

# Spatial Spillover Effects of the Impact of Agricultural Mechanization on Carbon Emission Intensity in Agriculture: An Empirical Study Based on the Panel Data of 282 Cities\*

> XU Qinghua<sup>a</sup>, ZHANG Guangsheng<sup>b</sup>

**Abstract** The extreme weather caused by the global warming effect has triggered huge losses to agricultural production. A hot issue for governments and scholars is how to effectively reduce carbon emission intensity in agriculture. The agricultural farming practices that are high pollution and high energy consuming have exacerbated the vulnerability of regional agroecosystems. The sustainable development of agriculture is faced with the two dilemmas of a low utilization rate of green resources and the serious pollution of farmland. Further, environmental and ecological carrying capacities have reached their limits, seriously hindering the high-quality development of low-carbon agriculture in China. Thus, based on the panel data of 282 cities, the Spatial Dubin Model (SDM) is employed to examine the impact of agricultural mechanization on carbon emission intensity in agriculture. It is found that from 1999 to 2019 carbon emission intensity in agriculture showed an overall downward trend; as of 2019, the agricultural field had completed the target of carbon emission reduction, one year ahead of schedule. From a local perspective,

approximately 14.89% of agricultural industries in prefecture-level city have still not achieved carbon emission reduction targets, and agricultural carbon emission reduction tasks were better completed in major grain-producing areas than in non-major grain-producing areas. Agricultural mechanization has significantly reduced carbon emission intensity in local agriculture production. The impact of agricultural mechanization on carbon emission intensity in agriculture has not only a significant negative spatial spillover effect but also a significant effect on spatial carbon emission reduction. Compared with non-major grain-producing areas, agricultural mechanization plays a greater role in reducing spatial carbon emissions in major grain-producing areas. Further studies find that agricultural mechanization is conducive to overcome difficulties, such as instability of property rights and land fragmentation, and to achieve large-scale

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<sup>a</sup> The College of Economics and Management, Shenyang Agricultural University, Shenyang 100866, China

<sup>b</sup> Business School, Liaoning University, Shenyang 110136, China

agricultural production, thereby reducing agricultural carbon emissions in nearby regions. However, the transfer of rural labor, adjustments to the structure of agricultural cultivation, and the centralized use of rural land restrict the development of the cross-regional service market for agricultural machinery, which in turn weakens its contribution to spatial carbon emission reduction. At the end of this paper, it is suggested that Chinese governments at all levels should introduce subsidy policies for the cross-regional operation of agricultural machinery to solve the problem of their service market failure. Efforts should be made to stimulate the market to develop more energy-efficient and environmentally friendly agricultural machinery products while strictly controlling changes in the use of arable land in non-grain-producing areas, which aims to serve further agricultural mechanization and boost the high-quality development of low-carbon agriculture.

**Keywords** agricultural mechanization, carbon emission intensity in agriculture, planting structure, spatial spillover effect, low-carbon agriculture

The economic losses on agricultural production caused by extreme weather brought about by the greenhouse effect have increased year by year. Therefore, agricultural carbon emission reduction is attracting more and more attention from policymakers and scholars. In 2016, the *Working Plan for Greenhouse Gas Emission Control During the 13th Five-Year Plan Period* prioritized the target of carbon emission reduction in agriculture for

the first time. In addition, the *14th Five-Year Plan for National Agricultural Green Development*, reiterated the idea of tapping farmland carbon sinks and other emission reduction and carbon sequestration potential, pointing out the direction for the implementation of major strategic decisions on carbon peak and carbon neutrality. The *Action Plan for Carbon Dioxide Peaking Before 2030*, which was promulgated and implemented in 2021, further boosted the carbon peaking action in the agricultural field. Guided by agricultural policies of carbon emission reduction, China's agricultural carbon emission reduction work is fruitful. It can be seen that total agricultural carbon emissions dropped from 81.9 million tons in 2014 to 74.67 million tons in 2019, reversing the long-term growth trend in total carbon emission in agriculture. In terms of integrity, China's carbon emission intensity in agriculture decreased from 361.61kg/10,000 yuan in 2005 to 140.91kg/10,000 yuan in 2019, a drop of 61.03%, indicating that the goal of carbon emission reduction in agriculture by 2020 was completed ahead of schedule. Due to factors such as low energy efficiency in agricultural production, excessive input of agrochemicals, and land fragmentation, agricultural carbon emissions have not yet been curbed effectively (Chen & Chen, 2018), and China's agriculture confronts great pressure to reduce carbon emissions. The problems of high energy consumption and high pollution caused by the pursuit of high yield have not been fundamentally resolved. Moreover, the uneven development of regional agriculture has seriously restricted the high-quality

development of low-carbon agriculture in China. As a labor substitution factor, agricultural mechanization helps to dissolve the close relationship between rural labor force and agricultural production. Against the backdrop of the wide application and popularization of agricultural machinery, in particular, the cross-regional service network of agricultural machinery avails the development of intra- and inter-regional resources allocation of agricultural machinery (Fang & Huang, 2019). Unfortunately, there is little literature evaluating the impact of agricultural mechanization on agricultural carbon emission intensity. The progress of agricultural technology is not always conducive to the reduction of agricultural carbon emissions. However, the progress of mechanical technology represented by the level of agricultural mechanization has actually increased total agricultural carbon emissions (Li & Zhou, 2020). In the context of improvement of agricultural mechanization, this conclusion is contrary to the fact that total agricultural carbon emissions have decreased. The reason may be that the negative impact of spatial agglomeration and differentiation of agricultural carbon emissions on the econometric results has been neglected (Xia et al., 2020). Recent studies have shown that regional agricultural carbon emissions present a spillover trend that extends from the center to the periphery (Zhao et al., 2020). This paper provides new advice for boosting carbon peak action in the agricultural field, based on the panel data of 282 cities from 1999 to 2019, which uses Spatial Durbin Model (SDM) to study the

impact of agricultural mechanization on agricultural carbon emission intensity.

# 1 Literature Review and Theoretical Mechanism

## 1.1 | Literature Review

Much existing literature can be found which discusses the influencing factors of agricultural carbon emissions. Scholars have probed into those factors such as regional differences in agricultural carbon emissions from the aspects of farmland management scale, carbon emission reduction policy, technological progress, and urbanization. The expansion of the agricultural land management scale has evoked changes in the integrity of agrochemical input and production technology. It can be seen from the perspective of the driving source that the improvement of carbon emission reduction efficiency mainly depends on the advancement of cutting-edge technology rather than the improvement of technical efficiency. The advancement of cutting-edge technology plays a positive role in promoting the efficiency of agricultural carbon emission reduction in different regions. The introduction of policies integrating “reward and subsidy” and “regulation” has also played a positive role in enhancing the efficiency of agricultural carbon emission reduction (Chu et al., 2020; Liu & Xiao, 2020). Moreover, urbanization is also considered to be an important, more long-lasting, and effective factor affecting agricultural carbon emissions (Zeng et al., 2021).

