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Measurement of Agricultural Eco-Efficiency and Analysis of Its Influencing Factors: Insights from 44 Agricultural Counties in Liaoning Province

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Abstract: Agricultural eco-efficiency (AEE) considers economic and environmental benefits and is a key indicator of green agricultural development. To achieve the multiple goals of improving agricultural production efficiency, reducing agricultural environmental damage, and reducing the input of agricultural resources, this study enriches the case study of agricultural production performance evaluation at the county level by measuring the AEE of 44 agricultural counties in Liaoning Province based on panel data and a super-efficient slacks-based measure model including undesired outputs. A two-way fixed-effects model was used to analyze the impact of agricultural development, macro-environment, and policy support on AEE. We found that the average AEE of the counties in Liaoning Province in 2014, 2016, 2018, and 2020 was 0.716, 0.735, 0.749, and 0.813, respectively, indicating a cumulative improvement rate of 13.55%. The average AEE levels gradually improved during the study period. Notably, the development of AEE among the counties was uneven. AEE was distributed in a "block-like" manner, and its local correlation presents a phenomenon of "small agglomeration and large dispersion". In addition, the level of the agricultural economy, industrialization, and urbanization significantly promoted the improvement of AEE, and the promoting effects varied between different income levels and regions. Therefore, Liaoning Province needs to improve the AEE of each county according to local conditions and narrow the differences in AEE between counties. To continuously improve the level of rural economic development, lead the development of agricultural modernization with new urbanization, and comprehensively improve the overall AEE of counties. The research results are of guiding significance for deepening the study of AEE and can provide decision-making support for optimizing the mode of agricultural production and promoting the green development of regional agriculture.

Keywords: S-SBM model; agricultural eco-efficiency; two-way fixed-effects model; level of agricultural economy

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1. Introduction

In the past decade, China has witnessed remarkable achievements in the reform and development of its agricultural and rural sectors; however, the problem of agricultural pollution has also become increasingly apparent, and agricultural development is faced with problems such as ecological environment improvement and efficiency improvement. Agriculture is a ballast stone of economic and social development. The convergence of rural areas, agriculture, and regional development is an important topic for the international community. Obtaining the greatest benefits of agricultural development with the lowest consumption of agricultural resources and environmental costs is one of the core issues facing the enduring development of agriculture in China. It is also a significant approach for implementing the concept of ecological civilization in the agricultural field and promoting high-quality rural development. Green circular agriculture, with its low pollution and high

utilization rates, is receiving increasing attention. Improving agricultural eco-efficiency (AEE) is important for achieving green agricultural development. The essence of AEE is to maximize agricultural economic benefits and minimize ecological damage through the rational allocation of agricultural resources. Therefore, studying AEE and its influencing factors has emerged as an important subject in sustainable agricultural development.

Liaoning Province is located in the geographical hub of Northeast China, North China, the Bohai Rim region, the Mongolian Plateau, and the Korean Peninsula. It is a major agricultural province in Northeast China and holds a crucial strategic position in maintaining China's food, ecological, and industrial security. Liaoning Province's economic increase in agriculture is also accompanied by increasingly serious diffuse agricultural pollution and large amounts of agricultural carbon emissions, and its agricultural pollution prevention and control is under pressure [1]. From 2000 to 2020, agricultural carbon emissions in Liaoning Province increased from 2.233 million tons to 2.835 million tons. This reflects the greater pressure on agricultural carbon emission reduction in Liaoning Province. From 2000 to 2020, the use of chemical fertilizers in Liaoning Province increased from 1.098 to 1.376 million tons, and the use of pesticides increased from 35,635 to 44,722 tons. Pressure for the prevention and control of diffused pollution in urban and rural areas remains significant, and the green development of agriculture is facing challenges. As the Chinese government gradually attaches importance to diffused agricultural pollution and agricultural carbon emission reduction, Liaoning Province is also facing important opportunities in agricultural ecological development. The "Fourteenth Five-Year Plan for Agricultural and Rural Modernization of Liaoning Province" proposed an initiative to "vigorously promote green agricultural production methods and carry out green agricultural development actions". It was also proposed that "by 2025, the rural ecological environment will be significantly improved, diffused agricultural pollution will be effectively curbed, the use of chemical fertilizers and pesticides will continue to decrease, resource utilization efficiency will steadily increase, and the green and low-carbon transformation of rural production and lifestyle will make positive progress". Therefore, an ecologically prioritized, green, and low-carbon agricultural development path is inevitable for agricultural development in Liaoning Province. Research on how to effectively improve AEE will help promote the sustainable development of agriculture in Liaoning Province.

Eco-efficiency refers to the ratio of added value to the environmental impact. The concept and methods of ecological efficiency (EE) are constantly being enriched and developed with the deepening of research. Some scholars have developed a bounded adjustment metric based on green indicators to calculate the EE of decision-making units [2]. Some scholars have used the relaxation-free directional distance function in the data envelopment analysis framework to evaluate the EE of the European Union from 1993 to 2010 [3]. AEE is an extension of EE and a further application and microscopic embodiment of it in agriculture.

Research on AEE in China and abroad has diverse content, scales, and methods. In terms of research content, the evaluation, influencing factors, spatiotemporal characteristics, and threshold effects of AEE have gradually become the focus of research. An increasing number of scholars are researching AEE from the comprehensive perspective of economics, management, geography, and other disciplines. Research on AEE has been carried out at multiple scales, such as country, urban agglomerations, provinces, cities, and counties [4,5]. Non-parametric methods based on data envelopment analysis are widely used in the evaluation of AEE, such as the data envelopment analysis (DEA) model [6], the three-stage DEA model [7,8], the slacks-based measure (SBM) model [9], and the super-efficiency slacks-based measure (S-SBM) model [10–12]. The S-SBM model, which includes undesired outputs (UOs), considers negative ecological output and can efficiently address the congestion or slack phenomenon caused by the input and output of the ordinary DEA model and the problem of fixed frontiers. This has gradually become the mainstream method for evaluating AEE. Although the parameter method represented by stochastic frontier analysis (SFA) has been widely used in EE [13,14], few studies have applied it to

measure AEE. Methods such as spatial autocorrelation and exploratory spatial data analysis (ESDA) are often used to further analyze spatial differences in AEE. The stochastic impacts of regression on population, affluence, and technology (STIRPAT) model [15,16], Tobit model [17], fixed-effects model, and threshold effect model have gradually become more commonly used methods in the analysis of influencing factors of AEE [18]. Some scholars tend to focus on the impact of certain factors on efficiency, such as fiscal decentralization, environmental regulation, and technological innovation [19]. Other scholars have also focused on the impact of multiple indicators on efficiency, including the urbanization rate, mechanization level, and planting structure [20].

