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Effects of Land Transfer on Agricultural Carbon Productivity and Its Regional Differentiation in China

Xisheng Liao [1], Shaoyi Qin [1], Yajuan Wang [1], Hongbo Zhu [1] and Xuexiang Qi [2,*]

[1] Department of Land Resource Management, School of Public Administration, Sichuan University, Chengdu 610065, China; liaoxisheng@scu.edu.cn (X.L.); qinshaoyi@stu.scu.edu.cn (S.Q.); wangyj@stu.scu.edu.cn (Y.W.); zhb@scu.edu.cn (H.Z.)
[2] Law School, Wenzhou University, Wenzhou 325035, China
* Correspondence: 20170075@wzu.edu.cn

Abstract: Facing the realistic threat of natural environment deterioration and frequent extreme weather, improving agricultural carbon productivity has become an objective requirement for achieving the goal of double carbon and for promoting the high-quality development of agriculture. As an important path toward improving land-use efficiency and promoting agricultural technological progress, land transfer has a potential positive effect on improving agricultural output and inhibiting agricultural carbon emissions. Based on the current situation of land transfer and the characteristics of agricultural carbon productivity in China, this study used the panel data of 30 provinces, from 2006 to 2019, in China to empirically test the relationship between land transfer and agricultural carbon productivity via the spatial Durbin model. The results show that (1) land transfer has a positive effect on agricultural carbon productivity; (2) agricultural carbon productivity has a spatial correlation, and the impact of land transfer on agricultural carbon productivity has a spillover effect; and (3) there are regional differences in the impact of land transfer on agriculture carbon productivity. Based on the results of the study, this paper puts forward policy recommendations from three aspects through which to optimize land transfer and enhance agricultural carbon productivity.

Keywords: land circulation; agricultural carbon productivity; regional differentiation

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1. Introduction

In recent years, the environmental problems caused by climate change have become increasingly prominent. How to reduce greenhouse gas emissions has become a difficult problem that has hindered the development of all countries. According to the report of the United Nations Intergovernmental Panel on Climate Change, agriculture has become the second largest source of greenhouse gases, accounting for 13.5% of total carbon emissions. From the perspective of the whole life cycle, the global agricultural sector accounts for 21–37% of total carbon emissions [1]. As a large agricultural country, how to achieve low carbon emissions, carbon reduction, and pollution reduction in agricultural production has become the focus of numerous scholars. At present, the measure of low-carbon transformation is the reduction in carbon intensity, but the concept of "carbon productivity" takes into account the dual objectives of economic development and low-carbon emission reduction; these can better measure the degree of green low-carbon development than carbon intensity. Improving agricultural carbon productivity means controlling greenhouse gas emissions, improving energy efficiency, and taking into account low-carbon agriculture and economic growth. Exploring the positive factors of agricultural carbon productivity has become an inherent requirement for the development of low-carbon agriculture. As an essential basic means of production in agricultural production, the transfer of land will have an impact on the flow of the rural labor force, the level of agricultural output, and the popularization of new technologies. In addition, there is a potential relationship between the transfer of land and the construction of low-carbon agriculture. Taking land transfer as the research object, exploring the mechanism and path of land transfer affecting agricultural carbon productivity is a rare research perspective in current academic circles. Based on the existing research, this work explored the impact mechanism of land transfer on agricultural carbon productivity and studied its regional differentiation characteristics in order to achieve the goal of agricultural economic growth and low-carbon green agriculture at the same time. In addition, this study sought a feasible path through which to enhance agricultural carbon productivity.

As a vital factor of production in agricultural production activities, the degree of the optimal allocation of land often determines the development of agriculture. In China, small farmers manage about 70% of the arable land [2], and the large-scale management of finely distributed land is an important way through which to improve the efficiency of agricultural production. Therefore, there have been many discussions on land transfer in academia. Certain scholars believe that land transfer is based on the rational transfer of land management rights for the purpose of enhancing the scale of agricultural management and ultimately achieving resource intensification [3]. Whether land transfer can take into account both economic and ecological benefits is related to the improvement of agricultural carbon productivity. From the perspective of economic benefits, land transfer can alleviate the mismatch of land resources [4], improve the efficiency of agricultural production and operation, and increase agricultural output [5,6]. Farmers with low productivity can obtain land rent or dividends by transferring land management rights, which can increase family property income from non-agricultural employment [7]. From the perspective of ecological benefits, chemical fertilizer is one of the main sources of agricultural carbon emissions. The expansion of the land-management scale is conducive to improving the efficiency of chemical fertilizer applications and reducing the intensity of chemical fertilizer use [8]. The large-scale management brought by land transfer can also promote the popularization of advanced low-carbon agricultural technology, thus effectively promoting agricultural carbon productivity.

