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The Spatial-temporal Pattern Evolution and Influencing Factors of Agricultural Carbon Emission Efficiency in Jiangsu Province

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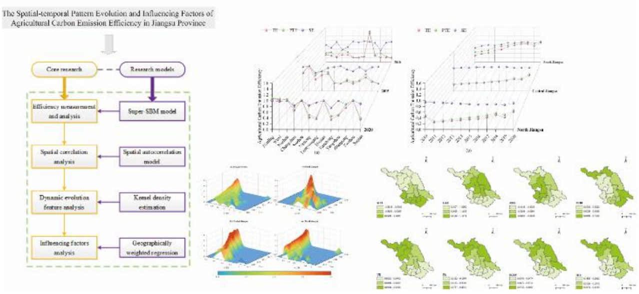
Graphical abstract



Abstract

Agriculture, as a pillar sector of the national economy, plays a crucial role in influencing the quality of the ecological environment through its carbon emissions. Jiangsu Province is a major agricultural region in China. Measuring agricultural carbon emission efficiency (ACEE), analyzing its spatiotemporal evolution characteristics, along with the influencing factors are of great significance for advancing the achievement of agricultural sustainable development goals in Jiangsu. This paper focuses on the 13 prefecture-level cities in Jiangsu Province and initially conducts a quantitative assessment of the carbon emission efficiency in the agricultural sector from 2010 to 2020 using the Super-SBM model. Subsequently, the paper investigates the temporal and spatial evolutionary characteristics of ACEE using spatial autocorrelation models and kernel density estimation. Finally, the paper employs the geographically weighted regression method to systematically analyze and interpret the key factors influencing efficiency. Based on the empirical research findings, three main conclusions can be drawn. (1) Regarding efficiency levels, the carbon emission efficiency in Jiangsu Province's agricultural sector has gradually improved, but it remains relatively low overall, with significant efficiency loss issues. (2) In terms of spatiotemporal evolution, the ACEE in Jiangsu Province improves over time and exhibits positive spatial clustering characteristics in space. (3) Concerning influencing factors, MCI, labor-land allocation efficiency, and other factors all have a significant impact on ACEE.

Keywords: Agricultural carbon emission efficiency, spatiotemporal characteristics, efficiency measurement, regional disparities

1. Introduction

1.1. Literature review

The intensifying trend of global warming, coupled with the frequent occurrence of extreme weather events, has posed severe environmental challenges that have become major obstacles on the path to sustainable development. Consequently, reducing carbon emissions to effectively address global climate change has become a core issue of widespread concern for governments worldwide. IPCC《AR6 Synthesis Report: Climate Change 2023》shows that the agriculture, forestry and other land uses sector, accounted for 13–21% of global total anthropogenic greenhouse gas (GHG) emissions in the period 2010–2019. As a major global player in the agricultural sector, the prominent carbon emission issues from China's agriculture have become a significant challenge that cannot be ignored in the field of environmental protection. Currently, China's agriculture is at a critical juncture, transitioning from extensive scale expansion to intensive deepening. During this phase, the widespread use of fertilizers, pesticides, and various agricultural production inputs, while enhancing agricultural output efficiency, also imposes more severe pressures and challenges on China's carbon emission management (Wang *et al.*, 2020).

Traditional agricultural efficiency assessment primarily focuses on desirable outputs such as agricultural output value and grain yield, while often overlooking undesirable outputs including various pollution emissions generated during agricultural production. This evaluation method tends to overestimate efficiency and underestimate policy effectiveness. Incorporating undesirable outputs such as carbon emissions allows for a more accurate measurement of agricultural efficiency. Scholars have employed various models, including DEA and SFA, to explore this topic from multiple perspectives. Research in this field not only reflects the academic community's high regard for environmental protection issues but also demonstrates proactive exploration of sustainable agricultural development pathways. In the course of academic research, the issue of agricultural carbon emissions initially attracted extensive attention in developed countries such as the United States, Germany, and Australia (Franzluebbers *et al.*, 2017; Nong, 2019; Vos *et al.*, 2019). Subsequently, academic attention has gradually expanded to developing countries that play an important role in global economic development, such as Brazil, India, China, and Egypt (Garofalo *et al.*, 2022; Radwan *et al.*, 2022; Sah & Devakumar, 2018; Zhu & Huo, 2022). As research deepened, some scholars have chosen representative organization members, such as EU member states and BRICS countries, as the object of comparative analysis. This approach aims to further broaden the theoretical perspective on agricultural carbon emissions research and enhance the understanding of issues within this field (Pata, 2021; Selvanathan *et al.*, 2023).

Taken together, discussions on agricultural carbon emissions primarily focus on two core topics. The first is the quantitative assessment of carbon emissions and the measurement of agricultural carbon emission efficiency (ACEE) (Zhang *et al.*, 2024). This area includes not only determining total emissions and defining efficiency metrics, but also analyzing spatiotemporal variations and regional interactions (Balsalobre-Lorente *et al.*, 2019; Cui *et al.*, 2021; Garnier *et al.*, 2019; Gui *et al.*, 2023; Hossain & Chen, 2022; Rong *et al.*, 2023; Żyłowski & Kozyra, 2023). The second core topic is the exploration of the factors influencing carbon emissions. Scholars have employed a variety of empirical models, such as LMDI, GMM, mediation effects, and moderation effects. In terms of driving factors, researchers have thoroughly studied the mechanisms by which a series of key factors, such as economic level, industrial structure, agricultural specialization, agricultural emission reduction policies, and urbanization level, affect carbon emissions (Agovino *et al.*, 2019; Solazzo *et al.*, 2016; Yang *et al.*, 2022; Yu *et al.*, 2020).

