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Analysis of regional differences and spatial spillover effects of agricultural carbon emissions in China

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ABSTRACT

In order to realize "double carbon" target in agriculture and high-quality development of the rural economy in China, it is crucial to study the regional differences and spatial spillover effects of agricultural carbon emissions (ACE). This paper measures ACE using panel data of 31 Chinese provinces from 2005 to 2020, examines the spatio-temporal evolution characteristics , the convergence of agricultural carbon emissions, compares and analyzes regional differences, and investigates the spatial correlation and spatial spillover effects. The study found that: (1) Total agricultural carbon emissions over the research period exhibit a rising and then reducing trend, the spatial distribution of total agricultural carbon emissions is described as high in east-central and low in west. The gap of agricultural carbon emissions is gradually declining in the east, and will eventually reach their respective steady-state levels in the west and northeast. (2) There is a strong spatial interprovincial link of ACE, which has a beneficial knock-on effect on the convergence of adjacent provinces. (3) Agricultural industrial structure, urbanization level, the size of the agricultural labor force, and the intensity of the agricultural machinery input all directly affect ACE in this province and indirectly affect ACE in adjacent provinces, with the exception of the negligible coefficient of economic development level on ACE. Hence, pertinent policy suggestions are put out to serve as a guide for reducing ACE.

1. Introduction

Global climate change has a significant impact on human production, quality of life, and the sustainable development ability of economy and society. The greenhouse effect has grown stronger in recent years, causing global warming, melting glaciers, increasing sea levels, threats to some plants' and animals' habitats, and more frequent extreme weather events like hurricanes, wildfires, and droughts [1–3]. Global agricultural output contributes roughly 13.5% of all greenhouse gas emissions, with carbon dioxide accounting for the majority of these emissions (72%) [4,5]. Countries around the world are paying great attention to this issue and trying to find solutions for sustainable development and effective control of environmental degradation [6]. Among them, the Chinese government has proposed a major strategy to actively respond to global climate change: achieving the goals of carbon peaking by 2030 and carbon neutrality by 2060 (ie,"double carbon"). We should work together to promote carbon reduction, pollution reduction, green expansion and growth, and accelerate the transformation of the development mode to green and low-carbon, which is also stressed in the report of the 20th National Congress of the Communist Party of China (CPC), for which the issue of carbon emission reduction is gradually

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becoming a research hotspot. Agricultural carbon sources release a significant amount of gases, including CO_2, N_2O, and CH_4, despite the fact that industrial carbon sources are the primary focus of regulation, it is also important to pay attention to the emissions of agricultural carbon sources [7,8]. According to the FAO, China accounts for 11–12% of the world's ACE. The development of low-carbon agriculture in China is of great significance to the world [9].

Consequently, reducing carbon emissions from agricultural output is a practical method and component of lowering future total carbon emissions, which is crucial for combating climate change [10]. Scientific analysis of the dynamic changes in ACE, spatial agglomeration characteristics, and influencing factors is of great practical significance for China to realize low-carbon agriculture, implement the rural revitalization strategies and build an ecologically civilized and beautiful countryside. In the process of promoting the transformation of agricultural development, it is not only necessary to control carbon emissions, but also to ensure the orderly development of the agricultural economy. Therefore, this paper studies the regional differences and spatial spillover effects of ACE, with a view to providing theoretical references for the coordinated promotion of agricultural carbon emission reduction in China's regions, providing quantitative support for the pace of carbon peaking and carbon neutrality, and providing a scientific basis for promoting high-quality agricultural development.

2. Literature review

There are plentiful studies on agricultural carbon. There are mainly two dimensions concerning the measurement of agricultural carbon emission indexes. One is in broad sense, where carbon sources involve multiple sectors and cover a comprehensive range [10, 11], the other is in narrow sense, where the carbon sources are mainly inputs of agricultural land materials such as fertilizers, pesticides, agricultural films, diesel, irrigation, and tillage [12,13]. After measuring the indicator data, scholars have focused their research on three main areas.

2.1. Emission characteristics

Researchers employed line graphs, histograms, and regional Thiel index maps of China's total ACE to examine the present status characteristics of carbon emissions, intensity, and its per capita carbon emissions from both time and spatial perspectives [14–16]. The overall studies demonstrated that there are phases of changes in China's ACE, with the total amount exhibiting a general increase trend until 2016, with specific spatio-temporal differences and spatial autocorrelation at the provincial scale [17,18]. In addition, scholars explored the changes and trends of ACE on specific provinces [19–21].

2.2. Influencing factors

In order to investigate the factors that affect ACE, some researchers used the LMDI decomposition method, the GTWR method, and the PVAR model. They came to the conclusion that while efficiency factors can prevent an increase in ACE, economic factors and labor factors can promote it [21,22]. According to research by other scholars, there is a two-way causal relationship between ACE and agroecosystem changes [23]. Apart from this, the research has shown that factors such as changes climate change [24], agricultural mechanization [25], economic growth [26], environmental regulation, and technological innovation [27] all have different degrees of influence on ACE.

2.3. Emission reduction strategy and tactics

The reduction of ACE can be aided by changes in food consumption, land use practices [28], low-carbon energy substitution, aggressive energy conservation strategies, energy efficiency enhancements, and industrial transformation [7,29]. Meanwhile, some academics also emphasize that the government has a significant impact on the process of reducing ACE. For instance, the government must implement green technologies, increase funding for green energy initiatives [8], create differentiated emission reduction policies, strengthen regional coordination, and take other steps to encourage low-carbon development in agriculture [14].

From the literatures above, the studies on ACE has, been expanding a lot recent years. The studies main focused on the analysis of indicators, measurements, status quo characteristics, and influencing factors etc. The research angles is or a particular province, a whole country. These serve as a strong theoretical underpinning and empirical base for this article. Nonetheless, there is still a great deal of potential for study in this area to be expanded, and we think that this paper adds to the literature in the following ways: (1) **From the scope of the study,** in order to clarify the current situation and evolution process of ACE in each province and region in China, or to provide some inspiration for current research insights, this paper begins its research at the national level of 31 provinces and divides China's economic regions into four major regions (See Appendix). (2) **From a research standpoint,** the studies on the convergence of carbon emissions primarily concentrate on the global and industrial perspectives, and the studies on the convergence of ACE are relatively understudied. In this study, we will examine the convergence and divergence of total ACE in various regions over the course of the sample period using the σ convergence model and the β convergence model, and we will also provide additional empirical analysis on the inter-provincial differences in ACE in China. (3) From the perspective of the mechanism of action, this question adopts a spatial econometric model to take into account each driver's influence on ACE from the spatial dimension. It then proposes targeted and optimized policy recommendations for the realization of green and low-carbon transformation development of agriculture in all provinces of China.

3. Theoretical analysis and selection of influencing factors

Compared with industrial carbon emissions and carbon emissions from residential consumption, carbon emissions from agriculture have their own special characteristics. Agriculture is an organic combination of economic reproduction and natural reproduction [13], and in the process of agricultural production, the energy consumed and agricultural material inputs will lead to the generation of carbon emissions, which are the carbon source of many kinds of greenhouse gas emissions. However, agriculture has the ability to collect and store carbon dioxide in the atmosphere, forming a carbon sink that is simply unmatched by other industries. Therefore, some general carbon reduction measures may not be applicable to agriculture, and agriculture needs to explore a "carbon peaking and carbon neutrality" pathway that fits its development characteristics.

