



OPEN

## Spatiotemporal evolution of agricultural carbon emissions intensity in China and analysis of influencing factors

Xue Zhu &amp; Xiwu Shao✉

This study aims to investigate the spatiotemporal evolution of China's agricultural carbon emissions intensity and their influencing factors from 2001 to 2022. It employs analytical methods such as kernel density estimation, Gini coefficient, Moran's index, spatial Markov analysis, and spatiotemporal geographically weighted regression (GWTR) to visualize the data and analyze the results. The study ultimately draws the following. Conclusions (1) China's agricultural carbon emissions intensity shows a decreasing trend, a noticeable decrease in the number of provinces below the medium level. Gini coefficient analysis indicates a significant disparity between eastern and western China, with agricultural carbon emissions intensity exhibiting the spatial pattern: east > central > west. (2) China's agricultural carbon emissions intensity exhibits clear spatial clustering characteristics and a stable transfer trend. High-high agglomeration areas are primarily located in the Northwest and Northeast, while low-low agglomeration areas are mainly found in Guangdong and Fujian provinces. Furthermore, the transfer of agricultural carbon emission levels is stable. (3) Financial support and the development level of technology markets positively impact China's agricultural carbon emissions, while research and development intensity, openness to the outside world, human capital level, and urbanization negatively affect these emissions.

**Keywords** Agricultural carbon emissions, Spatiotemporal evolution, Gini coefficient, Spatial Markov

In modern society, global warming has emerged as a critical issue that national leaders and policymakers cannot ignore<sup>1</sup>. As global warming becomes increasingly evident, extreme weather events are occurring more frequently worldwide<sup>2</sup>. Phenomena such as El Niño and La Niña cause significant disasters in the Pacific Ocean's atmosphere and ocean, further impacting precipitation and typhoons in Asia. These extreme climate phenomena are closely linked to interactions between the ocean and the atmosphere<sup>3,4</sup>. The Sixth Assessment Report of the IPCC, scheduled for release in the first half of 2023, states that for every 0.5 °C rise in global temperature, extreme high temperatures, heavy precipitation, and regional droughts will become more frequent and severe. Human activities have already increased the Earth's temperature by 1.1 °C. The report identifies carbon emissions as a major contributor to changes in greenhouse gas concentrations<sup>5,6</sup>. The report states that under the Paris Agreement, global greenhouse gas emissions in 2030 could lead to a temperature rise exceeding 1.5 °C in the 21st century, making it difficult to limit the increase to less than 2 °C<sup>7,8</sup>. Therefore, curbing greenhouse gas emissions has become a shared goal for all countries.

Agricultural activities are a significant aspect of human activities and a fundamental means of survival, leading to inevitable greenhouse gas emissions during production<sup>9,10</sup>. Agricultural carbon emissions intensity originates from various sources, including the production and application of chemical fertilizers and pesticides, the use of agricultural films, energy consumption by agricultural machinery, and electricity used for irrigation<sup>11,12</sup>. China has been a major agricultural nation since ancient times, with agriculture playing a crucial role in its gross domestic product (GDP). According to the 2024 China Agricultural and Rural Low Carbon Development Report, agricultural activities represent the third largest source of greenhouse gas emissions in China<sup>13,14</sup>. Although China's agricultural carbon emissions intensity have reduced in both total volume and intensity due to the rural revitalization strategy, many regions still engage in large-scale agricultural production. As farming methods gradually modernize, mechanize, and incorporate technology, significant greenhouse gas emissions continue to be released, making agricultural carbon emissions intensity an increasingly prominent issue<sup>15</sup>. Since

College of Economics and Management, Jilin Agricultural University, Changchun 130118, China. ✉email: xiwushao@126.com

the 1990 s, the ongoing expansion of agricultural production and the promotion of modernization have led to a significant increase in the use of chemical fertilizers, pesticides, and agricultural machinery, resulting in a rapid rise in agricultural carbon emissions<sup>16,17</sup>.

Since the beginning of the 21 st century, while the growth rate of agricultural carbon emissions has slowed, the total emissions remain high. Large agricultural provinces are the primary sources of carbon emissions due to extensive and intensive agricultural production<sup>18</sup>. In contrast, developed cities and eastern coastal areas exhibit lower carbon emissions due to reduced agricultural intensity; however, emissions are rising due to economic activities and urbanization<sup>19,20</sup>. To address the issues of agricultural carbon emissions in China, the Ministry of Agriculture and Rural Affairs and the National Development and Reform Commission developed the 'Implementation Plan for Agricultural and Rural Emission Reduction and Carbon Sequestration' in 2022, outlining ten strengths for reducing agricultural carbon emissions. The plan defines the direction for emission reduction and carbon sequestration in agriculture and rural areas, emphasizing the need to ensure effective agricultural product supply, enhance resource efficiency, improve the ecological environment, and achieve sustainable agricultural development. Additionally, it emphasizes that China's agricultural carbon reduction targets must align with the 'dual carbon' goals. Reducing carbon emissions in agriculture and rural areas is crucial for achieving the 'dual carbon' goals and represents significant potential<sup>21,22</sup>.

Based on the above analysis, this paper believes that the greenhouse gas emissions represented by CO<sub>2</sub> have a serious threat to the global living systems. Thus, this research examines the current situation and characteristics of agricultural carbon emissions in China from a spatial perspective, employing various spatial measurement tools to explore their spatiotemporal evolution and influencing factors. This paper may have the following three aspects of important significance. First, as a big agricultural country, China's agricultural carbon emissions account for a large proportion of the total carbon emissions. It is of great significance to study the spatial and temporal evolution characteristics and influencing factors of agricultural carbon emissions in China for the mitigation of global climate change. Second, the realization of the "dual-carbon" development goal requires not only cities to accelerate the pace of energy conservation and emission reduction, but also active participation in rural areas. Therefore, this paper can provide an important reference basis for the promotion of rural carbon emission reduction work. Third, through an in-depth analysis of the sources, distribution and influencing factors of agricultural carbon emissions, more scientific and reasonable agricultural production methods and policy measures can be formulated, and promote the green transformation and sustainable development of agricultural production.

## Literature review

From the existing literature, the research showed that agricultural carbon emissions can be divided into the measurement of agricultural carbon emission, the spatial and temporal evolution characteristics, the influencing factors of agricultural carbon emission reduction and increase. Therefore, this paper is analyzed from the above three aspects, respectively. First, the diverse sources of agricultural carbon emissions necessitate consideration of various factors to accurately assess their true levels. Smith, et al.<sup>23</sup> calculates the agricultural carbon emissions of European countries from three aspects: animal manure, woodland regeneration and energy utilization of bioenergy crop production. Li, et al.<sup>24</sup> assess agricultural carbon emissions by focusing on a narrow category, measuring emissions generated from agricultural material inputs in crop production. Wang, et al.<sup>25</sup> measure agricultural carbon emissions in China by selecting indicators such as agricultural land, rice cultivation, and ruminant animals, ultimately deriving emissions data for various provinces. They argue that energy consumption, chemical inputs, and farmland soil management significantly influence agricultural carbon emissions; thus, these indicators were included when measuring the carbon emission index of China's agricultural sector from 1995 to 2020. Bell, et al.<sup>26</sup> questions the approach for the Intergovernmental Panel on Climate Change (IPCC), shows that attributes emissions from both land-use conversion and agricultural land under continuous use to the agricultural sector, in addition to those emissions from livestock and energy use on farms. Guo, et al.<sup>27</sup> highlight the significant roles of fertilizers, pesticides, agricultural plastic films, diesel, tillage, and irrigation in China's agricultural carbon emissions. Consequently, they selected indicators from these areas to comprehensively assess the agricultural carbon emission levels in China from 2000 to 2019.

Second, some scholars have explored the spatial-temporal evolution characteristics of agricultural carbon emissions<sup>28</sup>. Huang, et al.<sup>29</sup> estimated the agricultural carbon emissions at the provincial level in China from 1997 to 2016 and analyzed their spatial agglomeration characteristics using spatial measurement tools. They concluded that while the total agricultural carbon emissions increased during this period, the intensity decreased, revealing more pronounced development disparities among provinces and a spatial high-high agglomeration pattern. Moucheng and Lun<sup>30</sup> analyzed the spatial characteristics of agricultural carbon emissions in China from 2009 to 2019 using tools like the Moran's index. They found that the provincial emissions exhibited a spatial distribution pattern of east > west > central, with spatial agglomeration characteristics, although these characteristics are showing a decreasing trend. Zhang, et al.<sup>31</sup> assessed China's agricultural carbon emissions from 2001 to 2020 and conducted a detailed analysis of its spatial distribution. Their findings confirmed that the primary sources of emissions are animal husbandry and agricultural inputs, with East China's emissions generally lower than those in Central and West China.

Third, some scholars are committed to the coordinated development of the environment and the economy, and analyze the influencing factors of agricultural carbon emission reduction. Wangari, et al.<sup>32</sup> evaluates the effects of land use, seasonality, soil type and slope on agricultural carbon emissions, and believes that agricultural carbon emissions were strongly affected by seasonality and land use, but not by soil type and slope. Guo, et al.<sup>33</sup> argued that aging and mechanization significantly impact agricultural carbon emissions. Their use of Granger causality analysis revealed a bidirectional relationship between mechanization and carbon emissions. Zang, et al.<sup>34</sup> emphasized that increased agricultural carbon emissions negatively affect agricultural trade and economic

development, whereas higher levels of agricultural economic development can significantly reduce carbon emissions. Zhang, et al.<sup>35</sup> confirmed the inhibitory effect of agricultural informatization on carbon emissions through a detailed data analysis, identifying high technology and broadband proliferation as key mechanisms. Li and Gao<sup>36</sup> discuss the negative impact of the digital economy on agricultural carbon emissions, with agricultural capital mismatch and green technology innovation acting as mediators.

Finally, some scholars explored the impact of agricultural carbon emissions from the perspective of influencing factors. Han, et al.<sup>37</sup> posited that expanding agricultural development scales increases regional carbon emissions, while advancements in agricultural technology significantly inhibit these emissions. Chen, et al.<sup>38</sup> employed the GTWR model to demonstrate that six selected factors influence cities in Fujian Province differently, providing valuable insights for municipal policymakers to develop reasonable and feasible strategies tailored to local conditions. Hu, et al.<sup>39</sup> investigated the factors influencing China's agricultural carbon emissions from 2005 to 2020, finding that population and agricultural industry structure promote emissions, while economic development level, technology, and urbanization significantly inhibit them.

According to the existing research literature, although the research on agricultural carbon emission has been increasing year by year in recent years, there is still a large space for the research in this field to expand. First, according to the measurement of agricultural carbon emissions, scholars mostly calculate carbon emissions from single farmland use and livestock breeding. Few literatures comprehensively consider the agricultural carbon emission level of land use, rice cultivation, farmland soil and livestock breeding. Thus, the existing literature measurement of agricultural carbon emissions has the problem of insufficient precision. Second, existing literature primarily analyzes China's agricultural carbon emissions from four dimensions: measurement, spatial distribution characteristics, interaction with other core explanatory variables, and influencing factors. However, studies utilizing the Gini coefficient to analyze regional differences in agricultural carbon emissions are limited, and research testing the dynamics of carbon emissions transfer across spatial locations is scarce. Third, the existing literature mostly explores the influencing factors of agricultural carbon emission reduction from the perspective of linear regression and spatial measurement. However, the influence of each variable on agricultural carbon emission reduction is different in the temporal and spatial dimensions, and these models cannot better analyze the relationship between variables from the spatial and temporal dimensions. In summary, this study employs the Gini coefficient, spatial Markov analysis and GTWR to address these gaps and enrich the existing body of research.

