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Spatiotemporal evolution of factors affecting agricultural carbon emissions: empirical evidence from 31 Chinese provinces

Xixian Zheng[1] · Haixia Tan[2] · Wenmei Liao[1]

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Abstract
Reducing agricultural carbon emissions is a crucial aspect of China's overall carbon emission reduction plan. In this study, we first analyzed the spatiotemporal trends in agricultural carbon emissions across 31 provinces in China from 2007 to 2020. Subsequently, we employed a geographically and temporally weighted regression model to analyze the spatiotemporal evolution of the factors influencing provincial agricultural carbon emissions. Our findings revealed that high carbon emission areas are primarily distributed in the central and northern regions. The center of gravity of carbon emissions is located within Henan Province (112°30′–113°30′ E; 34°10′–33°40′ N) and has gradually shifted in the northwest direction. Therefore, the central, northern, and western regions should become the focal areas for agricultural carbon emission mitigation efforts. The influencing factors demonstrate spatiotemporal heterogeneity in their impacts on agricultural carbon emissions, so differentiated emission mitigation strategies should be formulated according to local conditions. The central and northern regions should prioritize the adoption of green technologies, support zero growth of chemical fertilizers and promotion of organic alternatives, and promote urbanization. Western regions should be encouraged to use less harmful fertilizers and increase mechanization levels. Nationwide, green technology innovation in agriculture should be strengthened to promote sustainable agricultural development.

Keywords Agricultural carbon emissions · Center of gravity · Geographically and temporally weighted regression · Driving factors

Xixian Zheng, Haixia Tan, and Wenmei Liao contributed equally to this work.

Xixian Zheng
zxx19981114@163.com

Wenmei Liao
liaowenmei@126.com

Haixia Tan
504012537@qq.com

[1] School of Economics and Management, Jiangxi Agricultural University, Nanchang, China

[2] School of Accounting and Business Administration, Yunnan Minzu University, Kunming, China

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1 Introduction

In recent years, environmental challenges such as climate change, biodiversity loss, land desertification, and pollution have gained global attention (Celik, 2020; Moran et al., 2018), with a particular focus on reducing carbon emissions across various industries. China, as the world's largest emitter of carbon, plays a crucial role in achieving carbon peak and neutrality targets (Erdogan, 2021; Wen et al., 2020). While carbon emissions from industry, construction, transportation, and services have been extensively studied (Huo et al., 2021; Kou et al., 2022; Liu et al., 2021b; Sun et al., 2022; Wang et al., 2020), the impact of agriculture, particularly the plantation sector, on carbon emissions has received less attention. This study aims to fill this gap by examining the spatiotemporal dynamics of agricultural carbon emissions in China and their underlying drivers.

Agriculture is the primary industry in China (Chen et al., 2019; Zadgaonkar et al., 2022) and has been a key driver of economic and social prosperity since 1978 (Chen et al., 2019). However, this growth has come at the cost of increased consumption of natural resources, leading to concerns about the sustainability of China's agricultural sector (Lu et al., 2015; Norse & Ju, 2015). Notably, the plantation industry is the most representative of the primary agricultural industry (Cui et al., 2021a; Guan et al., 2018), and maintaining food security has become an essential policy in China, especially in light of the COVID-19 pandemic's negative impact on food cultivation (Bai et al., 2020; Wu et al., 2022).

Considering the regional disparities in natural environments, population qualities, economic development, and agricultural structures throughout China's vast territory (Cui et al., 2021b), our study examines the evolution of agricultural carbon emissions using the geographically and temporally weighted regression (GTWR) model to investigate their drivers. This research significantly enhances our understanding of agricultural carbon emissions by: (1) addressing the scarcity of comparative studies between provinces, offering a comprehensive analysis of spatiotemporal differences in agricultural carbon emissions; (2) advancing beyond traditional models and employing the GTWR model to concurrently assess spatial and temporal heterogeneity of influencing factors, expanding GTWR's application in the agricultural sector; (3) exploring a diverse set of seven drivers for agricultural carbon emissions based on data availability and relevance to China's current agricultural issues, yielding a more representative and accurate analysis of contributing factors in the plantation sector; and (4) providing a solid theoretical basis to assist local governments in formulating targeted agricultural carbon reduction policies adapted to local conditions, ultimately promoting sustainable agriculture in China and other developing countries. By building on prior research and addressing its limitations, our study offers valuable insights for policymakers in shaping tailored carbon emission reduction policies within the plantation sector, ultimately fostering sustainable agricultural practices in China and beyond.

2 Literature review

2.1 Characteristics of agricultural carbon emissions

In recent years, the study of geographical disparities, spatiotemporal characteristics, and agricultural carbon emission dynamics has gained increasing attention among scholars (e.g., Han et al., 2021). Existing research can be discussed at both national and regional levels, with some studies examining broader trends and others focusing on specific regions.

At the national level, Liu et al., (2021a, 2021b) found that China's agricultural carbon emissions (ACEs) follow an inverted "U" shape trend, with an overall decreasing growth rate. Simultaneously, the main concentration areas of ACEs exhibit a tendency to shift from eastern to central regions. Huang et al. (2019) further explored the changes in agricultural carbon emission intensity, discovering a noticeable downward trend. These findings align with studies like Rios and Gianmoena (2018), who developed a spatially augmented green Solow model that integrated technological interdependence in production, demonstrating that neighboring nations' economic features affect one another's carbon emissions.

At the regional level, Wang and Feng (2021) discussed the spatial distribution of ACEs across Chinese provinces, finding significant differences between regions. Liu and Yang (2021) investigated the regional differences in agricultural carbon emission efficiency, revealing spatial clustering effects and catch-up effects between regions. Cui et al. (2021a) compared the distribution characteristics of agricultural carbon emission intensity and per capita carbon emissions, finding that regional differences in agricultural carbon emission intensity gradually narrowed over time, while differences in per capita carbon emissions clustering levels gradually expanded. Cui et al. (2021b) further examined regional differences in the carbon emission intensity of plantations, finding "intra-regional convergence and inter-regional divergence." The spatiotemporal characteristics of ACEs in specific provinces in China, such as Xinjiang, Hubei, and Fujian, which represent western, central, and eastern coastal regions, respectively, are also remarkably different due to variations in geographical factors, economic levels, and policy orientations (Chen et al., 2019; Shan et al., 2022; Xiong et al., 2016).

Compared to previous studies, our research has several notable highlights. First, the past research mainly focused on discussing agricultural carbon emissions from the perspective of the country as a whole or specific provinces, while comparative studies between provinces have been relatively scarce. Furthermore, existing research on provincial disparities in agricultural carbon emissions has primarily explored spatial differences, often neglecting the temporal variation of these emissions. Therefore, this study combines both temporal and spatial perspectives to comparatively investigate the spatiotemporal differences in agricultural carbon emissions across provinces. Additionally, by incorporating the center-of-gravity model, we analyze the trends in changes in carbon emission gravity over time.

2.2 Driving factors of agricultural carbon emissions

Numerous factors influencing agricultural carbon emissions have been recently investigated, including agricultural production, economic growth, population size, technological advancement, and agricultural land (Chen et al., 2019; Long & Tang, 2021). These factors can be categorized as carbon sinks and carbon sources (Stevanovic et al., 2017). According to Ismael et al. (2018), agricultural production exerts a considerable dual effect on carbon emissions. While increased agricultural production inevitably generates carbon emissions (Ismael et al., 2018), organic agriculture production reduces them (Gomiero et al., 2008). Economic and population growth, as two critical elements of agricultural output, promotes agricultural carbon emissions (Ridzuan et al., 2020). Similarly, Zafeiriou et al. (2018) demonstrated a strong relationship between agricultural revenue and carbon emissions. Technological improvement in agriculture is also a key factor affecting agricultural carbon emissions. Gerlagh (2007) analyzed the impact of technological advancement on carbon emission reduction and discovered that technological innovation significantly reduced the cost of carbon emission reduction and increased societal benefits. However, technological innovation can also contribute to carbon emissions, particularly in the context of independent innovation or during the early stages of innovation focused on increasing production (Gu et al., 2019; Yu & Du, 2019). Agricultural land, encompassing per capita land-use area and farmland conversion, also influences agricultural carbon emissions. Zhao et al. (2018) ranked several factors that affect agricultural carbon emissions and concluded the economic output of water resources > the ratio of water and land resources > land-use area per capita. Sarauer and Coleman (2018) found that converting farmland to bioenergy crops could impact greenhouse gas (GHG) emissions, including those of carbon dioxide (CO_2), methane, and nitrous oxide, which could inform land-use modeling or life cycle analysis.

In summary, scholars from both domestic and international backgrounds have conducted extensive research on the factors influencing agricultural carbon emissions. However, due to variations in model selection, indicator choice, and the quantity and construction of influencing factors, the research results present certain discrepancies. Consequently, this study, considering data availability and the representativeness of influencing factors for contemporary agricultural issues in China, investigates seven driving elements of agricultural carbon emissions. These elements include agricultural economic level, agricultural structure, urbanization level, agricultural mechanization, fertilizer consumption, financial support for agriculture, and agricultural technology innovation.

2.3 Models to estimate driving factors

The most common methods for estimating driving factors of carbon emissions include the autoregressive distributed lag model (Owusu & Asumadu-Sarkodie, 2017), Granger causality test (Khan et al., 2018), and vector error correction model (Mourao & Domingues Martinho, 2017). Moreover, the logarithmic mean Divisia index (Gu et al., 2019; Shi et al., 2019) and variance decomposition methodology (Ismael et al., 2018) employ exponential decomposition to examine the primary factors influencing agricultural carbon emissions. Other innovative approaches encompass denitrification–decomposition models (Appiah et al., 2018), spatial econometric models (Khan et al., 2018), and fully modified ordinary least squares (OLS) models (Yadav & Wang, 2017; Ye et al., 2016).

Given that carbon emission driving factors exhibit spatial heterogeneity, geographically weighted regression (GWR) models can yield accurate predictions (Xu & Lin, 2021). However, these factors also vary over time, necessitating the incorporation of temporal heterogeneity to develop geographically and temporally weighted regression (GTWR) models (Li et al., 2021). GTWR models have been applied in the analysis of water quality (Chu et al., 2018), water resource carrying capacity (Zhang & Dong, 2022), and PM2.5 particulate matter concentrations (Guo et al., 2017; Mirzaei et al., 2019). Despite this, there is a limited body of research on geographical and temporal factors in carbon emission studies. For instance, Liu et al. (2021b) used the GTWR model to estimate carbon emission intensity in the transportation sector across 30 Chinese provinces. Zhang et al. (2022) examined the spatiotemporal heterogeneous effects of socioeconomic and meteorological factors on CO_2 emissions, employing the GTWR model and nighttime light data. Wang et al. (2022b) applied the GTWR model to investigate spatial and temporal differences in the impact of spatial structure on carbon emissions in various urban agglomerations.