3.1. Selection of influencing factors

Existing studies have demonstrated the factors affecting ACE from economic, technological, environmental, and demographic aspects. Based on the current characteristics of China's agricultural development and the availability of data in each province (city), this paper will analyze the mechanism of the impact of each factor on ACE using the following five specific indicators (Fig. 1):

Agricultural industrial structure: Among the agricultural industrial sectors, there are four major industries, including plantation, forestry, animal husbandry, and fishery, and each sector has its own inherent industrial characteristics due to its different production methods, and carbon emissions will be affected by this, thus showing different emission levels, for which changes in industrial structure will have an impact on ACE [30]. From the standpoint of agricultural industry restructuring, a higher proportion of

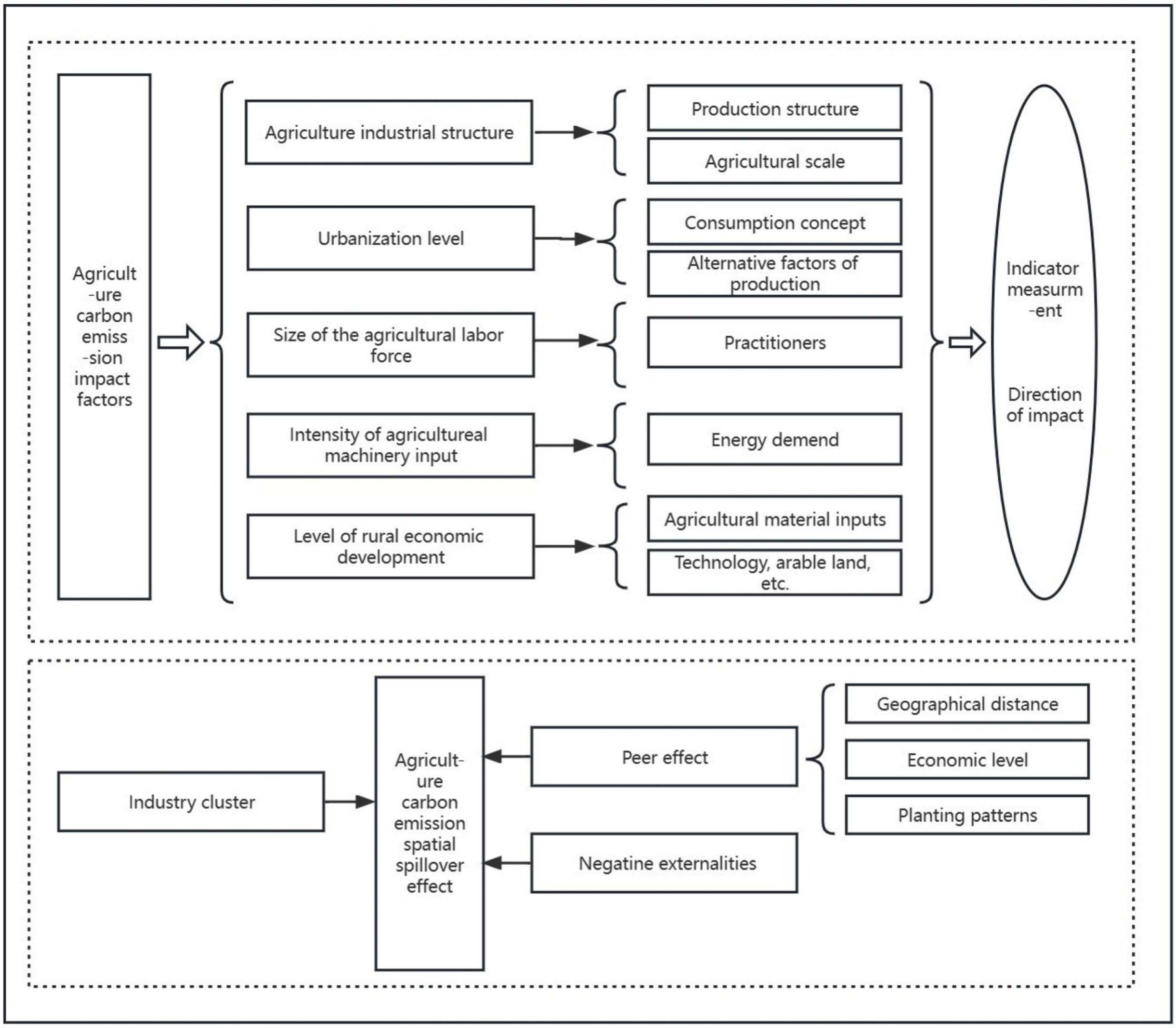

Fig. 1. Selection of influencing factors and spatial spillover effects.

agricultural output value means that agricultural scale expands and carbon emissions naturally rise. However, since planting has net carbon benefits, the larger its share in agriculture, the higher the degree of agricultural decarbonization [31]. This paper uses the ratio of agricultural output value to total agricultural, forestry, animal husbandry, and fishery output value to measure the agricultural industry structure.

Urbanization level: In the existing studies, the direction of the impact of urbanization development on ACE is not uniform. On the one hand, urbanization means that part of the labor force is transformed from producers to consumers, which will not only reduce the rural labor force but also prompt some consumers to change their consumption concepts, which will prompt agricultural production subjects to pay attention to large-scale, intensive, green, and low-carbon production, thus reducing ACE [18]. On the other hand, urbanization has led to an aging and part-time character of agriculture, and farmers may invest extensively in alternative production methods to prevent yield decline, which results in a significant output of agricultural carbon emission [32]. In this paper, we use the ratio of urban population to total population to measure the level of urbanization.

Size of the agricultural labor force: the agricultural labor force is a typical human capital input factor that has a direct impact on agricultural production. Numerous theories and practices show that the increase in the number of human capital inputs implies the expansion of agricultural scale and indirectly promotes the use of agricultural inputs [33], therefore, the increase in the number of agricultural employees causes the increase in ACE. In this paper, the number of people employed in the primary industry is selected as an indicator to measure the population.

Intensity of agricultural machinery input: the increase in agricultural machinery input makes the total energy demand increase, so it is seen that the increase in agricultural machinery input may produce more agricultural greenhouse gas emissions in the short term [10]. In this paper, the agricultural machinery input intensity index is measured using the total power of agricultural machinery.

Level of rural economic development: the development of rural economic level will prompt the transformation of agricultural production from labor-intensive to capital-intensive, and the relatively high amount of agricultural inputs will objectively lead to an increase in the absolute amount of GHG emissions [34]. However, at the same time, the development of economic level will promote the improvement of low-carbon technology level in agriculture, the increase of urbanization level, the decrease of arable land area, and the transfer of agricultural labor. And all these phenomena will reduce ACE to some extent. In this paper, the net per capita income of farmers is used as a proxy indicator for the level of rural economic development.

3.2. *Regional spillover effects of ACE*

The economies of scale brought by industrial agglomeration will increase the spillover effect on the food industry while promoting technology application and optimizing industrial structure. Existing studies have shown that total agricultural emissions, emission intensity, and emission efficiency all have spatial spillover effects [13,35,36], and the level of urbanization [32], agricultural mechanization [25], agricultural technology progress [34] and other factors will have an impact on these variables.

Jeroen (2012) argues that air pollution has negative externalities and that regions must act in concert when managing it in order to solve the problem [37]. According to the first law of geography, everything is related, and things that are close are more closely related. The cropping pattern, industrial development pattern, and policy implementation of one region are all influenced by the adjacent regions, and at the same time, they also influence the adjacent regions. Therefore, the increase or decrease of carbon emissions in a region will have a “peer effect,” i.e., while considering its own agricultural and economic development, it will further adjust its carbon emissions with reference to its adjacent regions [38](Fig. 1).

4. Materials and methods

4.1. *Measurement of ACE*

Referring to the study of Li et al. (2011) [39] and Wu et al. [40], the carbon sources are defined as fertilizer, pesticide, agricultural diesel, agricultural plastic film, tillage, and irrigation when measuring ACE in this paper, which correspond to emission factors of 0.8956 kg/kg, 4.9341 kg/kg, 0.5927 kg/kg, 5.18 kg/kg, 312.6 kg/km^2, and 19.8575 kg/hm^2. The equation for calculating ACE is:

$$y=\sum_{i=1}^{6} y_i \times p_i \tag{1}$$

In Eq. (1), y indicates the total amount of ACE, p_i indicates the carbon emission factor of the corresponding category i carbon source, y_i indicates the consumption of the corresponding category i carbon source.

4.2. *Moran’ s I index*

In this paper, the global Moran’s I index is used to test whether ACE are spatially correlated, that is, to test whether there is spatial dependence between the ACE of each province and its geographical location. The value range of this index is [−1, 1], and if the result of this value is significant and positive, it indicates that there is a positive spatial correlation between the ACE of each province, otherwise it is a negative spatial correlation. The global Moran index is calculated as

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \overline{y})(y - \overline{y})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \overline{y})^2} \tag{2}$$

In Eq. (2), n is the number of provinces in China (31), y_i and y_j indicate the ACE of each province, respectively. $\overline{y}$ indicates the mean value, w_{ij} indicates the spatial weighting matrix.

4.3. The convergence model

Convergence models were first used to study economic growth but have now been skillfully applied to other studies in the economic field. In this paper, two convergence models, σ convergence and β convergence, are chosen to investigate the convergence characteristics of ACE, i.e., the evolution of differences in ACE across regions.