Thus, AEE has become a popular topic of academic interest. Existing research on AEE is becoming increasingly refined, and the results are fruitful. Research on the cross-integration of different disciplinary perspectives has gradually increased. The research scale is gradually deepening, and the model methods and index systems have their own characteristics. However, there is still room for in-depth research, particularly on the spatial differences and determining factors of AEE at the county level. In addition, Liaoning Province, a major agricultural province facing the dual pressures of diffused agricultural pollution management and agricultural carbon reduction, is a typical region for AEE upgrading research. Therefore, the mainstream S-SBM model, which includes UOs, was selected to measure the AEE of counties in Liaoning Province and analyze the spatiotemporal evolution characteristics of efficiency. A two-way fixed-effects model was used to explore influencing factors. The purpose of this study was to summarize the spatiotemporal evolution characteristics of AEE in the study area and to identify the factors influencing AEE using regression analysis to propose effective countermeasures to improve the AEE of Liaoning Province.

2. Methods

2.1. Estimation of AEE and Analysis of Its Spatiotemporal Pattern

2.1.1. The S-SBM Model

The traditional DEA model has certain limitations in addressing negative external benefits. To this end, some scholars have proposed the S-SBM model with UOs to overcome the shortcomings of the traditional models [21,22]. The S-SBM model combines the advantages of both the super-efficiency and SBM models. It can re-decompose an effective decision-making unit with an efficiency value of one while bringing the UOs into the model to avoid the loss of effective decision-making unit information [23–25]. Therefore, this study adopted the S-SBM model, including UOs, to estimate the AEE of counties in Liaoning Province. Based on previous research [26–28], the model was constructed as follows:

$$\min p = \frac{\frac{1}{m}\sum_{i=1}^{m}(\overline{x}/x_{ik})}{\frac{1}{s_1+s_2}\left(\sum_{s=1}^{s_1}\overline{y}^g/y_{sk}^g + \sum_{q=1}^{s_2}\overline{y}^b/y_{qk}^b\right)} \quad (1)$$

$$\begin{cases} \overline{x} \geq \sum_{i=1,\neq k}^{n} x_{ij}\lambda_j; \overline{y}^g \leq \sum_{j=1,\neq k}^{n} y_{sj}^g\lambda_j; \overline{y}^g \geq \sum_{j=1,\neq k}^{n} y_{qj}^g\lambda_j; \\ \overline{x} \geq x_k; \overline{y}^g \leq y_k^g; \overline{y}^b \geq y_k^b; \\ \lambda_j \geq 0, i = 1, 2, \cdots, \text{m}; \text{j} = 1, 2, \cdots, \text{n}; \\ j \neq 0, s = 1, 2, \cdots, \text{s}_1; \text{q} = 1, 2, \cdots, \text{s}_2 \end{cases}$$

where p represents the evaluation value of AEE. The terms x, y^g, and y^b denote the input, expected output, and UOs indicator values, respectively; m denotes the number of input indicators; s_1 denotes the number of expected output indicators; s_2 denotes the number of unexpected output indicators; and n denotes the number of DUM. Each DMU comprises m inputs, s_1 expected outputs, and s_2 UOs. λ represents the weight of the corresponding input or output element.

2.1.2. Evaluation Indicators of AEE

AEE reflects the overall coordination between economic expansion in agriculture, resource conservation, and environmental protection. Based on existing research [29,30], this study used land, labor, chemical fertilizer, agricultural film, pesticides, machinery, and irrigation as input indicators to reflect the inputs in the process of agricultural production. Specific representations of the indicators are presented in Table 1. This study divides the output into desired output and UOs. The expected output was articulated in terms of the total agricultural output value and grain yield to measure agricultural economic benefits. Undesirable outputs include carbon emissions from agricultural land and diffuse agricultural pollution. The calculation of carbon emissions from agricultural land in this study pertains to Yang et al. [31], and the calculation of agricultural diffused pollution emission indicators refers to Lv et al. [32]. The data required for the above indicators were sourced from the statistical yearbooks of the Liaoning Province and prefecture-level cities.

Table 1. AEE evaluation index system of counties in Liaoning Province.

Category	Indicators	Indicator Representation	Units
input indicators	land investment	total sown area of crops	hm^2
	labor input	agricultural workers	thousands of people
	fertilizer input	fertilizer usage (converted to pure amount)	t
	agricultural film input	amount of agricultural film used	t
	pesticide input	pesticide usage	t
	mechanical investment	total power of agricultural machinery	thousands of watts
	irrigation input	effective irrigation area	hm^2
output indicators	expected output	gross agricultural output value	ten thousand yuan
		grain yield	t
	undesirable output	carbon emission from agricultural land	t
		agricultural diffused pollution emissions	t

2.1.3. Spatial Autocorrelation Analysis

Referring to related research [33], this study uses Moran's I as a global spatial autocorrelation statistic. The formula is as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}(x_i - \overline{x})^2\left(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\right)} \quad (2)$$

where $\overline{x}$ represents the average value of AEE in the county, x_i is the observed value of AEE in county I, x_j is the observed value of county j, W represents the spatial weight matrix, n is the total number of counties, I denotes the global Moran index, with a value range of $[-1, 1]$. The closer the value of I is to -1, the more pronounced the negative spatial correlation between regions. As I approaches 1, the positive spatial correlation strengthens, and as I approaches 0, it signifies the absence of spatial autocorrelation between regions.

