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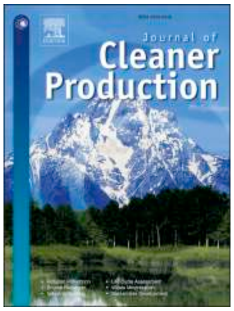

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Author contribution statement

Jianzhai Wu: Investigation, Writing - original draft, Writing - review and editing; **Zhangming Ge:** Development or design of methodology; Creation of models; **Shuqing Han:** Provision of study materials, computing resources, or other analysis tools; **Liwei Xing:** Writing - original draft; Writing - review and editing; **Mengshuai Zhu:** Analyzing data and results; **Jing Zhang:** Writing - Review & Editing; **Jifang Liu:** Methodology, Writing - Original Draft, Writing - Review and Editing.

Impacts of Agricultural Industrial Agglomeration on China's Agricultural Energy Efficiency: A Spatial Econometrics Analysis

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Abstract

The rapid development of traditional agriculture in China was achieved at the expense of high energy consumption and investments. However, the global green development trend made it necessary for the country to transform its agricultural energy utilization. Energy efficiency changes are affected by many factors, particularly industrial agglomeration. In recent years, the Chinese government has introduced a series of policies, including setting major producing regions for grains and advantageous regions for characteristic agricultural product. These have caused significant changes to the spatial layout of the agriculture industry. However, there is still a lack of research on the impact of these changes on agricultural energy efficiency (AEE). In this study, panel data of 30 Chinese provinces from 2000 to 2016 were entered into stochastic frontier models to measure the country's AEE at the provincial level. A series of spatial econometric models were also used to analyze the impact of agricultural industrial agglomeration on China's AEE. The results indicate that the country's AEE exhibited obvious spatial gradients and correlations. After controlling the impacts of spatial correlation and other factors in the models, agricultural industrial agglomeration was found to have an overall positive impact on China's AEE. In the future, policies should be formulated to increase AEE by establishing agricultural functional areas, strengthening the innovation and sharing of green development technologies at the farm level, and promoting the optimization of energy structures in agricultural and rural areas.

Keywords: Industrial agglomeration, energy efficiency, spatial econometrics, agriculture in China

1. Introduction

In recent years, energy shortages have limited socio-economic developments, and the adverse effects of energy consumption on the ecological environment are increasingly significant (Cherni and Jouini, 2017; Jiang and Lin, 2013). There is an extremely urgent need to improve energy efficiency to achieve the sustainable development goals (SDGs). Studies have found that the global environment and climate conditions are significantly affected by the energy consumption of agricultural activities (including fuel and electricity). The industry's contribution to the global emission of greenhouse gases ranges from 25% to 35% (David and Michael, 2014). Agricultural energy utilization is generally less efficient in comparison to that of the industrial sector (Wang et al., 2013). Thus, it is critical to reduce agricultural energy consumption and carbon emissions by improving AEE. Doing so will promote not only sustainable agricultural development (Alluvione et al., 2011; Rafiee et al., 2010) but also reduce agricultural production costs, increase agricultural competitiveness and profitability, and effectively alleviate poverty (De Janvry and Sadoulet, 2013; Omid et al., 2011).

Recently, there has been an increasing amount of research on the factors affecting energy efficiency. These factors include technological progress, management and infrastructural levels, energy prices, and systems and policies. Studies have shown that technological advances drive energy efficiency, and that the energy efficiency improvements arising from changes in technological factors are significant in most sectors (Makridou et al., 2016). The empirical analysis of China's textile industry by Lin and Zhao (2016) revealed that technology gaps caused regional energy efficiency differences in the industry. Energy prices also affect energy efficiency (Herrerias et al., 2013), though the related results differ across studies. For instance, the research findings were negative for the United States and European Union (EU) countries (Ball et al., 2015; Makridou et al., 2016) but were positive for China's transportation industry (Liu and Lin, 2018).

Furthermore, other studies ascertained that industrial energy efficiency is positively correlated with the level of regional economic development and the general provision of basic infrastructure (Cheng, 2016; Li et al., 2018; Vlontzos et al., 2014; Zheng and Lin, 2018). Vlontzos et al. (2014) conducted a representative study on the impact of policies by estimating the AEEs of EU member states. They found that the implementation of the Common Agricultural Policy (CAP) had a significant positive impact on energy and environmental efficiencies. For specific individual producers, the major obstacles to energy efficiency improvements were the scale of operation, management level, and return on assets (Haider et al., 2019; Moon and Min, 2017; Qin et al., 2017).

Industrial agglomeration generally refers to the proximity of related activities in the same industry at a specific geographical space (Billings and Johnson, 2016); it is a common phenomenon in industrial development. Studies have found that industrial agglomeration can have either positive or negative impacts on industrial development, thereby validating the Williamson hypothesis. The impact of industrial agglomeration on energy efficiency has recently received an increase in attention (Tanaka and Managi, 2017). Some studies suggested that the industrial agglomeration improve the scalar and distributional efficiencies of energy, leading to positive impacts on energy efficiency (Chang and Oxley, 2008; Liu et al., 2017). Nevertheless, some scholars believed that such effects could only be achieved after agglomeration had reached a certain level (Zheng and Lin, 2018). Other studies, however, highlighted that excessive agglomeration might lead to various problems, such as rising prices of production factors and overcapacity, which could lead to negative effects. This result means that there might be a non-linear and inverted U-shape relationship between industrial agglomeration and production efficiency (Brülhart and Mathys, 2008; Rizov et al., 2012).

Although China has less than 10% of the world's total arable lands, it has to provide food for more than 20% of the global population. This situation has led the agricultural industry to adopt the approach of high outputs accompanied by high energy consumption in recent decades (Chen et al., 2009). A sharp increase in energy consumption simultaneously accompanied rapid agricultural development. Between the 2000-2016 period, consumption increased from 42.33 million to 85.44 million tons of standard coal equivalent. This event represented an overall increase of 101.84%, or an average of 4.49% per annum, which was higher than the growth rate of the agricultural output value over the same period (4.10%). Some studies predicted that China's agricultural energy consumption would reach 161.61 million tons of standard coal equivalent by 2025 (Fei and Lin, 2017), which is almost double the amount in 2016.