Current studies have provided useful references for gaining insight into the differences in regional agricultural carbon emissions, focusing mainly on technological progress and agricultural policies, etc., rather than analyzing the causes of agricultural carbon emission reduction from the perspective of agricultural mechanization. Further, there are various views on the role of agricultural mechanization in agricultural carbon emission reduction. Those who support technicism believe that agricultural mechanization, as an advanced productive force, makes for improving the timeliness, quality, and efficiency of agricultural operations, and raises both agricultural productivity and profitability, thereby reducing regional agricultural carbon emissions (Benin, 2015). Scholars who hold the theory of substitution argue that agricultural mechanization is a kind of factor substitution. As labor-saving technological progress, agricultural machinery factors are increasingly substituting labor factors as labor prices rise (Yi et al., 2019). This reform in production will bring about high energy consumption and environmental pollution, reducing the use of low-carbon factors such as organic fertilizers by farmers. It is a pity in the context of increasing levels of agricultural mechanization that the decline trend in agricultural carbon emission intensity in recent years cannot be explained. As a result, the technical theory of agricultural mechanization has received increasingly more attention on the part of scholars (Yang, 2013).

Based on the literature, it is easy to see that existing studies have the following deficiencies. First, there are

few empirical analyses on the impact of agricultural mechanization on regional agricultural carbon emission intensity in agriculture. Only one paper similar to this study is found (Chen & Chen, 2018), but it targets only the relationship between agricultural mechanization and total agricultural carbon emissions, rather than the impact of agricultural mechanization on carbon emission intensity in agriculture. Consequently, it is of little significance to evaluate the effect of regional carbon emission reduction. Further, the study does not consider the adverse impact of spatial agglomeration of agricultural carbon emissions on the measurements. Second, resource concentration of agricultural machinery, agricultural policies, and agricultural development status differ greatly from region by region (Li & Zhu, 2021). Most studies have not further analyzed the impact of sample heterogeneity. Third, how does agricultural mechanization affect regional carbon emission intensity in agriculture? For this issue, there is a scarcity of literature that analyzes the impact of agricultural mechanization on agricultural carbon emissions from the perspective of spatial spillover, and there is even a greater lack of empirical analyses on the spatial carbon reduction mechanism of agricultural mechanization. Therefore, this study investigates thoroughly the impact of agricultural mechanization on carbon emission intensity in agriculture from the perspective of spatial spillover. Further, rural labor transfer and adjustments to agricultural planting structure are integrated into the analysis framework. This paper is designed to provide theoretical guidance

for the further development of agricultural mechanization.

### 1.2 | Theoretical Mechanism

The current status of agricultural production in China indicates the substantial scale that has been achieved. Benefiting from agricultural mechanization, the inhibitory effect of land fragmentation on the agricultural production scale has been eased to some extent. The using of agricultural machinery in sowing, harvesting, and other links has been increased year by year, and the substitution effect on labor factors has intensified as well. Some achievements have been made in the operational scaling of agriculture brought about by mechanization (Zhou et al., 2016). A new type of management organization, especially large grain growers and cooperatives, has appeared and increasingly boosted the scale of agricultural production. Although the shift in agricultural production methods from human and animal power to agricultural machinery has raised the level of carbon emissions in agricultural production, the duration of these emissions is relatively short and the total amount of carbon emission is controllable. The carbon-reducing effect of large-scale agricultural production brought about by mechanization can offset the carbon-increasing effect caused by the operation of agricultural machinery. Subsidies for the purchase of agricultural machinery and private agricultural machinery service providers have helped to improve the accessibility of agricultural machinery services, reduce the agricultural risks of drought, and raise crop yields. With changes

in the external environment of agricultural mechanization, trans-regional mobility of agricultural machinery has increasingly demonstrated strong productivity, which in turn affects the level of regional agricultural carbon emissions.

First, agricultural mechanization helps not only to optimize the allocation of agricultural production factors but also to eliminate the carbon increase effect caused by the distortion of agricultural land and labor factor allocations, thus lowering regional carbon emission intensity in agriculture. Benefiting from agricultural mechanization, small farmers withdrew from agricultural production (Takeshima, 2018). The carbon emission reduction on the scale of agricultural production can be realized by cultivating new agricultural management entities (Qiu et al., 2021). Moreover, farmers are inhibited from applying excessive amounts of pesticide and fertilizer in their pursuit of yield. In this case, conservation tillage practices are being implemented on a wider scale (Qiu & Luo, 2018). As proposed by the core-periphery theory, the impact of agricultural mechanization on the agricultural machinery service markets in nearby areas has a spillover effect. Farmers there can obtain agricultural machinery services, planting technology, and information on agricultural machinery at a lower cost. The development of cross-regional agricultural machinery markets is conducive to realizing rational allocation of low-carbon resources within and between regions (Fang & Huang, 2019), and reducing regional carbon emission intensity in agriculture. The agglomeration of agricultural

machinery resources further reinforces the effect of spatial carbon emission reduction of agricultural mechanization. The effect of substituting agricultural machinery factors for labor elements is gradually enhanced with the increase in the degree of rural labor transfer. In the context of land fragmentation and unclear land property rights, the enhanced factor substitution effect inhibits the cross-regional mobility of agricultural machinery factors and contorts the allocation of regional agricultural production factors, resulting in a negative impact on the spatial carbon emission reduction effect of agricultural mechanization (Qin & Wang, 2019).

Second, agricultural mechanization contributes to the rational optimization of the agricultural planting structure and makes for reducing carbon emission intensity in agriculture by expanding the planting area of food crops. Unlike commercial crops, food crops are characterized by “one family, two production systems” and relatively low carbon emissions from crop planting (Sun et al., 2020). The safety of grain rations restrains high-carbon emissions behavior such as excessive application of pesticides and fertilization by food growers. The substitution of food crops for commercial crops reduces the intensity of regional carbon emissions in agriculture (Dumortier & Elobeid, 2021). The grain-oriented effect of the planting structure of agricultural mechanization has inhibited the expansion of the scale of regional planting of economic crops and stimulated the import of oil crops, starchy root crops, etc. Agricultural carbon emissions are then transferred to other countries (Himics et al., 2018). The

carbon emission reduction effect resulting from adjustments to agricultural planting structure reduces the agricultural carbon emission level of the importing country. The impact of agricultural mechanization on the agricultural planting structure presents a positive spillover effect (Li & Zhu, 2021). The cross-regional operation of agricultural machinery increases the proportion of food crops cultivated in nearby regions, leading to a reduction in carbon emission intensity within the agriculture sector. As the planting area for food crops increases, however, the exclusivity of agricultural machinery assets suitable for food production raises the transaction cost of the cross-regional operation of agricultural machinery, puts off the formation of the cross-regional operation of an agricultural machinery market, and weakens the effect of spatial carbon emission reduction of agricultural mechanization. Hypothesis 1 is proposed on this basis.