The σ convergence reflects the deviation from the overall level of ACE in different regions over time. If the deviation of ACE in each region shows a decreasing trend over time, then ACE show σ convergence. In this paper, the coefficient of variation is used to measure σ convergence, which is calculated as follows:

$$\delta_j = \frac{\sqrt{\left[\sum_i^{n_j}(y_{ji} - \overline{y_j})\right]/n_j}}{\overline{y_j}} \tag{3}$$

In Eq. (3), y_{ji} is the ACE of province i in region j, $\overline{y_j}$ is the average value of ACE in region j, and n_j is the total number of provinces in region j.

β convergence refers to the fact that as time progresses, areas with high ACE have a faster rate of decline to catch up with areas with low ACE, and the growth rate of ACE in different provinces is negatively correlated with the initial level, with the gap between provinces narrowing and eventually reaching a steady-state level. β convergence can be divided into absolute convergence and conditional convergence; the difference between the two lies in whether the initial conditions for agricultural development are the same in each province (city). Absolute convergence assumes that all provinces (and municipalities) have the same development conditions in all aspects and that, without considering the influence of external factors on carbon emissions, the ACE of each province (or municipality) eventually converge to their respective steady-state levels. Conditional convergence takes into account the differences in economic level, industrial structure, resource conditions, production methods, etc., and the convergence of ACE to their respective steady-state values. Therefore, the conditional β convergence model is based on the absolute β convergence model with the addition of influencing factors to analyze whether ACE have a convergence trend, and the specific formula is as follows: absolute β convergence model

$$\ln\left(\frac{y_{i,t+1}}{y_{it}}\right) = \alpha + \beta \ln y_{it} + u_i + v_i + \varepsilon_{it} \tag{4}$$

Where: y_{it} denotes ACE in province i in year t, $y_{i,t+1}$ represents ACE in province i in year t+1, is the growth rate of ACE calculated using log difference, α is the intercept term, β is the convergence coefficient, and u_i is the area effect, v_i is the time effect, and ε_{it} is random error term, respectively.

Conditional convergence model

$$\ln\left(\frac{y_{i,t+1}}{y_{it}}\right) = \alpha + \beta \ln y_{it} + \delta X + u_i + v_i + \varepsilon_{it} \tag{5}$$

Where X represents the control variable, δ represents its coefficient, and the other letters have the same meaning as in equation (4).

In the above two equations (equation (4) and equation (5)), if the value of β is significantly negative, it indicates that there is convergence in ACE, the opposite is divergence.

4.4. Spatial econometric model

Given the existence of spatial agglomeration of ACE, general research methods may result in discrepancies between estimation results and reality when investigating the influencing factors of ACE, so spatial measurement methods must be introduced. Up to now, three types of spatial panel econometric models have been commonly applied, namely, spatial lag (SAR), spatial error (SEM), and spatial Durbin (SDM), with SDM as the base model, as shown in equation (6):

$$y_{it} = \alpha + \rho W y_{it} + \beta X_{it} + \theta W X_{it} + \mu_i + \gamma_i + \varepsilon_{it} \tag{6}$$

$$\varepsilon_{it} = \varphi W \varepsilon_{it} + v_{it} \tag{7}$$

In Eq. (6), where: subscript i denotes province, and subscript t denotes year. For instance, denotes ACE in province i in year t. α, ρ, β, θ andφare parameters to be estimated, where ρ andφdenote spatial autoregressive coefficients and spatial autocorrelation coefficients respectively. In Eq. (7), W is the spatial weight matrix, X is a vector of explanatory variables, i.e., factors influencing ACE. ε_{it} and v_{it} are random disturbance terms, μ_i and γ_t denote area fixed effects and time fixed effects, respectively.

When $\rho \neq 0$, $\theta = 0$, $\delta = 0$ and $\varphi = 0$, Eq. (6) is the spatial lag model (SAR/SLM), when $\rho = 0$, $\theta = 0$, $\delta = 0$ and $\varphi \neq 0$, Eq. (6) is the spatial error model (SEM), and when $\rho \neq 0$, $\theta \neq 0$, $\delta \neq 0$ and $\varphi = 0$, it is the spatial Durbin model (SDM).

The estimated results of the influence factors and regional ACE were decomposed into direct effect, indirect effect, and total effect, in the following order: $f_{ii}(W) = \frac{\partial Y_i}{\partial X_{im}}$, $f_{ij}(W) = \frac{\partial Y_i}{\partial X_{jm}}$, $f_{toal} = f_{ii}(W) + f_{ij}(W)$, One of the indirect effects is the spatial spillover effect.

4.5. Data resources

In this paper, the data on tillage, irrigation, fertilizer (in discounted amounts), pesticides, films, and diesel fuel are based on the actual values of the year. Tillage is the crop sown area of the year, irrigation is the effectively irrigated area of the year, fertilizer is the amount applied, and the remaining carbon source is the actual amount used. ACE data is calculated by Eq. (1). The data for the indicators and impact factors in the above table are from the China Rural Statistical Yearbook (2006–2021) and the China Statistical Yearbook (2006–2021), respectively, and the study excludes Hong Kong, Macao, and Taiwan of China due to data availability constraints. In particular, total agricultural output value and total agricultural, forestry, animal husbandry, and fishery output value were transformed using the deflator at constant 2005-based prices, and some missing data were interpolated to fill in the gaps. Table 1 reports the statistical results for each variable in detail.

5. Regional comparative analysis

5.1. Analysis of the temporal characteristics

The results of calculating the emissions of various carbon sources and total carbon emissions in China's agriculture according to the previous research method and their chain rate of growth are shown in Fig. 2. In 2005, China's ACE were 71,875,300 tons, and in 2020, they were 78,731,800 tons, with an overall increase of 9.54%. In terms of the chain rate of growth of total ACE, its value first fluctuates to increase, then subsequently decreases, and the latter years are negative. It deserves to be that after 2015, the growth rate of China's ACE decreases year by year, and the reason is that the local governments have been implementing a series of green development policies such as "pesticide and chemical fertilizer reduction" since 2015, which has reduced emissions to a certain degree. From the perspective of six carbon sources, ACE caused by fertilizer application account for more than half of the total, ranking first among carbon sources; carbon emissions caused by three types of inputs, namely agricultural film, pesticides, and agricultural diesel, do not differ much, accounting for about 10% of the total; the last in line are carbon emissions caused by tillage and irrigation, less than 1% of the total. In addition, except for the carbon emissions from crop cultivation and irrigation, which are increasing year by year, the carbon emissions from other carbon sources also show an increase and then decrease during 2005–2020. This shows that ACE are now showing a decreasing trend, which indicates that with the improvement of agricultural low-carbon technology and optimization of industrial structure, the effectiveness of energy conservation and emission reduction in China's agriculture is gradually emerging, and the level of low-carbon development is continuously improving.

Fig. 3 displays the results of our further calculations of the agricultural carbon emission statistics from four regions in China. Regional ACE from 2005 to 2020 exhibit the same upward and then downward trend as the overall trend, but the study period's peak years are not uniform due to differences in the pace of agricultural development and policy implementation in each region, which results in regional differences. The western region's change is the largest and most pronounced, with a distinct "hump" shape, which means ACE peak in the middle of the 2005–2020 period, while they are relatively low at the beginning and end of the period. This is likely because the western region contains more provinces and covers a larger area, making the change more pronounced. The share of ACE in the country by region shows the characteristics of differential changes: the eastern region declines (38.88% to 29.65%), the central region remains unchanged (28.1%), the western region rises (21.81% to 30.75%), and the northeast region rises (9.15% to 11.52%).

Table 1
Results of descriptive statistics for each variable.

Variables	Unit	Numbers	Mean	Stand error	Minimum	Maximum
ACE	million tons	496	271.3	200.5	5.728	871.6
IDS	%	496	38.31	9.713	17.00	71.70
URB	%	496	54.24	14.71	20.85	89.60
ICE	10,000 people	496	848.6	635.8	27	3139
AML	million kilowatts	496	3042	2817	93.97	13353
GDP	CNY/person	496	5082	2241	1104	18296

In Table 1, ACE denotes agricultural carbon emissions, IDS denotes agricultural industry structure, URB denotes urbanisation level, ICE denotes agricultural labour force size, AML denotes agricultural machinery input intensity and GDP denotes rural economic development level.