Agricultural development in the country faces the double constraints of resources and environment, and its relationship with energy efficiency has gradually received more research attention. A representative study by Zhang et al. (2019) analyzed the AEE and consumption issues of China's major producing regions for grains. They highlighted the significant and negative impact that agricultural energy consumption had on agricultural carbon emissions. Fei and Lin (2016) used the data envelopment analysis (DEA) method to measure the AEE of China's agricultural sector based on East, Central, and West China. The findings indicate that the agricultural output and mechanical energy had positive impacts on energy consumption, whereas the agricultural industrial structure, financial expenditures, and energy prices had negative impacts. Fei and Lin (2017) found that China's agricultural sector still has great potential in regard to saving energy. The Chinese government introduced a series of policies over the past several decades, including the setting up of major producing regions for grains and advantageous regions for characteristic agricultural product. These policies have brought about significant changes to the geographical distribution of the agriculture industry (Wang et al., 2018). However, research on the impact of such changes on AEE is still lacking.

In summary, although the impact of industrial agglomeration on AEE has been verified in many countries and industries, research in the field of China's AEE based on the perspective of agricultural industrial agglomeration is lacking. In addition, the mechanism by which agricultural industrial agglomeration affects AEE has not been identified. Moreover, although existing studies have adopted the DEA measurement method, the more effective parameter frontier model has yet to be applied. Consequently, the results of the existing studies contain inevitable estimation errors.

This study evaluated AEE at the provincial level using stochastic frontier models and analyzed the impact of agricultural industrial agglomeration using spatial econometric models. First, the study aimed to identify the regional differences in China's agricultural energy consumption. Second, the study clarified the impact of agricultural industrial agglomeration on energy efficiency and the mechanism by which the former exerts its effects. The findings will be significant in promoting the development of green agriculture, energy conservation, and emissions reduction in China.

The rest of the study is organized as follows. Section 2 introduces the data and models. Section 3 presents the empirical results. Section 4 discusses the implications of the results. Section 5 summarizes the research findings and proposes policy recommendations.

2. Data and methodology

2.1 AEE estimation

There are two main methods to measure AEE: The single-factor indicator and the total-factor AEE indicator. The former generally uses energy consumption per unit GDP as an inverse indicator but is unable to reflect the technical efficiency of energy use (Wilson et al., 1994). The latter is represented by the DEA and stochastic frontier analysis (SFA), both of which are based on the definition of the efficiency frontier. DEA, a non-parametric method with no predetermined frontier function, is widely used in research (Fei and Lin, 2016; Heidari et al., 2012; Mousavi-Avval et al., 2011). However, DEA-generated results are very sensitive to the selection of input and output variables; they are also easily affected by the sample size and data quality (Cook et al., 2014). In contrast, SFA is a parametric estimation method based on maximum likelihood estimation (MLE). The stochastic frontier model is easier to interpret than the non-parametric method. The reliability of the results can also be estimated, thereby improving comparability (Greene, 2008). This method has developed rapidly and has been widely applied in recent years (Boyd and Lee, 2019; Marin and Palma, 2017; Perroni et al., 2016).

This study employed stochastic frontier panel models for its estimations to obtain more results. This model was introduced by (Aigner et al., 1977) and its basic form is as follows:

$$y_{it} = f(\boldsymbol{z}_{it}, \boldsymbol{\beta})\xi_{it}\exp(v_{it}) \tag{1}$$

where y_{it} is the production of the i^{th} region at time t, $f(\boldsymbol{z}_{it}, \boldsymbol{\beta})$is the production function, $\boldsymbol{z}_{it}$ represents the inputs of production, ξ_{it} is the level of a degree of efficiency of the i^{th} region at time t, ξ_{it} must be in the interval (0,1), and v_{it} is the idiosyncratic error $v_{it} \sim N(0, \sigma_v)$.

We further assumed that the production function is a Cobb-Douglas function, such that Equation (1) can be transformed into the following Equation (2):

$$ln(y_{it}) = \beta_0 + \sum_{j=1}^{k} \beta_j\, ln\left(z_{jit}\right) + v_{it} - u_{it} \tag{2}$$

Where $u_{it} = -ln(\xi_{it}) \geq 0$. Two different models were derived from the specific settings of the u form: The time-variant and the time-invariant model.

As the temporal dimension of this study was longer than ten years, it was not realistic to assume that technical efficiencies remained unchanged over time. Thus, we used the Time-variant stochastic frontier production function models to predict efficiency. The time-variant model was in the form of an inefficiency effects model proposed by Battese and Coelli (1995). Lastly, MLE was used for estimating Equation (2).

This study employs labor (L), capital (K), energy consumption (E), and cultivated area (A) as input factors and the total value of agricultural output (Y) as the output variable to construct a stochastic frontier model of the panel data. There was a high probability of technological changes since the study spanned the 2000–2016 period. As such, an annual dummy variable *t* was added in Equation (3):

$$ln\,Y_{it} = \alpha_0 + \alpha_1\,ln\,L_{it} + \alpha_2\,ln\,K_{it} + \alpha_3\,ln\,E_{it} + \alpha_4\,ln\,A_{it} + t + v_{it} - u_{it} \tag{3}$$

where *i* represents the i^{th} province and *t* denotes time *t*; *Y* is the value-added to the GDP by the primary industry, which was converted to a constant price with 2000 as the base year; *L* is the number of people employed in the primary industry; *A* is the agricultural crop acreage; and *E* is the energy consumption of the primary industry, which could not be directly obtained from the existing statistics. Instead, the physical quantities of raw coal, electricity, natural gas, gasoline, and diesel consumed by the forestry, animal husbandry, and fishery industries of the various provinces were converted to standard coal equivalent to represent the energy consumption. Please refer to the annual *China Energy Statistical Yearbook* for the specific conversion factors, where v_{it} is random disturbance term, u_{it} is technical inefficiency studied above, and *K* is capital stock.