*H1: Agricultural mechanization can reduce regional carbon emission intensity in agriculture, and has a significantly negative spatial spillover effect on the impact of that intensity.*

The agricultural policies in major grain-producing areas have imposed relatively strict restrictions on changes in the use of arable land. As a result, the agricultural acreage used for the cultivation of food crops is larger, and the positive impact of the agglomeration of agricultural machinery factors on agricultural carbon emission reduction is more obvious as well. The agglomeration of agricultural machinery factors reduces the operating costs of cross-regional

operations of agricultural machinery in the region through input sharing, labor pools, and knowledge spillover (Zhang & Dou, 2015). If the absorptive capacity of farmers is stronger, the effect of spatial carbon emissions of the agglomeration of agricultural machinery resources will be satisfactory. Compared with non-major grain-producing areas, the agglomeration of agricultural machinery resources brings about a more obvious grain-oriented effect of agricultural mechanization in major grain-producing areas, as well as a greater inhibitory effect on agricultural carbon emission intensity in agriculture in nearby regions (Harris et al., 2019). The planting area of grain crops is always large in major grain-producing areas, and the effect of land scaling is beginning to appear. The exclusivity of agricultural machinery assets has motivated the cross-regional mobility of agricultural machinery factors, generating more evident effect of spatial carbon emission reduction of agricultural mechanization. Furthermore, compared with non-major grain-producing areas, the subsidy for agricultural machinery in major grain-producing areas is relatively high, enabling farmers more willing to purchase large-scale agricultural machinery. As a result, the direct carbon emissions per unit operating area of agricultural machinery drop significantly. Hypothesis 2 is proposed on this basis.

*H2:* Compared with non-major grain-producing areas, the degree of grain industry agglomeration, cultivated land protection, and agricultural machinery subsidies in major grain-producing areas are greater, and the spatial carbon reduction

effect of agricultural mechanization is also stronger.

## 2 Data, Model, and Variable

### 2.1 | Data

Urban data are excerpted from the *China City Statistical Yearbook* (2000–2020); inter-provincial data are taken from the *China Statistical Yearbook* (2000–2020), and the *China Rural Statistical Yearbook* (2000–2020); the data related to urban agriculture are recorded from the China Regional Economic Database of EPS. The data on urban carbon emissions in the Robustness Rest are excerpted from the China Emission Accounts and Datasets. The data of each city are matched and combined by city name and year, and the urban and inter-provincial data are matched and combined by province and city postal codes, and the values of some city-level indicators are given by the urban data and the inter-provincial data measurements. Samples with multiple missing index values are deleted. Meanwhile, the linear interpolation method is employed to fill in a small number of missing values. In the end, the panel data of 282 cities across China from 1999 to 2019 are obtained.

### 2.2 | Model

On the basis of measuring the carbon emissions per unit of agricultural GDP, the spatial commonality of urban areas in the city is greater than that of areas that are far apart, and the intensity of agricultural carbon emissions demonstrates strong

spatial agglomeration characteristics (Zhao et al., 2020). A spatial weight matrix is added to the model to modify the classical regression model. The model in this case is set as follows:

$$LCQ_{it} = \rho \times W \times LCQ_{it} + \lambda_1 LNM_{it} + \beta X_{it} \\ + \lambda_2 \times W \times LNM_{it} + \eta WX_{it} + k_i + v_t + \zeta_{it}, \\ \zeta_{it} = \rho \times W \times LCQ_{jt} + \tau_{it}.$$

$LCQ$  denotes carbon emission intensity in agriculture,  $LNM$  represents agricultural mechanization, and  $X$  stands for the control variable. In the equation,  $\tau$  refers to the residual term that follows the standard normal distribution. The model contains the spatial fixed effect ( $k_i$ ) and the time fixed effect ( $v_t$ ). Among others, the subscripts  $i$  and  $j$  stand for the  $i$ -th city and the  $j$ -th city, respectively, and  $t$  denotes the  $t$ -th year;  $\rho$  refers to the spatial correlation coefficient,  $W$  represents the spatial weight matrix, and  $\lambda_1$ ,  $\lambda_2$ ,  $\beta$ , and  $\eta$  refer to the parameters to be estimated in the measurement equation. The estimation results of agricultural mechanization and regional carbon emission intensity in agriculture are decomposed into direct effect, indirect effect, and total effect, which

are represented by  $f_{ii}(W) = \frac{\partial LCQ_i}{\partial LNM_{im}}$ ,  $f_{ij}(W) = \frac{\partial LCQ_j}{\partial LNM_{jm}}$ , and  $Total = f_{ii}(W) + f_{ij}(W)$ , where the indirect effect is spatial spillover effect.

## 2.3 | Variable

### 2.3.1 Explained Variable

Carbon emission intensity in agriculture ( $LCQ$ ). Carbon emission integrity is

generally measured using carbon emissions per unit of GDP, carbon emissions per unit area, and per capita carbon emissions. Carbon emissions per unit of GDP is selected to measure the carbon emission intensity in agriculture which is expressed by the ratio of total agricultural carbon emissions to the total value of agricultural output. At present, there is a lack of data on the use of pesticides, agricultural plastic film, and agricultural diesel within the city. On account of this, pesticide usage per unit of arable land area, the use of agricultural plastic film, agricultural diesel oil used, and actual arable land across the provinces are employed to measure those of city levels. With reference to the study of Liu et al. (2021), the coefficients of carbon emission reduction such as carbon emission coefficient of fertilizer application equivalent amount, pesticide usage, agricultural plastic film usage, agricultural diesel usage, total sown area of crops, and effective irrigation area are 0.8956kg/kg, 4.9341kg/kg, 5.1800kg/kg, 0.5927kg/kg, 312.60kg/km<sup>2</sup>, and 25kg/hm<sup>2</sup>, respectively. Total agricultural carbon emissions in prefecture-level city are equal to the sum of the amount of chemical fertilizer application, pesticide usage, usage of agricultural plastic film, usage of agricultural diesel, total sown area of crops, effective irrigation area, and the emission coefficient, respectively. Given the lack of data on the total agricultural output value of prefecture-level cities (which means planting that falls within the scope of agriculture, forestry, animal husbandry, and fishery), the total agricultural output value is represented by the product of the ratio between the total output value of

agriculture, forestry, animal husbandry, and fisheries in a city and that of agriculture in the province to the total output value of the four industries.

### 2.3.2 Core Explanatory Variable

Agricultural Mechanization (*LNM*). The total power of agricultural machinery is used to measure the variables of agricultural mechanization. In terms of time span, the total power of agricultural mechanization in prefecture-level cities on average in 1999 and 2019 was 1,679,900 kW and 3,219,300 kW, respectively, with a growth rate per annum of 4.58%. The overall level of agricultural mechanization showed an upward trend from 1999 to 2019. From 2015 to 2016, however, the level saw a downturn. The scope of machinery and tools required in the key links of agricultural production in purchase subsidies for agricultural machinery was reduced from 175 items in 2014 to the current 137 items, which was the main reason for the decline in the level of agricultural mechanization in 2015.

### 2.3.3 Control Variable

The variables such as infrastructure quality, arable land scale, irrigation conditions, industrial development, opening-up, and land urbanization are added to the model in a bid to eliminate the adverse effects of other factors on the measurement results. In terms of the control variables, the infrastructure quality (*RAD*) is measured by the mileage of classified highways and the logarithmic value is used. The arable land scale (*LAS*) is measured by the arable land area per capita and the logarithmic value is taken after adding 1 to the arable land area per capita.

The variable of irrigation conditions (*IRR*) is measured by the ratio of the effective irrigation area to the total sown area of crops. Industrial development (*IND*) is measured by the ratio of the total output value of industrial enterprises above the designated scale to the gross regional domestic product. The opening up (*TRA*) is measured by the ratio of total imports and exports of goods to the gross regional domestic product, where the total imports and exports of goods are equal to the product of the total imports and exports of goods denominated in U.S. dollars and the exchange rate over the years. Land urbanization (*URB*) is measured by the standardized urban built-up area, which is equal to the ratio of the built-up area in the cities and towns to the administrative area of the whole city, taking a logarithmic value. Each variable is winsorized at 1% of extreme value; the definition and descriptive statistical analysis of variables are shown in Table 1.