The local spatial autocorrelation method was further used for the analysis, and the calculation formula is as follows:

$$I_i = \frac{n(x_i - \overline{x})\sum_{j=1}^{n} W_{ij}(x_j - \overline{x})}{\sum_i (x_i - \overline{x})^2} \quad (3)$$

2.2. Analysis of Influencing Factors of AEE

To seek ways to improve AEE, this research further explored the factors influencing AEE and analyzed the main influencing factors. Based on existing research experience [34–37], this study attempts to determine the main factors affecting AEE from the following three aspects: agricultural development, economic development, and policy support (Table 2).

Table 2. Factors affecting AEE in the counties in Liaoning Province.

Category	Indicators	Indicator Representation	Units
agricultural development	level of agricultural economy	gross agricultural output value/number of permanent residents	Yuan/person
	agricultural human capital	number of employees in the primary industry/number of total employees	%
	density of agricultural machinery	total power of agricultural machinery/total sown area of crops	kW/hm^2
economic development	level of industrialization	GDP of secondary industry/gross regional product	%
	level of urbanization	urban population/total population	%
policy support	the level of fiscal support for agriculture	local fiscal expenditures on agriculture, forestry and water affairs/local fiscal general budget expenditures	%

The two-way fixed-effects model is an effective tool for analyzing the influencing factors. It can help solve the problems of endogeneity, heterogeneity, and correlation and allows researchers to compare different individuals or at different points in time. Therefore, a two-way fixed-effects model was used to analyze the factors influencing AEE. The model is expressed as follows:

$$y_{it} = c_{it} + \beta_1 \ln eco_{it} + capital_{it} + \ln mec_{it} + industry_{it} + urban_{it} + fina_{it} + \varepsilon_{it} \quad (4)$$

where C_{it} represents a constant term, ε_{it} is random interference items, y_{it} indicates AEE, $lneco_{it}$ indicates the level of agricultural economy, $capital_{it}$ represents agricultural human capital, $lnmec_{it}$ represents agricultural machinery density, $industry_{it}$ indicates the level of industrialization, $urban_{it}$ indicates the level of urbanization, and $fina_{it}$ represents the level of fiscal support for agriculture.

AEE is the explained variable in this study and is a crucial metric for assessing the overall coordination relationship between economic expansion in agriculture, resource conservation, and environmental protection.

Explanatory variables. This study selected influencing factor indicators from three levels: agricultural development, economic development, and policy support. Agricultural development is the economic cornerstone for achieving green agricultural development and improving AEE. It mainly includes indicators such as the agricultural economic level, agricultural human capital, and agricultural machinery density. Economic development includes indicators such as industrialization and urbanization. Although a higher level of economic development will encroach on the agricultural development space to a certain extent, it will also provide technical support for agricultural development and ecological agriculture, which is conducive to improving AEE. Policy support includes indicators of fiscal support for agriculture. The specific measurement methods used for these indicators are listed in Table 2. The data required for the above indicators were obtained from the statistical yearbooks of Liaoning Province and prefecture-level cities.

3. Results

3.1. Calculation Results of AEE

Drawing on the input–output panel data of 44 counties from 2014 to 2020, this study estimated the AEE of counties in Liaoning Province using the S-SBM model, including UOs. To further explore the differences in the overall efficiency values of different county units,

this study drew a map of the average AEE of each county (Figure 1). As depicted in Figure 1, the average AEE of Liaoning Province was relatively high, but the AEE of the counties was mostly below or close to the average level. To understand the AEE sequence each county in the province, this study further calculated the average AEE of each county from 2014 to 2020 and compared the average AEE of each county with the average AEE level of counties in the province. The average AEE of Liaoning Province reached 0.76, indicating that the average AEE of the counties in the province was relatively high. However, the AEE of 57% of the counties was below or close to the average level, with significant room for enhancement. The top five counties with the highest AEE are Beipiao City, Kalaqin Left-wing Mongolian Autonomous County (Kalaqin), Tieling County, Changtu County, and Benxi Manchu Autonomous County (Benxi). This shows that the agricultural resource input and benefit output in these counties are relatively coordinated, and the results of environmental pollution control are obvious. The AEE of counties such as Suizhong County, Gaizhou City, Xingcheng City, Fengcheng City, and Changhai County were all lower than 0.38, indicating that these counties should consider the control of diffused agricultural pollution and increase investment in environmental protection. Overall, the AEE of the counties shows a certain degree of differentiation. Some counties still have ample space for improvement in AEE, and the spatial and structural configurations of their factor inputs need to be further optimized.