Agricultural carbon productivity analyzes the grain system in the framework of the ecological environment with the dual objectives of "agricultural economic growth" and "agricultural carbon emission reduction" [9]. At present, there are two mainstream methods through which to measure agricultural carbon productivity: namely, the single-factor carbon productivity index method and the total-factor carbon productivity index method. The single-factor carbon productivity index method is achieved by using the ratio of carbon dioxide emissions to actual output as the carbon productivity. Certain scholars have used it to analyze the trend of carbon footprint and the carbon productivity of crops in China [10,11]. The index method of total-factor carbon productivity is to use the data envelopment analysis model to calculate the green total-factor productivity, take carbon emissions as the unexpected output, and to further consider the relationship between input factors and output results. Wang, Qin, and Zhang [12–14] used this method to assess the carbon emission efficiency of Chinese agriculture and its regional differences. In addition, research on the influencing factors of agricultural carbon productivity mainly focused on the technical level, industrial structure, individual quality of farmers, and urbanization level [15–17]. There are only a few pieces of literature on the impact of land transfer on agricultural carbon productivity. Song [16] found that farmers' specialized production significantly increased agricultural carbon productivity. Chen [18] believes that there is an "inverted U" relationship between land-scale and agricultural carbon productivity, where moderate-scale operations through land transfer will allow the agricultural carbon productivity to reach its optimal return. Therefore, it is necessary to explore the impact of land transfer on agricultural carbon productivity.

Based on the above research, it can be found that the research results around the intensity of agricultural carbon emissions are remarkable, but the research results with carbon productivity as the main body and those taking into account both carbon emissions and agricultural output are less so. At the same time, the existing literature focuses on the impact of urbanization, industrial structure, and technological level on agricultural carbon productivity, but few studies have discussed the role of land transfer on agricultural carbon productivity. This paper focuses on the analysis of the effect, mechanism, and regional heterogeneity of land transfer on agricultural carbon productivity. The possible marginal contributions are as follows: First, by linking land transfer with agricultural carbon productivity and conducting an in-depth analysis of the impact of land transfer on agricultural carbon productivity and regional differentiation characteristics, one can provide a new perspective and basis for relevant research and policy formulation; second, after clarifying the effect and mechanism of land transfer on agricultural carbon productivity, this study constructed a spatial Durbin model and further tested the robustness of the model by changing the spatial matrix and re-measuring the carbon productivity, which has a certain reference value for related research.

2. Research Hypothesis

Carbon productivity refers to the level of GDP output per unit of carbon dioxide emissions, which focuses on the output efficiency of energy, and improving carbon productivity is to "reduce emissions" while "maintaining growth". To improve agricultural carbon productivity, it is necessary to break the traditional view that "carbon emission reduction and economic growth can not be achieved at the same time". This is the case not only in stabilizing greenhouse gas emissions, but also in ensuring the positive growth of agricultural economies, so as to achieve the decoupling development of the economy and carbon dioxide [19]. Land transfer can give full play to the economic and ecological effects through the rational allocation of resources, the adjustment of household income structure, the development of green agriculture, and the upgrading of the agricultural industry [20], so as to achieve the goal of improving agricultural carbon productivity. Based on this, Hypothesis H1 is proposed:

H1. *Land transfer can promote agricultural carbon productivity.*

Different from other industries, agricultural production is highly dependent on natural factors such as topography, sunshine, and temperature, and it has evident regional and seasonal characteristics. The agricultural location conditions in adjacent areas are similar, which makes the provinces and adjacent areas converge in terms of agricultural production conditions, crop varieties, and production modes [21]. With the improvement of infrastructure, production factors such as talents and capital operate frequently across provinces, and agricultural production links between adjacent provinces are increasingly close, which makes agricultural carbon productivity have spatial correlation [22]. Land transfer will encourage large-scale agricultural production, accelerate the diffusion of production technology as a contributing resource in the region, and trigger regional carbon linkages. In addition, land transfer will affect the competitive position of agricultural production organizations, and organizations with competitive advantages will show a demonstrable effect in terms of attracting organizational learning in neighboring regions, thus strengthening the regional carbon correlation. It can be seen that land transfer has a spillover effect on agricultural carbon productivity.

H2. *There is spatial correlation in agricultural carbon productivity, and the impact of land transfer on agricultural carbon productivity spills over.*

China has a vast territory, and the circulation situation and land endowment of each region are different. Overall, the land transfer rate shows the characteristics of "high in the south and low in the north, high in the east and low in the west" [23]. However, due to the limitation of natural conditions, the difference in management modes, and the difference between individual farmers, there are differences in China's agricultural industry between the eastern, central, and western regions. The eastern region is characterized by a highly market-oriented and technology-intensive agriculture, the central region is dominated by mechanized agriculture, and the western region is still in the stage of extensive traditional agriculture [24]. Therefore, there may be certain differences in the degree of the impact of land transfer on agricultural carbon productivity between the eastern, central, and western regions of China. For example, the eastern region of China has vast plains, a low cost of land transfer, and convenient management, which can take into account both economic and ecological benefits. When compared with the central and western regions, its agricultural carbon productivity may be higher. Based on this, hypothesis H3 is proposed:

H3. *There are regional differences in the impact of land transfer on agricultural carbon productivity.*

