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# Spatial differentiation characteristics and driving factors of agricultural eco-efficiency in Chinese provinces from the perspective of ecosystem services

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A B S T R A C T

Farmland ecosystem service is an important output of agricultural production, but it has been incompletely reflected in current studies on eco-efficiency. In this study, the value of improved farmland ecosystem services is used as one of the expected outputs. The data envelopment method is used to evaluate the agricultural eco-efficiency (AEE) of 31 provincial administrative regions in China from 2006 to 2018. The spatial autocorrelation method is used to explore the characteristics of AEE in China. Geographical detector model (Geodetector) is adopted to detect the driving factors of AEE spatial differentiation in China. China's AEE trend from 2006 to 2018 was downward with the efficiency value decreasing from 1.023 to 0.995. China's AEE level has improved with an average of 1.004. The spatial distribution pattern represented in space is in the following order: eastern region > western region > northeast region > central region. The AEE gap among provinces in the western region is the largest, and that in the northeast region is the smallest. China's AEE spatial correlation distribution presents random distribution characteristics. During the research period, the low−high (LH) efficiency response area has centered on Yunnan Province. The low−low (LL) level concentration area has centered on Inner Mongolia autonomous region and Liaoning Province. The high−low (HL) level diffusion effect agglomeration area has centered on Heilongjiang Province. Energy input, water resource input, and carbon emission are the core drivers of AEE spatial differentiation in China. Water resource input, pesticide input and labor input are the significant control factors of AEE spatial differentiation in the eastern, central, and western regions of China.



## 1. Introduction

In 2019, the Food and Agricultural Organization of the United Nations released the report on the state of the world's food security and nutrition; the report indicated that 821.6 million people in the world are still dealing with food shortage by 2018; the solution for this problem is the profound change in the global food and agriculture system. The global demand for food is expected to double by 2050. Meeting the growing demand for food production while reducing adverse environmental impacts in the face of climate change and competition for natural resources is a major agricultural sustainability challenge (Cui et al., 2018). Sustainable agricultural production ensures high yield while protecting the local environment and ensuring livelihood (Pretty and Bharucha, 2014; Smith et al., 2017). Agricultural production in China has redundant inputs, unexpected outputs, and excessive application of materials that lead to high energy consumption and high pollution because of the country's relatively low agricultural eco-efficiency (AEE) level (Su et al., 2019; Zhang et al., 2012). The problem of supply and demand of cultivated land will seriously affect the sustainable development of agriculture in China. Therefore, the coordination of economic and ecological benefits needs to be the focus in agricultural production rather than the blind pursuit of high efficiency to solve the current agricultural development dilemma in China (Tilman et al., 2002). The scientific and reasonable evaluation of AEE and the formulation of corresponding

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countermeasures are important for sustainable development in agriculture (Table 1).

In this context, the concept of "eco-efficiency" was proposed by (Verfaillie, H.A, 2000) as meeting human needs and improving quality of life by creating products and services that has a competitive price, while keeping its environmental impact and resource utilization intensity within the Earth's carrying capacity level. Ecological efficiency is expressed by the ratio of the economic value of a product or service to its environmental impact. In 1998, the World Economic Cooperation Organization refined eco-efficiency as a measurement of input elements and output elements and defined it as "the efficiency of using ecological resources to meet human needs." Nowadays, with the more prominent resource and environmental problems, ecological efficiency is an effective tool to measure resource environment and social economy (Fet, 2004). The development of agricultural "ecological efficiency" plays a pivotal role in achieving the 2030 Sustainable Development Goals in the future (Mugambiwa and Tirivangasi, 2017; Shaofeng et al., 2019). AEE indicates that agricultural production activities are carried out within the carrying capacity of the agricultural ecosystem to produce good-quality agricultural output values and service with less resource loss and environmental damage. A high level of AEE affects the synergy between agricultural production, economic development, and ecological services. The research on AEE need to be done at micro, meso, and macro scales in recent years (Maxime et al., 2006; Zhang and Qing, 2010). Researchers are inclined to explore the influencing factors of AEE and analyze the reasons for low agricultural ecological benefits. Many factors affect AEE, including economic and social factors, such as industrial structure, production technology, and management policies (Zou et al., 2020), or natural environmental factors, such as geographic conditions and climate. Large-scale studies such as Italy (Coderoni and Esposti, 2014) have found a long-standing relationship between greenhouse gas emissions from agriculture and agricultural productivity, and climate change is associated with ecological efficiency in agriculture (Liu et al., 2020). Proposes to improve the efficiency of water use in agriculture, such as irrigation, regulated water shortage irrigation and fertilization, energy can improve AEE. Meso-scale studies such as those conducted in Spain (Maia et al., 2016) have found that the level of agricultural machinery, foreign investment in agriculture, and agricultural education are all important means to effectively improve AEE. With the help of existing farm-level technology, substantial increases in agricultural output and lower costs can be achieved as an important means to improve the level of efficiency (Binam et al., 2003). However, few micro-scale studies conducted in recent years. The inefficiency of analysis in Spain is closely related to the inefficiency of technology in input management, and the general agricultural policy agricultural environment plan is an effective policy to improve ecological efficiency (Picazo-Tadeo et al., 2011).

**Table 1**
Abbreviations.

| Abbreviation | Full name |
|---|---|
| AEE | Agricultural eco-efficiency |
| DEA | Data envelopment analysis |
| DMU | Decision making unit |
| SBM | Slack-based measure |
| ESV | Ecosystem Service Value |
| NDVI | Normalized Difference Vegetation Index |
| NPP | Net primary productivity |
| HH | High-High aggregation |
| HL | High-Low aggregation |
| LL | Low-Low aggregation |
| LH | Low-High aggregation |
| S-$SBM_1$ | Supper-efficiency slacks-based model without ESV |
| S-$SBM_2$ | Supper-efficiency slacks-based model with ESV |

AEE evaluation methods include Stochastic Frontier Approach (Kuosmanen and Kortelainen, 2010), ratio method (Godoy-Durán et al., 2017), Life Cycle Approach (Roy et al., 2009), etc., wherein packet analysis is the most used method to measure AEE. Data envelopment analysis (DEA) is a non-parametric statistical method based on the concept of relative efficiency proposed by other researchers (Charnes et al., 1982). It can evaluate the technical efficiency of multiple decision-making units and is widely used in agriculture, finance, transportation, and other fields. For example, researchers (Han et al., 2020) combined the analysis framework of meta-frontier analysis and inseparable hybrid model to analyze the in efficiency of agricultural ecology in each province from the two dimensions of management and technology. Biswas (2019) after using DEA to evaluate the efficiency of funds, the MABAC method is used to screen funds, and finally, the funds are selected to Ecosystem Service Value (ESV) form the best investment portfolio. The DEA method is used to measure the city's performance from the perspective of efficiency. In these studies, an undesired output SBM model (Tone, 2001) that considers slack measurement processing is often used to measure AEE. The SBM-DEA models adopted in this paper are used to construct a comprehensive measurement of sustainable agricultural development in the form of AEE. Compared with other models, the advantage of this method's framework is that it combines a set of indicators that can combine multiple and diverse ecological benefits and different evaluation perspectives. The index weight is randomly determined by the actual sample, which has the advantage of being insensitive to the dimension of input and output variables. It can effectively avoid the shortcomings of other methods, such as single index, multiple index, principal component analysis, and decoupling analysis. It objectively reflects the development status of AEE in each region.

Many previous studies on AEE evaluation have been based on environmental-social perspectives, mainly on human well-being and consumer benefits, and the evaluation process tends to overlook the efficacy of ecosystem services. A researcher (Costanza, 1987) believes that ecosystem services are the benefits that humans obtain directly or indirectly from nature when they come in contact with nature in the process of life and production. Constanza (Costanza, 1987) emphasized that if the value of ecosystem services is not fully embodied or fully quantified, its importance will be gradually ignored in future policies. Such neglect will negatively affect human sustainable development and cause a high amount of damage. Therefore, the main innovation of this paper is to integrate farmland ecosystem services as part of the expected output into the agricultural ecological efficiency index system. The level of farmland ESV can indicate whether the input and output of the research area are reasonable. When quantifying the value of farmland ecosystem services, the supply and demand of agricultural products need to be weighed, and agricultural welfare for human society need to be targeted to conduct agricultural production. (2) Geodetector is used to detect the spatial driving factors of China's agroecological efficiency to analyze the existing spatial differences at the national and regional levels and the key drivers of improving agroecological efficiency. The study helps determine the significant driving force of AEE at the national level. It helps discover the core driving factors that lead to regional differences in agroecological efficiency among provinces and cities in China and that quantify the impact of explanatory variables.

In order to realize the green transformation of agriculture and construct a resource-saving and eco-friendly agricultural production system, the differences in resource endowment, climatic conditions, farming structure and industrial system are reduced.

This article considers the heterogeneity of production of different regions of China, investigates the sources of agricultural inefficiency, and identifies the spatial distribution characteristics and regional differences of China's AEE from 2006 to 2018. Three research questions are raised, as follows. (1) How can a system that reflects nature and comprehensive ESV assessment models on ecological and agricultural industry characteristics be built? (2) What are the characteristics and spatial patterns of AEE evolution in the different provinces of China from 2006 to 2018 with the application of the Super-SBM model? (3) Through the use of geographic detectors, what are the reasons for the loss of AEE in each regional? The research results provide a scientific basis for increasing AEE, reducing regional agricultural development differences, and assisting in the formulation of local policies to coordinate agricultural growth of resource development and environmental protection.