In recent years, key paradigms such as technological innovation and digital transformation have been increasingly integrating with multiple fields and gradually extending into the agricultural sector, emerging as frontier issues promoting sustainable agricultural development (Cai *et al.*, 2025a; Cai *et al.*, 2025b; Jin & Lei, 2023; Lei & Xu, 2025; Tian *et al.*, 2024). Against this backdrop, emerging factors such as agricultural green technology innovation and digital inclusive finance have entered the academic spotlight, providing new theoretical research directions for exploring pathways to reduce agricultural carbon emissions (Abbasi & Zhang, 2024; Cai *et al.*, 2024; Deng & Zhang, 2024; Li, 2023). However, existing research has largely focused on macro-level national or provincial analyses. Limited by the availability and completeness of micro-level statistical data, rigorous empirical research on how micro-level units respond to these emerging factors remains relatively scarce.

In summary, scholars have conducted extensive research and analysis on the topic of carbon emissions in agriculture, covering carbon emission sources, quantitative assessment, and influencing factors. Although these studies have accumulated rich research results and provided important references for further exploration of ACEE, there is still room for improvement in certain core areas that require further research. In terms of research methodology, existing studies have predominantly focused on desired outcomes such as agricultural yield improvement and economic benefits, while relatively neglecting the environmental pollution issues associated with agricultural production. Furthermore, they have not incorporated carbon emissions, a critical indicator, into the assessment of undesired outputs. Regarding research perspective, the current literature largely centers on comprehensive analyses at the national macro level, with a noticeable lack of detailed investigations at the provincial or municipal levels. In terms of research content, ACEE exhibit significant spatial heterogeneity across geographical spaces and at different time points. However, there is still insufficient in-depth exploration and analysis of this characteristic.

1.2. Study area

As an eastern coastal area, Jiangsu Province has vast plains, favorable natural conditions, and a good economic foundation. Jiangsu is a large economic province, and its economic development has always been the focus of attention of all sectors of society. In 2023, Jiangsu Province realized a GDP of 1,282.22 billion yuan, an increase of 5.8% over 2022 at constant prices. This figure highlights the strong momentum and vitality of Jiangsu Province's dynamic development. At the same time, as a major agricultural region with outstanding natural endowments, Jiangsu possesses a solid foundation in its agricultural industry. In 2023, Jiangsu maintained good growth rates in grain area, yields, and total production, with total production remaining above $3.5x10^8$ tons for 10 consecutive years. As one of China's economically developed provinces with a high level of agricultural development, Jiangsu Province is remarkably representative of the results of carbon emission research and practice in agriculture. This representativeness is not only reflected in the scale and structure, but also in the exploration of sustainable agricultural development and low-carbon transition.

Based on the "green carbon reduction" perspective, this paper defines carbon emissions as undesired outputs. This paper quantitatively evaluates the ACEE in Jiangsu Province using the Super-SBM model. Subsequently, relying on spatial autocorrelation analysis and kernel density estimation, the distribution characteristics and evolution laws of this efficiency indicator in time and space dimensions are deeply explored. In addition, to examine the main elements influencing ACEE, this paper adopts the geographically weighted regression analysis method, which provides a more geographically oriented and detailed explanatory perspective.

1.3. Research Innovations

The innovations of this paper are primarily reflected in the following aspects: First, it incorporates carbon emissions from the agricultural sector as an undesirable output into the indicator system for measuring the ACEE in Jiangsu Province. This allows for a more scientific and rational assessment of agricultural environmental performance. Second, the research perspective focuses on prefecture-level cities, enabling a more precise revelation of the differences and characteristics of regional ACEE. Third, the study examines the spatiotemporal evolution of ACEE, providing a reference for local governments to formulate differentiated emission reduction policies.

2. Material and methods

2.1. Super-SBM model

The Super-SBM model exhibits superior performance and distinct advantages over classical DEA models. In contrast, traditional radial DEA models can only proportionally expand outputs or reduce inputs, while neglecting the influence of slack variables. This limitation tends to overestimate efficiency scores and often results in multiple efficient units that cannot be further differentiated or ranked. The Super-SBM model, effectively addresses slack variables by directly incorporating and minimizing input and output slacks. This capability allows it to capture the potential for non-proportional improvements in performance indicators, thereby achieving more accurate efficiency measurements. Furthermore, classical DEA models such as CCR and BCC are unable to appropriately handle undesirable outputs like carbon emissions. The Super-SBM model, on the other hand, formally integrates undesirable outputs into the analytical framework, thus providing a more realistic assessment of environmental efficiency(Aldamak & Zolfaghari, 2017; Huang *et al.*, 2021). Therefore, the Super-SBM model has demonstrated excellent adaptability and utility in assessing various scenarios such as environmental performance and energy use efficiency.

$$\min \rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1+\frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^+}{y_{rk}}+\sum_{h=1}^{q_2}\frac{s_h^{b^-}}{b_{hk}}\right)} \tag{1}$$

$$s.t.\begin{cases} x_k = X\lambda + s^- \\ y_k = Y\lambda + s^+ \\ b_k = B\lambda + s^{b^-} \\ \lambda, s^-, s^+, s^{b^-} \ge 0 \end{cases}$$

In Equation (1), we use ρ as a key indicator to specifically quantify and characterize the value of ACEE. The size of ρ is directly related to the level of efficiency. $\rho > 1$, indicating that the decision-making unit reaches the efficiency frontier; $\rho < 1$ indicates that there is a loss of efficiency. Each city in Jiangsu Province is regarded as an independent decision unit consisting of m inputs, q_1 desired outputs, as well as q_2 undesired outputs. The slack variables s^-, s^+, s^{b-} represent inputs, desired outputs, and undesired outputs, respectively.