3. Methods

3.1. Model

Existing studies show that there is a strong spatial correlation in land transfer [25], and the flow of production factors and carbon dioxide emissions is less restricted by regions. Therefore, it is appropriate and robust to introduce spatial factors into the study of land transfer and carbon productivity which can effectively reduce the bias of research results. Based on the above mathematical model and theoretical analysis, this paper uses the path of OLS-SAR/SEM-SDM to select the best-fitting econometric model. The specific model is as follows:

$$\begin{aligned} CE_{it} = \beta_0 + \rho W_{ij} CE_{it} + \beta_1 turn_{it} + \beta_2 disa_{it} + \beta_3 educ_{it} + \beta_4 indu_{it} + \beta_5 fin_{it} \\ + \beta_6 fdi_{it} + \theta_1 W_{ij} turn_{it} + \theta_2 W_{ij} disa_{it} + \theta_3 W_{ij} educ_{it} + \theta_4 W_{ij} indu_{it} \\ + \theta_5 W_{ij} fin_{it} + \theta_6 W_{ij} fdi_{it} + \mu_i + \varphi_t + \varepsilon_{it} \end{aligned} \tag{1}$$

CE_{it} is the explained variable and it represents agricultural carbon productivity, i.e., the level of agricultural output that can be provided by unit carbon emissions; $turn_{it}$ is the core explanatory variable and it indicates the level of land circulation; $Disa_{it}$, $educ_{it}$, $indu_{it}$, fin_{it}, ow_{it}, and con_{it} are the control variables and they are agricultural natural disasters, the education level of the labor force, the mechanization level, the financial support for agriculture and agricultural openness, and the consumption level of rural residents; ρ is the spatial lag coefficient, indicating the degree and direction of the impact on the carbon productivity of adjacent regions and on the carbon productivity of the province (if $\rho \neq 0$, then the spatial econometric regression coefficients need to be decomposed); W_{ij} is an adjacency matrix; β_0 is a constant term; β_1 is the regression coefficient; θ_1–θ_7 is the spatial regression coefficient; μ_i, φ_t is the area effect and time effect, respectively, which are used to control the influence of unobservable variables that do not change with time and instead change with time on the dependent variable; and ε_{it} is the error term.

As for the selection of the spatial weight matrix, this paper uses the "0–1" adjacency matrix (which is the mainstream at present) to determine the spatial correlation according to the geographical adjacency.

3.2. Variable Description and Measurement

3.2.1. The Explained Variable

The explained variable in this paper is agricultural carbon productivity (CE_{it}). Agricultural carbon productivity refers to the GDP output level per unit of carbon dioxide in agriculture, also known as "carbon per capita GDP". The basis of scientific research on the relationship with land transfer is the accurate measurement of agricultural carbon productivity. As the total-factor carbon productivity index takes carbon dioxide emissions as an unexpected output in the calculation, it cannot reflect the impact of the limited space of carbon emissions on agricultural production. Meanwhile, the single-factor carbon productivity index is convenient to calculate, and it can more intuitively reflect the dual development goals of carbon reduction and economic promotion [26]. Therefore, according to the definition of carbon productivity by Kaya et al. (1997), the agricultural carbon productivity is defined as the ratio of total agricultural output value to total agricultural carbon dioxide emissions, and the specific calculation formula is as follows:

$$CE = \frac{\sum P_i Q_i}{\sum C} \tag{2}$$

where CE represents the agricultural carbon productivity, P_i and Q_i represent the market price and total output of agriculture, and i and C represent the total carbon dioxide emissions of agriculture.

The calculation of total agricultural carbon emissions refers to the practice of Liu Yiwen et al. (2021), where chemical fertilizers, pesticides, agricultural films, diesel oil, agricultural cultivation, and agricultural irrigation are taken as carbon emission sources. The carbon emission coefficients of agricultural chemical fertilizer, pesticide, agricultural plastic film, agricultural diesel oil, the total sown area of agriculture, and the effective irrigation area of agriculture are 0.8956 kg/kg, 4.9341 kg/kg, 5.1800 kg/kg, 0.5927 kg/kg, 312.6000 kg/ha, and 266.4800 kg/cha, respectively. The sum of various carbon sources multiplied by the corresponding carbon emission coefficient is the total agricultural carbon emission [27].

3.2.2. Explanatory Variables

The explanatory variable of this paper is the level of land circulation ($turn_{it}$). Land transfer is conducted through the optimal allocation of resources against the background of urban–rural integration and rural labor flow to the city—this approach has been widely used in China. In reference to the practice of Kuang Yuanpei and Yang Jiali (2019), this paper uses the ratio of the total area of household-contracted-farmland circulation to the area of household-contracted-farmland management in order to measure the level of land circulation in different regions and in different periods. The data come from the "China Rural Operation and Management Statistical Yearbook" [28].

3.2.3. Control Variables

Based on the relevant research and mathematical model, the following control variables were selected: ① Agricultural natural disasters (disa). Agricultural production has a strong dependence on nature and is strongly affected by climatic conditions, which are measured by the ratio of the land-affected area to the total crop-sown area [29]. ② Agricultural openness (ow). Through trade with other countries, the efficiency of the allocation of agricultural production factors can be improved, so that agriculture can be developed. This was measured by the proportion of the agricultural import value to the total agricultural output value (when converted from the exchange rate of CNY to USD) [30]. ③ Financial support for agriculture (fin). The strength of fiscal support for agriculture reflects the strength of government financial support for agriculture, which mainly includes voluntary agricultural production expenditure, agricultural machinery purchase subsidies, direct grain subsidies, etc. Considering that there is a big gap in the level of agricultural development between provinces and cities, this parameter was measured by the ratio of financial support for agriculture to the total output value of agriculture, forestry, animal husbandry, and fishery. ④ Educational level of labor force (educ). A high-level labor force will inject vitality into agricultural innovation, and it was measured by the proportion of high school and above education in the agricultural labor force. ⑤ Mechanization level (indu). The level of mechanization affects the level of agricultural output and, thus, agricultural carbon productivity. It was measured by the ratio of the total power of agricultural machinery to the number of rural people. ⑥ Consumption level of rural residents (con). The consumption power of rural residents has an impact on agricultural carbon emissions by influencing the scale of agricultural planting, and it was measured by the per capita consumption expenditure of rural residents.