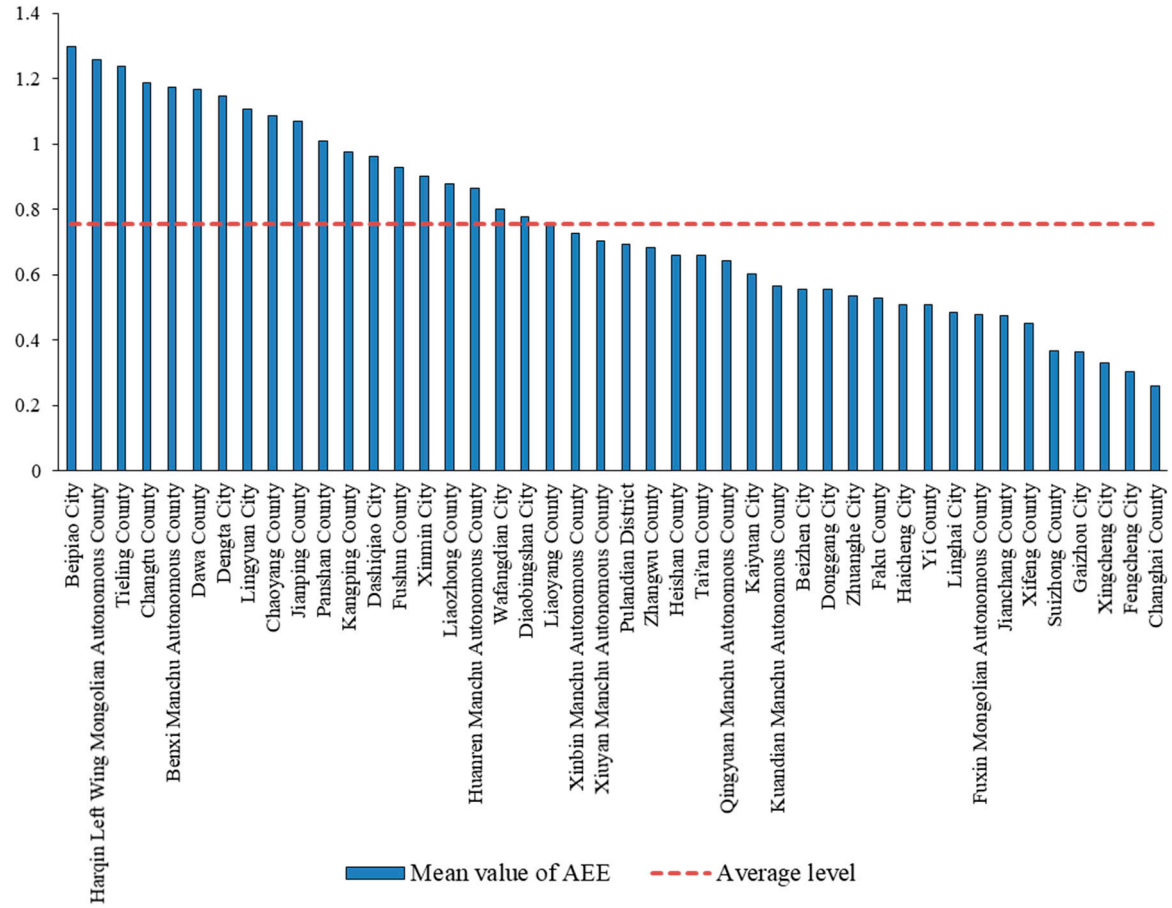


Figure 1. Average AEE of counties in Liaoning Province from 2014 to 2020.

The differences in AEE among counties in Liaoning Province generally showed an upward oscillating pattern, and the development of AEE showed an uneven state. To examine the dynamic evolution of differences in AEE among counties, we divided the standard deviation of AEE in counties for each year by the arithmetic mean to obtain the difference coefficient of AEE (Figure 2). The larger the coefficient, the greater the difference

in AEE among counties. As shown in Figure 2, the standard deviation and coefficient of variation in county-level AEE showed a fluctuating upward trend from 2014 to 2020. The coefficient of variation in AEE was 0.365 in 2014 and 0.448 in 2020, indicating an increase of 22.74% during this period. This shows that, during this period, the differences between counties in terms of ecological environment management and input factors gradually increased. While pursuing agricultural development, some counties have neglected the optimal allocation of input factors and the control of agricultural environmental pollution.

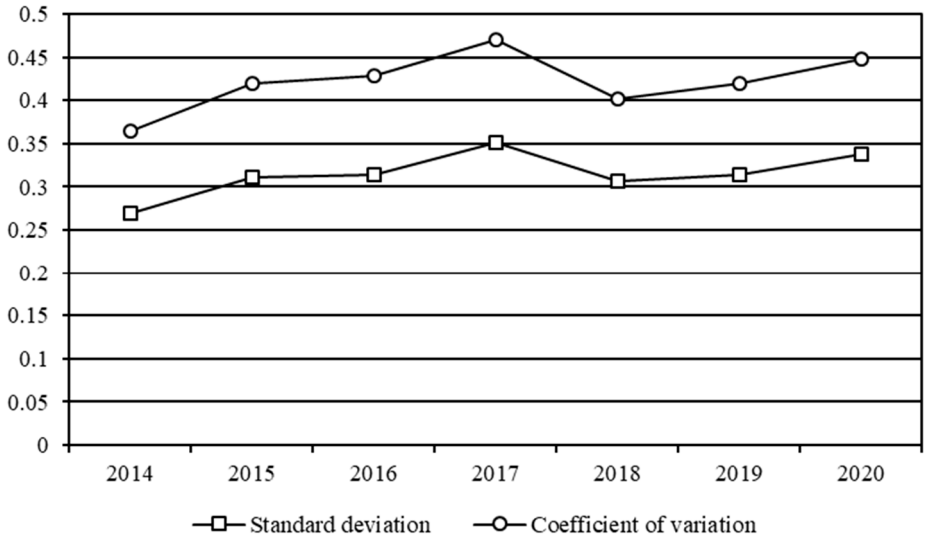


Figure 2. Coefficient of variation in AEE in Liaoning Province counties from 2014 to 2020.

3.2. Spatiotemporal Evolution and Correlation Characteristics of AEE

To better reveal the spatiotemporal evolution characteristics of AEE changes in Liaoning Province, this study used Arcgis10.5 software to draw a spatial distribution map of AEE based on the AEE estimation results from 2014 to 2020. Based on the AEE data of 2017, the natural breakpoint method was used to divide it into five categories from high to low, and by analogy to the other two years (Figure 3) [38–40], we then analyzed the spatiotemporal pattern characteristics of the AEE of counties in Liaoning Province.

