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Research Article

Study on the Spatial Spillover Effects of Agricultural Carbon Absorption in China

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Abstract

Improving agricultural carbon absorption is an effective means to reduce emissions and increase absorption in agriculture and to achieve carbon neutrality. Different regions in China have obvious differences in resource endowments, but few studies have studied the spatial effects of agricultural carbon absorption in China from a spatial perspective, and its spatial characteristics are still unclear. In the context of carbon neutrality, we measured agricultural carbon absorption in 30 Chinese provinces from 2000 to 2019 and measured the spatial spillover effects of agricultural carbon absorption by using a spatial panel Durbin model. The study finds that: agricultural carbon absorption in China is both positive from 2000 to 2019 but varied widely among provinces. Agricultural carbon absorption increases over time in 19 provinces, and decreases over time in the remaining 11 provinces. To measure the spatial correlation of inter-provincial agricultural carbon absorption, the global spatial autocorrelation Moran's I index shows that the inter-provincial agricultural carbon absorption in China presents a significant positive correlation in space and there is local clustering. As for the spatial effect of agricultural carbon absorption, agricultural industrial restructuring, economic development level, agricultural infrastructure level, and environmental regulation policies have a significant spatial spillover effect on the inter-provincial agricultural carbon absorption in China.

Keywords: agriculture; carbon absorption; spatial spillover effects

Introduction

Global climate change poses a great challenge to world food security, population health, and social development. Greenhouse gas emissions caused by human activities are the main factor contributing to global warming. With the expansion of global population and the increase of food demand, carbon emissions from agricultural production have become an attractive source of global greenhouse gas, while crop production itself is also a carbon absorption process. In September 2020, at the general debate of the 75th session of the United Nations General Assembly, the goal of carbon peaking and carbon neutrality was clearly presented to the world for the first time, stating that China will adopt stronger policies and measures and commit to strive to peak by 2030, reduce CO_2 emissions per unit of GDP by 60% to 65% in 2030 compared to 2005, and achieve the ambitious goal of carbon neutrality by 2060. Under the global trend of economic and social energy transformation, the carbon neutrality target is proposed to force China to accelerate the transformation of its development mode and build up a green and low-carbon economic system. Agricultural land is an essential carbon reservoir in terrestrial ecosystems. Therefore, it is of constructive significance to grasp the agricultural carbon absorption and analyze its spatial characteristics.

To combat climate change, reducing carbon emissions has become an outstanding goal around the world [1], while reducing emissions and increasing absorption to achieve carbon neutrality goals is an urgent mission for China. Many scholars have conducted detailed studies on forest carbon absorption, and their measurement methods are relatively well established [2-6].

As an influential contributor to climate change, agriculture's development must also be included in the response to the global climate crisis. Agriculture not only produces carbon emissions during production but also absorbs greenhouse gases, the agroecosystem itself is a large carbon absorption system, and it can offset 80% of agricultural greenhouse gas emissions [7]. Therefore, measuring the amount of agricultural carbon absorption, studying its spatial characteristics, and maximizing the potential of agricultural emission reduction and carbon absorption will become the critical to achieve carbon neutrality goals, promote the green and sustainable development of agriculture. Previous studies in the literature on carbon absorption in agriculture have mainly covered the following aspects. First, scholars have used different methods to measure agricultural carbon absorption. Annette et al. (2004) [8] analyzed the potential for technical and economic feasibility of carbon absorption in European agricultural soils for the period 2008-2012. Chen et al. (2021) [9] considered crop production systems contribute carbon to the atmosphere through four aspects: trees, soil organic carbon, fertilizers, and no-till farming. Li et al. (2011) [10] studied the effects of different amounts of rape straw return on soil carbon sequestration in no-till rice fields, and found that straw return significantly increased CO_2, N_2O and CH_4 emissions, while significantly increasing soil organic carbon content. Duan et al. (2012) [11] studied the changes of Soil Organic Carbon (SOC) and rice yield in direct-seeded rice fields under different tillage practices and straw return and showed that straw return could significantly increase SOC content, and also came to the same conclusion as Li et al. (2011) [10] that straw return could promote the increase of soil organic carbon. Li (2014) [12] argued that carbon absorption in crop production systems is mainly derived from three components: self-carbon sequestration during crop growth, soil carbon sequestration, and carbon sequestration by straw return. Freibauer et al. (2004)[13], Lu et al. (2009)[14], Islam et al. [15], and Wang et al. (2015b) [16], when measuring carbon absorption in cropland, identified fertilizer inputs, straw and straw return and no-till practices were identified as sources of carbon absorption in cropland. Also the carbon absorption role of fruit trees cannot be ignored [17-18]. Second, scholars have studied the carbon absorption capacity of different crops. Yu (2013) [19] found differences in the amount of methane released by different rice varieties. Super rice varieties not only have advantages in yield, but also have great advantages in methane emission reduction, so choosing the right variety increases agricultural crop yields while also increasing carbon absorption. Zhang et al. (2015) [20] and Wei et al. (2017) [21] came to the same conclusion as Yu (2013) [19]. Third, some scholars also study effective ways to increase agricultural carbon absorption. Smith et al. (2001) [22] found that using animal manure and grain straw as fertilizer can increase the efficiency of arable land use while returning the land to forest. Fan et al. (2019) [23] studied the use of organic fertilizers on Canadian farmland crops and found that by increasing organic fertilizer practices can effectively increase crop carbon absorption. There is still a great lack of exploring carbon absorption in a spatial perspective and grasping its spatial spillover effects. Currently, spatial econometric models are widely used [24-33]. Many spatial effects of carbon absorption in forestry [1,6] and agricultural carbon emission [25] have been studied. Yin et al. (2022) [1] found that China's Heilongjiang, Yunnan, Tibet, Sichuan and Inner Mongolia had the highest carbon absorption, while North China, East China and Southwest China had the highest carbon absorption efficiency. Liu et al. (2012) [6] found that the carbon absorption and carbon source of forest vegetation in China showed a clear spatial distribution pattern. Carbon absorptions are mainly located in the subtropical and temperate regions, and carbon sources are mainly distributed in the northeast to southwest regions of China.