3.3. Sample Selection and Data Sources

Based on the availability and completeness of the data, 30 provincial-level administrative regions in China (except the Tibet Autonomous Region) were selected as the research sample. The sample interval is from 2006 to 2019. The basic data were obtained from the China Rural Statistical Yearbook, the China Financial Yearbook, the China Agricultural Machinery Industry Yearbook, the China Population and Employment Statistical Yearbook, the China Agricultural Yearbook, and the statistical yearbooks of provinces (as well as those of municipalities and autonomous regions). The relevant economic variables in 2006 were dealt with as the base period, a small number of missing values were filled by multiple interpolation, and the natural logarithm of the data with larger magnitudes was taken to eliminate the dimension. Descriptive statistics for each variable are given in Table 1.

Table 1. Descriptive Statistics.

Variables	Meaning	Sample Size	Average Value	Standard Deviation	Minimum Value	Maximum Value
ce	Agricultural carbon productivity	420	1.123	0.161	0.838	1.750
turn	Land circulation level	420	0.238	0.174	0.013	0.873
disa	Agricultural natural disasters	420	0.199	0.145	0.006	0.695
ow	The degree of agricultural openness	420	0.233	0.731	0	5.812
fin	Financial support for agriculture	420	0.105	0.036	0.016	0.189
educ	Education level of the labor force	420	0.118	0.072	0.027	0.504
indu	Mechanization level	420	1.535	0.826	0.013	0.873
con	Consumption level of rural residents	420	8.823	0.539	7.467	10.019

4. Results

4.1. Spatial Correlation Test

4.1.1. Global Spatial Autocorrelation Test

Table 2 shows the overall Moran index of the land circulation level and agricultural carbon productivity of 30 provincial administrative regions in China from 2006 to 2019. According to the global Moran index test for agricultural carbon productivity, all of the years were significantly positive, except the years of 2015–2019, which indicates that there is a strong spatial correlation in China's agricultural carbon productivity from 2006 to 2019. As per the global Moran index test for land circulation, the land circulation was significantly positive from 2006 to 2019. This shows that the land circulation between provincial administrative regions in China has a strong spatial correlation and spatial spillover effect. It is also reasonable to consider the space factor when designing the model.

Table 2. Agricultural Carbon Productivity and the Global Moran Index of Land Circulation.

Year	Agricultural Carbon Productivity	Land Circulation	Year	Agricultural Carbon Productivity	Land Circulation
2006	0.412 ***	0.262 ***	2013	0.300 ***	0.311 ***
2007	0.175 **	0.268 ***	2014	0.219 **	0.365 ***
2008	0.236 **	0.245 ***	2015	0.061	0.356 ***
2009	0.256 **	0.236 **	2016	−0.096	0.425 ***
2010	0.255 **	0.253 **	2017	−0.062	0.391 ***
2011	0.313 ***	0.254 **	2018	−0.126	0.443 ***
2012	0.309 ***	0.273 ***	2019	−0.126	0.412 ***

Note: **, and *** mean significant at the 5%, and 1% levels, respectively.

4.1.2. Local Spatial Autocorrelation Test

The global Moran index can show the positive agglomeration relationship of agricultural carbon productivity in each province, but it cannot directly observe the specific spatial agglomeration characteristics of each province. In this paper, 2006, 2010, 2014, and 2019 were selected as examples through which to conduct partial Moran tests for agricultural carbon productivity. The test results are shown in Figure 1. It can be found that most provinces are located in the first and third quadrants, belonging to "high-high" agglomeration and "low-low" agglomeration, i.e., provinces with higher agricultural carbon productivity are located near provinces with high-carbon productivity, provinces with lower agricultural carbon productivity are located near provinces with low-carbon productivity, and provinces with high-carbon productivity belong to the same province. This is consistent with the fact that there are significant differences in the technology and resource utilization efficiency between the eastern coastal region and the central and western regions of China, which further verifies that there is a positive spatial correlation between agricultural carbon productivity.