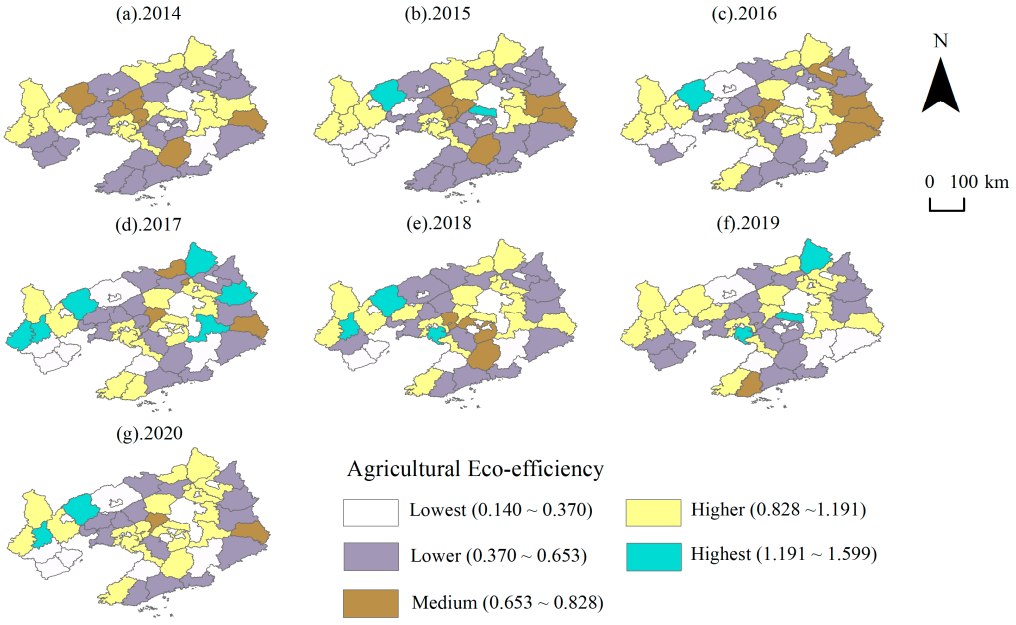


Figure 3. AEE of counties in Liaoning Province from 2014 to 2020.

On a time scale, the average AEE of counties in Liaoning Province in 2014, 2016, 2018, and 2020 were 0.716, 0.735, 0.749, and 0.813, respectively, showing a noticeable upward trend. The cumulative efficiency improvement rate was 13.55%. This shows that with the emphasis on the sustainable utilization of agricultural land, the AEE of Liaoning Province has gradually improved. Fifteen counties in Liaoning Province had relatively high AEE. In 2017, 18 counties had a relatively high efficiency or above. In 2020, 22 counties had high efficiency or higher. The proportion of counties with higher efficiency increased from 34.09% in 2014 to 50% in 2017. This shows that the proportion of counties with higher levels and above gradually increases as the year progress. However, there are still many counties with increasing potential. These counties need to increase investment in diffused agricultural pollution control, improve the distribution of agricultural production factors, and improve AEE in the future. In addition, the efficiency values of 61.36% of the counties improved significantly, while the efficiency of others fluctuated during the study period.

In terms of spatial pattern, AEE is distributed in a "block-like" distribution, with higher efficiency values in the northwest and central areas, and the disparity between the northern and southern regions is more pronounced than the contrast between the eastern and western regions. Counties with higher or the highest efficiency values were relatively concentrated in the northwestern and central parts of Liaoning Province, such as Kalaqin, Xinmin City, and Fushun County. This may be due to the development of water-saving agricultural facilities and high-quality agriculture and possible related to the relatively reasonable allocation of agricultural labor, machinery, irrigation, and other input factors. This distribution may be related to the development of water-saving agricultural facilities and boutique agriculture in these areas and the relatively reasonable allocation of agricultural labor, machinery, irrigation, and other input factors. Counties such as Jianchang County, Suizhong County, and Fengcheng City still have a certain gap compared to these high-efficiency counties. These countries must improve their agricultural technology, optimize the ratio of agricultural input factors, and improve their AEE. Under certain input levels and technical conditions, the gap between land, machinery, irrigation, and other factors in different regions, including investing in agricultural pollution prevention and control, have caused spatial differences in AEE. Unreasonable spatial and structural input factors lead to the waste of agricultural resources and factors [41,42]. Differences in factor inputs, natural background, and economic and social development among counties led to spatial differences in the AEE of each county. Achieving maximum agricultural economic benefits and minimum environmental damage under effective factor allocation is a common development goal pursued by all counties. It is essential to note the differences in resource endowments across regions [43–45]. Decision makers need to consider differentiated AEE improvement and optimization strategies from the perspective of different AEE agglomeration areas to promote the spatial balance of county development and the coordinated green development of the ecological economy. Therefore, it is imperative to scientifically identify the spatial distribution and correlation characteristics of AEE to lay a knowledge foundation for the coordinated development and comprehensive policy implementation in regional agriculture.

To reveal the spatially explicit characteristics of AEE in Liaoning Province, this study used the GeoDa platform to conduct a spatial correlation feature analysis based on the 7-period county AEE values to characterize the relationship between county AEE and their neighbors (Table 3). During the study period, the global AEE autocorrelation index ranged from 0.304 to 0.375, passed the 1% significance test, and exhibited an increasing trend. This indicates that AEE agglomeration gradually became more significant over time.

Table 3. Global autocorrelation index of AEE in Liaoning Province.

Year	2013	2014	2015	2016	2017	2018	2019
Moran's I	0.304	0.307	0.327	0.320	0.330	0.367	0.375
Z	5.984	5.89	5.012	4.838	5.165	4.823	4.599
P	0.013	0.021	0.010	0.012	0.010	0.032	0.011

To further reveal the local spatial agglomeration or abnormal spatial location of AEE in Liaoning Province, this study used the local autocorrelation method for analysis and drew local indicators of the spatial association (LISA) of AEE at a 0.05 significance level (Figure 4). As this study is a long-term series and the spatial correlation of AEE has an increasing trend, it selected the AEE in the initial period of 2014 and the final period of 2020 to analyze the changes in its local spatial correlation characteristics. Figure 4 illustrates that at a significance level of 0.05, H–H agglomerations are mainly distributed in the northwest, northeast, and central areas. This may be because the advancement of agriculture with a focus on water conservation and facility agriculture in the northwest counties provides advantages for improving the efficiency and prominent characteristics of commodity and suburban agriculture in the northeast and central areas. The AEE of these H–H clustered counties was maintained at a high level and had a driving effect on the surrounding areas, creating a diffusion effect. LH agglomeration occurred less frequently. For example, Fengcheng City in the southeast exhibited an LH agglomeration in 2020. This shows that the efficiency gap between Fengcheng City and the surrounding counties widened further. After analyzing the temporal changes in the local agglomeration characteristics of AEE in Liaoning Province, it was found that H–H agglomeration has spread to a certain extent. As Kaiyuan City is close to and driven by H–H agglomeration areas, its efficiency has improved significantly, and it will become an H–H agglomeration county by 2020. In short, the local correlation of AEE in Liaoning Province shows the phenomenon of "small agglomeration and large dispersion", and the coordination of AEE in different regions needs to be strengthened.

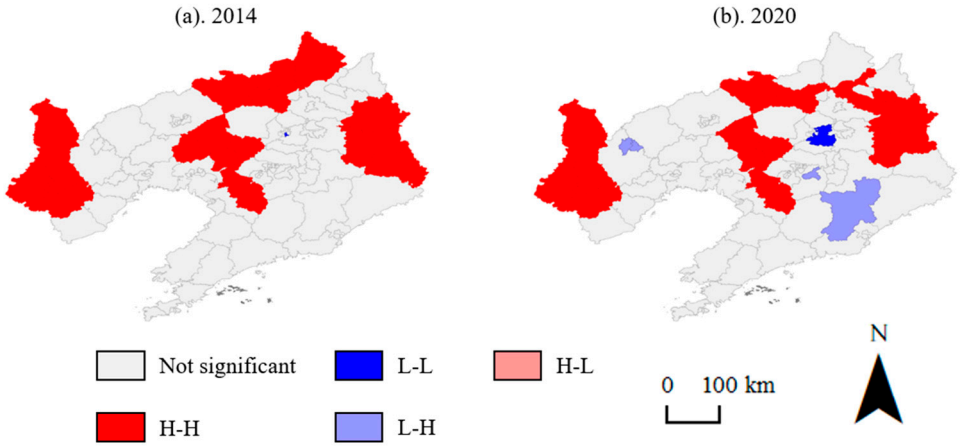


Figure 4. LISA of AEE in counties in Liaoning Province in 2014 and 2020.

3.3. Influencing Factors of AEE

3.3.1. Benchmark Regression Results

This study selected a fixed-effects model, using the stepwise regression method to gradually incorporate various influencing factors into the model and controlled for individual and time effects in column (8). The significance of each influencing factor was generally consistent with the sign of the estimated coefficient, and the results exhibited a degree of resilience.

The agricultural economy, industrialization, and urbanization levels significantly improve AEE, whereas the density of agricultural machinery, level of fiscal support for agri-

culture, and agricultural human capital have no significant impact. As depicted in Table 4, the estimated coefficient of the agricultural economic development level shows a highly significant positive correlation at the 1% significance level, and the estimated coefficient is larger and larger. This indicates that the level of agricultural economic development has a significantly positive effect on AEE. Improvement in agricultural economic development provides a solid economic foundation for the development of green agriculture and is conducive to promoting the improvement of AEE. For every 1% increase in agricultural economic development, the AEE increased by 0.529 units. The estimated coefficients of the levels of industrialization and urbanization are significantly positive, indicating that these levels of industrialization and urbanization significantly improve AEE. For every 1 unit increase in the levels of industrialization and urbanization, the AEE increased by 0.362 and 0.613 units, respectively. This confirms the previous view that an improvement in industrialization and urbanization will help provide technical support for and improve AEE. The estimated coefficient of agricultural human capital is positive, and the estimated coefficients of agricultural machinery density and fiscal support level are negative, but their influence on AEE is insignificant. In general, the levels of the agricultural economy, industrialization, and urbanization are the main factors affecting AEE.

Table 4. Benchmark regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lneco	0.193 ***	0.201 ***	0.227 ***	0.336 ***	0.395 ***	0.407 ***	0.407 ***	0.529 ***
	(2.76)	(2.77)	(3.09)	(4.33)	(5.03)	(5.17)	(5.17)	(5.78)
capital		−0.078	−0.091	0.150	0.147	0.103	0.103	0.127
		(−0.42)	(−0.50)	(0.79)	(0.78)	(0.54)	(0.54)	(0.66)
lnmec			−0.183 *	−0.169 *	−0.125	−0.151	−0.151	−0.064
			(−1.85)	(−1.75)	(−1.30)	(−1.55)	(−1.55)	(−0.54)
industry				0.369 ***	0.382 ***	0.362 ***	0.362 ***	−0.083
				(3.68)	(3.88)	(3.65)	(3.65)	(−0.43)
urban					0.648 ***	0.558 ***	0.558 ***	0.613 ***
					(3.20)	(2.65)	(2.65)	(2.90)
fina						−0.256	−0.256	−0.091
						(−1.47)	(−1.47)	(−0.50)
_cons	−0.821	−0.841	−0.713	−1.886 ***	−3.084 ***	−2.965 ***	−2.965 ***	−3.923 ***
	(−1.44)	(−1.46)	(−1.24)	(−2.92)	(−4.18)	(−4.00)	(−4.00)	(−4.28)
individual effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
time effect	No	No	No	No	No	No	No	Yes
N	308	308	308	308	308	308	308	308
R^2	0.028	0.029	0.041	0.089	0.123	0.131	0.131	0.187

Note: *** and * denote significance at the 1% and 10% levels.