Therefore, to investigate the spatial characteristics of agricultural carbon absorption in China, we used a panel spatial econometric model to study it. Studies on agricultural carbon absorption and its spatial effects have previously provided the basis for this paper. However, few studies have examined agricultural carbon absorption from a spatial perspective. The marginal contributions of this paper are as follows. First, agroecosystems are an integrated part of the global terrestrial ecosystem and an enormous source of atmospheric carbon. The carbon absorption capacity of agricultural soils makes them a substantial contributor to climate change alleviation. Several scholars have measured the carbon absorption including agriculture. However, few scholars have studied the spatial characteristics of agricultural carbon absorption in combination with spatial econometric models. We first used data from 2000-2019 to measure the detailed amount of agricultural carbon absorption in China, and then studied the spatial effects of agricultural carbon absorption in China from multiple perspectives by using Moran'I index and spatial econometric models in combination with various resource endowments. Second, we analyzed the spatial effects of agricultural carbon absorption from the spatial dimension, elucidated the changing trends of spatial characteristics of agricultural carbon absorption, and revealed the sources of regional differences in agricultural carbon absorption in China. Third, this study focuses on the development of provincial agriculture, and the findings have vital practical implications for promoting the coordinated and high-quality development of regional green agriculture in China.

Influence Mechanism

Spatial correlation theory assumes that observations are heterogeneous with respect to different geographical locations, and that homogeneous variables in different regions will exhibit different interactions with each other due to differences in geographical distance, and that when regions with similar values surround observations in neighboring regions, these observations will exhibit spatial clustering. The essential reason for spatial autocorrelation is that spatial interaction and perturbative spatial dependence [34].

The spatial interaction of agricultural carbon sequestration is reflected in the openness of agricultural production, and factors such as the flow of agricultural production factors, the diffusion of green technologies in agricultural production, and the convergence of environmental regulation policy tools all contribute to the formation of spatial interaction. Agricultural production is open-ended, and a region is the first to use green technologies to improve the ecological environment and increase green total factor productivity in agriculture. The green technology spillover from the pioneer region will bring a certain degree of latecomer advantage to the lagging region, which will lead to imitative learning in other regions. This low-cost technology diffusion contributes to green technology convergence and makes regional agricultural t carbon absorption convergence possible. Specifically, a region pioneers green technologies, such as no-till management systems, increased use of organic fertilizers, and environmental regulation policies to improve carbon sequestration in agricultural systems, which in turn reduces greenhouse gas emissions in the atmosphere and improves agroecosystems, thus advancing the process of sustainable agricultural development (Figure 1).

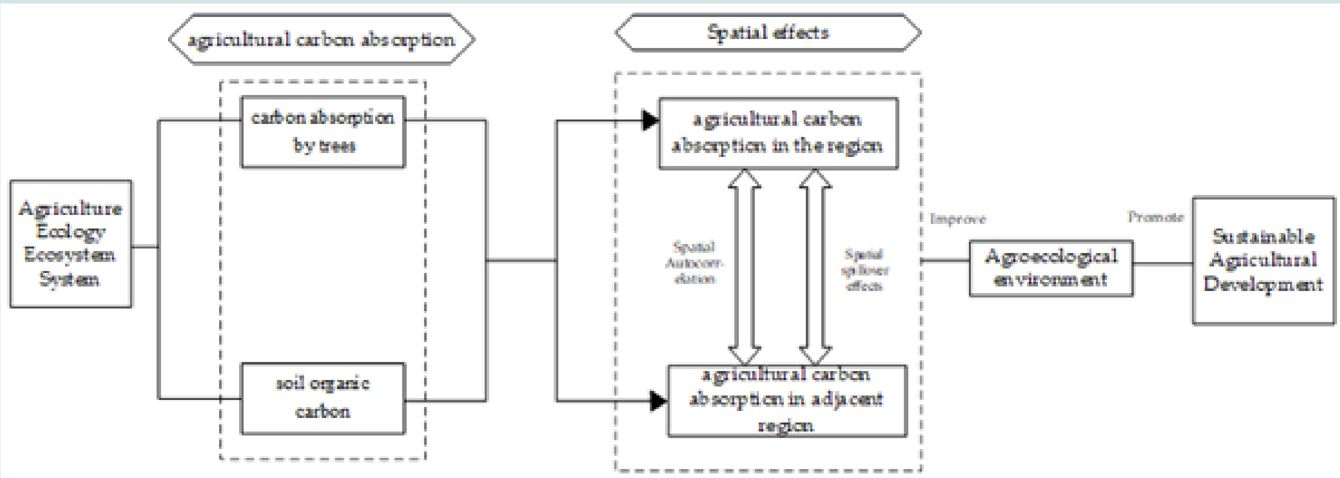

Figure 1: Logic mechanism analysis.