In this study, the agricultural capital stock was measured using the perpetual inventory method (Goldsmith, 1951). The specific equation for this is Equation 4, which is as follows:

$$K_{it} = K_{it-1}(1 - \delta_{it}) + I_{\mathrm{it}} \tag{4}$$

where *K* is the capital stock agricultural base year (2000), which referenced the research findings of Zong and Liao (2014), and *I* is the annual fixed assets investments. Generally, the ideal data would be the total fixed capital formation of the primary industry. Thus, considering the problem with data acquisition, this study used the fixed assets investments by the agricultural, forestry, animal husbandry, and fishery industries as the substitute. During the calculation process, it was necessary to first construct a price index for the annual fixed assets investments. Next, the index sequence was used to deflate the annual investments of several years before the amounts were converted to actual values expressed in the constant price of the base year; δ is the economic depreciation rate. The value of 9.6% was adopted (Zhang et al., 2004).

2.2 Independent and control variables

The independent variable of the study was the industrial agglomeration index (IAI). The control variables included the industrial economic level (lnGDP), basic infrastructure (INF), energy consumption structure (ENS), energy price (ENP), R&D expenditure (RND), and agricultural expenditure (AE). Table 1 displays the descriptive statistics of our data.

i. **IAI:** Position entropy was used to measure the level of agricultural industrial agglomeration, which is also known as the regional specialization index. It is an effective indicator for measuring the level of agricultural industrial agglomeration as in Equation (5) (Otsuka et al., 2014).

$$IAI_{ij} = \frac{\frac{e_{ij}}{\sum_i^{30} e_{ij}}}{\frac{\sum_j^{3} e_{ij}}{\sum_i^{30}\sum_j^{3} e_{ij}}} \tag{5}$$

Where IAI_{ij} represents the position entropy of the *j* industry in the *i* province, and e_{ij} represents the output value of the j industry in the i^{th} province (i=1,2.3... 30). *j* = 1,2,3, representing the first, second and third industries. This study only calculated the position entropy of the first industry in each province. The higher the position entropy is, the higher the degree of agglomeration is.

ii. **lnGDP:** Developed regions usually receive more financial support, which is accompanied by technological innovation, infrastructure, and other improvements. Higher levels of economic development generally have a positive impact on energy efficiency (Sadorsky, 2013). In this study, the level of economic development was represented by agricultural GDP in logarithmic form. A deflator was used to convert it to an index for a fixed base period.

iii. **INF:** Improvements to the basic infrastructure reduce transportation energy consumption and increase the efficiency of energy flow, thereby directly increasing AEE. This study used the road mileage per unit area in the various provinces to measure the regional infrastructure levels.

iv. **ENS:** Different types of energy have varying efficiencies. For example, the efficiency of diesel and coal are relatively low compared with other energy products (Lin and Zhu, 2017). The regional ENS also affects AEE. This study used the proportion of agricultural coal energy consumption of the various provinces to represent the regional ENS.

v. **ENP:** Fuel price changes have a significant impact on energy input costs. As a result, producers and operators pay more attention to energy conservation. Therefore, it is believed that a rise in energy prices helps improve energy efficiency (Bye et al., 2018). This study used the purchasing price index of raw materials, fuel, and power (PPIRM) of the various provinces to represent ENP.

vi. **RND:** High levels of scientific and technological knowledge can contribute to the heightening of energy-saving awareness, technological innovations, popularization, and application, which are the key factors to improving energy efficiency. The expenditure on scientific and technological knowledge was represented in this study by the share of research and development expenditure in the total regional fiscal expenditures.

vii. **AE:** It is generally believed that, on the one hand, the government's agricultural investments represent the government's intervention in the economy, which distorts resource allocation and therefore has an adverse impact on the long-term development of agriculture. On the other hand, these investments also improve the infrastructure and basic conditions of agriculture, forestry, and water, and increase the promotion of technology. Either way, AEE is affected. In this study, AE is represented by the share of agricultural expenditures in the total regional fiscal expenditures.

Table 1 Descriptive statistics of key variables

Variable Name	Obs	Mean	S.D.	Min	Median	Max
AEE	510	0.73	0.118	0.37	0.76	0.92
IAI	510	1.17	0.58	0.05	1.21	3.10
LnGDP	510	9.66	0.67	7.94	9.69	11.12
INF	510	0.69	0.46	0.02	0.59	2.11
ENS	510	0.28	0.24	0.00	0.20	0.95
ENP	510	5.21	0.36	4.59	5.24	6.41
RND	510	0.02	0.01	0.00	0.01	0.07
AE	510	0.09	0.04	0.01	0.09	0.19

2.3 Data source

The research subjects of this study were China's 30 provinces and cities (Tibet was excluded due to incomplete data) during the 2000–2016 period. For each province, the statistical yearbooks of China and the various provinces for the corresponding years were used to acquire the raw data of the following: the GDP and deflator index, agricultural population, fixed assets investments in agriculture, forestry, animal husbandry, and fishery, highway mileage, regional land area, fiscal expenditure, population engaged in the agricultural industry, and number of high school graduates. The PPIRMs were obtained from the various provincial statistical yearbooks. The physical consumption of raw coal, electricity, natural gas, gasoline, and diesel and the conversion coefficients for standard coal equivalent were obtained from the relevant *China Energy Statistical Yearbooks* and provincial statistical yearbooks.

2.4 Empirical models

2.4.1 Spatial autocorrelation test

We first used the Moran's I test method to verify the existence of spatial dependence in energy efficiency among the provinces. The Moran's I test that we used was as follows (Equation [6]):

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(AEE_i - \overline{AEE}\right)\left(AEE_j - \overline{AEE}\right)}{\sum_{i=1}^{n}\left(AEE_i - \overline{AEE}\right)^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (6)$$

A significant Moran's I index means that a global spatial correlation exists. Moran's Scatter Plots (MSP) and the Local Indication of Spatial Association (LISA) are then utilized to test the local spatial correlation of the provincial agricultural energy efficiency in China.