## 2. Methods and data

### 2.1. Super efficiency SBM model

Super efficiency SBM model (Andersen and Petersen, 1993; Tone, 2001) is a super efficiency DEA model, and its main feature is the consideration of relaxation variables. The super efficiency SBM model regards different evaluation elements as Decision making unit (DMUs), evaluates the effectiveness of the same type of DMUs with multi-input and multi-output index characteristics, and determines whether the efficiency is effective while judging the effective production frontier and comprehensively analyzing the gap between each the model and DMU. This study uses Max DEA software to select the super efficiency SBM model of non-radial and variable return scale to calculate the AEE values of 31 provinces and cities in China in 2006, 2010, 2014, and 2018. The specific structure of the model is as follows:

$$min\rho^* = (1 - 1\Big/m\sum_{i=1}^{m} s_1^- \Big/ x_{ik}) \Big/ \Big[1 + 1\Big/ (n_1 + n_2)\ (\sum_{r=1}^{n_1} s_r^+ \Big/ y_{rk} + \sum_{l=1}^{n_2} s_l^{z-} \Big/ Z_{lk})\Big] \tag{1}$$

$$st\begin{cases} X\lambda + S^- = X_K \\ Y\lambda - S^+ = Y_K \\ Z\lambda + S^{z-} = Z_k \\ \lambda \ge 0, S^- \ge 0, S^+ \ge 0, S^{z-} \ge 0 \end{cases} \tag{2}$$

In the above-mentioned equation, $\rho^*$ is the efficiency evaluation standard. The slack of the indexes of resource input, expected output, and non-expected output is respectively expressed as $s_i^-$、$s_r^+$、$s_l^{z-}$. The matrix of the indexes of resource input, expected output, and non-expected output is respectively represented by $X$, $Y$, $Z$. $\lambda$ represents the weight of each input index. The relaxation matrix of the indexes of resource input, expected output, and non-expected output is respectively represented by $s^-$、$s^+$、$s^{z-}$. The indexes of resource input, expected output, and non-expected output are respectively expressed as $x_k$、$y_k$、$z_k$.

### 2.2. Spatial autocorrelation analysis

Spatial autocorrelation imports the AEE value of a given year into ArcGIS 10.5 software (An et al., 2015) and sets the software to divide the 4-year efficiency value processing into seven levels of AEE value partition based on the natural breakpoint method. The hierarchical map is imported into Geoda software adjacent to rook in binary proximity. The global Moran index is calculated by repeating the random arrangement method for 999 times. The AEE scatter, LISA cluster, and LISA significant maps of the research area are obtained.

Global spatial autocorrelation is the representation of the global Moran index, which is used to determine whether the spatial distribution characteristics of AEE in China are clustered, random, or discrete. The calculation formula of global Moran's I value is as follows:

$$I = n\Big/\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} * \Big[\sum_{1=1}^{n}\sum_{i=1}^{n} w_{ij}\Big(x_i - \sum_{i=1}^{n} x\Big/n\Big)\Big(x_i - \sum_{j=1}^{n} x\Big/n\Big)\Big/\sum_{i=1}^{n}\Big(x_i - \sum_{i=1}^{n} x\Big/n\Big)^2\Big] \tag{3}$$

$n$ is the number of DMUs, $w_{ij}$ is the spatial weight between element $i$ and element $j$, and $x_i$ is the attribute value of element $i$. In this study, n = 31 and $I \in [-1,1]$. $I > 0$ indicates that each region has a positive correlation in space. $I = 0$ means that no spatial correlation exists among regions. $I < 0$ implies that the regions are negatively correlated in space. The significance level of spatial autocorrelation is tested using the standardized statistic Z, and the expression is as follows:

$$Z = [I - E(I)]\Big/\sqrt{VAR(I)} \tag{4}$$

In the formula, E(I) is the expectation of autocorrelation of observed variables, and VAR(I) is the variance.

Local spatial autocorrelation is the local expression of Moran index, which is used to judge the degree of clustering or dispersion in local areas and its significance level. The expression is as follows:

$$I_i = \Big(x_i - \sum_{j=1}^{n} x\Big/n\Big)\Big/\Big[\sum_{j=1, i\ne j}^{n} z_j\Big/(n-1) - \Big(\sum_{i=1}^{n} x_i\Big/n\Big)^2\Big] * \sum_{j=1, i\ne j}^{n} w_{ij} z_j \tag{5}$$

$I_i$ represents the local Moran index in region I, and other parameters are the same as above. $I > 0$ means the clustering together of a high-value region with another high-value region. When a low-value region and another low-value region cluster together, this case belongs to the positive correlation of space. A large I indicate a small spatial difference. $I < 0$ means the clustering of a high-value region with a low-value region, which is a space of negative correlation. A small I correspond to a large difference in space. $I = 0$ means that the attribute values are randomly distributed in space, and the clustering of the region can be intuitively analyzed through the Moran scatter diagram.

### 2.3. Pearson correlation model

Pearson correlation coefficient is a method proposed by British statistician Pearson in the 20th century to determine whether two datasets can be concentrated on a line function (Siegel and Castellan, 1988). It is often used to determine the linear relationship between variables.

$$r = \sum(X-\overline{X})(Y-\overline{Y}) \bigg/ \left[\sqrt{\sum(X-\overline{X})^2}\sum(Y-\overline{Y})^2\right] \quad (6)$$

The value of the Pearson correlation coefficient $r$ is in the range of $(-1, 1)$. Two variables, namely, X and Y, are assumed. If the calculated r is 0, then X and Y have no relationship or are not linearly correlated. If the correlation coefficient is greater than 0, then X and Y are positively correlated. If the correlation coefficient is less than 0, then X and Y are negatively correlated.

### 2.4. Index selection

Based on the perspective of ecological environment, the aim of AEE is to achieve the maximum number of agricultural products with as little resource loss and environmental pollution as possible. Therefore, evaluating AEE needs good understanding of economic, environmental, and ecological performance indicators. In recent years, many experts and scholars have continuously and deeply studied the construction of the evaluation index system, and a relatively complete evaluation system has been gradually established. Therefore, based on the specific conditions of China, this article introduces the establishment of sustainable development evaluation index systems at home and abroad. A set of AEE index systems that selects 10 conventional elements and 1 innovation index is constructed. The AEE evaluation system constructed in this paper is divided into two stages, namely, the AEE indicator system (stage 1) and the construction of the influencing factors of AEE evolution (stage 2). The two-stage AEE evaluation indicators are as follows:

#### 2.4.1. Phase 1: AEE indicator system

Input indicators: These refer to the eco-efficiency evaluation indicator system constructed by previous scholars (Pan, 2013a; Pan and Ying, 2013b). This paper selects the following: land, labor, machinery, water resources, fertilizers, pesticides, agricultural film, and energy input as resource input indicators; agricultural output value and farmland ecosystem services as expected output indicators; and carbon emissions as undesired output indicators. Land multiple cropping and intercropping are the factors considered in the selection. The total sown area of crops can be used to characterize land input indicators. The size of its area is expressed as the actual utilization rate of cultivated land, revealing the agricultural structure and production intensity, which play an important role in the balance of supply and demand of farmland in agricultural production and ultimately affect AEE. Considering the availability of data, the number of labors in the tertiary industry is used as an indicator of labor input, and agricultural production activities directly reflect the input of agricultural labor. Fertilizers, pesticides, and energy are closely related to agricultural carbon emissions, and the intensity of agricultural machinery input affects the use of chemical substances, such as agricultural fertilizers and pesticides, which in turn affect AEE. Therefore, this paper selects agricultural water consumption as the input index of natural resources, the total power of agricultural machinery as the input index of machinery, and the amount to pesticides, chemical fertilizers, and agricultural film as the input index of chemical substances. The use of agricultural diesel is selected as an energy input index (Table 2).

Output index: the total output value of agriculture is the ideal output index of agricultural production. Agricultural carbon emission is used as the poor output index of agricultural production in the stage of agricultural production. Agricultural undesired output includes two types of agricultural carbon emissions (Liu et al., 2014) and agricultural non-point source pollution (Tian et al., 2014). The two types of indicators are measured for each pollution source emission and their respective carbon emissions. This article chooses agricultural carbon emissions as the undesired output. On the one hand, agricultural carbon emissions cover a wider range compared with agricultural non-point source pollution. On the other hand, agricultural carbon emissions are easier to quantify for data collection.

#### 2.4.2. Phase 2: AEE evolution's influencing factors index construction

AEE is affected by many factors. Based on the results of a previous study (Liu et al., 2020) and other related studies and based on the principles of data availability, quantification, and comparability,

**Table 2**
China AEE evaluation index system.

| Index type | Indicators category | Variable | Variable declaration | Driving factors |
|---|---|---|---|---|
| Resource input | Agricultural resource consumption | Land input | Total sown area/$10^3$hm$^2$ | $x_1$ |
| | | Labour input | Agricultural workers/$10^4$ | $x_2$ |
| | | Machinery input | Total power of agricultural machinery/$10^4$kW | $x_3$ |
| | | Water resources input | Effective irrigated area/$10^3$hm$^2$ | $x_4$ |
| | Environmental pollution caused by agricultural production | Fertilisers input | The amount of chemical fertilizer applied to agriculture/$10^4$t | $x_5$ |
| | | Pesticides input | Consumption of pesticides/$10^4$t | $x_6$ |
| | | Agricultural film input | Consumption of agricultural film/$10^4$t | $x_7$ |
| | | Energy input | Consumption of agricultural diesel oil/$10^4$t | $x_8$ |
| Output indicators | Expected output | Agricultural output | The total value of agricultural output/$10^8$ ¥ | $x_9$ |
| | | Farmland ecological service system | Value of ecosystem services/$10^8$ ¥ | $x_{10}$ |
| | Unexpected output | Carbon emissions | Agricultural carbon emissions/$10^4$t | $x_{11}$ |

phase 1 is still used in the evaluation system. AEE is selected as the dependent variable. To avoid the two-way interaction between efficiency and explanatory variables leading to endogenous problems, the 11 variables of AEE are tested for Hausman endogeneity between dependent and explanatory variables. After excluding invalid variables, this paper selects $x_1$, $x_2$, $x_3$, $x_4$, $x_5$, $x_6$, $x_7$, $x_8$, $x_9$, and $x_{10}$, which are used as explanatory variables of AEE.

### 2.5. Geodetector analysis

Geodetector (Hu and Xu, 2018; Onozuka and Hagihara, 2017; Wang and Xu, 2017) is commonly used to detect the diversity of geospatial existence and reveal whether its driving factors are consistent in space and the interaction among factors. In this study, geodetector is used to analyze the driving factors of AEE spatial differentiation in China in 2006, 2010, 2014, and 2018. A total of 10 index data affecting AEE in each province are imported into ArcGIS 10.5. The software uses natural breakpoint method to discretize the data into five levels. After the geodetector data processing, the single factor $q$ value and the double factor $q$ value are judged after superposition. Therefore, the direction and strength of the interaction factors are determined. The driving force intensity $q$ value is calculated as follows:

$$q = 1 - 1\Big/ nz^2 \boxed{\sum_{k=1}^{l} n_k {z_k}^2} \tag{7}$$

In the formula, $q$ represents the detection force value of detection factor $X$. Its range is [0, 1], and a large $q$ value indicates a large influence on AEE. n represents all samples in the study area, $n_k$ represents the number of samples contained in the type $k$ of the driving factor, and $z^2$ represents the discrete variance of the area.