Carbon Absorption Space Model

The United Nations Framework Convention on Climate Change (UNFCCC) referred to the concept of carbon absorption as "processes or activities that reduce greenhouse gases in the atmosphere". Crop carbon absorption referred to the process by which crops convert CO_2 in the air into carbohydrates through photosynthesis, releasing oxygen while fixing the carbon in the crop for its own growth and development. This section draws on the calculations used by Chen et al. (2021) [9] to soil organic carbon (SOC) increases due to straw, litter, pruning and root residue return (CS_{SR}); manure calculate the carbon absorption by crop production systems, including carbon absorption by trees (CS_{TA}) and application (CS_{MA}); and no-tillage management (CS_{NT}).

$$TCS_i = CS_{TA} + CS_{SR} + CS_{MA} + CS_{NT} \quad (1)$$

where represents the total carbon absorption. CS_{TA} represents the carbon absorbed by tea and fruit trees aside from that removed by harvesting, pruning and litter, which was 527.5 (Li, 2012) [35] and 930 (Lv, 2019) [36] kg C ha^{-1} yr^{-1}, respectively. The detailed calculation methods for CS_{SR}, CS_{MA} and CS_{NT} are as follows:

$$CS_{SR} = \frac{SR_i + RB_i}{1000} \times 29.025 + 272.33 \quad (2)$$

where the tree body does not consider the root residue, and the litter, pruning is equivalent to straw return. The biomass of litter and pruning for tea and fruit trees (take citrus, for example) are 1682 (You, 2008) [37] and 1843 (Wu et al., 2010) [38] kg ha^{-1}, respectively.

$$CS_{MA} = M_{i,c} \times 19.1\% \quad (3)$$

where Mc refers to the carbon input due to manure application. This value can be calculated by formula Eq (5). The 19.1% refers to the percentage of input carbon converted into soil organic carbon (Wang Y 2015) [39].

$$CS_{NT} = 120 \times NTR \quad (4)$$

where 120 refers to no-tillage management can increase SOC by 120 kg ha^{-1} (Luo et al., 2010) [40]; NTR refers to the proportion of no-tillage area to total area.

Spatial Effect Model

Spatial econometric theory [34] assumes that a certain economic geographic phenomenon or an attribute value on a spatial unit in one region is correlated with the same phenomenon or attribute value on a spatial unit in a neighboring region. Almost all spatial data are characterized by spatial dependence or spatial autocorrelation, and the presence of spatial dependence breaks the basic assumption of mutual independence in most classical statistical and econometric analyses. And spatial econometrics is the study of how to deal with spatial interactions and spatial structure analysis in regression models of cross-sectional and panel data. To study the contribution of agricultural carbon absorption to sustainable agricultural development from the perspective of spatial statistics and spatial econometrics. We introduced the spatial statistical Moran index method to test whether the carbon absorption indicators are spatially autocorrelated among 30 Chinese provinces geographically; and then applied the spatial econometric method to study the spatial spillover effects of agricultural carbon absorption in China.

Method of Spatial Autocorrelation

Spatial autocorrelation is one of the most important concepts in studying spatial data distribution, and the primary method of studying it is calculating the degree of correlation in spatial autocorrelation [41]. The Greary's C coefficient and Moran'I index can be used in most cases to analyze the spatial agglomeration status of AGTFP. To test the spatial correlation of agricultural carbon absorption in China, we chose the global Moran'I index as it can more accurately reflect the similarity between neighboring regions. The formula for constructing the global Moran'I index is as follows.

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{N} w_{ij}(y_i-\bar{y})(y_j-\bar{y})}{S_0\sum_{i=1}^{N}(y_i-\bar{y})^2} \quad (5)$$

where and represents the agricultural carbon absorption of the *i-th* and *j-th* provinces, respectively; *n* = 1, 2, ..., 30 represents the number of provinces that we studied; represents the mean value of agricultural carbon absorption of the 30 provinces; is the spatial adjacency weight matrix; represents the spatial weight aggregation; and the Moran'I ∈ [−1,1]. The larger the value of Moran'I index, the higher the degree of spatial correlation between regions. The Moran'I index is significant above 0, meaning there is a significant spatial correlation between regions, which means there are "high-high" and "low-low" clusters. There is a negative spatial correlation between regions if the Moran'I index is significantly less than 0, which is reflected in the spatial clustering pattern of "high-low" or "low-high." There is no spatial correlation between regions if the Moran'I index is zero, and the agricultural carbon absorption are independently distributed between provinces. Specifically applied to the agricultural carbon absorption among Chinese provinces, the overall spatial pattern shows positive spatial autocorrelation when the agricultural carbon absorption in each province are similar in spatial location and also have similar attribute values. Negative spatial autocorrelation is shown when the data of spatially adjacent target regions are unusually dissimilar in terms of attribute values. Zero spatial autocorrelation occurs when the distribution of the attribute values is independent of the distribution of the locational data. After the Moran'I index is obtained, its significance needs to be tested. We will use the Z statistic test, which is calculated by the following formula.

$$\begin{cases} Z(I) = \frac{I-R(I)}{\sqrt{VAR(I)}} \\ R(I) = \frac{-1}{n-1} \\ VAR(I) = \left[\frac{1}{w_0^2(n^2-1)}(n^2w_1 + nw_2 + 3w_0^2)\right] - R^2(I) \\ w_0 = \sum_{i=1}^{N}\sum_{j-1}^{N} w_{ij},\ w_1 = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(w_{ij}+w_{ji})^2,\ w_2 = \sum_{i=1}^{N}(w_{i\cdot}+w_{\cdot j})^2 \end{cases} \quad (6)$$

where,.*wi* and *w.j* are the sum of the *i-th* row and *j-th* column in the spatial weight matrix. If the value of Z(*I*) is greater than zero, it means that there is a spatially positive correlation of agricultural carbon absorption between provinces; if the value of Z(I) is less than zero, it means that there is a spatially negative correlation of agricultural carbon absorption between provinces; if the value of Z(I) is equal to zero, it means that there is a spatially independent distribution of agricultural carbon absorption between provinces.