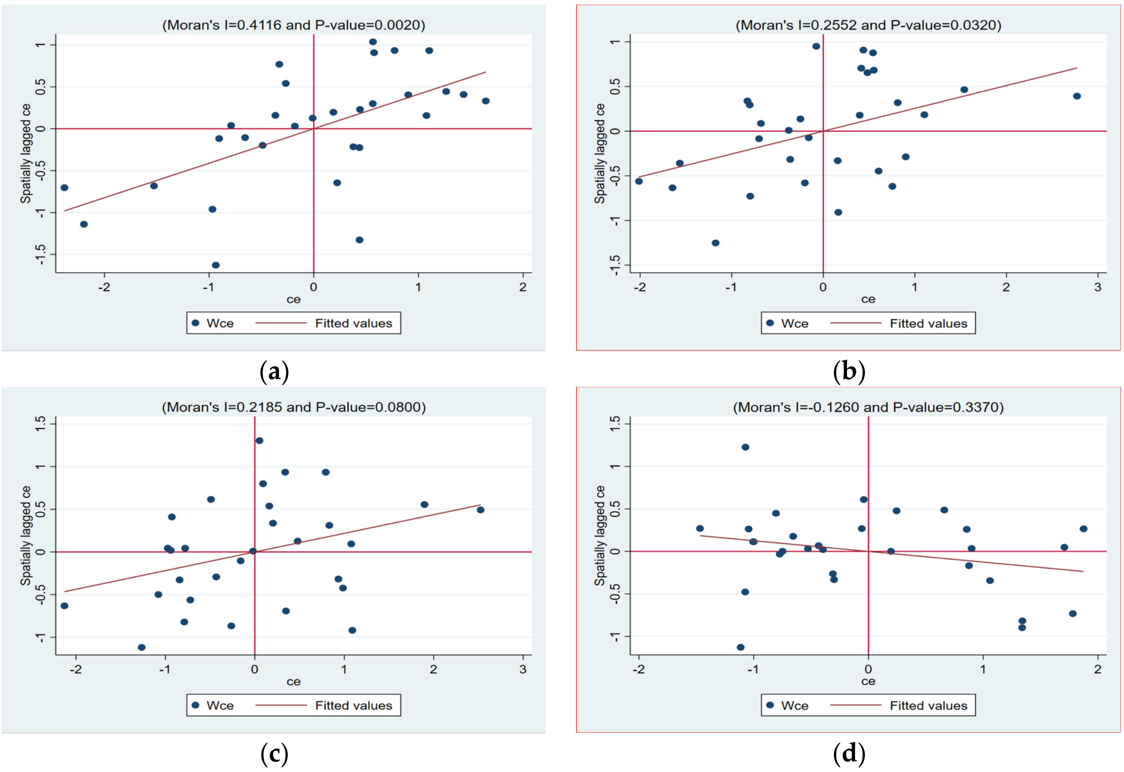

Figure 1. Scatter plot of the local Moran index for agricultural carbon productivity. (**a**) 2006, (**b**) 2010, (**c**) 2014, (**d**) 2019.

4.2. Spatial Econometric Model Testing

Before benchmark regression, the econometric model should be selected and tested. This paper used the LM test, LR test, and Wald test to select the specific form and model effect of the econometric model. Firstly, the LM test was used to test the spatial econometric model, as shown in Table 3.

Table 3. The LM test results of all samples.

Test	Statistic	df	*p*-Value
Spatial error:			
Moran's I	4.201	1	0.000
Lagrange multiplier	17.221	1	0.000
Robust Lagrange multiplier	12.136	1	0.000
Spatial lag:			
Lagrange multiplier	14.895	1	0.000
Robust Lagrange multiplier	9.809	1	0.002

The results reported in Table 3 show that both the LM error and LM lag statistics were significant at the 1% level. Further analysis of the results of the robust LM error and robust LM lag shows that the *p*-value of the LM test statistic was below 0.1; thus, the null hypothesis that there is no spatial lag and spatial error should be rejected, and the spatial econometric model should be used to study the problem. At the same time, the results in Table 3 also prove that both the SAR model and the SEM model are suitable. Therefore, this paper chose to use the spatial Durbin model SDM, which has the characteristics of both SAR and SEM.

Secondly, the results of the Hausman test prove that the fixed-effects model is better. In the further test, it was found that the two-way fixed-effects model is better than the regional fixed-effects and time fixed-effects models in the selection of an SDM model.

Finally, this paper used the Wald test and the LR test to judge the applicability of the SDM model and whether there was degradation. The test results are shown in Tables 4 and 5. The results show that the results of the Wald test and the LR test were significant at a 1% confidence level, which proves that the SDM model is better than the SAR and SEM models, and that the SDM model cannot be degraded to the SAR model or SEM model.

Table 4. Wald test results.

Wald Test for SAR	Wald Test for SEM
chi2 (6) = 52.01 Prob > chi2 = 0.0000	chi2 (6) = 46.71 Prob > chi2 = 0.0000

Table 5. LR test results.

Likelihood-Ratio Test	Likelihood-Ratio Test
LR chi2 (6) = 50.65 (Assumption: SAR nested in SDM) Prob > chi2 = 0.0000	LR chi2 (6) = 51.06 (Assumption: SEM nested in SDM) Prob > chi2 = 0.0000

4.3. Benchmark Regression Results and Analysis

The regression results are shown in Table 6. In the spatial Durbin model, the regression coefficient of land transfer level was 0.172, which was significant at the level of 5%. This means that the deepening of land transfer in the province is conducive to the improvement of agricultural carbon productivity in the province: thus, hypothesis H1 is established. By combining theory with practice, the possible explanations are the following: first, land transfer can optimize land-use efficiency, increase output, and optimize benefits, while large-scale production can reduce the cost of low-carbon production in the region and can ultimately improve agricultural carbon productivity; second, land circulation will accelerate large-scale agricultural technological innovation, and a higher level of land circulation can use idle resources to increase the research on green agriculture while using land intensively. In addition, it can help to promote the development of low-carbon agriculture so as to enhance agricultural carbon productivity.