2.2. Spatial autocorrelation model

Considering the mobility of carbon emissions, it is particularly necessary to analyze the spatial pattern of carbon emissions in the target regions in depth, and to reveal their intrinsic distribution patterns and trends. This initiative aims to accurately characterize the geographical distribution of carbon emissions and provide a scientific basis for the formulation of regional emission reduction strategies.

Compared to simple spatial visualization methods, Moran's I enables statistical inference regarding spatial autocorrelation through rigorous hypothesis testing, thereby effectively identifying spatial dependence and providing a theoretical foundation for further in-depth research. The global Moran's I, constructed on the spatial weight matrix, provides a comprehensive assessment framework for the spatial interconnectedness of regional carbon emission efficiency (Huang *et al.*, 2019). The expression is as follows:

$$\text{Global } I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\left(Y_i-\bar{Y}\right)\left(Y_j-\bar{Y}\right)}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\right)\sum_{i=1}^{n}\left(Y_i-\bar{Y}\right)} \tag{2}$$

In Equation (2), ω_{ij} is the sxpatial weight matrix. The Global Moran's index, denoted by I, is between -1 and 1. When I>0, there is positive spatial autocorrelation, indicating that the observations tend to be concentrated in the spatial dimension; when I<0, it indicates that the data show negative spatial autocorrelation, i.e., the outliers tend to be spatially clustered; and when I=0, it indicates that the data are randomly disordered in the spatial distribution. In addition, researchers can further combine the calculation results of the global Moran index with the P-value test and the Z-value statistics for in-depth statistical inference analysis. $Y_i, Y_j, \bar{Y}$ denote the observations and overall sample means of evaluation units *i*, *j*, respectively.

2.3. Kernel density estimation

To comprehensively analyze the level and characteristics of ACEE in Jiangsu Province, focusing only on efficiency measurement and spatial autocorrelation analysis is not deep enough, and further analysis of its dynamic distribution and change patterns is needed. In contrast to simple graphical representations, the Kernel density estimation (KDE) captures complex distributional features of datasets through a nonparametric approach, producing a smooth probability density function. This capability allows it to clearly reveal the distributional morphology of efficiency values over time, thereby effectively uncovering regional differentiation in efficiency (Lu *et al.*, 2018; Wen *et al.*, 2022). It is assumed that there exists an independent and identically distributed data set containing the elements $\{x_1, x_2, \cdots, x_n\}$. For these data points, an approximation of their potential probability density function f (x) can be obtained by the kernel density estimation method. The expression is shown in Equation (3):

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n}K\left(\frac{x_i-\bar{x}}{h}\right) \tag{3}$$

Where, $K\left(\frac{x_i-\bar{x}}{h}\right)$ is the kernel function; n is the number of samples; *h* is the bandwidth; and $x_i, \bar{x}$, denote the sample observation and mean value, respectively.

2.4. Geographically weighted regression

Geographically weighted regression (GWR) can effectively can efficiently handle geographical variation in data. In many fields such as economics, natural resource management, etc., the influencing factors of the research object will produce different estimated coefficients with the change of spatial location. Traditional global regression models cannot deal with nonlinear and nonstationary spatial data, resulting in inaccurate regression results. GWR has a good ability to deal with this kind of data, and can estimate the regression parameters more accurately based on building a local regression model for each observation (Wang *et al.*, 2018; Xu & Zhang, 2021). Consequently, GWR has a wide range of applications in exploring the relative drivers of spatial changes in research objects. In ArcGIS software, the optimal bandwidth of the GWR model can be determined by minimizing the corrected Akaike Information Criterion (AICc) through the integration of optimization algorithms. The regression model is constructed as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{n} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \tag{4}$$

y_i is the value of the dependent variable for the ith observation; (u_i, v_i) is the spatial coordinate position of the observation point; $\beta_k(u_i, v_i)$ is a function of geographic location (u_i, v_i) and indicates the extent to which the independent variable affects the dependent variable at a particular location; $\beta_0(u_i, v_i)$ represents a constant term at a specific location; x_{ik} is the value of the kth independent variable at the ith observation; and ε_i is the random error term for the ith observation.

3. Indicators and data sources

3.1. Indicators

3.1.1. Efficiency indicator system

The essence of enhancing low-carbon agriculture lies in maximizing desired returns with less input and lower carbon emissions. Establishing a scientific input-output indicator system not only allows for the accurate quantification and assessment of carbon emission levels in agricultural activities but also provides a basis for implementing low-carbon agricultural development strategies (Liu *et al.*, 2025). Currently, many researchers have constructed corresponding evaluation frameworks based on dimensions such as agricultural development level and input conditions. In light of existing studies, this paper incorporates undesirable outputs into the research scope and establishes an indicator system.