## Data resource and model design

### Variable selection

#### *Agricultural carbon emission intensity Estimation*

According to Yang, et al.<sup>40</sup> the carbon sources include fertilizers, pesticides, agricultural film, agricultural diesel, irrigation and plowing. SU and HE<sup>41</sup> believes that agricultural carbon emissions include both planting industry and animal husbandry. Thus, this paper first calculates agricultural carbon emissions from four aspects: carbon emissions from land use in agriculture, carbon emissions from rice cultivation, carbon emissions from agricultural soils and carbon emissions from livestock farming. The specific calculation procedure is shown in Appendix A. Therefore, the mathematical expression for calculating the agricultural carbon emission intensity is shown as follows:

$$E_{intensity} = E_{agriculture} / GDP_{agriculture} \quad (1)$$

In Eq. (1),  $E_{intensity}$  indicates the agricultural carbon emission intensity in each province,  $E_{agriculture}$  represents the level of agricultural carbon emissions in each province, while  $GDP_{agriculture}$  denotes the gross domestic product of agriculture in each province.

#### *Selection of influencing factors*

This research synthesizes literature on agricultural carbon emission studies both domestically and internationally, selecting six dimensions as control variables: financial support, R&D intensity, degree of openness to the outside world, human capital level, urbanization level, and technological market development. This approach aims to comprehensively assess their impact on the research<sup>42</sup>. The results of the selected impact factors, along with detailed socio-economic indicators, are presented in Table 1.

Factor	Socio-economic Indicators	Abbreviation
Intensity of Fiscal Support	Proportion of General Fiscal Budget Expenditure to Regional GDP	Fin
R&D Intensity	Proportion of Internal R&D Expenditure to Regional GDP	Res
Degree of Openness	Proportion of Total Import and Export of Goods to Regional GDP	Ope
Level of Human Capital	Proportion of Enrolled Students in Higher Education Institutions to Total Regional Population	Hum
Level of Urbanization	Proportion of Urban Population to Total Population	Urb
Level of Technology Market Development	Proportion of Transaction Volume in Technology Market to Regional GDP	Tec

**Table 1.** Selection of influencing factors for agricultural carbon Emissions.

## Data resource

This research primarily utilized the China Rural Statistical Yearbook, China Statistical Yearbook, and EPS database for collecting data on agricultural carbon emissions. For data related to impact factors, it focused on the EPS data platform (<https://www.epsnet.com.cn/index.html>), and the China Statistical Yearbook, China Rural Statistical Yearbook, China Regional Statistical Yearbook (<https://cnki.nbsti.net/CSYDMirror/trade/yearbook/Single/N2021120010?z=Z009>).

## Model design

### Kernel density estimate

Given the complexity of the variable data in this research, using a traditional pre-specified parametric model is not feasible. The traditional pre-specified parametric model is constrained by distributional assumptions, leading to inaccurate results. Furthermore, this model struggles to address non-linear relationships between variables, making it challenging to accurately fit the dataset and ultimately biasing the conclusions of this paper. In contrast, kernel density estimation embodies the core features of non-parametric estimation, as it does not require adherence to a priori assumptions during application. This flexibility and practicality facilitate data processing and allow researchers to intuitively observe the core characteristics of the data. Consequently, this research employs kernel density estimation, and the mathematical expression of this method is presented below:

$$\hat{f}_h(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x-x_i}{h}\right) \quad (2)$$

In this expression, observation points are represented by the symbol  $x$  and sample points by  $x_i$ , with sample point values ranging from 0 to N. The kernel function is denoted by the expression  $K\left(\frac{x-x_i}{h}\right)$ , which must be greater than 0 and integrate to 1. In the kernel function expression,  $h$  represents the variance of the Gaussian kernel, also referred to as the bandwidth. The bandwidth value significantly affects the performance of kernel density curves and the accuracy of the fitted data. Therefore, it is crucial to consider the bandwidth when setting its value to ensure that the fitting process includes enough data points. The bandwidth value is critical for both the performance of the kernel density curve and the accuracy of the fitted data. Thus, it should theoretically be greater than 0 to ensure that the fitting process contains sufficient data points.

### Dagum Gini coefficient

The Gini coefficient is a widely used economic indicator for measuring income disparity among residents. In this research, the Gini coefficient is employed to analyze the imbalance of agricultural carbon emissions intensity across regions in China. Among them, the overall developmental difference ( $G_T$ ) can be decomposed into intra-regional difference ( $G_W$ ), inter-regional difference ( $G_B$ ), and supervariable density contribution ( $G_D$ ). The specific calculation formula is as follows:

$$G_T = \frac{\sum_{j=1}^k \sum_{h=1}^k \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |x_{ji} - x_{hr}|}{2n^2 \bar{x}} \quad (3)$$

$$G_T = G_W + G_B + G_D = \sum_{j=1}^k G_{jj} p_j s_j + \sum_{j=2}^k \sum_{h=1}^j G_{jh} (p_j s_h + p_h s_j) D_{jh} + \sum_{j=2}^k \sum_{h=j+1}^k G_{jh} (p_j s_h + p_h s_j) (1 - D_{jh}) \quad (4)$$

In the above mathematical expression, the symbols k and n denote the number of regions included in the study and the number of samples collected from each region, respectively.  $s_j$  and  $s_h$  denote the number of samples from regions  $j$  and  $h$ , respectively.  $x_{ji}$  and  $x_{hr}$  indicate the current status of agricultural carbon emissions intensity in various regions.  $\bar{x}$  denotes the average level of agricultural carbon emissions intensity in the study region.

### Moran's index

Before investigating the spatiotemporal evolution characteristics of China's agricultural carbon emissions, it is crucial to verify whether the collected data are correlated at the geospatial level. Among the various methods for testing spatial autocorrelation, the Moran index holds a significant position. This is because the Moran's index can simultaneously provide a visual representation of spatial data clustering or dispersion characteristics, as well as a quantitative assessment of the degree of spatial autocorrelation. This advantage has led to its frequent use in spatial data analysis across various fields. In this research, the Moran's index is employed to analyze the spatial data comprehensively from both global and local perspectives. The mathematical expression for this method is presented below:

$$Moran's \quad I = \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n W_{ij}} \quad (5)$$

$$I_i = \frac{(x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \sum_{j=1}^n W_{ij}(x_j - \bar{x}) \quad (6)$$

Equation (5) presents the mathematical expression of the global Moran's index. Here, n represents the number of cities;  $x_i$  and  $x_j$  denote the sample values of agricultural carbon emissions intensity for cities i and j, respectively;  $W_{ij}$  denotes the spatial weight matrix;  $\bar{x}$  represents the sample mean; and  $S^2$  denotes the sample variance. In Eq. (6),  $I_i$  represents the local autocorrelation value, and the meanings of the remaining symbols are consistent with those in Eq. (5).

#### *Spatial Markov*

In the existing literature, researchers often employ Markov chains when dealing with random variables. This is because Markov chains operate under the principle of no posteriori, meaning that the change in a variable's state at the next moment is determined solely by its current state, with no relation to its prior state. This principle provides a framework for policy-making based on objective conditions. Conversely, the spatial Markov chain is a logical extension of traditional theory, integrating dynamic time series analysis with spatial interaction considerations to more accurately capture and measure the dynamic changes in spatial states. Therefore, this research employs the spatial Markov chain to explore the state transfer conditions of agricultural carbon emissions intensity in China across spatial locations. The mathematical expression of this method is as follows:

$$P_{ij} = \frac{Z_{ij}}{Z_i} \quad (7)$$

$$L_a = \sum_{b=1}^n W_{ab} x_b \quad (8)$$

In Eq. (7),  $P_{ij}$  represents the probability of a shift in China's agricultural carbon emissions intensity from level i to level j, while  $Z_i$  denotes the number of cities with agricultural carbon emissions intensity below level i, and  $Z_{ij}$  indicates the number of cities transitioning from state i to state j. Equation (8) outlines the calculation method for the spatial Markov chain, where  $L_a$  represents the spatial lag term and n indicates the number of cities included in the study.  $W_{ab}$  denotes the spatial weight matrix. In this research, when processing data using the neighboring spatial weight matrix, neighboring regions are represented by the number 1 and non-neighboring regions by 0. The value of the regional attribute is denoted by  $x_b$ .

#### *Spatiotemporal geographically weighted regression model*

The spatiotemporal geographically weighted regression model represents an advanced approach to spatial statistical analysis, offering flexible and precise methods for processing and analyzing spatial data across both spatial and temporal dimensions. During application, the model dynamically adjusts its parameters by incorporating temporal and spatial weighting functions, allowing it to accurately reflect data changes at different spatiotemporal points. This addresses the limitations of traditional geographically weighted regression models. In summary, this research employs the spatiotemporal geographically weighted regression model to analyze the variable data, as illustrated by the mathematical expression below:

$$C_i = \alpha_0(u_i, v_i, t_i) + \sum_k \alpha_k(u_i, v_i, t_i) x_{ik} + \beta_i \quad (9)$$

In Eq. (10),  $C_i$  represents the level of agricultural carbon emissions intensity in area i;  $x_{ik}$  denotes the observed value of indicator k in city i;  $(u_i, v_i, t_i)$  indicates the spatial coordinate position of city i;  $\alpha_0(u_i, v_i, t_i)$  refers to the spatiotemporal intercept for city i;  $\alpha_k(u_i, v_i, t_i)$  is the regression coefficient of indicator k in area i; and  $\beta_i$  denotes the residual.

$$(d_{ij})^2 = \lambda [(u_i - u_j)^2 + (v_i - v_j)^2] + \mu (t_i - t_j)^2 \quad (10)$$

$$W_{ij} = e^{-(d_{ij}/h)^2} \quad (11)$$

In Eq. (10),  $d_{ij}$  denotes the distance between city i and city j;  $\lambda$  and  $\mu$  represent the scaling factors for spatial and temporal distances, respectively, with both  $\lambda$  and  $\mu$  specified to be non-negative. In Eq. (11),  $W_{ij}$  is the calculated weight matrix, and h denotes the window width.