## 3 Results and Analysis

### 3.1 | Measurement Results of Carbon Emission Intensity in Agriculture

#### 3.1.1 Change Trend of Regional Agricultural Carbon Emissions

China's overall agricultural carbon emission level in 2019 was 140.91kg/10,000 yuan in its entirety. Statistics show that carbon emission integrity in 2019 was 991.66kg/10,000 yuan, indicating that the carbon emission status of the agricultural

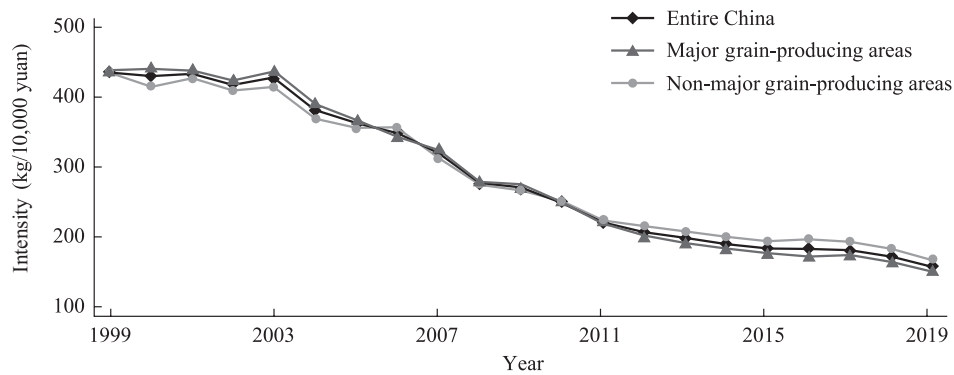
**Table 1** Description of Major Variables and Descriptive Statistical Analysis

Variable	Description	Sample Size	Mean	Standard deviation	Min.	Max.
LCQ	Carbon Emission Intensity in Agriculture (carbon emissions per 10,000 yuan of agricultural output value (kg/10,000 yuan, taking the logarithm))	5,922	5.51	0.58	4.03	6.70
LNM	Agricultural Mechanization (total power of agricultural machinery/10 <sup>4</sup> kW, taking the logarithm)	5,922	4.57	0.96	1.55	7.17
RAD	Infrastructure Quality (mileage of classified highways/km, taking the logarithm)	5,922	8.76	0.91	6.32	12.23
LAS	Arable Land Scale (arable land area per capita, taking the logarithm after adding 1)	5,922	0.64	0.35	0.11	1.87
IRR	Irrigation Conditions (effective irrigation area/10 <sup>3</sup> hm <sup>2</sup> to the total sown area of crops/10 <sup>3</sup> hm <sup>2</sup> )	5,922	0.38	0.18	0.07	1.00
IND	Industrial Development (ratio of the total output value of industrial enterprises above designated scale to the gross regional domestic product)	5,922	1.26	0.79	0.18	5.16
TRA	Opening up (ratio of total imports and exports of goods to the gross regional domestic product)	5,922	0.26	0.53	0.00	3.64
URB	Land Urbanization (ratio of the built-up area in cities and towns to the administrative area of the whole city)	5,922	4.19	1.32	1.05	8.38

industry was better than the national level overall. Figure 1 presents the changing trend of carbon emission intensity in agriculture from 1999 to 2019. From the perspective of time, it is evident that the average carbon emission intensity in agriculture decreased from 436.97 kg/10,000 yuan in 1999 to 159.21 kg/10,000 yuan in 2019, indicating that the level of agricultural carbon emissions had dropped by 63.57%. This further elucidates that the target of achieving a 40% to 45% reduction in carbon emissions per unit of GDP in the agricultural industry by 2020 was accomplished ahead of schedule. In these years, the decline in carbon emission intensity in agriculture was relatively gradual from 1999 to 2003. However, the reduction in agricultural taxes and the establishment of agricultural cooperatives facilitated the expansion of agricultural-scale production, leading to an accelerated decrease in carbon emission intensity in agriculture from 2003 to 2011. From 2011 to 2019, the rate of decline in

carbon emission intensity in agriculture gradually decelerated. However, in 2016, the *National Agricultural Modernization Plan (2016–2020)* introduced the concept of green and high-efficiency agriculture, which subsequently reinvigorated the decline in carbon emission intensity in agriculture.

According to the practices of the National Food and Strategic Reserves Administration, a total of 13 provinces (autonomous regions, and municipalities) including Liaoning, Hebei, Shandong, Jilin, Inner Mongolia, Jiangxi, Hunan, Sichuan, Henan, Hubei, Jiangsu, Anhui, and Heilongjiang are classified as major grain-producing areas, while other provinces are non-major grain-producing areas. A comparison of grain-producing areas shows that the carbon emission intensity in agriculture of major grain-producing areas was higher than that of non-major grain-producing areas from 1999 to 2009, but lower than that of non-major grain-producing areas from 2010 to 2019. In 2009, China promulgated



**Figure 1** Trend of Regional Carbon Emission Intensity in Agriculture from 1999 to 2019

and implemented the *National Plan for Expansion of Grain Production Capacity by 50 Billion Kilograms (2009–2020)*. Since then, the policy effect of grain production function in major grain-producing areas has played a positive influence on green and low-carbon agricultural development.

### 3.1.2 Spatial Distribution Characteristics of Regional Agricultural Carbon Emissions

The samples are grouped according to the 31 provinces (autonomous regions, and municipalities). The objective was to analyze the status of carbon emission reduction in agriculture across different regions by comparing the carbon emission intensity in agriculture between each provincial-level administrative region in 2005 and 2019. The statistical findings are presented in Table 2. In terms of regional distribution, the cities with high levels of agricultural carbon emissions in 2005 were primarily concentrated in Qinghai, Ningxia, Shanxi, Shaanxi, Shandong, Hebei, and other regions. In 2019, however, the cities with high levels of agricultural carbon emissions were mainly found in Jilin, Gansu, Fujian, Chongqing, Shanxi, Ningxia, Zhejiang, Anhui, and other regions. The distribution characteristics reveal that the carbon emission intensity in agriculture is higher in non-major grain-producing areas compared to major grain-producing areas. This discrepancy

can be attributed to the increased financial funds and investments in agricultural green technology, which have effectively reduced the carbon emission intensity in agriculture in major grain-producing areas.

During the period from 2005 to 2019, significant reductions in carbon emission intensity in agriculture were observed primarily in provinces such as Qinghai, Guizhou, Sichuan, Shaanxi, Hubei, Tianjin, Yunnan, Jiangxi, Heilongjiang, Jiangsu, and Hainan. It is important to note that the base year for these calculations is set as 2005. Furthermore, Xinjiang, Jilin, Gansu, Chongqing, and Fujian failed to meet the target of carbon emission reduction in agriculture in 2020. This indicates that the decrease in carbon emission intensity in agriculture is relatively lower in the northern regions compared to the southern regions. Additionally, it is noteworthy that the decline in carbon emission intensity in agriculture has been more pronounced in major grain-producing areas when compared to non-major grain-producing areas. In 2019, 92.22% of the prefecture-level cities in agricultural industries of major grain-producing areas achieved their target of reducing carbon emissions per unit of GDP by 40% to 45% by 2020 ahead of schedule. In non-major grain-producing areas, only 74.78% of the prefecture-level cities in agricultural industries have

completed the carbon emission reduction target ahead of time. The task completion of carbon emission reduction in agriculture in major grain-producing areas is better than that in non-major grain-producing areas.