In summary, previous research on carbon emission driving factors predominantly utilized traditional models without fully addressing the non-stationarity of time and space. Although a few studies have considered the spatial heterogeneity of carbon emission influencing factors by introducing the GWR model, the GTWR model—which accounts for both spatial and temporal heterogeneity—has been explored in only a limited number of fields, such as the transportation industry. Drawing from the methods and applications mentioned earlier, this study incorporates the GTWR model to examine the influencing factors of agricultural carbon emissions, providing an analysis of the spatiotemporal distribution differences of these factors. By doing so, the study offers a preliminary theoretical basis to support local governments in devising agricultural carbon reduction policies tailored to local conditions.

3 Methodology and data

3.1 Agricultural carbon emission measurement

Three main types of accounting methods are currently used for agricultural carbon emissions, namely, life cycle assessment (Hao et al., 2020), input–output analysis (Cao et al., 2010; Lal, 2007), and the Intergovernmental Panel on Climate Change (IPCC) method (Huang et al., 2019; Villarino et al., 2014). Considering the advantages and disadvantages of these methods and the accessibility of data, we used the widely applied IPCC method. Specifically, we chose plantation (narrow agriculture) as the subject of our study (Liu & Yang, 2021). Referring to Tian et al. (2014), the specific formula is as follows:

$$E = \sum E_i = \sum T_i \times \delta_i \tag{1}$$

where E represents agricultural carbon emissions, T_i represents the carbon emissions of source i, and δ_i represents the emission coefficient of source i. Furthermore, referring to Mostashari-Rad et al. (2021), we classified carbon sources into six categories: fertilizers, pesticides, agricultural films, diesel oil used in agriculture, tillage, and agricultural irrigation. Table 1 shows all of the agricultural sector's carbon emission sources and coefficients:

3.2 Methods for the analysis of the spatial distribution characteristics

3.2.1 Global spatial autocorrelation

Global spatial autocorrelation is an exploratory spatial data analysis approach mainly used to identify the spatial distribution characteristics of the study object. Moran's I

Table 1 Agricultural carbon emission sources and coefficients

Carbon-emission source	Coefficient	References
Fertilizer	0.8956 kg·kg^{-1}	West and Marland (2002)
Chemical pesticide	4.9341 kg·kg^{-1}	Zhou et al. (2022)
Agricultural film	5.18 kg·kg^{-1}	Liu et al. (2021a)
Diesel oil used in agriculture	0.5927 kg·kg^{-1}	IPCC (2007)
Tillage	312.6 kg·km^{-2}	He et al. (2021a)
Irrigation	20.476 kg·km^{-2}	Dubey and Lal (2009)

index is the most used indicator of global spatial autocorrelation (Mathur, 2015), which is calculated as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \tag{2}$$

where n represents the number of samples; x_i and x_j represent the agricultural carbon emissions of provinces i and j, respectively; $\bar{x}$ represents the average of all carbon emissions; w_{ij} is the corresponding element of the space weight matrix; and I is Moran's I index, the value of which ranges from − 1 to 1. A value larger than 0 indicates a positive spatial correlation, a value less than 0 indicates a negative correlation, and a value equal to 0 indicates no correlation. For Moran's I, the degree of spatial autocorrelation in a region can be assessed using the standardized statistic Z as follows:

$$Z = \frac{I - E(I)}{\sqrt{\mathrm{VAR}(I)}} \tag{3}$$

where $E(I)$ is the expectation of Moran's I, and $\mathrm{VAR}(I)$ is the variance of Moran's I.

3.2.2 The center-of-gravity model

The fundamental concept of the center-of-gravity model is drawn from physics and has been widely used in other areas of research, including economics (Lewer and Van den Berg 2008; Westerlund & Wilhelmsson, 2011) and environmental science (Wang & Feng, 2017; Zhang et al., 2012). In this study, we used the center-of-gravity model to analyze the spatial center of gravity and the evolutionary footprint of China's agricultural carbon emissions from 2007 to 2020. The center of gravity was calculated as follows:

$$X^t = \frac{\sum_{s=1}^{n} m_s^t \times x_s}{\sum_{s=1}^{n} m_s^t} \tag{4}$$

$$Y^t = \frac{\sum_{s=1}^{n} m_s^t \times y_s}{\sum_{s=1}^{n} m_s^t} \tag{5}$$

where (X^t, Y^t), respectively, represent the longitude and latitude coordinates of the center of gravity of agricultural carbon emissions; (x_s, y_s), respectively, represent the longitude and latitude coordinates of the capital city of province S; m_s^t is the degree of agricultural carbon emissions in year t for province S; and n represents the number of provinces in a given region. The offset distance is the distance from which an attribute's center of gravity moves, which is calculated using the following formula:

$$D^t = c \times \sqrt{\left(X^t - X^{t-1}\right)^2 + \left(Y^t - Y^{t-1}\right)^2} \tag{6}$$

where D^t is the offset distance, representing the movement distance of the gravity center of agricultural carbon emissions, and c is typically 111.111, which is the coefficient of converting spherical longitude and latitude coordinates to plane distance.

3.3 Estimation models for driving factors

3.3.1 Model comparison

The GWR model extends the OLS model, which permits local parameter estimation, as follows:

$$Y_i = \beta_{0\left(u_i,v_i\right)} + \sum_{k=1}^{q} \beta_{k\left(u_i,v_i\right)} X_{ik} + \varepsilon_i; i = 1, 2 \cdots n \tag{7}$$

where Y_i is the value at location i; (u_i, v_i) represent the geographic coordinates of city i; $\beta_{0\left(\mathrm{u_i},v_i\right)}$ is the local intercept; $\beta_{k\left(u_i,v_i\right)}$ is the local coefficient of city i; q is the number of factors; X_{ik} is the independent variable in province i; and ε_i is the random error.

In contrast to the commonly used GWR model, which only considers spatial variation in predicting parameter relationships, the GTWR model incorporates spatiotemporal heterogeneity through a weighting matrix that combines both spatial and temporal dimensions (Huang et al., 2010). The specific model is as follows:

$$Y_i = \beta_{0\left(u_i,v_i,t_i\right)} + \sum_{k=1}^{q} \beta_{k\left(u_i,v_i,t_i\right)} X_{ik} + \varepsilon_i; \quad i = 1, 2 \cdots n \tag{8}$$

where (u_i, v_i, t_i) denote the spatiotemporal coordinates (longitude, latitude, and time, respectively) of the given city i; $\beta_{0\left(u_i,v_i,t_i\right)}$ is the intercept; and $\beta_{k\left(u_i,v_i,t_i\right)}$ is the local regression coefficient of the kth variable in the ith province as a function of the spatiotemporal coordinates.

Furthermore, referring to Huang et al. (2010), the spatiotemporal distance is defined as follows:

$$d_{ij}^{ST} = \sqrt{\lambda\left[\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2\right] + \mu\left(t_i - t_j\right)^2} \tag{9}$$

where λ and μ are the scaling factors for spatial and temporal distances, respectively. When μ is 0, only spatial distance and heterogeneity are considered, and the model is a GWR; when λ is 0, only temporal distance and temporal non-stationarity are considered, and the model is a temporally weighted regression (TWR).

3.4 Data

This research examined agricultural carbon emissions in 31 provinces of China, excluding Taiwan, Hong Kong, and Macau, from 2007 to 2020. The provinces included in the study are shown in Fig. 1:

Fig. 1 Map showing the provinces included in this study

We calculated agricultural carbon emission statistics for 31 Chinese provinces from 2007 to 2020. Data on six carbon emission sources—namely fertilizers, agricultural films, pesticides, diesel, tillage data, and agricultural irrigation—were acquired from the China Rural Statistical Yearbook (2008–2021) and the China Statistical Yearbook (2008–2021). In selecting the influencing factors or independent variables, we thoroughly considered the current challenges faced by China's agriculture.

Firstly, as a major agricultural nation, China's agricultural economic level is a crucial indicator of its development. The transformation of agricultural production methods resulting from an improved agricultural economy leads to notable carbon emissions. Consequently, we include this factor in our research considerations. Secondly, Chinese agriculture is diverse, with the planting industry (rice and wheat) holding a dominant position. Therefore, we examine the role of agricultural structure in carbon emissions. At present, China is experiencing rapid urbanization, with population concentration in urban areas and a decline in rural labor. This trend alters agricultural production methods and impacts carbon emissions. In recent years, the Chinese government has vigorously promoted agricultural mechanization to enhance efficiency. However, this mechanization might also increase energy consumption and carbon emissions, making it a significant driving factor for agricultural carbon emissions. As the world's largest consumer of agricultural chemical fertilizers, China's agricultural carbon emissions are heavily influenced by fertilizer usage. By examining this driving factor, we can provide essential references for future transformation in fertilizer consumption across provinces. Meanwhile, financial support for agriculture in China is vital for production and technological innovation, consequently affecting carbon emissions. Financial assistance enables producers to adopt advanced technologies and production methods, reducing carbon emissions. Lastly, we highlight the crucial role of agricultural technological innovation in agricultural carbon emissions. The Chinese government has prioritized innovation to enhance efficiency, minimize resource consumption, and mitigate environmental pollution. Thus, the level of agricultural technological innovation is one of the key factors influencing China's agricultural carbon emissions.

In conclusion, we ultimately chose seven driving factors, with total agricultural carbon emissions selected as the dependent variable. The details of each independent variable are provided in Table 2.

We analyzed the variables using the variance inflation factor (VIF) and tolerance to avoid multicollinearity and found that the VIFs of all of seven driving factors were < 3, with tolerance values of > 0.4 (see Appendix 1, Table 5). As a result, this study included all seven driving factors as independent variables.

4 Results

4.1 Spatiotemporal analysis of provincial carbon emissions

4.1.1 Spatial pattern evolution

To visualize the development of spatial carbon emission patterns across China's 31 provinces from 2007 to 2020, ArcGIS software was used to calculate the spatial pattern evolution of total provincial carbon emissions for 2007, 2012, 2016, and 2020. The graph's colors indicate the intensity of carbon emissions: The closer to red, the higher the emissions. Color changes over time indicate how agricultural carbon emissions have evolved in each province.