2.4.2 Spatial econometric models

The majority of existing studies used the dynamic panel or Tobit model for their regression analyses to explore the factors affecting AEE. These methods ignore that, in reality, a geospatial AEE spillover effect exists (Pan et al., 2015). Studies have shown that there were obvious spatial spillover effects in energy consumption and that the regional differentiation of factors was obvious. Studies that ignore the spatial factors may produce estimation errors (Camioto et al., 2016; Liu et al., 2017). The Belgian economist Jean Paelinck proposed the spatial econometric model in the late 1970s (Paelinck and Klaassen, 1979). Since then, spatial econometric models that effectively identify spatial relationships in econometric models have gradually become the main method for studying economic spatial relationships. Elhorst (2017) and LeSage and Pace (2009) introduced spatial matrices and promoted the development of spatial empirical research. In this study, the form of the models proposed by Lee (2002) and Elhorst (2017) was improved to derive our models to further increase the accuracy of the spatial panel estimations. For the empirical analysis, the external commands in Stata were used for model building.

Three types of models were constructed in this study: a Spatial-Auto Regressive model (SAR) (specified in Equation [7]), a Spatial-Error model (SEM) (specified in Equation [8]), and a spatial Durbin model (SDM) (specified in Equation [9]).

$$AEE_{it} = \alpha + \gamma IAI_{it} + \beta Control_{it} + \rho \sum_{j}^{30} w_{ij}\, AEE_{jt} + u_i + \varepsilon_{it} \tag{7}$$

$$AEE_{it} = \alpha + \gamma IAI_{it} + \beta Control_{it} + u_i + \varepsilon_{it} + \lambda \sum_{j}^{30} w_{ij}\, \varepsilon_{jt} \tag{8}$$

$$AEE_{it} = \alpha + \gamma IAI_{it} + \beta Control_{it} + \rho \sum_{j}^{30} w_{ij}\, AEE_{j,t} + \theta \sum_{j}^{30} w_{ij}\, IAI_{jt} + \delta \sum_{j}^{30} w_{ij}\, Control_{jt} + u_i + \varepsilon_{it} \tag{9}$$

$$(i, j = 1, 2, \ldots, 30;\ t = 2000, 2001, \ldots, 2016)$$

Here, i and j denote provinces and t indicates time. AEE_{it} is the energy efficiency vector of the i^{th} province at time t. IAI_{it} is the vector of our main independent variable, industry agglomeration index. $Control_{it}$ represents the matrix of control variables, including lnGDP, INF, ENS, ENP, RND, and AE. u_i is the cross-sectional intercept term, which donates the spatial fixed effects. w_{ij} is the element of the i^{th} row and the j^{th} column of the spatial weight matrix that plays a different role in Equations (7), (8), and (9). For Equation (7), w_{ij} interacts with the spatially lagged dependent variable, AEE_{jt}. For Equation (8), w_{ij} interacts with the spatially dependent random error term, ε_{jt}. Finally, for Equation (9), w_{ij} interacts with the spatially lagged dependent variable, AEE_{jt}, and spatially lagged independent variables, including IAI_{jt} and $Control_{jt}$.

Our study selects the binary adjacency matrix as a spatial weight matrix. If the two regions have a common boundary, the weight of each other is set to 1, and 0 otherwise. We followed the research paradigm of LeSage and Pace (2009), when we conducted our research on spatial econometric models. First, we used Moran's I test to determine whether energy efficiency exists in the global and local spatial correlation. We then estimated the three types of models as stated in Equations (7), (8), and (9) before using the Hausman test to determine the spatial fixed effects panel model that should be selected to suit our data. During the subsequent SDM estimations, the following hypotheses were also tested.

Hypothesis 1: $H_0: \theta = \delta_1 = \delta_2 = \ldots = \delta_6 = 0$

Hypothesis 2: $H_0: (\theta = -\rho\gamma)(\delta_1 = -\rho\beta_1)(\delta_2 = -\rho\beta_2)\ldots(\delta_6 = -\rho\beta_6)$

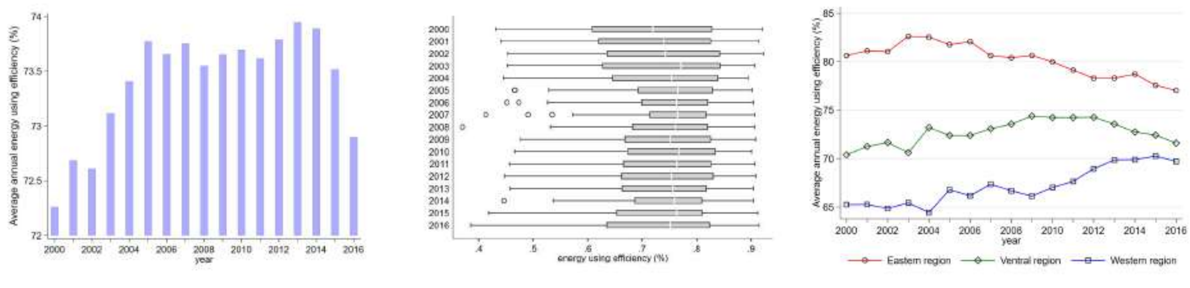
For Hypotheses 1 and 2, we applied the Wald tests to the above nonlinear or linear hypotheses about the parameters of our model. The SDM was a more suitable model than the SAR if Hypothesis 1 was rejected, while the SDM was more suitable than the SEM if Hypothesis 2 was rejected. Lastly, we replaced the binary adjacency matrix with the inverse-distance matrix to test for robustness.

