Analyzing agricultural ecological efficiency in Weihai City based on the SBM, STIRPAT and SLM models

Xiang Zhang1, Xungang Zheng1
1School of Management, Sichuan Agricultural University, Chengdu Sichuan 611130, China

Corresponding author and e-mail: Xungang Zheng, sicauzhangxiang@stu.sicau.edu.cn

Abstract. The essay is to study the development of ecological agriculture in Weihai city. The super slack-based measurement (SBM) model was adopted to measure the agricultural ecological efficiency of Weihai City’s seven districts and counties from 2008 to 2018. Based on the stochastic impacts obtained by conducting a regression on the STIRPAT model, the spatial lag model (SLM) was applied to empirically analyze the factors influencing agricultural ecological efficiency and the corresponding mechanisms. Our findings indicate that, in their direct effects, the population density, proportion of the primary industry, urbanization rate, agricultural mechanization rate, and agricultural development scale were significantly positive. Meanwhile, the rural labor transfer, agricultural output value per capita, and industrialization rate were significantly negative, and the planting structure was not significant. Under the spatial spillover effects, the rural labor transfer and agricultural output value per capita were significantly positive. The proportion of the primary industry and agricultural development scale were significantly negative, while the population density, urbanization rate, industrialization rate, agricultural mechanization rate, and planting structure were less significant. The suggestions put forward are to increase the level of scale, promote research and development, and adjust the industrial structure. The innovation and contribution of this paper lies in the application of the STIRPAT and SLM models to study the issue of agricultural ecological efficiency.

1. Introduction
40 years since China’s reform and opening up policies, the agricultural economy of the country has undergone unprecedented development. Specifically, it has seen an average annual growth rate of 9.81%, accompanied by an increasing grain yield. However, this type of agricultural development has had a negative effect on the environment, as it required high levels of agricultural inputs and outputs but results in high pollution. For example, the utilization rate of chemical fertilizers and pesticides is less than 33.3% and the recovery rate of agricultural film is lower than 66.7% [1]. This inefficient and pollution-heavy development has created negative externalities that severely restrict the sustainable development of agriculture in rural areas. Given this context, it is particularly important to balance the consumption of agricultural resources with environmental protection, so as to facilitate China’s transition to ecological forms of agriculture.

Weihai City is a National Modern Agriculture Demonstration Zone. It adheres to the concept of “lucid waters and lush mountains are invaluable assets”, proposed at the 19th National Congress of the...
Communist Party of China, seeking to promote the development of green agriculture. Achievements have been made in terms of enhancing the quality of cultivated land, green pest prevention and control, and the recycling of agricultural waste. Areas with acidic soil with a pH lower than 5.5 have been reduced by over 80%, green pest prevention and control are implemented over a total area of 20,000 hectares, and the comprehensive utilization rate of straw has reached 98.5%. Weihai City leads the country in sustainable agriculture but it also faces several problems. Through measuring the agricultural eco-efficiency of the city and analyzing the influencing factors and the corresponding mechanisms, practical recommendations were provided for guiding the further development of ecological agriculture and its expansion in underdeveloped areas.

The word "eco-efficiency", first used by Schaltegger and Sturm [2] in 1990, has been applied in the field of agriculture, as agricultural eco-efficiency. Data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are important methods for evaluating agricultural eco-efficiency due to the efficiency value when calculating multiple inputs and outputs. The studies by Tian et al. [3] and Wang et al. [4] are representative when it comes to the selection of input indexes for measuring agricultural eco-efficiency in China, which have similar values. Conversely, the selection of unexpected output varies, including agricultural non-point source pollution, agricultural carbon emission, and agricultural pollution [5-7]. While some scholars have studied the factors influencing agricultural eco-efficiency on the basis of measurement efficiency [8-10], few have researched the spatial spillover effects of the influencing factors. Hou et al. [11] prioritized the spillover effects of rural labor transfer while Xiong et al. [12] did not conduct a detailed analysis of the mechanism of influencing factors.

From this brief literature review, it can be seen that there is still room for further research on agricultural eco-efficiency. In this study, the super SBM model was adopted to measure the agricultural eco-efficiency of Weihai City's seven districts and counties from 2008 to 2018, demonstrating the features of agricultural eco-efficiency changes and regional differences. In addition, based on the STIRPAT model, an index system was established for the influencing factors. The spatial lag model was also used to empirically analyze the factors influencing agricultural eco-efficiency and its mechanisms of operation. Based on our findings, relevant suggestions aimed at guiding future eco-agricultural development was proposed in China.

2. Research methods and data indexes

2.1. Research methods

2.1.1. The super SBM model
The actual production is always accompanied by unexpected outputs, such as land acidification resulting from chemical fertilizer input. Tone [13] put forward an unexpected output-included super SBM model that not only comprises the slack and surplus variables but also further analyzes the decision-making unit with an efficiency value of 1. The model is based on previous related research.

2.1.2. The SLM and SDM models
Anselin [14] argued that economic phenomena in neighboring areas are to some extent interconnected (the closer the distance, the stronger the connection). The author constructed the SLM (spatial lag model) and SEM (spatial error model), and Lesage et al. [15] later constructed the SDM (spatial Dubbin model). The SLM introduces the spatial lag of the dependent variable while the SDM considers the lag of both the dependent and explanatory variables. The models have been applied in previous studies [16].
2.2. Index selection and data sources

2.2.1. Index selection for the measurement of agricultural eco-efficiency. With reference to relevant studies, an index (seen in Table 1) for measuring agricultural eco-efficiency in Weihai City was constructed while considering data availability and accuracy.

| First-level index | Second-level index | Index selected and unit |
|-------------------|--------------------|-------------------------|
| Labor input       | Labor input        | Number of people engaged in agriculture, forestry, animal husbandry and fishery/104 |
| Land input        | Land input         | Sowed area/103 hectares |
| Fertilizer input  | Application amount of agricultural chemical fertilizers/104 tons |
| Pesticide input   | Application amount of pesticides/104 tons |
| Agricultural film input | Application amount of agricultural film/104 tons |
| Capital input     | Agricultural mechanical input | Total mechanical power consumption at the end of the year/104 kilowatts |
| Application amount of agricultural diesel/104 tons | |
| Irrigation input  | Effectively irrigated area/103 hectares |
| Expected output   | Total agricultural output value | 108 yuan |
| Carbon emission   | Total amount of carbon emissions from chemical fertilizers, pesticides, agricultural film, agricultural diesel, agricultural irrigation and sowed area (104 tons) |
| Pollutant discharge | The comprehensive index of pesticide residues (104 tons), agricultural film residues (104 tons) and the loss amount of nitrogen and phosphorus in chemical fertilizers (104 tons) by using the entropy method |

The indexes for the input and output are shown in Table 1, with reference to existing studies. In addition, some aspects need to be specifically noted. (1) The uniform pure chemical fertilizer application amount was used to demonstrate the fertilizer input. (2) As it is difficult to classify pesticides in macro evaluation, the application amounts of pesticides and agricultural film were used to demonstrate their input. (2) With respect to the indexes for output: (1) The total agricultural output value was adjusted according to the base price in 2008 to offset the influence of price. (2) As agricultural carbon emissions mainly arise from chemical input and energy consumption, they were estimated by multiplying six items of input by their coefficients [17]. (3) In terms of agricultural pollutant discharge, agricultural film and fertilizer can seriously harm the ecological environment. The discharge was estimated by multiplying the application amounts by the residual and loss coefficients. The relevant coefficients were taken from the Handbook for the First National Pollution Source Survey on Industrial Pollution Source Production and Discharge Coefficient. They were adjusted for applicable areas and integrated into a single index by using the entropy method.

2.2.2. Index selection for influencing factors. In the IPAT model proposed by Ehrlich et al. [18], the factors influencing environmental efficiency were ascribed to three main categories: population (P), affluence (A) and technology (T). On this basis, Dietz et al. [19] constructed the STIRPAT model that is flexible in form and can be used as a basis for selecting the factors influencing environmental efficiency [20-22]. In this paper, the STIRPAT model was used to construct the index system for the influencing factors.
The expression of the model is as follows:

\[ I = \alpha \times P^\beta \times A^\gamma \times T^\theta \times \varepsilon \]

\( \alpha \) is the model coefficient, \( \beta, \gamma \) and \( \theta \) are the index parameters, and \( \varepsilon \) is the random error term.

Logarithms were taken and transformed into a linear form:

\[ \ln I = \ln \alpha + \beta \ln P + \gamma \ln A + \theta \ln T + \ln \varepsilon \]

**Table 2.** Index selection for the factors influencing agricultural eco-efficiency.

| First-level index | Second-level index                                      | Index selected and unit                                                                                       |
|-------------------|---------------------------------------------------------|---------------------------------------------------------------------------------------------------------------|
| Population (P)    | Population density X1                                   | Population density (Rural workforce - people engaged in agriculture, forestry, animal husbandry and fishery)/rural workforce |
|                   | Rural labor transfer X2                                | Output value of the primary industry/total output value                                                      |
|                   | Proportion of the primary industry X3                  | Output value of the primary industry/people engaged in agriculture, forestry, animal husbandry and fishery |
|                   | Per capita agricultural output value X4                | Urban population/resident population                                                                        |
|                   | Urbanization rate X5                                   | Output value of the secondary industry/regional total output value (%)                                      |
|                   | Industrialization level X6                             |                                                                                                              |
| Affluence (A)     | Agricultural mechanization rate X7                     | Total agricultural mechanical power consumption/total sowed area of crops (kilowatt/hectare)                  |
|                   | Large-scale development of agriculture X8              | Sowed area/people engaged in agriculture, forestry, animal husbandry and fishery (666 m²/number of people)   |
|                   | Planting structure X9                                  | Sowed area for cereals/total sowed area                                                                      |
|                   | Weight matrix                                           | 0-1 weight matrix                                                                                                |

As shown in Table 2, the agricultural eco-efficiency was taken as the explained variable, based on existing studies. Regarding the explanatory variables, the population density (P) may influence the technological innovation and demand for agricultural products, so as to affect agricultural eco-efficiency. The rural labor transfer can affect the input of chemicals, the mechanization rate, the circulation of agricultural land, etc. With respect to affluence (A), the rise in the proportion of the primary industry shows that the growth rate of agricultural output value is faster than that of the secondary and tertiary industries. While it is difficult for traditional agriculture to maintain a high growth rate, the development of ecological agriculture can make that happen. The increase in the value of agricultural output per capita demonstrates the improvement in the yield and income of farmers. The rise in the urbanization rate to a certain extent reflects the higher living standards of the population in urbanized rural areas. When it comes to technology (T), the industrialization process brings both chemicals and green technological products to the field of agriculture. Agricultural machinery reduces the labor input and enhances resource utilization, but also increases unexpected output. Under current policies, the future of large-scale agricultural development is promising. The index of planting structure was selected as the influence of the planting structures of commercial crops and grain crops usually vary.

The data were obtained from the Weihai Statistical Yearbook, the Shandong Statistical Yearbook and the official website of the Bureau of Agriculture and Rural Affairs in Weihai City. To offset the influence of inflation on the output values of the primary and secondary industries and the total agricultural output value, they were adjusted to the base period values in 2008 according to the corresponding indexes.
3. Measurement of agricultural Eco-efficiency in Weihai City

The measurement results for agricultural eco-efficiency in Weihai City are shown in Table 3.

**Table 3.** Measurement results for agricultural eco-efficiency in Weihai City from 2008 to 2018.

| Year | Huan Cai District | Torch Hi-tech Science Park | Economic and Technological Development Zone | Lingang District | Wen Deng City | Rongcheng City | Rushan City | Mean value in the whole city |
|------|-------------------|---------------------------|---------------------------------------------|------------------|--------------|----------------|-------------|-----------------------------|
| 2008 | 1.012             | 0.740                     | 0.869                                       | 0.954            | 0.810        | 1.020          | 0.905       | 1.016                        |
| 2009 | 1.012             | 0.730                     | 0.878                                       | 0.957            | 0.801        | 1.023          | 0.935       | 0.905                        |
| 2010 | 1.010             | 0.780                     | 0.882                                       | 0.961            | 0.832        | 1.003          | 0.954       | 0.917                        |
| 2011 | 1.008             | 0.760                     | 0.887                                       | 0.981            | 0.840        | 0.996          | 0.959       | 0.919                        |
| 2012 | 1.033             | 0.750                     | 0.891                                       | 0.991            | 0.886        | 1.009          | 0.990       | 0.936                        |
| 2013 | 1.019             | 0.752                     | 0.926                                       | 1.001            | 0.896        | 1.000          | 1.000       | 0.942                        |
| 2014 | 1.009             | 0.724                     | 0.958                                       | 1.004            | 0.910        | 1.023          | 1.004       | 0.947                        |
| 2015 | 1.017             | 0.717                     | 0.979                                       | 1.004            | 0.936        | 1.004          | 1.005       | 0.952                        |
| 2016 | 1.003             | 0.712                     | 0.990                                       | 1.020            | 0.888        | 1.006          | 1.013       | 0.947                        |
| 2017 | 1.020             | 0.705                     | 1.014                                       | 1.019            | 0.917        | 1.007          | 1.013       | 0.956                        |
| 2018 | 1.038             | 0.700                     | 1.020                                       | 1.015            | 0.911        | 1.007          | 1.015       | 0.958                        |

The mean value of agricultural eco-efficiency in Weihai City from 2008 to 2018 was 0.935. In other words, the ideal decision-making unit reached by the average output was 93.5%. As shown in Figure 1, the efficiency was gradually increased from 0.901 to 0.958, which was linked to the long-standing government investment into the eco-agricultural mode. In 2010, the municipal government established agricultural cooperatives that integrate production and sales. In 2012, Weihai City was designated a National Modern Agriculture Demonstration Zone. The "Soil Ecosystem Construction
Planning initiative was promulgated in 2016, aiming to solve the soil acidification problem caused by chemical fertilizers. In 2018, a quality supervision system for agricultural products was formed. Adhering to the green modernization mode, the municipal government has actively promoted the region’s eco-agricultural development.

The agricultural eco-efficiency for the different districts and counties of Weihai City is shown in Figure 2. The average agricultural eco-efficiency values in both Huancui District and Rongcheng City exceeded 1, representing the ideal decision-making unit and high efficiency. Average eco-efficiency in the Economic and Technological Development Zone, the Lingang District, Rushan City, and Wendeng City exceeded 0.8, which represents a medium efficiency level. The Torch Hi-tech Science Park was found to be a low-efficiency region. The agricultural eco-efficiency values in the high-efficiency regions fluctuated near the mean value, those in the medium-efficiency regions grew fast, while eco-efficiency in the low-efficiency region declined year by year. This is because the high-efficiency regions implemented eco-agriculture earlier, which matured but was restricted by factors such as land and resources. These regions were eventually surpassed by the medium-efficiency regions. The population density in the low-efficiency region, the Torch Hi-tech Science Park, was four times higher than in Weihai City. The Torch Hi-tech Science Park also has a large quantity of land available for construction, but the proportion of cultivated land in this region was less than 50% of the total in Weihai City. The fragmentation of cultivated land was outstanding, the agricultural production pattern was prone to small-scale farm management, and this status was increasingly aggravated, thus leading to the decline in eco-efficiency over the years.

![Figure 2. Changes in agricultural eco-efficiency in different districts and counties.](image-url)
4. Analysis of the factors influencing agricultural Eco-efficiency in Weihai City

4.1. Spatial correlation test
The Moran index results are listed in Table 4. As we can see, the Moran index values in all years except for 2012 were significant, indicating the spatial correlation of data.

| Year | Moran index | p value |
|------|-------------|---------|
| 2008 | 0.081**     | 0.034   |
| 2009 | 0.057*      | 0.085   |
| 2010 | 0.227**     | 0.012   |
| 2011 | 0.114*      | 0.053   |
| 2012 | 0.038       | 0.147   |
| 2013 | 0.098**     | 0.026   |
| 2014 | 0.074***    | 0.002   |
| 2015 | 0.136***    | 0.000   |
| 2016 | 0.176***    | 0.001   |
| 2017 | 0.185***    | 0.000   |
| 2018 | 0.091**     | 0.035   |

4.2. Robustness test

| Test method                                      | Test value | p value |
|-------------------------------------------------|------------|---------|
| Hausman test                                     | 22.59***   | 0.000   |
| LR test (SDM is reduced into SEM)                | 18.89**    | 0.026   |
| LR test (SDM is reduced into SLM)                | 15.04*     | 0.090   |
| Log-likelihood (SLM)                             | 133.51     | -       |
| Log-likelihood (SDM)                             | 142.96     | -       |

According to the LR test results shown in Table 5, the original hypothesis that SDM is reduced into SLM was not rejected at the significance level of 5%. Meanwhile, both the log-likelihood value and fitting degree of the two were approximate. Therefore, the SLM with better results was adopted. Due to the spatial lag terms in the SLM and SDM models, the estimation coefficient failed to reflect the influence degree, so the direct effect, spatial spillover effect and total effect were further estimated. The results are presented in Table 6 and Table 7:

| Variable                                         | Total effect | Direct effect | Spatial spillover effect |
|--------------------------------------------------|--------------|---------------|--------------------------|
| Population density X1                            | 0.101(1.59)  | 0.15*(1.65)   | -0.049(-1.45)            |
| Rural labor transfer X2                          | -0.128**(-2.38) | -0.188***(-2.61) | 0.06**(2) |
| Proportion of the primary industry X3             | 0.151***(4.06) | 0.224***(4.86) | -0.072***(-2.61)         |
| Per capita agricultural output value X4          | -0.184***(-3.84) | -0.272***(-4.58) | 0.088***(2.58)          |
| Urbanization rate X5                             | 0.044(1.63)   | 0.065*(1.68)   | -0.021(-1.43)            |
| Level of industrialization X6                    | -0.258*(-1.87) | -0.388*(-1.87) | 0.13(1.52)               |
| Agricultural mechanization rate X7                | 0.057*(1.64)  | 0.085*(1.66)   | -0.029(-1.4)             |
Table 7. Spatial Dubbin model results.

| Variable                                | Total effect | Direct effect | Spatial spillover effect |
|-----------------------------------------|--------------|---------------|-------------------------|
| Population density X1                   | -0.314*(-1.71)| 0.007(0.07)   | -0.321*(-1.67)          |
| Rural labor transfer X2                 | 0.004(0.02)  | -0.254***(-3.08) | 0.258(1.31)            |
| Proportion of the primary industry X3   | 0.315***(2.64)| 0.207****(4.09) | 0.107(1.1)             |
| Per capita agricultural output value X4 | -0.189(-1.4) | -0.257***(-3.21) | 0.068(0.67)            |
| Urbanization rate X5                    | 0.072(0.92)  | -0.001(-0.02)  | 0.073(0.86)             |
| Level of industrialization X6           | -1.101**(-2.3)| -0.319(-1.44)  | -0.783*(-1.84)          |
| Agricultural mechanization rate X7      | -0.046(-0.47)| 0.064(1.13)    | -0.11(-1.02)            |
| Agricultural development scale X8       | 0.208*(1.73) | 0.408****(5.04) | -0.2(-1.36)             |
| Planting structure X9                   | 0.139(0.9)   | 0.034(0.28)    | 0.105(0.61)             |

4.3. Analysis of results

The direct effect reflects the influence of an index on the local agricultural eco-efficiency, while the spatial spillover effect embodies the influence of adjacent regions on the local region.

The direct effect of population density (X1) on the agricultural eco-efficiency was positive and significant at the 10% level. The increasing population density promotes technological innovation [23] and increases the demand for agricultural products. Due to high levels of household consumption, the demand for green agricultural products is greater in Weihai City. The combined action of technological innovation and demand for green agricultural products accelerates the transformation of traditional agriculture into eco-agriculture. The spatial spillover effect was not significant because the interregional diffusion of new agricultural technologies is difficult to achieve due to complex factors related to policy, market and information [24]. In addition, the efficiency measurement results showed that the eco-agricultural development was balanced among the regions. For this reason, it was difficult to realize the cross-regional transfer of agricultural product demand.

The direct effect of rural labor transfer (X2) was negative, and significant at the 1% level. Moreover, it positively acted upon the chemicals input, agricultural mechanization level and farmland transfer [25-27], which exerted a combined negative influence. The spatial spillover effect was positive, and significant at the 1% level. This is because the eco-agricultural development momentum is considerable in all regions, and the mode of input and production increase cannot be effectively transferred across different regions. The improvement of mechanical efficiency regarding cross-regional operation presents a weak positive spillover effect. On average, only 333 m² of land is circulated by each peasant household in Weihai City, and the farmland circulation scale resulting from the rural labor force transfer is small. Thus, the spatial spillover is difficult to achieve. The three factors showed a combined positive spatial spillover effect.

The direct effect of the primary industry proportion (X3) was positive and significant at the 1% level. The reason is that the eco-agriculture policies have been in place for a long time, and the growth speed of eco-agriculture has surpassed traditional agriculture. The proportion of the primary industry in Weihai City has fluctuated between 7% and 8% for over 11 years. The growth level of agriculture has caught up with that of the secondary and tertiary industries, and it must therefore rely on eco-agriculture. The spatial spillover effect was negative and significant at the 1% level. That the proportion of the primary industry is elevated is attributed to the eco-agriculture. By reference to the
X8 results in this study, the eco-agricultural development scale appeared to exert a negative spatial spillover effect.

The direct effect of the agricultural output value per capita (X4) was negative and significant at the 1% level. This indicates that, although eco-agriculture is developing at full speed, the yield increase that only depends on the traditional pattern will still have a large negative impact on the environment. The spatial spillover effect was positive and significant at the 1% level. Due to the elevated agricultural output value per capita, the economic strength of peasant households engaged in traditional agriculture has been enhanced. Moreover, the policies have been conducive to large-scale eco-agriculture, so peasant households are motivated to engage in cross-regional land circulation, in an effort to transition to eco-agriculture.

The direct effect of the urbanization rate (X5) was positive and significant at the 10% level. From 2008 to 2018, the rural population was reduced by 220,000 inhabitants and the rural labor force saw a reduction of 100,000 workers in Weihai City, while the urban population contained some of the labor force that transferred from the rural areas. The urbanization rate only reflected the partial negative influence of the index X2. In addition, the consumption expenditure per capita for urban residents accounted for about 2.5 times that of rural residents in Weihai City. Urban residents generally presented a relatively higher consumption level, demanding more green agricultural products, which promoted the development of eco-agriculture. The results show that the two presented a weak positive influence in a combined way. The spatial spillover effect was insignificant, due to the relatively balanced eco-agricultural development among the regions.

The direct effect of the industrialization level (X6) was negative and significant at the 10% level. Traditional industrialization provides a necessary condition for the development of traditional petroleum agriculture, which, however, brings about a series of ecological problems. Currently, the industrialization level has been gradually transformed and upgraded. The emergence of new-type machinery for straw recycling in the field, along with agricultural film recycling and processing technology, has provided a new development opportunity for eco-agriculture. Our results indicate that the influence of current industrialization on traditional petroleum agriculture exceeded its influence on eco-agriculture. The spatial spillover effect of the industrialization level (X6) did not pass the test. This is because industrial products like chemical fertilizers and pesticides are usually sold to local cooperatives, and local peasant households are not willing to purchase them in other regions.

The direct effect of the agricultural mechanization rate (X7) was positive and significant at the 10% level. The agricultural mechanization reduced the labor input and improved the resource utilization efficiency, but increased the unexpected output, which resulted in a positive influence. In addition, the influence of agricultural mechanization was minor because of the limitation in the total power of agricultural machinery [28]. In 2016, the agricultural machinery field power in China per 666 m² was six times that of America, but the unit power of agricultural machinery did not reach 50% of the level of developed countries. This indicates a large input of high-power and low-efficiency agricultural machinery in China. Moreover, the mechanization rate in the whole chain is also an important factor. The spatial spillover effect was insignificant. The cross-regional operation of agricultural machinery improved the utilization efficiency of agricultural machinery and reduced the cross-regional input of agricultural machinery. However, the spillover effect of the agricultural mechanization rate was restricted due to factors like the mechanical operation link [29] and the efficiency of agricultural machinery.

The direct effect of the agricultural development scale (X8) was positive and significant at the 1% level. This coefficient represents the maximum value, indicating that the agricultural development scale is a key influencing factor. Under the policy orientation, the scale merits of eco-agriculture showed up step by step, and the eco-agricultural production mode was perfected and promoted. The spatial spillover effect was negative and significant at the 1% level. As the scale merits of cross-regional cooperation was transferred to the uncooperative regions, it created an urgent demand for the increase in output value in the uncooperative regions. Due to the possibly low agricultural
development level in the uncooperative regions, the output value was elevated by sacrificing the natural environment within the short term.

Neither the direct effect nor the spatial spillover effect of the planting structure(X9) were significant, and the chemicals input into commercial crops was generally higher than for grain crops [30]. This suggests that the ecological development of commercial crops is favorable in the regions with a non-obvious cross-regional demonstration effect.

5. Discussion and conclusions
Based on the panel data for seven districts and counties in Weihai City from 2008 to 2018, the SBM, STIRPAT, and SLM models were used to empirically study the city’s agricultural eco-efficiency in our study and finally come out of the following conclusions.

(1) The mean value of agricultural eco-efficiency steadily rose in Weihai City from 2008 to 2018 and the mean annual value was 0.938, indicating a benign overall development. Regional differences were manifested: the eco-agricultural development was stagnated in the high-efficiency regions, while the growth level was high in the low-efficiency regions. Given this, future studies should explore the new-type ecological development direction in Weihai City in order to overcome the eco-agricultural development bottlenecks faced by the high-efficiency regions.

(2) The population density, proportion of the primary industry, urbanization rate, agricultural mechanization rate and agricultural development scale had significantly positive influences on agricultural eco-efficiency in Weihai City. The rural labor transfer, agricultural output value per capita, and industrialization level had significant negative influences. Among the spatial spillover effects, the rural labor transfer and agricultural output value per capita showed significant positive influences. The proportion of the primary industry and agricultural development scale exerted significant negative influences, but the influences of population density, urbanization rate, industrialization level, agricultural mechanization rate and planting structure were insignificant.

Hence, the following suggestions are proposed regarding the large-scale development of eco-agriculture in Weihai City. Decision makers should promote the construction of modern large-scale agriculture demonstration zones, cultivate new-type scale management subjects, subsidize large-scale farmland transfers, mobilize the initiatives of cross-regional agricultural cooperative organizations, and encourage the uncooperative towns to increase their production and income by means of green agriculture while considering the spillover competitive effect. From the perspective of technology, the municipal government should support the research and development of agricultural technology within scientific research institutions, facilitate cooperation between agricultural organizations and universities, strengthen the grassroots’ training capacity, and attach importance to the tracking, guidance and supervision of technology acceptors. Moreover, the municipal government should adjust the industrial structure and conduct the industrialization transformation in order to improve the environmental benefits and produce more green agricultural technologies and products. Finally, attention should be paid to the influences of operational links and efficiency of agricultural machinery.

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