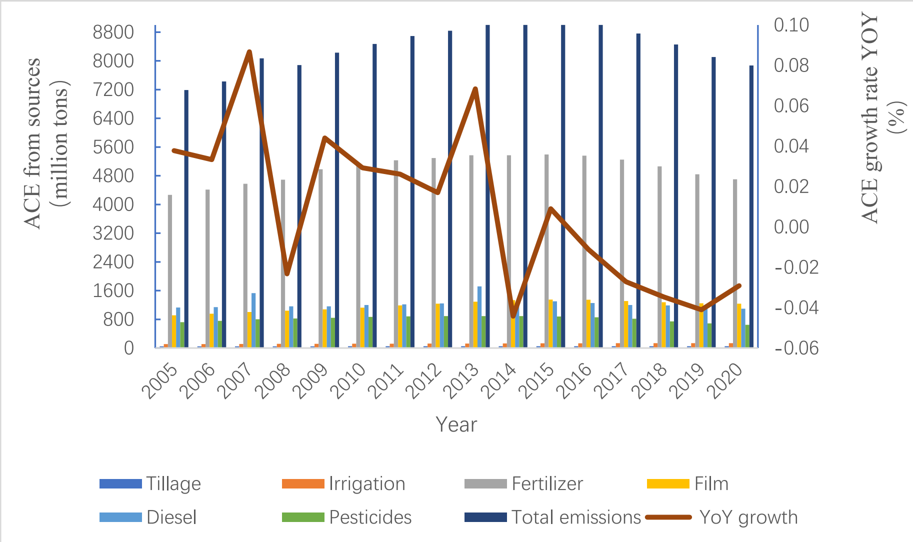

Fig. 2. Evolutionary characteristics of ACE in time series.

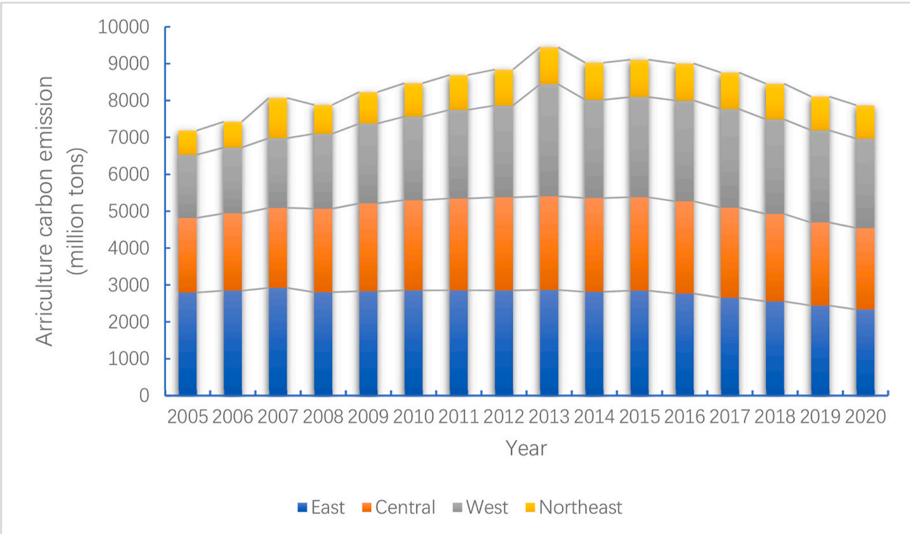

Fig. 3. Regional temporal evolution characteristics.

5.2. Analysis of the spatial distribution characteristics

For further understanding, this paper selects four years of ACE data: 2005, 2010, 2015, and 2020, visualizes the national ACE using ArcGIS software, obtains the spatial distribution map of ACE in each province of China, and divides each province into five classes according to the natural breakpoint method: high carbon emission areas, higher carbon emission areas, medium carbon emission areas, lower emission areas, and low carbon emission areas (Figs. 4–7).

From the spatial perspective: **(1)** It can be seen that the provinces with low ACE in China are concentrated in the eastern region and the western region. Among them, Beijing, Tianjin, and Shanghai are the provinces in the eastern region, mainly because of their high level of economic development and urbanization, which means that the scale of agricultural production is smaller and therefore the emissions are lower, and also because the land area in this region is smaller and the crops are less cultivated than those in other regions. The provinces in the western region are Tibet, Qinghai, and Ningxia. The low ACE in Tibet and Qinghai are mainly due to their complex topography and being covered by mountains, deserts, and glaciers, which are not conducive to crop cultivation. Ningxia is not a large province and is located on the Loess Plateau, so its ACE are low. **(2)** Xinjiang, Heilongjiang, the North China Plain, and the Middle and Lower Yangtze River Plains have higher ACE. The agricultural development in Xinjiang has the advantages of sufficient light and heat, biological resources, and a vast land area, but the disadvantages, such as insufficient soil fertility, an arid climate, and backward

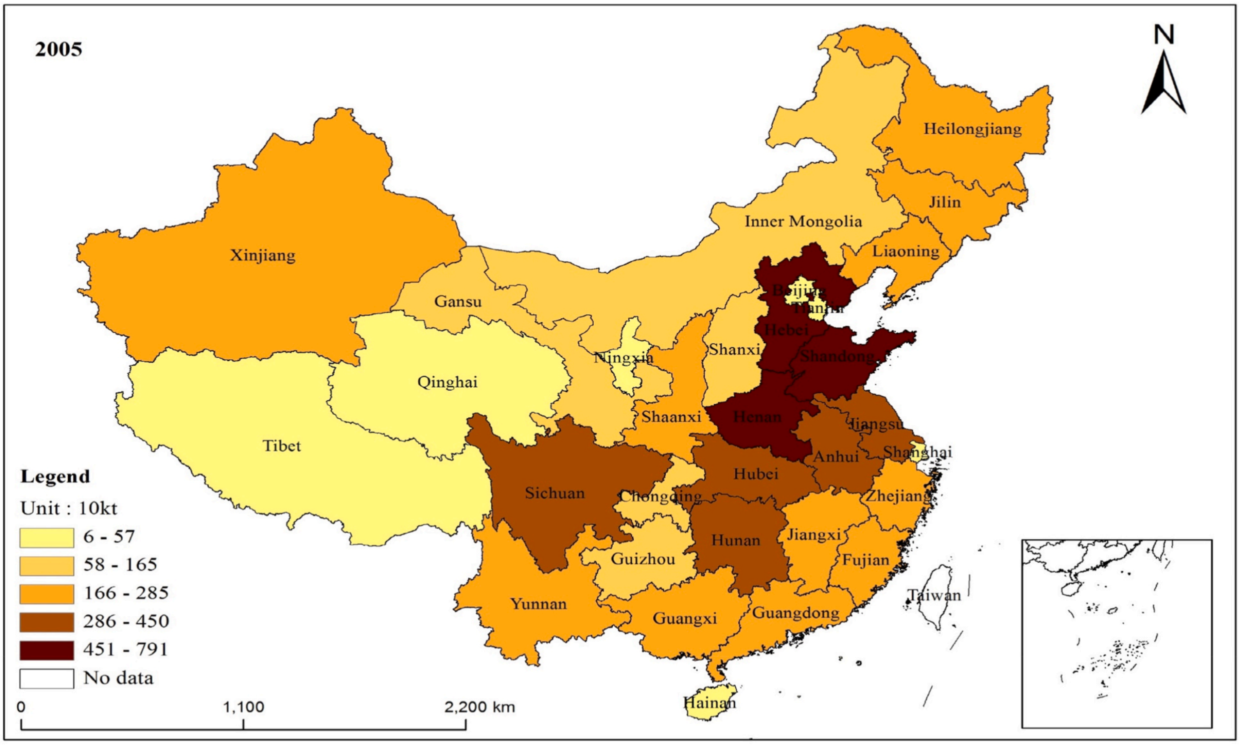

Fig. 4. Spatial evolution characteristics (2005).