Table 6. Benchmark Regression Results.

Variables	OLS	SDM
turn	0.234 ***	0.172 **
	(0.074)	(0.071)
disa	−0.039	−0.048
	(0.036)	(0.035)
ow	−0.053 ***	−0.044 ***
	(0.013)	(0.012)
fin	0.853 ***	1.121 ***
	(0.323)	(0.325
educ	−0.660 **	−0.698 ***
	(0.265)	(0.249)
indu	−0.013	−0.042 ***
	(0.013)	(0.014)
con	0.136 **	0.146 **
	(0.065)	(0.063)

Table 6. *Cont.*

Variables	OLS	SDM
W * turn		0.331 **
		(0.142)
W * disa		0.061
		(0.061)
W * ow		0.096 ***
		(0.029)
W * fin		−1.049 **
		(0.532)
W * educ		−0.790
		(0.539)
W * indu		0.104 ***
		(0.025)
W * con		0.306 ***
		(0.112)
ll		544.131
ρ/λ		0.273 **
		(0.076)
N	420	420
R-squared	0.720	0.590

Note: *, **, and *** mean significant at the 10%, 5%, and 1% levels, respectively. And the R^2 of the panel data is usually lower than that of the mixed cross-section and time series models, and in this case the within R-sq of the fixed-effect model was used.

According to Lesage et al. (2009), when the spatial lag coefficient is $\neq$0, the regression coefficient of the SDM model cannot accurately measure the influence of explanatory variables; thus, it was necessary to use the partial differential method to decompose the model into direct and indirect effects. The results of the decomposition are reported in Table 7.

Table 7. Decomposition of the results for the impact of land transfer on agricultural carbon productivity.

Variables	Direct Effect	Indirect Effect	Total Effect
turn	0.157 **	0.233 *	0.390 ***
	(0.077)	(0.122)	(0.105)
disa	−0.054	0.069	0.014
	(0.036)	(0.054)	(0.045)
ow	−0.049 ***	0.092 ***	0.043 *
	(0.019)	(0.025)	(0.026)
fin	1.200 ***	−1.152 **	0.048
	(0.332)	(0.485)	(0.392)
educ	−0.672 ***	−0.478	−1.150 **
	(0.242)	(0.475)	(0.461)
indu	−0.048 ***	0.096 ***	0.048 ***
	(0.015)	(0.022)	(0.016)
con	0.129 *	0.232 **	0.361 ***
	(0.070)	(0.095)	(0.091)

Note: *, **, and *** mean significant at the 10%, 5%, and 1% levels, respectively.

It can be seen from Table 6 that the spatial autoregression coefficient was 0.273 and was significantly positive, indicating that there is a positive spatial spillover effect of agricultural carbon productivity between the provinces, i.e., the improvement of agricultural carbon productivity in this province will optimize the agricultural carbon productivity in neighboring provinces. From Table 7, we can see that the direct effect of land circulation was 0.188, indicating that the agricultural carbon productivity will increase by 0.188% when the level of land circulation in the province increases by 5%—which confirms hypothesis H1 again. The indirect effect of land transfer was 0.233, indicating that the agricultural carbon productivity of the neighboring provinces is 0.233% when the level of land transfer in the province increases by 10%. Furthermore, the total effect of the land circulation level on agricultural carbon productivity was 0.39, indicating that the agricultural carbon productivity at the national level increases by 0.39% when the land circulation level increases by one percentage point. This may be due to the existence of the demonstration and imitation effect, the competition effect, and the personnel flow effect of land transfer behavior across regions [31]. This makes land transfer significantly affect the spatial spillover of agricultural carbon productivity, i.e., the degree of land transfer improvement in this region will have an impact on the agricultural carbon productivity in adjacent regions. Moreover, the indirect effect of land circulation on agricultural carbon productivity was greater than the direct effect, which indicates that the impact of coordinated regional development and the spatial spillover effect of agricultural carbon productivity is more significant. If the indirect effect is positive, it reflects the positive spatial correlation between land circulation and agricultural carbon productivity. Among the control variables, the indirect effects of agricultural openness, mechanization, and rural residents' consumption level were stronger, showing similar spillover characteristics. To summarize, there is a spatial correlation of agricultural carbon productivity, and the impact of land transfer on agricultural carbon productivity spills over—thus, H2 is assumed to be established.

4.4. Robustness Test

1. Regarding changing the space matrix, the selection of a spatial matrix had a significant impact on the measurement results. Considering that there may be spatial correlations between provinces that are far away from each other, and due to the fact that the strength of the correlation is limited by the geographical distance, this paper chose the geographical distance matrix to test the robustness. The geographical distance space matrix was specifically constructed as follows: d_{ij} represents the geographic distance between city i and city j, and is calculated based on latitude and longitude:

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}},\ i \neq j \\ 0,\ i = j \end{cases} \quad (3)$$

The spatial measurement results of the geographical distance matrix are shown in Table 8. It can be found that a change in the spatial matrix had little effect on the land circulation effect, and its effect on the improvement of agricultural carbon productivity was still significant, which is consistent with the previous regression results, thus proving the robustness of the conclusions in this paper.