Spatial Econometric Model

When spatial factors are included, one can not only avoid the endogeneity of spatial spillover effects, but also study their direction. The majority of researchers study spatial characteristics using spatial econometric models [42]. The spatial error model is as follows.

$$\begin{cases} y_{it} = \theta\sum_{j=1}^{M} w_{ij}y_{it} + \beta x_{it} + \gamma\sum_{j=1}^{M} w_{ij}x_{it} + \mu_i + \lambda_i + \varepsilon_{it} \\ \varepsilon_{it} = \rho\sum_{j=1}^{M} w_{ij}\varepsilon_{jt} \\ \xi \sim N(0,\sigma^2) \\ (\varepsilon \sim N(0,\sigma^2), i = 1,\ldots,M, t = 1,\ldots,t) \end{cases} \quad (7)$$

Where is the agricultural carbon absorption of the ith province in period t; is the spatial weight matrix; is the spatial lagged variable of agricultural carbon absorption, which can reflect the influence of a province on its neighboring provinces' agricultural carbon absorption; and are spatial coefficients, where is the spatial autoregressive coefficient, which can reflect information such as the strength of spatial autocorrelation; is the spatial error coefficient, which can reflect the impact of the error of the dependent variable of a province's neighboring provinces on that province. is the control variable, is the coefficient of the control variable, which can reflect the degree of influence of the control variable on the explained variable; is the spatial lag variable of the control variable, which can also reflect the interaction effect of the control variable between a province and its neighboring provinces; is the interaction coefficient of the control variable, which reflects the degree of interaction effect; and represent the individual effect and time effect of the *i*-th province, respectively; is the spatial error lag variable; is the random disturbance term. Then the spatial autoregressive model SAR (7) and the spatial error model SEM (8) are constructed, and the meanings of each variable are the same as those represented by model (6). The SAR model and the SEM model are two special forms of SDM model, which will degenerate to a SAR model when and to a spatial error model when. In order to avoid the endogeneity problem that will result from the introduction of spatial factors, the spatial econometric model will be treated in this section using maximum likelihood estimation [34].

$$y_{it} = \theta \sum_{j=1}^{M} w_{ij} y_{jt} + \beta x_{it} + \mu_i + \lambda_i + \varepsilon_{it} \quad (8)$$

$$\begin{cases} y_{it} = \beta x_{it} + \mu_i + \lambda_i + \varepsilon_{it}, \ i = 1, \ldots, M, t = 1, \ldots, t \\ \varepsilon_{it} = \rho \sum_{j=1}^{M} w_{ij} \varepsilon_{jt} + \xi_{it}, \ \xi \sim N(0, \sigma^2) \end{cases} \quad (9)$$

Variable Selection and Data Source

On the basis of the characteristics of agricultural carbon absorption, this paper selected relevant data from 2000 to 2019 from 30 provinces in mainland China (excluding Tibet) for the study. In addition, we selected the economic development level (RGDP), agricultural industrial restructuring (AIR), electricity utilization rate (DPU), effective irrigation rate (EI), disaster incidence rate (DOR), financial support for agriculture (FS), and environmental regulation policies (ERP) of each province as control variables when calculating the spatial econometric model. The specific indicator selection and data sources are shown in Table 1 [43-48].

Table 1: Assessment indicators and data sources.

<table>
<tr><th rowspan="2"></th><th>Assessment</th><th rowspan="2">Indicators' Explanation</th><th rowspan="2">Unit</th><th rowspan="2">Source</th><th rowspan="2">Reference</th></tr>
<tr><th>Indicators</th></tr>
<tr><td rowspan="9">control variables</td><td>RGDP</td><td>GDP per capita</td><td>10^4 CNY</td><td>China Statistical Yearbook</td><td>Liu et al. (2021) [43]</td></tr>
<tr><td rowspan="2">AIR</td><td rowspan="2">the total output value of planting industry/total agricultural output value</td><td rowspan="2">%</td><td rowspan="2">"China Agricultural Statistics" and "China Rural Statistical Yearbook"</td><td>Yu et al. (2022) [7,44]</td></tr>
<tr><td>Liu et al. (2021) [43]</td></tr>
<tr><td>AID</td><td>number of road miles/administrative area</td><td>Hundred Miles / Hundred Square Kilometers</td><td>China Regional Economic Statistics Yearbook</td><td>Wang et al. (2012) [45]</td></tr>
<tr><td>DPU</td><td>Electricity consumption per hectare</td><td>Billion kWh/ha</td><td>China Agricultural Statistics</td><td>Wang et al. (2010) [46]</td></tr>
<tr><td rowspan="2">EI</td><td rowspan="2">the effective irrigated area/total sown area of crops</td><td rowspan="2">%</td><td>"China Agricultural Statistics" and "China Rural</td><td rowspan="2">Kumar et al. (2008) [47]</td></tr>
<tr><td>Statistical Yearbook"</td></tr>
<tr><td rowspan="2">DOR</td><td>the agricultural land area affected by natural disasters/ total sown</td><td rowspan="2">%</td><td>"China Agricultural Statistics" and "China Rural</td><td rowspan="2">Nwaiwu et al. (2015) [48]</td></tr>
<tr><td>area of crops</td><td>Statistical Yearbook"</td></tr>
<tr><td></td><td>FS</td><td>local financial expenditure on agriculture, forestry and water affairs</td><td>10^8 CNY</td><td>National Bureau of Statistics</td><td>Gong (2020) [49]</td></tr>
<tr><td></td><td>EPR</td><td>EPR is a dummy variable, where EPR=1 if a province belongs to the carbon trading eating point area, otherwise EPR=0.</td><td>-</td><td>Ministry of Agriculture and Rural Affairs of the People's Republic of China</td><td>Yu et al. (2022) [7]</td></tr>
</table>

Note: GVAO represents gross value of agriculture, NP represents agricultural non-point pollution, NCP represents agricultural net carbon emissions, GDP represents GDP per capita, AIR represents agricultural industrial restructuring, AID represents agricultural infrastructure, EC represents energy consumption, EI represents effective irrigation rate, DOR represents disaster occurrence rate, FS represents financial support for agriculture, and MGP represents major grain producing areas.