## Analysis of empirical Trend analysis of the Spatiotemporal evolution of agricultural carbon emissions intensity in China

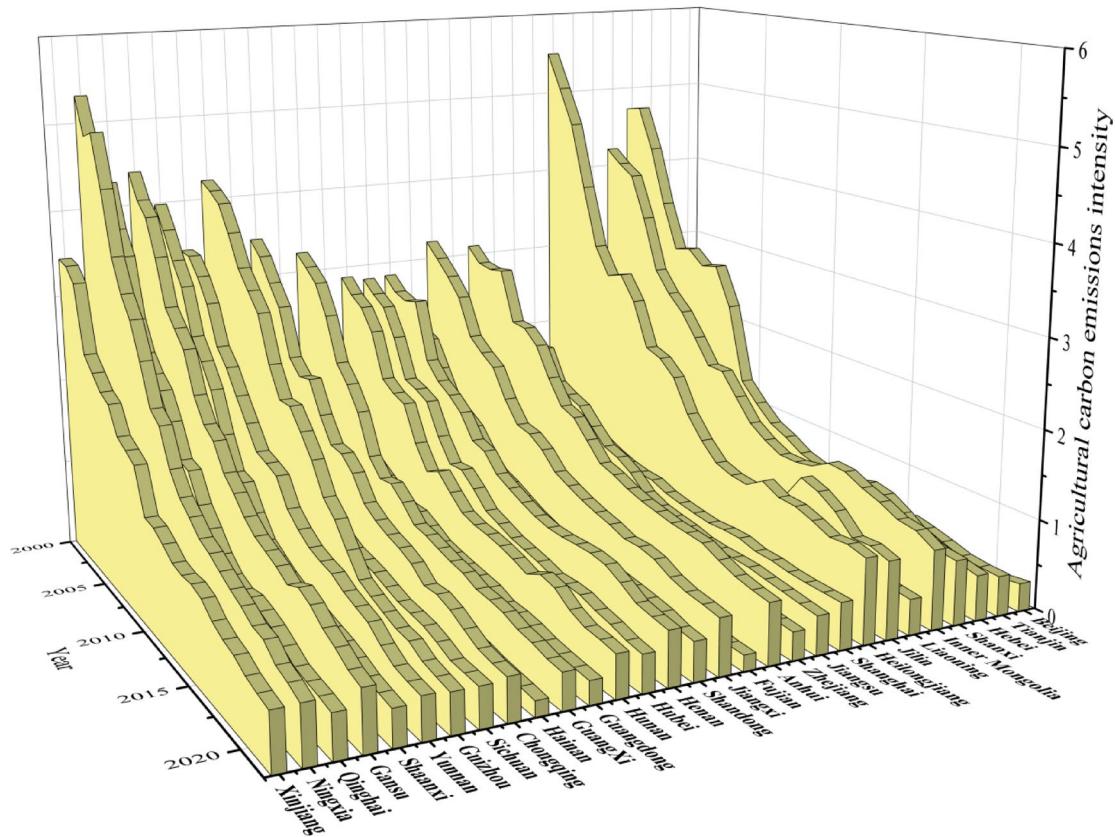
Based on the calculation method of agricultural carbon emission intensity, the agricultural carbon emission intensity index of 30 provinces in China from 2001 to 2022 is calculated. Therefore, this paper was used to draw 3D wall charts of agricultural carbon emission intensity using Origin 2018 software.

In Fig. 1, Heilongjiang and Ningxia had the highest agricultural carbon emission intensity index in 2001, generating more than 5 tons of carbon emissions per 10,000 yuan of GDP. With China's continuous promotion of environmental protection and carbon emission reduction policies, the agricultural carbon emission intensity index of all provinces in China showed a significant downward trend between 2001 and 2022. It can be found that although China's agricultural carbon emissions are on an upward trend, their emission intensity is in a downward trend. This is mainly due to the improvement of agricultural production capacity and resource utilization rate. In the agricultural production process, the use of chemical fertilizers, plastic film, agricultural diesel oil and pesticides are the main sources of carbon emissions. With the progress of agricultural technology and the enhancement of farmers' awareness of environmental protection, agricultural production is more efficient and resource consumption is reduced, thus reducing the intensity of carbon emissions.

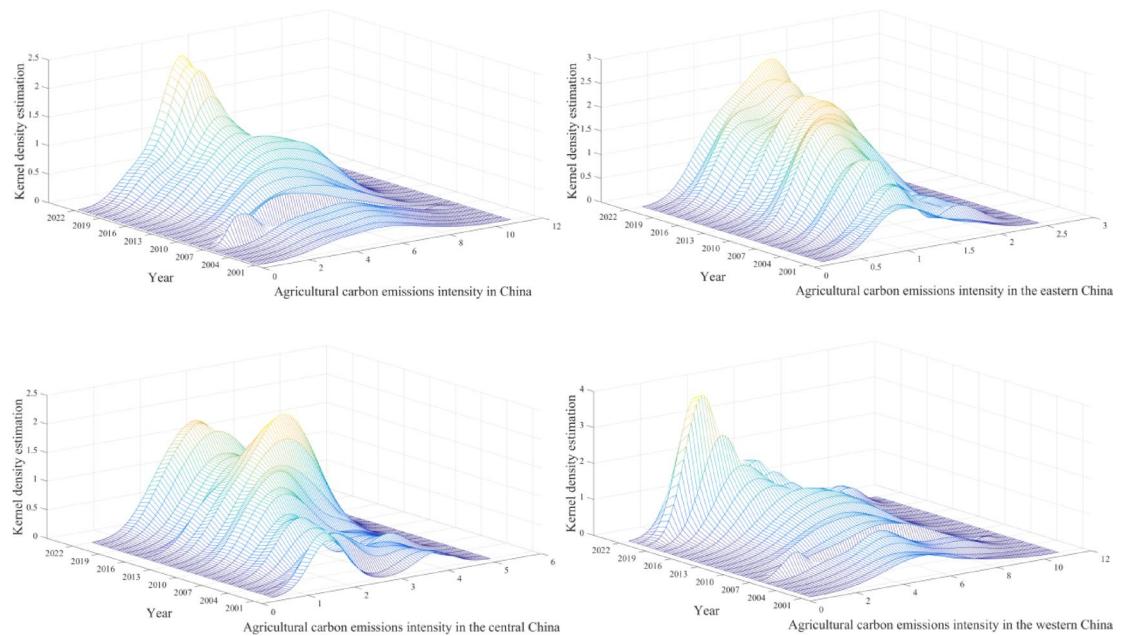
### *Characteristics of Time-series distribution of agricultural carbon emissions intensity in China*

This research presents the kernel density estimates of agricultural carbon emissions intensity for China as a whole, as well as for the eastern, central, and western regions, as shown in Fig. 2. The overview of the figure indicates that the centers of the kernel density curves for agricultural carbon emissions intensity in China, including the eastern, central, and western regions, have all shifted to the right, indicating an increase in agricultural carbon emissions intensity across these areas. In contrast to the eastern and central regions, the density curve for the western region exhibits a double-peak phenomenon starting in 2016, along with a trailing effect from 2019 onward. The density curves for the eastern and central regions, however, remain relatively smooth without a double peak. This indicates that agricultural carbon emissions intensity in the western region of China exhibit significant inter-provincial differences and polarization after 2016, with some provinces experiencing extremely high emissions while others have notably low levels. Such polarization does not occur in the eastern or central regions. The national kernel density curve also exhibits a mild trailing phenomenon after 2019, attributed to the significant influence of the western region, resulting in slight variability in the national level of agricultural carbon emissions.

The reason for this phenomenon is the continuous innovation and promotion of agricultural technology, which improves the efficiency of agricultural production and reduces carbon emissions. For example, with



**Fig. 1.** Agricultural carbon emission intensity in all provinces of China from 2001 to 2022.



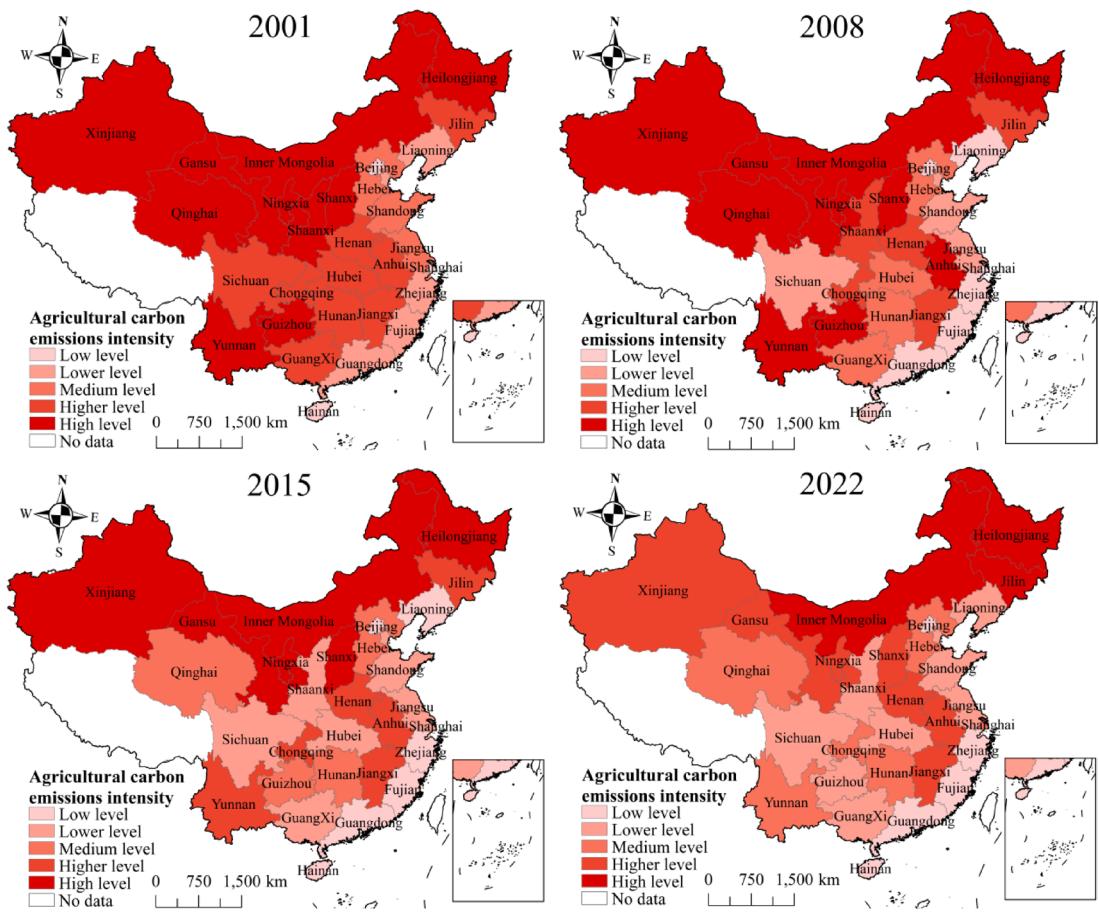
**Fig. 2.** Kernel Density Estimation of Agricultural Carbon Emissions Intensity in Different Regions of China.

its good economic foundation and scientific and technological resources, the eastern region took the lead in realizing the eco-friendly transformation of agricultural production mode. The central and western regions have also gradually adjusted to the direction of diversified and efficient agricultural industrial structure, which has promoted the reduction of agricultural carbon emission intensity. At the same time, because of the different implementation of environmental protection policies and the degree of technology application, the control effect of agricultural carbon emission level is affected. In particular, the western region has complex natural conditions and different resource endowments, which leads to a large economic base and industrial structure, leading to significant differences in agricultural carbon emission intensity.

#### *Spatial distribution characteristics of agricultural carbon emissions intensity in China*

To reveal the specific characteristics of the spatial evolution of China's agricultural carbon emissions intensity, this study employs the natural breakpoint classification method to categorize these emissions into low, medium, high, and very high levels, ultimately resulting in the spatial distribution map shown in Fig. 3. Analyzing the spatial distribution maps for China in 2001, 2008, 2015, and 2022 reveals a pattern of agricultural carbon emissions intensity that is 'high in the west and low in the east, high in the north and low in the south'. This distribution is influenced by the relationship between agricultural production activities, regional resource endowments, and variations in economic development levels and agricultural structures. A closer examination of the figure shows an overall decreasing trend in China's agricultural carbon emissions intensity. In 2001, the only provinces with emissions below the medium level were Beijing, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, and Hainan, while the remaining provinces were at or above the medium development stage. By 2008, agricultural carbon emissions intensity in Zhejiang, Jiangsu, and Guangdong provinces had decreased to a low level, and most southern provinces exhibited a downward trend in emissions. However, carbon emissions in the northwestern and northeastern regions remained high, highlighting a significant regional imbalance. By 2022, no provinces in southern China had high levels of agricultural carbon emissions intensity, and emissions continued to decline. The northwestern region also showed improvement, with most areas transitioning from high to medium or lower levels of emissions. In contrast, the northeastern region consistently maintained high levels of agricultural carbon emissions intensity.