### 3.1.3 Moran's I Test for Spatial Autocorrelation

The global Moran's I spatial autocorrelation is employed to examine the spatial autocorrelation of each index and assess the level of spatial correlation between each city and its neighboring cities in terms of

carbon emission intensity in agriculture. The equation is as follows:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (r_i - \bar{r})(r_j - \bar{r})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (r_i - \bar{r})^2} = \frac{\sum_{i=1}^n \sum_{j \neq i}^n w_{ij} (r_i - \bar{r})(r_j - \bar{r})}{S^2 \sum_{i=1}^n \sum_{j \neq i}^n w_{ij}}$$

where  $n$  denotes the number of spatial locations,  $w$  is the spatial weight matrix,  $r_i$  and  $r_j$  are the residual terms after the regression of carbon emission intensity in agriculture and agricultural mechanization;

**Table 2** Comparison of Carbon Emission Intensity in Agriculture of Each Province (autonomous region, and municipality) in 2005 and 2019

Province (autonomous region, and municipality)	Intensity (kg/10,000 yuan)			Province (autonomous region, and municipality)	Intensity (kg/10,000 yuan)		
	2005	2019	Change rate (%)		2005	2019	Change rate (%)
Qinghai	812.71	113.55	+86.03	Guangdong	237.53	92.82	+60.92
Guizhou	306.64	69.06	+77.48	Liaoning	356.85	142.61	+60.04
Sichuan	295.67	80.02	+72.94	Guangxi	328.53	137.47	+58.16
Shaanxi	414.56	114.72	+72.33	Anhui	419.23	178.85	+57.34
Hubei	394.90	109.56	+72.26	Zhejiang	433.30	186.20	+57.03
Tianjin	368.69	107.97	+70.71	Henan	343.18	153.52	+55.27
Yunnan	423.62	124.34	+70.65	Shanxi	418.69	194.14	+53.63
Jiangxi	379.93	113.16	+70.22	Shanghai	335.03	159.06	+52.52
Heilongjiang	305.38	92.78	+69.62	Beijing	246.10	117.52	+52.25
Jiangsu	323.02	104.93	+67.52	Inner Mongolia	316.38	170.34	+46.16
Hainan	269.12	91.44	+66.02	Fujian	363.49	285.84	+21.36
Hebei	432.71	151.99	+64.87	Chongqing	286.86	259.30	+9.61
Tibet	257.60	91.75	+64.38	Gansu	368.78	340.68	+7.62
Hunan	323.31	116.36	+64.01	Jilin	617.10	610.71	+1.04
Ningxia	517.65	188.11	+63.66	Xinjiang	147.72	156.23	-5.77
Shandong	391.52	143.78	+63.28				

*Note.* The change of carbon emission intensity in agriculture is the ratio of the change value of carbon emission intensity in agriculture in the time period to the value of carbon emission integrity at the beginning of the period. It is important to note that the base year for the calculations was set as 2005. Positive values indicate that carbon emission intensity in agriculture has decreased in some regions, while negative values represent that intensity has increased.

$\bar{r}$  is the average of the residual terms, and  $S$  is the standard deviation. The diagnostic results of spatial correlation and spatial dependence of agricultural mechanization and carbon emission intensity in agriculture are presented in Table 3. The findings indicate that Moran's  $I$  index values remained consistently at around 0.29 between 1999 and 2019. Moreover, the statistical significance of Moran's index at the 1% level indicates a significant spatial correlation between agricultural mechanization and carbon emission intensity in agriculture.

### **3.2 | Test Results of the Impact of Agricultural Mechanization on Regional Carbon Emission Intensity in Agriculture**

#### *3.2.1 Benchmark Regression Results of Agricultural Mechanization*

The regression results of the SDM are shown in Table 4. The spatial correlation coefficients ( $\rho$ ) of carbon emission intensity in agriculture in Model (1) to Model (8) are all statistically significant at the 1% level, indicating that there is an obvious spatial correlation between agricultural mechanization and regional carbon emission intensity in agriculture. Model (1) in Table 4 represents the measurements obtained using the spatial distance weight matrix. The findings demonstrate that the direct effect of agricultural mechanization on carbon emission intensity in agriculture is significantly negative at the 1% level. This indicates that agricultural mechanization plays a significant role in reducing carbon emission intensity within

the local agricultural sector, showcasing a clear direct effect on carbon emission reduction. The spatial spillover effect of agricultural mechanization on carbon emission intensity in agriculture is found to be significantly negative at the 1% level. This implies that for every 1 percentage point increase in the level of agricultural mechanization, there is a corresponding decrease of 1.737 percentage points in carbon emission intensity in nearby regions. Hence, agricultural mechanization demonstrates a significant effect on spatial carbon emission reduction. *HI* is thus verified. Considering the spatial spillover effect of agricultural mechanization, the effect of carbon emission reduction of agricultural mechanization will be greater. There are two primary reasons for the observed spatial spillover effect. Firstly, the cross-regional utilization of agricultural machinery facilitates the overcoming of unfavorable conditions such as land fragmentation and property rights, enabling the expansion of agricultural production on a larger scale. Subsequently, through the substitution effect of cross-regional factors, it helps to curtail the excessive application of agrochemicals resulting from inadequate labor inputs in agriculture. This, in turn, reduces the input levels of high carbon emission factors in per unit of arable land in nearby regions (Fang & Huang, 2019; Qiu et al., 2021). However, it should be noted that the improvement of the substitution effect of agricultural machinery on labor factors has somewhat impeded the cross-regional mobility of agricultural machinery, thereby weakening the spatial carbon emission reduction

effect of agricultural mechanization to some extent. Secondly, agricultural mechanization exhibits a grain-oriented effect and positive spillover impact. The cross-regional operation of agricultural machinery fosters the optimization of agricultural planting structure, leading to a reduction in carbon emission intensity in nearby regions through the expansion of food crop cultivation (Li & Zhu, 2021).

### 3.2.2 *Measurement Results of Control Variable*

The measurement results of Model (1) in Table 4 are used to illustrate that of the control variables, the direct effect of infrastructure quality on carbon emission intensity in agriculture is not statistically significant at the 10% level. The spatial spillover effect on carbon emission intensity in agriculture and the total effect are significantly negative at the 1% level. The enhancement of infrastructure quality does not have a direct and substantial impact on carbon emission intensity in local agriculture. However, the improvement of circulation infrastructure quality can effectively reduce carbon emission levels in cities along the way (Zhang & Li, 2021). This demonstrates that the positive effect of infrastructure quality on carbon emission reduction should be observed within the agricultural industry.

The direct effect of arable land scale on carbon emission intensity in agriculture is significantly positive at the 1% level. Specifically, when the arable land scale increases by 1 percentage point, there is a corresponding increase of 0.476 percentage

points in carbon emission intensity in local agriculture. It is important to note that in the absence of large-scale planting, the traditional farming method involving the use of fertilizers, pesticides, and other agrochemical inputs contributes to an elevated regional carbon emission intensity in agriculture. However, when considering the impact of improved factor use efficiency resulting from the expansion of the scale of arable land, it becomes evident that the scaling of arable land can effectively reduce the regional carbon emission intensity in agriculture.