Results

Calculation Results of Agricultural Carbon Absorption

Based on the methods in Section 2.1, we calculated the agricultural carbon absorption for each province in China. The following Table 2 lists the mean value of China's agricultural carbon absorption from 2000-2019. In the first time period 2000-2009, Qinghai had the smallest agricultural carbon absorption, with a mean value of 8.292 × 10^4 tons. Hebei had the largest agricultural carbon absorption, with a mean value of 1056.192 × 10^4 tons. Carbon absorption by trees were highest in Hebei, while lowest in Qinghai. Soil organic carbon were highest in Guangdong, while lowest in Qinghai. Carbon absorption from manure application were highest in Chongqing, while lowest in Ningxia. Carbon absorption from no-till management were highest in Beijing, while lowest in Hainan. In the second time period 2010-2019, Guangxi had the largest agricultural carbon absorption, with a mean value of 1126.937 × 10^4 tons. Qinghai had the lowest mean value of agricultural carbon absorption, with a mean value of 13.058 × 10^4 tons. Carbon absorption by trees were highest in Guangxi, while lowest in Qinghai. Soil organic carbon were highest in Hainan, while lowest in Shanghai. Carbon absorption from manure application were highest in Shandong, while lowest in Shanghai. Carbon absorption from no-till management were highest in Beijing, while lowest in Guangdong.

Table 2: Agricultural carbon absorption in China's provinces from2000–2019. Unit: 10,000 t.

Area	2000-2009					2009-2019				
	CS_{TA}	CS_{SR}	CS_{MA}	CS_{NT}	TCS	CS_{TA}	CS_{SR}	CS_{MA}	CS_{NT}	
Beijing	73.312	4.22	0.008	3.697×10^{-5}	77.54	51.717	2.977	0.004	5.748×10^{-5}	54.699
Tianjin	34.977	2.015	0.005	1.428×10^{-5}	36.997	29.927	1.729	0.005	2.214×10^{-5}	31.661
Hebei	998.615	57.513	0.064	2.303×10^{-5}	1056.192	798.777	46.053	0.057	3.100×10^{-5}	844.887
Shanxi	258.466	14.891	0.013	3.499×10^{-6}	273.37	324.226	18.691	0.014	6.756×10^{-6}	342.93
Inner Mongolia	49.076	2.843	0.043	6.960×10^{-6}	51.962	67.341	3.921	0.049	1.846×10^{-5}	71.311
Liaoning	309.569	17.811	0.04	2.720×10^{-6}	327.42	344.667	19.84	0.052	5.199×10^{-6}	364.56
Jilin	80.603	4.668	0.03	2.777×10^{-6}	85.302	38.065	2.23	0.032	1.007×10^{-5}	40.327
Heilongjiang	38.409	2.288	0.026	2.580×10^{-6}	40.723	29.658	1.871	0.031	3.436×10^{-6}	31.56
Shanghai	20.348	1.173	0.005	2.566×10^{-6}	21.527	14.305	0.827	0.002	5.244×10^{-7}	15.134
Jiangsu	181.068	10.903	0.042	1.260×10^{-6}	192.012	210.521	12.821	0.045	4.324×10^{-6}	223.387
Zhejiang	351.321	23.023	0.019	3.230×10^{-7}	374.363	402.835	26.72	0.017	2.001×10^{-7}	429.572
Anhui	156.668	11.225	0.041	3.080×10^{-6}	167.933	202.821	14.709	0.049	1.105×10^{-6}	217.579
Fujian	590.806	36.841	0.019	2.146×10^{-9}	627.666	536.48	34.931	0.03	4.226×10^{-9}	571.441
Jiangxi	301.422	18.108	0.029	1.379×10^{-7}	319.559	416.755	25.551	0.04	9.423×10^{-7}	442.346
Shandong	669.984	38.862	0.095	1.188×10^{-5}	708.941	572.15	33.496	0.106	4.024×10^{-5}	605.753
Henan	390.936	23.227	0.086	6.665×10^{-5}	414.249	475.26	29.381	0.09	2.411×10^{-5}	504.731
Hubei	334.306	21.96	0.038	1.238×10^{-7}	356.304	508.517	34.57	0.052	1.387×10^{-6}	543.14
Hunan	430.11	26.217	0.057	1.266×10^{-7}	456.385	565.586	34.993	0.065	3.041×10^{-7}	600.644
Guangdong	944.751	55.077	0.055	1.228×10^{-7}	999.884	1009.191	59.016	0.061	9.720×10^{-9}	1068.268
Guangxi	811.252	47.372	0.044	1.744×10^{-6}	858.668	1064.43	62.452	0.056	1.706×10^{-6}	1126.937
Hainan	151.408	8.746	0.008	4.317×10^{-9}	160.162	158.987	9.175	0.01	8.112×10^{-8}	168.172
Sichuan	172.425	10.394	0.021	2.266×10^{-7}	182.839	289.464	17.364	0.024	2.399×10^{-7}	306.853
Chongqing	477.983	30.078	0.083	2.269×10^{-8}	508.144	768.138	49.919	0.093	2.511×10^{-8}	818.149
Guizhou	139.074	9.243	0.027	5.467×10^{-8}	148.344	493.547	34.903	0.026	4.501×10^{-8}	528.476
Yunnan	351.972	24.643	0.041	5.575×10^{-8}	376.657	658.863	45.624	0.05	8.088×10^{-8}	704.536
Shanxi	754.534	43.42	0.016	9.712×10^{-6}	797.969	1063.003	61.179	0.015	1.432×10^{-5}	1124.197
Gansu	351.888	21.278	0.021	8.508×10^{-7}	373.188	424.852	26.582	0.022	2.706×10^{-6}	451.455
Qinghai	7.722	0.555	0.015	2.079×10^{-6}	8.292	12.138	0.906	0.014	5.350×10^{-6}	13.058
Ningxia	53.196	3.063	0.005	6.431×10^{-7}	56.264	106.876	6.152	0.005	3.887×10^{-6}	113.033
Xinjiang	427.223	24.584	0.031	1.504×10^{-6}	451.839	888.569	51.144	0.031	2.026×10^{-6}	939.743

