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Original Research

Spatial-Temporal Pattern Evolution and Influencing Factors of Agricultural Carbon Emissions in the Process of Rapid Urbanization: A Case Study of the Yangtze River Delta, China

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Abstract

Strengthening agricultural carbon emissions (ACE) reduction is an inherent requirement to promote the integrated development of ecological greenery in the Yangtze River Delta (YRD), and it has a significant driving effect and benchmarking significance for China to achieve carbon peaking and carbon neutrality. Based on panel data of 41 cities in the YRD from 2001 to 2019, this study reveals the spatial and temporal evolution pattern of ACE and identifies the influencing factors through methods such as CV, SDE, ESDA and SDM. The results are summarized as follows: (1) the ACE in the YRD show a fluctuating downward trend, and the gap between cities tends to widen; (2) the YRD shows emission characteristics dominated by agricultural material input, with a proportion of over 50% over the years, followed by rice cultivation and livestock breeding with the lowest proportion. In addition, Jiangsu and Anhui have higher proportions, followed by Zhejiang, and Shanghai; (3) these cities with high ACE are mainly located in the northwest regions of the YRD, and those with low ACE are mainly located in the southeast regions of the YRD. Furthermore, cities in the YRD have a positive global spatial autocorrelation, and the local spatial agglomeration pattern has strong characteristics of stability and spatial dependence; (4) the agricultural economic development level has an inverted U-shaped effect on ACE in the YRD. Meanwhile, the total rural population, total power of agricultural machinery, and urbanization level have a significant positive impact, while the agricultural planting structure and trade openness level are not significantly affected, but the rural non-farm employment level have a significantly negative impact on ACE. SDM further supports the influence of various factors, and it can be found that the agricultural economic development level and trade openness level exhibit significant negative spillover effects.

Keywords: agricultural carbon emissions, spatial-temporal pattern evolution, spatial Durbin model, Yangtze River Delta

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Introduction

Global warming caused by man-made greenhouse gases is a serious threat to human survival and development, and the formulation of relevant carbon reduction policies has gradually become an important issue for major countries in the world [1]. As the world's largest emitter of greenhouse gases, China has made voluntary emission reduction commitments at international conferences and put them into practice, making an important contribution to the regulation and control of global greenhouse gases. President Xi Jinping attended the 75^{th} United Nations General Assembly in September 2020, and proposed to strive to peak China's carbon dioxide emissions by 3030 and achieve carbon neutrality by 2060, demonstrating the responsibility of a major responsible country [2].

Industry and services are the main sources of carbon emissions, but the boosting role of the rapid development of agriculture cannot be ignored [3]. Over the past 40 years of reform and opening up, China's agricultural development has achieved remarkable results, and its grain production capacity has reached new heights, ensuring national food security [4]. However, China's agricultural production mode is still dominated by decentralized management, with scattered agricultural land and excessive use of agricultural materials such as pesticides, fertilizers, and agricultural films, resulting in high energy consumption in agricultural production and a large amount of greenhouse gas emissions [5]. Some data show that China's agricultural carbon emissions (ACE) account for 17% of the country's total carbon emissions, far exceeding the global average [6]. Statistics from the Food and Agriculture Organization (FAO) of the United Nations show that in 2017, China's ACE accounted for approximately 29.01% of Asia's ACE and 12.54% of the world's ACE [7]. Therefore, ACE reduction is not only related to the high-quality development of agriculture, but also directly affects the realization of China's "dual carbon" goal.

ACE are accompanied by agricultural development, run through all stages of human social development, and has become a key research topic in environmental science, agronomy, geography and other disciplines. Currently, relevant studies on ACE can be roughly divided into several categories. The first is the measurement and evaluation of ACE. For example, West and Marland conducted systematic research on the measurement of ACE in the USA, involving four dimensions: fertilizers, pesticides, agricultural irrigation and seed cultivation [8]. Johnson et al. believed that the ACE should involve five types of carbon emission sources in the agricultural production process: agricultural management activities, poultry farming, agricultural energy consumption, solid waste disposal and biomass burning. Based on this, they built a detailed index system to measure carbon emissions from agricultural production in the USA [9]. Lal systematically determined the carbon emissions generated by agricultural operations, pointing out that farming and irrigation were the most direct sources of ACE, and chemical fertilizers and pesticides were the most important indirect sources of ACE [10]. Thus, the diversification and complexity of agricultural production determine ACE diversity.

The second is the multi-dimensional relationship between ACE and agricultural economic growth. On the one hand, some studies investigate whether the environmental Kuznets curve (EKC) hypothesis exists between ACE and agricultural economic growth. For example, Managi was the first to discuss the EKC relationship between agricultural activities and greenhouse gases, and believed that agricultural technology innovation would have a long-term positive effect on reducing carbon emissions in the USA [11]. Based on the time series data of Sichuan province in China from 1997 to 2008, Li and Zheng found that the agricultural industry in Sichuan was in a stage of rapid development and had not yet reached the EKC inflection point [12]. Yan et al. found that China's ACE had an "inverted-N" EKC relationship with double inflection points [13]. On the other hand, some scholars have used the Tapio model to analyze the decoupling relationship between ACE and agricultural economic growth. Xiong et al. explored the relationship between ACE and the agricultural economy in Hotan, China, and found that the decoupling index between the two presented a dynamic evolution process of "decoupling, hooking, and decoupling" [14]. Han et al. examined the decoupling relationship between agricultural carbon emissions and agricultural economic growth in 30 provinces in China, and found that Beijing, Shanghai, Guangdong and other eastern provinces were in a state of strong decoupling, whereas most central and western provinces had a low degree of decoupling [15]. Additionally, in-depth studies have been conducted on the causal relationship between ACE and agricultural economic growth. For example, Zhang et al. based on time series data of China's major grain producing areas from 1996 to 2015, found that there was a two-way causal relationship between ACE and agricultural economic growth in the short and long term [16]. In general, the relationship between ACE and agricultural economic growth shows great heterogeneity in different regions and periods.

The third is an analysis of the factors that influence ACE. Most of the literature applies the Kaya identity, logarithmic mean Divisia index (LMDI) model, STIRPAT model, computable general equilibrium (CGE) model and other methods to conduct detailed research on the influencing factors. For example, using an improved Kaya identity, Li et al. found that economic development significantly increased China's ACE, while agricultural subsidies could effectively reduce ACE [17]. Using LMDI model, Zhao et al. believed that a higher proportion of water and soil resources would lead to higher agricultural inputs and more ACE [18]. Nguyen et al. used the STIRPAT analytical framework to examine the drivers of the ACE in major global economics. They found that trade openness and FDI inflows were beneficial for increasing ACE in the short run, but had negative effects in the long run [19]. Laborge et al. established a global CEG model to simulate and estimate the impact of current agricultural support measures on ACE, and found that coupled subsidies made ACE show an increase trend [20]. Additionally, some scholars have used econometric model methods such as quantile regression and geographically weighted regression to further explain the causes of ACE at the provincial scale in China [21, 22]. Overall, ACE is a complex formation process, and its dominant influencing factors may differ in different research areas and development stages.