2. Regarding a remeasurement of carbon productivity, at present, carbon productivity is mainly divided into two types: single-factor carbon productivity and total-factor carbon productivity. Total-factor carbon productivity refers to the use of the SBM-Gml index to calculate the annual change in carbon productivity. This is achieved by taking the total sown area of agriculture, the total power of agricultural machinery, the converted amount of agricultural chemical fertilizer application, and the number of agricultural employments as the input indicators. The actual gross agricultural product is the expected output, and the carbon dioxide emissions are the unexpected output. The total-factor carbon productivity of agriculture from 2006 to 2018 can be obtained by stipulating that the carbon productivity in 2005 was 1. Observing the results in Table 8, it can be found that the regression results were still significant after re-measuring the explained variables, indicating that the conclusion that land transfer plays a positive role in agricultural carbon productivity is robust.

Table 8. Robustness test results.

Variables	Geographic Distance Matrix		Replacing the Explained Variable	
	Direct Effect	**Indirect Effect**	**Direct Effect**	**Indirect Effect**
turn	0.163 **	0.375 ***	0.151 *	0.729 ***
	(0.077)	(0.129)	(0.078)	(0.210)
disa	−0.063 *	0.049	−0.069 *	0.064
	(0.036)	(0.065)	(0.036)	(0.096)
ow	−0.045 ***	0.053 ***	−0.049 ***	0.074 **
	(0.012)	(0.019)	(0.012)	(0.034)
fin	1.253 ***	−0.955	1.301 ***	−2.218 **
	(0.339)	(0.637)	(0.336)	(0.983)
educ	−0.916 ***	−0.477	−0.937 ***	−0.203
	(0.250)	(0.529)	(0.246)	(0.838)
indu	−0.014	0.008	−0.013	0.009
	(0.015)	(0.027)	(0.014)	(0.044)
con	0.155 **	0.351 ***	0.162 **	0.679 ***
	(0.068)	(0.109)	(0.067)	(0.173)
R-squared	0.576		0.400	
N	420		420	

Note: *, **, and *** mean significant at the 10%, 5%, and 1% levels, respectively.

4.5. Regional Differentiation Characteristics of the Impact of Land Transfer on Agricultural Carbon Productivity

In order to further explore the regional differentiation of the impact of land circulation on agricultural carbon productivity, and due to the differences in natural resource endowments and economic development levels in the eastern, central, and western regions of China, this paper selected the spatial Durbin model for determining the regression in the eastern, central, and western regions according to the official statistical yearbook data. The results are shown in Table 9.

Table 9. Regional Differentiation Characteristics of Land Transfer on Agricultural Carbon Productivity.

Variables	East		Central		West	
	Direct Effect	**Indirect Effect**	**Direct Effect**	**Indirect Effect**	**Direct Effect**	**Indirect Effect**
turn	0.294 ***	0.165 *	0.113 **	0.248 ***	0.249	0.084
	(0.063)	(0.095)	(0.201)	(0.242)	(0.188)	(0.293)
disa	−0.024	0.066	−0.057	0.084	−0.075	−0.085
	(0.032)	(0.055)	(0.110)	(0.120)	(0.052)	(0.081)
ow	−0.046 ***	0.141 ***	−4.648 ***	−1.243	−1.240	1.001
	(0.009)	(0.018)	(1.444)	(1.707)	(1.009)	(2.176)
fin	0.421	−1.429 **	1.819 **	−0.343	1.148 **	0.745
	(0.362)	(0.560)	(0.856)	(1.012)	(0.490)	(0.844)
educ	−0.034	−0.666	−0.931	−1.008	−1.466 ***	1.347 *
	(0.221)	(0.429)	(0.763)	(1.055)	(0.412)	(0.789)
indu	0.053 **	0.030	−0.032	−0.014	−0.028	0.016
	(0.022)	(0.031)	(0.028)	(0.033)	(0.026)	(0.058)
con	−0.032	0.400 ***	0.124	0.892 ***	0.538 ***	0.064
	(0.065)	(0.090)	(0.219)	(0.257)	(0.116)	(0.192)

Note: *, **, and *** mean significant at the 10%, 5%, and 1% levels, respectively.

It can be further seen from Table 8 that, in terms of direct effects, the direct effects of the eastern and central regions were 0.294 and 0.113, respectively. This indicates that the improvement of land circulation level in the eastern and central provinces will promote the improvement of agricultural carbon production in the province. In terms of spillover effects, the indirect effects of the eastern and central provinces were 0.165 and 0.248, respectively, which indicates that the improvement of land-transfer levels in the eastern and central provinces will have a positive impact on the agricultural carbon productivity of neighboring provinces. However, the direct and indirect effects in the western region were not significant. The above results show the following: first, there are positive direct and indirect effects of land transfer on agricultural carbon productivity in the eastern and central regions; second, compared with the western region, the effect of land transfer on agricultural carbon productivity in the eastern and central regions is more evident.