Table 1. The input and output indicators

Indicator type	Indicators	Definition	Unit
Input	Labor input	Rural employees	Ten thousand persons
	Land input	Total sown area	Thousand hectares
	Fertilizer input	Fertilizer usage	Ton
	Pesticide input	Pesticide usage	Ton
	Agricultural plastic film	Agricultural plastic film usage	Ton
	Mechanical input	Total power of agricultural machinery	Ten thousand kW
	Irrigation input	Effective irrigated area	Thousand hectares
Desired output	Economic output	Gross agricultural output	Hundred million yuan
Undesired output	Carbon output	Agricultural carbon emissions	Ten thousand tons

From **Table 1**, it can be seen that indicators are selected from both socio-economic and natural factors. Among them, agricultural carbon emissions, as an undesired output, cannot be obtained directly. Therefore, this paper adopts the emission factor method to calculate the agricultural carbon emissions in Jiangsu Province according to the latest IPCC guidelines. This study only accounts for carbon emissions from crop production inputs, excluding CH_4 and N_2O emissions related to livestock farming as well as sources such as straw open burning. The formula is given below:

$$C = \sum T_i \cdot \delta_i \tag{5}$$

In Equation (5), *C* is the total carbon emissions from agriculture; the carbon emissions and emission factors for each source are T_i and δ_i, respectively.

The specific coefficient values are as follows: sown area 16.47 (*kg*(C)/*hm*^{2}), fertilizer 0.8956 (*kg*(C)/*kg*), pesticide 4.9341 (*kg*(C)/*kg*), agricultural film 5.18 (*kg*(C)/*kg*), machinery 0.18 (*kg*(C)/*kW*), irrigation 266.48 (*kg*(C)/*hm*^{2}).

3.1.2. Influencing factor index system

Apart from the allocation effects of land resources, labor inputs, and diversified agricultural resource factors, agricultural characteristics, economic indicators, and social development factors, also have a significant impact on ACEE. When selecting an indicator system for influencing factors, it is essential to comprehensively and thoroughly examine various relevant factors to ensure the rigor and validity of the analytical conclusions. Based on existing research findings, this paper selects the following key influencing factors for in-depth exploration:

Table 2. Definition and description of variables

Category of variables	Definition	Symbol	Unit
Cultivated land utilization efficiency	Crop sown area/cultivated land	MCI	%
Labor-land allocation efficiency	Area of grain sown/ rural employees	LAE	*hm^2/person*
Agricultural mechanization level	Total power of agricultural machinery/cultivated land	AML	*kW/hm^2*
Economic development	Per capita disposable income of rural residents	PCDI	Yuan/person
Urban-rural development	Urbanization rate	UR	%
Population ageing	Proportion of the population aged 65 and over	PA	%
Environmental regulation	Energy conservation and environmental protection expenditures/GDP	ECEP	%
Technological innovation	Science and education expenditure/fiscal expenditure	TI	%

Table 3. Statistical table of ACEE in Jiangsu Province

Year	TE	PTE	SE
2010	0.3511	0.4296	0.8287
2011	0.3109	0.3697	0.8673
2012	0.3453	0.4012	0.8814
2013	0.3997	0.4831	0.8691
2014	0.4270	0.5027	0.8798
2015	0.4979	0.5538	0.9049
2016	0.5338	0.5980	0.9014
2017	0.5850	0.6375	0.9124
2018	0.6326	0.6834	0.9112
2019	0.5630	0.6397	0.8823
2020	0.7328	0.7769	0.9261

*Note: TE=PTE*SE*

3.2. Data sources

The data utilized in this paper are sourced from the Jiangsu Statistical Yearbook, the Jiangsu Rural Statistical Yearbook, and statistical yearbooks compiled by the 13 prefecture-level cities in Jiangsu Province, as well as their respective statistical bulletins on national economic and social development. This ensures the authority, credibility, and comprehensive coverage of the data sources. Due to missing data on agricultural plastic film consumption and pesticide application in 2017 for cities such as Yancheng and Suqian, this paper employed an interpolation method to estimate the missing values. Additionally, the GWR model is sensitive to the units of measurement of variables. To prevent bias in regression coefficients resulting from differences in measurement units and to ensure comparability among various influencing factors in the model. All explanatory variables were normalized to the [0,1] range using min-max scaling before running the GWR model. This approach effectively eliminates the influence of measurement units while preserving the distribution characteristics of the original data (Cao *et al.*, 2019; Peng *et al.*, 2024) (**Tables 2 and 3**).

4. Results and discussion

4.1. Efficiency measurement and analysis

The following table summarizes the specific values of ACEE in Jiangsu Province between 2010 and 2020, which provides data support for evaluating the carbon utilization efficiency in Jiangsu Province's agricultural production process.

The mean Technical Efficiency (TE) of agricultural carbon emissions is 0.4890, with the mean Pure Technical Efficiency (PTE) at 0.5523 and the mean Scale Efficiency (SE) at 0.8877. As the PTE and SE improve, the TE has been continuously increasing, rising from 0.3511 in 2010 to 0.7328 in 2020. It can be observed that the enhancement of agricultural technological levels and the development of agricultural economies of scale have substantially promoted the overall level of ACEE in Jiangsu Province. However, this positive change does not imply that Jiangsu's ACEE has reached the efficiency frontier. The fact that all types of efficiency values remain less than one indicates that there is still room for efficiency improvement. This also highlights the current issues with efficiency losses and insufficient resource utilization in the agriculture of Jiangsu Province. Furthermore, the fact that the PTE values are lower than the SE values indicates that the technology for energy conservation and carbon reduction in agriculture in Jiangsu Province is still in its initial stages, and agricultural resources are not being fully and effectively utilized. There is considerable scope for Jiangsu Province to advance agricultural technological progress. It is urgent to further expand efforts in technology research and development and dissemination to achieve the long-term goals of green and low-carbon development in agriculture.

Due to dimensional constraints, traditional two-dimensional charts are limited to presenting unidirectional correlations between spatial or temporal dimensions and efficiency values, making them inadequate for supporting multi-element coupling analysis. The 3D waterfall plot, by constructing a three-dimensional data field, effectively enhances the capture capability for dynamic evolution characteristics of the data, thereby achieving integrated three-dimensional visualization of spatial-temporal-efficiency dimensions. As illustrated in subplot (a) of **Figure 1**, this paper conducts a longitudinal comparison of efficiency values across 13 prefecture-level cities in Jiangsu Province for the years 2010, 2015, and 2020. Time-series analysis reveals that the comprehensive TE, PTE and SE of most cities demonstrate a significant upward trend, corroborating the continuous improvement of ACEE in Jiangsu Province. At the city level, Xuzhou exhibits the most pronounced gains across all three efficiency values, while Yancheng registers the lowest level of efficiency improvement. In subplot (b) of **Figure 1**, the research scope is expanded to the regional scale, dividing Jiangsu Province into three major regions—South Jiangsu, Central Jiangsu, and North Jiangsu—based on geographical location. Dynamic analysis reveals that the efficiency values across all three regions generally maintained a fluctuating upward trend. Among these, South Jiangsu demonstrated outstanding performance in TE and PTE metrics, leveraging dual advantages in economic foundation and environmental policies. Central Jiangsu, through its efficient resource allocation mechanisms, established comparative advantages in SE. In contrast, North Jiangsu faces constraints from the dominance of traditional cropping patterns, relatively outdated agricultural management practices, and insufficient large-scale operational capacity. These factors collectively contribute to its relatively lagging agricultural modernization trajectory, directly limiting the holistic improvement of its ACEE.

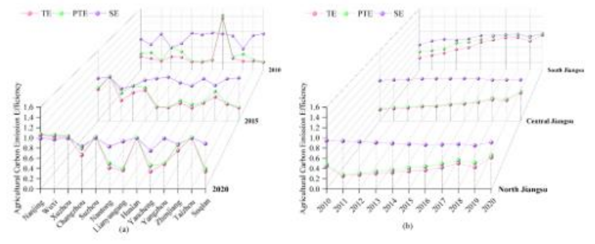


Figure 1. 3D waterfall plot of ACEE in Jiangsu Province

4.2. Spatial correlation analysis

Due to differences in geographical environment and agricultural structure, the ACEE in various cities of Jiangsu Province exhibits a certain degree of spatial heterogeneity. Exploring the spatial distribution characteristics of ACEE is of significant importance for developing a precise and efficient low-carbon agricultural development strategy in Jiangsu Province. In the Global Moran's I index, the spatial adjacency matrix serves as the weight matrix.

Table 4. Global Moran's index of ACEE in Jiangsu Province

Year	I	Z	p
2010	0.365	3.31	0.001
2011	0.149	1.707	0.088
2012	0.454	3.92	0.000
2013	0.47	4.024	0.000
2014	0.515	4.333	0.000
2015	0.469	4.052	0.000
2016	0.434	4.106	0.000
2017	0.505	4.301	0.000
2018	0.404	3.569	0.000
2019	0.197	2.016	0.044
2020	0.322	2.953	0.003

As shown in **Table 4**, the Global Moran's I statistics for ACEE in Jiangsu Province during 2010-2020 are all positive and statistically significant, indicating robust positive spatial autocorrelation in ACEE over the study period. This implies a spatial clustering pattern of efficiency values among adjacent regions. Despite variations in economic foundation, social structure, and environmental governance capacity across Jiangsu's prefecture-level cities, the high homogeneity of natural baseline characteristics such as climatic conditions and soil types, coupled with similarities in dominant agricultural industrial structures, collectively shape the convergent development pattern of inter-regional ACEE. In addition to environmental homogeneity, factors such as knowledge spillover and technology diffusion must also be considered. Cities with advanced low-carbon agricultural technologies often exert positive spillover effects on neighboring regions, facilitating cross-regional technology mobility and promoting spatial convergence of efficiency levels. Furthermore, within the unified provincial administrative framework, policy coordination and emulation mechanisms fostered by this structure drive synchronized changes in regional ACEE performance.

4.3. Dynamic evolution feature analysis

To analyze the dynamic changes in ACEE in Jiangsu Province, the non-parametric kernel density estimation is adopted for evaluation. The method overcomes the limitations of traditional estimation methods and can flexibly show the subtle dynamics of efficiency changes, increasing the uniqueness and innovation of the study. **Figure 2** presents the regression results.

Figure 2 presents the spatiotemporal distribution characteristics of ACEE across Jiangsu Province and its three major regions. First, regarding the evolution of the distribution centroid, a notable rightward shift is observed in the ACEE distribution centroids of Jiangsu Province and its southern, central, and northern regions during the period, indicating sustained optimization of agricultural ecological efficiency across all regions. This also indicates that alongside the overall enhancement of provincial ACEE, certain "leading cities" have emerged. Therefore, proactive efforts should be made to establish cross-regional technology promotion service platforms. These platforms will facilitate technology transfer from high-efficiency cities to low-efficiency cities, narrow the spatial disparity in efficiency distribution, and ultimately foster coordinated and balanced ACEE development across the entire region. Second, based on peak characteristic analysis, the peak values of the horizontal ACEE distribution for Jiangsu Province and its three regions showed a declining trend during the observation period. The peak shape gradually transformed from sharp peaks to broader peaks. Traditional one-size-fits-all policies would prove ineffective, necessitating tailored strategies that differentiate between cities with varying efficiency levels. Finally, further analysis of the number of peaks and the distribution pattern reveals that the number of side peaks in South Jiangsu is higher than in Central Jiangsu and North Jiangsu. Specifically, South Jiangsu exhibits multi-peak distribution characteristics accompanied by a distinct right-skewed tail. In contrast, Central Jiangsu and North Jiangsu have fewer side peaks and less prominent tailing characteristics, reflecting a relatively balanced distribution of ACEE levels in these two regions. Overall, while the ACEE in Jiangsu Province demonstrates an upward trajectory, the issue of inter-regional development disparity persists.

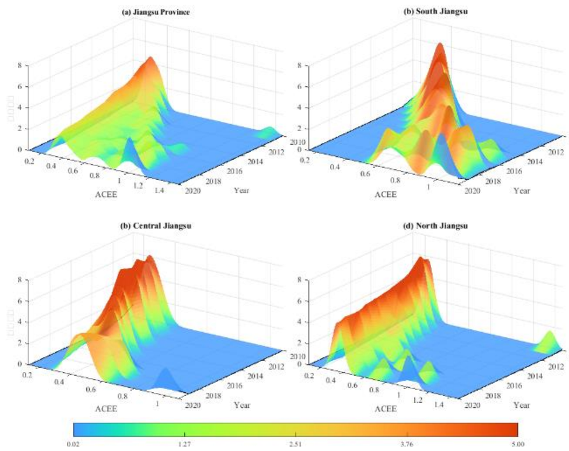


Figure 2. Kernel density estimation of ACEE in Jiangsu Province

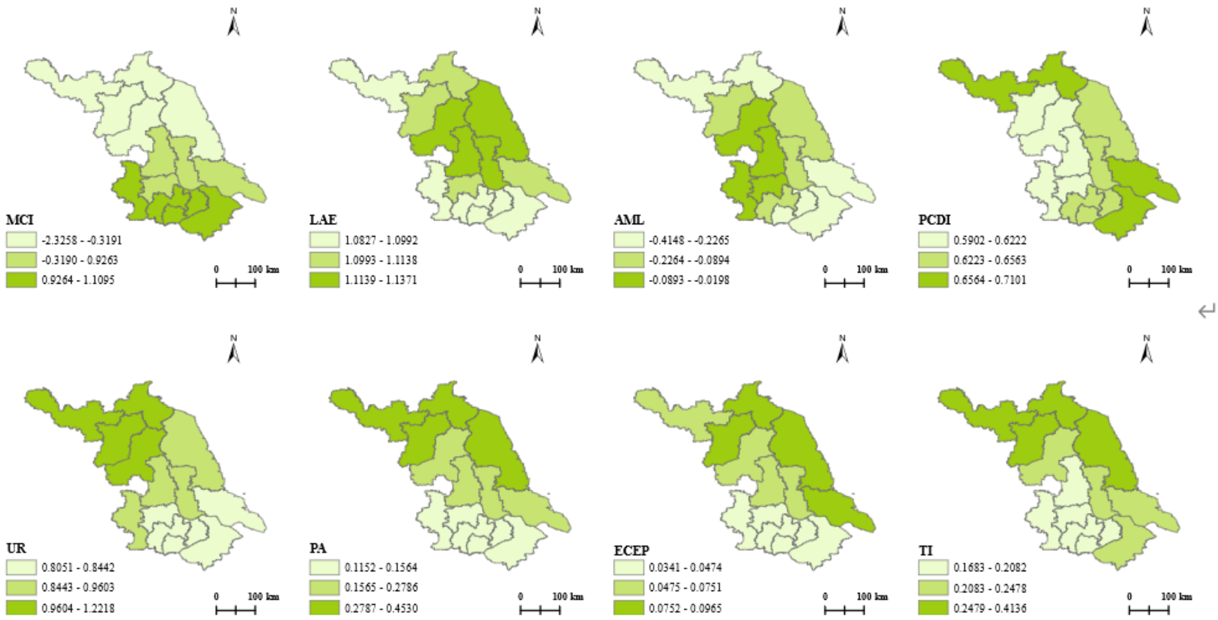


Figure 3. Spatial distribution of estimated regression coefficients for influencing factors of the GWR model

4.4. Influencing factors analysis

There are significant differences in socio-economic factors in different regions, which may have a direct or indirect effect on the efficiency of agricultural carbon emissions. In this paper, the geographically weighted regression (GWR) is used, with the ArcGIS software, and the coefficient estimates of the influencing factors were presented in a spatial visualization. The GWR model achieved an adjusted R^2 of 0.7664, outperforming the global OLS model (adjusted R^2 = 0.6940), indicating that spatial heterogeneity is important in explaining ACEE.

(1) The Multiple Cropping Index (MCI) is a comprehensive indicator used to quantify the intensity of cultivated land utilization under specific topographic and climatic conditions(Li *et al.*, 2023). Regression analysis shows that the impact of MCI on ACEE exhibits significant spatial dependence. The regression coefficients of MCI exhibit a distinct latitudinal gradient, increasing progressively from north to south. The northern region constitutes a negative-value zone, the central region represents a transition zone, and the southern region is a positive-value zone. Previous studies in agricultural domains have similarly identified spatial heterogeneity in MCI impacts, analyzing from perspectives of natural endowments and socioeconomic factors (Zhang *et al.*, 2019; Zhao *et al.*, 2016).

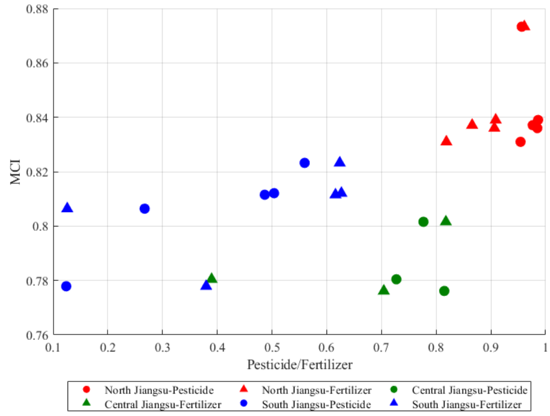


Figure 4. Scatter plot of fertilizer and pesticide usage in three regions of Jiangsu

Specifically in Jiangsu Province, as shown in **Figure 4**, the agricultural production in North Jiangsu heavily relies on the input of fertilizers and pesticides, resulting in a decrease in carbon emission efficiency. In contrast, the South Jiangsu has achieved a more low-carbon and intensive agricultural management model with its higher level of economic development and technological capabilities. The transitional characteristics observed in Central Jiangsu reflect a dynamic interplay between these opposing effects.

(2) This paper selects “area of grain sown/ rural Employees” as a key influencing factor reflecting labor-land allocation efficiency (LAE). An increase in LAE corresponds to a lower degree of land fragmentation, facilitating the adoption of mechanized farming and precision agriculture technologies (Li *et al.*, 2024). The GWR results indicate that the regression coefficient for LAE remains positive across the entire province, suggesting that expanding per capita cultivated land area serves as a positive driver for enhancing ACEE. As illustrated in **Figure 3**, the intensity of this factor forms distinct high-value aggregation clusters in central Jiangsu. Compared to southern Jiangsu, where per capita arable land resources face urbanization-induced constraints, and northern Jiangsu, which is limited by capital and technological constraints, the central region effectively converts scale advantages into improvements in ACEE. Previous studies examining the impact of per capita cultivated land on agricultural sectors in other regions have also identified spatial heterogeneity, leading to recommendations for differentiated policy approaches (Chen *et al.*, 2022). Regarding the spatial characteristics exhibited by LAE, northern and southern regions should further explore highly intensive agricultural management models, while central regions need to continue encouraging land circulation and scale-based cultivation practices.

(3) The agricultural mechanization level (AML), serving as an indicator of agricultural production modernization, exerts a negative impact on ACEE without demonstrating a significant spatial clustering pattern. This finding contradicts some previous studies, primarily due to the following two reasons(Chen *et al.*, 2024; Cheng *et al.*, 2023). On one hand, agricultural mechanization heavily relies on fossil energy consumption, and its energy intensity increases proportionally with the mechanization rate. On the other hand, a technological path dependency has formed between mechanization and high-carbon agricultural practices, reinforcing the use of inputs such as pesticides and chemical fertilizers, thereby creating a feedback loop that generates substantial carbon emissions. Consequently, cities in Jiangsu must shift their policy focus from general mechanization promotion to targeted adoption of green energy agricultural machinery.

(4) Per capita disposable income (PCDI) serves as an indicator for assessing economic development levels. Regression analysis reveals that higher income level significantly promotes the reduction of agricultural carbon emissions(Wang *et al.*, 1996). Although no spatially heterogeneous pattern is observed, this finding suggests that increased income drives agricultural green transformation beyond traditional regional gradients, functioning as a common motivating force across regions. This also implies that raising farmers’ income could stimulate intrinsic motivation for adopting green production practices at the micro-level, thereby facilitating the overall transition to low-carbon agricultural development in Jiangsu Province.

(5) The urbanization rate (UR) serves as a critical indicator for assessing urban-rural development. Urbanization has accelerated rural-to-urban population migration. As illustrated in **Figure 3**, regression coefficients for UR's impact on ACEE remain universally positive across the province, indicating that urbanization progress significantly enhances agricultural sustainable development (Zhao *et al.*, 2023). However, a distinct spatial pattern of "high in the north, low in the south" emerges, reflecting the interplay between modernization effects and negative land-use consequences. In North Jiangsu, urbanization's positive modernization effects dominate. Rural labor outflow stimulates socialized service development, thereby enhancing agricultural scale management and resource efficiency. Conversely, in highly urbanized South Jiangsu, arable land scarcity weakens the marginal benefits of urbanization while intensifying environmental constraints on agricultural production.

(6) The intensification of population ageing (PA) leads to a decline in physical labor capacity and exacerbates environmental constraints. Experience from Japan has demonstrated that, with supportive policy frameworks, land consolidation and mechanization can partially alleviate labor shortages. However, studies by scholars from different countries have reached divergent conclusions regarding the impact of PA on agricultural development (Akdemir *et al.*, 2021; Seok *et al.*, 2018). Regression results from this study indicate that PA exerts a positive effect on ACEE, particularly more in the northern regions. Labor shortages have accelerated land transfer and the expansion of large-scale farming, thereby enhancing land use efficiency and reducing carbon emissions. Furthermore, in recent years, cities in Jiangsu Province have promoted the application of novel farming

techniques while continuously improving socialized services and ecological compensation mechanisms, actively responding to the dual challenges of demographic transition and "carbon neutrality", which has yielded positive outcomes.

(7) Energy conservation and environmental protection (ECEP) expenditure serves as a key indicator for measuring the intensity of environmental regulations, reflecting government policy guidance and fiscal support, and constitute a vital safeguard for sustainable agricultural development(Chen *et al.*, 2023; Wang *et al.*, 2022). Empirical results from the GWR model indicate that ECEP exhibits a positive yet relatively low coefficient for ACEE. First, evaluating environmental fiscal policies requires a long-term perspective. The impact of fiscal policies exhibits a certain degree of time lag. The actual effects on agricultural production may only become apparent after an extended period following the allocation of fiscal funds. This may lead to an underestimation of the ECEP impact coefficient. Furthermore, the dispersion of fiscal funds across multiple agricultural projects may also weaken their marginal impact on agricultural carbon sinks.

(8) Technological innovation (TI) is crucial for the agricultural green transition (He *et al.*, 2021). As shown in **Figure 3**, the coefficients of TI are positive across all cities, indicating that science and education expenditure can effectively enhance ACEE. The effect is particularly more pronounced in northern Jiangsu, where technology is relatively underdeveloped. Government science and education expenditure can promptly address technological gaps and generate high marginal benefits. Furthermore, North Jiangsu can introduce mature agricultural technologies from South Jiangsu, reducing trial-and-error costs and thereby contributing to the improvement of carbon emission efficiency. In contrast, as agricultural technology in South Jiangsu is already among the most advanced in the province, the impact of TI on ACEE exhibits a certain trend of diminishing marginal returns, resulting in relatively lower regression coefficients. Additionally, the long-time lag between investment in technological R&D and the application of outcomes may also contribute to the currently modest regression coefficients of TI.

5. Conclusion and Recommendation

To realize the "Dual Carbon" goal proposed by the Chinese government, it is important to promote a low-carbon green transition in agriculture. This process requires not only efforts to alleviate environmental pressure and improve carbon emission efficiency in agricultural production but also an in-depth exploration of its spatiotemporal evolution characteristics and key influencing factors. Based on the above research, the following conclusions can be drawn: (1) Although the ACEE in Jiangsu Province shows a gradual upward trend, the current overall efficiency level remains relatively low, with a certain degree of efficiency loss. (2) From a spatial perspective, Jiangsu Province's ACEE has exhibited positive spatial agglomeration characteristics in recent years. From a temporal perspective, the ACEE has shown an overall improvement trend, but there is also a certain degree of polarization. (3) As for the influencing factors, MCI, labor-land allocation efficiency, and other factors all have a significant impact on ACEE. The regression results indicate that the strength of the impact of some variables on ACEE exhibits significant spatial heterogeneity.

To promote the low-carbon and sustainable development of agriculture in Jiangsu Province, this paper proposes the following policy recommendations based on empirical findings: (1) Jiangsu should continue to advance low-carbon agricultural development and enhance the overall level of ACEE. Efforts should be made to strengthen the promotion and application of low-carbon and intelligent agricultural machinery, and to organize large-scale training programs on green farming techniques, so as to consolidate the foundation for overall ACEE improvement. (2) The government should enhance regional coordination and targeted support mechanisms. On one hand, high-efficiency regions should be encouraged to pursue technological innovation and facilitate the transfer of low-carbon technologies and management models. On the other hand, targeted assistance should be provided to cities with lower efficiency to help them overcome bottlenecks in the transition to green agriculture. (3) Differentiated strategies tailored to local conditions are necessary. Northern regions should prioritize the adoption of low-carbon technologies such as side-deep fertilization and slow-release fertilizers, as listed in the Jiangsu Agricultural Carbon Reduction Technology Catalogue (2022), to mitigate the carbon penalty from increased MCI. Southern regions, which possess stronger economic and agricultural foundations, should focus on developing cutting-edge low-carbon technologies such as smart agriculture and digital agriculture.

6. Limitation

Currently, many regions face environmental constraints similar to those in Jiangsu Province during the transition toward green agriculture. The modeling framework and findings of this paper provide an analytical framework and policy insights for other regions at comparable development stages. However, this research has certain limitations, mainly including: (1) The study is conducted at the municipal scale, which may overlook more granular differences at the county level regarding ACEE, thus failing to fully capture intra-regional heterogeneity. (2) Due to data availability constraints, several potential influencing factors—such as the level of agricultural digitalization and the stringency of environmental penalties—were not incorporated into the empirical model, possibly leading to incomplete model settings.

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