The direct effect of irrigation conditions on carbon emission intensity in agriculture is significantly negative at the 5% level. Specifically, a percentage point increase in irrigation conditions leads to a corresponding decrease of 0.085 percentage points in carbon emission intensity in local agriculture. Furthermore, enhancing irrigation conditions contributes to higher crop yields per unit of land area. It is worth noting that in areas with higher output value per unit arable land area, the carbon emission intensity in agriculture tends to be relatively low, even when maintaining the same level of carbon emissions. The spatial spillover effect and the total effect of irrigation conditions on carbon emission intensity in agriculture are significantly negative at the 1% level. Given the cross-regional nature of irrigation projects, enhancing local irrigation conditions has paved the way for upgrading irrigation infrastructure quality in nearby regions. By improving water resource accessibility, there is a remarkable potential to expand food crop cultivation, consequently leading

to a reduction in regional carbon emissions in agriculture (Zhao et al., 2018).

The direct effect of industrial development on carbon emission intensity in agriculture is significantly positive at the 1% level, and the spatial spillover effect and overall effect of agricultural carbon emission intensity are not statistically significant at the 10% level. Industrial development has played a pivotal role in driving agricultural modernization. However, the utilization of high-carbon inputs such as agrochemicals has led to an increase in regional carbon emission intensity in agriculture. Nonetheless, it is worth noting that the industrial agglomeration effect of industrial development exerts a “Siphon Effect” on regional rural labor and land factors (He et al., 2021). Fortunately, the reconfiguration effect of agricultural production factors helps counterbalance the adverse impact

of industrial development on agricultural carbon reduction efforts.

The direct effect of opening-up on carbon emission intensity in agriculture is not statistically significant at the 10% level. However, this effect on the spatial spillover effect and the total effect of carbon emission intensity in agriculture are significantly negative at the 1% level. The higher the level of regional opening-up, the greater the promotion of the formation of a green development highland in the agricultural sector through the high standards for agricultural exports and the introduction of green technologies. The “trickle-down effect” of low-carbon agriculture and the diffusion of green technologies enhances the scale of low-carbon agricultural industries in the region, thereby achieving a spatial carbon reduction effect through the spatial spillover of industrial agglomeration.

**Table 3** Results of the Spatial Autocorrelation Test

Year	Moran's I	Z value	Year	Moran's I	Z value
1999	0.1855***	4.07	2010	0.2830***	6.14
2000	0.1420***	3.14	2011	0.3507***	7.59
2001	0.1693***	3.72	2012	0.3641***	7.88
2002	0.2017***	4.42	2013	0.3739***	8.10
2003	0.1556***	3.43	2014	0.3760***	8.14
2004	0.2124***	4.64	2015	0.3972***	8.60
2005	0.1747***	3.83	2016	0.4136***	8.95
2006	0.1943***	4.25	2017	0.4268***	9.23
2007	0.1921***	4.20	2018	0.4369***	9.44
2008	0.2425***	5.27	2019	0.5069***	10.94
2009	0.2064***	4.50			

Note. \*\*\* $P < 0.01$ .

**Table 4** Estimation Results of the SDM

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
<i>P</i>	1.787*** (41.30)	2.259*** (35.29)	3.350*** (20.89)	0.618*** (60.54)	1.929*** (45.53)	1.257*** (25.87)	2.191*** (50.40)	2.163*** (47.40)
Direct effect								
<i>LNM</i>	-0.032*** (-2.71)	-0.027 (-1.64)	-0.026 (-1.44)	-0.052*** (-4.22)	-0.060*** (-5.31)	-0.046*** (-3.66)	-0.101*** (-5.88)	-0.002 (-0.06)
<i>LNM</i> × <i>MIG</i>							0.182*** (5.56)	
<i>MIG</i>							-0.901*** (-6.16)	
<i>LNM</i> × <i>GRA</i>								-0.082** (-2.52)
<i>GRA</i>								0.339** (2.22)
<i>RAD</i>	-0.003 (-0.44)	-0.056*** (-5.70)	0.045*** (4.11)	-0.002 (-0.29)	-0.018** (-2.43)	-0.032*** (-3.15)	-0.013* (-1.77)	-0.014* (-1.96)
<i>LAS</i>	0.476*** (11.89)	0.705*** (13.12)	0.375*** (5.98)	0.395*** (8.96)	0.420*** (10.52)	0.319*** (7.72)	0.332*** (8.37)	0.404*** (10.28)
<i>IRR</i>	-0.085** (-1.96)	-0.427*** (-7.09)	0.114* (1.76)	-0.133*** (-3.00)	-0.128*** (-3.02)	-0.072 (-1.59)	-0.113*** (-2.60)	-0.097** (-2.16)
<i>IND</i>	0.029*** (4.32)	0.042*** (5.22)	-0.010 (-0.87)	-0.004 (-0.73)	0.029*** (4.34)	0.160*** (24.77)	0.027*** (3.79)	0.029*** (4.13)
<i>TRA</i>	-0.016 (-1.28)	0.112*** (4.53)	-0.007 (-0.43)	0.011 (0.88)	-0.021* (-1.71)	0.141*** (10.82)	-0.029** (-2.42)	-0.032*** (-2.80)
<i>URB</i>	-0.045*** (-5.82)	-0.060*** (-6.04)	-0.042*** (-3.67)	-0.017** (-2.35)	-0.051*** (-6.73)	-0.037*** (-3.72)	-0.040*** (-5.64)	-0.048*** (-6.59)
Spatial spillover effect								
<i>LNM</i>	-1.737*** (-10.68)	-1.616*** (-9.27)	-0.599*** (-4.39)	-0.324*** (-10.52)	-1.321*** (-9.30)	-1.072*** (-11.62)	-9.737*** (-4.56)	-9.221*** (-4.75)
<i>LNM</i> × <i>MIG</i>							16.754*** (4.07)	
<i>MIG</i>							-77.436*** (-4.25)	
<i>LNM</i> × <i>GRA</i>								10.240*** (4.00)
<i>GRA</i>								-42.574*** (-3.85)
<i>RAD</i>	-0.474***	-0.201**	-0.774***	-0.166***	-0.240**	0.185***	-0.067	-0.082

(To be continued)

(Continued)