Empirical Results of Spatial Autocorrelation

Using spatial autocorrelation calculation methods, we tested the mean value of China's agricultural carbon absorption, and the results are shown in Table 3. The Moran'I index for carbon absorption in 2000 and 2017-2019 was greater than 0 and passed the 1% significance level test, while the Moran'I index for carbon absorption in 2007, 2011, 2013 and 2014 was greater than 0 and passed the 5% significance level test, and the remaining years passed the 10% significance level test. Overall, there is a significant positive spatial correlation among the carbon absorption of Chinese provinces. Also, a higher Moran'I value indicates a more significant spatial correlation, with 0.085 being the highest value in 2002 and 2003. In the years 2000-2019, Moran'I fluctuated between 0.076

and 0.090. The overall trend for Moran'I was upward between 2000 and 2019. This indicates that there is a spatial spillover effect of carbon absorption between neighboring provinces, and this spatial spillover effect shows an increasing trend. In neighboring or closer provinces, agricultural green development conditions are more likely to be convergent because of resource endowment and natural location conditions. Therefore, the agricultural carbon absorption in neighboring provinces is spatially correlated.

Table 3: Global correlation test results of agricultural carbon absorption in China.

Year	AGTFP		
	Moran'I	Z Value	*p* Value
2000	0.076	1.275	0.001***
2001	0.08	1.384	0.083*
2002	0.085	1.531	0.063*
2003	0.085	1.526	0.063*
2004	0.082	1.458	0.072*
2005	0.082	1.443	0.075*
2006	0.078	1.332	0.091*
2007	0.072	1.144	0.026**
2008	0.066	0.955	0.070*
2009	0.058	0.705	0.080*
2010	0.057	0.685	0.097*
2011	0.05	0.465	0.021**
2012	0.045	0.316	0.076*
2013	0.042	0.212	0.016**
2014	0.041	0.187	0.026**
2015	0.051	0.038	0.085*
2016	0.064	2.055	0.22
2017	0.074	2.372	0.009***
2018	0.079	2.811	0.002***
2019	0.09	3.147	0.001***

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Empirical Resultss of SDM model

Before carrying out the spatial econometric model empirical testing, the results of LM (error) test, LM (lag) test, Robust LM-err test, Robust LM-lag test and Hausman test need to be combined to test whether the spatial Durbin model is applicable to our study (Table 4). Table 4 presents the results of a series of tests with significant coefficients for both LM-err, Robust LM-err, LM-lag, Robust LM-lag, Hausman, that indicating the panel space Durbin fixed effects model is applicable to our study. Then we used the SDM model to test the spatial spillover effect of agricultural carbon absorption, and the test results list in Table 5. Table 5 showed that the spatial autoregressive coefficient rho in the 1% significant level is 0.563, which indicates that Chinese agricultural carbon absorption has a significant positive spatial correlation, which is also consistent with the previous results of Moran'I. (1) lists the main coefficients of the empirical results of SDM (Main), (2) lists the coefficients of the lagged variables of the empirical results of SDM (Wx), (3) lists the direct effects of SDM, (4) lists the indirect effects of SDM (5) lists the total effects of SDM. The direct effect reflects the degree of influence of the independent variable on the dependent variable of this province, the indirect effect reflects the degree of influence of the independent variable on the dependent variable of other provinces, and the total effect reflects the average degree of influence of the independent variable on all provinces.

Table 4: Statistical tests of the spatial econometric model.

	Statistic	*p* Value
LM-err	11.479	0.001 ***
Robust LM-err	26.961	0.000 ***

LM-lag	2.397	0.022 **
Robust LM-lag	17.879	0.000 ***
Hausman	13.238	0.000 ***

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Model (1) shows that RGDP, AIR, ERP, and AID have significant positive effects on agricultural carbon absorption, with the coefficients of ERP and RGDP passing the 1% significant level test, and the coefficients of AIR and AID passing the 5% significant level test. Model (2) shows that RGDP, and AIR have a significant positive effect on agricultural carbon absorption in neighboring provinces, with the coefficients of RGDP passing the 1% significant level test, DOR have a negative effect on agricultural carbon absorption in neighboring provinces, and the coefficients of AIR and DOR passing the 5% significant level test. The total effect of the SDM model (model 5) shows RGDP, AIR, ERP, and AID have significant average impact on all provinces, with the coefficients of RGDP and EPR passing the 1% significant level test, and the coefficients of AIR, AID and DOR passing the 5% significant level test.

Table 5: Results of SDM model of agricultural carbon absorption.

	-1	-2	-5	-6	-7
Variables	**Main**	**Wx**	**Direct**	**Indirect**	**Total**
	-1.102***	0.662***	-1.093***	0.085***	-1.008***
	-0.031	-0.056	-0.03	-0.062	-0.066
AIR	0.048**	0.803**	0.186*	1.463	1.650**
	-1.003	-0.589	-0.105	-2.099	-3.558
RGDP	0.581***	0.006***	0.063***	0.051***	0.114***
	-0.034	-0.041	-0.032	-0.071	-0.079
AID	0.035**	0.022	0.041**	0.075	0.117**
	-0.035	-0.084	-0.041	-0.175	-0.204
EI	0.159	0.147	0.232	0.535	0.767
	-0.513	-0.072	-0.633	-0.408	-0.875
DOR	-0.168	-0.811**	-0.339	-0.934**	-2.273**
	-0.245	-0.457	-0.285	-0.979	-1.142
FS	0.247	0.134	0.687	0.31	0.697
	-653	-0.583	-672	-0.919	-0.645
DPU	-0.335	-0.578	-0.953	-0.568	-0.263
	-0.073	-0.109	-0.213	-0.954	-0.149
ERP	0.168***	0.002	0.182***	0.195	0.378***
	-0.065	-0.11	-0.071	-0.228	-0.265
rho	0.563***	-	-	-	-
	-0.038				
sigma2_e	0.384***	-	-	-	-
	-0.023				
R-squared	0.709	-	-	-	-

Standard errors in parentheses*** $p<0.01$, ** $p<0.05$, * $p<0.1$. AIR represents agricultural industrial restructuring. RGDP represents economic development level. AID represents agricultural infrastructure level. EI represents effective irrigation rate. DOR represents disaster incidence rate. FS represents financial support for agriculture. DPU represents electricity utilization rate. ERP represents environmental regulation policies.

