indicates a suppression effect of agricultural GDP in enhancing carbon balance, with negative spatial spillover effects.

Table 5. Robustness Test Results

Variant	Neighborhood space weight matrix	Geographic distance spatial weight matrix (inverse of distance squared)	Geographic distance spatial weighting matrix (inverse of distance)
TI	0.0213***	0.0220***	0.0194***
	(0.00433)	(0.00447)	(0.00428)
DENSITY	-0.889**	-0.621*	-0.510
	(0.364)	(0.339)	(0.334)
INDUSTRY	700.0***	735.8***	692.7***
	(99.35)	(99.00)	(97.14)
GOV	249.4	-129.7	-14.06
	(648.7)	(661.4)	(670.3)
GDP_PC	-0.00121	-0.00154	-0.00274
	(0.00215)	(0.00228)	(0.00239)
GROWTH RATE	523.2	391.1	372.4
	(425.7)	(447.6)	(464.6)
FINANCIAL	64.22	60.74	11.23
	(109.6)	(111.6)	(113.8)
Constant	1,315**	87.37	157.4
	(615.1)	(619.7)	(1,073)
rho	0.129*	0.0275	-0.446**
	(0.0705)	(0.0985)	(0.209)
R-squared	0.168	0.145	0.167
N	364	364	364

*Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.*

Table 6. Mediation Effect Test Results

Variant	CB	lnGDP_pc	CB
TI	0.085***	4.57e-06***	0.0178***
	(0.012)	(1.60e-06)	(0.00417)
lnGDP_pc			-663.1***
			(145.0)
DENSITY	0.432***	-1.350***	-2.338***
	(0.129)	(0.274)	(0.538)
INDUSTRY	1621.075***	-5.76e-06***	909.6***
	(143.249)	(1.00e-06)	(105.3)
GOV	-2642.020***	0.200	-433.7
	(912.520)	(0.193)	(734.2)
GDP_PC	-0.014***	-0.0361	-0.00379
	(0.005)	(0.0477)	(0.00272)
GROWTH RATE	-6819.871***	-0.000956***	431.3
	(1268.608)	(0.000201)	(498.1)
FINANCIAL	-1755.535***	0.248***	-85.52
	(236.798)	(0.0383)	(123.2)
Constant	4385.594***	5.549***	2,080**
	(0.420)	(0.157)	(901.4)
sobel test			Z=-2.429
			|Z|>0.97
Mediation effect			statistically significant
R-squared	0.618	0.994	0.978
N	364	364	364

*Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.*

4.5.2. Mediation effects of relative advantages of agricultural production

To express the relative advantages of agricultural production in various regions, the proportion of each region's crop planting area in all regions' total planting area year by year is used to as a proxy index. We examined whether this ratio serves as a mediation in the impact of technological innovation on agricultural carbon balance, and to what extent it mediates the effects.

Sobel tests were used to examine the role of this ratio as a mediation in the process of technological innovation promoting agricultural carbon balance (see Table 7). The Sobel coefficient was 0.00365, with an indirect effect of -0.003365 and a direct effect of 0.018114, both statistically significant. Specifically, column 2 shows a positive effect of technological innovation on carbon balance. The negative coefficient in column 3 indicates that as the level of technological innovation increases, the proportion of regional crop planting areas decreases. Column 4 shows that technological innovation and the proportion of regional crop planting areas are significant at the 1% level, indicating a suppression effect of the proportion of regional crop planting areas in impact of technological innovation on carbon balance, along with spatial negative spillover effects.

The above mediation tests demonstrate that the diffusion and promotion of technological innovation increase the demand for agricultural products and consequently increase the total regional agricultural production value. Changes in the supply and demand of agricultural products lead to regions with agricultural advantages obtaining negative marginal output values, thus experiencing negative spatial spillover effects. Conversely, regions with non-advantages exhibit positive spatial spillover effects. This paper calculates the median value of the proportion of annual crop planting areas in each region to the total planting area of all regions. Regions where the proportion of annual crop planting areas to the total planting area of all regions is greater than the median value are defined as advantaged regions; conversely, they are defined as disadvantaged regions. In total, agricultural areas accounting for 80.1% in advantaged regions and 19.9% in disadvantaged regions, advantaged regions have a larger total cultivated area, leading to an overall negative spatial spillover effect of technological innovation on carbon balance. In summary, we have validated hypotheses 3 and 4, namely that the carbon balance effects of technological innovation will heterogeneously impact agricultural advantaged and disadvantaged regions, with the proportion of planting scale serving as a negative mediation effect in technological innovation on carbon balance.

