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Research article

Study on the spatial correlation network structure of agricultural carbon emission efficiency in China

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Abstract: Achieving carbon neutrality requires high efficiency in agricultural carbon emissions. This study employs a super efficiency Slack Based Measure-Data Envelopment Analysis (SBM-DEA) model to measure the Agricultural Carbon Emission Efficiency (ACEE) of 31 provinces, cities, and autonomous regions within the Chinese Mainland from 2001 to 2021. Additionally, it utilizes the modified gravity model and a social network analysis to establish the spatial correlation relationship of ACEE, and extensively investigates the characteristics and transmission mechanism of China's spatial correlation network structure regarding ACEE. The findings reveal the following: 1) The spatial correlation relationship of China's ACEE from 2001 to 2021 exhibits a complex network structure; 2) in terms of the overall network structure characteristics of the spatial correlation, the ACEE network demonstrates a high degree of correlation and displays a stable temporal evolution trend; 3) concerning the centrality network structure characteristics of the spatial correlation, most provinces in China experience a continuous decline in point centrality and near centrality, while the interdependence of the ACEE between provinces increases; and 4) regarding the clustering characteristics of the spatial correlation, variations exist in the correlation among the four plates of the ACEE. However, they mostly assume a mediating role, and in 2021, the ACEE network sectors witnessed a robust interoperability.

Keywords: Agricultural Carbon Emission Efficiency (ACEE); spatial correlation network structure; super-efficient SBM model; social network analysis

1. Introduction

The urgency of improving the Agricultural Carbon Emissions Efficiency (ACEE) has become an important issue for the green and sustainable development of countries worldwide [1–4]. The Intergovernmental Panel on Climate Change (IPCC) determined that the agricultural sector is responsible for 23% of carbon dioxide emissions in the ecosystem [5]. Globally, agricultural carbon emissions are the second largest source of greenhouse gas emissions, contributing approximately 14% of anthropogenic greenhouse gas emissions and 58% of non-anthropogenic carbon dioxide emissions [5,6]. As a major agricultural country, China must actively respond to climate change in alignment with its national strategies [7–10]. This includes addressing and enhancing carbon emissions in agricultural development, thereby achieving the 'dual carbon' goals. The promotion of low-carbon development in agriculture and the improvement of the ACEE form an essential aspect of this process. The study on the ACEE holds great significance, as it endeavors to strike a balance between agricultural economic benefits and environmental impacts, while aiming for optimal resource allocation and minimal carbon dioxide emissions. It serves as a comprehensive indicator that not only evaluates agricultural economic benefits, but also takes the impact on the agricultural environment into consideration. Additionally, it provides an objective evaluation of the level of agricultural ecology and offers a comprehensive reflection of the low-carbon transformation of the agricultural economy.

China is witnessing an era of rapid progress in agricultural technology with uneven regional development observed in the agricultural sector. The regional linkage is of great importance and much attention should be given to any regional differences. There is a significant gap in China's regional development with a regional imbalance being particularly noticeable. The trend of regional differentiation is increasingly evident. To some extent, the potential for regional development has been unleashed by the strategic layout of national and regional coordinated developments, as well as by the innovation and development of transportation and information technology. Economic and social connections between regions are growing closer, and administrative barriers to economic development are gradually being dismantled, thereby leading to the increased economic interconnectivity between regions. However, due to disparities in agricultural resource endowments, geographical environment, and convenient transportation, the distinct characteristics of agricultural development among provinces in China are becoming more pronounced. These disparities have further strengthened the agricultural economic connections rooted in geographical space, owing to the inherent correlation of agricultural resources and geographic proximity. Against the backdrop of resource and environmental constraints, there has been an increase in cross-regional technological exchanges and energy cooperation, consequently leading to a systematic and complex network structure in terms of the ACEE.

Previous research efforts on the ACEE can be categorized into three main categories. First, research has been conducted related to measuring agricultural carbon emissions. The primary factor contributing to the differences in the measurement of agricultural carbon emissions is the determination of carbon source types. Many scholars [11–14] believe that the main carbon sources of agricultural carbon emissions are emissions generated by the use and production of fertilizers, pesticides, and agricultural films, emissions generated by the consumption of fossil energy during the use of agricultural machinery, emissions generated by the destruction of organic carbon reservoirs during agricultural tillage, and emissions indirectly generated by the use of fossil energy in agricultural irrigation. Additionally, Johnson [15] suggests that agricultural carbon emissions mainly come from five aspects: waste generated during agricultural production, livestock gut fermentation, livestock manure management, agricultural resource utilization, and crop straw burning. Some studies [16,17] approach the measurement of agricultural carbon emissions from the perspective of agricultural output by appropriately categorizing carbon sources. For example, they consider adding carbon emissions during rice growth and development, as well as the addition of carbon emissions during animal breeding, particularly ruminant breeding, to the aforementioned five carbon sources to calculate the total agricultural carbon emissions. Meanwhile, agricultural carbon sources could also be distinguished based on carbon emission source tracing, with a division into agricultural non-energy carbon emissions and agricultural energy carbon emissions [18]. Other methods for measuring carbon emissions in agriculture are relatively scattered. For instance, Gao et al. [19] adopted fertilizer usage, pesticide usage, diesel usage, agricultural plastic film usage, effective irrigation area, and tillage area as the main sources of carbon emissions. West and Marland [20] concluded that the primary sources of agricultural carbon emissions are generated by the process of agricultural land cultivation, including agricultural inputs such as production, transportation, energy consumption during utilization, and the use of machinery. On the other hand, Lal [21] took the hidden carbon costs of agricultural inputs such as fertilizers, pesticides, agricultural films, farmland irrigation, and crop cultivation into account when estimating the net carbon sequestration of a region.

The second aspect pertains to the research associated with measuring the ACEE. Differences in research perspectives and the assimilation of diverse methodologies account for the variations in measurement methods regarding the ACEE. Input-output models, including the traditional Data Envelopment Analysis (DEA) model and its derivative models, constitute the primary measurement methods utilized for the ACEE. The ACEE has been calculated by several scholars [22–24] employing DEA models. Subsequently, some scholars have incorporated unexpected outputs into the measurement scope of the model. Nonetheless, in numerous instances, the radial conditions in the application of the DEA model cannot be completely satisfied, thereby rendering it incapable of addressing the issue of unexpected outputs. Consequently, improved methods have emerged, such as the Slack Based Measure (SBM) model and DEA Malmquist index method. The SBM model, which is a non-radial DEA model, was originally proposed by Tone [25]. Additionally, it can measure the efficiency value in inefficient decision units, thus enhancing the balance between the present state and the highly efficient target value, thereby overcoming the inherent limitations in traditional DEA models. This approach has been widely employed in calculating the ACEE [26–29]. Several scholars have combined DEA with pertinent indicators, such as performance indices, to compute carbon emission indices, which serve as reflections of the ACEE [30–33]. Additionally, there are scattered methods available for measuring the ACEE [34–36].

The third aspect of the research pertains to the evolution characteristics of the ACEE. As research within this field continues to deepen, the spatiotemporal differences and changing trends of this efficiency have garnered increased attention from scholars. The ACEE in China was first calculated by several scholars [33,37,38], who also conducted extensive studies on the variations and trends in ACEE among different provinces. Other studies [39,40] focused on the provincial ACEE and incorporated regional factors such as the eastern and western regions to analyze the spatiotemporal evolution characteristics of the efficiency.

In this article, the aforementioned achievements provide ideas and methods to study the spatial evolution characteristics of China's ACEE. At the same time, there are urgent issues that need to be addressed. One is that the measurement of the ACEE has not been unified. Previous studies have mostly started with the types of carbon sources and selected different indicators to measure the ACEE based on different carbon sources. Most of the research is based on input-output methods, DEA methods that consider unexpected outputs, and calculation methods combined with indices. This article takes capital and labor based on traditional economic growth models and further combines the ecological perspective to incorporate agricultural ecosystem service indicators as independent factors affecting agricultural economic growth into the model framework for carbon emission efficiency measurement, in order to reasonably and accurately measure China's ACEE. Second, there is limited research on the spatiotemporal evolution characteristics of Chinese ACEE. Most existing research is based on the same space to study the ACEE, thereby neglecting the characteristics and differences of its cross temporal and spatial evolution. Based on this, this article mainly uses social network analysis methods to divide 31 provinces (cities and autonomous regions are both expressed as province in the following text) in China from 2001 to 2021 into multiple regional blocks through spatial clustering. Using panel data and spatial econometric models from each province, the spatial correlation relationship of the ACEE between provinces is quantified, and the transmission mechanism of the ACEE between different regions is clarified. The selected provinces in this study do not include Taiwan, Hong Kong, and Macau, mainly for two reasons: first, there is no statistical data for the Taiwan province within the China Statistical Yearbook; and second, the agricultural output value of Hong Kong and Macau is too small, and the authors believe that calculating the ACEE of these locations is not feasible and has little significance. For the study, we selected a period of time from 2001 to 2021, mainly considering two factors: timeliness and data availability. From the perspective of timeliness, this study has a relatively long duration, and it is known that a longer time span makes the research conclusions of this article more convincing. From the perspective of data availability, the time point starts from 2001 mainly due to the evolutionary process of the economic structure and the establishment of the market economy system. The Chinese Mainland has established a market economy since 1992. The process of urbanization in the mid and late 1990s made great changes in China's economic structure, which was relatively stable around 2001. At the same time, data before 2001 was not considered since they were partially missing, which made it impossible to calculate the ACEE values through the applied model.

Consequently, our work seeks to make the following contributions to the existing literature. First, this article uses social network analysis methods to deeply characterize the evolution characteristics of the ACEE in Chinese provinces, and reveal its spatiotemporal differentiation characteristics. Second, this study intends to conduct an in-depth analysis from different levels and dimensions such as time-varying trends, dynamic evolution trajectories, convergence and divergence, spatial distribution patterns, spatial change trajectories, regional differences and their decomposition, spatial clustering patterns, etc. of the ACEE. Third, the clever use of social network analysis methods effectively overcomes the previous regional limitations on central spatial research, and comprehensively reflects the regional correlation of the ACEE and the dynamic evolution characteristics of its overall network.

2. Materials and methods

2.1. Method for measuring ACEE

2.1.1. Unexpected output SBM model

In the process of using traditional DEA efficiency measurement models (radial CCR, BCC), as they are all from a comparison perspective, some problems may arise, such as the inability to compare when the efficiency value is 1. For example, the influence of relaxation variables may be ignored, and the efficiency value of decision units located at the efficiency front are all 1, resulting in the inability of a comparison. In 1993, Andersen et al. [41] proposed the super-efficient DEA model based on the traditional DEA, allowing for the efficiency level of effective decision-making units to be greater than 1. In 2001, Tone [25] proposed the SBM model, which directly added relaxation variables to the objective function, thereby solving the problem of selecting input-output relaxation variables in traditional DEA models.

The super efficiency SBM model further evolves based on the DEA model, which is a more comprehensive model that combines the super efficiency DEA and SBM models. It not only solves the problem of traditional DEA models not being able to calculate decision-making units with efficiency values greater than 1, but also incorporates the input and output relaxation variables into the objective function, thereby making the efficiency calculation results more accurate. This article considers incorporating agricultural carbon emissions into non-expected outputs, and therefore selects the super-efficient SBM-DEA model to construct a Chinese ACEE model. The specific expressions are shown in Eqs (1)–(3):

$$P^G(x) = \left\{ (y^t, b^t): \begin{array}{c} \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t y_{km}^t \geq y_{km}^t,\ \forall m; \\ \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t b_{ki}^t \geq b_{ki}^t,\ \forall i; \\ \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_{kn}^t,\ \forall n; \\ \sum_{k=1}^{K} z_k^t = 1,\ z_k^t \geq 0,\ \forall k; \end{array} \right\} \tag{1}$$

$$\vec{S}^G\left(x^{t,k'}, y^{t,k'}, b^{t,k'}, g^x, g^y, g^b\right) = \max_{s^x,s^y,s^b} \frac{\left(\frac{1}{N}\right)\sum_{n=1}^{N}(s_n^x/g_n^x) + (1/(M+I))\left(\sum_{m=1}^{M} s(_m^y/g_m^y) + \sum_{i=1}^{I}(s_i^b/g_i^b)\right)}{2}$$

$$s.t.\ \begin{cases} \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t x_{kn}^t + s_n^x = x_{k'n}^t, & \forall n; \\ \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t y_{km}^t + s_m^y = y_{k'm}^t, & \forall m; \\ \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t b_{ki}^t + s_i^b = b_{k'i}^t, & \forall i; \\ z_k^t \geq 0, & \forall k; \\ s_m^y \geq 0, & \forall m; \\ s_i^b \geq 0, & \forall i; \end{cases} \tag{2}$$

$$GML^{t,t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1+\vec{S}^G(x^t, y^t, b^t; g^x, g^y, g^b)}{1+\vec{S}^G(x^{t+1}, y^{t+1}, b^{t+1}; g^x, g^y, g^b)} \tag{3}$$

In Eq (3), the Global Malmquist-Leuenberger (GML) presents the rate of change. Given the time range of the selected samples and assuming that the ACEE in the year 2000 for each province is 1, the ACEE of each province in 2001 is shown in Eq (4):

$$ACEE_{2001} = ACEE_{2000} \times GML_{2000-2001} \tag{4}$$

In Eqs (1)–(4), $x = (x_1, \cdots, x_n) \in R_N^+$ represents the input indicators for measuring the ACEE, specifically including four basic input indicators: labor, land, capital, and agricultural materials. $y = (y_1, \cdots, y_n) \in R_M^+$ is the expected output of the ACEE; this work selects the total agricultural output value for characterization. $b = (b_1, \cdots, b_n) \in R_I^+$ is an unexpected output; this work selects the total agricultural carbon emissions as the characterization indicator. For example, $z_k^t \geq 0$ indicates that the returns-to-scale remains unchanged, while $\sum_{k=1}^{K} z_k^t = 1,\ z_k^t \geq 0$ indicates the variable returns-to-scale. $\vec{S}^G(x^t, y^t, b^t; g^x, g^y, g^b)$ is a global SBM based on non-radial and non-directional measurements.

2.1.2. Input-output indicator system for ACEE

This study draws on previous research and constructs an input-output indicator system for the ACEE in 31 Chinese provinces, as shown in Table 1. Selected agricultural input variables include labor input, land input, capital input, agricultural machinery input, fertilizer input, pesticide input, and agricultural film use. Agricultural output indicators include expected output and non-expected output, which are the total agricultural output value and agricultural carbon emissions, respectively.

Table 1. Input-output indicator system for the ACEE.

Indicator type	Indicator name	Characterization variable	Units	Declaration
Input Indicators	Labour force	Employees in the primary industry at the end of the year	10,000 people	None
	Land	Crop planting area	1000 hectares	None
	Capital	Agricultural fixed capital stock	10,000,000 yuan	Calculate capital using the perpetual inventory method
	Agricultural machinery	Total power of agricultural machinery	10,000 kilowatts	None
	Chemical fertilizer	Usage of agricultural fertilizer	10,000 ton	None
	Pesticide	Pesticide usage	10,000 ton	None
	Agricultural film	Usage of agricultural film	10,000 ton	None
Expected output	Total agricultural output value	Total output value of agriculture, forestry, animal husbandry, and fishery	10,000,000 yuan	None
Undesirable output	Agricultural carbon emissions	Agricultural carbon emissions	10,000 ton	Calculate according to carbon emission coefficient method of IPCC

The stock of agricultural fixed capital refers to the perpetual inventory method, and the specific calculation method is shown in Eq (5):

$$K_{i,t} = I_{i,t} + (1 + \delta)K_{i,t-1} \tag{5}$$

where $K_{i,t}$ is the agricultural capital stock of the region in year t, $I_{i,t}$ is the agricultural investment of the region in year t, and δ is the depreciation rate of fixed assets for the region in year t.

Table 2. Indicators and corresponding coefficients for the agricultural carbon emissions.

Carbon emission source	Corresponding indicator name	Carbon emission coefficient
Chemical fertilizer	Usage of agricultural fertilizers	0.8956Kg CE/Kg
Pesticide	Pesticide usage	4.9341Kg CE/Kg
Agricultural film	Usage of agricultural film	5.18Kg CE/Kg
Agricultural diesel	Agricultural diesel usage	0.5927Kg CE/Kg
Agricultural sowing area	Crop planting area	3.126Kg CE/hm^2
Agricultural irrigation area	Effective irrigation area for agriculture	20.475Kg CE/hm^2

There are many methods for measuring carbon emissions. Based on the IPCC carbon emission coefficient, this work adopts the emission factor method to calculate agricultural carbon emissions. Selected agricultural production carbon sources include fertilizers, pesticides, agricultural films, agricultural diesel, land tillage, and agricultural irrigation. The specific calculation method is shown in Eq (6):

$$C = \sum C_i = \sum (T_i \times \lambda_i) \tag{6}$$

where C represents the total carbon emissions from the agricultural production, C_i is the carbon emissions of the i-th carbon source, T_i is the carbon emissions of the i-th carbon source, and λ_i is the emission coefficient of the i-th carbon source. The relevant emission coefficients of each carbon source are shown in Table 2.

2.2. Analysis method of spatial association network structure

2.2.1. Revised gravity model

This work constructs the modified gravity model to measure the correlation strength of the carbon emission efficiency between provinces. A series of expressions for the model are shown in Eqs (7)–(10):

$$Y = \frac{GM_1M_2}{r^2} \tag{7}$$

$$r_{ij} = k_{ij}\frac{M_iM_j}{D_{ij}^2} \tag{8}$$

$$k_{ij} = \frac{G_i}{G_i+G_j} \tag{9}$$

$$D_{ij} = \frac{d_{ij}}{G_i-G_j} \tag{10}$$

In the above equations, i and j represent two different Chinese provinces. The symbol r_{ij} represents the strength of the correlation between the ACEE of provinces i and j. k_{ij} is the correlation strength of the ACEE between provinces i and j. G_i and G_j represents the added value of the primary industry in provinces i and j. D_{ij} represents the comprehensive distance between provinces i and j, which considers both geographical and economic distances. In Eq (8), M_i and M_j represent the ACEE of provinces i and j, respectively. In Eq (10), d_{ij} represents the geographical distance between provinces i and j. According to Eq (8), a gravity matrix for the ACEE $(r_{ij})_{31\times 31}$ is constructed. To reduce the interference of a weak correlation between the ACEE in the provinces, the mean of each row in the gravity matrix is taken as the threshold. When the element in the gravity matrix is greater than the threshold, it is denoted as 1, thereby indicating that there is a connection between the ACEE in provinces i and j. If the element in the gravity matrix is less than the threshold, it is marked as 0, indicating that there is no connection between the ACEE.

2.2.2. Social network analysis method

A social network analysis is a method based on 'relationship' data for the study of the spatial network structure of relationships among individuals. This method overcomes the constraint of geographic 'adjacency' or 'proximity', thereby allowing for a holistic investigation of the spatial correlation effects across multiple nodes, as opposed to typical spatial metrics approaches. Thorough explanations and analyses of intricate network interactions are provided, making it widely applicable in various industries. The current study of spatial correlation network structure serves as a reference for this analysis. In this work, the application of a social network analysis is employed to examine the geographical network features of the ACEE in the 31 Chinese provinces.

1) Spatial correlation network overall structure characteristics. This feature mainly focuses on four indicators: network density, relevancy, hierarchy, and efficiency. Network density reflects the strength of the relationships between nodes in the spatial network, indicating the intensity of interactions among nodes in the spatial network. Network relevancy signifies the resilience of the spatial network. When the network relevancy is equal to 1, it signifies the presence of a spatial network effect in the ACEE among the 31 Chinese provinces, further indicating a highly robust spatial network. Network hierarchy reflects the status differences in the ACEE of the 31 Chinese provinces. The higher the hierarchy, the greater the hierarchy status difference formed in the spatial correlation network. Additionally, the network efficiency serves as a stability indicator of the spatial network. When the network efficiency is lower, it indicates a more stable spatial network of the ACEE of the 31 Chinese provinces.

2) Spatial correlation network centrality structure characteristics. This feature mainly focuses on three indicators: degree centrality, closeness centrality, and betweenness centrality. When a province has a higher degree centrality, it indicates that the province is closer to the center of the spatial network of the ACEE among the 31 Chinese provinces, Furthermore, nodes with a higher degree centrality exert a stronger influence on other nodes within the network. When a province has a higher closeness centrality, it indicates that the province is closer to other provinces in terms of the ACEE in the spatial network among the Chinese provinces. When a province has a higher betweenness centrality, it indicates that the province has a stronger control and regulatory role in the ACEE of other provinces in the spatial network of ACEE among the 31 Chinese provinces.

3) Spatial association network clustering structure feature analysis. This analysis primarily evaluates the roles and functions of different plates in the spatial network of the ACEE among the 31 Chinese provinces using the block model analysis method. It conducts a clustering analysis of the spatial network of the ACEE of the 31 Chinese provinces. The spatial network is divided into four plates, and the attributes of each plate are determined based on the ratio of internal and external relationships and the number of members within the plate (Table 3). Here, $\mathrm{N_k}$ represents the number of provinces within the plate in the network, and N represents the total number of provinces in the

entire network.

Table 3. Plate classification criteria of block model.

Proportion of intra-plate relationships	**Proportion of plate receiving relation**	
	≈0	>0
$\geq \frac{N_k - 1}{N - 1}$	bidirectional spillover sectors	primary beneficiary sectors
$\leq \frac{N_k - 1}{N - 1}$	primary spillover sectors	brokerage sector

2.3. Data source

Our main sources of information are the China Statistical Yearbook, China Agricultural Yearbook, and China Rural Statistical Yearbook. Matlab is used to compute the distances of provinces, combining the latitude and longitude of the capital city of each province.

3. Analysis of the measurement results of ACEE in China

Analysis of the ACEE measurement results is based on the ACEE input-output indicator system proposed earlier in this paper. The non-desirable output SBM model is applied to calculate the ACEE of the 31 Chinese provinces from 2001 to 2021 using the MaxDEA software.

3.1. Kernel density estimation of ACEE

This work applies the kernel density estimation approach to better define the temporal evolution process of absolute differences in the ACEE. It explains the distribution features and evolutionary tendencies of China's ACEE by examining the distribution location, peak form, and dispersion. Figure 1 displays the precise kernel density estimate findings.

From the perspective of distribution location, the ACEE shows a phased trend and a rightward shift, with the differences between provinces tending to flatten. Overall, the ACEE has gradually improved over time. As time goes by, the ACEE of the provinces exhibits certain stages, which is divided into three stages: 1) the period from 2001 to 2008, characterized by a relatively low overall level and significant fluctuations; 2) the period from 2009 to 2016, during which the ACEE steadily increased; 3) and from 2016 to 2021, a downward trend was observed in the overall ACEE. Differentiation in the ACEE is evidenced by the shape of the main peak distribution. The continuous decrease in the peak value is depicted by the kernel density curve, indicating diversification in the ACEE. The perspective of distribution locations of three stages in Figure 1 reveals the following economic conclusions: the narrowing of the horizontal width suggests a dynamic convergence in the ACEE during 2001 to 2010, accompanied by the rapid development of agricultural finance and an overall nationwide improvement in the agricultural production efficiency, leading to a significant reduction in regional differences. Moreover, a slow expansion of the width during the period from 2011 to 2021 indicates slow differentiation and a differentiated development in the ACEE.

From the perspective of distribution spread, there is a significant right-tail phenomenon. There is a significant right-trailing phenomenon in all distribution curves, indicating that the ACEE in some regions is significantly higher than in others. Specifically, in the period from 2001 to 2008, there was a noticeable difference in the ACEE among the provinces, implying a considerable nationwide spatial disparity in the ACEE. After 2009, the right-tail phenomenon weakened, and the distribution curves tended to have an overall distribution, indicating a more balanced nationwide development of the ACEE among the provinces and an enhancement of the ACEE synergy. Additionally, the distribution curves show a transformation from a multi-peak shape to a single-peak shape, thereby indicating a reduction in the multi-level differentiation of the ACEE at the provincial level. The multi-peak shape indicates the nationwide existence of multi-level differentiation in the ACEE. For example, there are four peaks in the distribution curve in 2000, indicating a phenomenon of 'each region having its own policies'. After 2009, the distribution curve had only one peak, indicating a reduction in the spatial differentiation of the ACEE and a trend of differentiated development, even in agricultural production efficiency.

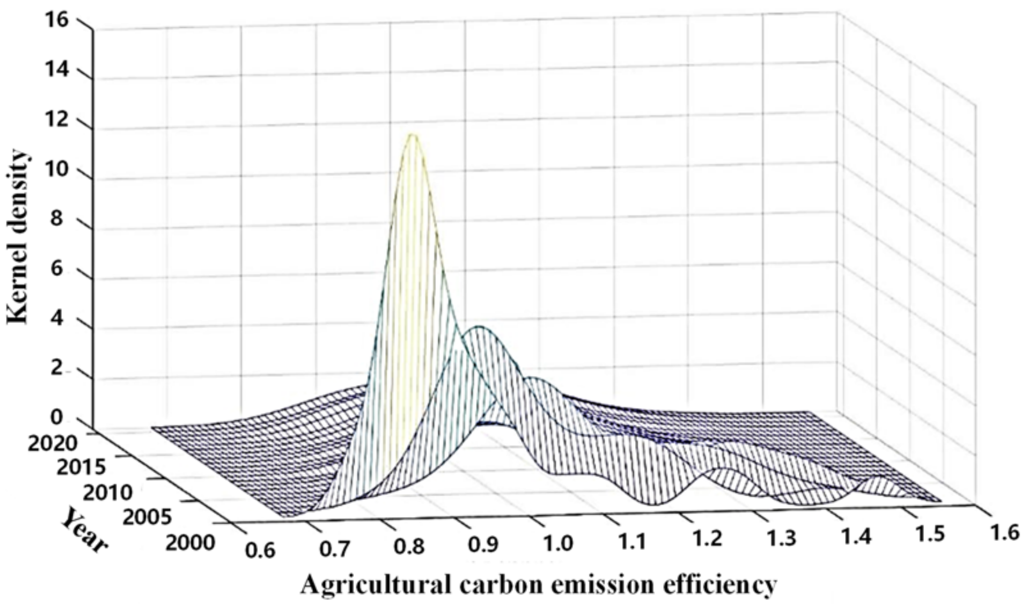

Figure 1. Evolution of the kernel density estimation for the ACEE.

3.2. Temporal evolution of ACEE and efficiency changes

In order to analyze the temporal evolution characteristics of the ACEE and the efficiency growth rate, this study measures the central tendency and the discrete tendency to analyze their temporal evolution characteristics. The time trend chart of the average ACEE from 2001 to 2021, as well as the time trend of standard deviation and variance, are shown in Figure 2.

On the one hand, this study analyzes the temporal evolution characteristics of the ACEE values using time series plots of central tendency and discrete tendency measurements. From the central tendency measurement, the average level of the ACEE shows a decreasing trend from 2001 to 2021. From the discrete tendency measurement, there is an increasing differentiation of the ACEE among different Chinese provinces during the sample period. The main reason is that with the diversification of economic models, policy formulation in each province tends to be customized. On the other hand, this study analyzes the temporal evolution characteristics of the growth rate of the ACEE using the two aforementioned measurements. From the central tendency measurement, the overall level of the ACEE shows a declining trend, thereby experiencing a process of rapid decline followed by a slower decline. From the discrete tendency measurement, the differences in the ACEE changes among the Chinese provinces gradually tend to become more balanced from 2001 to 2021. This is because with the deepening of reforms, policies and technologies related to the agricultural carbon emissions have gradually stabilized. Some advanced technologies for reducing agricultural carbon emissions have been promoted nationwide, resulting in stable ACEE changes across provinces.

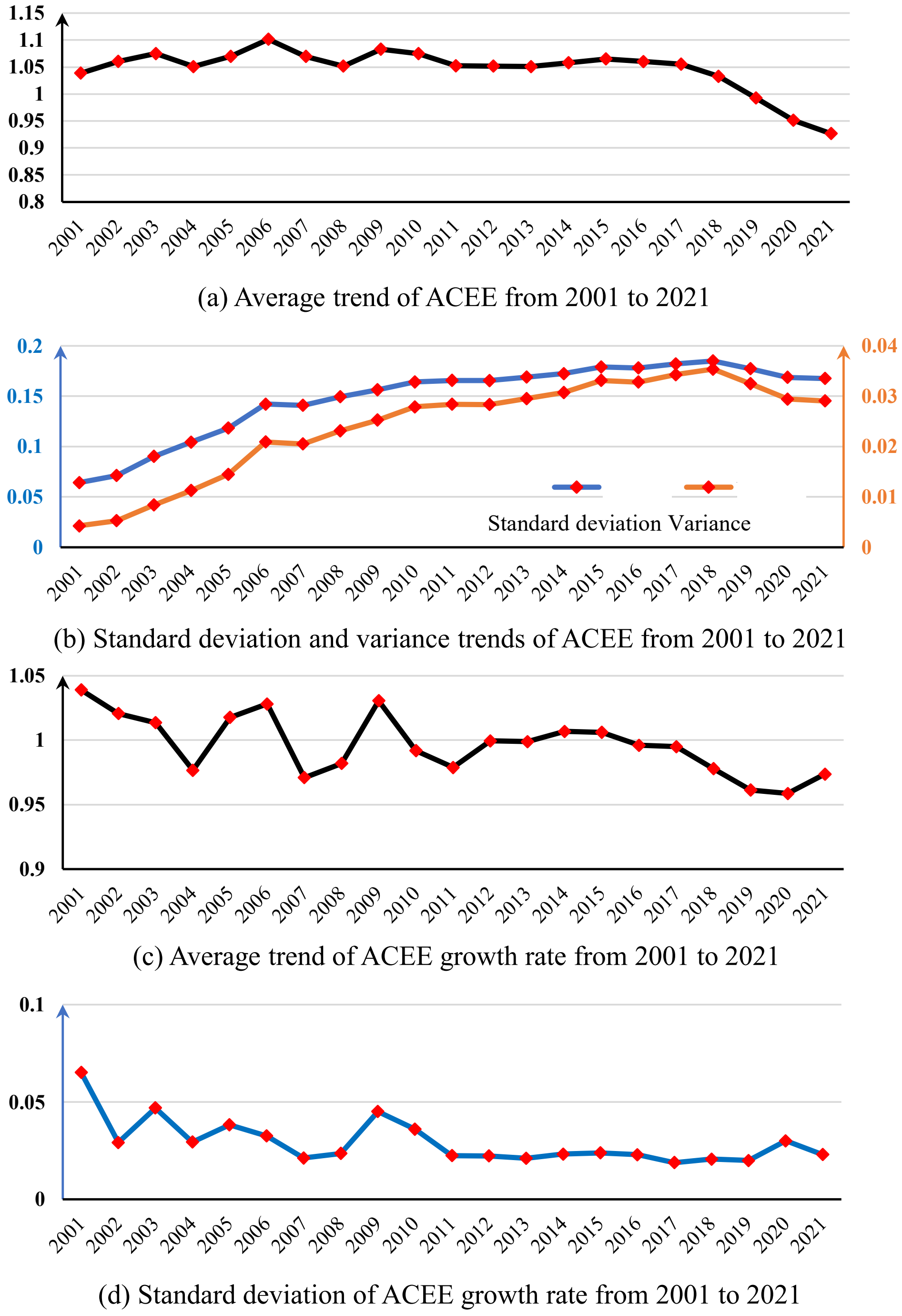

Figure 2. Trends of the ACEE indexes from 2001 to 2021.

3.3. Spatial distribution and evolution characteristics of ACEE and its changes

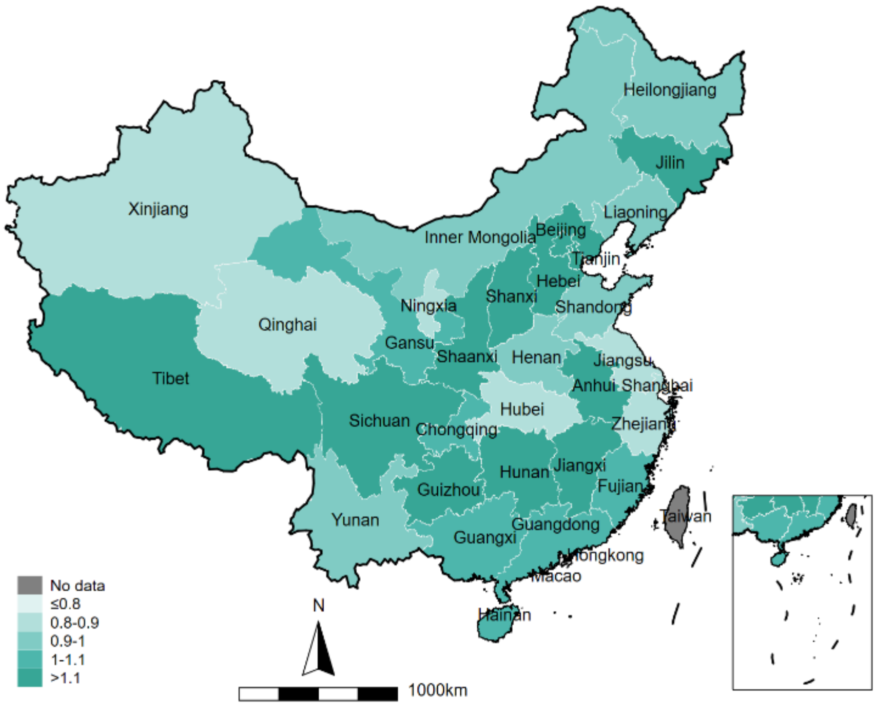

Figure 3. Distribution of the average ACEE in China from 2001 to 2021.

In this paper, the calculated results of the ACEE of China's provinces from 2001 to 2021 are utilized in this paper to display and analyze the spatial distribution and evolution characteristics during the sample period. On the one hand, a general overview of the geographical features for the efficiency change index and the ACEE of Chinese provinces from 2001 to 2021 is offered. By computing the average values of the ACEE and the efficiency change index for each identifier from 2001 to 2021, data sequences are formed using provinces and municipalities as identifiers. Following that, a map is created using these data sequences, as seen in Figures 3 and 4. Additionally, the number of times each identifier had a GML value greater than 1 from 2001 to 2021, which represents the number of efficiency increases, is summarized. Then, the data sequence is superimposed and mapped to the map layer (Figure 4). These visualizations and analyses provide insights into the spatial distribution and evolution characteristics of ACEE in China's provinces and municipalities from 2001 to 2021.

To further observe and compare the changes in the ACEE and the efficiency change index, this paper provides a map description of the average ACEE of China's provinces from 2001 to 2021, as well as the average GML index of the agricultural carbon emission for each Chinese province from 2001 to 2021. The spatial characteristics of the ACEE in China's provinces are supplemented by this additional analysis. Due to space limitations, this paper presents the data choropleth maps of the ACEE in each Chinese province for the years 2001, 2008, 2015, and 2021. These locations are depicted in Figure 5.

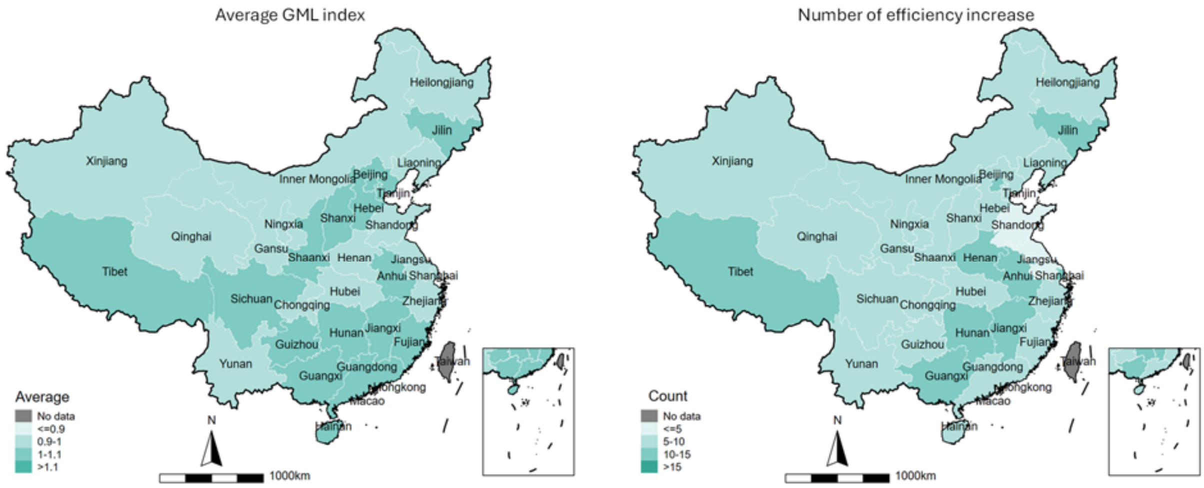

Figure 4. Distribution of the average GML index and number of the efficiency increase for the agricultural carbon emission in China from 2001 to 2021.

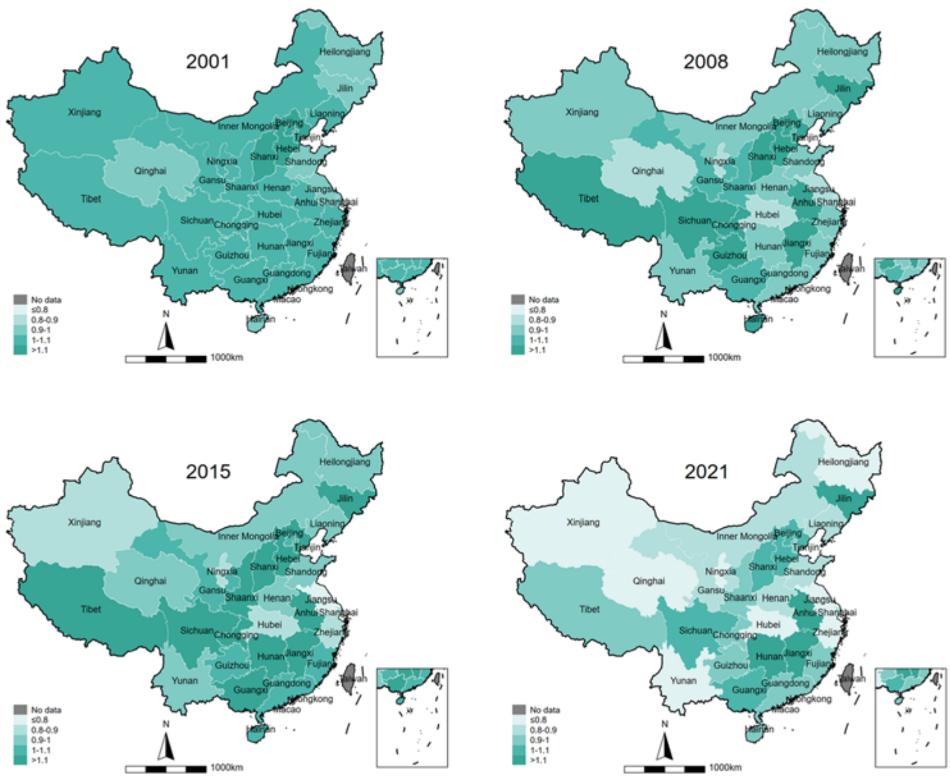

Figure 5. Trend chart of the ACEE in Chinese provinces.

On the one hand, data charts are presented based on the calculation results of the ACEE and a descriptive analysis of its spatial characteristics is provided. The charts indicate that an east-high-west-low pattern is observed in China's total ACEE. This pattern is strongly influenced by the main industries and agricultural growth environment specific to each province. A downward trend in China's

ACEE could be seen in the majority of provinces, with notable variations in the efficiency between them becoming increasingly evident. On the other hand, data charts are presented based on the calculation results of the agricultural carbon emission GML index and an analysis of its spatial characteristics is conducted. The charts demonstrate that the average rate of improvement in the ACEE is relatively consistent and balanced among provinces in China, with better efficiency improvement observed in the monsoon region as compared to the non-monsoon region. In most Chinese provinces, the ACEE fluctuates around the original level, and it is becoming increasingly clear how these efficiencies are consistently growing across provinces.

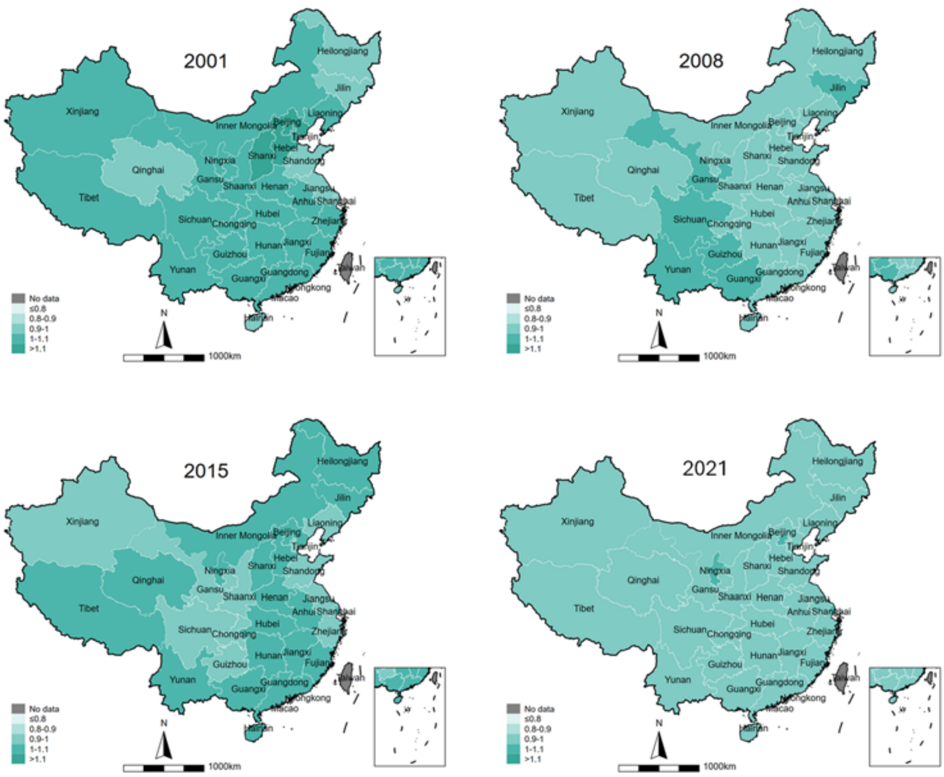

Figure 6. Trend chart of GML index for the agricultural carbon emission in Chinese provinces.

4. An investigation of the spatial correlation network structure of ACEE in China

The spatial correlation binary matrix of the ACEE of the 31 Chinese provinces is constructed followed by the construction of a spatial network structure.

4.1. Analysis of the general characteristics of the ACEE network

The Ucinet6.0 software is used to establish the overall characteristic index of the spatial correlation network of the ACEE of the 31Chinese provinces from 2001 to 2021, as shown in Table 4.

From the standpoint of network density, the ACEE network density is constantly at a high level over the study period, which suggests that there is a high degree of correlation between provinces in the network. From the perspective of network correlation, the ACEE of each province shows a strong connection. That is to say, the ACEE of each province can be indirectly connected through many other paths. The ACEE network is in a robust state. From the perspective of network hierarchy and network efficiency, the network hierarchy reflects the poor hierarchical structure between provinces in the ACEE network. The low network effectiveness shows the closeness of the indirect connection between provinces and the stability of the network.

Next, the overall trend of the ACEE network is further examined by analyzing the change in the network density, the network correlation, the network rank, and the network efficiency over time. The evolution trend of network density and correlation in China's ACEE network from 2001 to 2021 is illustrated in Figure 7. Similarly, Figure 8 depicts the evolution trend of the network hierarchy and the network efficiency in China's ACEE network during the same period.

Table 4. Analysis of the overall characteristics of China's ACEE network.

Year	Network density	Network correlation degree	Network hierarchy	Network efficiency
2001	0.7419	1.0000	0.0000	0.1264
2002	0.7419	1.0000	0.0000	0.1264
2003	0.7495	1.0000	0.0000	0.1218
2004	0.7581	1.0000	0.0000	0.1149
2005	0.7602	1.0000	0.0000	0.1195
2006	0.7677	1.0000	0.0000	0.1218
2007	0.7720	1.0000	0.0000	0.1172
2008	0.7656	1.0000	0.0000	0.1218
2009	0.7656	1.0000	0.0000	0.1172
2010	0.7656	1.0000	0.0000	0.1287
2011	0.7581	1.0000	0.0000	0.1287
2012	0.7591	1.0000	0.0000	0.1287
2013	0.7624	1.0000	0.0000	0.1264
2014	0.7419	1.0000	0.0000	0.1264
2015	0.7538	1.0000	0.0000	0.1287
2016	0.7484	1.0000	0.0000	0.1287
2017	0.7516	1.0000	0.0000	0.1333
2018	0.7527	1.0000	0.0000	0.1264
2019	0.7505	1.0000	0.0000	0.1149
2020	0.7484	1.0000	0.0000	0.1195
2021	0.7462	1.0000	0.0000	0.1310

According to Figure 7, the dynamic change in the network density of the ACEE is observed to initially increase and then decrease, while the network correlation degree remains relatively stable. From 2001 to 2007, the network density of the ACEE showed a continuous upward trend, reaching its peak value of 0.772 in 2017. Subsequently, it declined to the initial level from 2008 to 2015, and then stabilized from 2016 to 2021. In general, the network density of the ACEE remained above 0.74 throughout the 21-year observation period. Despite a recent decline, the correlation degree among provinces remains strong. In terms of network robustness, the correlation degree of the ACEE network remained at 1 from 2001 to 2021, thereby indicating a high level of stability. This suggests that provinces can maintain connections through various routes, even if there is a heavy dependence on specific provinces. As a result, the ACEE network is not easily disrupted.

According to Figure 8, the network hierarchy of the ACEE remains consistently at the minimum value, while its network efficiency fluctuates continuously. Throughout the period from 2001 to 2021, the ACEE network rank remains constant at 0, thereby indicating a lack of hierarchy and dominance within the hierarchical structure of the network. Typically, a higher network rank suggests an increased presence of edge regions in the network, whereas most provinces within the ACEE network tend to be central. Examining the trend of network efficiency from 2001 to 2010, the ACEE network efficiency witnessed a quick fall in the first half of the period, followed by fluctuation and a return to the initial level. From 2011 to 2017, the network efficiency of the ACEE has gone through a stable development stage. However, from 2018 to 2021, the network efficiency of the ACEE exhibited a significant decrease, followed by a sharp rise in the latter half of the period, reaching its peak in 2017. Although the variation trend of the ACEE network efficiency is complex, the range of variation is small and maintains at a low level. Therefore, based on the development trend of the ACEE network efficiency, the network structure demonstrates a high stability, and the provinces within the network can generate spillover effects through increased geographical network linkages.

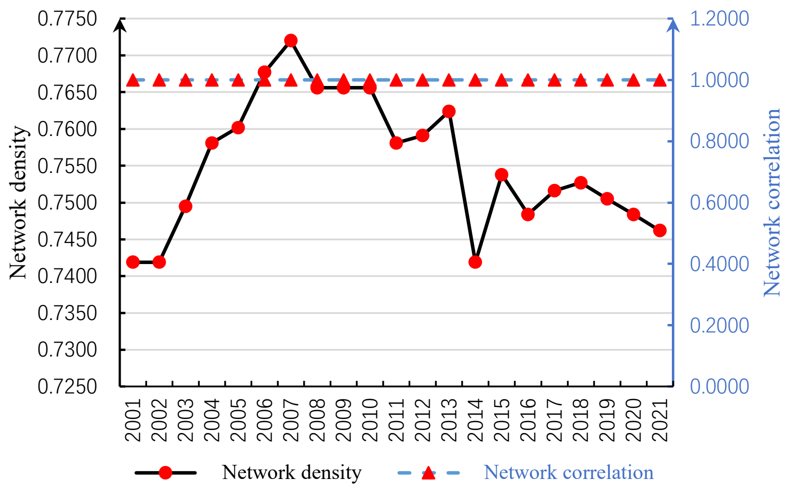

Figure 7. Network density and correlation trend of China's ACEE network from 2001 to 2021.

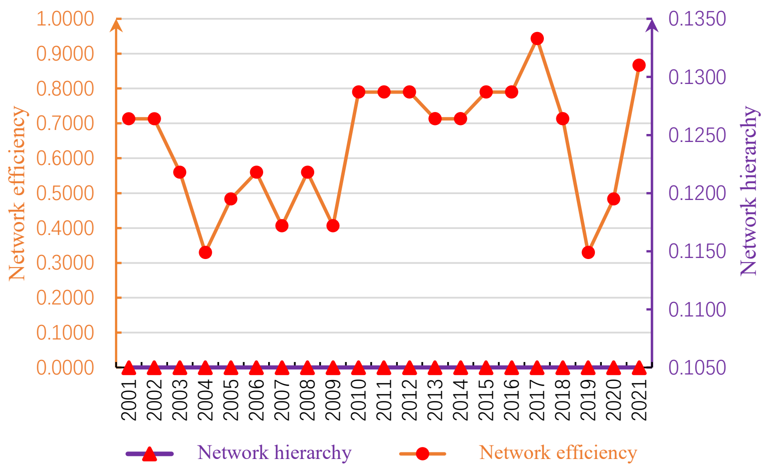

Figure 8. Network hierarchy and efficiency trend of China's ACEE network from 2001 to 2021.

4.2. Analysis of the centrality characteristics of the ACEE network

In this study, the Ucinet6.0 software is used to estimate the three indicators of node centrality, proximity centrality and betweenness centrality of China's ACEE network from 2001 to 2021, followed by an investigation of the characteristics of each centrality. While examining the evolution of the centrality features, due to the extensive research time span, the three years 2001, 2011 and 2021 are chosen as representations for a longitudinal comparison, as stated in Tables 5–7.

Table 5. Results of the degree centrality of the Chinese ACEE network.

	Province (2001)	**Centrality of point degree**	**Province (2011)**	**Centrality of point degree**	**Province (2021)**	**Centrality of point degree**
1	Fujian	100	Fujian	96.6667	Fujian	96.6667
2	Heilongjiang	100	Heilongjiang	96.6667	Heilongjiang	96.6667
3	Xinjiang	100	Liaoning	96.6667	Liaoning	96.6667
4	Jilin	96.6667	Anhui	93.3333	Jilin	93.3333
5	Liaoning	96.6667	Jilin	93.3333	Inner Mongolia	93.3333
6	Inner Mongolia	96.6667	Inner Mongolia	93.3333	Xinjiang	93.3333
7	Jiangsu	93.3333	Xinjiang	93.3333	Zhejiang	93.3333
8	Zhejiang	93.3333	Zhejiang	93.3333	Chongqing	93.3333
9	Beijing	90	Guangxi	90	Gansu	90
10	Hainan	90	Hainan	90	Guangxi	90
11	Qinghai	90	Hebei	90	Hainan	90
12	Shanxi	90	Jiangsu	90	Jiangsu	90
13	Tianjin	90	Jiangxi	90	Tianjin	90
14	Tibet	90	Qinghai	90	Yunnan	90
15	Chongqing	90	Shanxi	90	Anhui	86.6667
16	Anhui	86.6667	Tianjin	90	Guangdong	86.6667
17	Gansu	86.6667	Yunnan	90	Hebei	86.6667
18	Guangxi	86.6667	Chongqing	90	Hubei	86.6667
19	Hebei	86.6667	Beijing	86.6667	Hunan	86.6667
20	Hubei	86.6667	Guangdong	86.6667	Shanxi	86.6667
21	Jiangxi	86.6667	Shandong	86.6667	Shaanxi	86.6667
22	Shanghai	86.6667	Shanghai	86.6667	Shanghai	86.6667
23	Yunnan	86.6667	Tibet	86.6667	Beijing	83.3333
24	Guangdong	83.3333	Shaanxi	83.3333	Jiangxi	83.3333
25	Henan	83.3333	Gansu	80	Qinghai	83.3333
26	Shandong	83.3333	Guizhou	80	Shandong	83.3333
27	Guizhou	80	Henan	80	Tibet	83.3333
28	Shaanxi	80	Hubei	80	Guizhou	80
29	Hunan	76.6667	Hunan	80	Henan	80
30	Ningxia	73.3333	Ningxia	76.6667	Ningxia	76.6667
31	Sichuan	73.3333	Sichuan	76.6667	Sichuan	76.6667
	Mean value	88.1721	Mean value	87.9570	Mean value	87.7419
	Above average	15	Above average	18	Above average	14
	Below average	16	Below average	13	Below average	17

As shown from Table 5, the average degree centrality of provinces in the ACEE network in 2001, 2011, and 2021 are 88.1721, 87.9570, and 87.7419, respectively, demonstrating a declining trend. The reason for this phenomenon is that agricultural production relies on the use of chemicals and fossil energy, which is often accompanied by a large amount of greenhouse gas emissions, and is the largest source of agricultural emissions, thereby resulting in a decrease in the ACEE.

Table 6. Results of closeness centrality of China's ACEE network.

	Province (2001)	**Closeness centrality**	**Province (2011)**	**Closeness centrality**	**Province (2021)**	**Closeness centrality**
1	Fujian	100	Fujian	96.7742	Fujian	96.7742
2	Heilongjiang	100	Heilongjiang	96.7742	Heilongjiang	96.7742
3	Xinjiang	100	Liaoning	96.7742	Liaoning	96.7742
4	Jilin	96.7742	Anhui	93.75	Jilin	93.75
5	Liaoning	96.7742	Jilin	93.75	Inner Mongolia	93.75
6	Inner Mongolia	96.7742	Inner Mongolia	93.75	Xinjiang	93.75
7	Jiangsu	93.75	Xinjiang	93.75	Zhejiang	93.75
8	Zhejiang	93.75	Zhejiang	93.75	Chongqing	93.75
9	Beijing	90.9091	Guangxi	90.9091	Gansu	90.9091
10	Hainan	90.9091	Hainan	90.9091	Guangxi	90.9091
11	Qinghai	90.9091	Hebei	90.9091	Hainan	90.9091
12	Shanxi	90.9091	Jiangsu	90.9091	Jiangsu	90.9091
13	Tianjin	90.9091	Jiangxi	90.9091	Tianjin	90.9091
14	Tibet	90.9091	Qinghai	90.9091	Yunnan	90.9091
15	Chongqing	90.9091	Shanxi	90.9091	Anhui	88.2353
16	Anhui	88.2353	Tianjin	90.9091	Guangdong	88.2353
17	Gansu	88.2353	Yunnan	90.9091	Hebei	88.2353
18	Guangxi	88.2353	Chongqing	90.9091	Hubei	88.2353
19	Hebei	88.2353	Beijing	88.2353	Hunan	88.2353
20	Hubei	88.2353	Guangdong	88.2353	Shanxi	88.2353
21	Jiangxi	88.2353	Shandong	88.2353	Shaanxi	88.2353
22	Shanghai	88.2353	Shanghai	88.2353	Shanghai	88.2353
23	Yunnan	88.2353	Tibet	88.2353	Beijing	85.7143
24	Guangdong	85.7143	Shaanxi	85.7143	Jiangxi	85.7143
25	Henan	85.7143	Gansu	83.3333	Qinghai	85.7143
26	Shandong	85.7143	Guizhou	83.3333	Shandong	85.7143
27	Guizhou	83.3333	Henan	83.3333	Tibet	85.7143
28	Shaanxi	83.3333	Hubei	83.3333	Guizhou	83.3333
29	Hunan	81.0811	Hunan	83.3333	Henan	83.3333
30	Ningxia	78.9474	Ningxia	81.0811	Ningxia	81.0811
31	Sichuan	78.9474	Sichuan	81.0811	Sichuan	81.0811
	Mean value	89.7695	Mean value	89.4801	Mean value	89.2842
	Above average	15	Above average	18	Above average	14
	Below average	16	Below average	13	Below average	17

Table 7. Results of betweenness centrality of China's ACEE network.

	Province (2001)	Betweenness centrality	Province (2011)	Betweenness centrality	Province (2021)	Betweenness centrality
1	Fujian	2.490894	Heilongjiang	2.408498	Heilongjiang	2.40134
2	Heilongjiang	2.490894	Jilin	2.408498	Jilin	2.40134
3	Xinjiang	2.490894	Liaoning	2.408498	Liaoning	2.40134
4	Jilin	2.456411	Fujian	2.310513	Fujian	2.299567
5	Liaoning	2.456411	Anhui	2.246989	Zhejiang	2.231687
6	Jiangsu	2.289324	Jiangsu	2.246989	Jiangsu	2.146542
7	Zhejiang	2.289324	Zhejiang	2.246989	Xinjiang	2.036217
8	Inner Mongolia	2.085355	Xinjiang	2.180512	Hainan	1.997301
9	Hebei	2.030005	Shanghai	2.120178	Shanghai	1.979731
10	Shanghai	1.985391	Hebei	2.05292	Chongqing	1.958845
11	Beijing	1.929754	Inner Mongolia	1.969488	Inner Mongolia	1.921068
12	Shanxi	1.929754	Qinghai	1.923299	Hebei	1.918641
13	Tianjin	1.929754	Shanxi	1.906368	Guangxi	1.902738
14	Shandong	1.909603	Tianjin	1.906368	Anhui	1.872869
15	Qinghai	1.824119	Shandong	1.894057	Yunnan	1.853453
16	Guangxi	1.804465	Hainan	1.891765	Tianjin	1.852221
17	Tibet	1.79057	Guangdong	1.882421	Guangdong	1.811411
18	Hainan	1.787287	Yunnan	1.881166	Shandong	1.800051
19	Yunnan	1.681442	Guangxi	1.880125	Shanxi	1.770555
20	Guangdong	1.657508	Beijing	1.820914	Beijing	1.7251
21	Jiangxi	1.545446	Tibet	1.796178	Hunan	1.698846
22	Chongqing	1.508327	Jiangxi	1.732271	Gansu	1.680874
23	Anhui	1.490373	Chongqing	1.550641	Tibet	1.665936
24	Henan	1.463205	Henan	1.339813	Qinghai	1.660481
25	Hubei	1.35897	Shaanxi	1.283957	Hubei	1.64956
26	Gansu	1.357052	Hunan	1.207775	Jiangxi	1.536256
27	Guizhou	1.069199	Hubei	1.196369	Guizhou	1.498687
28	Sichuan	1.004851	Guizhou	1.126985	Shaanxi	1.490534
29	Shaanxi	0.990036	Gansu	1.094962	Henan	1.30422
30	Hunan	0.953349	Ningxia	1.054962	Ningxia	1.280079
31	Ningxia	0.950036	Sichuan	1.02953	Sichuan	1.25251
	Mean value	1.7742	Mean value	1.8065	Mean value	1.8387
	Above average	18	Above average	20	Above average	16
	Below average	13	Below average	11	Below average	15

Second, in that year, the point degree centrality is higher than the average in 15, 18, and 14 provinces, respectively. Provinces with a higher than average point degree centrality have stronger connections in terms of agricultural carbon emissions as compared to other provinces, and occupy a central position in the ACEE network, exerting a gravitational force. Among them, there are 11 provinces whose midpoint centrality values have consistently been higher than the yearly average during the 3-year research period. These provinces include five border provinces, five coastline provinces, and Chongqing, which is an inland municipality directly under the Central Government. These provinces have unique geographical distributions and significantly influence the overall correlation and spatial spillover effects within the ACEE network. They play a pivotal role in the formation and stable development of the overall network. Particularly, Fujian, Heilongjiang, Liaoning, and Jilin consistently rank among the top four provinces and their centrality far exceeds that of other provinces. As prominent agricultural provinces, they continuously absorb information and technical experience from the surrounding areas, alongside promoting the deepening development of their own agricultural industry chains, thereby assuming leadership roles.

In addition, there are 16, 13 and 17 provinces lower than the average centrality of the point degree in that year, respectively. The number of provinces that are lower than the average point degree centrality has a small number of agricultural carbon emission linkages with other provinces; most of them only have the ACEE linkages with either the top provinces or neighboring provinces. Provinces with a low centrality degree include Sichuan, Ningxia, Hunan, and other places. These regions are all located within the interior of China, and their agricultural development is faced with obstacles such as an inferior geographical position and transportation, a weak economic basis, and a low level of agricultural technology. Therefore, they are in a marginal position in the ACEE network, thereby displaying insufficient forward and backward linkage. It can neither produce large spillover effect on other provinces nor successfully accept technology and factor spillovers from other provinces. In general, the border and coastal provinces are close to the center of China's ACEE network and have a large influence, while the inland provinces are located in the periphery, and there is still a large room for improvement.

The closeness centrality of most provinces in China indicates a continual reduction. According to the data in Table 6, the closeness centrality of most provinces in 2001, 2011, and 2021 is in the range of [78, 100], indicating that the ACEE linking ability among provinces is strong, the overall spatial correlation network flow efficiency is high, and the network structure is balanced.

Next, according to the data in Table 6, the mean closeness centrality of provinces in the ACEE network in 2001, 2011, and 2021 are 89.7695, 89.4801, and 89.2842, respectively. Specifically, the closeness centrality of Fujian, Heilongjiang, and Liaoning is ahead of that of other provinces, which indicates that the aforementioned provinces play the role of central actors in the spatial network, and the improvement of their ACEE can promote the improvement of the ACEE of other provinces more quickly and effectively. The reason is that the aforementioned five border provinces and one coastal province are more likely to rely on the advantages of the surrounding investment and cooperation greatly promoted by the open economy to generate spatial correlation with other provinces, which makes the agricultural ecological factors rapidly flow among each other, and thus has a significant role in promoting the improvement of the ACEE in other provinces. However, the closeness centrality of inland provinces such as Sichuan, Ningxia and Hunan are low. The spatial network connection is difficult, and the promotion effect of receiving other provinces is not significant, which is mainly related to the location of the provinces, agricultural development and other factors.

Additionally, the ranking fluctuation of the closeness centrality value of Yunnan, Guangdong, and Shaanxi increased. It can be seen that Yunnan fiercely expanded its open agriculture, achieved results in regional cooperation and exchange, established an external cooperation and development platform, and increasingly interacted with other provinces in the agricultural economy. Shaanxi is located in the hinterland and the important node of 'the Belt and Road', with numerous adjacent provinces. Under the promotion of 'the Belt and Road' and other programs, the spatial connection strength with surrounding provinces continues to strengthen. Guangdong has a good geographical advantage. Relying on the economic basis and traffic conditions, Guangdong can swiftly absorb the overflow of agricultural elements from nearby provinces and quickly create correlation links with other provinces.

An overall upward trend can be observed in the betweenness centrality of most provinces in

China, as indicated by Table 7. In the ACEE network, the mean betweenness centrality of each province in 2001, 2011, and 2021 are 1.7742, 1.8065, and 1.8387, respectively, indicating that the betweenness centrality of the ACEE of most provinces showed an overall upward trend, and the interdependence was enhanced with a stronger correlation.

Second, it is noted that a higher intermediary centrality is observed in 18, 20, and 16 provinces, which include Heilongjiang, Jilin, and Liaoning, among others when compared to the average of that year. These provinces are known to have better agricultural resource endowment. The ACEE improvement process has identified these provinces as the core of the ACEE network. This positioning enables them to effectively control and influence the efficiency improvement of other provinces, thereby serving as 'intermediaries' and agents of 'transmission'. Additionally, the analysis reveals that there are 13, 11, and 15 provinces with lower than average betweenness centrality in that year. Notably, provinces such as Henan, Shaanxi, and Guizhou fall into this category. These provinces are more susceptible to the ACEE levels of other provinces. To achieve a positive development, they need to rely on support from the top provinces in enhancing their efficiency.

4.3. Analysis of plate characteristics of the ACEE network

In this paper, the Ucinet6.0 software is used to conduct a block model analysis based on the CONCOR algorithm on the ACEE network of the 31 Chinese provinces in 2021 in order to examine its geographical clustering characteristics. The maximum segmentation depth is set as 2, the concentration degree is 0.2, and four plates are distinguished. In order to show the number and distribution of provinces in each segment of the network, this research collates the plate distribution content of China's ACEE network in 2021 and maps it, as detailed in Figure 9. It can be seen that the ACEE of China in 2021 has obvious geographical regional agglomeration.

In order to comprehend the relationship between the inside and outside of the plate, this study sorted out and counted the number of relationships between the inside and outside of the plate on the basis of the segmentation findings, and the particular results are provided in Table 8.

Table 8. Plate characteristics of China's ACEE cyberspace network in 2021.

Spillover	Receptive relationship section				Total overflow	Inside the plate	Outside the plate	
relationship plate	1	2	3	4	relation		Receiving	sending
Plate 1	52	37	50	79	218	52	168	166
Plate 2	51	19	39	63	172	19	169	153
Plate 2	46	25	30	40	141	30	174	111
Plate 4	71	38	29	47	185	47	149	138
Total receive relation	220	119	148	229	716	148	568	

The correlation of the ACEE varies among the plates. There are 716 correlations in the ACEE network, of which 148 are intra-plate and 568 are inter-plate. There is an obvious spatial connectivity, with the structure of each plate being close and the spillover effect between plates being very strong. By aggregating the number of receiving relations of each plate, the ACEE of the fourth plate is more influenced by the outside world as compared to other plates, while the second plate is substantially less affected. After summing the spillover relationship number of each plate, the spillover effect of the ACEE in the first plate is rather strong, and the third plate is relatively weak. By comparing the number of receiving relations and the associated spillover relations of each plate, the difference between the first and third plates is minor, while the difference between the second and fourth plates is substantial. Among them, the ACEE relationship between the second plate and other plates primarily relies on a spillover relationship, while that between the fourth plate and other plates is mainly based on a receiving relationship. When the association within the plate is not regarded, the difference between the number of acceptance relations and spillover relations of the third plate is considerable, and the ACEE relationship of the third plate is dominated by the acceptance relationship. The number of external receiving relationships of each plate is always larger than the number of emitting relationships, indicating that, on the whole, the ACEE relationship between each plate and other plates is mainly a receiving relationship when the internal correlation of the plate is not considered.

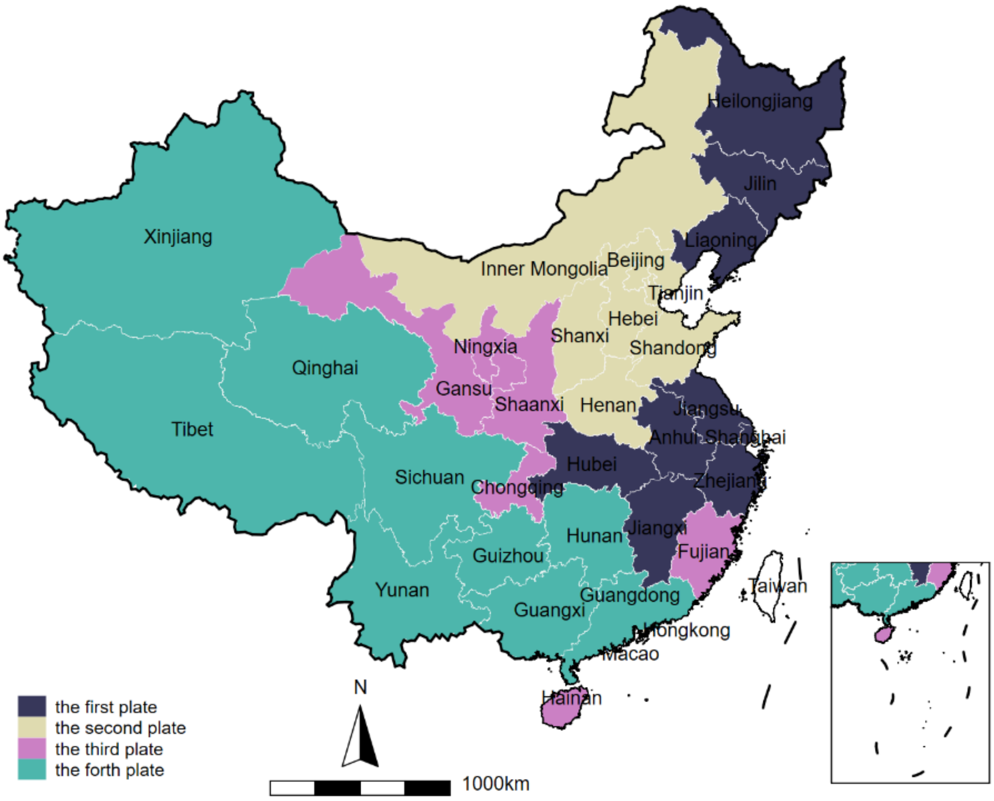

Figure 9. Plate distribution of China's ACEE network in 2021.

Based on Table 8, this paper calculated the proportion of the plate acceptance relationship, the expected proportion, and the actual proportion of the plate internal relationship, and carried out feature positioning of four plates in the ACEE network. The specific results are shown in Table 9.

It can be observed from Table 9 that the plates generally play an intermediary function in the ACEE network of China in 2021. The figures of the proportion of accepting relations of the first, second and fourth plates are all around 50%, which both accept connections while sending links out. However, the actual proportion of internal relations of these three plates is smaller than the expected value of the proportion of the internal relations, which has a low proportion of internal relations. The acceptance proportion value of the third plate is 51.21%, and the actual proportion of internal relations is higher than the expected proportion of internal relations. It demonstrates that the third plate also accepts links and sends links to the outside; however, more links are sent to the inside, with a large proportion of internal relations, therefore the third plate is the main beneficiary plate. Plate qualities may be connected with the geographical location of the plate. For example, the provinces in the third plate are mainly located in the central region of China, with a comparatively low agricultural development level, and are more dependent on resource spillovers from provinces rich in agricultural resources.

Table 9. Plate feature positioning table of each ACEE network in China in 2021.

Plate	Reception relation ratio		Internal relation ratio			Role of plate
	Practice	Compare to 0	Practice	Expectation	Comparing the two	
1	50.23%	>	23.85%	26.67%	<	Broker plate
2	40.89%	>	11.05%	20.00%	<	Broker plate
3	51.21%	>	21.28%	16.67%	>	Main benefit plate
4	55.31%	>	25.41%	26.67%	<	Broker plate

Note: proportion of receive relations = total number of receive relations/(total number of overflow relations + total number of receive relations); Expected internal relationship ratio = (number of provinces in the plate -1)/(number of all provinces in the network -1); Proportion of actual internal relations = number of plate internal relations/number of plate spillover relations.

In order to depict the strength of connections inside and across plates more intuitively and concisely, this paper constructs an image matrix equivalent to the density matrix. Taking the overall network density as the threshold, the density matrix is assigned a value of 1 if it is more than the threshold; otherwise, it is assigned a value of 0, and the specific results are shown in Table 10.

Table 10. Plate density and image matrix of the network spatial association of the ACEE in 2021.

Plate	Density matrix				Image matrix			
	Plate 1	Plate 2	Plate 2	Plate 4	Plate 1	Plate 2	Plate 2	Plate 4
1	0.722	0.968	0.963	0.975	0	1	1	1
2	0.968	0.429	0.929	1	1	0	1	1
3	0.963	0.929	0.867	0.796	1	1	1	1
4	0.975	1	0.796	0.639	1	1	1	0

Note: “1” means there is a row to column relationship, “0” means there is no relationship.

The network plates of China’s ACEE in 2021 had significant interoperability. Based on the density matrix and image matrix provided in Table 10, two crucial pieces of information may be obtained: the existence of a relationship and the strength of the link. Overall, the values in the density matrix are rather substantial, except for the somewhat decreased density value within the second plate, which suggests that there are correlations within and across plates. From the perspective of the plate interior, the third plate achieves the largest density value of 0.867, and the second plate achieves the smallest density value of 0.429, indicating that the third plate has the strongest internal interoperability, while the second plate has the weakest internal interoperability. From the perspective of the exterior of the plate, the density values within the third plate and between the third plate and other plates are quite high, and the image matrix values are all 1, indicating that the third plate has superior connectivity with other plates. By comparing the internal density of each plate and the density between them and other plates, the exterior interoperability of the plates is better than the internal interoperability of the plates, save the third plate.

5. Conclusions

Based on the panel data of 31 Chinese provinces from 2001 to 2021, the SBM-DEA is adopted as the ACEE measurement model by comparing different carbon emission efficiency simulations, calculates China's ACEE, and analyzes its basic characteristics. On this basis, this work uses social network analysis methods to conduct in-depth research on the characteristics and transmission mechanisms of the spatial correlation network structure of China's ACEE. The research conclusions are as follows.

First, from the perspective of the concentration trend, the average level of the ACEE from 2001 to 2021 showed a decreasing trend year by year, while the overall level of the ACEE showed a decreasing trend, experiencing a process of rapid decline and slowdown. From the perspective of discrete trends, the differentiation of the ACEE among different provinces in China has intensified, and the degree of difference in the ACEE between provinces in China from 2001 to 2021 has gradually become balanced.

Second, the overall ACEE of China shows a spatial pattern of being high in the east and low in the west, which is closely related to the economic leading industries and agricultural development environment of various provinces. Most provinces in China have shown a decreasing trend in the ACEE, and the differences in the ACEE levels between provinces have become more prominent. The average improvement rate of the ACEE in various provinces in China is relatively consistent and balanced; however, the overall efficiency improvement in monsoon areas is better than that in non-monsoon areas. The ACEE of various provinces in China mostly fluctuates around the original level, and the characteristic of consistent growth rates of the ACEE between provinces is becoming increasingly evident.

Third, the spatial correlation of China's ACEE from 2001 to 2021 presents a complex network structure. In terms of the overall network structure characteristics of the spatial correlation, the ACEE network has a high degree of correlation, and its temporal evolution shows a stable trend. In terms of the centrality network structure characteristics of the spatial correlation, the point centrality and near centrality of most provinces in China continue to show a downward trend, while the interdependence of the ACEE between provinces increases. In terms of the clustering characteristics of the spatial correlation, there are differences in the correlation of ACEE among the four plates, though they mostly play a mediating role. Moreover, in 2021, the China ACEE network sector has a strong interoperability.

Additionally, this study has provided some implications on China's green and sustainable development. First, the relevant research findings on the inter-provincial ACEE provide a reference for the formulation of agricultural policies in various provinces of China, serving their industrial development. Second, it urges governments at all levels to pay attention to the development of green energy, especially in the field of green agriculture, and make planned investments based on their specific circumstances. There are two shortcomings in this study. First, considering the accessibility and coherence of the data, the data in this paper mainly comes from the National Statistical Yearbook, and the data type leans towards a macro analysis. Therefore, the paper mainly focuses on a macro analysis and lacks a micro analysis of the ACEE. Second, this study uses social network analysis methods to deeply discuss the evolution characteristics of ACEE of China, though the reasons for its formation and impact have not been thoroughly studied. In a later stage, the authors will further conduct in-depth research on the influencing factors and effects of China's ACEE, and focus on collecting micro data to supplement micro discussions and research.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors have no relevant financial or non-financial interests to disclose.

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