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
	(-4.37)	(-2.17)	(-5.17)	(-8.17)	(-1.98)	(2.94)	(-0.24)	(-0.34)
LAS	-1.102***	-1.150***	0.572*	0.435***	-1.146***	0.431***	-0.720	1.509*
	(-3.65)	(-3.96)	(1.93)	(4.97)	(-3.09)	(2.75)	(-0.96)	(1.85)
IRR	-3.340***	-4.901***	-1.045	-0.091	0.282	0.198	-0.553	0.960
	(-4.19)	(-5.66)	(-1.44)	(-0.56)	(0.27)	(0.30)	(-0.26)	(0.45)
IND	0.025	-0.068**	0.015	-0.123***	0.207***	0.355***	0.374***	0.072
	(0.75)	(-2.03)	(0.34)	(-9.89)	(4.02)	(13.95)	(3.04)	(0.91)
TRA	-1.322***	-0.259	-0.911***	0.126***	-1.886***	-1.126***	-4.649***	-2.498***
	(-5.55)	(-0.75)	(-5.83)	(3.41)	(-5.85)	(-7.70)	(-4.22)	(-3.63)
URB	0.728***	0.652***	0.376***	-0.059***	0.068	-0.969***	0.273	0.544***
	(9.26)	(8.51)	(4.95)	(-3.66)	(0.96)	(-9.06)	(1.48)	(3.03)
Gross effect								
LNM	-1.769***	-1.644***	-0.625***	-0.375***	-1.381***	-1.118***	-9.838***	-9.223***
	(-11.05)	(-9.65)	(-4.64)	(-11.11)	(-9.92)	(-12.56)	(-4.60)	(-4.73)
LNM×MIG							16.936***	
							(4.10)	
MIG							-78.337***	
							(-4.29)	
LNM×GRA								10.159***
								(3.95)
GRA								-42.235***
								(-3.81)
RAD	-0.477***	-0.257***	-0.729***	-0.168***	-0.258**	0.153**	-0.079	-0.096
	(-4.45)	(-2.84)	(-4.89)	(-7.77)	(-2.16)	(2.43)	(-0.29)	(-0.39)
LAS	-0.626**	-0.445	0.946***	0.831***	-0.726**	0.750***	-0.388	1.913**
	(-2.09)	(-1.56)	(3.28)	(9.00)	(-1.97)	(5.00)	(-0.52)	(2.35)
IRR	-3.425***	-5.328***	-0.930	-0.224	0.154	0.126	-0.666	0.863
	(-4.33)	(-6.18)	(-1.29)	(-1.25)	(0.15)	(0.19)	(-0.31)	(0.41)
IND	0.054	-0.027	0.005	-0.127***	0.236***	0.515***	0.401***	0.102
	(1.60)	(-0.80)	(0.11)	(-9.32)	(4.56)	(20.58)	(3.25)	(1.28)
TRA	-1.338***	-0.147	-0.918***	0.136***	-1.907***	-0.986***	-4.678***	-2.530***
	(-5.68)	(-0.43)	(-5.90)	(3.54)	(-5.95)	(-6.93)	(-4.24)	(-3.67)
URB	0.683***	0.592***	0.334***	-0.076***	0.017	-1.006***	0.233	0.496***
	(8.67)	(7.70)	(4.32)	(-4.28)	(0.23)	(-9.34)	(1.26)	(2.75)
Log-Likelihood	381.39	430.16	-44.19	531.95	453.65	687.49	508.62	439.95
AIC	-726.79	-824.32	124.38	-1027.91	-871.29	-1338.97	-973.24	-835.90

Note: \* $P < 0.10$ , \*\* $P < 0.05$ , \*\*\* $P < 0.01$ ; the bracketed values stand for  $t$  values.

The direct effect of land urbanization on carbon emission intensity in agriculture is significantly negative at the 1% level. However, the effect on the spatial spillover effect and the overall effect of agricultural carbon emission intensity are significantly positive at the 1% level. Land urbanization rectifies the misallocation of land resources and labor resources by reallocating regional agricultural production factors, leading to a significant reduction in carbon emissions. Nevertheless, the unbalanced development of regional land urbanization leads to a misallocation of agricultural production factor resources, hindering the utilization of regional green resources and efficient land use. As a result, it contributes to higher carbon emission intensity in agriculture within the region (Zeng et al., 2021).

### **3.3 | Regional Differences in the Impact of Agricultural Mechanization on Carbon Emission Intensity in Agriculture**

Regional variations exist in terms of arable land protection, factor endowments, and agricultural economy development. Group regression analysis is conducted separately for major grain-producing areas and non-major grain-producing areas. The findings from Model (2) presented in Table 4 reveal a notable negative spatial spillover effect (which is significantly negative at the 1% level) of agricultural mechanization on carbon emission intensity in agriculture within major grain-producing areas. This implies that for every 1 percentage point increase in the level of agricultural mechanization, there is a corresponding decrease of 1.616 percentage points in

carbon emission intensity in nearby major grain-producing areas. The findings from Model (3) presented in Table 4 indicate that the spatial spillover effect of agricultural mechanization on carbon emission intensity in agriculture within non-major grain-producing areas is found to be significantly negative at the 1% level. This means that for every 1 percentage point increase in the level of agricultural mechanization, there is a corresponding decrease of 0.599 percentage points in carbon emission intensity in nearby non-major grain-producing areas. Compared with non-major grain-producing areas, the effect of spatial carbon emission reduction of agricultural mechanization on spatial carbon emission reduction in major grain-producing areas is greater. *H2* is thus verified. The rapid growth of the agricultural economy has brought about several challenges, including excessive input of high carbon factors in agriculture along with increased pollution. However, as the development level of low-carbon agriculture improves, there is a gradual reduction in regional carbon emission intensity in agriculture (Zhao et al., 2018). The degree of grain industry agglomeration, cultivated land protection, and agricultural machinery subsidies in major grain-producing areas are greater, and the comparative advantages of grain crop planting make the spatial carbon reduction effect of agricultural mechanization greater than that of non-main grain-producing areas.

### **3.4 | Robustness Test**

The spatial distance weight matrix may

overlook the impact of regional adjacency on carbon emission intensity in agriculture. In contrast, Model (4) in Table 4 presents the findings obtained by utilizing the spatial adjacency weight matrix rather than the spatial distance weight matrix. The direct effect, spatial spillover effect, and total effect of agricultural mechanization on carbon emission intensity in agriculture are significantly negative at the 1% level. After replacing the spatial weight matrix, the original conclusion still holds.

When measuring agricultural mechanization, it is important to consider potential measurement errors in the total power of agricultural machinery. To obtain more accurate results, it may be preferable to use the original value of regional agricultural machinery from the perspective of capital factors as a measure of the agricultural mechanization variable. The original value of regional agricultural machinery can be measured by multiplying the average number of regional households, the number of rural households, and the original value of agricultural machinery per capita owned by rural households. The findings from Model (5) in Table 4 indicate a significantly negative spatial spillover effect of agricultural mechanization on carbon emission intensity in agriculture, with a 1% statistical significance level. Moreover, even after replacing the measurement method for agricultural mechanization, the effect of spatial carbon emission reduction due to agricultural mechanization remains evident.

The total agricultural carbon emissions are estimated by using the fertilizer application equivalent amount,

pesticide usage, agricultural plastic film usage, agricultural diesel usage, total sown area of crops, and effective irrigation area, which may cause an underestimation in this respect. Carbon emissions per unit of GDP are used as a proxy for carbon emission intensity in agriculture, and the data on total urban carbon emissions are excerpted from the China Emission Accounts and Datasets (CEDAs). The CEDAs only put out the carbon emission data from 1997 to 2017. The panel data of 281 cities from 1999 to 2017 are matched through city names and years. The carbon emission intensity in agriculture is expressed by the ratio of total urban carbon emission to gross urban regional product, which measurement results are shown in Model (6) in Table 4. The findings show that the direct effect, spatial spillover effect, and total effect of agricultural mechanization on carbon emission intensity in agriculture are significantly negative at the 1% level. After replacing the measurement method of carbon emission intensity in agriculture, the main conclusions above are verified to be robust again.