Table 7. Mediation Effect Test

Variant	**CB**	**PS**	**CB**
TI	0.0147***	-4.85e-08**	69,436***
	(0.00425)	(2.14e-08)	(10,488)
PS			0.0181***
			(0.00402)
DENSITY	-1.704***	-5.94e-06**	-1.292**
	(0.536)	(2.69e-06)	(0.507)
INDUSTRY	745.2***	0.00380***	481.0***
	(102.0)	(0.000513)	(103.7)
GOV	461.6	-0.00261	642.6
	(729.5)	(0.00367)	(685.2)
GDP_PC	3.74e-05	7.82e-09	-0.000505
	(0.00267)	(1.34e-08)	(0.00250)
GROWTH RATE	298.9	-0.00249	472.1
	(512.6)	(0.00258)	(481.9)
FINANCIAL	-61.59	-0.000455	-30.02
	(126.9)	(0.000638)	(123.2)
Constant	6,134***	0.0256***	-1,712***
	(1,943)	(0.00977)	(393.3)
sobel test			Z=-2.147
			|Z|>0.97
Mediation effect			statistically significant
R-squared	0.976	0.998	0.979
N	364	364	364

*Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.*

5. Conclusion and recommendations

The effect of technological innovation on the carbon balance of agriculture and animal husbandry is a contentious issue. This study employs ArcGIS spatial analysis and spatial Durbin model to discuss the spatial effects of technological innovation on the carbon balance of agriculture section across 28 provinces in China from 2009 to 2021. By controlling for major confounding factors such as population density, agricultural industry agglomeration, government intervention, economic development, financial development, and economic growth, the following main conclusions and recommendations are derived:

5.1. Main conclusions

(1) Technological innovation has a significantly positive effect on the carbon balance of agriculture, notably increasing the carbon balance positively. The direct effect of technological innovation occurs through influencing the combination and reconfiguration of production factors within a region, leading to enhancements in the quantity or quality of production factors. This efficiency improvement promotes an increase in regional carbon balance.

(2) Technological innovation exhibits a significant negative spatial spillover effect on agricultural carbon balance. The direct effect of technological innovation first impacts the supply of production factors. This increase in supply triggers changes in the supply and demand of agricultural products and production factors. For regions with agricultural advantages, the efficiency gains and output expansion effects due to economies of scale result in a positive spatial spillover effect. Conversely, for non-agricultural advantaged regions, the spatial spillover effect is negative due to the relative price decrease of production factors, who favoring imported agricultural products over themselves' production, thereby lowering their carbon balance of agriculture. By examining the mediation effect of agricultural product demand in agriculturally advantaged areas, the study confirms the basic conclusion that both spatial spillover effects and total effects are negative. This suggests that although technological innovation enhances agricultural production efficiency and increases carbon surplus, competition and suppression from neighboring regions actually result in an overall negative impact on carbon balance.

(3) Agricultural industry agglomeration has a significantly positive direct effect on the carbon balance, without showing significant spatial spillover effects. Thus, the clustering of agricultural industries can increase the regions' carbon balance along with no significantly affecting the carbon balance of adjacent regions.

5.2. Policy recommendations

(1) Encourage and support technological innovation, especially innovations that can enhance the carbon surplus of agriculture and animal husbandry, to promote carbon emission reduction.

(2) Consider the negative spatial spillover effects across provinces when formulating policies, and fully consider the diffusion and impact of technological innovation between different regions. It is necessary for all regions to continuously increase investment in agricultural and animal husbandry production, enhancing the relative advantage of local agricultural production. This should not be abandoned based on market principles or by assuming agriculture and animal husbandry are weak industries in the region economics. The advantageous position of agricultural and animal husbandry production will play a crucial role in continuously enhancing carbon surplus through ongoing technological innovation.

(3) Implement national-level low-carbon strategic subsidies for technological innovation among agricultural and animal husbandry practitioners. By subsidizing technological innovation, the spillover effects of innovation can be realized, thereby increasing the overall effect of carbon surplus in agricultural and animal husbandry production. Preserve and gradually expand agricultural and animal husbandry production, appropriately control agricultural product imports, or adopt quota management for agricultural product imports, vigorously promote the application and implementation of technological innovation projects in large-scale agricultural production, and fully exploit the effect of enhancing carbon surplus in advantageous agricultural and animal husbandry production.

(4) Further promote and facilitate the industrial clustering of agricultural and animal husbandry production through various means, including low-carbon policy subsidies or tax reductions, to achieve scale and industrialization. This will help enhance the local carbon surplus level.