3. Results

3.1 Spatial characteristics of AEE

3.1.1 Changes and spatial differences in AEE

The SFA estimation results indicate the trend of China's average AEE in the 2000–2016 period (Figures 1a, 1b). This result means that the industry's management efficiency and technical level unceasingly improved. Among the three regions, East China had the highest AEE during that period, followed by Central and West China (Figure 1c). The average values were 0.8, 0.726, and 0.671, respectively, reflecting an obvious gradient from east to west. In terms of the changes, the value for East China declined from 0.806 to 0.771, that for Central China was basically stable, and that for West China rose from 0.653 to 0.697. The AEE gaps between the three regions gradually narrowed over time.



a b c

Figure 1 Average annual energy efficiency (%)

The AEE at the provincial level similarly exhibited significant regional differentiation (Table 2). Over the study period, Hainan Province had the highest average AEE at 0.90, and Shanxi Province had the lowest at 0.45. The latter is located in the country's interior. Being a large coal-producing province, its proportion of coal consumption was high. In contrast, the former is located in the south with a well-developed sea transportation system. The transportation conditions for the respective ENS of the two provinces might have caused the gap. At the same time, it can be seen from Figure 1 that the inter-provincial AEE gaps exhibited an expanding trend.

Table 2 Provincial annual average AEE in 2000–2016

Province	AEE	Province	AEE	Province	AEE
Shanghai	0.754	Shanxi	0.445	Hubei	0.803
Yunnan	0.597	Guangdong	0.832	Hunan	0.743
Inner Mongolia	0.709	Guangxi	0.841	Gansu	0.539
Beijing	0.718	Xinjiang	0.744	Fujian	0.863
Jilin	0.847	Jiangsu	0.885	Guizhou	0.551
Sichuan	0.808	Jiangxi	0.813	Liaoning	0.836
Tianjin	0.704	Hebei	0.775	Chongqing	0.643
Ningxia	0.614	Henan	0.695	Shaanxi	0.665
Anhui	0.753	Zhejiang	0.780	Qinghai	0.677
Shandong	0.769	Hainan	0.901	Heilongjiang	0.718

3.1.2 Spatial autocorrelation of AEE

Figure 2 shows that the Moran's I statistics are positively significant at the 10% significance level for the 2000–2016 period, which means that a global spatial correlation exists in agricultural energy efficiency among the Chinese provinces. This result was also consistent with the phenomena of agglomerations of the high and low AEE values (Figure 3). The Moran's I statistics had a growing trend over time, indicating that the spatial agglomeration of AEEs became increasingly obvious.

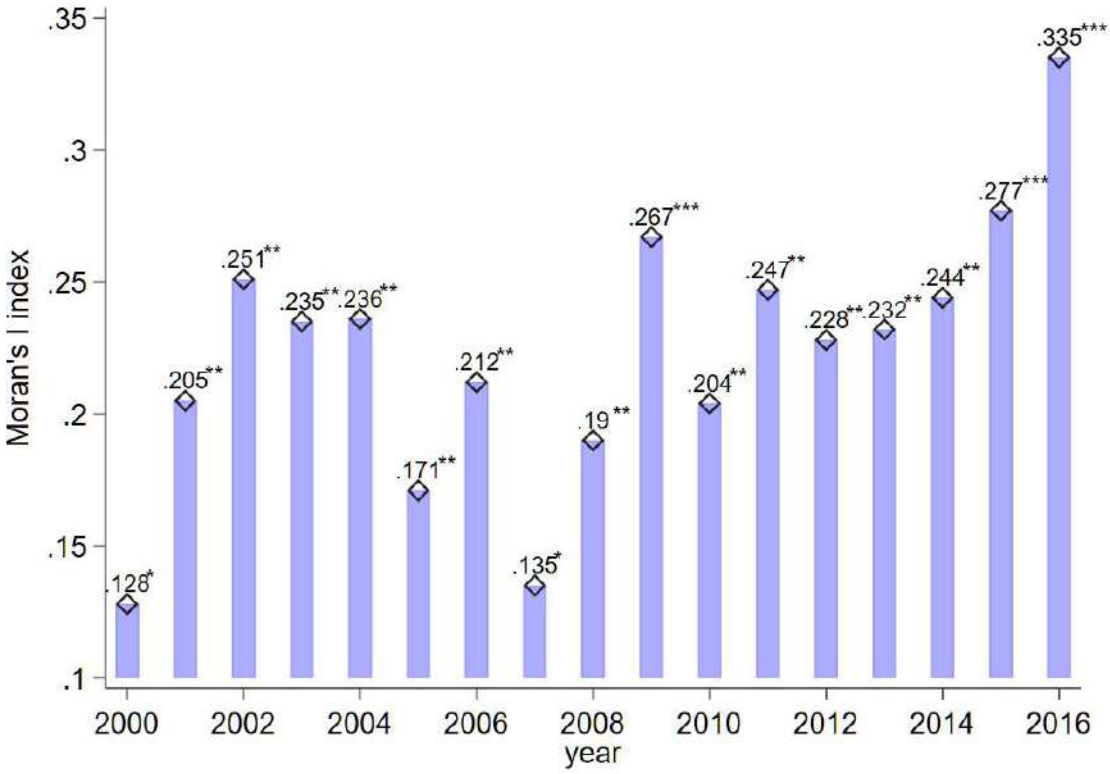
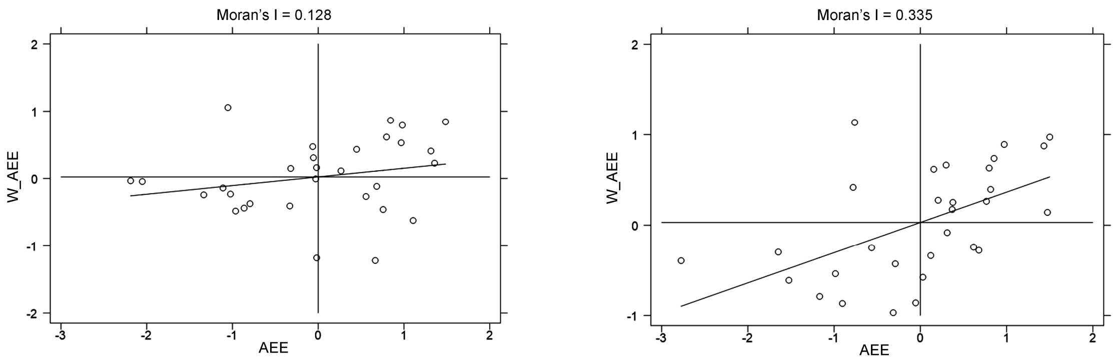