Robustness Tests

In this section, in order to test the robustness of the model and empirical results in section 4.3, the inverse distance matrix will be used to test the robustness of the spatial spillover effect of agricultural carbon absorption in China, and the test results are shown in Table 6. Table 6 shows that in the test results using the inverse distance spatial weight matrix, the direction of the coefficients and the degree of significance of the main influencing factors did not change significantly, except for a change in the magnitude of the coefficients. Among the direct effects only the significance of two influencing factors, agricultural infrastructure level and effective irrigation rate, has changed. This may be due to the fact that the direct effects of these factors have changed after changing the spatial weight matrix. However, the overall model is still robust, and the test results are credible [49].

Table 6: Results of SDM estimation of carbon sequestration in agriculture based on inverse distance matrix.

	-1	-2	-5	-6	-7
VARIABLES	Main	Wx	Direct	Indirect	Total
	-1.112***	0.134***	-1.217***	-3.471***	-4.688***
	-0.513	-0.209	-539	-1.163	-1.183
AIR	0.521*	0.862*	0.679	0.556	0.626**
	-0.303	-0.192	-0.443	-0.953	(0,987)
RGDP	0.270***	0.170***	0.561***	0.921***	0.977***
	-0.103	-0.541	-0.16	-0.352	-0.365
AID	0.637**	0.371	0.108	0.169	0.168**
	-0.102	-0.541	-0.154	-0.284	-0.296
EI	0.75	0.523	0.159***	0.275	0.291
	(0. 153)	-0.979	-0.368	-0.895	-0.93
DOR	-0.101	-1.004**	-0.265	-0.550**	-0.576**
	-0.718	-0.454	-0.106	-0.258	-0.262
FS	0.910*	0.773*	0,219	0.415	0.437
	-0.545	-0.436	-0.108	-0.248	-0.258
DPU	-0.452	-0.527	-0.334	-0.457	0.427
	-0.946	-0.499	-0.135	-0.252	-0.262
ERP	0. 680***	0.199	0.472*	0.74	0.692***
	-0.214	-0.151	-0.262	-0.778	-0.795
rho	0.784***	-	-	-	-
	-0.048				
sigma2_e	0.310***	-	-	-	-
	-0.189				
R-squared	0.699	-	-	-	-

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1. AIR represents agricultural industrial restructuring. RGDP represents economic development level. AID represents agricultural infrastructure level. EI represents effective irrigation rate. DOR represents disaster incidence rate. FS represents financial support for agriculture. DPU represents electricity utilization rate. ERP represents environmental regulation policies.

Discussion

The measured agricultural carbon absorption in China is all positive, and most of the regions show a stable growth. Xiong et al. (2017) [50] and Cao (2022) [51] came to the same conclusion. However, our calculations showed that the agricultural carbon absorption increases over time in Shanxi, Inner Mongolia, Liaoning, Jiangsu, Zhejiang, Anhui, Jiangxi, Henan, Hunan, Guangdong, Guangxi, Hainan, Sichuan, Chongqing, Guizhou, Yunnan, Shanxi, Ningxia, Xinjiang, and decreased in the rest of the provinces. This is inconsistent with the findings of Xiong et al. (2017) [50] and Cao (2022) [51] and may be due to the different methods used to measure carbon absorption. Cao (2022) [50] regarded the carbon absorption of crops as the agricultural carbon absorption, while we calculated agricultural carbon absorption by carbon absorption by trees and soil organic carbon increases due to straw, litter, pruning and root residue return; manure application; and no-tillage management. One conclusion that is consistent with other scholars' studies is that there are large differences in agricultural carbon absorption between regions [51-53]. Each province has different natural conditions, agricultural structures, and production inputs, which are objective gaps that lead to obvious differences in agricultural carbon absorption.

Although the eastern region has more agricultural input factors, the same higher agricultural output also makes the agricultural carbon absorption higher. In contrast, Southwest China, and Inner Mongolia, on the one hand, the amount of agricultural cultivation is relatively small, and the carbon absorption of crop growth is not obvious, on the other hand, agriculture is dominated by livestock, and the carbon emission brought by livestock breeding is instead larger. Meanwhile, the western farming regions, due to their own poor agricultural farming conditions, apply a large amount of agricultural input factors such as chemical fertilizers, pesticides and mulch in the agricultural production process in order to improve yields, resulting in larger total agricultural carbon emissions, and the unsustainable agricultural production methods make agricultural carbon absorption less. In addition, spatial geography has a significant positive effect on the amount of carbon absorption in agriculture. Spatial proximity can promote the dissemination of green technologies and knowledge such as agricultural emission reduction and absorption enhancement. Neighboring regions can share high-quality agricultural resource elements. The results of the study through the spatial econometric model showed that the Moran'I index of agricultural carbon absorption in each province is significantly positive, which indicated that agricultural carbon absorption between different provinces is spatially interlinked, and cross-regional cooperation and agricultural extension is of great importance. Li et al. (2019) [54] found that the inter-provincial net agricultural carbon absorption efficiency in China showed a significant positive spatial correlation and there was local clustering; the local spatial autocorrelation Moran's I index also indicated that the inter-provincial net agricultural carbon absorption efficiency showed a clustering effect in space, the above conclusions were consistent with the findings of this paper. Chen et al. (2022) [55] also argued that cross-regional cooperation's was critical for green agricultural development. On the other hand, the SDM model showed that Agricultural Industrial Restructuring (AIR), economic development level (RGDP), agricultural infrastructure level (AID), and Environmental Regulation Policies (ERP) had a significant positive effect on local agricultural carbon absorption. Since there are few studies to study agricultural carbon absorption in China from a spatial perspective, no research has directly shown the effect of the influencing factors mentioned above on agricultural carbon absorption, but some studies showed that GDP has a significant spatial spillover effect on agricultural carbon emissions and net carbon emissions [54,56-59]. The significant impact of the above mentioned influencing factors on the green agricultural development had also been confirmed [59-60]. Therefore, the control variables chosen in this paper are appropriate and the conclusions obtained are realistic.