The possible explanations for the above phenomena are as follows: First, the direct and indirect effects of the eastern region were significantly positive, and the positive effect of agricultural carbon productivity brought about by land transfer is evident. On the one hand, this may be because the eastern region has a superior natural environment, perfect infrastructure, a high level of economic development, and its land transfer market is more mature, which allows it to create a prerequisite for giving full play to the reallocation of agricultural resources by land circulation. On the other hand, the eastern region is often the pilot area for China's policies, and the spillover of the circulation policy makes the indirect effect of the eastern region significant. Second, the direct and indirect effects of the central region were also significantly positive, which may be related to its agricultural production mode. Most of the eight provinces in the central region are large agricultural provinces dominated by mechanization, and the large areas of the mechanized agricultural production mode will make them produce more regional carbon associations. Finally, the impact of the western region was not found to be significant, which may be due to the irregular behavior of land circulation and the single-planting mode of agriculture.

To summarize, there are significant regional differences in the impact of land transfer on agricultural carbon productivity; thus, Hypothesis H3 is valid.

5. Conclusions

Based on the dynamic panel data of 30 provincial-level administrative regions from 2006 to 2019, this study linked land transfer with agricultural carbon productivity, constructed a spatial Durbin model, clarified the impact of land transfer on agricultural carbon productivity and regional differentiation characteristics, and—finally—further tested the robustness of the model by changing the spatial matrix and re-measuring carbon productivity. The results show the following: (1) land transfer has a significant effect on agricultural carbon productivity, which is still valid after the robustness test of changing the spatial matrix and re-measuring carbon productivity; (2) the direct and indirect effects of land transfer on agricultural carbon productivity are significantly positive, and there is a spatial spillover effect, that is, land transfer can not only affect the agricultural carbon productivity of the province, but also improve the agricultural carbon productivity of neighboring provinces through the demonstration effect and the diffusion effect; (3) there are regional differences in the impact of land circulation on agricultural carbon productivity. The direct effect of land circulation in the eastern region is the strongest, the indirect effect is strongest in the central region, and the impact in the western region is not significant. The possible explanation of the above results is that the land circulation market in the eastern region is mature and the policy environment is superior, so its direct effect is the strongest, while the central region is dominated by large-scale mechanized agriculture, so its indirect effect is stronger, and the western region is not significant due to its irregular land circulation behavior and the implementation of a single-planting model.

Based on the above conclusions, the following policy recommendations are put forward:

Firstly, we should attach importance to the role of land transfer in improving agricultural carbon productivity and improving the quality of land transfer. This study shows that the improvement of the land-transfer level significantly improved the agricultural carbon productivity during the study period. However, at present, there are certain non-standard land circulation phenomena in our country, such as the phenomenon of "three more and three less" [32]. Moreover, the speed of land circulation in China has slowed down [33], and in order to improve the agricultural carbon productivity by improving the level of land circulation in the future, we should focus on the improvement of the quality of land circulation rather than the improvement of the rate of land transfer. This will further strengthen the positive role of land transfer in agricultural carbon productivity.

Secondly, we should improve the land transfer system, choose the best land transfer mode according to the local conditions, and stimulate the potential for regional emission reductions. For a long time, China's unique rural land policy restricted the development of the agricultural economy to a great extent. In recent years, however, the reform measures implemented by the state in rural areas—such as the "separation of powers" and rural land marketization—have provided conditions for land transfer in the system, which also provides an opportunity for improving the agricultural carbon productivity through land transfer. Therefore, we should give full play to the role of the market in the allocation of agricultural resources, actively and steadily guide land transfer and improve the efficiency of land transfer, promote the scale of agricultural production and operation, and promote the development of green low-carbon agriculture. At the same time, in the construction of the agricultural land-transfer market, we should consider not only the scale of agricultural land transfer, but also the scope of the land transfer. We should also promote land transfer and choose the best mode of land transfer according to the local conditions, so as to better stimulate regional emission reduction potential.

Thirdly, we should take ecological low-carbon agriculture as the basis of development, and we should attach importance to the emission reduction effect in the spillover of agricultural technological progress. The government can encourage leading enterprises, universities, and research institutes to strengthen the research and development of green low-carbon agricultural production technologies, such as deep water saving, precise fertilization, and medication, to meet the needs of farmers through incentives such as preferential taxation and scientific research projects. At the same time, the government should also integrate resources such as talents, capital, and technology to promote the integration of regional advantages. In addition, they should improve the whole process of agricultural technology from research and development, from application to promotion, and also provide the possibility of "increasing agricultural efficiency", "increasing farmers' income", and "increasing rural greening". This will make the channel of technology spillover smoother, and will allow the effect of technology emission reductions to be more significant.

There are certain limitations to this study. Firstly, this study used provincial data to study the impact of land transfer on agricultural carbon productivity. If municipal- or county-level data can be used, regional differences in land transfer on agricultural carbon productivity can be observed in more detail. Secondly, this study overlooked the correlation between agricultural carbon productivity and its influencing factors, which may have had a slight impact on the empirical results. Finally, due to the difficulty in measuring carbon dioxide emissions and the lack of official data, this study used fertilizers, pesticides, agricultural film, diesel, agricultural cultivation, and agricultural irrigation as carbon emission sources to calculate the approximate carbon emissions, which may differ from the actual emissions. The calculation model for carbon emissions needs further precision.

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