### 3.5 | Further Analysis

Agricultural mechanization has the potential to contribute to spatial carbon emission reduction through enhanced element substitution and adjustments in the agricultural planting structure. To examine this impact mechanism, the author introduces an interaction term between the moderating variable and the agricultural mechanization variable into the SDM. Additionally, the author

incorporates the moderating effect model to validate the spatial spillover mechanism of agricultural mechanization on regional carbon emission intensity in agriculture.

Regarding the transfer of the rural labor force, the variable for the transfer of the rural labor force is represented by the ratio of the number of rural non-agricultural employees to the total number of rural employees. The number of rural non-agricultural employees is calculated as the difference between the total number of rural employees and those in the primary industry. Data on the rural employed population are obtained by multiplying the number of rural households by the average number of rural employees per household. The average rural employed population per household is expressed as the ratio of the number of rural employees in the province to the total number of rural households. The measurement results adding the interaction term can be found in Model (7) of Table 4. The results reveal that the spatial spillover coefficient of the interaction term between agricultural mechanization and rural labor force transfer is calculated to be 16.754. This coefficient is statistically significant at the 1% level, suggesting that the impact of agricultural mechanization on spatial carbon emission reduction is more pronounced in regions with lower transfer levels of the rural labor force. These findings indicate that rural labor transfer plays a positive moderating role in the relationship between agricultural mechanization and carbon emission intensity in agriculture. Constrained by the instability of land property rights and land fragmentation,

agricultural mechanization overcomes these challenges by implementing large-scale crop cultivation through cross-regional agricultural machinery operation services in regions with low levels of labor transfer (Fang & Huang, 2019). This approach effectively reduces carbon emissions in nearby regions. However, it is important to note that a higher level of factor substitution limits the mobility of agricultural machinery across regions. Additionally, the transfer of the rural labor force weakens the spatial impact of carbon emission reduction achieved through agricultural mechanization.

Regarding the agricultural planting structure, it is evaluated commonly using the planting ratio of food crops. It represents the ratio of the sown area of food crops to the total sown area of crops. In Table 4, Model (8) demonstrates the measurement outcome after including the interaction term of the planting ratio of food crops and agricultural mechanization. The results reveal that the spatial spillover coefficient of the interaction term between agricultural mechanization and the planting ratio of food crops is 10.240. This coefficient is statistically significant at the 1% level, suggesting that the impact of agricultural mechanization on spatial carbon emission reduction is more pronounced in regions with a lower planting ratio of food crops. These findings indicate that the planting ratio of food crops plays a positive moderating role in the relationship between agricultural mechanization and carbon emission intensity in agriculture. Given the grain orientation feature of

agricultural mechanization (Qiu & Luo, 2018), agricultural mechanization has a greater role in promoting the grain orientation of the agricultural planting structure in areas where the proportion of grain crops is low, and the proportion of grain crops is relatively low. The low level improves the cross-regional mobility of agricultural machinery factors, and the effect of agricultural mechanization on spatial carbon emission reduction is also more evident.

## 4 Conclusion and Suggestion

The continuous rise in global carbon emissions has increased the vulnerability of regional agricultural ecosystems. Consequently, studying the correlation between agricultural mechanization and carbon emission intensity in agriculture holds crucial theoretical and practical implications for the sustainable development of low-carbon agriculture. Based on the panel data of 282 cities across China, the SDM is used to analyze the impact of agricultural mechanization on regional carbon emission intensity in agriculture. The study reveals a consistent decline in carbon emission intensity in agriculture from 1999 to 2019. In different stages, regional carbon emission intensity in agriculture experienced a relatively slow decline from 1999 to 2003. However, from 2003 to 2011, the rate of decline accelerated significantly. Subsequently, from 2011 to 2019, the pace of reduction in regional carbon emission intensity in agriculture gradually decelerated. In terms of regional

distribution, the carbon emission intensity in agriculture of major grain-producing areas was significantly higher than that of non-major grain-producing areas from 1999 to 2009, but lower than that of non-major grain-producing areas after 2010 to 2019. In 2019, 92.22% of the prefecture-level cities in agricultural industries of major grain-producing areas achieved the target of reducing carbon emissions per unit of GDP by 40% to 45% by 2020 ahead of schedule. In non-major grain-producing areas, only 74.78% of the prefecture-level cities in agricultural industries have completed the carbon emission reduction target ahead of schedule. The task of carbon emission reduction finished in agriculture in major grain-producing areas is better than that in non-major grain-producing areas. Agricultural mechanization not only contributes to reducing carbon emission intensity in local agriculture but also demonstrates a substantial impact on spatial carbon emission reduction. In areas with higher levels of agricultural mechanization, the carbon emission intensity in nearby regions tends to be lower. Furthermore, the robustness of these findings remains consistent even when replacing the spatial weight matrix and adjusting the measurement methods for both explained and explanatory variables. Compared with non-major grain-producing areas, the effect of spatial carbon emission reduction of agricultural mechanization in major grain-producing areas is greater. Regarding the mechanism of impact, agricultural mechanization contributes to lowering carbon emission intensity in nearby regions through

two main channels. Firstly, it enhances the level of cross-regional substitution of factors. Secondly, it promotes the adoption of a grain-oriented agricultural planting structure, which further aids in decreasing carbon emissions. However, the transfer of the rural labor force and the adjustments in the agricultural planting structure have weakened the spatial effect of agricultural mechanization on carbon emission reduction.

The authors thus propose the following policy recommendations. First, to promote the coordinated development of regional agricultural mechanization and address the issue of market failure in cross-regional agricultural machinery services, it is crucial to proactively implement a subsidy policy that encourages the cross-regional operation of agricultural machinery. Information asymmetry within the cross-regional agricultural machinery service market leads to higher transaction costs. Implementing a subsidy policy can help mitigate this issue by reducing the transaction prices associated with regional agricultural machinery services. By making these services more affordable and accessible, the subsidy policy facilitates the spatial effect of carbon emission reduction of agricultural mechanization. Second, subsidy policies should also be leveraged to encourage the development and adoption of energy-saving and environmentally friendly agricultural machinery. These policies should minimize carbon emissions of agricultural machinery during operation. The conventional production mode of agricultural machinery, reliant on diesel as its power source, is associated with high

carbon emissions. To transition toward a low-carbon agricultural mechanization approach, it is essential to support the innovation of new energy agricultural machinery products through agricultural policies. These policies should support the innovation of new energy agricultural machinery products and reduce carbon emissions in the agricultural production process. Third, it is necessary to strengthen the protection of non-major grain-producing areas and strictly control changes to land use in non-major grain-producing areas. Non-major grain-producing areas often have weaker arable land protection and control policies, which results in a relatively small effect of agricultural mechanization on spatial carbon emission reduction in these regions. However, by implementing strict controls over the agricultural planting structure in non-major grain-producing areas and increasing the proportion of non-grain crop cultivation, the spatial effect of regional agricultural mechanization on carbon reduction can be significantly improved. Fourth, land fragmentation has diminished the demand for cross-regional agricultural machinery services in agricultural production. To address this issue, China should continue to support new rural business entities to expand the scale of agricultural production, which will pave the way for further agricultural mechanization and foster the high-quality development of low-carbon agriculture.

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