Conclusions and Recommendations

Conclusions

In this paper, we calculated the agricultural carbon absorption in 30 provinces of China from a spatial perspective. Then, we analyzed the spatial concentration of agricultural carbon absorption in each province of China using the global Moran'I index and studied the spatial spillover effect of agricultural carbon absorption in China by using the SDM model. The findings of our study give insight into the reasons for regional differences in the agricultural carbon absorption in China, alleviating regional differences, and serve as a theoretical foundation for regional green agriculture development. Our study also contributes to the development of a balanced institutional mechanism for promoting green agriculture development at the regional level. Following are the main research findings.

a) Carbon absorption by trees is the largest among the four agricultural carbon absorption sources in China, followed by and soil organic carbon, carbon absorbed by manure application; and carbon absorbed by no-till management. The average value of agricultural carbon absorption in Hainan, Sichuan, Chongqing, Guizhou, Yunnan, Shanxi, Gansu, Qinghai, Ningxia, Xinjiang show an increasing trend, while the average value of agricultural carbon absorption in the remaining provinces show a decreasing trend.

b) The interprovincial differences in agricultural carbon absorption in China are obvious and have significant spatial correlation. The Moran'I index of agricultural carbon absorption in China showed a fluctuating upward trend during the study period, from 0.076 in 2000 to 0.090 in 2019. The conclusion indicated that there is a diffusion of agricultural green technology and flow of factors between neighboring provinces, and the agricultural carbon absorption in neighboring or closer provinces is spatially correlated.

c) Economic development level, agricultural industrial restructuring, disaster incidence rate, agricultural infrastructure level, and environmental regulation policies have a significant spatial spillover effect on agricultural carbon absorption in China. Economic development level, agricultural industrial restructuring, agricultural infrastructure level, and environmental regulation policies has a significant positive spatial spillover effect on China's agricultural carbon absorption, and disaster incidence rate has a significant negative spatial spillover effect on China's agricultural carbon absorption.

Recommendations

a) According to the situation of agricultural carbon absorption in different provinces, local policies will become one of the effective ways to promote sustainable agricultural development. Therefore, the government should formulate policies to improve the agricultural carbon absorption capacity for different carbon absorption sources combined with the natural conditions of each region, in order to reduce the concentration of greenhouse gases in the atmosphere to improve the agricultural ecological environment and promote the development of green agriculture. First, afforestation and reforestation in eligible areas can increase the carbon absorption of trees in provinces with low absorption, such as Qinghai, Tianjin, and Heilongjiang. Second, for provinces such as Qinghai, Inner Mongolia and Shanghai where carbon absorption by straw is referred to as low, farmland can be made more carbon absorption by reducing the use of production materials, reducing straw burning, and promoting straw return to farmlands. As a third recommendation, for Tianjin, Shanghai, and Ningxia, where agriculture carbon absorption from manure is a low, animal husbandry should be rationally planned, livestock and poultry manure should be treated with modern composting processes, and biogas projects must be vigorously promoted in order to increase agricultural capacity to absorption carbon dioxide. Fourth, for provinces like Fujian, Guangdong and Hainan, where no-till management of carbon absorption is called low, government subsidies can be used to further strengthen conservation tillage systems, pay attention to conservation tillage systems and carefully implement crop rotation, thus increasing agricultural carbon absorption.

b) Policy makers should take into account the spatial characteristics of China's agricultural carbon absorption and develop policies to increase carbon absorption for different provinces. Endowment conditions, such as geography and natural conditions, vary greatly among regions in China, but there is a clear spatial correlation between agricultural carbon absorptions in different provinces. Therefore, policy makers should consider the advantages of each province's factor endowment and the carrying capacity of resources and environment, tap the potential of carbon absorption market, and formulate relevant measures to achieve emission reduction and increase absorptions, prevent and control pollution, and improve ecological environment. Provinces with higher carbon absorption should further exert the spatial spillover effect, improve the radiation demonstration role, optimize the agricultural ecological environment through mutual project sharing and exchange, and realize the docking of increased agricultural carbon absorption and sustainable agricultural development.

c) The government is required to increase efforts to improve the agricultural and rural environment and focus on improving the efficiency of public investment. Further optimizes the structure of the agricultural industry, strengthens the construction of agricultural infrastructure, and makes an early warning prevention and control mechanisms for major natural disasters. The government should actively advocate the concept of win-win cooperation and fully guide the interaction of inter-provincial emission reduction and absorption increase. The government should continuously improve the win-win cooperation mechanism between provinces, so that each region can give full play to its own advantages in agricultural resource endowments, thus promoting the formation of scale effects to avoid "factor congestion". At the same time, the government need actively to create favorable conditions for its own experience to be fully manifested, to drive neighboring provinces agricultural emission reduction and absorption increase.

Author Contributions

Conceptualization, Z.Y.; Data curation, C.H. and Z. Y.; Methodology, C.H. and Z.Y.; Resources, X.Y.; Software, C. H.; Validation, X.Y.; Writing - original draft, C.H. and X.Y.; Writing - review & editing, Z.Y.

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Not applicable.

Data Availability Statement

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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