In Fig. 2, the high-emission region expands over time, while the number of green areas is relatively stable, indicating that China's agricultural carbon emissions increased over the study period and that the areas with high carbon emissions expanded over time. From 2007 to 2020, the region of higher emissions steadily expanded from the center to the north, indicating that the northern region is gradually becoming the epicenter of China's agricultural carbon emissions. In addition, the spatial distribution pattern of provincial agricultural carbon emissions in China was relatively consistent and similar

Table 2 Definition of independent variables

Variable name	Variable code	Variable definitions	References	Data sources
Agricultural economic level	X_1	Total output value of agriculture/rural population	Han et al. (2021)	China Statistical Yearbook
Agricultural structure	X_2	Output value of planting/total output value of agriculture	Xiong et al. (2020)	China Rural Statistical Yearbook
Urbanization level	X_3	Urban permanent population/total population	Yang et al. (2019)	China Statistical Yearbook
Agricultural mechanization level	X_4	Total power of agricultural mechanization/rural population	Han et al. (2021)	China Rural Statistical Yearbook
Fertilizer consumption level	X_5	Fertilzer consumption/sown area of crops	Rehman et al. (2022)	China Rural Statistical Yearbook
Financial support for agriculture	X_6	Agricultural financial expenditure/total financial expenditure	Li and Li (2022)	China Statistical Yearbook & China Rural Statistical Yearbook
Agricultural technology innovation level	X_7	Number of agricultural patent applications	He et al. (2021b)	CNKI Patent Database

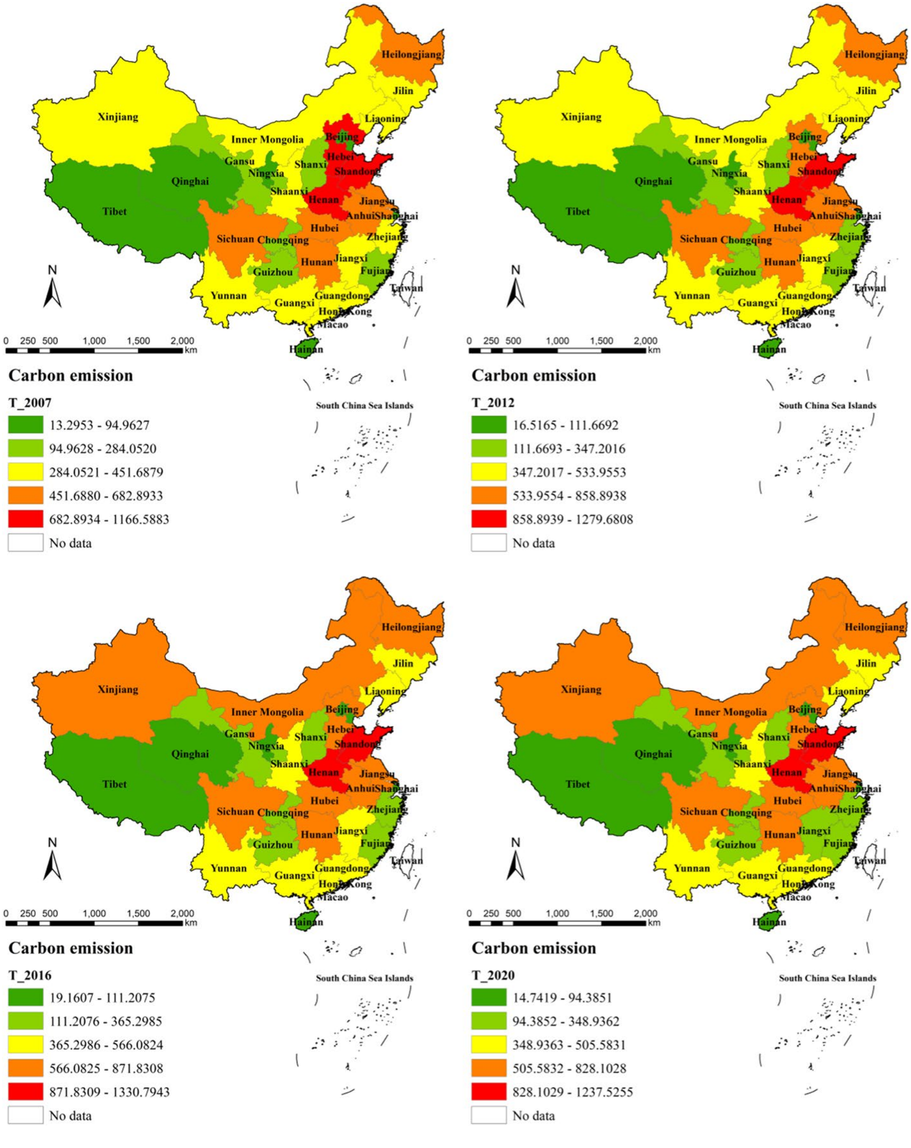

Fig. 2 Evolution of the spatial pattern of total agricultural carbon emissions

to those in other studies (Liu et al., 2021a; Yang et al., 2022). Specifically, low carbon emission areas were concentrated in the southeastern coastal and western regions, high carbon emission areas were concentrated in the central and northern regions, and moderate carbon emission areas surrounded the high emission areas, primarily in the middle and lower reaches of the Yangtze and Yellow Rivers. This suggests that China's agricultural carbon emissions were spatially clustered and that most provinces with high carbon emissions were adjacent to each other.

4.1.2 Global spatial autocorrelation analysis

We used Eq. (2) with ArcGIS to determine each province's global Moran's *I* for total agricultural carbon emissions (see Table 3).

As seen in Table 3, a significant positive correlation existed between the total agricultural carbon emissions of the provinces from 2007 to 2020. Furthermore, there was a clear spatial autocorrelation of the emissions of nearby provinces, as shown by their spatial clustering. These results are consistent with those of Liu and Yang (2021). However, this effect diminished over time as local geographic variability increased, with Moran's *I* reaching 0.158 in 2020.

4.1.3 Center-of-gravity analysis

We calculated yearly center-of-gravity coordinates and migration distances using 14-year agricultural carbon emission statistics from the 31 provinces (see Fig. 3 and Appendix 1, Table 6).

From 2007 to 2020, the center of gravity of agricultural carbon emissions was in Henan Province at 112°30′–113°30′ E and 34°10′–33°40′ N latitude. Other studies have also found that Henan was the center of gravity (Song et al., 2015; Wang & Feng, 2017). Given Henan's location in the Yellow River Valley, which is ideal for agricultural production due to its terrain and climate, it is logical that the center of gravity of carbon emissions from agriculture is in this province. Nonetheless, the rapid agricultural development in the west has created a northwestward shift in the center of gravity. China's center of agricultural carbon emissions shifted every year from 2007 to 2020 in general accordance with the results of Zhang et al. (2018). From 2007 to 2009, it showed a southwestward shift, whereas in the later period (2010–2020), a northwestward shift occurred. As in earlier research (Li et al., 2020), we found that agricultural and industrial carbon emission centers were both in Henan Province and migrating westward. The center of gravity of agricultural carbon

Table 3 Global Moran's I index of agricultural carbon emissions from 2007 to 2020

Year	Moran's *I* Index	*P* value	*Z* score
2007	0.226**	0.014	2.255
2008	0.224**	0.015	2.332
2009	0.221**	0.016	2.322
2010	0.218**	0.016	2.300
2011	0.209**	0.019	2.100
2012	0.201**	0.023	2.001
2013	0.194**	0.027	1.946
2014	0.174**	0.030	2.031
2015	0.164**	0.036	1.842
2016	0.167**	0.036	1.092
2017	0.163**	0.037	1.845
2018	0.161**	0.038	1.740
2019	0.155**	0.040	1.780
2020	0.158**	0.044	1.765

*, **, and *** denote passing the significance test at 10%, 5%, and 1% levels, respectively

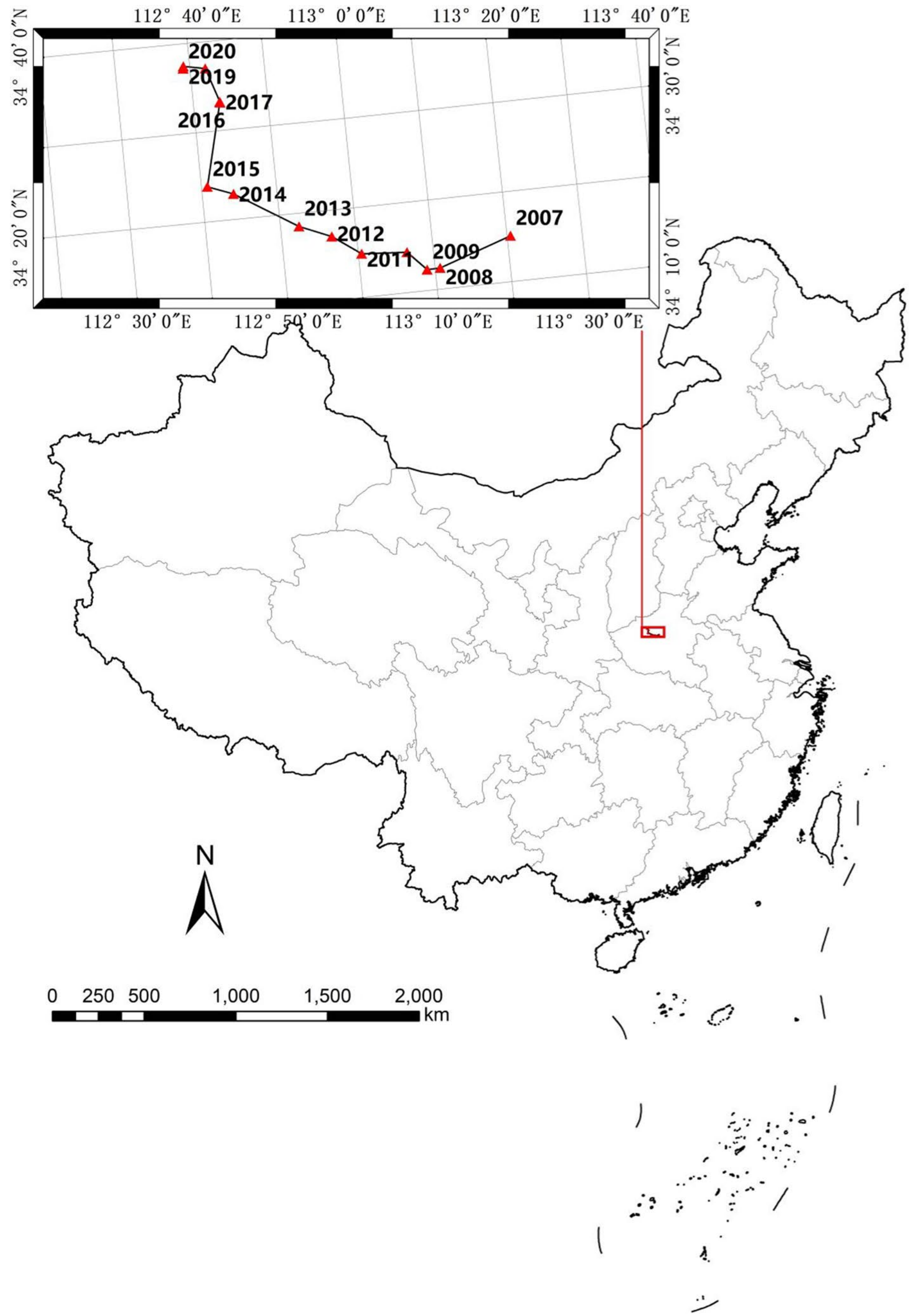

Fig. 3 Agricultural carbon emission center moving track in China

emissions generally shifted to the northwest over the study period, primarily due to continued “Western Development” (Cui et al., 2019), as energy-intensive industries relocated from eastern regions to central–western China (Zhang et al., 2018).