(5) Encourage sustainable agricultural and animal husbandry practices to reduce carbon emissions and increase carbon surplus. This includes adopting more environmentally friendly agricultural and animal husbandry technologies, reducing resource waste, and improving production efficiency.

(6) Provide training and support for agricultural and animal husbandry practitioners to help them better adapt to changes in new technologies and industrial structures. This will facilitate the smooth implementation of carbon emission reduction policies.

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Appendix

Appendix 1. Carbon Emission Sources and Carbon Emission Coefficients for Agricultural Land Use

Carbon source	Carbon emission factor	Data sources
Fertilizer	$0.8956 kg\cdot kg^{-1}$	Oak Ridge National Laboratory
Pesticides	$4.9341 kg\cdot kg^{-1}$	Oak Ridge National Laboratory
Agricultural Film	$5.1800 kg\cdot kg^{-1}$	Nanjing Agricultural University
Agricultural Diesel	$0.5927 kg\cdot kg^{-1}$	United Nations Intergovernmental Panel on Climate Change
Plowing	$312.6000 kg\cdot hm^{-2}$	China Agricultural University

Irrigation	25.0000kg· hm^{-2}	Dubey

Appendix 2. Types of Livestock Breeding and Emission Coefficients

Emission source	Enteric fermentation	Fecal emissions		Data sources
	CH4 Kg/(head·year)	CH4 Kg/(head·year)	N2O Kg/(head·year)	
cow	80.47	5.14	1.320	Guidelines for the preparation of provincial greenhouse gas inventories
Horses	18	1.09	0.330	
Donkey	10	0.6	0.188	
Mule	10	0.6	0.188	
camel	46	1.28	0.330	
Pig	1	3.12	0.227	
goat	8.33	0.17	0.093	
Sheep	8.13	0.15	0.093	

Appendix 3. Methane Emission Coefficients from Rice Fields

Shore	Emission factor	Data sources
North China	234.0kg· hm^{-2}	Guidelines for the preparation of provincial greenhouse gas inventories
Eastern China	216.9kg· hm^{-2}	
South Central China	250.3kg· hm^{-2}	
Southwest China	161.4kg· hm^{-2}	
Northeast China	168.0kg· hm^{-2}	
Northwest China	231.2kg· hm^{-2}	

Note: North China: Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia; East China: Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong; Central and South China: Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan; Southwest China: Chongqing, Sichuan, Guizhou, Yunnan, Tibet; Northeast China: Liaoning, Jilin, Heilongjiang; Northwest China: Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.

Appendix 4. Carbon sequestration rate, Water content and Economic factor to crops

Kind	Carbon sequestration rate	Water content (%)	Economic factor
rice (crop)	0.414	12	0.45
Wheat	0.4853	12	0.4
Corn	0.4709	13	0.4
Beans	0.45	13	0.34
Potato	0.4226	70	0.65
Cotton	0.45	8	0.1
Rapeseed	0.45	10	0.25
Peanuts	0.45	10	0.43
Sugar cane	0.45	50	0.5
Sugar beet	0.4072	75	0.7
Tobacco	0.45	85	0.55
Vegetables	0.45	90	0.6

Appendix 5. Descriptive Statistics of Variables

Variant	Sample size	Average value	Standard deviation	Minimum value	Maximum values
Carbon Surplus (CS)	364	1396.539	1472.598	-483.911	5829.203
Technological Innovation (TI)	364	7154.997	8068.394	9	50674
Population Density (DENSITY)	364	495.716	718.044	7.711	3950.794
Agricultural Industry Agglomeration (INDUSTRY)	364	1.161	0.629	0.048	3.543
Government intervention (GOV)	364	0.249	0.111	0.105	0.758
Level of Financial Development (FINANCIAL)	364	1.438	0.461	0.665	2.774
Level of Economic Development (GDP_PC)	364	53371.753	29466.588	12802	187526
Economic Growth Rate (GROWTH RATE)	364	0.104	0.056	-0.053	0.282
Value of agricultural production(lnGDP_pc)	364	7.154	1.108	4.469	8.708
Planting scale(PS)	364	0.036	0.026	0.001	0.096

Appendix 6. Inspection Results

Model checking	**W**
LMlag	23.183***
R-LM-lag	0.099*
LM-error	22.888***
R-LM-error	2.433
Wald-spatial-lag	43.20***
Wald-spatial-error	36.13***
LR-spatial-lag	40.97***
LR-spatial-error	40.40***

*Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.*