This phenomenon can be attributed to the arid climate in the northwest, the greater sensitivity of agro-ecosystems to climate change and environmental pollution, and the higher resource and energy inputs required for agricultural production, resulting in elevated carbon emissions. Additionally, the economy of Northwest China is relatively underdeveloped, with agricultural production methods and technologies often being traditional, resulting in a lack of advanced emission reduction technologies. As the primary grain-producing region, the Northeast faces significant agricultural production volumes influenced by climate and soil conditions, resulting in concentrated production activities. Its geographical distance from technologically advanced regions poses greater challenges in adopting advanced agricultural technologies, contributing to relatively high carbon emissions.



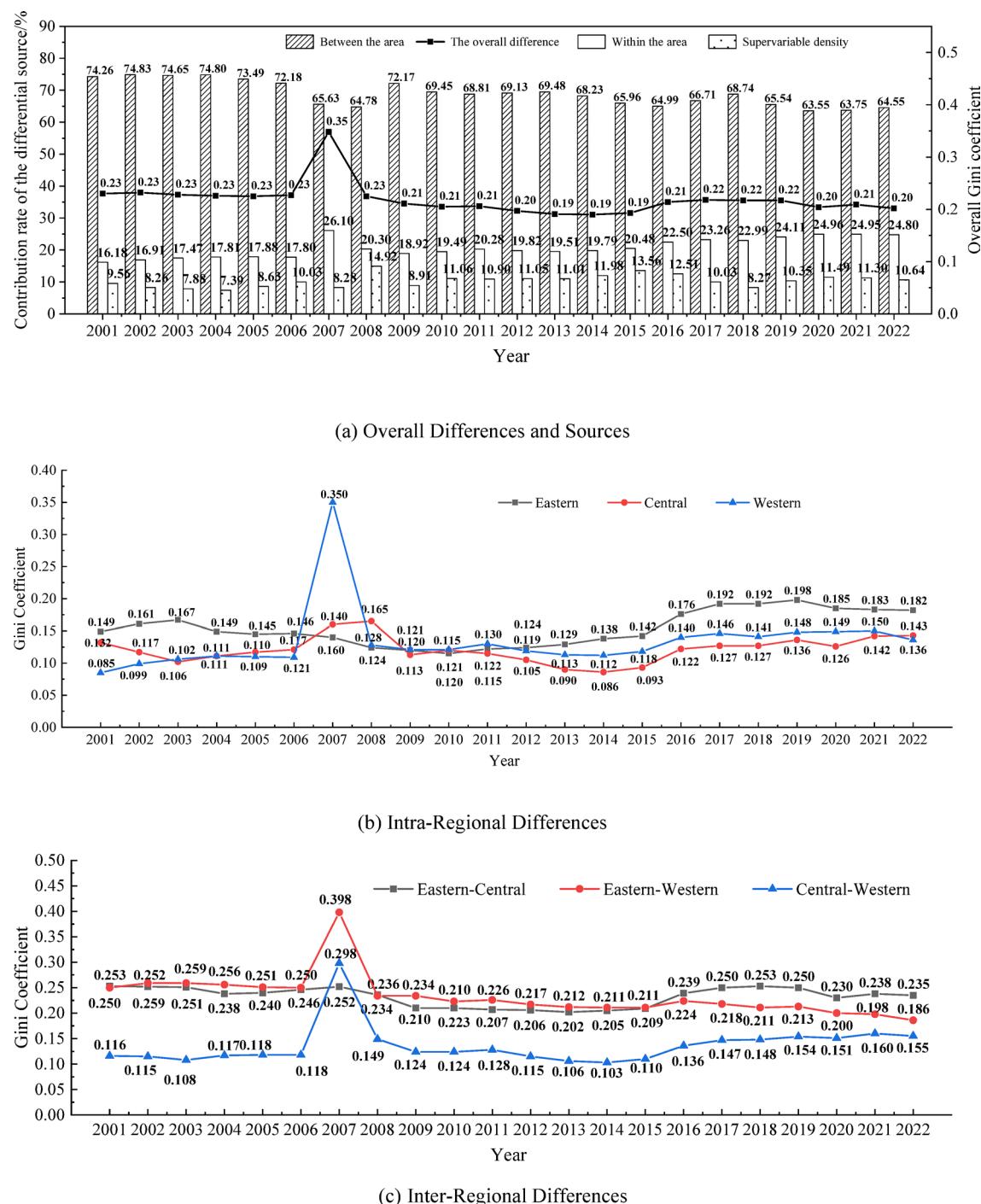
Note: This map is produced using the standard map with review number GS (2023) 2764, downloaded from the Standard Map Service of the Ministry of Natural Resources, with no modifications to the base map.

**Fig. 3.** Spatial Distribution of Agricultural Carbon Emissions Intensity in China. Note: This map is produced using the standard map with review number GS (2023) 2764, downloaded from the Standard Map Service of the Ministry of Natural Resources, with no modifications to the base map.

#### *Spatiotemporal difference characteristics of agricultural carbon emissions intensity in China*

Using Gini coefficient assessment data, this research plotted the spatiotemporal differences in China's overall, intra-regional, and inter-regional agricultural carbon emissions intensity to further reveal the current status of spatial disparities in these emissions. The results are presented in Fig. 3.

First, the overall Gini coefficient for agricultural carbon emissions intensity in Fig. 4(a) remained stable at 0.23 from 2001 to 2006, fluctuating around 0.20 in 2018 after an 'inverted V-shaped' change from 2006 to 2008. This indicates that regional differences in agricultural carbon emissions intensity in China have persisted, with variability showing a declining trend over time. Second, the intra-regional Gini coefficients for agricultural carbon emissions intensity in Fig. 4(b) are consistently lower than the overall Gini coefficient. In most years, the intra-regional Gini coefficient for the eastern region exceeds that of the central region, while the western region exhibits the smallest intra-regional Gini coefficient. This demonstrates that, in terms of intra-regional differences, agricultural carbon emissions intensity in China exhibit a spatial pattern of east > central > west. Finally, Fig. 4(c) shows that the inter-regional Gini coefficients for agricultural carbon emissions intensity between the central and western regions are consistently the smallest, remaining below the overall Gini coefficient throughout the observation period. In contrast, the inter-regional Gini coefficients for the eastern and western regions, as well as for the eastern and central regions, are consistently higher than the overall Gini coefficient, with the eastern-western coefficient leading in most years. This indicates that the most pronounced inter-regional differences in agricultural carbon emissions intensity in China are between the eastern and western regions, followed by the eastern and central regions, while the smallest differences are between the western and central regions. This disparity arises because the western region experiences relatively slow economic and technological development, with agriculture still primarily relying on traditional production methods. In contrast, the central region largely comprises major grain-producing areas with high agricultural inputs, leading to elevated carbon emissions. The eastern region, characterized by advanced economic development and high agricultural modernization,

**Fig. 4.** Trend of Differences in Agricultural Carbon Emissions Intensity in China.

emphasizes ecological and sustainable practices, further accentuating the differences with the western and central regions.

From the overall trend of Fig. 4, it can be found that the coefficient value of agricultural carbon emissions intensity in 2007 is relatively large, indicating that there is a large gap between the groups of agricultural carbon emissions intensity in 2007. The main reason for this phenomenon is: the State Council issued the No. 1 central document is the core theme of developing modern agriculture promoting socialist new rural construction. Under the circumstances of increasing investment in “agriculture, rural areas and farmers” and the difference in agricultural infrastructure construction, there are significant differences in agricultural carbon emissions intensity among regions. With the popularization of the policy throughout 2007, the phenomenon of differentiation narrowed in 2008.

### *Spatial correlation analysis of agricultural carbon emissions intensity in China*

This research explores the spatial correlation of China's agricultural carbon emissions intensity using Moran's index as an analytical tool. Utilizing the global Moran's index, the results of the global autocorrelation analysis are presented in Table 2. The value of Moran's I remains stable and positive, consistently above 1.90 during the sample period, with the corresponding P-value below 0.01 in most years. This indicates a significant positive spatial correlation in China's agricultural carbon emissions intensity. Additionally, the lowest Z value in Table 6 is 1.961, suggesting a notable spatial clustering trend in China's agricultural carbon emissions intensity, warranting further exploration of this clustering.

To further analyze the spatial agglomeration characteristics of China's agricultural carbon emissions intensity, this research employs the local Moran index and selects data from 2001, 2008, 2015, and 2022, which is illustrated in the local Moran LISA map (see Fig. 5). Figure 5 illustrates that China's agricultural carbon emissions intensity exhibit spatial concentration patterns, characterized by high-high and low-low concentrations. The high-high concentration areas are primarily located in the northwestern and northeastern regions, while the low-low concentration areas are mainly in Guangdong and Fujian. The Northwest and Northeast regions, characterized by intensive agricultural production and reliance on traditional agricultural technologies and energy, exhibit relatively high carbon emissions. In contrast, the coastal regions of Guangdong and Fujian, with advanced agricultural development, high energy efficiency, and stringent environmental protection policies, emphasize effective emission reduction measures, leading to comparatively low carbon emissions.