4.2 Analysis of the driving factors of total agricultural carbon emissions

4.2.1 Comparative analysis of fitting results

Like Li et al. (2022), we used R^2, adjusted R^2, and corrected Akaike information criterion (AICc) to estimate the model fit. Generally, a high R^2 and a low AICc absolute value suggest a good model fit. We began by investigating the factors that contribute to total carbon emissions and developing a total regression model. The goodness-of-fit values for the OLS, TWR, GWR, and GTWR models were calculated using ArcGIS (see Table 4). As expected, the TWR, GWR, and GTWR models demonstrated better goodness-of-fit than the OLS model. The GTWR model, in particular, had a higher adjusted R^2 and AICc than the GWR model. Thus, the GTWR model was chosen for driving factor analysis.

4.2.2 Driving factor analysis using the GTWR model

(1) Time evolution of driving factors

To accurately observe the temporal trends of the influence coefficients of various driving factors on agricultural carbon emissions, boxplots of each influencing factor were generated (see Appendix 2, Fig. 4). Overall, the impacts of the seven factors on agricultural carbon emissions showed significant differences during the study period. Specifically, except for the negative mean coefficient values of urbanization level and financial support for agriculture across the timeframe, indicating their inhibitory effects, the mean coefficient values for the remaining factors were positive, suggesting their promotional roles in agricultural carbon emissions.

Moreover, the regression coefficients of the influencing elements fluctuated to some extent over time. The promotive effects of agricultural economic level, fertilizer consumption level, and agricultural technology innovation level on agricultural carbon emissions decreased annually, while the facilitative role of agricultural mechanization level rebounded in recent years, and the propelling impact of agricultural structure remained stable. This implies that while developing the economy, innovating technologies, and increasing yields by fertilizer use, China has also balanced carbon reduction in recent years

Table 4 Comparison of the goodness-of-fit of the total regression models

Model	R^2	Adjusted R^2	AICc
OLS	0.502	0.494	944.084
TWR	0.645	0.639	853.679
GWR	0.936	0.935	177.092
GTWR	0.949	0.949	168.874

OLS Ordinary Least Square, *TWR* Temporally Weighted Regression, *GWR* Geographically Weighted Regression, *GTWR* Geographically and Temporally Weighted Regression

(Cheng et al., 2011; Kwakwa et al., 2023). The suppressive effect of urbanization level weakened gradually, whereas the inhibitory influence of financial support for agriculture first declined and then ascended. According to the 2020 data, agricultural mechanization level, fertilizer consumption level, and agricultural technology innovation level exerted relatively strong promotional effects on agricultural carbon emissions, while the inhibitory effect of urbanization level was pronounced.

(2) Spatial heterogeneity of driving factors

In order to more intuitively visualize the spatial differences for each influencing factor, this study summarizes and depicts the regression coefficients in 2007, 2012, 2016, and 2020 (see Appendix 1, Tables 7, 8, 9, 10, 11, 12, and 13 and Appendix 2, Figs. 5, 6, 7, 8, 9, 10, and 11). Moreover, special attention was given to three factors—agricultural mechanization level, fertilizer consumption level, and agricultural technology innovation level—which exhibited strong promoting effects on carbon emissions based on the 2020 data. Additionally, the factor of urbanization level was highlighted due to its noticeable suppressive impact on carbon emissions revealed in the 2020 data. Therefore, this study focuses the analysis on these four influencing factors.

In most provinces, agricultural mechanization increased carbon emissions, aligning with findings from several studies (Fabiani et al., 2020; Jiang et al., 2020). However, mechanization actually reduced emissions in some western provinces (Sichuan, Yunnan, Tibet, Gansu, Qinghai, and Xinjiang) and some northeastern provinces (Liaoning, Jilin, and Heilongjiang). This divergence can be attributed to two key factors: First, the underdeveloped agriculture in western and southwestern regions benefited from mechanization's efficiency improvements (Benin, 2015), and second, the favorable economic and geographical conditions in northeastern provinces promoted large-scale agriculture (Friel et al., 2009). The effect of agricultural mechanization in increasing agricultural carbon emissions is primarily concentrated in the central and southern provincial regions of China (see Appendix 1, Table 10 and Appendix 2, Fig. 8). Consequently, these provinces should prioritize the adoption of green agricultural technologies and enhancing production scale to mitigate emissions (Zhang et al., 2019).

Most Western, Central, and Northern provinces exhibited positive correlations between fertilizer consumption and agricultural carbon emissions, which aligns with findings from other studies (Guo et al., 2022; Ju et al., 2009). This positive correlation can be attributed to the fact that increased fertilizer use often results in soil nutrient runoff, diminished soil fertility, and subsequently higher emissions (Guo et al., 2022; see Appendix 1, Table 11 and Appendix 2, Fig. 9). However, in comparison with previous years, the promoting effect of fertilizer consumption on carbon emissions has shown a decline, suggesting a shift toward the adoption of organic fertilizers (Wang et al., 2018). In contrast, the Northeastern region displayed a negative correlation between fertilizer consumption and carbon emissions. This phenomenon can be attributed to the implementation of less harmful fertilizers as part of green agriculture promotion efforts, which has led to a reduction in emissions (Liu et al., 2015).

Up until 2020, all Chinese provinces exhibited a positive correlation between agricultural technology innovation and carbon emissions, which contradicts prevailing findings suggesting that innovation leads to emission reduction (Chang, 2022; Zhao et al., 2021). However, the contribution of agricultural technology innovation to agricultural carbon emissions differed across regions, with greater contributions in western and northwestern regions and smaller contributions in eastern and southeast coastal regions. In contrast to previous years, a notable reduction in the coefficients reflecting the impact of agricultural technology innovation on agricultural carbon emissions has been observed across nearly all provinces. Notably, in Heilongjiang Province, the coefficient depicting the influence of agricultural technology innovation on agricultural carbon emissions has shifted from negative to positive (see Appendix 1, Table 13 and Appendix 2, Fig. 11).

In most provinces, except for several western provinces (such as Tibet and Xinjiang), urbanization was negatively correlated with agricultural carbon emissions, in line with other studies (Chen & Lee, 2020; Han et al., 2021). Rapid urbanization improves agricultural efficiency and decreases emissions (Zhang et al., 2016). However, in certain western provinces (such as Tibet and Xinjiang), the process of urbanization has led to an increase in agricultural carbon emissions. This phenomenon can be attributed to the relatively low level of agricultural development in these provinces, coupled with their dependence on elevated agricultural factor inputs as a means to counterbalance the reduction in agricultural labor force (see Appendix 1, Table 9 and Appendix 2, Fig. 7).

5 Conclusion and suggestions

5.1 Conclusion

This study analyzed the spatiotemporal heterogeneity of factors influencing provincial agricultural carbon emissions in China and investigated reduction strategies for each province. The following are the key findings.

High agricultural carbon emissions were primarily concentrated in central, and northern China, with apparent spatial clustering, indicating mutual influence between provinces. Meanwhile, the changing center of gravity for emissions was mainly in Henan, moving northwestward due to agricultural development regions and policy adjustments, such as "Western Development" and carbon emission reduction. Therefore, agricultural carbon reduction in central, northern, and western regions of China is of great significance for achieving the "dual carbon" goals in China’s agricultural sector (Zhuo et al., 2023).

This study examined seven driving factors of agricultural carbon emissions using the GTWR model, revealing their spatiotemporal heterogeneity. Temporally, the regression coefficients of the influencing factors fluctuated over time. The promoting effects of agricultural economic level, fertilizer consumption level, and agricultural technology innovation level on carbon emissions decreased annually, while the facilitating role of agricultural mechanization level rebounded in recent years, and the propelling impact of agricultural structure remained stable. The suppressive effect of urbanization level weakened gradually, whereas the inhibitory influence of financial support for agriculture first declined and then ascended.

Spatially, the impacts of different factors on agricultural carbon emissions varied across regions. This study focused on the factors with strong promotional effects on carbon emissions in 2020 (e.g., agricultural mechanization level, fertilizer consumption level, and agricultural technology innovation level), and the factors with pronounced inhibitory effects (e.g., urbanization level). Specifically, agricultural mechanization level mainly increased the agricultural carbon emission levels in central and southern regions but inhibited emissions in several western provinces. Except northeastern regions, elevated fertilizer consumption level universally intensified agricultural carbon emissions in other areas. Meanwhile, agricultural technology innovation level was positively correlated with carbon emissions in all provinces, but the contributions of innovation levels differed across regions. Western and northwestern areas' innovation levels contributed more substantially to agricultural carbon emissions, while eastern and southeastern coastal regions' contributions were smaller. Additionally, Urbanization level played a suppressive role in agricultural carbon emissions in most provinces except western regions. Consequently, provinces should adopt tailored countermeasures for carbon emissions based on their unique situations.

5.2 Suggestions

China's agricultural carbon reduction should primarily focus on the central, northern, and western regions. Given the high agricultural carbon emissions in central and northern China (Liu et al., 2021a), the government should take actions in several aspects: (1) Prioritize the adoption of green and low-carbon technologies, and gradually phase out traditional high energy-consuming agricultural machinery (Lin & Xu, 2018); (2) support zero-growth action of chemical fertilizers and promote organic alternatives (Jiang et al., 2022); (3) promote urbanization to rationally reallocate surplus rural labor (Wang et al., 2022a). For the relatively underdeveloped western regions, on one hand, the government should promote less damaging fertilizers, limit synthetic nitrogen fertilizers, and encourage targeted fertilization based on soil fertility and deficiencies (Wang & Lu, 2020). On the other hand, the government should increase subsidies for agricultural machinery purchases and motivate farmers to use large machinery instead of small machinery (Lin & Xu, 2018); concurrently, proactively introduce policies on inter-regional agricultural machinery operation to effectively improve machinery utilization. Finally, all provinces should shift development goals through technological innovation from productivity improvement to sustainable agricultural development, supported by government economic incentives (Zhu & Huo, 2022), accelerate green technology innovation in agriculture, improve the transformation rate of agricultural science and technology achievements (Liu et al., 2021a, 2021b), so that agricultural technology innovation can truly become a catalyst for carbon reduction.

Appendix 1: The tables section of the manuscript

See Table 5, 6, 7, 8, 9, 10, 11, 12, and 13.

Table 5 Variance inflation factor (VIF) and tolerance of variables

Variable	VIF	Tolerance
Agricultural economic level	2.177	0.459
Agricultural structure	1.127	0.887
Urbanization level	2.272	0.44
Agricultural mechanization level	1.752	0.571
Fertilizer consumption level	1.481	0.675
Fiscal support for agriculture	2.458	0.407
Agricultural technology innovation level	1.19	0.84

Table 6 Location of the center-of-gravity coordinates and migration distances for agricultural carbon emissions

Year	*X* (Longitude)	*Y* (Latitude)	Moving distance (km)
2007	113° 20′ 28.728″ E	34° 15′ 6.448″ N	
2008	113° 10′ 40.565″ E	34° 12′ 22.552″ N	15.6080
2009	113° 8′ 55.942″ E	34° 12′ 19.622″ N	2.6330
2010	113° 6′ 29.842″ E	34° 14′ 29.271″ N	5.3791
2011	113° 0′ 26.616" E	34° 14′ 50.202″ N	9.1582
2012	112° 56′ 41.831″ E	34° 17′ 3.826″ N	6.9516
2013	112° 52′ 28.298″ E	34° 18′ 33.443″ N	6.9258
2014	112° 44′ 10.708″ E	34° 22′ 51.602″ N	14.7398
2015	112° 40′ 47.307″ E	34° 23′ 56.095″ N	5.4653
2016	112° 43′ 33.909″ E	34° 33′ 13.422″ N	17.2194
2017	112° 43′ 36.483″ E	34° 33′ 7.531″ N	0.1895
2018	112° 42′ 3.183″ E	34° 37′ 3.657″ N	7.5156
2019	112° 39′ 9.807″ E	34° 37′ 32.309″ N	4.4215
2020	112° 39′ 6.138″ E	34° 37′ 16.942″ N	0.4738

E East longitude, *N* North latitude

Table 7 Agricultural economic-level coefficients

Province	2007	2012	2016	2020	Province	2007	2012	2016	2020
Beijing	0.988	0.560	0.365	0.253	Hubei	0.434	0.114	0.001	−0.064
Tianjin	0.942	0.482	0.305	0.222	Hunan	−0.003	−0.121	−0.164	−0.160
Hebei	1.238	0.689	0.416	0.142	Guangdong	−0.461	−0.380	−0.351	−0.297
Shanxi	1.005	0.483	0.273	−0.027	Guangxi	−0.868	−0.651	−0.661	−0.658
Inner Mongolia	1.036	0.572	0.388	0.150	Hainan	−0.671	−0.551	−0.549	−0.583
Liaoning	0.008	0.123	0.129	0.123	Chongqing	0.627	0.406	0.089	0.019
Jilin	0.007	0.105	0.087	0.067	Sichuan	1.460	1.051	0.519	0.305
Heilongjiang	0.200	0.159	0.093	0.042	Guizhou	−0.221	−0.236	−0.352	−0.327
Shanghai	0.598	0.265	0.141	0.065	Yunnan	−0.186	−0.130	−0.265	−0.153
Jiangsu	0.565	0.240	0.129	0.047	Tibet	−0.420	0.097	0.336	0.317
Zhejiang	0.431	0.217	0.139	0.066	Shaanxi	0.966	0.519	0.126	−0.096
Anhui	0.651	0.242	0.119	0.033	Gansu	1.459	1.219	0.788	0.373
Fujian	0.040	0.095	0.127	0.059	Qinghai	1.223	1.094	0.886	0.644
Jiangxi	0.072	0.022	0.037	−0.001	Ningxia	1.007	0.790	0.515	0.111
Shandong	1.266	0.583	0.276	0.078	Xinjiang	−0.045	0.048	0.070	0.080
Henan	1.235	0.465	0.146	−0.066					

Table 8 Agricultural structure coefficients

Province	2007	2012	2016	2020	Province	2007	2012	2016	2020
Beijing	0.269	0.157	0.154	0.260	Hubei	0.448	0.407	0.374	0.419
Tianjin	0.391	0.228	0.202	0.296	Hunan	0.408	0.330	0.201	0.221
Hebei	0.171	0.056	0.118	0.265	Guangdong	0.501	0.304	0.107	0.070
Shanxi	−0.042	−0.182	−0.122	0.045	Guangxi	−0.106	−0.127	−0.179	−0.278
Inner Mongolia	−0.079	−0.122	−0.101	−0.056	Hainan	0.298	0.118	0.030	−0.058
Liaoning	0.123	0.154	0.162	0.166	Chongqing	−0.127	−0.176	−0.215	−0.145
Jilin	−0.018	0.095	0.094	0.031	Sichuan	0.032	−0.021	−0.090	−0.080
Heilongjiang	−0.024	0.088	0.098	0.006	Guizhou	−0.380	−0.382	−0.408	−0.380
Shanghai	0.907	0.820	0.659	0.562	Yunnan	−0.432	−0.202	−0.156	−0.205
Jiangsu	0.849	0.800	0.718	0.676	Tibet	0.020	0.037	0.026	0.028
Zhejiang	0.879	0.815	0.661	0.560	Shaanxi	−0.149	−0.233	−0.212	−0.068
Anhui	0.758	0.725	0.696	0.688	Gansu	0.024	0.033	0.017	−0.016
Fujian	0.825	0.739	0.550	0.391	Qinghai	0.067	0.094	0.089	0.061
Jiangxi	0.685	0.623	0.528	0.491	Ningxia	−0.021	−0.014	−0.074	−0.086
Shandong	0.453	0.320	0.348	0.465	Xinjiang	0.007	−0.036	−0.011	0.015
Henan	0.196	0.046	0.121	0.268					

Table 9 Urbanization-level coefficients

Province	2007	2012	2016	2020	Province	2007	2012	2016	2020
Beijing	−1.361	−1.217	−1.122	−1.126	Hubei	−0.850	−0.673	−0.631	−0.777
Tianjin	−1.296	−1.161	−1.073	−1.085	Hunan	−0.592	−0.444	−0.479	−0.637
Hebei	−1.505	−1.340	−1.214	−1.162	Guangdong	−0.212	−0.155	−0.257	−0.463
Shanxi	−1.534	−1.378	−1.303	−1.276	Guangxi	−0.055	0.024	0.165	0.116
Inner Mongolia	−1.573	−1.349	−1.255	−1.301	Hainan	0.102	0.066	0.092	0.129
Liaoning	−0.748	−0.679	−0.631	−0.672	Chongqing	−0.885	−0.870	−0.768	−0.833
Jilin	−0.323	−0.400	−0.456	−0.513	Sichuan	−0.961	−0.994	−0.880	−0.854
Heilongjiang	0.043	0.099	−0.037	−0.393	Guizhou	−0.332	−0.264	−0.188	−0.307
Shanghai	−0.934	−0.730	−0.560	−0.524	Yunnan	−0.049	−0.179	−0.162	−0.303
Jiangsu	−0.915	−0.711	−0.561	−0.533	Tibet	0.163	0.234	0.048	0.059
Zhejiang	−0.833	−0.682	−0.536	−0.494	Shaanxi	−1.605	−1.455	−1.293	−1.435
Anhui	−0.964	−0.740	−0.606	−0.599	Gansu	−1.135	−1.094	−0.959	−0.828
Fujian	−0.659	−0.674	−0.644	−0.608	Qinghai	−0.646	−0.754	−0.741	−0.646
Jiangxi	−0.647	−0.543	−0.548	−0.631	Ningxia	−1.463	−1.202	−1.074	−1.107
Shandong	−1.358	−1.161	−1.014	−0.968	Xinjiang	0.310	0.318	0.312	0.320
Henan	−1.441	−1.229	−1.124	−1.172					

Table 10 Agricultural mechanization-level coefficients

Province	2007	2012	2016	2020	Province	2007	2012	2016	2020
Beijing	−0.219	−0.021	0.130	0.245	Hubei	0.631	0.650	0.761	0.828
Tianjin	−0.213	−0.029	0.114	0.210	Hunan	0.978	0.855	0.877	0.833
Hebei	−0.176	0.028	0.201	0.430	Guangdong	1.180	0.830	0.801	0.708
Shanxi	0.009	0.216	0.309	0.547	Guangxi	1.555	1.098	0.786	0.558
Inner Mongolia	−0.176	0.106	0.184	0.350	Hainan	1.436	0.998	0.846	0.645
Liaoning	0.309	0.132	−0.016	−0.074	Chongqing	0.377	0.296	0.356	0.420
Jilin	0.310	0.094	−0.038	−0.084	Sichuan	−0.646	−0.568	−0.391	−0.134
Heilongjiang	0.282	0.175	0.028	−0.053	Guizhou	0.819	0.633	0.477	0.407
Shanghai	0.284	0.368	0.506	0.577	Yunnan	−0.349	−0.195	−0.300	−0.333
Jiangsu	0.308	0.390	0.529	0.614	Tibet	−0.189	−0.203	−0.131	−0.074
Zhejiang	0.371	0.412	0.546	0.630	Shaanxi	0.532	0.562	0.578	0.675
Anhui	0.309	0.392	0.529	0.630	Gansu	−0.312	−0.393	−0.294	−0.115
Fujian	0.507	0.383	0.474	0.622	Qinghai	−0.669	−0.616	−0.552	−0.544
Jiangxi	0.598	0.564	0.637	0.719	Ningxia	0.240	0.152	0.177	0.435
Shandong	−0.097	0.033	0.222	0.410	Xinjiang	−0.211	−0.272	−0.253	−0.242
Henan	0.205	0.360	0.495	0.665					

Table 11 Fertilizer consumption-level coefficients

Province	2007	2012	2016	2020	Province	2007	2012	2016	2020
Beijing	0.547	0.481	0.381	0.407	Hubei	0.359	0.338	0.247	0.220
Tianjin	0.476	0.398	0.314	0.350	Hunan	0.436	0.357	0.233	0.185
Hebei	0.636	0.651	0.538	0.505	Guangdong	0.366	0.193	0.105	0.081
Shanxi	0.655	0.690	0.550	0.470	Guangxi	0.336	0.209	0.166	0.147
Inner Mongolia	0.698	0.666	0.491	0.415	Hainan	0.222	0.146	0.116	0.117
Liaoning	−0.277	−0.252	−0.180	−0.157	Chongqing	0.208	0.198	0.176	0.123
Jilin	−0.519	−0.413	−0.341	−0.366	Sichuan	0.182	0.236	0.270	0.192
Heilongjiang	−0.669	−0.527	−0.466	−0.488	Guizhou	0.064	0.033	0.029	0.009
Shanghai	0.103	0.080	0.049	0.079	Yunnan	0.020	0.120	0.169	0.066
Jiangsu	0.136	0.134	0.103	0.145	Tibet	0.878	0.514	0.395	0.381
Zhejiang	0.172	0.120	0.065	0.093	Shaanxi	0.480	0.402	0.381	0.290
Anhui	0.153	0.185	0.149	0.183	Gansu	0.320	0.203	0.198	0.212
Fujian	0.280	0.134	0.022	0.037	Qinghai	0.352	0.199	0.125	0.113
Jiangxi	0.331	0.259	0.142	0.135	Ningxia	0.440	0.285	0.259	0.286
Shandong	0.411	0.445	0.377	0.383	Xinjiang	0.806	0.706	0.645	0.592
Henan	0.460	0.558	0.456	0.364					

Table 12 Financial support for agriculture coefficients

Province	2007	2012	2016	2020	Province	2007	2012	2016	2020
Beijing	−0.176	−0.048	−0.031	−0.134	Hubei	−0.328	−0.260	−0.340	−0.628
Tianjin	−0.172	−0.035	−0.014	−0.109	Hunan	−0.358	−0.295	−0.408	−0.537
Hebei	−0.294	−0.118	−0.094	−0.242	Guangdong	−0.327	−0.329	−0.410	−0.425
Shanxi	−0.358	−0.144	−0.099	−0.278	Guangxi	−0.177	−0.161	0.041	0.158
Inner Mongolia	−0.315	−0.109	−0.030	−0.162	Hainan	−0.187	−0.224	−0.166	0.006
Liaoning	−0.145	−0.035	0.169	0.240	Chongqing	−0.347	−0.293	−0.174	−0.193
Jilin	−0.009	0.055	0.217	0.300	Sichuan	−0.171	−0.116	−0.080	−0.156
Heilongjiang	0.043	0.122	0.229	0.269	Guizhou	−0.216	−0.137	0.027	0.016
Shanghai	−0.261	−0.141	−0.091	−0.177	Yunnan	0.011	0.022	0.104	−0.003
Jiangsu	−0.264	−0.132	−0.076	−0.161	Tibet	−0.018	−0.016	−0.008	−0.002
Zhejiang	−0.235	−0.130	−0.101	−0.197	Shaanxi	−0.633	−0.536	−0.396	−0.559
Anhui	−0.296	−0.156	−0.106	−0.225	Gansu	−0.243	−0.054	−0.005	−0.109
Fujian	−0.235	−0.203	−0.297	−0.467	Qinghai	−0.082	0.016	0.068	0.022
Jiangxi	−0.245	−0.158	−0.259	−0.491	Ningxia	−0.497	−0.387	−0.249	−0.314
Shandong	−0.313	−0.142	−0.097	−0.211	Xinjiang	0.106	0.055	0.038	0.029
Henan	−0.437	−0.310	−0.313	−0.569					

Table 13 Agricultural technology innovation-level coefficients

Province	2007	2012	2016	2020	Province	2007	2012	2016	2020
Beijing	0.968	0.449	0.379	0.294	Hubei	0.171	0.095	0.046	0.005
Tianjin	0.860	0.442	0.365	0.286	Hunan	0.156	0.045	0.027	0.047
Hebei	0.675	0.367	0.331	0.256	Guangdong	0.174	0.066	0.071	0.126
Shanxi	0.942	0.434	0.377	0.282	Guangxi	0.399	0.117	0.097	0.108
Inner Mongolia	1.134	0.518	0.457	0.328	Hainan	0.118	0.048	0.054	0.079
Liaoning	1.864	0.544	0.409	0.350	Chongqing	0.872	0.415	0.404	0.428
Jilin	0.777	0.332	0.331	0.383	Sichuan	0.346	0.385	0.494	0.568
Heilongjiang	−0.972	−0.873	−0.392	0.185	Guizhou	0.915	0.338	0.269	0.273
Shanghai	0.134	0.089	0.054	0.030	Yunnan	1.387	0.552	0.423	0.393
Jiangsu	0.169	0.103	0.055	0.020	Tibet	4.932	0.758	0.612	0.550
Zhejiang	0.136	0.084	0.041	0.012	Shaanxi	1.083	0.555	0.495	0.362
Anhui	0.196	0.129	0.074	0.028	Gansu	0.693	0.574	0.598	0.651
Fujian	0.189	0.130	0.084	0.033	Qinghai	0.585	0.463	0.428	0.448
Jiangxi	0.191	0.089	0.048	0.009	Ningxia	2.244	1.141	0.945	0.797
Shandong	0.437	0.312	0.272	0.212	Xinjiang	0.375	0.407	0.451	0.461
Henan	0.380	0.295	0.253	0.160					

Appendix 2: The figures section of the manuscript

See Figs. 4, 5, 6, 7, 8, 9, 10, 11.

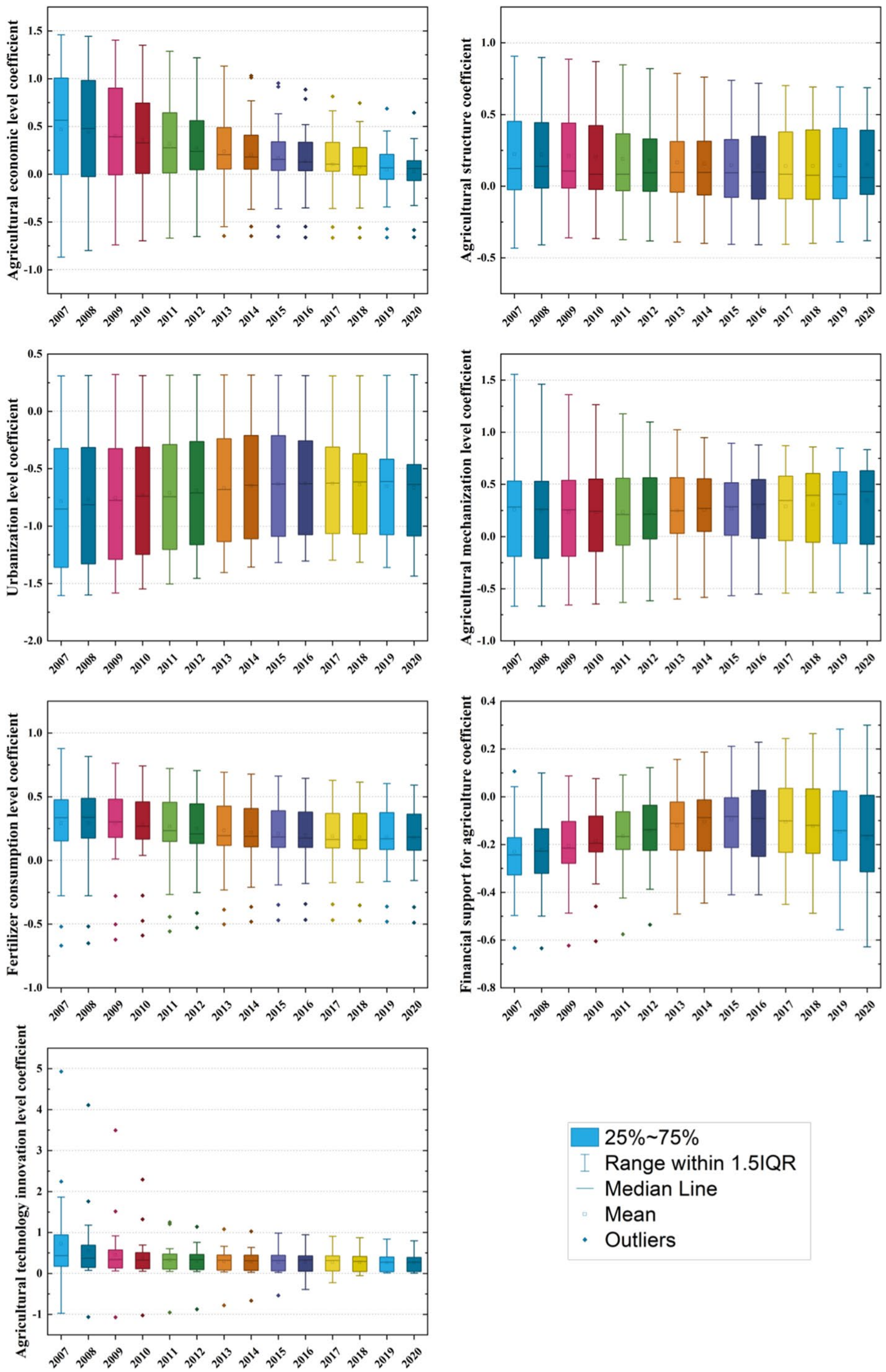

Fig. 4 Time variation trend of GTWR regression coefficients from 2007 to 2020

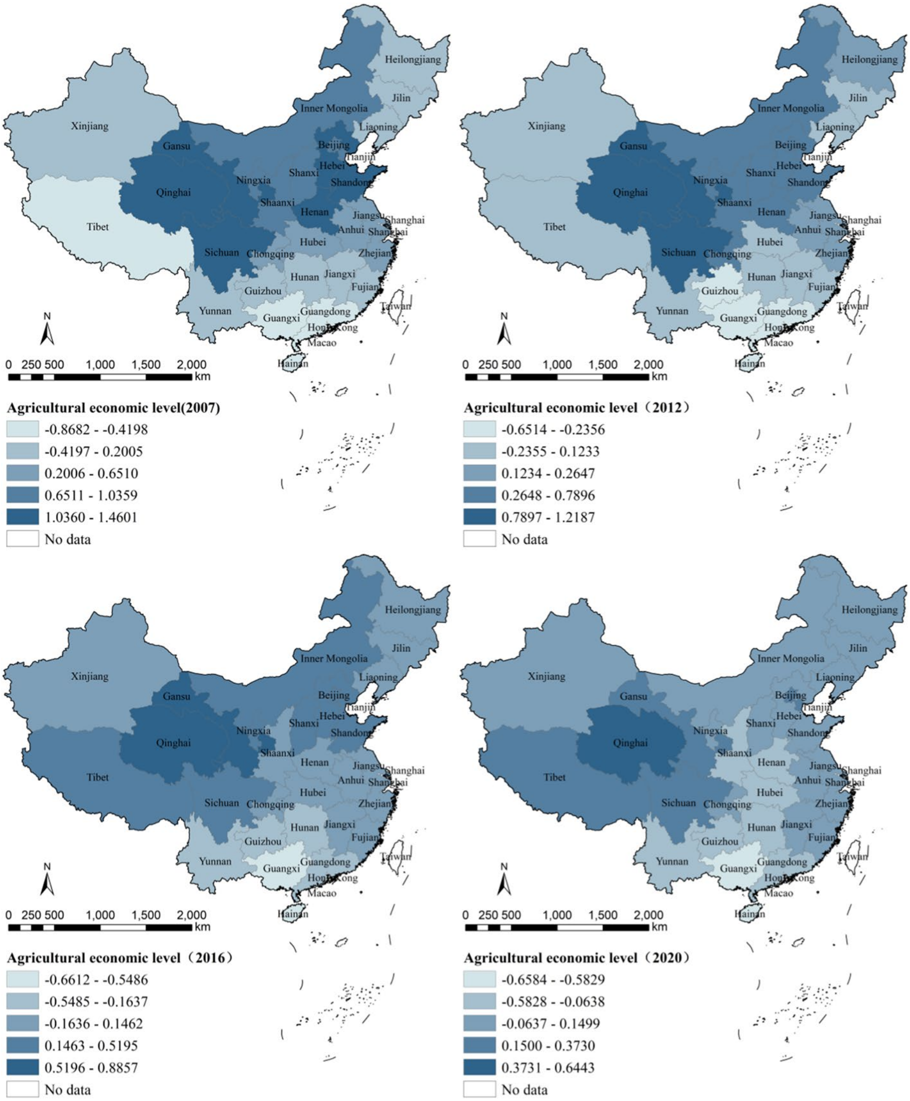

Fig. 5 Agricultural economic level coefficient from 2007 to 2020

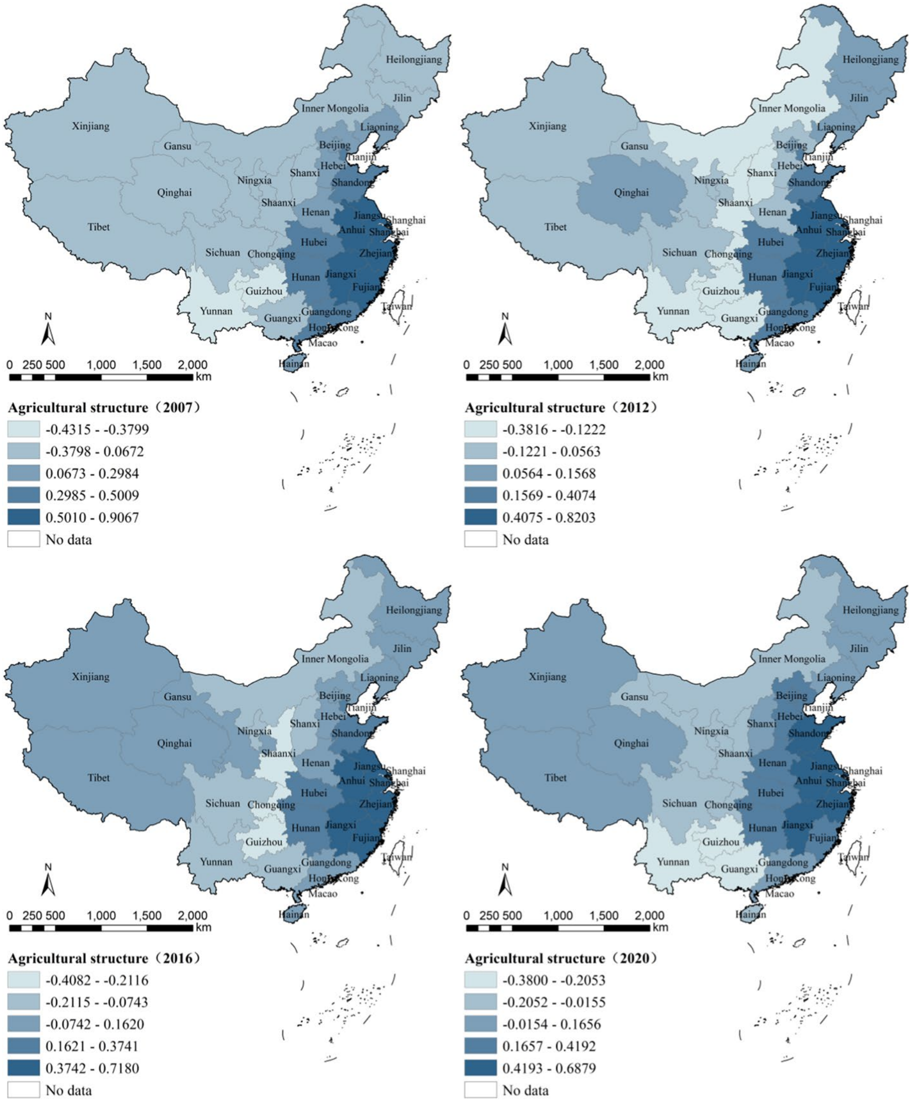

Fig. 6 Agricultural structure coefficient from 2007 to 2020

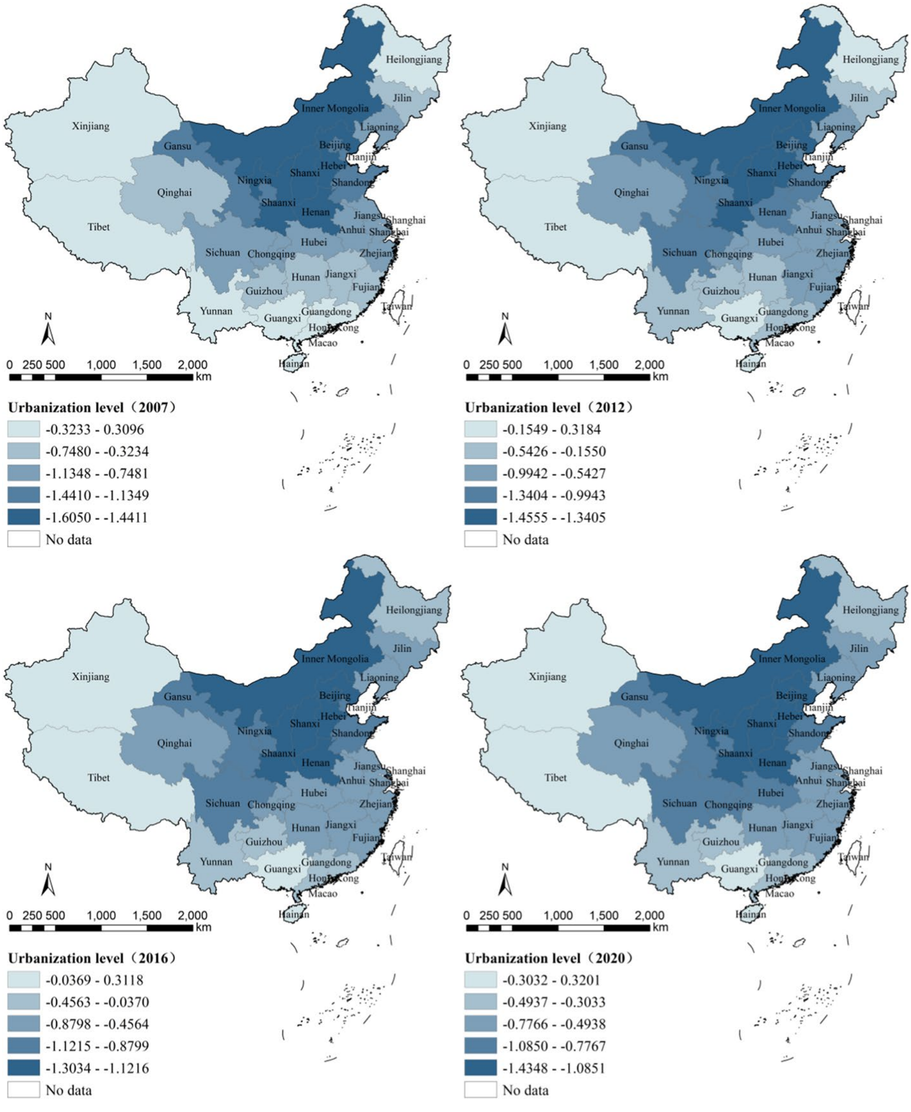

Fig. 7 Urbanization-level coefficient from 2007 to 2020

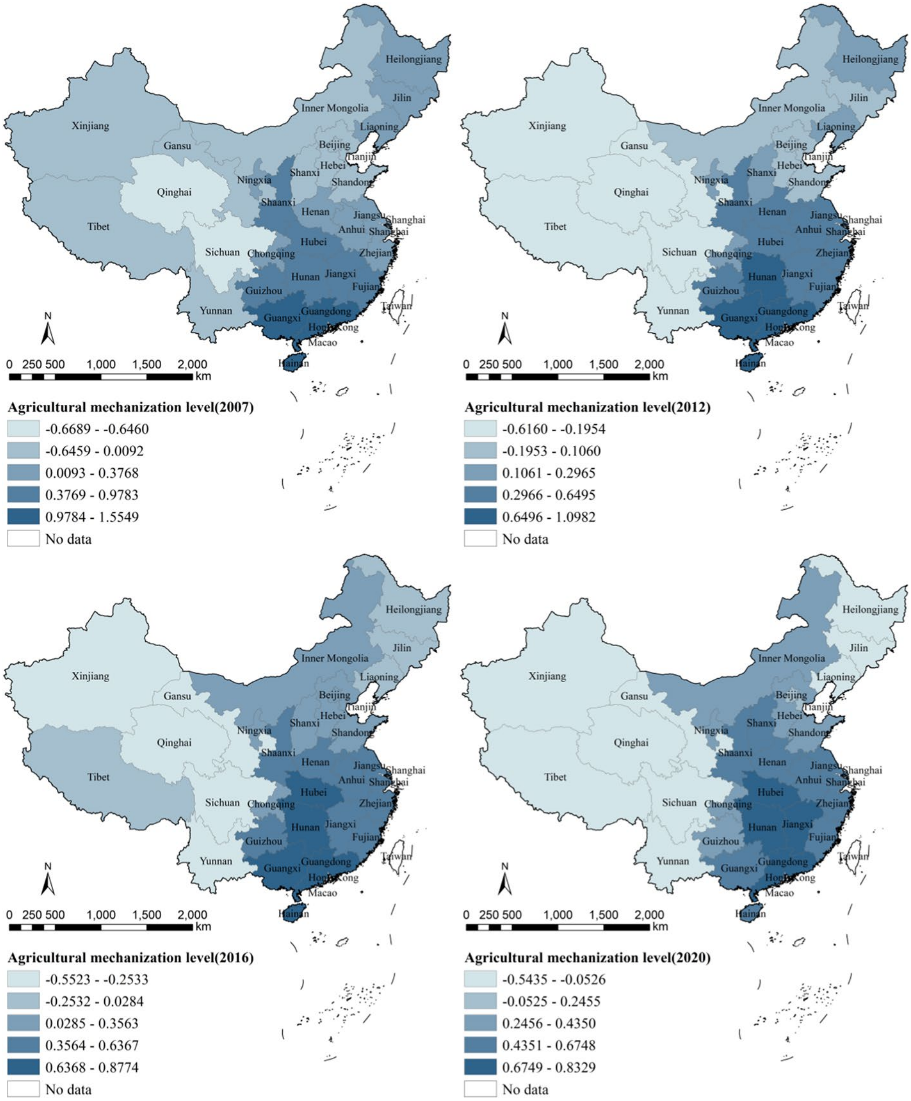

Fig. 8 Agricultural mechanization-level coefficient from 2007 to 2020

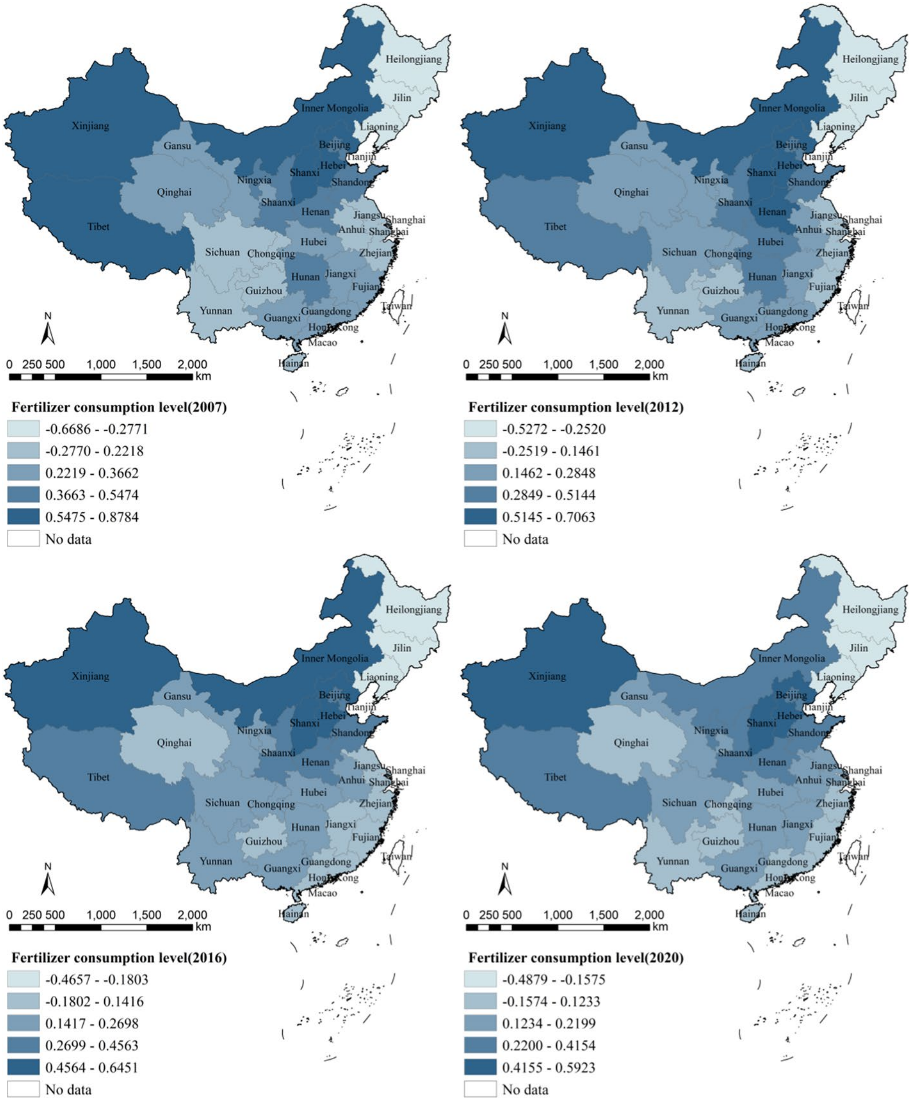

Fig. 9 Fertilizer consumption-level coefficient from 2007 to 2020

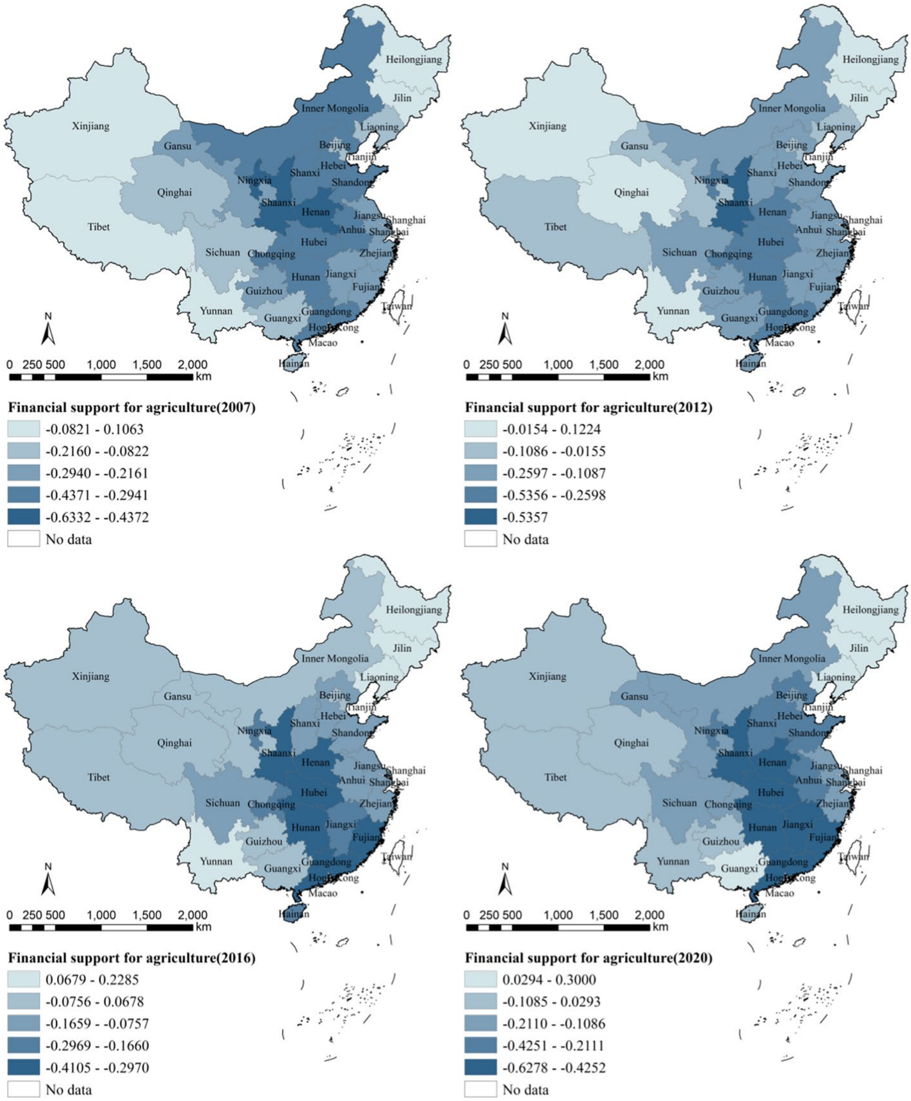

Fig. 10 Financial support for agriculture coefficient from 2007 to 2020

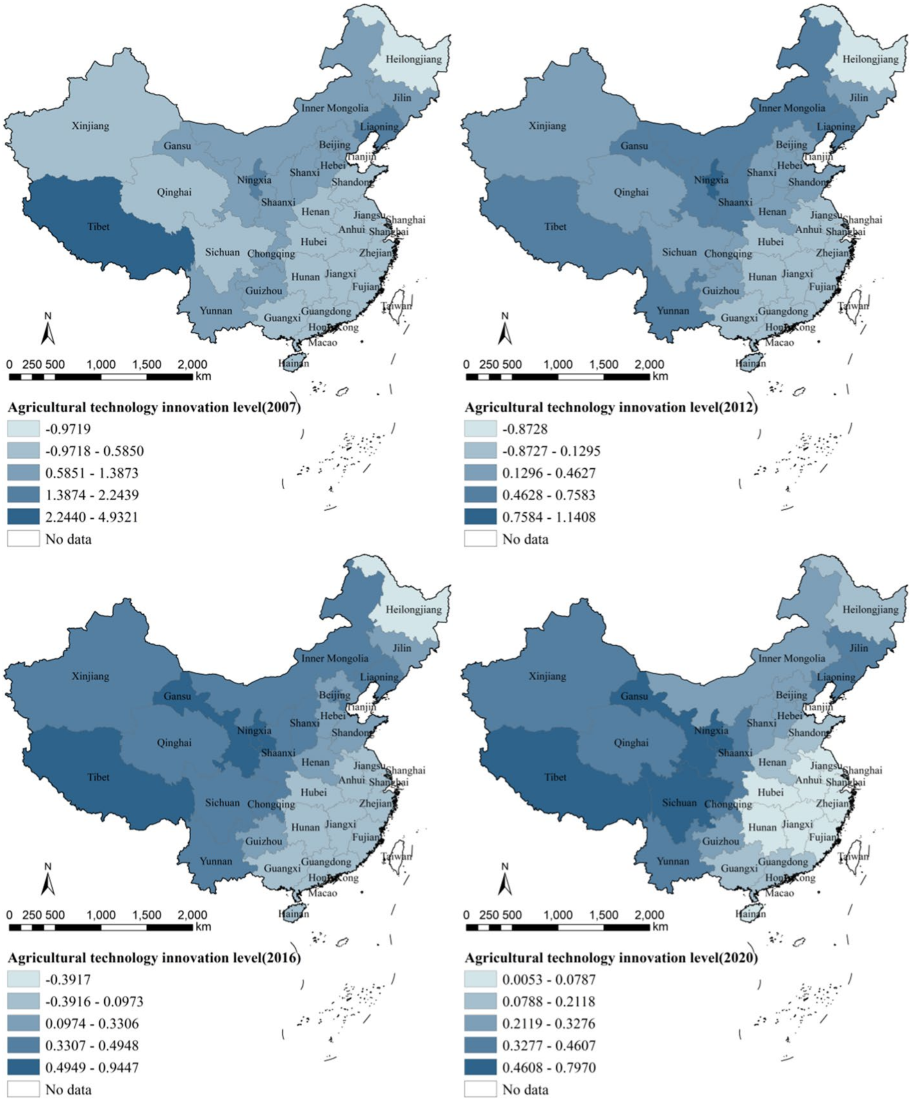

Fig. 11 Agricultural technology innovation-level coefficient from 2007 to 2020

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Author contribution Xixian Zheng conceived the study idea, designed the study, supervised the data collection and analysis, and drafted the manuscript. Haixia Tan participated in data collection and analysis. Wenmei Liao provided critical revision of the manuscript, particularly the conclusion and suggestions section. All authors have read and approved the final manuscript.

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Declarations

Conflict of interest The authors declare no conflict of interest.

Ethical approval All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors and are aware that with minor exceptions, no changes can be made to authorship once the paper is submitted.

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