The purpose of interaction detection is to evaluate whether the influence factors $x_1$ and $x_2$ increase or decrease the explanatory power of poverty incidence y when they work together or whether the effects of these factors on poverty incidence y are independent. The evaluation method calculates the $q$ values of two influencing factors $x_1$ and $x_2$ for y, namely, $q\ (x_1)$ and $q\ (x_2)$; calculates the $q$ values when they interact, namely, $q\ (x_1 \cap x_2)$; and compares $q\ (x_1)$, $q\ (x_2)$, and $q\ (x_1 \cap x_2)$. The relationship between the two factors can be divided into five categories.

### 2.6. Calculation method of ESV

This study is based on the ecological service value of Costanza (1987) and Xie (2003). Using the equivalent factor method, 31 provinces and cities in the study area are revised regionally. The dynamic coefficient is revised to construct a dynamic evaluation model of regional farmland ESV and to calculate the dynamic changes in ESV in the four periods, namely, 2006, 2010, 2014, and 2018. The value of farmland ecosystem services in this study refers to the basic equivalent table of ecosystem service functions per unit area in 2011 presented previously (Xie et al., 2015). The value of ecosystem services using a standard equivalent factor is 3406.5 yuan/hm$^2$; 1 standard unit ESV of equivalent factor refers to the economic value of food produced by 1 hm$^2$ farmland each year (Table 3).

The study area is revised according to farmland. First, the equivalent standard proposed by Xie Gaodi and others is adjusted from the average grain output value of farmland in China to the grain output value of 31 provinces and cities. This study focuses on narrow sense agriculture. Thus, the annual average agricultural output values of provinces and cities in 2006, 2010, 2014, and 2018 are considered the representative grain output. The revised formula of regional ecological service equivalent (Li et al., 2015; Xie and Xiao, 2013) is as follows:

$$\lambda = Q/Q_0 \tag{8}$$

$\lambda$ stands for the regional revision coefficient of ecological services. Q and $Q_0$ stand for the total agricultural output value of the study area and China in that year.

With the basic value equivalent table of ecosystem services, the equivalent value correction of spatiotemporal dynamic change of farmland ecosystem services is constructed, as follows:

$$F_{ci} = P_i {*} F_c \tag{9}$$

$F_{ci}$ refers to the unit area value equivalent factor of farmland ecosystem in class C ecological service function of province $i$; $P_i$ refers to the Net Primary Productivity (NPP) regulation factor of the year in province $i$ of farmland ecosystem; and $F_c$ refers to the value of one standard equivalent factor of agricultural system service in 2011, which is 3406.5 yuan/hm$^2$.

The calculation method of NPP spatiotemporal adjustment factor is as follows:

$$P_i = B_{ij}/B \tag{10}$$

$B_{ij}$ refers to the NPP of the $j$ month in the $i$ region of such an ecosystem, and $B$ refers to the annual average NPP of such ecosystem in China. Some studies have shown that the normalized vegetation index (NDVI) value has a strong correlation with the value of ecological services. Moreover, NPP data are lacking. Thus, this study replaces NPP with NDVI data to reflect the spatial differ (Han and Deng, 2020)ences in the value of farmland ecosystem services. After data processing by ArcGIS 10.5 software, NDVI coefficient is selected as the index to revise the dynamic equivalent.

$$EAV_{it} = \lambda \times S_k \times F_{ci} \quad (\mathrm{I} = 1, \ 2, \ \ldots\ldots, \ 31) \tag{11}$$

In the formula, $EAV_{it}$ represents the service value of farmland ecosystem in the $t$ year of $i$ province. The area of farmland ecosystem type in the study period is represented by $S_k$. $F_{ci}$ is the same as above, and $E_1$ is the same as above.

### 2.7. Data sources

The data of this study come from the statistical data of the National Bureau of Statistics, China Rural Statistical Yearbook

**Table 3**
Value equivalent of farmland ecosystem services in China.

| Supply service | Regulating service | | | | Support service | | | Cultural service |
|---|---|---|---|---|---|---|---|---|
| Water supply | Gas regulation | Climate regulation | Purify environment | Hydrological regulation | Soil conservation | Nutrients cycle maintenance | Biodiversity | Aesthetic landscape |
| 0.02 | 0.67 | 0.36 | 0.1 | 0.27 | 1.03 | 0.12 | 0.13 | 0.06 |

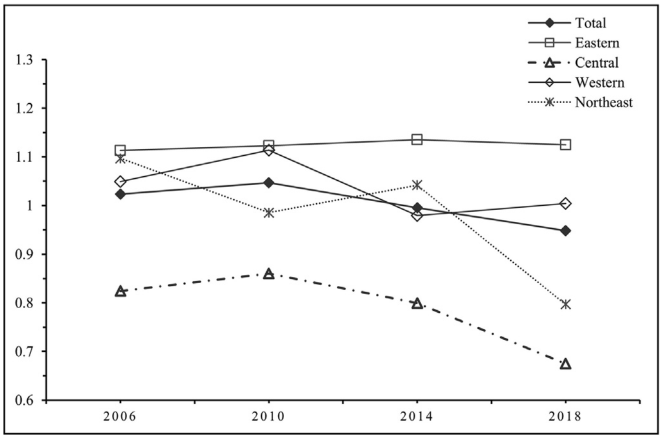


**Fig. 1.** Evolution trend of AEE in 2006–2018.

(2006–2018), statistical yearbook of provinces and cities (2006–2018), and China Statistical Yearbook (2006–2018). MODIS NDVI data come from the international scientific data image center of the computer network information center of the Chinese Academy of Sciences. In 2006, 2010, 2014, and 2018, the monthly composite data of MODND1M of Terra, which is a synthetic product of the NDVI vegetation in China, are processed by ArcGIS 10.5 software to generate the NDVI value during the research.

## 3. Results and discussion

### 3.1. Measurement and analysis of AEE in China

Fig. 1 Evolution trend of AEE in 2006–2018 has remained in the range of 3% with a weak inverted V-shaped downward fluctuation.

**Table 5**
Comparison of provinces and municipalities with S-SBM.

| DMU | Area | S-SBM$_1$ | Ranking (1) | S-SBM$_2$ | Ranking (2) |
|---|---|---|---|---|---|
| Shanghai | Eastern | 1.222 | 5 | 1.215 | 5 |
| Guangdong | Eastern | 1.184 | 6 | 1.131 | 10 |
| Beijing | Eastern | 1.602 | 2 | 1.554 | 2 |
| Shandong | Eastern | 1.102 | 12 | 1.09 | 12 |
| Hainan | Eastern | 1.15 | 7 | 1.135 | 9 |
| Jiangsu | Eastern | 1.103 | 11 | 1.078 | 13 |
| Zhejiang | Eastern | 1.045 | 15 | 1.043 | 16 |
| Hebei | Eastern | 0.807 | 23 | 0.896 | 21 |
| Fujian | Eastern | 1.069 | 13 | 1.051 | 14 |
| Tianjin | Eastern | 1.047 | 14 | 1.047 | 15 |
| Henan | Central | 1.12 | 10 | 1.193 | 6 |
| Shanxi | Central | 1.224 | 4 | 1.166 | 7 |
| Hunan | Central | 0.922 | 19 | 0.914 | 19 |
| Hubei | Central | 0.828 | 22 | 0.895 | 22 |
| Anhui | Central | 0.433 | 31 | 0.477 | 28 |
| Jiangxi | Central | 0.553 | 27 | 0.45 | 29 |
| Shanxi | Central | 0.457 | 30 | 0.434 | 30 |
| Tibet | Western | 3.218 | 1 | 2.565 | 1 |
| Guizhou | Western | 1.277 | 3 | 1.245 | 4 |
| Sichuan | Western | 1.125 | 9 | 1.153 | 8 |
| Xinjiang | Western | 1.133 | 8 | 1.095 | 11 |
| Inner | Western | 0.661 | 25 | 0.736 | 25 |
| Guangxi | Western | 0.867 | 21 | 1.016 | 17 |
| Ningxia | Western | 0.915 | 20 | 0.839 | 24 |
| Yunnan | Western | 0.519 | 28 | 0.587 | 27 |
| Chongqing | Western | 0.961 | 16 | 0.912 | 20 |
| Gansu | Western | 0.495 | 29 | 0.383 | 31 |
| Qinghai | Western | 0.954 | 17 | 0.872 | 23 |
| Heilongjiang | northeast | 0.805 | 24 | 1.32 | 3 |
| Liaoning | northeast | 0.925 | 18 | 0.932 | 18 |
| Jilin | northeast | 0.577 | 26 | 0.689 | 26 |

Note: S-SBM$_1$ does not have an ESV-based super-efficiency relaxation model, and S-SBM$_2$ has an ESV-based super-efficiency relaxation model.

**Table 4**
Shows the calculation of AEE in China.

| DMU | Area | 2006 score | 2010 score | 2014 score | 2018 score | Average | Comprehensive ranking |
|---|---|---|---|---|---|---|---|
| Shanghai | Eastern | 1.334 | 1.296 | 1.129 | 1.102 | 1.215 | 5 |
| Guangdong | Eastern | 1.202 | 1.117 | 1.101 | 1.102 | 1.131 | 10 |
| Beijing | Eastern | 1.165 | 1.337 | 1.673 | 2.042 | 1.554 | 2 |
| Shandong | Eastern | 1.142 | 1.101 | 1.081 | 1.037 | 1.090 | 12 |
| Hainan | Eastern | 1.129 | 1.117 | 1.152 | 1.140 | 1.135 | 9 |
| Jiangsu | Eastern | 1.042 | 1.088 | 1.086 | 1.096 | 1.078 | 13 |
| Zhejiang | Eastern | 1.041 | 1.063 | 1.030 | 1.039 | 1.043 | 16 |
| Hebei | Eastern | 1.027 | 1.048 | 1.003 | 0.505 | 0.896 | 21 |
| Fujian | Eastern | 1.023 | 1.045 | 1.063 | 1.073 | 1.051 | 14 |
| Tianjin | Eastern | 1.022 | 1.018 | 1.037 | 1.109 | 1.047 | 15 |
| Henan | Central | 1.299 | 1.336 | 1.077 | 1.061 | 1.193 | 6 |
| Shanxi | Central | 1.197 | 1.213 | 1.184 | 1.070 | 1.166 | 7 |
| Hunan | Central | 1.033 | 1.094 | 1.058 | 0.469 | 0.914 | 19 |
| Hubei | Central | 0.759 | 0.807 | 1.002 | 1.013 | 0.895 | 22 |
| Anhui | Central | 0.553 | 0.542 | 0.446 | 0.366 | 0.477 | 28 |
| Jiangxi | Central | 0.526 | 0.455 | 0.406 | 0.411 | 0.450 | 29 |
| Shanxi | Central | 0.402 | 0.576 | 0.423 | 0.335 | 0.434 | 30 |
| Tibet | Western | 2.855 | 2.787 | 2.491 | 2.125 | 2.565 | 1 |
| Guizhou | Western | 1.247 | 1.141 | 1.218 | 1.374 | 1.245 | 4 |
| Sichuan | Western | 1.236 | 1.108 | 1.142 | 1.127 | 1.153 | 8 |
| Xinjiang | Western | 1.129 | 1.155 | 1.040 | 1.055 | 1.095 | 11 |
| Inner | Western | 1.088 | 1.001 | 0.468 | 0.386 | 0.736 | 25 |
| Guangxi | Western | 1.019 | 1.029 | 1.004 | 1.013 | 1.016 | 17 |
| Ningxia | Western | 1.015 | 1.004 | 0.319 | 1.017 | 0.839 | 24 |
| Yunnan | Western | 0.696 | 0.504 | 0.578 | 0.569 | 0.587 | 27 |
| Chongqing | Western | 0.541 | 1.014 | 1.057 | 1.034 | 0.912 | 20 |
| Gansu | Western | 0.430 | 0.454 | 0.346 | 0.300 | 0.383 | 31 |
| Qinghai | Western | 0.284 | 1.051 | 1.111 | 1.042 | 0.872 | 23 |
| Heilongjiang | northeast | 1.224 | 1.219 | 1.412 | 1.423 | 1.320 | 3 |
| Liaoning | northeast | 1.051 | 1.032 | 1.016 | 0.630 | 0.932 | 18 |
| Jilin | northeast | 1.016 | 0.705 | 0.697 | 0.338 | 0.689 | 26 |

The overall level is better, but the ineffectiveness can still be improved. The average values of China's AEE in the four periods are 1.023 (2006), 1.047 (2010), 0.995 (2014), and 0.948 (2018). In 2006–2010, AEE values in China grew the fastest with values from 1.023 to 1.047. In 2010–2018, AEE values continued to decline from 1.047 to 0.948. AEE gradually increased in the early stage of the study but decreased in the later stage of the study. During the study period, only 17 provinces and cities, such as Beijing, Fujian, Guangdong, Guangxi, Guizhou, Hainan, and Henan, kept AEE completely effective. Among them, nine provinces and cities were along coastal areas in the east, five in the west, two in the middle, and one in the northeast. Other provinces, such as Liaoning, Hunan, Chongqing, Hebei, Hubei, Qinghai, Ningxia, Inner Mongolia, Jilin, Yunnan, Anhui, Jiangxi, Shanxi, and Gansu, had AEE means of less than 1. They were noneffective AEE areas, and the inputs and outputs of the provinces needed to be changed for efficiency value to reach the efficiency level (Table 4).

To judge the importance of the ecological index ESV to the evaluation of AEE, this paper uses S-SBM to calculate the feasibility test of the Chinese provincial AEE with the 4-year average efficiency value (Table 5).

ESV is not considered in S-SBM$_1$, and the result shows that there are 15 provinces and cities valid. The eastern region except Hebei Province is effective. The average value of the eastern region is 1.133. Compared with the eastern region, none of the other three regions are effective. The average values are 0.79 (Central Region), 0.89 (Western Region) and 0.769 (Northeast Region). In the calculation of S-SBM$_2$, the effective provinces and cities of S-SBM$_1$, Guangxi and Heilongjiang, which are included in the dynamic ESV the calculation, have also achieved effectiveness, and the ranking has risen significantly. Whether or not ESV is considered, the average AEEs in the eastern region are still the highest (1.124). However, before the inclusion of ESV, the AEE performance is in the following order: eastern > central > western > northeast. After adding ESV, the efficiency value of northeast and western regions has improved, and the performance is in the following order: eastern > western > northeast > central. The results show that Guangxi, Heilongjiang, and other western provinces and cities have low S-SBM$_1$, but S-SBM$_2$ increases sharply. As shown in a previous study (Yuan, 2020; Zhang et al., 2019), agricultural ecology areas with high system service value are concentrated in Inner Mongolia, Xinjiang, Heilongjiang, Yunnan, and other places. Higher ESV has effectively improved the AEE of these places. In addition, the AEE gap between regions has also changed. Compared with S-SBM$_1$, the gap between the east and northeast of S-SBM$_2$ has narrowed the most. This finding reflects the current status of China's ecological environment. The eastern and western desert regions of China are of low ecological importance. The western plateau, undeveloped areas, and the northeastern region are rich in forest resources and have high ecological importance, thereby providing higher ESV. However, some provinces in the central and western regions, such as Ningxia, Qinghai, and Chongqing, show a small decline. This difference may be due to the unexpected effects of some ecological protection projects (Zhang et al., 2019).

According to the above analysis, ESV is an important factor that can be used to accurately assess the sustainability of regional agricultural production development. If the regional ESV is ignored, then the assessment of sustainability of regional agricultural efficiency may be biased. Therefore, considering both ESV and agricultural production value is necessary to assess China's provincial AEE.

### 3.2. Correlation among factors

To further verify whether the selected indicator variables conform to the law of macroeconomic production and whether the input variables and output variables meet the "homotropy hypothesis," taking 9 indicator data from 31 provinces and cities in China as the object, using Pearson's correlation theory and stata software to analyze and test the correlation between China's agricultural production value and other 8 index variables. Among them, I represent the input item (using undesired output as input), O represents the output item, and the data processing is shown in the following (Table 6):

The analysis results show the correlation strength and direction between input and output indicators, as well as the correlation coefficients between input and output variables, are all positive. The tested P values are less than the critical value of 0.01 and have passed the two-tailed test. During the study period, the optimization of the indicator is conducive to the improvement of efficiency. If the correlation coefficient is negative, then the opposite is true (Table 7).

Results of comparison of the AEE correlation coefficients of eastern, central, and western regions indicate that labor input, agricultural film input, carbon emission, fertilizer input, and land input have all passed the AEE significance test of 5% in the eastern region. However, land input shows a positive effect, and the others show a negative effect and have decreased in turn. Land investment is also significant in the two other regions. A negative effect is seen on the western region, but the opposite effect is obvious on the central region. A strong positive correlation is observed. In the western region, except for the agricultural film input, the remaining driving factors have passed the 1% level of the significance test. These factors exert varying degrees of inhibition on AEE. The central region's AEE impact is positive. Specifically, labor input, energy input, fertilizer input, and carbon emissions are all significant at levels above 1%. The correlation coefficients are all greater than 0.4, which indicates a strong correlation.

### 3.3. Spatial change pattern of AEE in China

Fig.2 show that the average AEEs of each region in four years are 1.12, 1.04, 0.79, and 0.98 in the eastern, western, central, and northeastern regions, respectively. They show a spatial distribution pattern in the following order: eastern > western > northeast > central. Among the regions, Tibet has a high efficiency value of 2.564, followed by Beijing (1.554), Heilongjiang (1.319), Guizhou (1.245), Shanghai (1.215), Henan (1.193), Shaanxi (1.166), Sichuan (1.153), Hainan (1.134), and Guangdong (1.13). The main reason may be that the eastern region

**Table 6**
China AEE isotropic test.

| O | I | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | $x_6$ | $x_7$ | $x_8$ | $x_{11}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| $x_9$ | Pearson correlation coefficient | 0.829*** | 0.573*** | 0.880*** | 0.887*** | 0.744*** | 0.611*** | 0.491*** | 0.775*** | 0.872*** |
| | Test P value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $x_{10}$ | Pearson correlation coefficient | 0.577*** | 0.545*** | 0.708*** | 0.714*** | 0.572*** | 0.509*** | 0.474*** | 0.822*** | 0.717*** |
| | Test P value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Note: ***, **, and * represent 1%, 5%, and 10% significance levels.

**Table 7**
Correlation coefficient of AEE factors in China.

| y | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | $x_6$ | $x_7$ | $x_8$ | $x_9$ | $x_{10}$ | $x_{11}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Eastern | 0.209** | −0.240** | −0.099 | −0.127 | −0.223** | −0.172* | −0.233** | −0.138 | −0.135 | −0.013 | −0.225** |
| Central | 0.414** | 0.617*** | 0.327* | 0.295 | 0.523*** | 0.071 | 0.309 | 0.609*** | 0.456** | 0.448** | 0.491*** |
| Western | −0.365** | −0.332** | −0.338** | −0.385** | −0.348** | −0.305* | −0.235 | −0.426*** | −0.366** | −0.319** | −0.375** |
| China | −0.18** | −0.152* | −0.087 | −0.123 | −0.138 | −0.214** | −0.167* | −0.057 | −0.079 | 0.03 | −0.155 |

Note: ***, **, and * represent 1%, 5%, and 10% significance levels.

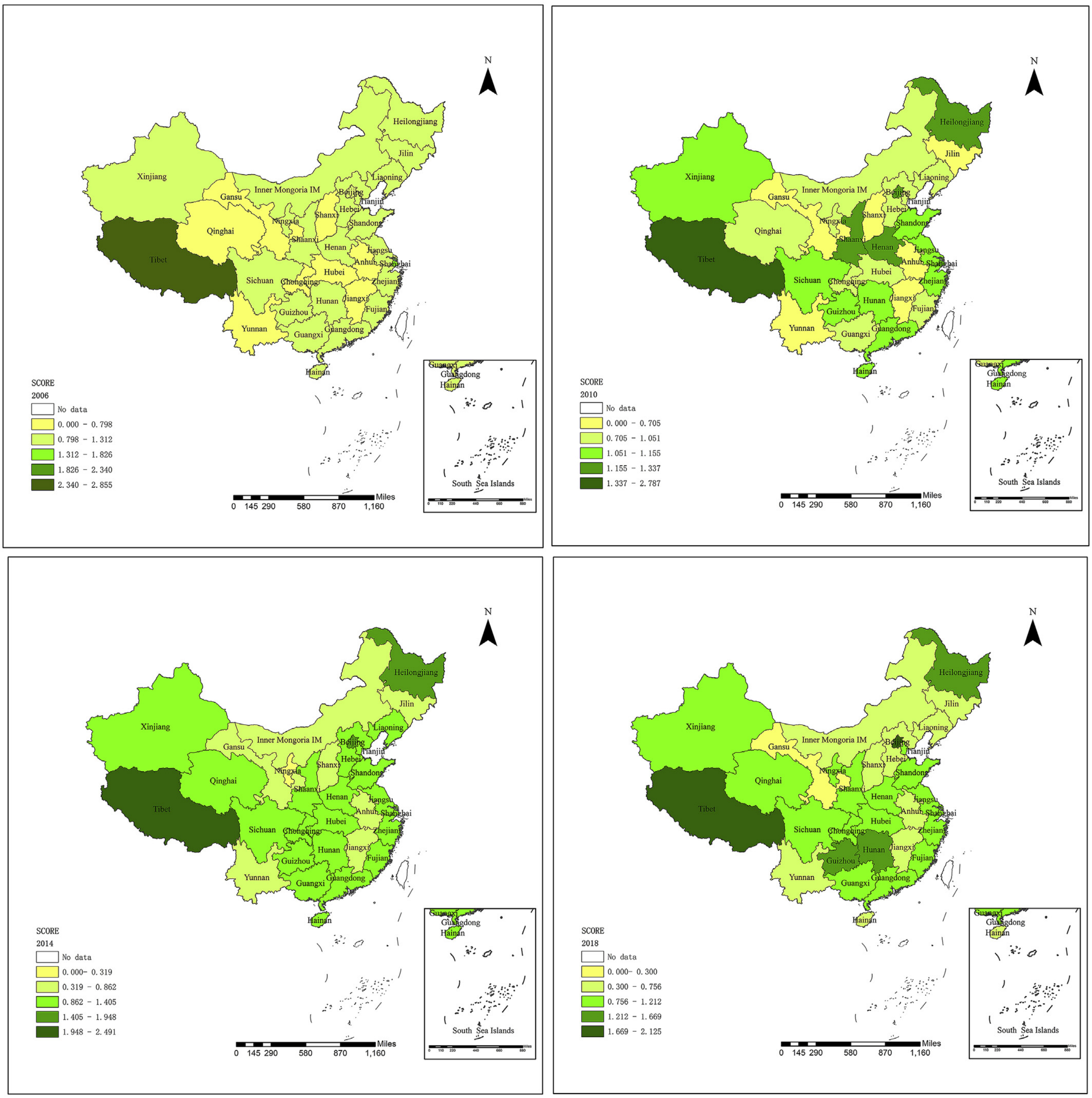


**Fig. 2.** Spatial distribution pattern of AEE in 2006, 2010, 2014 and 2018.

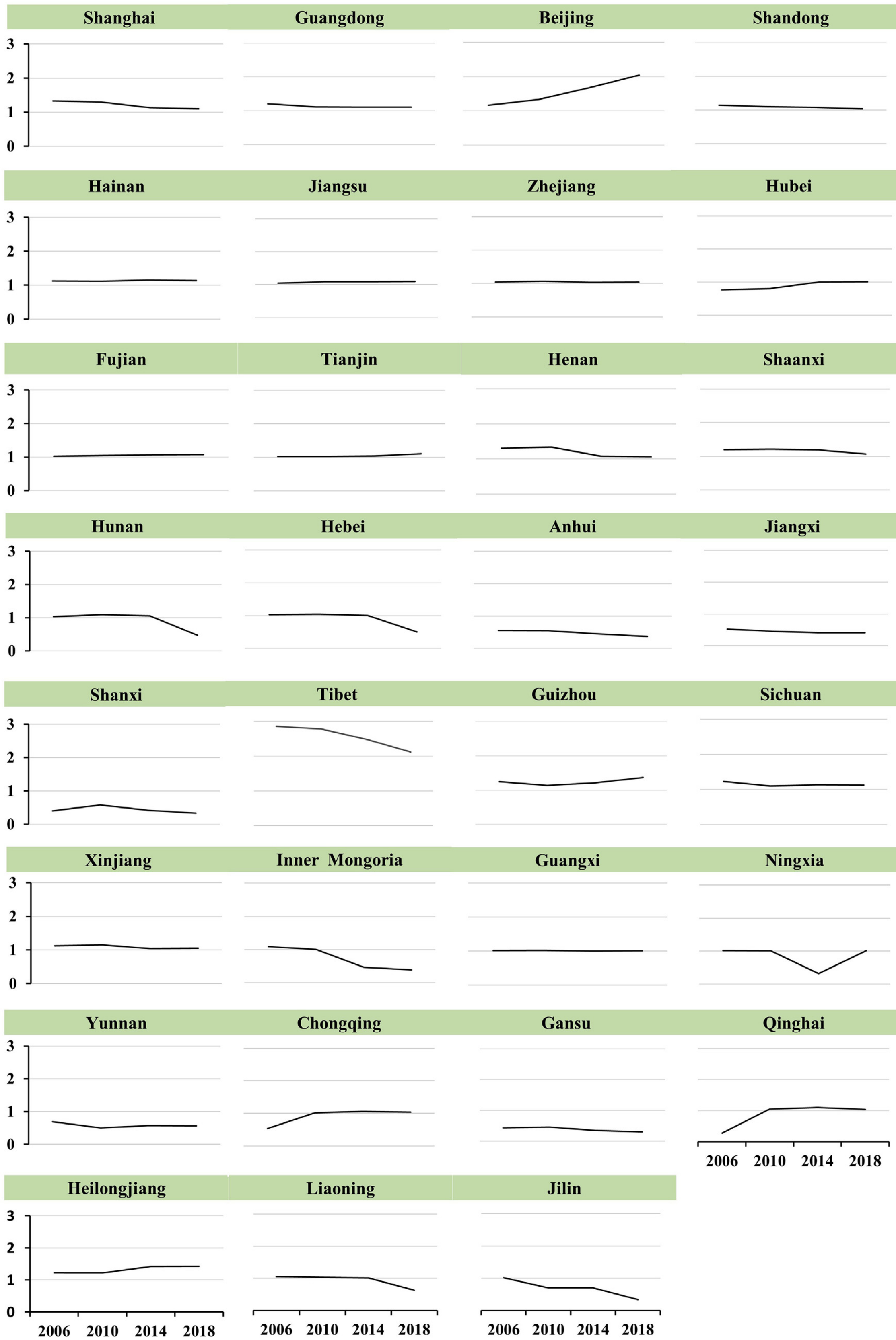


**Fig. 3.** AEE of Chinese provinces in 2006, 2010, 2014, and 2018.

pays more attention to the coordinated development of resources and the environment than other regions, and at the same time, the agricultural technology is more advanced. Although the central and western regions, such as Sichuan and Guizhou, are relatively lacking in terms of scientific research investment technology, their agricultural carbon pollution control is relatively low. Therefore, the efficiency value of these regions is high. Provinces and cities with low AEE, such as Gansu, Shanxi, and Jiangxi, are underdeveloped. They have long been dominated by extensive industries with high resources that result in pollution, thereby seriously affecting the improvement of AEE in the region.

### 3.4. Analysis of the evolution of China's AEE time series

From the perspective of the time series (Fig. 3), the efficiency value of the eastern region in 2006–2018 shows a gentle trend that is relatively stable. The gap between provinces is small. The AEEs of Beijing, Tianjin, Guangdong, and other provinces and cities increase significantly. In 2006, 2010, and 2014, the AEE of regional provinces and cities achieve full efficiency, except for that in 2018 in Hebei Province, which did not reach the effective level. The trend of efficiency value in the central region decreases annually, and the overall AEE is also low. In 2006, 2010, and 2018, four provinces and cities have failed to reach the effective surface, among which Jiangxi, Shanxi, and Anhui provinces have shown a significant decline trend. The overall efficiency value trend in the western region is in the form of "N" and the gap between the efficiency values of regional provinces and cities is the most significant. The sudden decline of the western region in 2010–2014 is probably due to the increase in over investment and ineffective use of agricultural machinery and land, which have resulted in the reduction of efficiency in Inner Mongolia during this period. The gap between AEE provinces in northeast China is the smallest. The efficiency value of Jilin Province decreases continually with fluctuations, possibly because the excessive investment in land, pesticide, and machinery in Jilin Province has been relatively prominent in 2006–2018, thereby decreasing the AEE value. From 2010 to 2014, Heilongjiang increased the input of agricultural labor force, thereby promoting the AEE value to some extent. This event causes a short-term recovery in the northeast region.

### 3.5. Spatial correlation analysis of Chinese AEE

Table 8 reflects the global autocorrelation results of AEE in the 31 provinces of China in 2006, 2010, 2014, and 2018.

Table 8 shows that the global Moran index of AEE from 2006 to 2018 fluctuates up and down between [−0.1, 0.02], and the p-value fluctuates up and down within [0.1, 0.5]. During the study period, Moran's I are negative except in 2014. However, none of the study years have passed the 10% significance test. Thus, no significant spatial autocorrelation is shown, and the null hypothesis cannot be rejected. Therefore, the spatial correlation of AEE from 2006 to 2018 does not show a regular distribution. The overall performance of the characteristics of random distribution is shown in Fig. 4.

Using Geoda software, based on the 0-1 adjacency matrix, the Moran scatter plots of 31 provinces and cities in China are drawn.

**Table 8**
Spatial autocorrelation Moran index of agricultural eco-efficiency.

| Year | Moran's I | Z-value | P-value |
|---|---|---|---|
| 2006 | −0.148 | −1.217 | 0.103 |
| 2010 | −0.089 | −0.610 | 0.281 |
| 2014 | 0.017 | 0.415 | 0.337 |
| 2018 | −0.042 | −0.126 | 0.464 |

The results show that China's AEE is dominated by two distribution types, namely, LL and HL. From 2006 to 2010, the number of LH, LL, and HL types of provinces and cities has increased, whereas the number of HH types has decreased. Thus, provinces and cities that coordinated with environmental and economic conditions have excessively pursued economic output value, neglected environmental coordination, and turned into low-efficiency AEE. They cannot form sufficient spillover effects on the surrounding cities, which in turn causes the surrounding cities to gradually turn into a double-low type. From 2010 to 2018, the number of LL-type provinces and cities has increased, whereas the number of HL-type provinces and cities has decreased, indicating that the original low-efficiency provinces and cities have reduced pollution-inducing production, have strengthened their compliance with national policies, and have pursued the continuous strengthening of environmental governance. Eco-friendly construction has obvious effects on ecological environment protection and shows a higher level of spillover effect; it plays a good leading role in surrounding provinces and cities with low AEE.

Spatial correlation scatter plot cannot show the significance of each province and city. By analyzing the LISA spatial agglomeration map, we can show the efficiency similarities and differences between each province and city and the surrounding provinces and cities.

Fig. 5 shows that only Yunnan Province has passed the 5% significance level test in 2006 and 2010, and Yunnan Province is in the LH agglomeration area. In 2014, only Yunnan Province has passed the 1% significance level test. Inner Mongolia Autonomous Region and Shaanxi Province have passed the 5% significance level test. Yunnan is still in the LH agglomeration area, Inner Mongolia Autonomous Region is in the LL agglomeration area, and Shaanxi Province is in the agglomeration area. Yunnan and Liaoning provinces have passed the 1% significance level test in 2018, and Inner Mongolia and Heilongjiang provinces have passed the 5% significance level test. Liaoning and Inner Mongolia Autonomous Region are in the LL aggregation area. Yunnan has always remained in the LH aggregation area, and Heilongjiang is in the HL aggregation area. Therefore, China's AEE has formed an LH effect area centered on Yunnan Province for a long time, and its influence by the high value area is not significant. In the later stage of the study, a horizontal concentration of LL centered on Inner Mongolia Autonomous Region and Liaoning Province was formed. Heilongjiang Province is an HL concentration area because it has little effect on nearby provinces and cities, which contributes to polarization.

### 3.6. Quantitative attribution of spatial differentiation of Chinese AEE

This study imports the data of 31 provinces in China from 2006 to 2018 into the geodetector and identifies which variable factors are the significant factors affecting the spatial differentiation of China's AEE. Whether the force between the two factors and AEE is positive or negative and whether the effect is an independent influence, or a two-way influence are determined. The number is relatively small given that the northeast region has only three research provinces and cities. The three northeast provinces are merged into the eastern region for analysis and accurate calculation.

The running result of the factor detector shows the following:

Table 9 shows that from the Chinese level, the explanatory power of the 10 explanatory variables on the spatial differentiation of AEE in China is small, the performance of the core impact factors is not prominent, and the spatial differentiation at the national level is affected by its basic factors. Fertilizer usage ($q = 0.287$), pesticide discharge ($q = 0.308$), water resource input ($q = 0.37$), and land

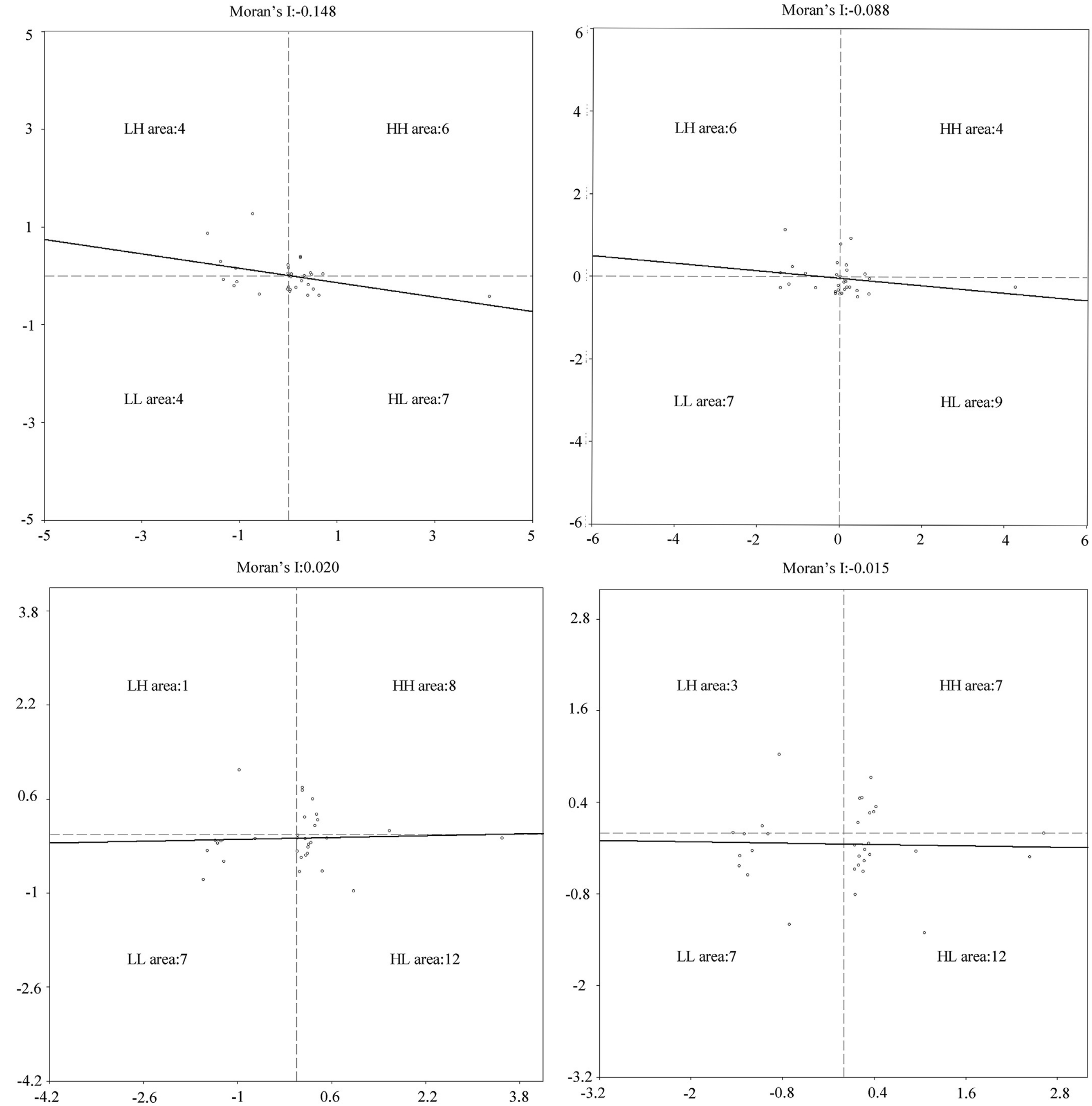


**Fig. 4.** Moran's I scatter plot of China's agricultural eco-efficiency in 2006, 2010, 2014 and 2018.

input ($q = 0.468$) are significant control factors of AEE at different time points in China. Among these, water resource input has the most prominent explanatory power for AEE. In 2007, the No.1 Document of the CPC Central Committee stated the following: "We will continue to make solving problems of agriculture, rural areas, and farmers the top priority in the work of the whole Party. We will increase investment in agriculture, promote agricultural modernization, and establish an agricultural risk prevention mechanism (Chen et al., 2020)." The provinces have begun to emphasize energy conservation, emission reduction, and ecological environmental protection, focusing on the coordination of economic and social development and ecological construction. In the early stage of policy implementation, the eastern region implemented measures first. At this stage, the central and western regions still had a large amount of resource consumption and serious environmental pollution. The maintenance of extensive agricultural economic development methods has created the increasing gap in AEE between the east and the west (Pan and Ying, 2013b). From 2010 to 2014, China has entered a new normal period. The agricultural industry structure has been optimized and adjusted, and the government's environmental governance has intensified. As a result, the drawbacks of the early stage, in which industries relied on

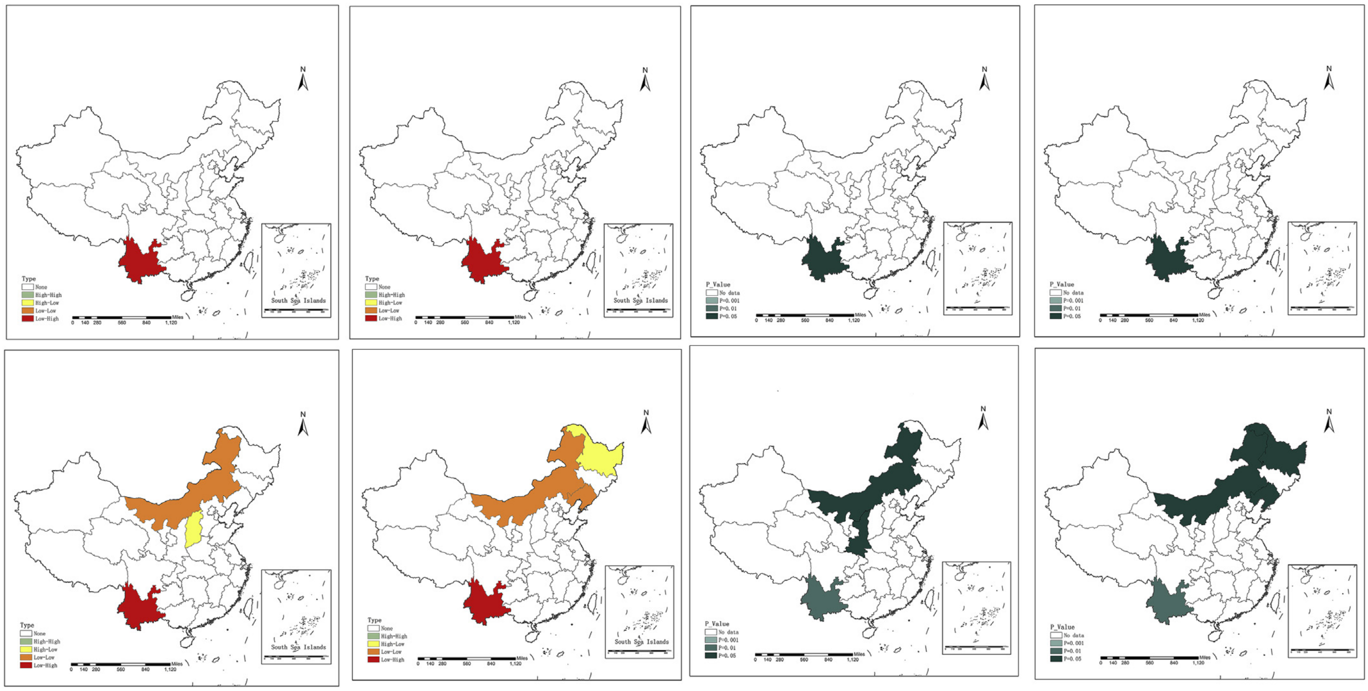

**Fig. 5.** LISA agglomeration map of AEE in China in 2006, 2010, 2014 and 2018.

**Table 9**
Statistical table of Q-value of AEE influencing factors in China.

| Detection | year | Western | Central | Eastern | China |
|---|---|---|---|---|---|
| $x_1$ | 2006 | 0.194 | 0.173 | 0.395 | 0.129 |
| $x_2$ | 2006 | 0.168 | 0.968 | 0.369 | 0.131 |
| $x_3$ | 2006 | 0.088 | 0.618 | 0.140 | 0.159 |
| $x_4$ | 2006 | 0.310 | 0.682 | 0.395 | 0.215 |
| $x_5$ | 2006 | 0.252 | 0.682 | 0.522 | 0.287 |
| $x_6$ | 2006 | 0.181 | 0.586 | 0.363 | 0.165 |
| $x_7$ | 2006 | 0.252 | 0.555 | 0.379 | 0.216 |
| $x_8$ | 2006 | 0.225 | 0.533 | 0.299 | 0.129 |
| $x_9$ | 2006 | 0.168 | 0.682 | 0.586 | 0.108 |
| $x_{10}$ | 2006 | 0.077 | 0.682 | 0.465 | 0.193 |
| $x_1$ | 2010 | 0.576 | 0.535 | 0.560 | 0.289 |
| $x_2$ | 2010 | 0.127 | 0.826 | 0.215 | 0.293 |
| $x_3$ | 2010 | 0.264 | 0.814 | 0.345 | 0.235 |
| $x_4$ | 2010 | 0.476 | 0.702 | 0.255 | 0.221 |
| $x_5$ | 2010 | 0.152 | 0.963 | 0.458 | 0.258 |
| $x_6$ | 2010 | 0.638 | 0.702 | 0.188 | 0.266 |
| $x_7$ | 2010 | 0.401 | 0.479 | 0.272 | 0.200 |
| $x_8$ | 2010 | 0.227 | 0.311 | 0.603 | 0.264 |
| $x_9$ | 2010 | 0.376 | 0.926 | 0.379 | 0.308 |
| $x_{10}$ | 2010 | 0.227 | 0.684 | 0.379 | 0.279 |
| $x_1$ | 2014 | 0.333 | 0.389 | 0.641 | 0.201 |
| $x_2$ | 2014 | 0.261 | 0.176 | 0.383 | 0.131 |
| $x_3$ | 2014 | 0.059 | 0.473 | 0.490 | 0.279 |
| $x_4$ | 2014 | 0.486 | 0.858 | 0.439 | 0.370 |
| $x_5$ | 2014 | 0.038 | 0.448 | 0.288 | 0.185 |
| $x_6$ | 2014 | 0.328 | 0.297 | 0.389 | 0.168 |
| $x_7$ | 2014 | 0.462 | 0.342 | 0.439 | 0.255 |
| $x_8$ | 2014 | 0.383 | 0.459 | 0.603 | 0.414 |
| $x_9$ | 2014 | 0.155 | 0.692 | 0.389 | 0.277 |
| $x_{10}$ | 2014 | 0.354 | 0.313 | 0.633 | 0.259 |
| $x_1$ | 2018 | 0.670 | 0.328 | 0.824 | 0.468 |
| $x_2$ | 2018 | 0.524 | 0.514 | 0.184 | 0.172 |
| $x_3$ | 2018 | 0.161 | 0.735 | 0.370 | 0.162 |
| $x_4$ | 2018 | 0.161 | 0.867 | 0.388 | 0.329 |
| $x_5$ | 2018 | 0.292 | 0.735 | 0.449 | 0.257 |
| $x_6$ | 2018 | 0.378 | 0.523 | 0.486 | 0.283 |
| $x_7$ | 2018 | 0.286 | 0.514 | 0.266 | 0.091 |
| $x_8$ | 2018 | 0.360 | 0.735 | 0.431 | 0.330 |
| $x_9$ | 2018 | 0.449 | 0.540 | 0.489 | 0.374 |
| $x_{10}$ | 2018 | 0.298 | 0.867 | 0.627 | 0.291 |

chemical pollutants and extensive development, have been alleviated. In this context, regional differences have narrowed due to pesticide emissions. Yet, as shown previously (Pan, 2013a), the excessive redundancy of water resources in the central and western regions has increased in prominence; this has become the reason for the restriction of AEE at this stage. From 2014 to 2018, after the accumulation of early resource elements, residents' awareness of environmental protection has increased, and people have focused more on the coordination of resources and the environment. However, the scale of land management is small, the degree of land marketization is low, and the resources have not been used well, thereby resulting in the large redundancy of land input.

From the regional analysis, the main reason for the significant difference in factor detection force q is that the regional economic development level and natural resources are similar, but there are certain differences in the timing of the country's construction in the three major regions; thus, its effect is more prominent under similar levels of economic, social, and environmental development (Qian and He, 2011; Yang et al., 2020). The results in Table 9 reveal that the significant impact factors of AEE in the eastern and western regions during the study period are the land inputs. The former has increased from 64.1% to 82.4% in 2018, and the latter has a weaker explanatory power of AEE (19.4%) at the beginning of the study period. However, the explanatory power was as high as 67% in 2018. According to the survey and evaluation data of China's cultivated land reserve resources, the cultivated land reserve resources have been concentrated on the economically underdeveloped areas in the central and western regions from 2006 to 2018. Five provinces, namely, Xinjiang, Heilongjiang, Henan, Yunnan, and Gansu, accounted for the reserve resource area, nearly half of the country and the 11 eastern provinces with faster economic development accounted for only 15.4%. In this context, insufficient agricultural planting of the available land in the eastern region makes it difficult to meet the needs of agricultural production and severely checks and balances the improvement in efficiency in the eastern region (Jiang et al., 2020). In addition, the total land area of the western

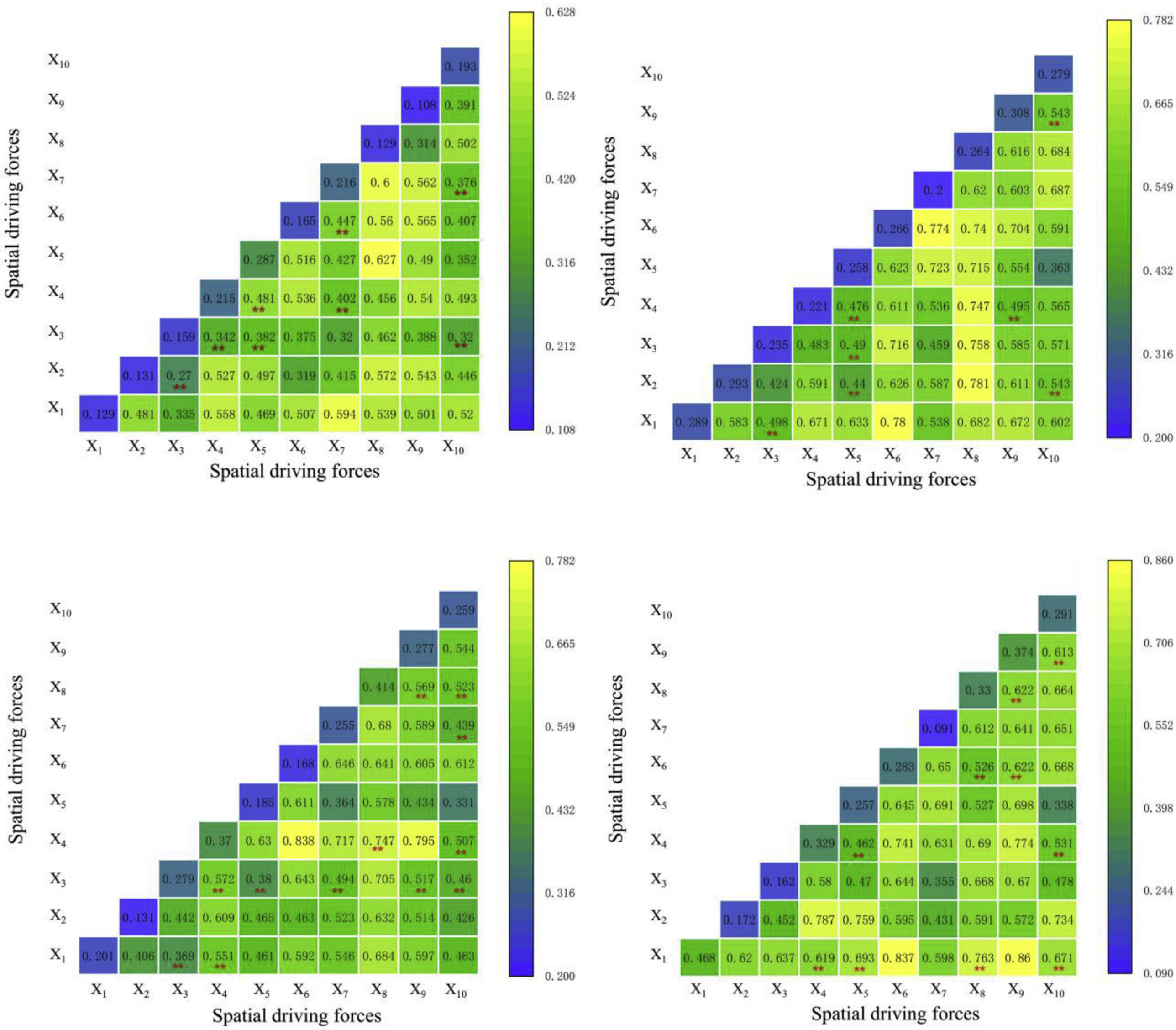


**Fig. 6.** The driving force of the AEE drivers (q value) in 2006, 2010, 2014 and 2018 Note: The test chart with ** represents the two-factor enhanced type. The diagonal value is the driving force q value of each factor. The rest are nonlinear enhanced types.

region is about 491.1889 million hm$^2$, accounting for 67.19% of the total land area of the country, of which the arable land area accounts for 10.27% of the total land area in the western region, the per capita arable land area is 0.136 hm$^2$, far higher than the national average of 0.098 hm$^2$/person (Zhu et al., 2018). However, the overall efficiency of land use of the western region is not high, extensive waste and inefficient land use are common (Yang, 2017). The reasons for these phenomena may be the excessive land release, unreasonable supply structure, imperfect land supply mode, and the failure of relevant departments to form a joint regulatory force. As the redundancy problem of land input becomes increasingly serious, it has become a controlling factor restricting the difference in efficiency between provinces and cities in the western region. Since the central region initiated the central region's rise strategy in 2006, the proportion of total industrial output values in the country's total output value increased from 17.5% in 2005 to 21.5% in 2012. According to the 2017 National Water Resources Development Bulletin, the effective utilization coefficient of agricultural irrigation is 0.548, i.e. only 0.548 cubic meters of irrigation water are absorbed and utilized by crops. The dense population and the development of industry and agriculture in the central region increase the demand for water resources, while the low utilization rate of water resources. In addition, the aging water conservancy facilities and the frequent occurrence of flood and water logging disasters in the central region have made the problem of agricultural water in the central region increasingly prominent in recent years (Chang et al., 2020).

The interaction detector results in Fig. 6 show a nonlinear enhancement among most factors, that is, the influence of the factor on the interaction was greater than the sum of the two-factor independent forces. Only two types of AEE driving factor interaction force, namely, two-factor and nonlinear enhanced types, are observed in China. No independent factor has been found. Among the years 2006, 2010, 2014, and 2018, the synergy between x1 and $x_9$ was strongest in 2018 ($q = 0.86$). The two-factor superposition of $x_1$ and $x_9$ could explain 86% of the AEE the difference, which is the significant control factor of AEE. The remaining significant factors are $x_4$ and $x_6$ in 2014 ($q = 0.838$), $x_8$ and $x_5$、$x_1$、$x_3$ in 2006 and 2010. Rationally distributing clean energy, increasing the precise supply of fertilizers and the scale of agricultural labor input, and developing emerging agricultural high-tech industries have a significant positive impact on AEE. Compared with the nonlinear enhanced type, the two-factor enhanced type is insignificant. The weakest two-factor enhanced model is $x_2 \cap x_3$ in 2006, which has an explanatory power of 27%. The rest are $x_1 \cap x_{11}$ in 2014 ($q = 0.345$), $x_2 \cap x_3$ in 2006 ($q = 0.424$), and $x_4 \cap x_5$ ($q = 0.462$) in 2018. Among the two-factor interaction types, the highest explanatory power of AEE is 86%, and the lowest is 27%.

## 4. Discussion

The spatial evolution and driving factors of AEE in China are analyzed. The results show some differences among the research results of scholars in similar research years. For example, some scholars (Akbar et al., 2020) believe that the spatial order for China's AEE is as follows east > central > western > northeast. Some scholars believe that a significant positive spatial correlation and a constantly changing spatial agglomeration of AEE exist (Zeng and Liu, 2019; Wang et al., 2020). Thus, this article attributed this phen omen on to two reasons. First, it may be due to different years of data selection. Second, the main reason may be that the ESV evaluation index system constructed in this paper quantifies the value of farmland ecosystem services as part of the expected output. Through comparison, it is found that after adding dynamic farmland ecosystem service factors, AEE in some coastal provinces in the east has decreased, whereas AEE in some provinces in the west and northeast has increased. The AEE frontiers in the northeast and western regions with ecological value advantages move as a whole, and AEE increases.

The above results show that the following problems still exist in the AEE development process: (1) AEE regional gap is too large; (2) AEE significant factors are different among regions; and (3) the importance of ESV in various regions has not been the focus of research. To improve the AEE, this article puts forward the following suggestions. First: improve the implementation of the overall AEE. The difference between the eastern region and the central and western regions of the country as a whole shows that the amount of land input and the state of water resources input are the factors to eliminate the large efficiency gap, the area of agricultural cultivated land available in most eastern provinces is not enough to meet the demand of local agricultural production, the use of land in the western region is inefficient, resulting in land redundancy, while the overall efficiency of water resources utilization in the central region is low. Through the geographical exploration of various factors, it can be found that the two factors of land input and agricultural output value, water resources and pesticide input have the strongest co-action force, which means that the two-way balance between the factors is the key entry point to optimize and enhance AEE. This puts forward strict requirements for the balance between agricultural land and total agricultural output value, optimizing the use of various agricultural factor inputs under limited farming land, improving the scientific utilization rate of agricultural materials, and encouraging the effective use of factors of production in each regional ecosystem. At the same time, in optimizing the water resources system to achieve efficient water use, save water in the field, reduce the loss of water transmission at the same time, to ensure the accurate delivery of pesticides. This is a long-term, dynamic combination that needs to consider not only regional advantages, but also integration and coordination with national policy implementation. In addition, considering the heterogeneity of regional technology, the central and western regions should also strengthen technical exchanges and cooperation with the eastern regions and strive to promote the rational interregional flow of agricultural production factors. Second: the implementation of reducing regional differences. In the process of upgrading AEE, the eastern region needs to pay more attention to land utilization rate. The government should give policy support to create convenient conditions for the large-scale production and operation of agricultural production, promote the process of large-scale operation of agricultural land, alleviate the contradiction between economic development and the protection of agricultural land, strictly protect basic agricultural land, and plant suitable agricultural products according to local conditions, thereby increasing the output of agricultural products such as grain. The central region needs to emphasize the improvement of water resources management measures and the development of sustainable water resources suitable for the local strategy. In general, we should correct the polluting agricultural water use methods and establish the agricultural water use methods of water-saving irrigation and ecological irrigation. The western region should focus on improving the structure and mode of supply of agricultural land and improving the efficiency of land use. Develop healthy green agriculture, cleaner production, and reduce the use of toxic chemical products such as fertilizers and pesticides. Third: the implementation of ESV measures. The importance of the service value of farmland ecosystem should be fully recognized, and farmland should be used rationally and effectively protected. Agricultural production should be reasonably developed according to the natural conditions in different regions, and scientific planting techniques and efficient management methods should be used to ensure the quality of agricultural products. Local governments should, in the light of their own realities, formulate measures that are consistent with the region's efforts to increase the value of ad agricultural ecosystem services. We will further build a resource-saving and eco-friendly agricultural production system.

This paper proposes a wireless hypothesis method of detecting AEE spatial data. At present, the regional differentiation of AEE driving factors subjected to quantitative analysis can hardly do both considering the influences of the factors of the AEE simultaneously. Solving the problem of spatial stratified heterogeneity is also an issue. Geographic detectors can meet both requirements at the same time. They can test the spatial differentiation of univariate factors and can also quantitatively evaluate the driving factors and detect their interactions, thereby effectively solving the qualitative problem of AEE in spatial stratification. Finally, there are still some defects to be solved in this paper. First, although this article has created an AEE indicator evaluation system based on the dynamic ESV model, the calculation of coefficients in this article does not include all spatial characteristics. For example, a previously published article (Xie et al., 2015) provides a value coefficient table of China, but it may not be enough for application to all areas. In China, its assessment does not reflect the regional natural geography and social economic characteristics (Liu and Sun, 2019). Therefore, subsequent studies can reflect the regional physical geography and socio-economic characteristics of the dynamic adjustment of the value coefficient. Secondly, the exploration of the drivers for AEE space differentiation factor only discusses the interaction between the two factors. Interactions between three or more factors are not explored in this study; thus, they require further in-depth exploration.

## 5. Conclusion

This study attempts to build an AEE evaluation index system from the perspective of agricultural ecological services. The super efficiency SBM model is used to measure the AEE of 31 provinces and cities in China (excluding Hong Kong, Macao, and Taiwan) in 2006, 2010, 2014, and 2018. The spatial autocorrelation method is utilized to analyze the spatial distribution characteristics of efficiency in China's four periods. The geodetector method is used to analyze the leading factors of AEE spatial differentiation. The degree of interaction among these factors is obtained as follows. The AEE of China fluctuates within 3% and shows a decreasing trend in 2006−2018. The average AEEs of the four periods are 1.023, 1.047, 0.995, and 0.948. However, the level can still be improved. The AEE development of each province is not balanced. During the study period, the average AEEs of the eastern, western, central, and northeast regions are 1.12, 1.04, 0.79, and 0.98, respectively. The ranking among the regions is as follows: eastern > western > northeast > central. The gap between the western region and the other regions is the widest, whereas that between the northeast region and other regions is the smallest. From the perspective of spatial correlation, the global Moran's I of AEE in China has failed to pass the 10% significance test during the study period. The spatial distribution shows the characteristics of random distribution. During the research period, AEE in China has formed a low−high effect area centered on Yunnan Province and a low−low level agglomeration area centered on Inner Mongolia Autonomous Region and Liaoning Province. Heilongjiang Province was in the high−low level diffusion effect agglomeration area. From the perspective of spatial differentiation effect, no significant difference has been observed in AEE driving factor $q$ values on a national scale. The core factor is not prominent. A significant difference has been found in driving factors at the regional scale, and the leading factor is prominent. Energy input and water resource input are significant driving factors of AEE spatial differentiation among the provinces and cities of China. Thus, this paper emphasizes the introduction of agricultural high-technology machinery and the improvement of the utilization rate of agricultural land. Central financial support for agriculture in the central and western regions needs to be increased to narrow regional disparities. The central government's agricultural support to the central and western regions needs to be increased to narrow regional differences. Ecological protection measures need to be introduced to further build a resource-saving and ecological-friendly agricultural production system.

Regarding the question on how to expand the Super-SBM model used in this article for future applications, the construction of sustainable indicators and the scope of expected output can be further extended. The inclusion of different types of public products can be considered. In addition, the combination of Super-SBM and geospatial detection methods can also be applied to macro-level data analysis to detect and analyze the efficiency values of different departments in the country (Guan et al., 2020) to promote ecological protection. The planning and implementation of high-quality development strategies provide references to explore the driving factors of the comprehensive energy efficiency of the Yellow River Basin. To improve the efficiency of comprehensive transportation, the coordinated development of regional transportation and regional economy needs to be promoted. To detect the efficiency of comprehensive transportation, the geographic detector models are adopted. Potential limitations related to this method are quantifiable indicators required by the DEA model. However, it is difficult to quantify indicators that have important impacts on AEE, such as the level of national policy implementation and environmental protection. These issues still need to be addressed and provide direction for future research.

## CRediT authorship contribution statement

**Jiajia Liao:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Visualization. **Chaoyue Yu:** Data curation, Visualization, Investigation. **Zhe Feng:** Conceptualization, Methodology, Resources, Supervision, Funding acquisition. **Huafu Zhao:** Conceptualization, Methodology, Writing - review & editing, Resources. **Kening Wu:** Conceptualization, Methodology, Writing - review & editing, Resources. **Xiaoyan Ma:** Data curation, Formal analysis, Validation.

## Declaration of competing interest

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

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