To summarize, there is abundant research on ACE, which lays a good foundation for the analysis in this paper, but there are still the following shortcomings: (1) in terms of research scale, most of them focus on the national or provincial level, while research on the perspective of urban agglomeration is relatively lacking. Although urban agglomeration plays a crucial role in China's urbanization process, the contradiction between human and land is also extremely prominent. How to effectively reduce the carbon emission level of urban agglomerations has become the key to China's regional carbon emission governance; (2) in terms of research content, existing studies mostly focus on how to measure ACE, but fail to reveal their spatial-temporal evolution characteristics, and ignore the spatial heterogeneity and inter-regional correlation effect of ACE. The spatial autocorrelation method can describe the spatial relationship and degree of correlation between any regional unit and its neighboring units through the spatial weight matrix. Therefore, the application of this method can clarify the degree of spatial correlation of ACE and reveal its spatial distribution pattern; (3) in terms of influence method, the traditional econometric method treats the research units as independent and homogeneous individuals, ignoring the spatial connection between neighboring units. However, by nesting the spatial and temporal effects, the spatial econometric model can clarify the direct and indirect effects of various factors on ACE.

The Yangtze River Delta (YRD) is one of the regions with the highest comprehensive strength in China. However, in the process of rapid urbanization of the YRD, ecological problems such as water pollution, climate warming, and deteriorating air quality are becoming increasingly serious. In addition, with the continuous accumulation of a large number of people in urban centers, the increasing demand for agricultural production and the intensification of urban-rural conflicts pose challenges to the sustainable development of agriculture. In view of this, this study takes the YRD as the research object, and first conducts an effective measurement of ACE of the 41 cities in China from 2001 to 2019. Then, this paper also uses methods such as coefficient of variation (CV), standard deviation ellipse (SDE), and exploratory spatial data analysis (ESDA) to reveal the evolutionary characteristics of the spatial-temporal pattern of ACE. Finally, the main influencing factors are discussed in combination with the ordinary panel model and the spatial Dubin model (SDM) to provide certain decision-making thinking for promoting agricultural emission reduction and assisting the "dual carbon" goal.

Materials and Methods

Study Area

According to the "the Outline of the Yangtze River Delta Regional Integrated Development Plan" issued by the Central Committee of the Communist Party of China and the State Council in 2019, the YRD includes the Shanghai, Jiangsu, Zhejiang and Anhui provinces (Fig. 1). The YRD is located on the eastern coast of mainland China, with an area of 356,700 km^2. It is one of the regions with the most dynamic economy, the highest degree of openness, and the strongest innovation capability in China. It is also an important production area for a variety of agricultural products. In 2019, the YRD accounted for 3.72% of China's land, creating 13.12% of China's total agricultural output value and 12.73% of its grain output.

The study takes the four provinces of the YRD as the research area. According to the current administrative divisions in 2019, there were 13 prefecture-level cities in Jiangsu, 11 prefecture-level cities in Zhejiang, and 16 prefecture-level cities in Anhui. Thus, there are 41 basic units in the study area (Fig. 1).

Data Sources

This study employs a panel dataset consisting of 41 cities in YRD between 2001 and 2019. Agricultural data and relevant socio-economic data are obtained from China City Statistical Yearbook, China Rural Statistical Yearbook, Shanghai Statistical Yearbook, Jiangsu Statistical Yearbook, Zhejiang Statistical Yearbook and Anhui Statistical Yearbook from 2001 to 2019. Geographical data of provincial boundaries in China and city boundaries in the YRD, at a spatial resolution of 1:4000,000 are released by the National Geomatics Center of China. Considering that the current price of the total agricultural output value cannot be compared across years, this study uses constant prices in 2001 to eliminate the effect of inflation. Because the number of livestock provided by the official data is the number of livestock at the end of the year, the feeding cycle, breeding and slaughter of different species of livestock will have an impact on the number of livestock raised in the year. Therefore, this study adjusts the average annual feeding quantity of pigs, cattle and sheep by referring to Tian et al. [23].

Fig. 1. Map of the YRD.

Research Method

Measurement of ACE

Referring to the existing literature [12-15, 21-24], ACE are mainly based on three aspects: agricultural material input, rice cultivation and livestock breeding (Table 1). Agricultural material input includes the six sources of fertilizers, pesticides, agricultural plastic films, diesel oil, irrigation and tillage. For livestock breeding in the study, I only measure the three main types of poultry: pigs, cattle and sheep. Based on agricultural carbon sources, this study chooses the corresponding carbon emission coefficients to measure the ACE in the YRD. The formula is as follows:

$$E = \sum E_i = \sum T_i \times \delta_i \quad (1)$$

where E is the quantity of ACE (10^4 t); E_i is the carbon emission of specific source i; T_i is the amount of specific source i; δ_i is the ACE coefficient of specific source i. The ACE coefficients and the reference sources corresponding to each ACE source are listed in Table 1. For comparison and analysis, all values are converted to units of standard carbon equivalents.

Coefficient of Variation

CV is usually expressed as the ratio of the standard deviation to the mean of the sample and is used to reflect the discrete degree of the sample data. CV can be expressed as:

$$CV = \frac{1}{\bar{x}}\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2/n} \quad (2)$$

where x_i is the ACE value of city i; $\bar{x}$ is the average ACE value of all cities; n represents the number of cities, $n = 41$.

Standard Deviation Ellipse

The SDE is an analytical method used to characterize the spatial orientation distribution of geographic elements [29]. It mainly includes four basic elements: the ellipse center, rotation angle, long axis and short axis, which represent the relative position of the spatial distribution pattern, the main trend direction, and the degree of dispersion in the main and secondary directions. The specific calculation formula for the four elements can be found in earlier research [30].

Spatial Autocorrelation Analysis

In this study, the ESDA is introduced to reveal the degree of spatial clustering of ACE in the YRD. Among them, Global Moran's I is used to judge whether the distribution of attribute values in global space exhibits clustering or dispersion phenomenon [31]. Global Moran's I can be expressed as:

Table 1. ACE sources, coefficients and references.

Types	ACE sources	ACE coefficients	References
Agricultural material input	Fertilizers	0.8956 kg CE/kg	West and Marland [8]
	Pesticides	4.9341 kg CE/kg	Li et al. [12]
	Agricultural plastic films	5.1800 kg CE/kg	Tian et al. [23]
	Diesel oil	0.5927 kg CE/kg	IPCC [25]
	Irrigation	266.4800 kg CE/hm^2	Dubey and Lal [26]
	Tillage	3.1260 kg CE/hm^2	Wu et al. [27]
Rice cultivation		1.4322 t CE/hm^2	NDRC [28]
Livestock breeding	Pigs	34.0910 kg CE/(head·year)	IPCC [25]
	Cattle	415.9100 kg CE/(head·year)	IPCC [25]
	Sheep	35.1819 kg CE/(head·year)	IPCC [25]

$$GlobalMoran'sI = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{3}$$

where $x_i(x_j)$ is the value of ACE of city $i(j)$; $\bar{x}$ is the average value of ACE of all cities; W_{ij} is the spatial weight matrix, space adjacency is equal to 1, and non-adjacent is equal to 0; when the value of global Moran's I is close to 1, -1 and 0, it presents the cluster, disperse and random states of the ACE pattern, respectively; $S^2 = \Sigma^n_{i=1}(x_i - \bar{x})^2$.

In terms of local spatial autocorrelation, Local Moran's I can be used to explain the spatial correlation types and distribution pattern of attribute values between each regional unit and its neighboring units [32]. Local Moran's I can be expressed as:

$$LocalMoran'sI = \frac{(x_i-\bar{x})\sum_{j=1}^{n} W_{ij}(x_j-\bar{x})}{S^2} \tag{4}$$

where the value range of the Local Moran's I is [-1, 1]. When the value is greater than 0 and passes the 5% significance test, it means that the city is of the High-High (HH) or Low-Low (LL) agglomeration type; when the value is less than 0 and passes the 5% significance test, it means that the city is of the High-Low (HL) or Low-High (LH) agglomeration type; if the value fails the significance test, it is not significant.

Influence Model Setting

The STIRPAT model is used to quantify the effects of human activities on the ecological environment [33], which originates from the IPAT identity ($I = P \times A \times T$). The standard form of the STIRPAT model is as follows:

$$I = aP^bA^cT^de \tag{5}$$

where I, P, A, and T represent the ecological environment impact, population size, affluence and technology, respectively; a is a constant coefficient; b, c, and d are the parameters to be estimated for P, A and T; e is the error term. After taking the logarithm of both sides of Equation (5), Equation (5) can be transformed into:

$$lnI = lna + blnP + clnA + dlnT + lne \tag{6}$$

To study the factors influencing ACE, combined with the availability of data and the actual situation of YRD, this study establishes the extended STIRPAT model. The specific equation is as follows:

$$lnI = a_0 + a_1lnP + a_2lnA + a_3lnT + a_4lnS + a_5lnE + a_6lnU + a_7lnO + \varepsilon \tag{7}$$

where I is the total amount of ACE; P is population size, expressed by the total rural population; A is agricultural economic development level, expressed by the total agricultural output value; T is technology, expressed by the total power of agricultural machinery; S is agricultural planting structure, expressed by dividing the grain planting area by the crops planting area; E is rural non-farm employment level, expressed by percentage of rural non-agricultural employees in rural employees; U is urbanization level, expressed by percentage of urban population in total population; O is trade openness level, expressed by percentage of total import and export trade in GDP; a_1, a_2, ..., a_7 are exponents for the independent variables to be estimated; a_0 is the constant coefficient and ε is the error term. To test whether there is an inverted U-shaped curve between the agricultural economic development level and ACE, this study decomposes ln$A$ in Equation (7) into ln$A$ and (ln$A$)^2. Equation (7) can be transformed into:

$$lnI = \beta_0+\beta_1lnP+\beta_2lnA+\beta_3(lnA)^2+\beta_4lnT + \beta_5lnS + \beta_6lnE + \beta_7lnU + \beta_8lnO + \varepsilon \tag{8}$$

where β_2, β_3 are the regression parameters for ln$A$ and (ln$A$)^2, respectively. If β_2 is significantly positive

Table 2. Explanation and descriptive statistics of independent variables.

Independent variable	Definition	Unit	Minimum	Maximum	Mean
P	Total agricultural population	Ten thousand people	15.780	691.980	216.436
A	Total agricultural output value	One hundred million yuan	7.896	647.444	159.045
T	Total power of agricultural machinery	Million kilowatts	31.015	874.620	278.326
S	Grain planting area/crops planting area	%	30.260	94.952	63.794
E	Rural non-agricultural employees/rural employees	%	6.415	94.677	60.323
U	Urban population/total population	%	17.720	89.600	54.024
O	Total import and export trade/GDP	%	0.530	280.750	32.517

and β_3 is significantly negative, indicating that there is an inverted U-shaped curve between the agricultural economic development level and ACE in the YRD. Explanations of the specific variables are shown in Table 2.

The ordinary panel model does not consider the spatial interaction effect of the dependent variable, leading to biased parameter estimation results. Since ACE between cities may have spatial autocorrelation, the influence of each variable on ACE in the YRD can be explored through a spatial econometric model incorporating spatial-temporal effects based on the ordinary panel model [34]. Spatial error model (SEM), spatial lag model (SLM) and SDM are the three main types of spatial econometric model. In contrast to SEM and SLM, SDM fully considers the spatial correlation of independent and dependent variables and focuses on reveal the exogenous interaction effect caused by the correlation between the ACE of a certain city and various influencing factors of neighboring cities [35]. The formula used is as follows:

$$\begin{aligned} lnI = \gamma_0 + \rho WlnI + \gamma_1 lnP + \gamma_2 lnA + \gamma_3 lnT + \gamma_4 lnS \\ + \gamma_5 lnE + \gamma_6 lnU + \gamma_7 lnO + \gamma_8 WlnP + \gamma_9 WlnA \\ + \gamma_{10} WlnT + \gamma_{11} WlnS + \gamma_{12} WlnE + \gamma_{13} WlnU \\ + \gamma_{14} WlnO + \varepsilon \end{aligned} \tag{9}$$

where ρ is the spatial autoregressive coefficient; W is the spatial weight matrix; γ_1, γ_2, ..., γ_7 are the influence coefficients of all factors on ACE; γ_8, γ_9, ..., γ_{14} are the influence coefficients of the explanatory variables of spatial lag; γ_0 is the constant coefficient and ε is the error term.

Results and Discussion

Temporal Evolution Characteristics of ACE

As shown in Fig. 2, ACE in the YRD present a fluctuating downward trend overall, from 24.58×10^6 t in 2001 to 23.19×10^6 t in 2019, with an average annual decrease of 0.32%. Specifically, ACE have five-stage evolution characteristics: (1) the first stage (2001-2003), ACE are in steadily declining. The reasons may be as follows: on the one hand, because of the heavy burden on farms, the "three rural issues" have become increasingly prominent, and the enthusiasm of farms to cultivate land has been frustrated, resulting in a significant slowdown in the growth rate of agricultural material input [13]. On the other hand, China joined the WTO in 2001, and YRD is located on the frontier of China's opening up, which has effectively promoted the transformation of farms from farming to labor [36]; (2) the second stage (2003-2004), ACE show a linear upward trend, with an increase of 6.99%. The central government gradually increased its emphasis on agricultural development and issued the "No.1 Document" to benefit farmers. The overall recovery of agricultural production led to an increase in agricultural inputs and the continuous expansion of the scale of rice cultivation; (3) the third stage (2004-2008), ACE fall again. At this stage, the national government emphasized the importance of sustainable agricultural development and encouraged the development of circular agricultural and ecological agriculture. In addition, the frequent occurrence of natural disasters in 2007-2008, coupled with the outbreak of the international financial crisis, had a very significant negative impact on agricultural production; (4) the fourth stage (2008-2013), ACE show a steady upward trend, accompanied by the emergence of "carbon peaks", from 24.12×10^6 t in 2008 to 26.07×10^6 t in 2013. After 2008, agricultural production gradually recovered. The increase in input of agricultural materials was the key factor for the significant increase in ACE during this period; (5) the fifth stage (2013-2019), ACE show a plummeting trend. The energy conservation and emission reduction targeted of the "Twelfth Five-Year Plan" and the continuous introduction of a series of agricultural ecological governance policies by the state and local governments put forward new requirements for agricultural development. According to the formula (2), this study uses CV to measure the difference in ACE in the YRD. CV shows a slight upward trend, from 0.52 in 2001 to 0.64 in 2019, which indicates that the gap in ACE between cities in the YRD tends to widen.

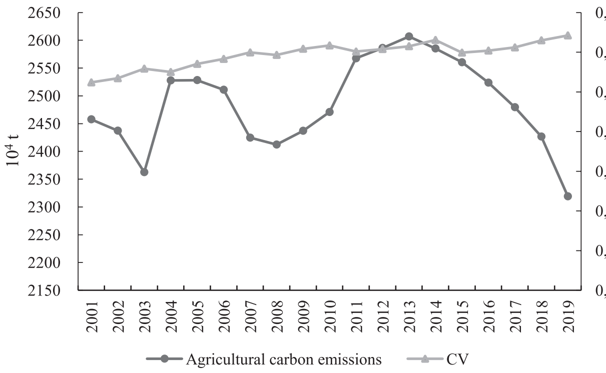

Fig. 2. The trend of ACE in the YRD.

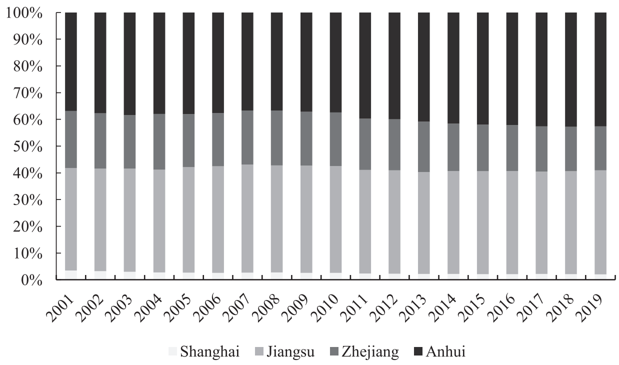

Fig. 4. The trend of ACE in different provinces in the YRD.

Fig. 3 shows the evolution of the proportions of these three types. It can find that the YRD presents the characteristics of the ACE structure dominated by agricultural material input. In 2019, agricultural material input accounts for 58.32% of the total ACE, followed by rice cultivation at 33.33%, while livestock breeding is the lowest at 8.35%. This has some similarities with the research conclusions of Wang et al., who found that carbon emissions from agricultural material input accounted for a relatively high proportion of China's ACE, reaching 40.65% in 2016 [37]. From the perspective of the change in proportion, only livestock breeding shows a downward trend, from 19.60% in 2001 to 8.35% in 2019, with a decrease of 11.25%. Due to the outbreak of major animal diseases such as African swine fever, the increased efforts of local governments to remediate the rural environment and the tightening of land resource constraints, the animal husbandry industry has shrunk sharply [38]. In general, the carbon emissions from agricultural material input far exceed those of the other two types. Therefore, to effectively control ACE in the YRD, inputs of chemical fertilizers, pesticides, and other materials should be reduced to ensure grain yield.

Fig. 4 shows the evolution of the ACE proportion in the four provinces. Jiangsu and Anhui have higher proportions, followed by Zhejiang, and Shanghai. From the perspective of the change in proportion, Anhui shows a relatively obvious upward trend, from 36.81% in 2001 to 42.64% in 2019, with an increase of 5.83%. In addition, Jiangsu's share has remained at approximately 38%, while Zhejiang and Shanghai both show a certain downward trend. In terms of regional prevention and control, attention should be paid to sustainable agricultural governance in Jiangsu and Anhui.

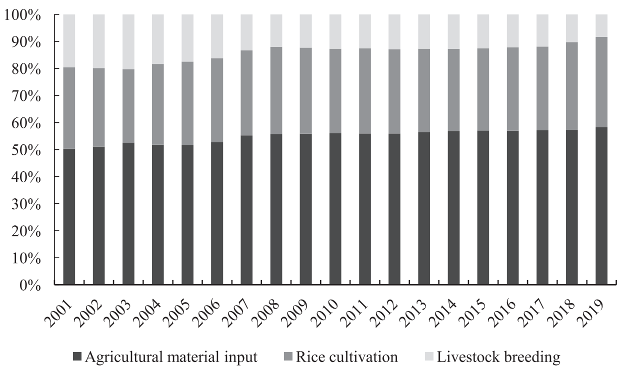

Fig. 3. The structure and trend of ACE in the YRD.

By choosing the above typical years involving 2001, 2008, 2013, and 2019, with the help of ArcGIS 10.2 software, this study calculates the parameters of SDE (Table 3), and draws the trajectory of the center of gravity and the distribution of the standard deviation ellipse (Fig. 5). From the center of gravity path, the center of ACE moves with Nanjing, and movement direction is generally toward the northwest, roughly moving 31.81 km, which fully indicates that ACE in the northwest of the YRD are relatively high. From the rotation angle, it increases from 132.79° to 134.53° with a small change, which indicates that the main development direction of ACE in the YRD is the northwest-southeast. This is probably because, the southeastern part of the YRD, involving southern Jiangsu, Shanghai and Zhejiang, has rapid non-agricultural economic development and a high level of urbanization, which has increased the occupation of arable land, resulting in a low ACE. Correspondingly, the northwestern part of the YRD, involving northern Jiangsu and Anhui, is rich in arable land resources, and agriculture plays a vital role in local economic development, therefore the ACE in this region are relatively high. From long and short axis of ellipse, the length of long axis decreases from 300.42 km to 280.45 km, and the length of short axis increases from 189.00 km to 190.84 km, indicating that ACE in the YRD show a shrinking and concentrated trend in the northwest-southeast direction, and a slight expansion trend in the southwest-northeast direction.

Spatial Evolution Characteristics of ACE

To visually reflect the different spatial distribution pattern of ACE in the YRD, this study grades ACE values and draws spatial distribution maps for ACE

Table 3. Parameters of SDE of ACE in the YRD.

Year	Long Axis (km)	Short Axis (km)	Rotation Angle (°)	Center of Gravity Path			
				Longitude (X)	Latitude (Y)	Moving Direction	Moving Distance(km)
2001	300.42	189.00	132.79	118.83°E	31.91°N		
2008	292.29	194.04	136.21	118.81°E	31.97°N	Northwest	7.04
2013	287.35	193.51	135.99	118.70°E	32.02°N	Northwest	11.98
2019	280.45	190.84	134.53	118.67°E	32.12°N	Northwest	12.79

in 2001, 2008, 2013, and 2019 (Fig. 6). As shown in Fig. 6, the spatial differences in ACE at the city scale are obvious, with the characteristics of high in the northwest and low in the southeast. In 2001, Yancheng, Xuzhou, Bozhou, Fuyang, and Lu'an are the 5 cities with the highest ACE, followed by Shanghai, Nantong, Anqing, Chuzhou, Huaian, Suqian, and Suzhou (in Anhui), whereas the ACE values of Huaibei, Ma'anshan, Tongling, and Huangshan are the lowest. In 2008, Yancheng, Xuzhou, Anqing, Lu'an, and Chuzhou are the 5 cities with the highest ACE, followed by Nantong, Huaian, Suqian, Lianyungang, Fuyang, and Suzhou (in Anhui), and the cities with the lowest ACE do not change. Overall, it still shows a trend of being high in the northwest and low in the southeast. In 2013, the number of cities with the highest ACE increase significantly, forming a "band-like" distribution in space, followed by Nantong, Suqian, Lianyungang, Bengbu, and Suzhou (in Anhui), whereas Huaibei, Tongling, and Huangshan continue to display the lowest ACE. In 2018, the number of cities with the highest ACE has decreased to a certain extent, whereas the number of cities with the lowest ACE has increased significantly. In short, the spatial pattern of high northwest and southeast low is clearer. In terms of the change in the number of categories, the proportion of cities with the ACE between 25 and 100 t decreases from 78.05% in 2001 to 65.85% in 2019. The number of cities with ACE greater than 100 t remained stable, while the proportion of cities with ACE less than 25 t increased from 9.75% in 2001 to 12.20% in 2019. It can be seen that the number of cities with higher ACE tends to decrease and the number of cities with lower ACE increases significantly, which further proves the objective reality of the decline of ACE in the YRD.

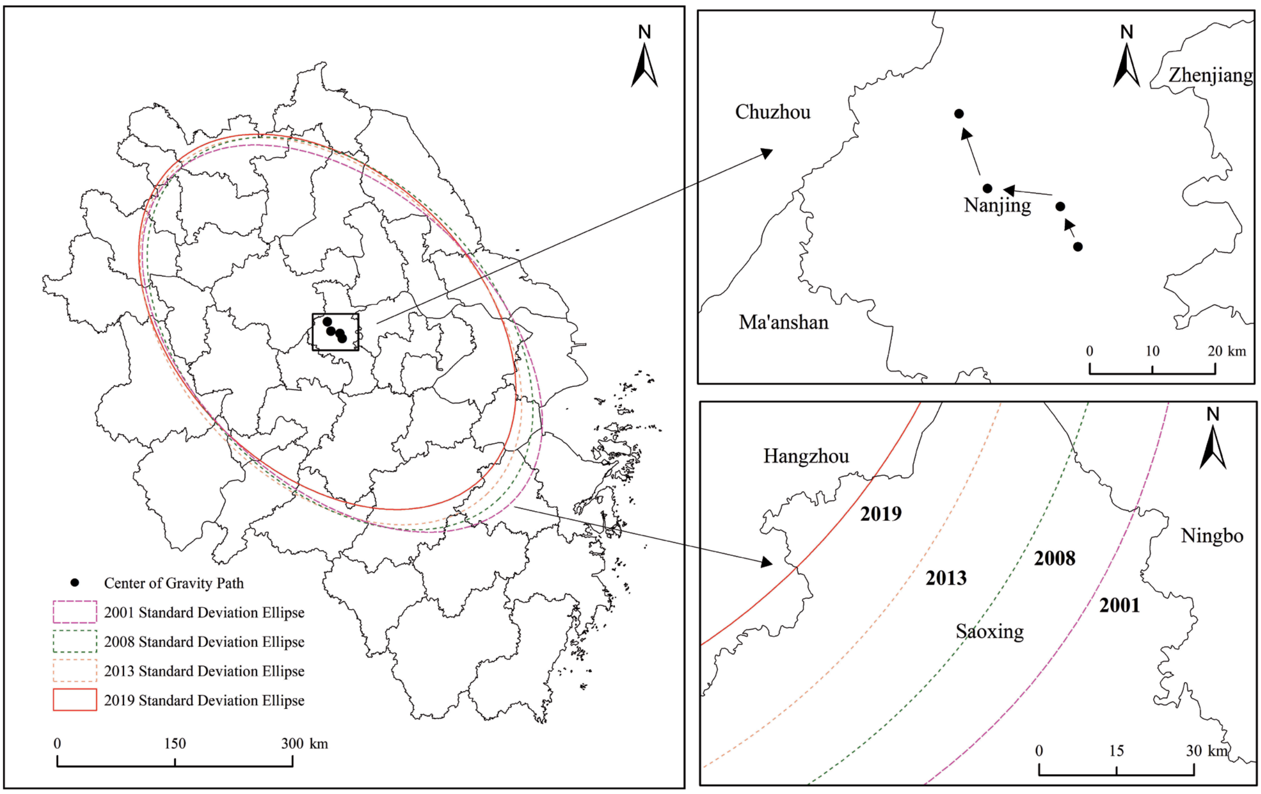

Fig. 5. SDE and center of gravity path of ACE in the YRD.

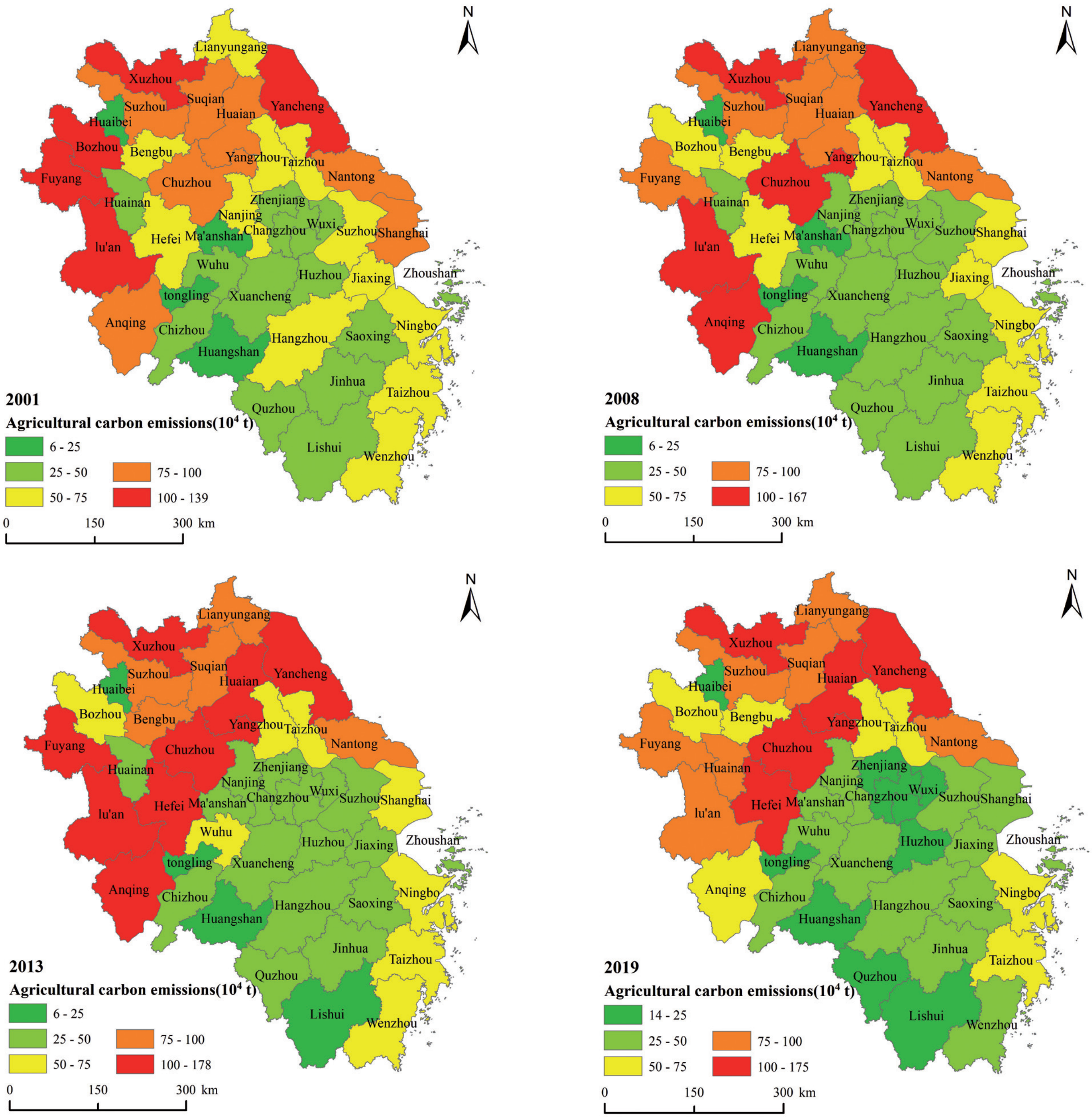

Fig. 6. Spatial distribution of ACE in the YRD.

Using GeoDa software, this study calculates the Global Moran's I to conduct the global spatial autocorrelation analysis from 2001 to 2019. During the study period, Global Moran's I is all positive and all P values are less than 0.05 (at the 5% significance level), indicating that cities in the YRD have a positive global spatial autocorrelation, that is, cities with high ACE or cities with low ACE tend to gather together. In addition, the evolution of Global Moran's I for ACE shows three stages of development. In the first stage, Global Moran's I presents a slight upward trend from 2001 to 2008, which means that the spatial autocorrelation of ACE is increasing. In the second stage, after 2008, Global Moran's I shows a steady development trend, mainly because of the negative impact of the 2008 international financial crisis on the agricultural economic development of the YRD. In the last stage, Global Moran's I shows a significant upward trend, from 0.36 in 2013 to 0.50 in 2019. With the continuous strengthening of agricultural ecological regulation by the state and local governments, the spatial concentration of ACE has increased significantly.

In order to reveal the local spatial correlation of ACE in the YRD, according to the time period characteristics of the Global Moran's I, with the help of GeoDa software and ArcGIS 10.2 platform, LISA cluster map of ACE in 2001, 2008, 2013, and 2019 is drawn, respectively (Fig. 7). As shown in Fig. 7, the local spatial agglomeration characteristics of ACE are evident, with HH agglomeration and LL agglomeration being the main types. In 2001, HH agglomeration cities include Nantong, Huaian, Suqian, and Lianyungang, while LL

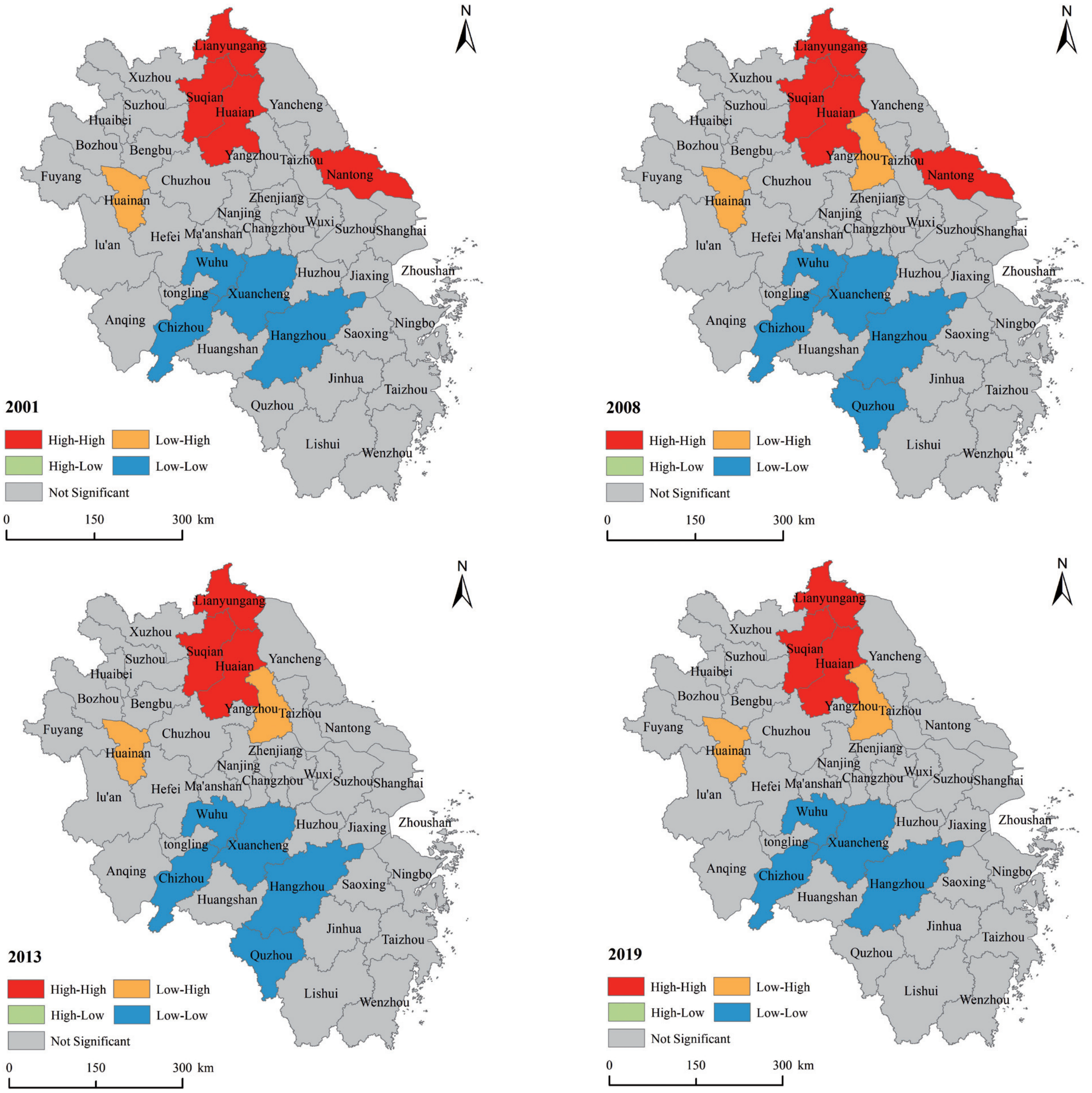

Fig. 7. LISA cluster map of ACE in the YRD.

agglomeration cities include Hangzhou, Xuancheng, Chizhou, and Wuhu, and LH agglomeration city is Huainan. In 2008, HH agglomeration cities don not change, HH agglomeration cities add Quzhou, and LH agglomeration cities add Yangzhou. In 2013, HH agglomeration cities reduce Nantong. In 2019, only Quzhou changes from LH agglomeration to an insignificant one. In general, the local spatial agglomeration pattern has strong stability and spatial dependence.

Influencing Factors Analysis of ACE

Before estimating the spatial panel model, this paper first conducts a regression analysis on the two-way fixed effect model that does not consider the spatial correlation of ACE. At the same time, in order to eliminate the multicollinearity between variables, this study also uses the stepwise regression method to analyze the influencing factors of ACE (Table 4). As shown in Table 4, when independent variables are gradually introduced, the sign and statistical significance of the independent variables do not change significantly. The only change is the size of the parameter estimates, and the range of change is not large, which indicates that the influence of the above factors on ACE in the YRD is real without the spatial effect. The specific results are as follows:

The primary and secondary terms of the agricultural economic development level are positive and negative at the significance levels of 1% and 5%, respectively, indicating that the impact of the agricultural economy on ACE is an inverted U type. It can be seen that in the early stage of agricultural development, a large amount of ACE are generated because agricultural economic growth is strongly dependent on the input of agricultural production factors. After the development of agriculture to a certain stage, with the wide application of agricultural technology and more emphasis on high-quality development of agriculture, the input of pesticides, fertilizers and other elements has gradually reduced, so ACE will drop significantly [15].

The influence coefficient of the total rural population on ACE in the YRD is positive, passing the significance test at the 1% level. This means that the more concentrated rural population will promote ACE. A possible reason is that, on the one hand, the agglomeration of rural population increases the demand for crops such as grain, which increases the input of pesticides, fertilizers and other elements; on the other hand, it has also brought about the construction of a large number of agricultural infrastructures, resulting in a large amount of resource consumption and environmental pollution in rural areas, and an increase in ACE.

The influence coefficient of the total power of agricultural machinery on ACE in the YRD is positive, passing the significance test at the 1% level. This means that the higher agricultural machinery level will promote ACE. Agricultural mechanization is rapidly spreading in rural areas of the YRD, but the agricultural technology level is low and still requires a large amount of fossil fuel consumption [21]. Therefore, while accelerating economic development, the YRD should pay more attention to agricultural science and technology, and gradually reduce the use of high-energy-consuming agricultural machinery and equipment.

The influence coefficient of the agricultural planting structure on ACE in the YRD is negative and does not pass the significance test at the 10% level. The reason why the agricultural planting structure has no significant impact on ACE may involve positive and negative effects. In terms of negative impact, different crops have different growth characteristics, and there are certain differences in the demand for agricultural chemicals. Compared with commercial crops, food crops generally have less demand for agricultural chemicals such as fertilizers, pesticides, and agricultural films [39]. Therefore, as the proportion of food crops increases, the input of agricultural factors may show a downward trend, and ACE will also decrease. In terms of positive impact, due to its unique natural geographical advantages, the YRD is very suitable for rice production. With the expansion of the planting area, ACE is bound to increase. Therefore, the influence of positive and negative interactions are not significant.

The influence coefficient of the rural non-farm employment level on ACE in the YRD is negative, passing the significance test at the 1% level. This means that the shift of farmers to non-agricultural industries will limit the ACE. This conclusion differs from those in the existing literature. For example, some scholars believe that the accumulation of surplus rural labor in cities and non-agricultural industries has led to a surge in the consumption of agricultural chemicals such as pesticides and fertilizers, as well as energy consumption such as diesel and electricity, in order to alleviate the impact of the reduction of rural labor force on agricultural production, which in turn worsens the rural ecological environment [40]. However, we believe that the transfer of rural labor to the manufacturing and service industries can effectively improve their cultural literacy and make rational use of advanced agricultural technology. In addition, the transfer of rural labor has promoted large-scale agricultural production. The emergence of new business entities, such as large-scale farms and family farms, has paid more attention to investment in machinery and technology, which has a positive impact on agricultural production and the agricultural ecological environment.

The influence coefficient of the urbanization level on ACE in the YRD is positive, passing the significance test at the 10% level. This means that the more agglomerated urban population and the higher the urbanization rate will promote ACE. With the acceleration of urbanization, the rural population moving into cities and occupying part of the arable land resources will inhibit agricultural carbon emissions to a certain extent. However, an improvement in the level of urbanization means that the scale of cities will expand and secondary and tertiary industries will continue to develop, which in turn will place higher requirements on agricultural production and aggravate the contradiction between supply and demand between urban and rural areas. In addition, young labor is transferred to cities and towns, and rural labor is characterized by aging, feminization and part-time employment. To avoid agricultural production reduction, a large amount of agricultural chemicals has been invested in, thus significantly increasing agricultural carbon emissions.

The influence coefficient of the trade openness level on ACE in the YRD is negative, not passing the significance test at the 10% level. Grossman and Krueger [41] divided the environmental effect of foreign trade into scale, structure and technology effects. In terms of the scale effect, the development of regional foreign trade will promote the expansion of agricultural production scale and the input of more agricultural factors, thereby causing resource consumption and environmental pollution. In terms of the structure effect, the development of trade can introduce regional agriculture into the international market and then force the internal structure of agriculture to adjust and reorganize the layout of agricultural production. This may lead to a series of changes in agricultural factor inputs, surface planted crop varieties, poultry feeding, etc., and there are uncertainties in the impact on the ecological environment. In terms of the technology effect, trade openness not only provides opportunities for the exchange of international agricultural production technology, promotes technology spillover in the import process, and improves the input-output efficiency of agricultural production, but also reduces environmental

Table 4. Baseline regression results.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ln$P$	0.130***	0.128***	0.108***	0.183***	0.194***	0.173***
ln$A$	0.599***	0.604***	0.599***	0.576***	0.569***	0.763***
(ln$A$)^2						-0.030**
ln$T$	0.369***	0.372***	0.392***	0.379***	0.382***	0.398***
ln$S$		-0.032	-0.033	-0.032	-0.039	-0.015
ln$E$			-0.138***	-0.139***	-0.136***	-0.125***
ln$U$				0.131*	0.157**	0.140*
ln$O$					-0.013	-0.015
Constant	-1.371***	-1.272***	-0.710***	-1.428***	-1.510***	-1.805***
City-Fe	Yes	Yes	Yes	Yes	Yes	Yes
Time-Fe	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.743	0.743	0.751	0.752	0.752	0.754

Note: *, ** and *** indicate that statistics are significant at the 10%, 5% and 1% level of significance, respectively.

pollution in the production process through the introduction of green technology, clean technology, and good land management. Therefore, by combining these three effects, this study presents an insignificant effect.

According to the above calculation results of Global Moran's I, there is a significant positive agglomeration effect of ACE between cities, and it shows the local spatial autocorrelation characteristics of HH agglomeration and LL agglomeration. Considering the spatial interaction effect, the SDM of two-way fixed effect is used to estimate the impact of different factors on ACE.

Because SLM and SEM are non-nested models, the test results of SDM should be further considered. This study adopts the Wald and LR tests and determines whether SDM can be reduced to SLM or SEM according to the two hypotheses ofH0: $\gamma = 0$ and H0: $\gamma + \delta\beta = 0$. If the hypothesis of H0: $\gamma = 0$ cannot be rejected, SDM should be reduced to SLM; if the hypothesis of H0: $\gamma + \delta\beta = 0$ cannot be rejected, the SDM should be reduced to SEM; the SDM is the optimal model if both hypotheses are rejected. The relevant test statistics are calculated using Stata 10.6 software, as shown in Table 5. According to the results in Table 5, the Wald and LR tests of the SLM and SEM all passed the significance test at the 1% level, and the two hypotheses are rejected, so the SDM cannot be simplified to SLM and SEM.

Compared with Model 5 in Table 4, there are some similarities and differences in the influence of the independent variables on SDM (Table 5). In terms of similarities, regardless of whether spatial interaction is considered, the significances of the respective variables remain unchanged. For example, the agricultural economic development level, total rural population, total power of agricultural machinery, and urbanization level all show a significant positive impact, while rural non-farm employment has a significant negative effect, while the agricultural planting structure and trade openness level have no significant effect. However, in terms of different points, if the spatial interaction effect is considered, the impact of the total rural population is significantly enhanced, and the total power of agricultural machinery is significantly reduced.

In this study, partial differential equations are used to decompose the influence effects of independent variables in the SDM into direct and indirect effects (or spillover effects) [42]. Among them, direct effects are the influence of the independent variables of this city on the ACE of this city, and indirect effects are the influence of independent variables of this city on the ACE of adjacent cities. As shown in Table 5, the direct effect of agricultural economic development level on local city is 0.464, and the indirect effect on neighboring city is -0.912, both of which pass the significance test of 1%, indicating that enhancing the agricultural economic development level has a promoting effect on ACE in local city, but has an inhibiting effect on neighboring city. The direct effect of the total rural population on local city is 0.287, and the indirect effect on neighboring city is 0.685, both of which pass the significance test of 1%, indicating that promoting rural population agglomeration has an enhanced effect on ACE in both the local city and the neighboring city. The direct effect of the total power of agricultural machinery on local city is 0.317, and the indirect effect on neighboring city is 0.475, both of which pass the significance test of 1%, indicating that the promoting agricultural machinery level has an enhanced effect on ACE. The direct effect of the agricultural planting structure on local city is -0.066, and the indirect effect on neighboring city is 0.128, both of which not pass the significance

Table 5. Regression results of the SDM.

Variable	Coefficient	T Value	P Value	Direct Effects	P Value	Indirect Effects	P Value
ln*P*	0.251***	5.200	0.000	0.287***	0.000	0.685***	0.000
ln*A*	0.567***	15.560	0.000	0.464***	0.000	-0.912***	0.000
ln*T*	0.274***	9.810	0.000	0.317***	0.000	0.475***	0.000
ln*S*	-0.070	-1.300	0.193	-0.066	0.189	0.128	0.246
ln*E*	-0.119***	-4.240	0.000	-0.148***	0.000	-0.039	0.662
ln*U*	0.158**	2.250	0.024	0.110	0.113	0.520**	0.022
ln*O*	-0.005	-0.470	0.638	-0.002	0.842	-0.073**	0.047
W×ln*P*	0.190*	1.730	0.083	rho = 0.305*** (P = 0.000)			
W×ln*A*	-0.458***	-5.410	0.000	R^2 = 0.761			
W×ln*T*	0.106**	2.110	0.035	Wald test spatial lag = 61.010*** (P = 0.000)			
W×ln*S*	0.047	0.560	0.577	LR test spatial lag = 57.690*** (P = 0.000)			
W×ln*E*	0.087	1.450	0.148	Wald test spatial error = 46.510*** (P = 0.000)			
W×ln*U*	0.452***	3.250	0.001	LR test spatial error = 243.580*** (P = 0.000)			
W×ln*O*	-0.061***	-2.830	0.005				

Note: *, ** and *** indicate that statistics are significant at the 10%, 5% and 1% level of significance, respectively.

test of 10%, indicating that the agricultural planting structure has no impact on ACE. The direct effect of the rural non-farm employment level on local city is -0.148 (P<1%), and the indirect effect on neighboring city is -0.039 (P>10%), indicating that promoting non-agricultural economic development and guiding non-agricultural employment of rural surplus labor are of great significance in reducing the local city's ACE. The direct effect of urbanization level on local city is 0.110 (P>10%), and the indirect effect on neighboring city is 0.520 (P<5%), indicating that accelerating local urbanization will significantly increase the level of ACE in surrounding cities. The direct effect of the trade openness level on local city is -0.002 (P>10%), and the indirect effect on neighboring city is -0.073 (P<5%), indicating that the development of trade has a spillover effect, which will significantly improve the level of agricultural technology in surrounding cities, thereby reducing ACE.

Conclusions

Based on panel data of 41 cities in the YRD from 2001 to 2019, this study measures ACE and analyzes the spatial-temporal evolution pattern of ACE in the YRD. On this basis, the ordinary panel model and SDM are used to empirically test the driving effects of the agricultural economic development level, rural population, agricultural machinery, agricultural planting structure, and other factors on ACE. The following conclusions are drawn.

Overall, the ACE in the YRD show a fluctuating downward trend, with an average annual decrease of 0.32%, and the gap between cities tends to widen. In terms of internal structure, the YRD shows emission characteristics dominated by agricultural material input, with a proportion of over 50% over the years, followed by rice cultivation and livestock breeding with the lowest proportion. In addition, Jiangsu and Anhui have higher proportions, followed by Zhejiang, and Shanghai. In terms of the center of gravity path, the center of the ACE moves with Nanjing, and the movement direction is generally toward the northwest. In terms of spatial distribution, cities with high ACE are mainly located in the northwest regions of the YRD, and those cities with low ACE are mainly located in the southeast regions of the YRD. In addition, cities in the YRD have a positive global spatial autocorrelation, and the local spatial agglomeration pattern has strong characteristics of stability and spatial dependence, for example, Huaian, Suqian, and Lianyungang have always been HH agglomeration, whereas Hangzhou, Xuancheng, Chizhou, and Wuhu have been LL agglomeration. In the regression analysis of factors affecting ACE in the YRD, the ordinary panel model shows that the agricultural economic development level has an inverted U-shaped effect on ACE, and the total rural population, total power of agricultural machinery, and urbanization level show a significant positive impact. Meanwhile, the agricultural planting structure and trade openness level are not significantly affected, but the rural non-farm employment level is significantly negative impact on ACE. Further, this study also uses SDM to analyze the spillover effects of influencing factors, and find that the agricultural economic development level and trade openness level exhibit significant negative spillover effects.

Based on the above conclusions, we put forward the following suggestions.

First, under the integrated development framework of ecological and green development in the YRD, at the government level, an interactive cooperation mechanism for ACE reduction and high-quality agricultural development should be established between different cities; at the enterprise level, the level of green technology development of family farms, cooperatives or agricultural enterprises should be improved; at the farmer level, improving the farmer's own cultural quality and cultivating awareness of low-carbon development, such as the rational application of chemical fertilizers and pesticides.

Second, there is a significant spatial autocorrelation of ACE in the YRD, which provides favorable evidence for regional integrated governance. While focusing on coordinated development, we should also pay attention to adapting measures to local conditions and adopting corresponding low-carbon agricultural development strategies for different types of cities. For LL agglomeration cities, they should make reasonable use of their own development advantages, and focus on breakthroughs in agricultural low-carbon technologies and changes in low-carbon agricultural management concepts; for HH agglomeration cities, they should improve the efficiency of agricultural resource allocation and minimize pesticides and fertilizers and other factorsThird, the significant inverted U-shaped relationship between ACE and agricultural economy in the YRD indicates that the inflection point of agricultural development has come. Therefore, in the future process of the agricultural economy, a modern agricultural industrial system, production system, and management system should be constructed to develop low-carbon agriculture and ecological agriculture, and then improve agricultural quality and competitiveness. In addition, differentiated agricultural development models should be developed according to the natural geographical conditions and economic advantages of each region. For the southeastern part of the YRD, the proportion of traditional agriculture should be reduced, and the advantages of economy, talents, science and technology should be used to vigorously develop modern agriculture, urban agriculture, tourism agriculture, sightseeing agriculture, leisure agriculture, etc., so as to improve the versatility of agricultural production and effectively reduce ACE; for the northwest of the YRD, it is necessary to make full use of local advantageous agricultural resources, effectively improve traditional agricultural production efficiency, and moderately develop modern agriculture.

Finally, the YRD should pay attention to the level of agricultural science and technology, and strengthen the improvement of traditional agricultural machinery and equipment, so that agricultural mechanization can be accelerated in the direction of large-scale, complex, energy-saving, efficient, intelligent, and precise. The speed of urban expansion in the YRD is too fast, and urbanization process should be promoted reasonably, and the development of low-carbon agriculture should be integrated into the whole process of urban and rural coordinated development. Trade openness has a significant negative spillover effect on the ACE of surrounding cities, indicating that the YRD should continue to expand the regional openness pattern, actively introduce advanced international low-carbon agricultural technologies, and realize the complementary advantages of the domestic and international markets.

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Conflict of Interest

The authors declare no conflict of interest.

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