Figure 2 Moran's I index bar graph

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



(i) 2000 (ii) 2016

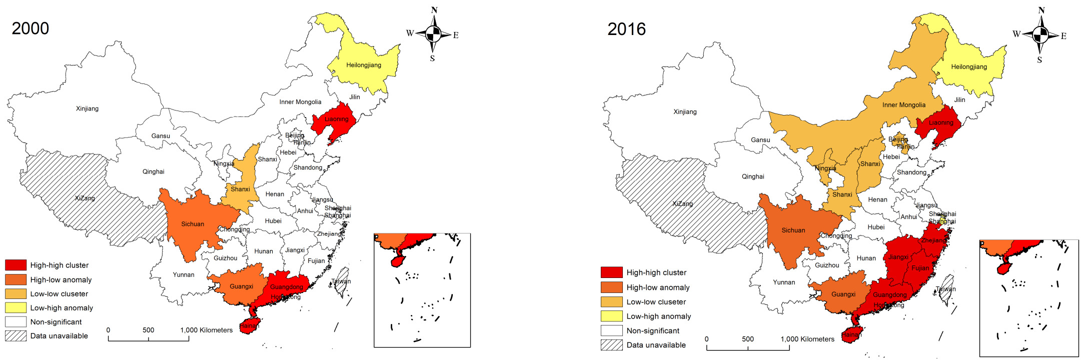
Figure 3 Moran scatter plot for Chinese provincial energy efficiency

The next step is to explore the local spatial correlations. We separately use the Moran Scatter Plots (MSP) and the Local Indication of Spatial Association (LISA) figure to examine the existence of local spatial correlation of provincial agriculture energy efficiency in China. Figure 3 reports the Moran Scatter Plots of AEE in 2000 and 2016, where the solid line in the figure is the regression line of Moran's I global test, and its slope represents the test statistic. Every dot represents the province's

AEE. The abscissa and ordinate are the provincial AEEs after standardization and the spatial lag in AEEs, respectively.

The MSPs are divided into four quadrants. Quadrants 1 and 3 represent the positive spatial autocorrelation of the observed values, while Quadrants 2 and 4 represent the negative spatial autocorrelation. The MSPs for the 2000–2016 period show that most provinces were located in Quadrants 1 and 3, with only a few in Quadrants 2 and 4. This indicates that the characteristic of spatial agglomeration by AEE levels was obvious. The provinces with similar AEE levels often formed clusters: those with high AEE levels were spatially correlated, while those with low AEE levels were adjacent to one another. From 2000 to 2016, the distribution of provinces had converged towards Quadrants 1 and 3, indicating that the characteristic of AEE spatial clustering had strengthened over time.

Figure 4 shows the local LISA clustering pattern on a Chinese map. The high-high and low-low agglomerations were mostly concentrated in the southeast and northwest regions, respectively. The former region has better economic development, infrastructural conditions, and technological innovation capabilities, which promoted better AEE. The high-high versus low-low agglomerations became increasingly apparent over the years, resulting in greater inter-provincial differentiation. The number of high AEE provinces along the southeast coast increased, whereas those with low AEEs became more concentrated in Central China (especially Inner Mongolia and Shanxi Province). The supporting conditions for agriculture in that region are poor, the infrastructural level is low, and the ENS is relatively simple. The contribution rate of technological innovation to economic growth is also low.



(i) 2000 (ii) 2016

Figure 4 LISA cluster map for Chinese provincial energy efficiency

3.2 Impact of agricultural industrial agglomeration on AEE

Table 3 Estimation results of the spatial panel models

Variables	SAR FE	SAR RE	SEM FE	SEM RE	SDM FE	SDM RE
IAI	0.229***	0.141***	0.228***	0.146***	0.216***	0.137***
	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)	(0.016)
lnGDP	0.235***	0.040***	0.233***	0.074***	0.224***	0.026*
	(0.020)	(0.012)	(0.021)	(0.014)	(0.022)	(0.014)
INF	0.109***	0.052***	0.108***	0.111***	0.086***	0.014
	(0.013)	(0.014)	(0.013)	(0.017)	(0.017)	(0.018)
ENS	-0.099***	-0.125***	-0.097***	-0.093***	-0.108***	-0.132***
	(0.020)	(0.023)	(0.020)	(0.021)	(0.020)	(0.022)
ENP	0.000	-0.039***	0.011	-0.036*	-0.022	-0.042**
	(0.022)	(0.015)	(0.022)	(0.020)	(0.021)	(0.018)
RND	0.183	-1.246***	0.081	-0.907***	-0.142	-1.440***
	(0.336)	(0.356)	(0.334)	(0.335)	(0.323)	(0.361)
AE	0.031	-0.457***	0.042	-0.296**	0.138	-0.322**
	(0.142)	(0.142)	(0.142)	(0.150)	(0.140)	(0.156)
Con		0.260***		0.028		0.481***
		(0.100)		(0.132)		(0.111)
W × AEE	0.389***	0.293***			0.312***	0.339***
	(0.091)	(0.078)			(0.097)	(0.081)
W × u			0.427***	0.806***		
			(0.106)	(0.045)		
W × IAI					-0.194***	-0.264***
					(0.063)	(0.060)
N	510.000	510.000	510.000	510.000	510.000	510.000
Regional control effect	Yes	Yes	Yes	Yes	Yes	Yes
Time control effect	Yes	Yes	Yes	Yes	Yes	Yes
rsq	0.353	0.499	0.528	0.564	0.569	0.665
Hausman_chi^2	39.927***		33.919***		125.526***	
LM test	10.755***		19.952***		____	
Wald test	____		____		76.31***	51.30***
L ratio test	____		____		99.63***	47.99***