### *Analysis of Spatial transfer characteristics of agricultural carbon emissions intensity in China*

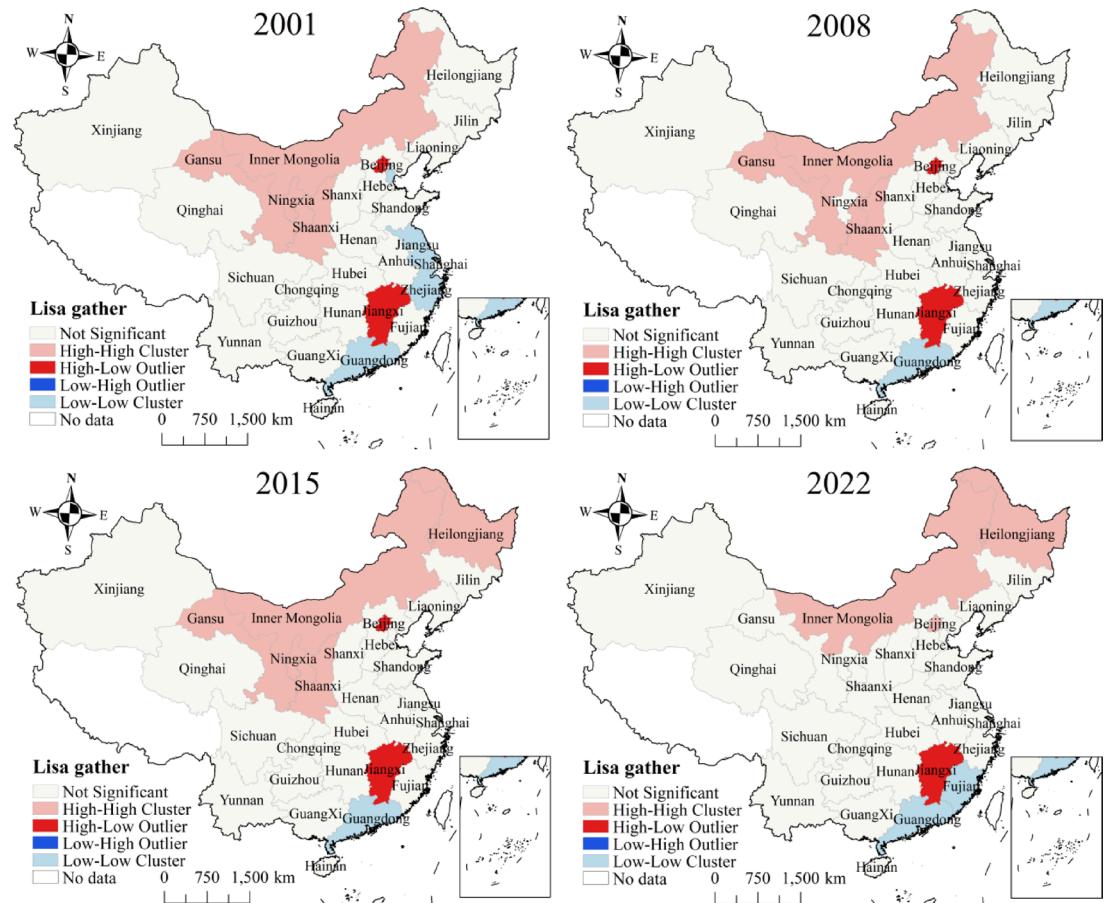
To intuitively illustrate the spatial transfer characteristics of China's agricultural carbon emissions intensity, this research employs a quartile division standard to categorize urban agricultural carbon emissions intensity into four levels: less than 25%, 25–50%, 50–75%, and 75% or above. The resulting Markov transfer probability matrix for China's agricultural carbon emissions intensity is presented in Table 3.

The levels I, II, III, and IV in Table 3 correspond to the four categories of agricultural carbon emissions intensity. By examining the Markov transfer probability values between these levels, we can infer the transfer characteristics of carbon emissions over time. Firstly, the diagonal probability values show a maximum of 0.985 and a minimum of 0.716 during the sample period. This indicates that the probability of maintaining a low agricultural carbon emission intensity level over the next five years is 98.5%, while the probability for higher emission levels is 71.6%. Thus, China's agricultural carbon emissions intensity levels demonstrate significant stability over time. Conversely, the non-diagonal probability values indicate a maximum of 0.272 and a minimum of 0.000. Specifically, there is a 27.2% chance of a higher agricultural carbon emissions intensity level transitioning to a lower level over the next five years. However, the probability of transferring from a lower to a higher emission level is zero. This suggests that the level of agricultural carbon emissions intensity in China is likely to remain stable over the next five years, with minimal chances of movement either up or down, but not crossing levels.

Building on the previous analysis, this paper further investigates the spatial transfer of China's agricultural carbon emissions intensity. It introduces a spatial lag term to the original model, remeasures the spatial Markov transfer probability matrix presented in Table 4, and provides a reinterpretation of the data. The results indicate that, while the values of the elements in both diagonal and non-diagonal positions fluctuate, the overall probability of the diagonal position remains greater than that of the non-diagonal position. Additionally, an analysis of neighborhood types and the number of cities they encompass at times t and t + 1 reveals a clear 'spatial synergy' in China's agricultural carbon emissions intensity. Specifically, the data highlights that if a neighborhood exhibits a low level of agricultural carbon emissions intensity at time t, the number of cities maintaining this status at time t + 1 reaches 16, the highest among all cities in any status. Similarly, for neighborhoods at emission levels II, III, and IV, the number of cities sustaining the same status at time t + 1 is 39, 54, and 51, respectively, also ranking first across all statuses.

Year	Moran's I	Z_values	P_values	Year	Moran's I	Z_values	P_values
2001	0.386	3.641	0.000	2012	0.193	1.961	0.050
2002	0.377	3.565	0.000	2013	0.192	1.956	0.050
2003	0.367	3.480	0.001	2014	0.207	2.088	0.037
2004	0.339	3.234	0.001	2015	0.225	2.240	0.025
2005	0.308	2.963	0.003	2016	0.295	2.871	0.004
2006	0.288	2.788	0.005	2017	0.298	2.903	0.004
2007	0.286	2.753	0.005	2018	0.286	2.797	0.005
2008	0.217	2.183	0.029	2019	0.321	3.102	0.002
2009	0.249	2.450	0.014	2020	0.323	3.129	0.002
2010	0.224	2.246	0.025	2021	0.312	3.058	0.002
2011	0.194	1.984	0.047	2022	0.276	2.730	0.006

**Table 2.** Global autocorrelation analysis of agricultural carbon emissions intensity in China.



Note: This map is produced using the standard map with review number GS (2023) 2764, downloaded from the Standard Map Service of the Ministry of Natural Resources, with no modifications to the base map.

**Fig. 5.** LISA Clustering Map of Agricultural Carbon Emissions Intensity in China. Note: This map is produced using the standard map with review number GS (2023) 2764, downloaded from the Standard Map Service of the Ministry of Natural Resources, with no modifications to the base map.

$t_i/(t_i + 1)$	From 2001 to 2011					From 2012 to 2022				
	$n$	I	II	III	IV	$n$	I	II	III	IV
I	65	0.985	0.015	0.000	0.000	67	0.985	0.015	0.000	0.000
II	72	0.264	0.736	0.000	0.000	74	0.216	0.784	0.000	0.000
III	81	0.000	0.272	0.716	0.012	78	0.000	0.231	0.769	0.000
IV	82	0.000	0.000	0.256	0.744	81	0.000	0.000	0.160	0.840

**Table 3.** Markov transition probability matrix of agricultural carbon emissions intensity in China from 2001 to 2022.

#### Analysis of influencing factors of agricultural carbon emissions intensity in China

This paper selects six explanatory variables, including intensity of fiscal support, R&D intensity, degree of openness, level of human capital, level of urbanization and level of technology market development, and uses the GTWR model to explore the influencing factors of agricultural carbon emission reduction in China. The results of descriptive statistics and collinearity tests for each variable are shown in Table 5. From the descriptive statistics, the sample data of 30 provinces in China from 2001 to 2022 was selected, and the total number of samples was 660. At the same time, it can be found from the table that the variance of all variables is less than the average, thus indicating that there is no abnormality in the data, so the data meets the basic requirements of the regression model. In addition, before conducting the model fitting analysis, this research employs the Variance Inflation Factor (VIF) method to address potential covariance issues among variable data. The results of this

ti/(ti + 1)		From 2001 to 2011					From 2012 to 2022				
		n	I	II	III	IV	n	I	II	III	IV
I	I	16	1.000	0.000	0.000	0.000	10	1.000	0.000	0.000	0.000
	II	3	0.000	1.000	0.000	0.000	9	0.111	0.889	0.000	0.000
	III	0	0.000	0.000	0.000	0.000	2	0.000	0.500	0.500	0.000
	IV	0	0.000	0.000	0.000	0.000	0	0.000	0.000	0.000	0.000
II	I	37	0.973	0.027	0.000	0.000	30	1.000	0.000	0.000	0.000
	II	39	0.308	0.692	0.000	0.000	32	0.313	0.688	0.000	0.000
	III	22	0.000	0.318	0.682	0.000	21	0.000	0.333	0.667	0.000
	IV	2	0.000	0.000	1.000	0.000	6	0.000	0.000	0.333	0.667
III	I	12	1.000	0.000	0.000	0.000	27	0.963	0.037	0.000	0.000
	II	24	0.292	0.708	0.000	0.000	30	0.100	0.900	0.000	0.000
	III	54	0.000	0.259	0.722	0.019	44	0.000	0.205	0.795	0.000
	IV	29	0.000	0.000	0.310	0.690	63	0.000	0.000	0.159	0.841
IV	I	0	0.000	0.000	0.000	0.000	0	0.000	0.000	0.000	0.000
	II	6	0.000	1.000	0.000	0.000	3	0.667	0.333	0.000	0.000
	III	5	0.000	0.200	0.800	0.000	11	0.000	0.091	0.909	0.000
	IV	51	0.000	0.000	0.196	0.804	12	0.000	0.000	0.083	0.917

**Table 4.** Spatial Markov transition matrix of agricultural carbon emissions intensity in China from 2001 to 2022.

Variable	Obs	Mean	Std.	Min	Max	VIF	1/VIF
Intensity of Fiscal Support	660	0.218	0.100	0.077	0.758	1.25	0.798
R&D Intensity	660	0.014	0.011	0.002	0.065	4.24	0.236
Degree of Openness	660	0.289	0.036	0.000	1.721	1.96	0.509
Level of Human Capital	660	0.017	0.008	0.003	0.044	2.61	0.384
Level of Urbanization	660	0.530	0.156	0.139	0.896	3.17	0.384
Level of Technology Market Development	660	0.013	0.025	0.000	0.191	2.39	0.419

**Table 5.** Descriptive statistics of variables and collinearity Test.

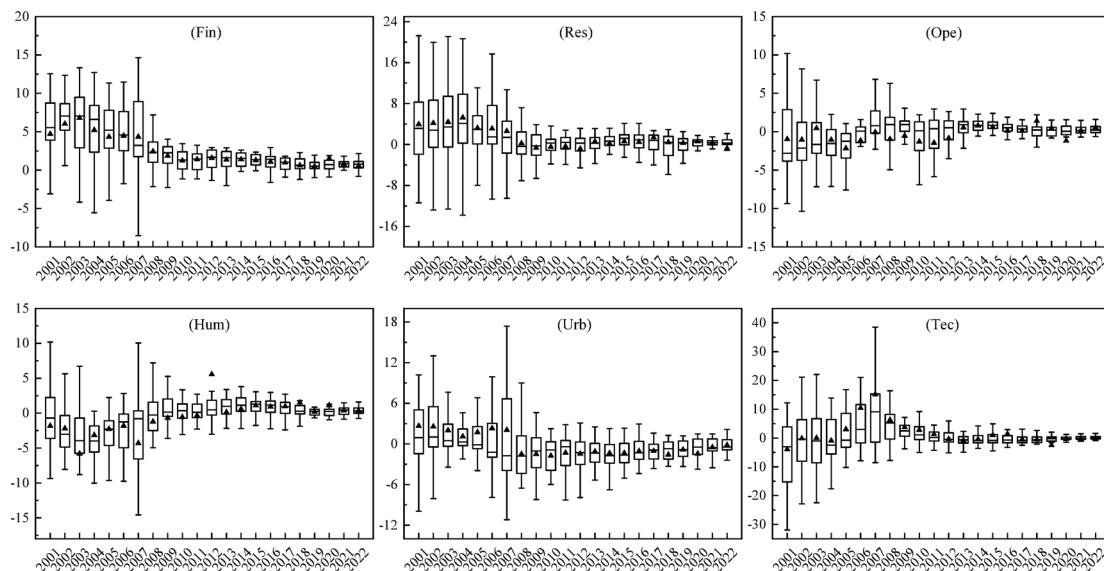
Model	R <sup>2</sup>	AICc
GTWR	0.873	99.08
GWR	0.788	647.87
TWR	0.746	819.43
OLS	0.450	1469.66

**Table 6.** Comparison of regression model fitting Results.

test are statistically presented in Table 5. Previous studies have established a VIF threshold of 10, which this research adheres to. The data indicate that the maximum VIF value for each variable is 4.24, significantly lower than the threshold. This finding confirms the absence of covariance issues among the variables, providing a solid foundation for subsequent in-depth analyses using the corresponding model.