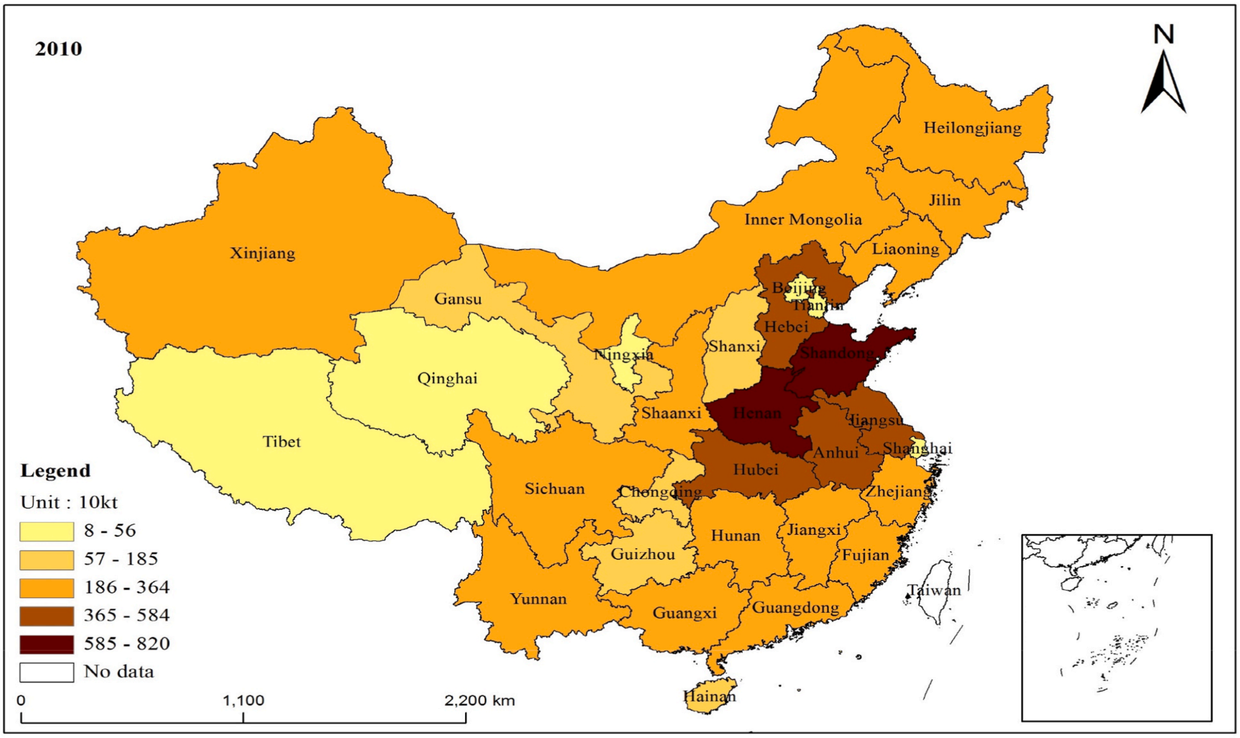

Fig. 5. Spatial evolution characteristics (2010).

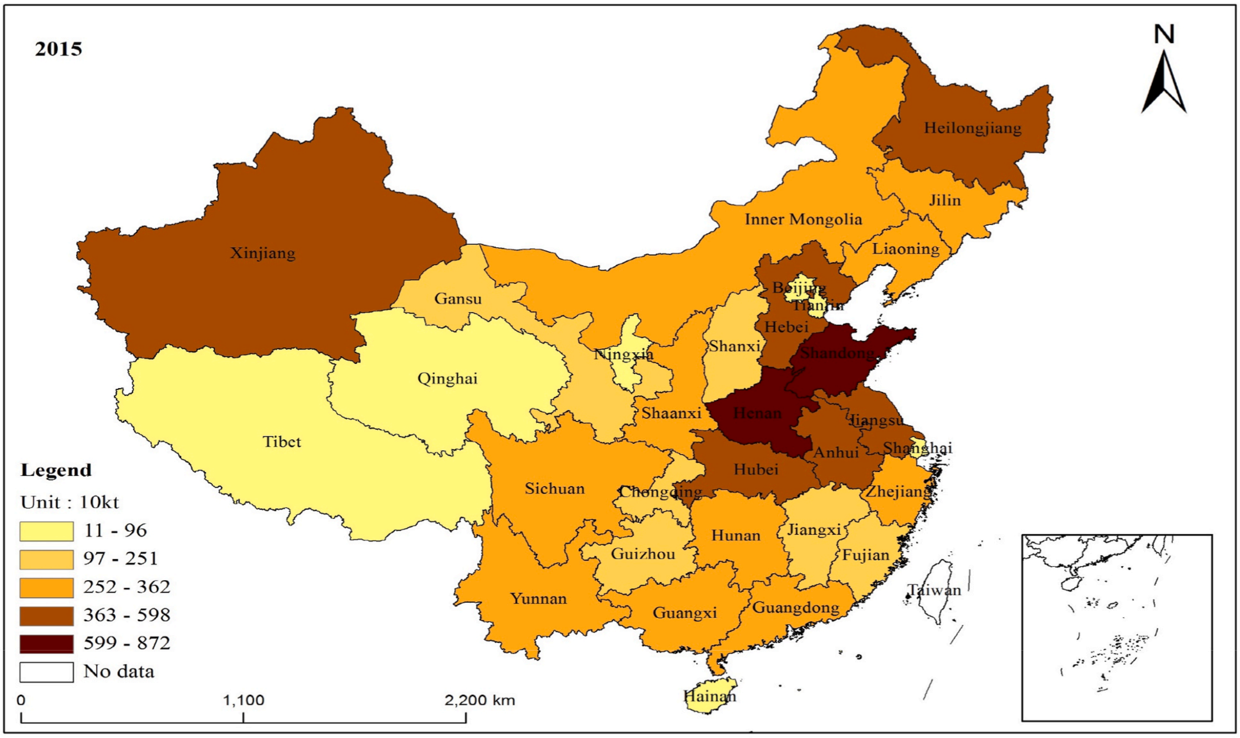

Fig. 6. Spatial evolution characteristics (2015).

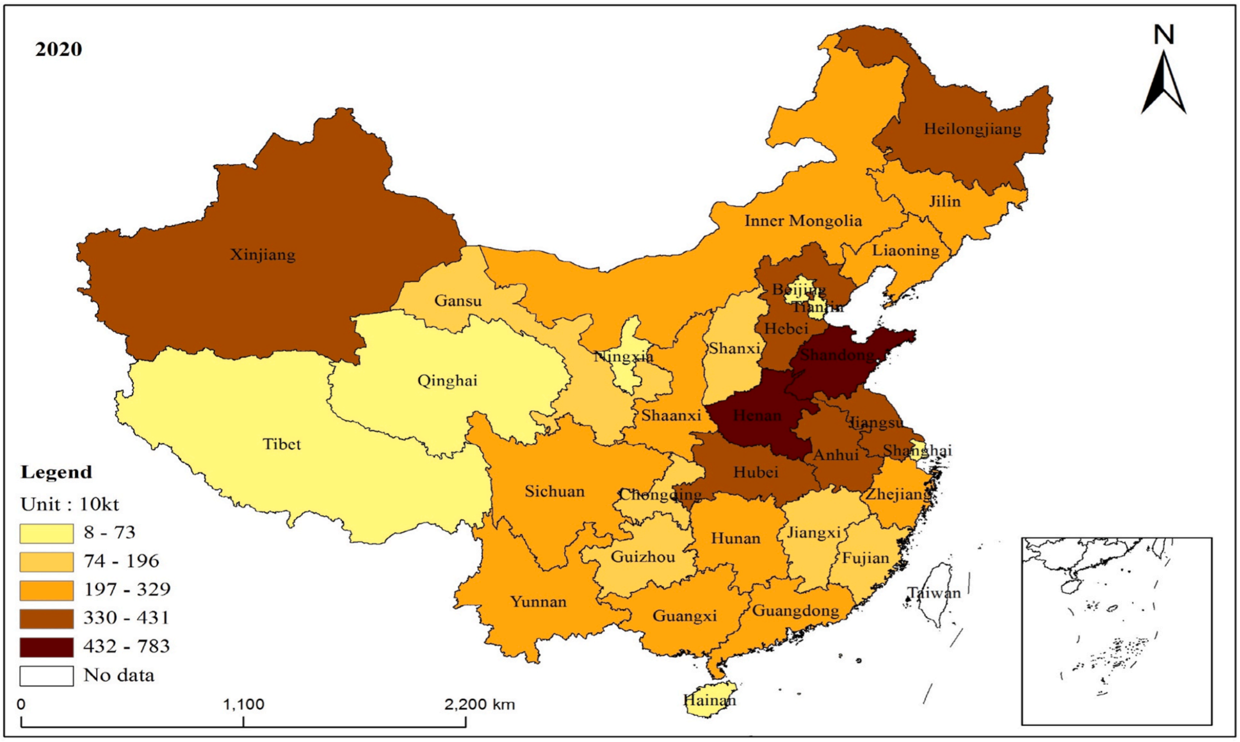

Fig. 7. Spatial evolution characteristics (2020).

production technology, lead to high agricultural material input and high ACE. Heilongjiang is a spring wheat-producing area in China, with abundant land resources and a large scale of agricultural cultivation. Provinces with high ACE also exist in the North China Plain, mainly because these areas have vast plains, moderate geoclimatic conditions, abundant arable land resources, and sufficient light, rain, and heat at the same time, making them suitable for a variety of crop production. Coupled with a large population and sufficient labor force, which is conducive to agricultural production activities, large-scale agricultural cultivation will inevitably increase ACE. The middle and lower reaches of the Yangtze River are known as the "land of fish and rice," and the natural environmental conditions are favorable for agricultural cultivation.

Specifically, in 2005, there was a pattern of "high east-central low west" with significant regional differences. The average value of ACE in that year was 2,138,600 tons, and there were 12 provinces and regions that were larger than the average value, accounting for 38.7% of the total sample. Three distinct high-emission zones and four low-emission zones are formed in the east, the central region has the largest number of higher-emission provinces, whereas the majority of provinces in the west are found in the low and moderate emission zones. And all three provinces in the northeast are in the moderate emission zones.

The mean value of ACE in 2010 was 2,732,600 tons, and the number of provinces and regions larger than the mean value increased to 14, accounting for 45.2% of the total sample. The most obvious change is that Hebei dropped from a high emission area to a medium-high emission area. In fact, Hebei is working to alter how agriculture develops, implement strong agricultural regulations, employ and promote essential technologies, which will reduce the usage of chemical fertilizers and pesticides. Secondly, Sichuan Province, Hunan Province and Inner Mongolia become moderate emission area. Because the scale of agricultural planting will be reduced in Sichuan and Hunan during this time due to low levels of agricultural industry, a lack of skilled labor, and high prices for agricultural materials. In contrast, in 2010, the central government and autonomous regions increased support for the Nenggu "three agricultural," resulting in a "double increase" in the total area of crops and grains sown in the region. The above results lead to a significantly higher number of moderate emission areas than several other types, but still show a gradual decreasing trend from east to west.

In 2015, compared with 2010, the average value increased to 2,937,900 tons, and the number of provinces and regions larger than the average value increased to 14. The changes in Heilongjiang and Xinjiang are particularly striking, as the color of the two provinces significantly increased and became medium-high emission areas. The area planted with grain crops in Heilongjiang has steadily increased over the past few years as a result of the addition of farmers' cooperatives, family farms, and agricultural machinery co-operatives. While Xinjiang's industrial structure was altered in 2015, and the characteristics of "grain increase and cotton decrease" are now apparent. This will result in a change in the amount of ACE in Xinjiang. In contrast, Jiangsu and Fujian Province became medium-low emission areas. This, in turn, results from the two provinces speeding up the modernization of agriculture during this time, as well as a change in the direction of growth that has increased the size and dynamism of the second and third sectors. The degree of change in the other provinces is not significant.

The type of ACE of each province (city) in 2020 did not change, but the average value plummeted to 2,539,700 tons and the number of provinces and regions was larger than the average value and decreased to 16 compared with 2015. Reducing ACE is inevitable since modern agriculture has evolved in the direction of ecological agriculture and tourism agriculture, making scientific production a trend.

5.3. Convergence analysis

Fig. 8 shows the results of σ convergence of ACE for the whole country and the eastern, central, western, and northeastern regions from 2005 to 2020. From the national level, from 2005 to 2010, the σ value continued to rise from 0.71 to 0.83, implying that the gap between ACE in various regions of China is widening and does not show σ convergence characteristics, after 2010, the σ value only

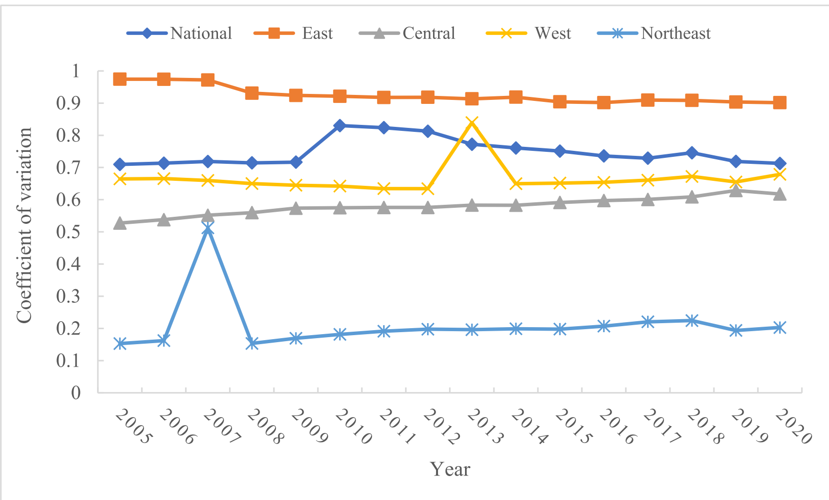

Fig. 8. σ convergence test.

fluctuated once in 2018 and still shows a decreasing trend overall, from 0.83 to 0.71 in 2020, implying that the gap of ACE among regions in China is gradually decreasing after 2010. By region, the σ value in the eastern region decreases slowly and flattens out throughout the sample period, indicating that the gap between ACE in the eastern provinces continues to decrease. In contrast to the eastern region, the σ value in the central region increases slowly throughout the sample period, indicating that the gap between ACE in the central provinces is widening. The σ value in the western region has been fluctuating, with a general trend of decreasing and then increasing. The σ value of the northeast region reached its maximum value in 2007, the possible reason is that, in the spirit of the Central Government's Document No. 1, grain production in Liaoning and crop sowing in Heilongjiang Province in that year were at record highs, and the material inputs used in agriculture increased year-on-year, resulting in greater intra-regional variation. And the years after that have shown an increasing trend, so there is no σ convergence in the northeast region during this period until 2019, when the σ value decreases.

Overall, the internal gap of ACE in the eastern region is significantly larger than that in the central, western, and northeastern regions; the internal gap of ACE in the western region is significantly larger than that in the central and northeastern regions; and the internal gap of ACE in the northeastern region is at the lowest level in all the study periods. This is due to the fact that the eastern region differs significantly from the western and central regions in terms of natural conditions, economic development status, and demographic traits. These differences are related to agricultural development and account for the largest internal variations in ACE. The variances within the northeast area are the lowest because it only has three provinces and shares characteristics with the western region in terms of geography, policy support, economic development, and other factors.

As shown in Table 2, the regression coefficient of absolute β convergence of ACE is −0.454 from the national perspective, which is less than 0 and passes the convergence test at the 1% significance level, indicating that there is a trend of absolute β convergence of ACE nationwide under similar development conditions and levels. This indicates that the regions with a higher level of ACE decrease faster than those with a lower level of ACE, and each region will eventually reach its own steady-state level of ACE. By region, except for the eastern region, where the convergence coefficient is greater than 0 and insignificant, the central, western, and northeastern regions all pass the convergence significance test at the 1% level, so it can be concluded that there is absolute β convergence in the central, western, and northeastern regions.

Nationally, the sign of the conditional β convergence coefficient of ACE is negative and passes the significance test at the 1% level. The results are shown in Table 3, which indicates that after taking into account economic and social factors such as agricultural industrial structure, urbanization level, agricultural machinery input intensity, agricultural labor force size, economic development level, etc., the ACE of each province (city and district) in China are developing toward their respective steady-state levels, and there is a conditional β convergence phenomenon.

Regionally, the convergence coefficients of ACE in the eastern, western, and northeastern regions are all negative and pass the significance test at the 1% level, so it can be concluded that the conditional β convergence phenomenon also exists in the eastern, western, and northeastern regions. The conditional convergence coefficients of ACE in the central region are not significant, then it can be concluded that there is no conditional convergence in the central region.

6. Analysis of spatial spillover effects

6.1. Global spatial autocorrelation test

The global spatial autocorrelation test needs to select the spatial weight matrix first. In this paper, a sparse adjacency matrix (the majority of elements in the matrix are 0) will be selected according to the research results of Lesage (2014) [41] and others, following the principles of simplicity and efficiency. Based on Eq. (2), the results of Moran's I index for total ACE in China are shown in the following table.

As shown in Table 4, the global Moran's index of ACE in 31 Chinese provinces from 2005 to 2020 is significantly positive, indicating that the spatial distribution of ACE in Chinese provinces is characterized by agglomeration. Specifically, the values of global Moran's I index range from 0.183 to 0.315, but the values generally show a decreasing trend from 2005 to 2020, indicating that the spatial correlation of the ACE is gradually weakening. The primary factor may be that secondary and tertiary industries have experienced significant growth in recent years as a result of widespread industrial restructuring. Secondly, due to administrative fragmentation, economic efficiency and the fragmentation of industries within regions, all parties will choose the priority industries to be developed in consideration of their own interests, and will no longer be vigorously promoting agricultural development. Lastly, the characteristics of

Table 2
Absolute β convergence.

	National	East	Central	West	Northeast
β	−0.454***	0.014	−0.190***	−0.491***	−0.790***
	(0.038)	(0.050)	(0.035)	(0.061)	(0.141)
_cons	125.122***	−7.071	77.284***	101.139***	247.908***
	(10.406)	(13.996)	(13.838)	(12.543)	(44.102)
N	465	150	90	180	45
r^2	0.250	0.001	0.264	0.278	0.434

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

Table 3
Conditional β convergence.

	National	East	Central	West	Northeast
β	−0.150***	−0.093***	−0.011	−0.316***	−1.132***
	(0.026)	(0.024)	(0.012)	(0.057)	(0.161)
IDS	0.476**	0.332**	0.365**	0.505	−3.130
	(0.201)	(0.144)	(0.163)	(0.409)	(2.061)
URB	−0.271*	−0.325**	−0.260	−1.112**	−3.533
	(0.161)	(0.124)	(0.318)	(0.526)	(2.910)
ICE	0.023***	0.027***	0.015***	0.040***	0.358***
	(0.005)	(0.006)	(0.003)	(0.014)	(0.130)
AML	0.005***	−0.000	−0.001	0.005	0.046***
	(0.002)	(0.001)	(0.001)	(0.007)	(0.013)
GDP	0.003***	0.002*	−0.002*	0.015***	−0.003
	(0,001)	(0.001)	(0.001)	(0.004)	(0.006)
_cons	−11.757	4.186	−2.501	−8.097	303.086
	(11.836)	(9.394)	(18.951)	(27.851)	(189.432)
N	465	150	90.000	180.000	45.000
r^2	0.100	0.268	0.686	0.165	0.578

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

Table 4
Global Moran's I index.

Year	Moran's I	Z-Statistics	*P*-value	Year	Moran's I	Z-Statistics	*P*-value
2005	0.315	3.295	0.000	2013	0.135	1.555	0.060
2006	0.314	3.288	0.001	2014	0.224	2.400	0.008
2007	0.304	3.143	0.001	2015	0.206	2.232	0.013
2008	0.293	3.067	0.001	2016	0.195	2.131	0.017
2009	0.286	2.993	0.001	2017	0.196	2.148	0.016
2010	0.276	2.899	0.002	2018	0.190	2.087	0.018
2011	0.262	2.770	0.003	2019	0.184	2.032	0.021
2012	0.254	2.686	0.004	2020	0.183	2.028	0.021

agricultural carbon emission concentration will also be weakened by the "double carbon" target and the environmental protection of each region. However, since ACE still show positive spatial correlation and agglomeration effect characteristics up to now, and this paper will use a spatial econometric model to examine the spatial spillover effect of ACE.

6.2. Model selection for spatial effect test

Before choosing the spatial econometric model, the natural logarithms of the four variables ACE, ICE, AML, and GDP need to be taken to make the data smooth. The LM test can determine whether there is a spatial lag term and a spatial error term, and the results show that the p-values for the SEM model were all significant at the 5% level, and the SAR model was not significant. Elhorst (2010) [42] points out that if either or both of the SEM and SAR models pass the LM test, the SDM model needs to be further estimated.

Therefore, this paper needs to do further tests on the model: the Wald test and the LR test, and the results are shown in Table 5. The p-values of the LR and Wald tests for both SAR and SEM models are 0, which are significant at the 1% level, i.e., both pass the test, indicating that the SDM model cannot be degraded to a SAR or SEM model, and therefore, it is more appropriate to choose the SDM model. After the SDM model was selected, the Hausman test was used to determine whether to use fixed effects or random effects, and the Hausman test for the model yielded a result of 18.78, which was significant at the 1% level, so fixed effects were selected.

6.3. Analysis of the effect results of each factor on ACE

Before analyzing the impact results of ACE, it is also necessary to choose the appropriate model among the three types (shown in Table 6) of area fixed effects (column 1), time fixed effects (column 2) and time individual two-way fixed effects (column 3), taking into

Table 5
Results of spatial panel model selection.

Variables	Statistic	*P*-value	Variables	Statistic	*P*-value
LM-Lag	0.284	0.594	LR-SDM-SEM	75.82	0.000
RobustLM-Lag	1.853	0.173	LR-SDM-SAR	37.12	0.000
LM-Error	4.204	0.040	Wald-SDM-SEM	36.47	0.000
RobustLM-Error	5.773	0.016	Wald-SDM-SAR	72.54	0.000

Table 6
Estimation results of the spatial Durbin model.

Variables	(1) Regional fixed effects	(2) Time fixed effects	(3) Two-way fixed effect
Main			
IDS	−0.007***	0.005***	−0.008***
	(0.001)	(0.002)	(0.001)
URB	0.007**	0.005***	0.004
	(0.003)	(0.002)	(0.003)
LnICE	0.081**	0.756***	0.054
	(0.041)	(0.037)	(0.041)
LnAML	0.169***	0.246***	0.162***
	(0.032)	(0.038)	(0.032)
LnGDP	−0.037	0.739***	−0.033
	(0.038)	(0.045)	(0.042)
Wx			
IDS	−0.004*	0.002	−0.010***
	(0.002)	(0.004)	(0.003)
URB	−0.014***	0.011***	−0.017***
	(0.004)	(0.003)	(0.006)
LnICE	0.248***	−0.094	0.154**
	(0.059)	(0.072)	(0.066)
LnAML	0.099	0.079	0.159**
	(0.061)	(0.068)	(0.066)
LnGDP	0.109**	−0.070	0.109
	(0.051)	(0.105)	(0.080)
Spatial			
rho	0.333***	−0.031	0.194***
	(0.054)	(0.068)	(0.062)
Variance			
sigma2_e	0.007***	0.062***	0.007***
	(0.000)	(0.004)	(0.000)
N	496	496	496
r2	0.582	0.937	0.514

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

account the significance of each variable, spatial autoregressive coefficients ρ, the goodness of fit of the model and other indicators, and the number of samples in this paper is larger than the number of periods, so that the selection of regional fixed-effects spatial Durbin model is more appropriate.

In the regional fixed-effect model, the spatial correlation coefficient ρ for ACE was 0.333 and significant at the 1% statistical level, indicating that there was a significant spatial correlation effect between each influencing factor and regional ACE. And except for a few variables, all other influencing factors have significant effects on ACE in both local and adjacent areas. However, LeSage and Pace (2009) [43] mentioned in their article that the spatial lag term introduced in the spatial Durbin model (SDM) affects the model estimation results when the coefficient ρ is significantly non-zero, which in turn leads to the inaccuracy of the estimated coefficients. Therefore, this paper will use partial differential methods to decompose the total spatial effects into direct and indirect effects as a way to explore the effects of each driver on ACE.

6.4. Spatial spillover effects of each factor on ACE

Based on the previous analysis, the total effect in space will be decomposed, and the decomposition results are shown in Table 7.

Impact of IDS: In terms of the decomposition of the direct effect, the IDS is negatively correlated to ACE; this indicates that the industry structure negatively affects ACE in the province. The probable reason is that, in this article, only the planting industry is considered in the measurement, and the carbon emissions of the livestock and forestry sectors are not added, which will affect the estimation results [32]. The plantation industry, in turn, has a carbon absorption function, which will reduce the atmospheric carbon stock to a certain extent. The indirect effect is manifested by the negative spillover effect of the industrial structures of adjoining provinces on the province's ACE. This is because the region will be affected by the emission reduction effect of the optimization of the IDS in the adjacent provinces, because when the proportion of agriculture in a certain region decreases, the supply of agricultural products may not be able to meet the needs of local people, and at this time, the demand for agricultural products in adjacent provinces will increase, which will promote the development of the plantation industry in adjacent provinces, thus bringing out an increase in native carbon emissions.

The coefficient of direct influence of URB level on ACE is significantly positive; the other thing is that because URB accelerates the migration of young rural populations to cities, which leads to the aging characteristics of agricultural production, and due to reasons such as ideology and the limited ability of individuals to master advanced technology, it is difficult to change agricultural production methods for a while, and in order to ensure the yield, the rational allocation of agricultural production factor inputs is not achieved, which thus increases ACE. The coefficient of the spatial spillover effect of URB is negative, indicating that the level of URB in adjacent

Table 7
Decomposition of the effect of spatial Durbin model.

Variables	Direct effect	Indirect effect	Total effect
IDS	−0.0071***	−0.0083**	−0.0154***
	(-5.525)	(-2.520)	(-3.998)
URB	0.0058*	−0.0159***	−0.0101
	(1.870)	(-2.852)	(-1.613)
LnICE	0.1086***	0.3847***	0.4934***
	(2.785)	(4.878)	(5.360)
LnAML	0.1823***	0.2255***	0.4078***
	(6.265)	(3.057)	(5.479)
LnGDP	−0.0274	0.1325**	0.1051
	(-0.769)	(2.024)	(1.454)

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

provinces may cut down ACE in the province. That's because adjacent provinces with high urbanization levels attract labor from their own provinces, which affects the scale of local agricultural operations, prompting agricultural producers to focus on large-scale and intensive production, improving the efficiency of green agricultural production, and thereby reducing ACE.

The coefficients for the direct and indirect effects of ICE on ACE are both positive and pass the significance level test. Possible explanations are that most of the primary industry employees are not highly educated, do not have a deep enough understanding of policies related to carbon reduction and sequestration in agriculture and rural areas, and do not have a good grasp of agricultural green and low-carbon production technologies, which can easily cause problems such as high resource consumption and excessive chemical inputs in the cultivation process. At the same time, the increase in the number of employees means further expansion of the agricultural process scale, an increase in material inputs to agricultural land, and an increase in the level of ACE. The competitive connection between adjacent areas and local areas will stimulate adjacent areas to enhance production as well, thus leading to increased ACE.

The coefficients of both direct and indirect effects of AML on ACE are significantly positive. The reason for this is that agricultural machinery can only operate normally after adding energy such as diesel and oil and then being put into agricultural production, so the greater the intensity of agricultural machinery input, the more energy is also consumed and the higher the ACE. Under the natural environment and the level of agricultural development, agriculture shows the characteristics of inter-regional operation, and the province will learn from and emulate the use and input of agricultural machinery in adjacent provinces.

The direct effect of economic development level on ACE shows a non-significant inhibitory effect, which is to say that the increase in agricultural development standards in this area can lessen ACE in this area. In contrast, an improvement in the level of economic development in adjacent provinces will lead to a dramatically improved reduction in ACE in the region. An increase in the level of economic development in a certain region may result in a decrease in agricultural production when the consumption demand of local residents shifts to adjacent provinces, prompting them to expand production and increase ACE. Simultaneously, economic development will attract labor migration, and producers will use alternative factors, such as machinery and fertilizers, for crop yield.

In terms of the gross effect, industrial structure had a significant inhibiting effect on reducing agricultural CO_2 emissions, while the amount of agricultural labor and the input intensity of agricultural mechanization had a significant facilitating effect on agricultural CO_2emissions, while the overall effect of other variables on agricultural emissions were not significant.

7. Main conclusions and policy implications

7.1. Conclusions

According to the data of 31 Chinese provinces from 2005 to 2020, the paper analyzes the temporal characteristics, spatial distribution characteristics, and convergence features of ACE in China, meanwhile applying a spatial econometric model to analyze the effects of each driver on ACE, and obtains the following results:

(1) During the research epoch, China's ACE showed a rising and then declining trend. By stages, emissions have been increasing from 2005 to 2013, and gradually decreasing from 2013 to 2020. The growth rate continued to decline after 2015. The spatial distribution of ACE is characterized as "East > Northeast > Central > West."
(2) From the results of convergence, it can be seen that except for the east, there is no σ convergence in the country and other three regions, that is, the gap of ACE in the region is widening. However, absolute β convergence exists in the central, western and northeastern regions, and ACE will eventually reach a steady-state level. After considering different influencing factors, it is found that conditional β convergence exists in the eastern, western and northeastern regions.
(3) Using the spatial econometric model for analysis, the results indicate that all the explanatory variable positively affect ACE, except for the insignificant influence generated by the level of rural economic development. The coefficients of the spatial lag term of agricultural industrial structure and urbanization level are significantly negative, that is, there is a negative spatial spillover effect of agricultural industrial structure and urbanization level in adjacent provinces, while other influencing factors show positive spillover effects.

(4) From the decomposition of the spatial spillover effect, except for the insignificant coefficient of economic development level on ACE, the other four influencing factors directly affect the ACE of this province, meanwhile indirectly affect the ACE of adjacent provinces, and some of the influencing factors have the phenomenon that the direct effect and spatial spillover effect cancel each other out.

7.2. Policy recommendations

Several policy implications of this study's conclusions are as follows:

Initially, distinct policies for the development of agricultural production. Due to regional differences in total volume, trend, carbon source structure, and steady-state characteristics, as shown by the temporal characteristics of ACE, unified development policies are not helpful for advancing efforts to reduce agricultural carbon emission levels. specialized subsidies for the introduction and education of low-carbon technology, production experiences, and planting patterns can be established in provinces with greater emissions. In order to encourage each unit to take the initiative to lower ACE, it is also important to establish a regulatory mechanism, an accounting system, improve the legal and regulatory framework, and set assessment standards in light of local conditions. Additionally, financial incentives and loan subsidies are provided to companies that use cutting-edge and environmentally friendly agricultural production technologies, and local agricultural producers are advised to buy new agricultural tools with a variety of functions, energy conservation and environmental protection, and efficiency colleges and universities.

Second, overcome the geographic restriction and improve the ties inside the region. It is essential to fully utilize the spatial effect and improve communication and collaboration because ACE have a positive spatial correlation, indicating the possibility of regional cooperation. On the one hand, to lessen the consequences of reciprocal competition, adjacent regions should overcome geographical barriers, exchange low-carbon technology successes, boost the transmission of low-carbon knowledge, and use demonstrative effects. On the other hand, by regulating macropolicies, enhancing interprovincial cooperation and linkage, maximizing the benefits of local climatic and resource endowments, and actively promoting leisure agriculture, ecological agriculture, urban agriculture, etc., we can jointly achieve the transformation of agriculture to a low-carbon industry.

Lastly, the results of the geographic panel regression also offer suggestions for cutting carbon emissions. Further optimize the agricultural structure and reduce the cultivation of crops with high resource consumption and large chemical inputs. Moderate promotion of urbanization promotes the scale and intensive operation of agriculture. Supports the growth of green industries to increase employment opportunities and entice agricultural workers to move into other industries. Optimizes the structure of agricultural machinery and equipment, speeds up the replacement of older, inefficient agricultural machinery with more advanced, low-carbon, and energy-saving agricultural machinery, and lowers the energy consumption of agricultural machinery. And raises the income level of farmers to make changes in their production methods and consumption concepts.

7.3. Deficiencies and prospects

There are still some limitations in this paper. (1) Only six agricultural carbon sources—fertilizer, pesticide, agricultural diesel, agricultural plastic film, tillage, and irrigation—are chosen for indicator measurement in this paper. Important sources of carbon, like burning straw and raising livestock, are not taken into account, and the breadth and accuracy of the sources are supplemented and improved in subsequent studies. (2) In terms of research perspective, carbon emission reduction in agriculture has its inherent characteristics, i.e., it can be carried out in terms of both carbon reduction and sink increase. Because the data for some early crops are insufficient, the carbon sink is not taken into account in this paper. Future studies must analyze and explore the carbon sink in greater detail in order to make the research conclusions more thorough. (3) Last but not least, the selection of control variables in this study is largely influenced by social and human factors rather than natural ones, which are unable to accurately reflect the underlying causes of ACE. Future analyses of agricultural carbon emission components could incorporate a system of natural indicators based on particular circumstances.

Declarations

Author contribution statement

Lijuan Su, Yatao Wang and Fangfang Yu: Conceived and designed the research, Performed the research, Analyzed and interpreted the data, Contributed reagents, materials, analysis tools or data and Wrote the paper.

Data availability statement

Data will be made available on request.

Additional information

No additional information is available for this paper.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Referring to the methodology of the National Bureau of Statistics of China, the eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan provinces; the central region includes Shanxi, Henan, Hubei, Hunan, Anhui and Jiangxi provinces; the western region includes Inner Mongolia Autonomous Region, Chongqing, Sichuan, Guangxi Zhuang Autonomous Region, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region and Tibet Autonomous Region; the northeast region includes Liaoning, Jilin and Heilongjiang provinces.

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