Note: The standard deviations are indicated in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In Table 3, we present six models, including the fixed-effect model and random effect of SAR, SEM and SDM. The Hausman test shows that all Hausman chi^2 estimators were significant at the 5% level, which demonstrates that the fixed-effect model is suitable for our estimate. The results of LM of SAR and SEM test indicate that spatial models are more appropriate than non-spatial models. Further, we apply the Wald test (Hypothesis 1) and the L ratio test (Hypothesis 2) to verify which model (SAR, SEM, or SDM) is the most appropriate for our study. The null hypotheses of Wald test and L ratio test are rejected by all the results, indicating that neither SAR nor SEM can accurately describe the spatial relationships of our data and that SDM should be used for analysis. According to the Hausman chi^2, the fixed effect model is more appropriate for our study. Thus, SDM FE is selected for providing the explanations. After the main control variables are controlled for in the models, the results indicate that the coefficient of local agricultural agglomeration index is positive and significant at the 1% significance level However, the spatial lag term of the agricultural agglomeration index has a significantly negative impact on AEE, which indicates there is a negative spatial spillover effect of IAI. Finally, we also find the spatial lag term of AEE has a significantly positive impact on AEE, which shows the positive spillover effect of AEE.

Further, we report the margin effects of agricultural industrial agglomeration on energy efficiency based on the method proposed by LeSage and Pace (2009). The direct, indirect, and overall average impacts are shown in Table 4. The direct effect coefficient of industrial energy agglomeration was 0.215, which was significant at the 1% significance level. The implication was that a 1% increase in the average local energy agglomeration would increase AEE by 0.215%. The indirect impact was negative but not significant. The overall impact was affected because the indirect negative effects offset some of the direct positive effects. As a result, when the energy agglomeration level increased by 1%, the overall AEE increased by only 0.157%. The findings of this study are consistent with those of other studies about other industries (Liu et al., 2017; Wang et al., 2018; Zheng and Lin, 2018).

In regard to the effect of control variables, the result also demonstrate that the impact of agricultural GDP on AEE is actually positive. For every 1% increase in agricultural GDP, the energy efficiency increases by 0.444%, and this result is significant at the 1% level. The consumption structure and price of energy have a negative impact on energy efficiency, while infrastructure and R&D expenditure have a positive impact on energy efficiency. For every 1% increase in R&D expenditure, energy efficiency will increase by 4.381%. This illustrates the importance of scientific and technological innovation. The influence of agricultural expenditure was not statistically significant.

Table 4 Average marginal effects

Variables	Direct effect	Indirect effect	Total Effect
IAI	0.215***	-0.058	0.157***
	(0.017)	(0.050)	(0.059)
lnGDP	0.228***	0.216***	0.444***
	(0.021)	(0.054)	(0.055)
INF	0.087***	-0.023	0.064**
	(0.016)	(0.033)	(0.030)
ENS	-0.111***	-0.104	-0.215***
	(0.020)	(0.068)	(0.074)
ENP	-0.024	-0.135***	-0.159***
	(0.020)	(0.042)	(0.052)
RND	-0.045	4.426***	4.381***
	(0.317)	(1.134)	(1.211)
AE	0.135	-0.322	-0.187
	(0.144)	(0.330)	(0.354)

Note: The standard deviations are indicated in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.3 Robustness analysis

For the robustness test, we replaced the binary adjacency matrix with the inverse-distance matrix as the spatial matrix. The inverse-distance matrix, defined as the reciprocal matrix of the distance from the provincial administrative center, was used to re-estimate the SDM. The Spatial Autocorrelation model (SAC), which is specified in Equation (10), is also replaced to compare the estimation results (Elhorst, 2017; LeSage and Pace, 2009).

$$AEE_{it} = \alpha + \gamma IAI_{it} + \beta Control_{it} + \rho \sum_{j}^{30} w_{ij} \, AEE_{jt} + u_i + \lambda \sum_{j}^{30} w_{ij} \, \varepsilon_{jt} + \varepsilon_{it} \tag{10}$$

where w_{ij} interacts with the spatially lagged dependent variable AEE_{jt} and the spatially dependent random error term ε_{jt}. The results (Table 5) are similar to the previous estimates. According to the Hausman test, the SDM FE is found to be more appropriate than the SDM RE. The results of the SDM RE (Column 1) show that the main effect coefficient of agricultural industrial agglomeration remained positive. The spatial lag terms of agricultural industrial agglomeration and AEE remain negative and positive, respectively. These results are basically consistent with the estimates stated earlier in the paper. The SAC estimation method is replaced (Column 3). Both the main effect of the coefficient of agricultural industrial agglomeration and the spatial lag term of the AEE remained positive. The two aforementioned methods demonstrate the robustness of the earlier estimates.

Table 5 Estimation results of the SpatialDurbin model and Spatial Autocorrelation model using the inverse-distance matrix

Variables	SDM FE	SDM RE	SAC
IAI	0.163*** (0.017)	0.128*** (0.014)	0.223*** (0.016)
lnGDP	0.221*** (0.019)	0.063*** (0.012)	0.239*** (0.018)
INF	0.130*** (0.014)	0.135*** (0.016)	0.105*** (0.012)
ENS	-0.095*** (0.020)	-0.102*** (0.022)	-0.104*** (0.020)
ENP	0.018 (0.020)	-0.003 (0.014)	-0.023 (0.021)
RND	0.475 (0.326)	-0.778** (0.327)	0.584* (0.354)
AE	0.036 (0.130)	-0.295** (0.126)	-0.052 (0.141)
Con		0.110 (0.126)	
W × AEE	0.246** (0.108)	0.549*** (0.078)	0.691*** (0.080)
W × u			-0.817*** (0.248)
W × IAI	-1.077*** (0.145)	-0.207*** (0.077)	
N	510.000	510.000	510.000
Regional control effect	Yes	Yes	Yes
Time control effect	Yes	Yes	Yes
rsq	0.569	0.63	0.452
Hausman_chi^2	59.046***	59.046***	____