3.3.2. Inspection in Groups

Considering that the agricultural economic level had the greatest impact on AEE in the regression results, this study used the per capita net income data of rural residents in counties in Liaoning Province in 2020 to perform grouping. Referring to the grouping of different income groups in the "National Economy and Society of the People's Republic of China in 2021", the counties in Liaoning Province were divided into two groups: the lower–middle income group and below and the middle-income group and above. The regression results (Table 5) show that the estimated coefficients of the agricultural economic level in the lower–middle income and below groups were 0.396 and 0.520, respectively. The estimated coefficients of the agricultural economic level in the middle income and above groups were 0.612 and 0.802, respectively. The estimated coefficients of urbanization in the lower–middle income and below groups were 0.525 and 0.551, respectively. The estimated coefficients of urbanization in the middle income and above groups were 1.124 and 1.312, respectively. This shows that the improvement of the agricultural economy and urbanization of the lower middle income and below group and the middle income and above group positively impact AEE improvement. The estimated coefficients of agricultural machinery density are all negative, which is not conducive to improving AEE. However, compared to the lower–middle-income and below-income groups, the agricultural economy

level, urbanization level, and agricultural machinery density in middle-income and above-income counties had a stronger impact on AEE. Among them, the estimated coefficients of the agricultural economic and urbanization levels in middle-income and above-income counties are significantly positive, indicating that the higher the agricultural economic and urbanization levels in middle-income and above-income counties, the more conducive they are to improving AEE. The estimated coefficient of agricultural machinery density is significantly negative, indicating that the greater the density of agricultural machinery in counties with middle and higher incomes, the less conducive it is to improving AEE. This may be because agricultural development in middle- and above-income counties already has a good foundation, and the degree of mechanization is relatively high. The greater the density of agricultural machinery, the greater the waste of resources and increase in energy consumption and carbon emissions, which are not conducive to improving AEE [46,47].

Table 5. Group regression for different income groups.

Variables	(1)	(2)	(3)	(4)
	Lower Middle Income and below		Middle Income and above	
lneco	0.396 ***	0.520 ***	0.612 ***	0.802 ***
	(4.42)	(4.95)	(3.99)	(4.98)
capital	0.095	0.142	−0.014	−0.154
	(0.44)	(0.65)	(−0.04)	(−0.45)
lnmec	−0.151	−0.075	−0.538 **	−0.462 *
	(−1.35)	(−0.56)	(−2.35)	(−1.80)
industry	0.340 ***	−0.137	0.476 ***	−0.128
	(2.78)	(−0.56)	(3.96)	(−0.62)
urban	0.525 **	0.551 **	1.124 **	1.312 ***
	(2.18)	(2.28)	(2.16)	(2.82)
fina	−0.394	−0.308	−0.147	0.134
	(−1.37)	(−1.06)	(−1.08)	(0.91)
_cons	−2.796 ***	−3.705 ***	−4.401 ***	−5.891 ***
	(−3.21)	(−3.46)	(−3.33)	(−3.92)
individual effect	Yes	Yes	Yes	Yes
time effect				
time effect	No	Yes	No	Yes
N	252	252	56	56
R^2	0.122	0.175	0.357	0.567

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Considering that the main factors affecting AEE may be different in different areas, this article draws on the regional divisions of the "Territorial Spatial Plan of Liaoning Province (2021–2035)" to further divide counties in Liaoning Province into agriculture and forestry areas and pastoral areas. The findings indicate that the economic levels of agriculture, forestry, and pastoral areas positively impact AEE (Table 6). The estimated coefficients of the agricultural economic level in the agriculture and forestry area groups were 0.391 and 0.508, respectively. The estimated coefficients of the agricultural economic level in the pastoral area group were 0.429 and 0.608, respectively. Compared to agricultural and forestry areas, the agricultural economic level of pastoral areas had a stronger impact on AEE. The estimated coefficient of agricultural machinery density in agricultural and forestry areas was significantly negative, indicating that an increase in agricultural machinery density in these areas was not conducive to improving AEE. The possible reason for this is that the terrain conditions in agricultural and forestry areas are relatively complex, and mechanized and large-scale production may not be suitable for all areas. The improvement in mechanization levels is conducive to improving agricultural production efficiency to a certain extent. However, if the means of food production are not fully utilized in mechanized and large-scale operations, agricultural inputs and pollution will increase. An increase in the density of agricultural machinery did not lead to a substantial improvement in efficiency. In addition, the levels of industrialization and urbanization in pastoral areas significantly promoted AEE improvement according to the results of Table 6.

Table 6. Group regression in different areas.

Variables	(1)	(2)	(3)	(4)
	Agriculture and Forestry Area		Pastoral Area	
lneco	0.391 ***	0.508***	0.429 **	0.608 **
	(5.10)	(6.25)	(2.20)	(2.02)
capital	0.055	0.162	0.142	−0.133
	(0.23)	(0.68)	(0.42)	(−0.36)
lnmec	−0.212 **	−0.200 *	−0.042	0.215
	(−2.19)	(−1.68)	(−0.18)	(0.74)
industry	0.267 ***	−0.293	0.566 **	0.067
	(2.83)	(−1.61)	(2.12)	(0.12)
urban	0.354	0.405	0.612	0.777 *
	(1.27)	(1.47)	(1.60)	(1.91)
fina	−0.219	0.002	−0.421	−0.527
	(−1.37)	(0.01)	(−0.84)	(−0.97)
_cons	−2.511 ***	−3.294 ***	−3.298 *	−4.810
	(−3.40)	(−3.82)	(−1.75)	(−1.64)
individual effect	Yes	Yes	Yes	Yes
time effect				
time effect	No	Yes	No	Yes
N	203	203	105	105
R^2	0.151	0.250	0.139	0.207

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4. Discussion

This study found that the average AEE in Liaoning Province increased by 13.55% from 2014 to 2020. This shows that AEE is increasing, consistent with the conclusions of relevant studies at the national and provincial levels [48,49]. Compared with previous studies [50], to further analyze the impact of the agricultural economic level on AEE, this study grouped and further compared according to the income situation and discussed the differential impact of different factors on AEE at different income levels. The results of the grouping regression show that the agricultural economic level, urbanization level, and agricultural machinery density of middle-income and above-income counties have a stronger impact on AEE than those of the low- and middle-income groups. To further explore the differential impact of different agricultural topographical areas on AEE, this study also divided the county into agricultural, forestry, and pastoral areas according to the positioning of relevant government planning. The results showed that the influence coefficients of the agricultural and forestry areas' agricultural economic level on AEE were 0.391 and 0.508, respectively. The coefficients of the cattle Murray economy and the pastoral area were 0.429 and 0.608, respectively. This shows that compared with agriculture and forestry areas, the agricultural economic level of pastoral areas has a stronger impact on AEE. The estimation coefficient of the agricultural machinery density of the agricultural and forestry areas was −0.212, indicating that mechanized and large-scale production may not be suitable for all regions. The above results are a useful supplement to research on the factors influencing AEE. In addition, the research methods and framework of the AEE evaluation and influencing factor identification in this study can provide a comparison and reference for similar studies at the county level in other provinces.

By considering the S-SBM model of non-expected output, this study solved the problem of the relaxation of input and output in the AEE evaluation and further distinguished the decision-making units that achieved complete efficiency. However, scale efficiency was not considered in this research. Therefore, the scale benefit of AEE is a key factor to consider in future AEE assessments. Given the reasons for the availability of data, this study did not analyze the impact of location factors, agricultural disasters, labor force education levels, or other factors on AEE. Therefore, the mechanism of action of additional influencing factors on AEE is a topic that can be deepened in analysis of influencing factors of AEE in the future.

5. Conclusions

Based on panel data of counties in Liaoning Province from 2014 to 2020, this study measured the AEE of counties in Liaoning Province using the S-SBM model, including UOs. The evolution rules and spatial interaction characteristics of AEE among counties were elaborated from the perspective of regional differences and the dynamic evolution of AEE. The main factors affecting the county's AEE were empirically analyzed, and grouped tests were conducted. In this study, through the evaluation of AEE and analysis of the influencing factors, it is helpful to find differences in the distribution of AEE among different counties so that decision makers can easily formulate differentiated AEE promotion policies according to the actual situation.

The average AEE value in the Liaoning Province was relatively high. The cumulative improvement rate of the average AEE in Liaoning Province reached 13.55% from 2014 to 2020, and the average level of AEE in the counties gradually improved. However, there is still considerable scope for enhancing the AEE. The differences in AEE among counties generally demonstrated an upward fluctuating trajectory. AEE is distributed in a "block-like" distribution, with higher efficiency values in the northwest and central parts, and the contrast between the northern and southern regions is more pronounced than the disparity between the eastern and western regions. The local correlation of AEE shows the phenomenon of "small agglomeration and large dispersion", and the coordination of AEE in different regions needs to be strengthened.

The agricultural economy, industrialization, and urbanization levels are the three main factors affecting AEE. Compared with the lower–middle-income and below-income groups, the agricultural economic level, urbanization level, and agricultural machinery density of middle-income and above-income counties had a stronger impact on AEE. Among them, the level of the agricultural economy and urbanization significantly promoted the improvement of AEE, whereas the heightened density of agricultural machinery did not contribute to the enhancement of AEE. Compared to agriculture and forestry areas, the agricultural economic level of pastoral areas has a stronger influence on AEE, followed by industrialization and urbanization. By identifying the factors influencing AEE, this study analyzed the restricting and promoting factors of AEE in Liaoning Province, providing a useful reference for the promotion and convergence of AEE.

Based on the above conclusions, we draw the following policy implications:

Close the gap in AEE among counties and improve the AEE of each county according to local conditions, especially the AEE of counties lagging behind the average efficiency level. Differences in factor inputs, natural backgrounds, economic and social development, etc., among counties lead to spatial differences in AEE. Decision makers should propose targeted optimization strategies based on an understanding of the spatial difference characteristics of efficiency. Counties with high-efficiency values, such as Kalaqin, Xinmin City, and Fushun County, must summarize their own agro-ecological development experiences and adhere to scientific agro-ecological development strategies. They should also maintain the momentum of ecologically efficient agricultural development and fully utilize their role as catalysts and exemplars for neighboring counties. For counties, such as Jianchang County, Suizhong County, and Fengcheng City, there is still considerable potential for enhancing AEE. These counties should formulate sustainable agricultural development strategies based on the natural and socio-economic characteristics of their regions. As Jianchang County, Suizhong County, and Fengcheng City are all located in mountainous and hilly areas with large terrain undulations and low agricultural mechanization, agricultural development in these counties lags. While pursuing increased income from agricultural products, farmers neglect agriculture to a certain extent. The control of source pollution has led to a low AEE. Therefore, these areas can combine their own resources and environmental advantages to moderately develop leisure agriculture and rural tourism, cultivate an understory economy, and promote agricultural ecological transformation and green development while maintaining the natural landscape.

The government should improve rural infrastructure, accelerate the adjustment of the agricultural industry structure, and improve the development of characteristic agriculture and modern agriculture to enhance the degree of rural economic development and develop agricultural modernization with new urbanization. Therefore, it is necessary to establish a new agricultural management system and encourage and support new agricultural management entities, promoting rural economic development to improve quality and efficiency, thus promoting AEE. The dynamic mechanism of rural development should be reconstructed, and a high level of urbanization should be used to improve AEE. Policymakers should facilitate the transition of rural labor to nonagricultural industries, rely on cities and central market towns to develop agricultural industrialization parks and other economic agglomerations, and encourage urban capital investment to develop industries suitable for rural development, such as processing, homestays, tourism, and other industries. It is necessary for cities and towns to develop high-tech agricultural and biotechnological parks, introduce and improve agricultural science and technology, improve agricultural ecological systems, and develop a circular economy. Rural residents can also promote urbanization and agricultural modernization by attracting external resources to achieve the simultaneous advancement of agricultural development and urbanization. In addition, mechanization and large-scale development must be adapted to local conditions to prevent resource waste, aggravation of pollution, and damage to farmers' enthusiasm caused by the over-saturation of agricultural machinery.

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