This research presents the results of fitting four regression models—GTWR, geographically weighted regression (GWR), temporal weighted regression (TWR), and OLS—in Table 6, aiming to identify the most suitable model by comparing the fitting results across these models. When comparing the fitting results, both the R<sup>2</sup> and AICc values must be considered. Scholars have established that a R<sup>2</sup> value closer to 1 and a smaller AICc value indicate better model fit. According to the data in the table, the GTWR model exhibits an R<sup>2</sup> value closer to 1 and a smaller AICc value. Therefore, this paper ultimately selects the GTWR model for subsequent investigations.

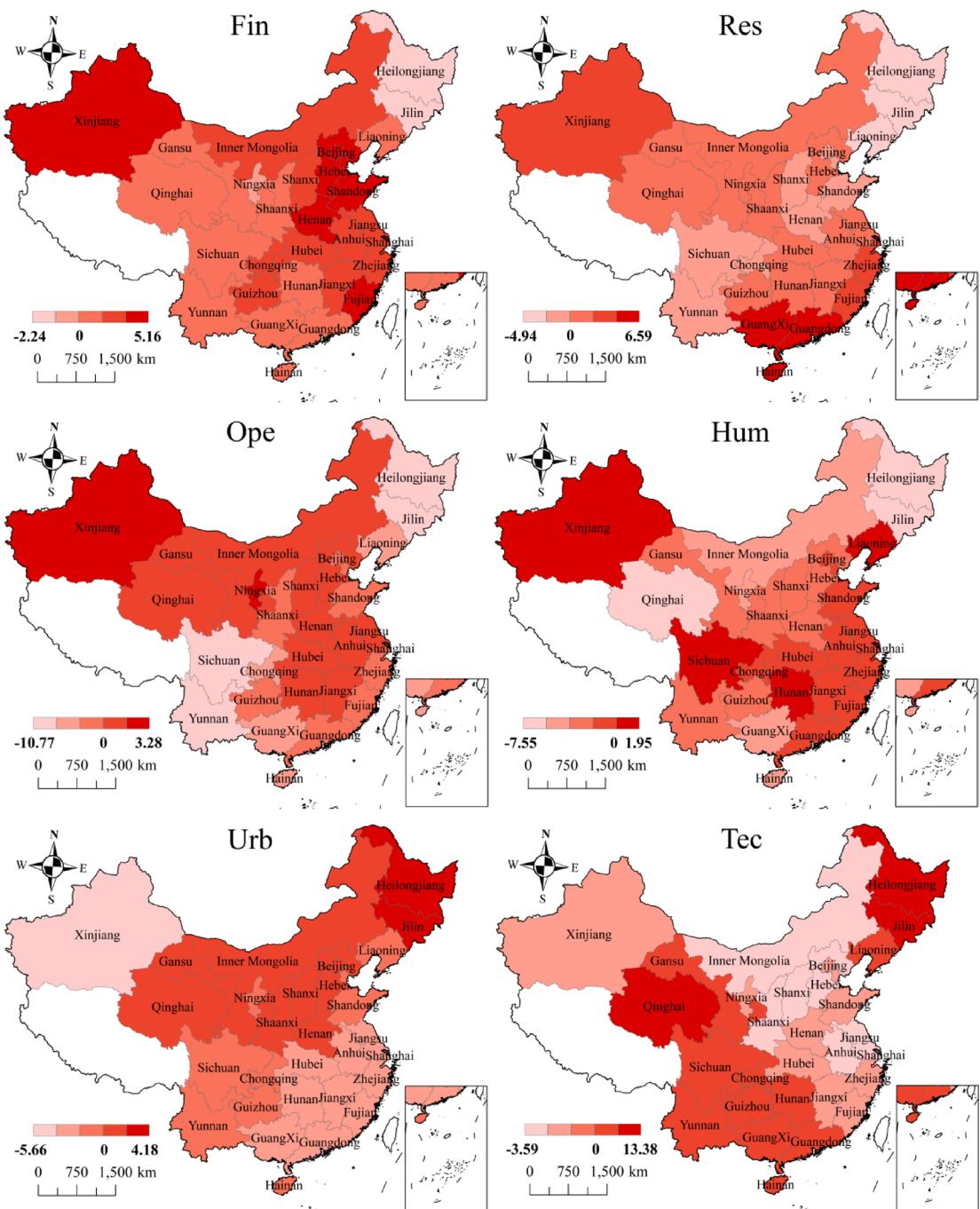
Figure 6 illustrates the time distribution of regression coefficients for each variable in the GTWR model. A closer examination reveals that the average regression coefficient for financial support regarding agricultural carbon emissions intensity is 2.4809. This indicates that financial support significantly promotes agricultural carbon emissions intensity; however, its average regression coefficient exhibits a clear decreasing trend over the study period, suggesting that its effectiveness in promoting emissions is weakening annually. The average regression coefficient for R&D intensity is 1.131, decreasing from 4.689 in 2001 to -1.190 in 2022. This indicates



**Fig. 6.** Temporal Distribution of Regression Coefficients for Each Variable in the GTWR Model.

that while R&D intensity contributes to China's agricultural carbon emissions intensity, it has exhibited a declining trend in recent years, likely due to the increased effectiveness of R&D and the carbon reduction impacts of R&D achievements. The average regression coefficient for the degree of openness to the outside world during the study period is  $-0.967$ , with a negative value in most years. This suggests that this variable significantly inhibits the level of China's agricultural carbon emissions intensity. The average regression coefficient for Human Capital Level is  $-1.186$ , indicating that this variable inhibits agricultural carbon emissions intensity. Notably, while both the degree of openness to the outside world and Human Capital Level exhibited inhibitory effects on China's agricultural carbon emissions intensity during the study period, their average regression coefficients have shown positive values in recent years. This trend can be attributed to certain cities increasing resource investments in agriculture during the early phases of openness and Human Capital introduction, which temporarily elevated China's agricultural carbon emissions intensity before the adoption of advanced low-carbon production technologies. The average regression coefficient for urbanization level is  $-0.74$ , while that for technology market development level is  $1.439$ . Their temporal evolution reveals distinct phases. The average regression coefficient for urbanization level declines from  $3.026$  in 2001 to  $-2.966$  in 2008 and further to  $-0.462$  in 2022. This change indicates that urbanization's influence has shifted from promotion to suppression, with the suppressive effect weakening over time. Factors such as agricultural structure, resource reorganization, and policy orientation during the early to middle stages of urbanization, along with regional performance disparities, are also significant contributors.

To explore the effects of the variables on agricultural carbon emissions intensity across spatial locations, this study plots the spatial distribution of regression coefficients from the GTWR model, as shown in Fig. 7. The figure reveals that financial support has a negative impact on agricultural carbon emissions intensity only in Heilongjiang Province, Jilin Province, and the Ningxia Hui Autonomous Region, while all other regions exhibit positive coefficients. The provinces contributing most significantly to agricultural carbon emissions intensity include Xinjiang, Beijing-Tianjin-Hebei, Shandong, and Fujian. This may relate to various factors, such as agricultural development characteristics, production scale, technological progress, and energy consumption in these areas. The regions where R&D intensity inhibits agricultural carbon emissions intensity are primarily concentrated in Northeast and Southwest China. Investment in agricultural R&D in these areas likely emphasizes technological innovations aimed at improving production efficiency and resource utilization. Such advancements can help reduce the use of agricultural inputs, such as chemical fertilizers and pesticides, thereby lowering carbon emissions during agricultural production. Regions exhibiting strong promotional effects are primarily in Guangxi and Guangdong. This may relate to factors such as increased agricultural production scale and inputs, technological innovation, and structural adjustments, all of which influence carbon emissions. The impact coefficient of openness to the outside world on agricultural carbon emissions intensity exhibits a pattern of "high in the north and low in the south, with low values on the sides and high in the middle." This may relate to the agricultural production structure influenced by international trade. The northern region primarily exports grain, meat, and other high-carbon products requiring significant chemical fertilizers, pesticides, and energy inputs. In contrast, the southern region, characterized by higher economic and technological development, focuses on ecological and organic agriculture, resulting in a smaller proportion of high-carbon products among its exports. The influence coefficient of Human Capital Level on agricultural carbon emissions intensity exhibits a spatial pattern of "low around and high in the middle," with higher values concentrated in Xinjiang, Liaoning, Sichuan, and Hunan. In contrast, the human capital levels in other regions tend to inhibit agricultural carbon emissions intensity. These high-value regions likely align well with local agricultural technology levels, resulting in a more efficient allocation of resources during agricultural production. However, this alignment may also



Note: This map is produced using the standard map with review number GS (2023) 2764, downloaded from the Standard Map Service of the Ministry of Natural Resources, with no modifications to the base map.

**Fig. 7.** Spatial Distribution of Regression Coefficients for Each Variable in the GTWR Model. Note: This map is produced using the standard map with review number GS (2023) 2764, downloaded from the Standard Map Service of the Ministry of Natural Resources, with no modifications to the base map.

contribute to increased carbon emissions due to limitations or inefficiencies in technology application. The influence coefficient of urbanization level on agricultural carbon emissions intensity exhibits a pattern of "high in the north, low in the south, high in the west, and low in the east." This trend is primarily due to the significantly faster urbanization process in the south and east compared to the north and west, which may lead to greater resource consumption pressures during urbanization. As urbanization advances, rural areas may rely heavily on inputs such as chemical fertilizers and pesticides to support agricultural production, which can subsequently

increase carbon emissions. The influence of technology market development on agricultural carbon emissions intensity exhibits a trend of “high in the east and low in the west, high in the south and low in the north.” The technology market in the southern region is more advanced, facilitating the introduction and application of diverse agricultural technologies. These technologies may include energy-efficient agricultural machinery and intelligent agricultural systems, as well as some high-energy consumption and high-emission technologies. In contrast, the technology market in the northern region is relatively underdeveloped, leading to more conservative approaches in the introduction and application of agricultural technologies. This conservatism may lead the northern region to rely on traditional and inefficient technologies in agricultural production, thereby reducing carbon emissions.

## Discussion

In order to explore the spatial and temporal evolution characteristics and influencing factors of agricultural carbon emission intensity in China. This paper analyzes 30 provinces in China.

First, this paper calculates the agricultural carbon emission intensity index from 2001 to 2022. First, this paper calculates the agricultural carbon emission intensity index from 2001 to 2022. The study finds that China's agricultural carbon emission intensity shows an obvious downward trend from 2001 to 2022<sup>43,44</sup>. Zhang, et al.<sup>45</sup> shows that China's agricultural carbon emission intensity showed a downward trend, with high-carbon emission intensity provinces remaining stable and low-intensity provinces expanding. Huang, et al.<sup>29</sup> believes that China's agricultural carbon emissions were on the rise in 1997–2016, but the agricultural carbon emission intensity showed a decline. Through comparison, the conclusions of this study are consistent with the existing conclusions, verifying the accuracy of the conclusions.

Second, the spatiotemporal evolution characteristics of agricultural carbon emission intensity were explored by nuclear density estimation, Dagum Gini coefficient, spatial Markov chain and Moran index. The study found that the carbon emission intensity of agriculture in China has obvious spatial agglomeration characteristics and a stable spatial transfer trend<sup>46</sup>. Zhao, et al.<sup>47</sup> shows that agricultural energy-related CO<sub>2</sub> emissions per capita showed a significant upward trend, with prominent polarization and right-tailing phenomena from 1997 to 2021.

Third, the GTWR model was used to explore the influencing factors of agricultural carbon emission intensity reduction. The study found that the improvement of financial support and science and technology market development had a positive impact on China's agricultural carbon emission intensity, while the improvement of R&D intensity, openness to the outside world, human capital level and urbanization level had a restraining effect on China's agricultural carbon emission intensity. Huang, et al.<sup>48</sup> indicates that the main factors affecting agricultural carbon emission reduction include agricultural production efficiency, agricultural industrial structure adjustment, economic structure and output, and urbanization level. Among them, the effects of economic output and urbanization are considered to be the main drivers of increased carbon emissions. Sun, et al.<sup>49</sup> shows that environmental regulation has a positive impact on green total factor productivity, which is enhanced by technological progress.

Based on the above analysis, there may be three marginal contributions in this paper: First, this paper innovatively measures the agricultural carbon emission intensity in various provinces of China from four aspects: land use in agriculture, rice cultivation, agricultural soils and livestock farming, enriching the theoretical basis of agricultural carbon emission measurement. Second, this paper uses spatial Markov chain to explore the spatial migration characteristics of agricultural carbon emission intensity, and explores the spatiotemporal evolution characteristics of agricultural carbon emission intensity by using nuclear density estimation and spatial autocorrelation model. In this way, the spatial distribution and change characteristics of agricultural carbon emission intensity can be comprehensively grasped, which is conducive to each region to put forward emission reduction policies according to local conditions. Third, this paper uses the GTWR model to comprehensively analyze the influencing factors of agricultural carbon emission reduction from the perspective of time and space. Therefore, compared with the traditional linear regression model, it can fully grasp the impact of various factors on agricultural carbon emission reduction from the perspective of time and space, and then provide theoretical support for the realization of the “two-carbon” development goal.

Although a large number of rich studies have been conducted in this study, there are still the following three limitations and prospects: First, this paper explored the spatial and temporal evolution characteristics and influencing factors of agricultural carbon emission intensity in China from 2001 to 2022 from a provincial perspective. The study failed to analyze from a microscopic perspective, and the study sample still needs further refinement. Therefore, in future research, the data of agricultural carbon emissions can be collected from the perspective of prefecture-level cities, so as to grasp the changing trend and influencing factors of agricultural carbon emission intensity more carefully. Second, although this study comprehensively grasped the influencing factors of agricultural carbon emission intensity from a spatiotemporal perspective, there is usually a bidirectional causal relationship between the variables in the actual development process. Therefore, in future studies, the relationship between the agricultural carbon emission intensity and each explanatory variable can be fully grasped using the bidirectional causality model. Third, the sample data of this study is mainly derived from China Agricultural Statistical Yearbook. According to the limitations of the publication restrictions of economic and social data, the agricultural carbon emissions measured in this paper may be insufficient in measurement accuracy and accuracy. Therefore, in future studies, we can try to reverse agricultural carbon emissions from the night light remote sensing impact data, so as to calculate agricultural carbon emissions more accurately.

## Results

This research introduces a series of spatial econometric models to explore the spatiotemporal evolution and influencing factors of China's agricultural carbon emission intensity levels. The following conclusions are drawn after in-depth data processing and analysis using Kernel Density Estimation, Gini Coefficient, Moran's Index, and spatial Markov and spatiotemporal geographically weighted regression models:

(1) China's agricultural carbon emission intensity levels show a decreasing trend, with significant differences in development across provinces and regions in spatiotemporal dimensions. Comparing 2001 and 2022, the number of provinces and regions with agricultural carbon emission intensity levels below the medium level has significantly decreased, and most regions have transitioned from high levels of emissions to higher or medium levels. Additionally, China's agricultural carbon emissions intensity exhibit a spatial distribution pattern of "high in the west and low in the east, high in the north and low in the south." The Gini coefficient results indicate a decreasing overall difference in China's agricultural carbon emissions intensity, with intra-regional differences reflecting the spatial pattern of east > center > west. Notably, inter-regional differences between the eastern and western regions are most pronounced.

(2) China's agricultural carbon emission intensity levels exhibit clear spatial agglomeration characteristics and stable spatial transfer trends. Statistical results from the global Moran index reveal a positive spatial correlation and clustering in China's agricultural carbon emission intensity data. The local Moran index indicates that high-high clustering areas are primarily located in the Northwest and Northeast regions, while low-low clustering areas are found mainly in Guangdong and Fujian provinces. Both the Markov chain and spatial Markov chain analyses indicate that China's agricultural carbon emission intensity levels are likely to maintain the status quo over the next five years. While there is a small probability of slight shifts forward or backward, significant level jumps are unlikely. Furthermore, an analysis of neighbor types at time  $t$  and time  $t+1$  reveals that China's agricultural carbon emissions intensity exhibit significant "spatial synergy."

(3) Numerous factors influence China's agricultural carbon emissions intensity, all exhibiting spatial distribution characteristics. Enhancements in financial support and technology market development positively affect China's agricultural carbon emissions intensity, while improvements in R&D intensity, openness to the outside world, human capital level, and urbanization level exert an inhibitory effect. Increased financial support in Heilongjiang Province, Jilin Province, and the Ningxia Hui Autonomous Region inhibits agricultural carbon emissions intensity, while the remaining regions tend to promote emissions. The increase in R&D intensity primarily inhibits agricultural carbon emissions intensity in Northeast and Southwest China. Increased human capital promotes agricultural carbon emissions intensity only in Sichuan Province, Xinjiang Autonomous Region, Liaoning Province, and Hunan Province, while suppressing emissions in other regions. Increased urbanization levels promote agricultural carbon emissions intensity in most northern provinces, while suppressing emissions in the southern region. Increased technology market development promotes agricultural carbon emissions intensity in the northeastern and southwestern regions, but suppresses them in most other areas.

## Recommendations

Based on the in-depth analysis of the spatiotemporal evolution of China's agricultural carbon emissions intensity and their influencing factors, this research proposes the following suggestions:

(1) Regional Differentiation of Emission Reduction Strategy: In light of the spatial distribution pattern of China's agricultural carbon emissions—characterized by 'high in the west and low in the east, and high in the north and low in the south'—regional differentiation in emission reduction strategies should be implemented. The western and northern regions should intensify emission reduction efforts by optimizing agricultural structures and promoting low-carbon agricultural technologies. Simultaneously, considering intra-regional differences, the eastern region should focus on balancing internal emission reduction measures to prevent imbalances in reduction effects. Meanwhile, the central region must strengthen supervision and guidance to avoid a rebound in carbon emission levels.

(2) Strengthening Spatial Agglomeration Management: Targeted management measures should be implemented for high-high agglomeration areas in the Northwest and Northeast regions, as well as low-low agglomeration areas in Guangdong and Fujian provinces. High agglomeration areas should prioritize the investigation and rectification of high-emission agricultural activities, while low agglomeration areas should continue to promote low-carbon agricultural practices to reinforce emission reduction achievements. The results from spatial Markov and spatiotemporal geographically weighted regression models should be utilized to predict and guide a stable shift in agricultural carbon emission levels, thereby avoiding the adverse effects of abrupt changes.

(3) Optimizing the Regulation of Influencing Factors: To address the promotion of agricultural carbon emissions intensity by financial support and technology market development, financial policies should be rationally adjusted, R&D of low-carbon agricultural technologies increased, and the activity and transformation rate of the technology market improved. Simultaneously, regulation of inhibiting factors such as R&D intensity, openness to the outside world, human capital level, and urbanization should be strengthened, promoting these factors in a direction conducive to emission reduction through policy guidance and market mechanisms. Special attention should be given to the unique circumstances in Heilongjiang Province, Jilin Province, and the Ningxia Hui Autonomous Region, where financial support exerts an inhibitory effect on agricultural carbon emissions. Appropriate financial support methods should continue to be explored to ensure effective emission reduction.

## Data availability

The data that support the findings of this study are openly available in China Statistical Yearbook at <https://data.stats.gov.cn/publish.htm?sort=1>. The data also supporting the findings of this study are also available from the corresponding author.

Received: 19 February 2025; Accepted: 29 May 2025

Published online: 01 June 2025

## References

- Su, S., Zhu, C., Li, X. D. & Wang, Q. Dynamic global warming impact assessment integrating Temporal variables: application to a residential Building in China. *Environ. Impact Assess. Rev.* **88** <https://doi.org/10.1016/j.eiar.2021.106568> (2021).
- Schuur, E. A. G. et al. Permafrost and climate change: carbon cycle feedbacks from the warming Arctic. *Annu. Rev. Environ. Resour.* **47**, 343–371. <https://doi.org/10.1146/annurev-environ-012220-011847> (2022).
- Cao, P., Li, X. X., Cheng, Y. & Shen, H. Temporal-Spatial evolution and driving factors of global carbon emission efficiency. *Int. J. Environ. Res. Public Health.* **19** <https://doi.org/10.3390/ijerph192214849> (2022).
- Keerthan, K. B., Wu, S. W., Wu, M. E. & Kokulnathan, T. The united States energy consumption and carbon dioxide emissions: A comprehensive forecast using a regression model. *SUSTAINABILITY* **15** <https://doi.org/10.3390/su15107932> (2023).
- Kanitkar, T., Mythri, A. & Jayaraman, T. Equity assessment of global mitigation pathways in the IPCC sixth assessment report. *Clim. Policy.* **24**, 1129–1148. <https://doi.org/10.1080/14693062.2024.2319029> (2024).
- May, A. & Crok, M. Carbon dioxide and a warming climate are not problems. *Am. J. Econ. Sociol.* <https://doi.org/10.1111/ajes.12579> (2024).
- Terhaar, J., Frölicher, T. L., Aschwanden, M. T., Friedlingstein, P. & Joos, F. Adaptive emission reduction approach to reach any global warming target. *Nat. Clim. CHANGE.* **12**, 1136–. <https://doi.org/10.1038/s41558-022-01537-9> (2022).
- He, Z., Ma, S., Deng, Z. & Meng, Y. Carbon emission reduction enabled by informatization construction: an analysis of Spatial effects based on china's experience. *Environ. Sci. Pollut. Res.* **31**, 35595–35608. <https://doi.org/10.1007/s11356-024-33565-7> (2024).
- Wang, S. Q. et al. Spatiotemporal variations of carbon emissions and their driving factors in the yellow river basin. *Int. J. Environ. Res. Public Health.* **19** <https://doi.org/10.3390/ijerph191912884> (2022).
- Ali, S., Li, G., Ying, L., Ishaq, M. & Shah, T. The relationship between carbon dioxide emissions, economic growth and agricultural production in pakistan: an autoregressive distributed lag analysis. *ENERGIES* **12** <https://doi.org/10.3390/en12244644> (2019).
- Xiao, P. N. et al. Spatiotemporal characteristics, decoupling effect and driving factors of carbon emission from cultivated land utilization in Hubei Province. *Int. J. Environ. Res. Public Health.* **19** <https://doi.org/10.3390/ijerph19159326> (2022).
- Zhou, Y., Wang, T., Peng, R. C. & Hu, H. M. Spatial-Temporal characteristics and factors of agricultural carbon emissions in the belt and road region of China. *Pol. J. Environ. Stud.* **30**, 2445–2457. <https://doi.org/10.1524/pjoes127414> (2021).
- Sun, Z. Y., Deng, M. X., Li, D. D. & Sun, Y. R. Characteristics and driving factors of carbon emissions in China. *J. Environ. Planning Manage.* **67**, 967–992. <https://doi.org/10.1080/09640568.2022.2142906> (2024).
- Song, R., Liu, J. & Niu, K. Y. Agricultural Carbon Emissions Embodied in China's Foreign Trade and Its Driving Factors. *SUSTAINABILITY* **15** <https://doi.org/10.3390/su15010787> (2023).
- Cui, Y., Khan, S. U., Deng, Y. & Zhao, M. J. Regional difference decomposition and its Spatiotemporal dynamic evolution of Chinese agricultural carbon emission: considering carbon sink effect. *Environ. Sci. Pollut. Res.* **28**, 38909–38928. <https://doi.org/10.1007/s11356-021-13442-3> (2021).
- Liu, F. S. & Lin, J. The Impact of High-Standard Farmland Construction Policies on the Carbon Emissions from Agricultural Land Use (CEALU). *LAND* **13** (2024). <https://doi.org/10.3390/land13050672>
- Tang, Y. & H Chen, M. Impact mechanism and effect of agricultural land transfer on agricultural carbon emissions in china: evidence from mediating effect test and panel threshold regression model. *SUSTAINABILITY* **14** <https://doi.org/10.3390/su142013014> (2022).
- Lu, X. H., Kuang, B., Li, J., Han, J. & Zhang, Z. Dynamic evolution of regional discrepancies in carbon emissions from agricultural land utilization: evidence from Chinese provincial data. *SUSTAINABILITY* **10** <https://doi.org/10.3390/su10020552> (2018).
- Xu, X. C., Yang, H. M. & Yang, H. R. The threshold effect of agricultural energy consumption on agricultural carbon emissions: a comparison between relative poverty regions and other regions. *Environ. Sci. Pollut. Res.* **28**, 55592–55602. <https://doi.org/10.1007/s11356-021-14831-4> (2021).
- Wen, C. C., Zheng, J. R., Hu, B. & Lin, Q. N. Study on the Spatiotemporal evolution and influencing factors of agricultural carbon emissions in the counties of Zhejiang Province. *Int. J. Environ. Res. Public Health.* **20** <https://doi.org/10.3390/ijerph20010189> (2023).
- Liao, Y. J. & Zhou, X. K. Can Digital Finance Contribute to Agricultural Carbon Reduction? Evidence from China. *SUSTAINABILITY* **15** (2023). <https://doi.org/10.3390/su152215824>
- Asumadu-Sarkodie, S. & Owusu, P. A. The causal nexus between carbon dioxide emissions and agricultural ecosystem—an econometric approach. *Environ. Sci. Pollut. Res.* **24**, 1608–1618. <https://doi.org/10.1007/s11356-016-7908-2> (2017).
- Smith, P., Powson, D. S., Smith, J. U., Falloon, P. & Coleman, K. Meeting europe's climate change commitments: quantitative estimates of the potential for carbon mitigation by agriculture. *Glob. Change Biol.* **6**, 525–539. <https://doi.org/10.1046/j.1365-2486.2000.00331.x> (2000).
- Li, J., Jiang, L. Y. & Zhang, S. H. How land transfer affects agricultural carbon emissions: evidence from China. *LAND* **13** <https://doi.org/10.3390/land13091358> (2024).
- Wang, G. F., Liao, M. L. & Jiang, J. Research on agricultural carbon emissions and regional carbon emissions reduction strategies in China. *SUSTAINABILITY* **12** <https://doi.org/10.3390/su12072627> (2020).
- Bell, M. J., Cloy, J. M. & Rees, R. M. The true extent of agriculture's contribution to National greenhouse gas emissions. *Environ. Sci. Policy.* **39**, 1–12. <https://doi.org/10.1016/j.envsci.2014.02.001> (2014).
- Guo, L. L., Zhao, S., Song, Y. T., Tang, M. Q. & Li, H. J. Green finance, chemical fertilizer use and carbon emissions from agricultural production. *AGRICULTURE-BASEL* **12** <https://doi.org/10.3390/agriculture12030313> (2022).
- Abate, M. C. et al. Environmental Impact of Agricultural Land Transfer in China: A Systematic Review on Sustainability. *SUSTAINABILITY* **16** (2024). <https://doi.org/10.3390/su16156498>
- Huang, X. Q. et al. Assessment of agricultural carbon emissions and their Spatiotemporal changes in china, 1997–2016. *Int. J. Environ. Res. Public Health.* **16** <https://doi.org/10.3390/ijerph16173105> (2019).
- Moucheng, L. & Lun, Y. Spatial pattern of China's agricultural carbon emission performance. *Ecol. Ind.* **133** <https://doi.org/10.1016/j.ecolind.2021.108345> (2021).
- Zhang, X. D., Zhang, J. & Yang, C. B. Spatio-Temporal evolution of agricultural carbon emissions in china, 2000–2020. *SUSTAINABILITY* **15** <https://doi.org/10.3390/su15043347> (2023).
- Wangari, E. G. et al. Number of chamber measurement locations for accurate quantification of landscape-Scale greenhouse gas fluxes: importance of land use, seasonality, and greenhouse gas type. *J. Geophys. RESEARCH-BIOGEOSCIENCES.* **127** <https://doi.org/10.1029/2022JG006901> (2022).

33. Guo, L. L. et al. Dynamic linkage between aging, mechanizations and carbon emissions from agricultural production. *Int. J. Environ. Res. Public Health.* **19** <https://doi.org/10.3390/ijerph19106191> (2022).
34. Zang, D. G., Hu, Z. J., Yang, Y. Q. & He, S. Y. Research on the Relationship between Agricultural Carbon Emission Intensity, Agricultural Economic Development and Agricultural Trade in China. *SUSTAINABILITY* **14** (2022). <https://doi.org/10.3390/su141811694>
35. Zhang, Z., Chen, Y. H. & Yan, Q. X. Effects of agricultural informatization on agricultural carbon emissions: a quasi natural experiment study in China. *Appl. Econ.* <https://doi.org/10.1080/00036846.2024.2354118> (2024).
36. Li, B. & Gao, Y. T. Impact and transmission mechanism of digital economy on agricultural energy carbon emission reduction. *Int. Rev. Econ. FINANCE* **95** <https://doi.org/10.1016/j.iref.2024.103457> (2024).
37. Han, H. B., Zhong, Z. Q., Guo, Y., Xi, F. & Liu, S. L. Coupling and decoupling effects of agricultural carbon emissions in China and their driving factors. *Environ. Sci. Pollut. Res.* **25**, 25280–25293. <https://doi.org/10.1007/s11356-018-2589-7> (2018).
38. Chen, Y., Li, M., Su, K. & Li, X. Spatial-Temporal Characteristics of the Driving Factors of Agricultural Carbon Emissions: Empirical Evidence from Fujian, China. *Energies* **12** (2019).
39. Hu, C., Fan, J. & Chen, J. Spatial and Temporal characteristics and drivers of agricultural carbon emissions in Jiangsu province, China. *Int. J. Environ. Res. Public Health.* **19** <https://doi.org/10.3390/ijerph191912463> (2022).
40. Yang, N., Sun, X. & Qi, Q. Impact of factor quality improvement on agricultural carbon emissions: evidence from china's high-standard farmland. *Front. Environ. Sci.* **10**–2022. <https://doi.org/10.3389/fenvs.2022.989684> (2022).
41. SU, H. M. & HE, A. X. Temporal-Spatial evolution and influencing factors of agricultural carbon emissions in Anhui province, China. *Appl. Ecol. Environ. Res.* **22**, 5541–5558. [https://doi.org/10.15666/aeer/2206\\_55415558](https://doi.org/10.15666/aeer/2206_55415558) (2024).
42. Liu, D. D., Zhu, X. Y. & Wang, Y. F. China's agricultural green total factor productivity based on carbon emission: An analysis of evolution trend and influencing factors. *J. Clean. Prod.* **278** <https://doi.org/10.1016/j.jclepro.2020.123692> (2021).
43. Sun, X., Meng, Z., Zhang, X. & Wu, J. The role of institutional quality in the nexus between green financing and sustainable development. *Res. Int. Bus. Finance.* **73**, 102531. <https://doi.org/10.1016/j.ribaf.2024.102531> (2025).
44. Xiong, C., Wang, G. & Xu, L. Spatial differentiation identification of influencing factors of agricultural carbon productivity at City level in Taihu lake basin, China. *Sci. Total Environ.* **800**, 149610. <https://doi.org/10.1016/j.scitotenv.2021.149610> (2021).
45. Zhang, X., Zhou, X. & Liao, K. Regional differences and dynamic evolution of china's agricultural carbon emission efficiency. *Int. J. Environ. Sci. Technol.* **20**, 4307–4324. <https://doi.org/10.1007/s13762-022-04196-7> (2023).
46. Sun, X. et al. Exploring ways to improve china's ecological well-being amidst air pollution challenges using mixed methods. *J. Environ. Manage.* **364**, 121457. <https://doi.org/10.1016/j.jenvman.2024.121457> (2024).
47. Zhao, X., Li, X. & Xi, Y. Evolution and driving factors of inequality in CO2 emissions from agricultural energy consumption in China. *Sci. Rep.* **14**, 12991. <https://doi.org/10.1038/s41598-024-63977-x> (2024).
48. Huang, X. J., Wu, X. Y., Guo, X. Y. & Shen, Y. Agricultural carbon emissions in china: measurement, Spatiotemporal evolution, and influencing factors analysis. *Front. Environ. Sci.* **12** <https://doi.org/10.3389/fenvs.2024.1488047> (2024).
49. Sun, X. et al. Revisiting the Porter hypothesis within the economy-environment-health framework: empirical analysis from a multidimensional perspective. *J. Environ. Manage.* **349**, 119557. <https://doi.org/10.1016/j.jenvman.2023.119557> (2024).

## Acknowledgements

This work was supported by the Key research and development plan project of the Ministry of Science and Technology, China (No. 2023YFD1501105).

## Author contributions

The preparation of this article involved collaboration among multiple authors. The conceptual framework was developed by Xue Zhu and Xiwu Shao. The methodology was crafted by Xue Zhu and Xiwu Shao. Xue Zhu were responsible for the software aspect. Xue Zhu and Xiwu Shao contributed to the validation process. For formal analysis, Xue Zhu and Xiwu Shao were in charge. Xue Zhu handled the data compilation. The initial draft was written by Xue Zhu and Xiwu Shao. Xue Zhu and Xiwu Shao worked on the review and editing of the manuscript. All contributors have reviewed and approved the final version of the paper.

## Declarations

### Competing interests

The authors declare no competing interests.

### Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

### Informed consent

This article does not contain any studies with human participants.

### Additional information

**Supplementary Information** The online version contains supplementary material available at <https://doi.org/10.1038/s41598-025-04973-7>.

**Correspondence** and requests for materials should be addressed to X.S.

**Reprints and permissions information** is available at [www.nature.com/reprints](http://www.nature.com/reprints).

**Publisher's note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

**Open Access** This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

© The Author(s) 2025