Note: The standard deviations are indicated in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4. Discussion

In regard to the direct impact, the results of the spatial statistical models confirmed that an increase in agricultural industrial agglomeration had a positive impact on local AEE. There are three main possible mechanisms underlying this effect— technology spillover, competition, and a more mature factor market. First, agricultural industrial agglomeration itself can promote technology and knowledge spillover to popularize energy efficient agricultural technology and improve the quality of agricultural labor resources. Second, the industrial agglomeration area generally enhanced competition in the agricultural industry. Such agglomeration is likely to force those in the agricultural industry to take the initiative to learn advanced technology, upgrade equipment, reduce costs, improve competitiveness, and improve energy efficiency through energy conservation and emission reduction techniques. Third, the regions with high agglomeration levels have larger energy demands and more mature factor markets, which could provide more high-quality energy or better optimized energy structures and ultimately improve energy efficiency.

In regard to the indirect impact, we also found that an improvement in neighboring regions' agglomeration levels would have a negative effect on AEE. According to the regional division of labor theory within the larger agriculture and new economic geography framework (Krugman, 1991), a region can become differentiated into an industrialized "core" and an agricultural "periphery." Our results indicate that the agricultural industrial agglomeration had a negative spillover effect and that certain production factors, such as capital, technology, and agricultural labor, gathered to the peripheral regions. This subsequently led to a weakening of the AEE in the core regions. Moreover, the econometric results showed that the AEE in the neighboring regions also had a positive effect on the local AEE. It is possible that this finding can be explained by agricultural technology spillover theory (Evenson, 1989). Energy efficiency is highly related to the agriculture technology and management pattern, which neighboring regions can easily introduce and learn. Ultimately, when neighboring regions have higher energy efficiency, this will lead to a higher local energy efficiency.

The Chinese government's promulgation, titled *Opinions on Innovating Systems and Mechanisms to Advance Green Agricultural Development*, proposed that the country should form a green agricultural production mode gradually. The ultimate aim was to promote the introduction of green agricultural production methods that improve energy efficiency by increasing outputs while reducing inputs and emissions. The proposal to "accelerate the construction of a rural clean energy system" will facilitate the increase of energy efficiency through improving energy consumption structure. The reduction of energy consumption was also an area of concern in the *Sustainable Development Plan of Agriculture in China (2015-2030)*. Both aforementioned planning documents mentioned the need to optimize the spatial layout and accelerate the construction of agricultural functional zones. In the future, there will inevitably be a further promotion of spatial agglomeration of the agricultural industries. From the perspective of spatial layout, the Chinese government has launched a development strategy for the construction of major producing regions for grains and advantageous regions for characteristic agricultural product. It will further tap the value of agricultural products in remote and backward areas in the central and western regions, and it will increase the proportion of agricultural output value in the central and western regions in the whole country. It is expected that with the expansion of local industrial scale, the efficiency of agricultural energy utilization in the central and western regions will be improved. Of course, agricultural industrial agglomeration may also lead to excessive market competition and rising prices of production factors, which are not conducive to AEE. Therefore, in the future, scientific and reasonable agricultural industry development expectations and regional layout should be formed in the whole country and all localities, and healthy market operation order should be established, which is of great significance to improve agricultural energy efficiency.

5. Conclusion and Recommendations

This study analyzed the impact of the agglomeration of agricultural industries on AEE. The results show that China's average AEEs have continuously improved from 2000 to 2016, and there were obvious positive spatial correlations, as well as spatial differentiations, with the high-high agglomerations located in East China and the low-low agglomerations in Central and West China. At the state level, the agricultural industrial agglomeration has a statistically significant impact on AEE. Overall, China's AEE was positively affected by the level of agricultural economic development, the basic infrastructure, and R&D expenditure, whereas the agricultural coal energy consumption and energy input costs had negative impacts.

Based on these conclusions, this paper puts forward several policy suggestions to improve the efficiency of agricultural energy utilization in China. First, the spatial distribution of agricultural productivity should be further optimized based on regional comparative advantages. Management should provide more effective measures for the construction of main agricultural production areas such as grain and characteristic agricultural products aiming to improve the level of production specialty and industrial agglomeration. Secondly, we should make full use of the spillover effect of knowledge and technology to strengthen regional technology cooperation, especially mature technology transfer to the central and western regions. Different energy-saving and efficiency enhancing measures should be adopted based on its natural and economic endowment in different regions. Thirdly, we need to promote the research and application of energy-saving technologies in the agricultural sector by gathering the resources of relative departments such as agriculture and sci-tech. Technology extension in Green Development should be promoted, with an emphasis on circular economy. Fourthly, the energy supply structure of agriculture and rural areas should to be optimized. It would be effective measures to increase investment in new energy and renewable energy equipment, and increase the proportion of renewable energy such as water, wind and solar energy.

We have explored the impact of AEE on energy efficiency in this article and there are more in-depth research projects for the future. First, our results show that China's provincial energy efficiency has simultaneous space lag and space error effects. Agglomeration can promote the improvement of energy efficiency at the provincial level, but the effects at the municipal and county level remain unknown, because the data at the municipal and county level are not available at present. Hence, the researches using the data in smaller scale are necessary in the future with the improvement of statistical data. Second, we mainly use the spatial parametric models in this study to estimate the linear spatial effect. The spatial nonparametric models also can be adopted to analyze the nonlinear relationship between AEE and agricultural industrial agglomeration in the future.

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Highlights

- We analyzed the impact of industrial agglomeration on agricultural energy efficiency (AEE)
- Spatial econometric models were used to evaluate the impact
- China's AEE exhibited significant spatial autocorrelation and differentiation
- Industrial agglomeration could promote AEE improvements

Declaration of interests

☒ 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.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: