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RURAL SOCIOLOGY

Impact of urbanization on agricultural ecological efficiency: evidence from China

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ABSTRACT: *Agricultural ecological efficiency is of great value to the government's agricultural policy formulation. Research on the factors affecting agricultural ecological efficiency can provide support for the formation of countermeasures to improve agricultural ecological efficiency. Existing research has not conducted an in-depth analysis of the impact of urbanization on agricultural ecological efficiency, and there is a lack of relevant research on the impact of urbanization on agricultural ecological efficiency. This article is based on the data of 30 provinces and cities in China from 2009 to 2018, using the SBM model that considers undesired output, entropy method, Tobit model and other models and methods to measure agricultural ecological efficiency and urbanization comprehensive index, and analyze the impact of urbanization comprehensive index and urbanization indicators on agricultural ecological efficiency. The research results are as follows: 1) The overall agricultural ecological efficiency in China's 30 provinces and cities has been increasing from 2009 to 2018. The eastern region has the highest agricultural ecological efficiency, followed by the western region, and the central and northeastern regions have relatively low values; 2) The comprehensive urbanization index of China's 30 provinces and cities continued to grow from 2009 to 2018.The level of urbanization in the eastern region is the highest, in the central region has increased rapidly from 2009 to 2018, and in the western and northeastern regions is relatively low; 3) The overall increase in urbanization can promote the improvement of agricultural ecological efficiency. The impact of specific urbanization indicators on agricultural ecological efficiency is complex. Therefore, discussing the impact of urbanization on agricultural ecological efficiency cannot be considered from a single aspect, but should be analyzed from multiple perspectives.*
Key word: *Sustainable development of agriculture, Agricultural ecological efficiency, SBM, Entropy method.*

Impacto da urbanização na eficiência ecológica agrícola: evidência da China

RESUMO: *A eficiência ecológica agrícola é de grande valor para a formulação da política agrícola do governo. A pesquisa sobre os fatores que afetam a eficiência ecológica agrícola pode fornecer suporte para a formação de contramedidas para melhorar a eficiência ecológica agrícola. A pesquisa existente não conduziu uma análise aprofundada do impacto da urbanização na eficiência ecológica agrícola, e há uma falta de pesquisas relevantes sobre o impacto da urbanização na eficiência ecológica agrícola. Este artigo é baseado em dados de 30 províncias e cidades na China de 2009 a 2018, usando o modelo SBM que considera produção indesejada, método de entropia, modelo Tobit e outros modelos e métodos para medir a eficiência ecológica agrícola e índice abrangente de urbanização, e analisar o impacto do índice abrangente de urbanização e dos indicadores de urbanização na eficiência ecológica agrícola. Os resultados da pesquisa são os seguintes: 1) A eficiência ecológica agrícola geral nas 30 províncias e cidades da China aumentou de 2009 a 2018. A região leste apresenta a maior eficiência ecológica agrícola, seguida pela região oeste, e as regiões centro e nordeste apresentam valores relativamente baixos; 2) O índice de urbanização abrangente das 30 províncias e cidades da China continuou a crescer de 2009 a 2018. O nível de urbanização na região leste é o mais alto, na região central aumentou rapidamente de 2009 a 2018, e no oeste e no nordeste regiões é relativamente baixo; 3) O aumento geral da urbanização pode promover a melhoria da eficiência ecológica agrícola. O impacto de indicadores específicos de urbanização na eficiência ecológica agrícola é complexo. Portanto, discutir o impacto da urbanização na eficiência ecológica da agricultura não pode ser considerado sob um único aspecto, mas deve ser analisado sob múltiplas perspectivas.*
Palavras-chave: *desenvolvimento sustentável da agricultura, eficiência ecológica agrícola, SBM, método de entropia.*

INTRODUCTION

In recent years, the sustainable development of agriculture has received extensive attention NOTARNICOLA et al., 2017). China is the most populous country in the world, and it is also a large agricultural country. For more than ten years, China's agricultural development has also increased environmental pollution. In the fifteen years from 2004 to 2018, China's agriculture has achieved sustained growth. The total agricultural output value has increased from 1,813.836 billion

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yuan in 2004 to 61,452.60 billion yuan in 2018 (CBS, 2018), an increase of nearly 2.5 times. At the same time, pollution in the agricultural sector has also increased. The amount of fertilizer used has increased from 46.366 million tons in 2004 to 56.534 million tons in 2018, pesticide application increased from 1.386 million tons in 2004 to 1.5036 million tons in 2018, and agricultural film used increased from 1.68 million tons in 2004 to 2.4668 million tons in 2018 (CBS, 2018). Agriculture that relies on factor inputs to achieve agricultural growth is an inefficient agricultural model (LIU et al., 2019; ZOU et al., 2020), and it is not conducive to the sustainable development of China's agriculture. In order to achieve sustainable agricultural development, on the basis of guaranteeing agricultural output, reducing the input of chemical elements and reducing the impact of agricultural activities on the environment have become important considerations of the Chinese government when formulating agricultural policies.

The indicator of ecological efficiency is an important indicator for evaluating the sustainability of specific economic sectors such as agriculture in terms of resource use and environmental pressure (UNESCAP, 2009). Ecological efficiency was first proposed by German scholars SCHALTEGGER & STURM (1990). Later, OECD (1998) defined it as "the efficiency of using ecological resources to meet human needs." The improvement of ecological efficiency depends on less resource consumption in the production of products and the reduction of environmental impact (PICAZO-TADEO et al., 2011; KHAREL & CHARMONDUSIT, 2008). Agricultural ecological efficiency indicates that agricultural production activities are carried out within the carrying capacity of the agricultural ecosystem, producing high-quality agricultural output value and services with less resource loss and environmental damage (JIAJIA LIAO et al., 2021). It is a tool for sustainable development analysis that indicates the relationship between economic development and the environment. From a social, economic and ecological perspective, the efficiency level represents the quality of agricultural resource development (LINLIN ZENG et al., 2020 agricultural ecological efficiency is of great value for government agricultural policy formulation (PICAZO-TADEO et al., 2011).

The research on agricultural ecological efficiency has achieved rich results. Scholars have measured the agriculture ecological efficiency in various regions and provided references for the development of these regions, such as North America (KONEFAL et al., 2019), South America (ROSANO PEÑA et al., 2018), Europe (AGITA GANCONE et al. , 2017; BENEDETTA COLUCCIA et al, 2020), Asia (HALDER, 2019; LIU, 2020), Africa (NSIAH & FAYISSA, 2019). Scholars have also conducted in-depth studies on China's agricultural ecological efficiency. For example, WANG et al. (2018) used DEA to estimate the agricultural ecological efficiency of China's provinces from 1996 to 2015. He pointed out that the overall trend of China's agricultural ecological efficiency is on the rise, with inter-provincial differences; LIU et al. (2020) used the super-efficiency SBM model to estimate China's agricultural ecological efficiency from 1978 to 2018, and also pointed out the overall improvement of China's agricultural ecological efficiency.

Research on the factors affecting agricultural ecological efficiency can provide important support for the formation of measures to improve agricultural ecological efficiency. Scholars have analyzed the impact of agricultural labor force (YANG et al., 2016), agricultural resource input (HUANG & JIANG, 2019), agricultural policy (WAGAN et al., 2018), agricultural machinery (ZHOU & KONG, 2019) and other factors on agricultural ecology. The impact of efficiency is analyzed, and corresponding countermeasures and suggestions are put forward accordingly.

In summary, agriculture ecological efficiency is an important reference for the government's agricultural policy formulation. Scholars have conducted extensive research and obtained rich results. However, in existing studies, most scholars are limited to agricultural production itself in the selection of factors affecting agricultural ecological efficiency, and less consider factors other than agriculture, and fewer studies consider that urbanization has an important impact on agricultural and rural development.

The term "urbanization" was first proposed by Serda in 1867 in "Introduction to Urbanization", where in urbanization was defined as the process of gathering rural populations in cities and towns. Urbanization is a process of rural population to urban transfer, and also a process of rural economy to urban agglomeration (BERRY, 1961; FUCHS & PERNIA, 1987). This process will have a central impact on rural and agricultural development. On the one hand, urbanization can promote the development of agriculture and rural areas. For example, FENG et al. (2019) believe that urbanization can drive rural economic development, while MOHAMED AROURI et al. (2016) believe that urbanization will increase farmers' income. On the other hand, urbanization will also have an adverse impact on the development of agriculture and rural areas. For example, the study of DENG et al. (2015) shows that urbanization will cause the loss of agricultural land, while YUHENG LI et al. (2018) believe that urbanization will cause the loss of rural labor.

Existing research estimates the agricultural ecological efficiency through the accounting of agricultural resource input, agricultural output, and agricultural pollution. But urbanization will affect these agricultural resource inputs, which will further affect agricultural output and agricultural pollution, and ultimately affect agricultural ecological efficiency. Existing studies have conducted in-depth discussions on the impact of urbanization on agricultural resource input, such as agricultural labor input (YUHENG LI, et al, 2018; DAZHUAN GE et al., 2020), agricultural land (DENG et al., 2015; JOHN et al., 2019; MAN YU et al., 2019; MOULA BUX PEERZADO et al., 2019), agricultural water (TINGTING YAN et al., 2015; RAI S. KOOKANA et al., 2020), urbanization affects the agricultural ecological efficiency through the influence of these factors. However, existing research has not yet analyzed the effect of urbanization, a factor that has an important impact on agricultural and rural areas, on agricultural ecological efficiency. This may affect the formulation of agricultural policies and is not conducive to the coordination of urbanization and agricultural ecological environment, especially for those countries where urbanization is developing rapidly.

China is one of the countries with the fastest urbanization in the world, and its speed and scale far exceed those of other countries in the same period (LONGWU LIANG, 2019). Urbanization is an important driving force for China's economic development, but it also brings a series of environmental problems to China (ALI et al., 2019). According to the theory of NORTHAM (1979), China is currently in an accelerated stage of urbanization. Promoting the coordinated development of urbanization and agricultural ecological environment during this period is of great significance to the sustainable development of China's agriculture. Therefore, this article takes China as an example to analyze the impact of urbanization on agricultural ecological efficiency.

It should be noted that the agriculture studied in this article is narrow-sense agriculture, that is, planting. The agriculture mentioned below refers to planting.

The expansion of this article mainly includes the following three points: (1) Based on the unique perspective of urbanization, which is rarely involved in existing research, discuss the impact of urbanization on agricultural ecological efficiency; (2) Construct an evaluation index system of agricultural ecological efficiency that considers undesired output to reflect the situation of agricultural ecological efficiency, and construct a comprehensive evaluation index system of urbanization from the three aspects of population, economy, and land urbanization to fully reflect the situation of urbanization; (3) Use undesired output SBM-DEA model, entropy method, Tobit regression model and other quantitative methods to conduct research to improve the accuracy of research.

MATERIALS AND METHODS

Study area

China is one of the fastest urbanizing countries in the world, and it is also an important agricultural country in the world. There are 34 provincial-level administrative regions in China. This paper selects 30 provincial-level administrative regions as the research area, including Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Hainan, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Inner Mongolia, Guangxi, Ningxia, Xinjiang, Beijing, Shanghai, Tianjin, Chongqing, etc. First of all, the 30 regions involved in this paper are first-tier cities or second-tier cities in China, which are more representative, and the agriculture of the selected cities is very developed. Secondly, the above 30 areas are distributed in all directions on the map of China, and they are representative cities. Finally, due to the limitation of the database, it is not possible to make a statistical description of all cities. Therefore, the 30 regions mentioned in this paper are selected.

Data sources

The study time of this article is from 2009 to 2018. The relevant data comes from China Statistical Yearbook (2010-2019), China Agricultural Statistical Yearbook (2010-2019), China City Statistical Yearbook (2010-2019), China Population and Employment Statistical Yearbook (2010) —2019).

Research methods

This paper uses the entropy method to measure the comprehensive index of urbanization, using Tobit regression to analyze the impact of urbanization on agricultural ecological efficiency, it is easy to be interfered by indicator units. For this reason, some indicators need to be standardized. This article standardizes the data using maximum-minimum method .Here are the main approach:

SBM model considering undesired output

This article intends to use the SBM model considering undesired output to measure the agricultural ecological efficiency. The DEA model was first proposed by CHARNES et al., (1978). When analyzing the situation of multiple inputs and multiple outputs, DEA has unparalleled special advantages. The CCR model and the BBC model are the most traditional DEA models, both of which use radial and angular measurements. However, if the DUM input is too much or the output is insufficient, the use of the radial DEA model for efficiency measurement will lead to an overestimation of the efficiency of the DEA model; If there are multiple aspects of the input or output of the evaluation object, the use of the angular DEA model may cause errors in the efficiency measurement (LIN & TAN, 2016). To solve this problem, TONE (2001) proposed a non-radial, non-angle, relaxation-based metric (SBM) efficiency evaluation model. Using the SBM model to measure the efficiency of DUMk can be expressed as:

$$AEE = \min \frac{1-\frac{1}{N}\sum_{1}^{N}\frac{S_n^X}{X_{kn}^t}}{1+\frac{1}{M}\sum_{1}^{M}\frac{S_m^Y}{Y_{km}^t}}$$

$$s.t.\begin{cases}\sum_{K=1}^{K} Z_K^t X_{Kn}^t + S_n^X = X_{kn}^t, n=1,2,3\cdots\cdots N;\\ \sum_{K=1}^{K} Z_K^t Y_{Km}^t - S_m^Y = Y_{km}^t, m=1,2,3\cdots\cdots M;\\ Z_K^t \geq 0, S_n^X \geq 0, S_m^Y \geq 0, k=1,2,3\cdots\cdots K\end{cases} \tag{1}$$

In the formula (1), AEE is efficiency, S_n^X means excessive input, S_m^Y means insufficient output, X_{ki}^t, Y_{ki}^t is the input and output value of DUMk in period *t*. In practice, DUM not only has expected output, but also undesired output. Tone proposed an SBM model that considers undesired output based on the SBM model. The SBM model that considers undesired output has been widely used in efficiency measurement, such as water (CHEN, 2015), energy (YU SHANG et al., 2020) And environmental efficiency (CHOI et al., 2012). The SBM model considering undesired output is as follows:

$$AEE = \min \frac{1-\frac{1}{N}\sum_{1}^{N}\frac{S_n^X}{X_{kn}^t}}{1+\frac{1}{M+1}(\sum_{1}^{M}\frac{S_m^Y}{Y_{km}^t}+\sum_{1}^{I}\frac{S_i^U}{U_{ki}^t})}$$

$$s.t.\begin{cases}\sum_{K=1}^{K} Z_K^t X_{Kn}^t + S_n^X = X_{kn}^t, n=1,2,3\cdots\cdots N;\\ \sum_{K=1}^{K} Z_K^t Y_{Km}^t - S_m^Y = Y_{km}^t, m=1,2,3\cdots\cdots M;\\ \sum_{K=1}^{K} Z_K^t U_{Ki}^t - S_i^U = U_{ki}^t, i=1,2,3\cdots\cdots I;\\ Z_K^t \geq 0, S_n^X \geq 0, S_m^Y \geq 0, S_i^U \geq 0, k=1,2,3\cdots\cdots K\end{cases} \tag{2}$$

In the formula (2), $X_{Kn}^t, Y_{Km}^t, U_{Ki}^t$ is the input value, expected output value, and undesired output value of DUM_k in period *t*; S_n^X, S_m^Y, S_i^U is the redundant value of input, expected output, and undesired output. When these variables are greater than or equal to 0, they represent overuse of inputs, underproduction of expected output, and excessive emissions of bad output.

Entropy method

In the process of calculating the comprehensive urbanization index, this article refers to HE et al., (2017) & NANA LIU et al., (2018) and other practices, and uses the entropy method to determine the weight of each index in the comprehensive evaluation of urbanization, and calculate the comprehensive index of urbanization based on this. In the process of calculating the comprehensive index of urbanization, referring to HE et al., (2017) & NANA LIU et al., (2018), and other practices, the entropy method is used to determine the weight of each index in the comprehensive evaluation of urbanization, and the comprehensive index of urbanization is calculated accordingly.

Entropy method is an objective method to determine the index weight. In information theory, the larger the amount of information, the smaller the uncertainty and the smaller the entropy. On the contrary, the smaller the amount of information, the larger the entropy. Therefore, entropy can be used to judge the randomness and disorder degree of an event, and also can be used to judge the dispersion degree of an index. The greater the dispersion degree of the index, the greater the influence of the index on the comprehensive evaluation. The method of entropy method to calculate index weight is as follows:

If there are *m* items to be evaluated and *n* indicators are given, the original data matrix is:

$$A^t = (x_{ij}^t)_{m*n} = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{3}$$

After standardizing the original matrix *A*, the decision matrix is marked as $A'^t = \left(x'^t_{ij}\right)_{m*n}$ and its information entropy is:

$$e_j = -K\sum_{j=1}^{m} p_{ij}^t \ln p_{ij}^t \tag{4}$$

In the formula (5), $p_{ij}^t = x'^t_{ij} / \sum_{i=1}^{m} x'^t_{ij}$, $K = 1/\ln(m*T)$ (M is the total number of provinces and cities, T is the total number of years).

The corresponding entropy weight ω_j of the *j*the index is:

$$\omega_j = (1-e_j) / \sum_{j=1}^{n} (1-e_j) \tag{5}$$

Finally, according to the scores of various indicators, the project score is calculated as:

$$F_i = \sum_{j=1}^{n} \omega_j x_{ij}^{'t} \tag{6}$$

Tobit regression

Tobit regression model was first proposed by TOBIN (1958). It is a regression model with limited dependent variables. This model describes the association between non-negative dependent variables (latent variables) and independent variables when the data is truncated or truncated (ÜMIT, 2018). Considering that the value of agricultural ecological efficiency is between 0 and 1, this paper chooses the Tobit regression model to analyze the impact of urbanization on agricultural ecological efficiency on the basis of standardizing the explanatory variables:

$$\begin{cases} Z_{it}^{*} = \beta_0 + \beta_1 UI_{it} + \beta_x \ln X_{it} + \mu_i + \varepsilon_{it} \\ AEE_{it} = Z_{it}^{*}, if\ 0 < Z_{it}^{*} \le 1; \\ AEE_{it} = 0, if\ Z_{it}^{*} < 0; \\ AEE_{it} = 1, if\ Z_{it}^{*} > 1; \end{cases} \tag{7}$$

In the formula (7), Z_{it}^{*} is a latent variable, AEE_{it} is the measured agricultural ecological efficiency of province i during t period, UI_{it} is the comprehensive evaluation index of urbanization in i province and city in t period, X_{it} is the control variable of i province and city in t period, β is the correlation coefficient vector, μ_i is the non-observed individual fixed effect, ε_{it} is the disturbance term and satisfies $\varepsilon_i \sim N(0,\ \sigma^2)$.

Index system and variable setting

Agricultural ecological efficiency measurement index system

Agricultural ecological efficiency is the agroecological input-output relationship of ecological products. MIHCI & MOLLAVELIGIU (2011) in choosing indicators of agricultural ecological efficiency, uses labour, capital, fertilizer, energy use as input indicator, value added as desirable outputs and CO_2 as undesirable outputs. BENEDETTA COLUCCIA et al., (2020) used labor, gross capital, land, total irrigation area and fertilizer as input indicator. Choosing agricultural production as an output indicator. LINLIN ZENG et al., (2021) considered in the process of agroecological production, labor, land, use of fertilizer, pesticide, plastic membrane, machinery, irrigated area and draught animals are considered as inputs; the gross output value of farming, carbon emission and non-point-source pollution are considered as outputs.

On the basis of the reference to the above academic research, combined with reference to the existing literature (HAN et al., 2018; FEI & LIN, 2016a, 2016b; SHEN et al., 2018; HAIBIN HAN et al. 2020). This article selects agricultural labor input, Agricultural land input, irrigation input, fertilizer input, pesticide input, agricultural film input, agricultural machinery input as the input indicators of agricultural ecological efficiency. The total agricultural output value is used as the expected indicator, and the carbon emissions and pollution emissions from the agricultural production process are used as undesired output. The indicator system is shown in table 1.

Agricultural labor is the front-line personnel engaged in agricultural production. This article uses agricultural practitioners to represent, and uses the following formula to calculate agricultural practitioners: Agricultural practitioners = first industry practitioners * total agricultural output value / total output value of agriculture, forestry, animal husbandry and fishery.

Land resources are an important basis for agricultural activities. In this study, the total area of sown crops was used to reflect the land resources used in agricultural activities.

Water resources are also a necessary foundation for agricultural production activities. The effective irrigation area was used to reflect the water resources used for irrigation in agricultural activities.

Fertilizers and pesticides are important products in modern agricultural production. In this study, the input of chemical fertilizers and pesticides during agricultural activities was used to reflect the amount of fertilizer and pesticides used.

Agricultural machinery is important equipment for improving agricultural output. In this study, the total power of the agricultural machinery was used to reflect the use of agricultural machinery in agricultural activities.

The total agricultural output value reflects the results of the agricultural production activities. Therefore, in this study, the total agricultural output value was used as the expected output index of the agricultural ecological efficiency.

Various activities in agricultural production processes generate carbon dioxide. In this study, the carbon emissions from agricultural activities were considered to be an undesirable output of agricultural ecological efficiency. According to the

Table 1 - Agricultural ecological efficiency input-output index system.

Index type	Sub index	symbol	Variables and descriptions	Computational method
Input index	Labour force	X_1	Number of employees in farm ($\times 10^4$person)	Agricultural practitioners = first industry practitioners * total agricultural output value / total output value of agriculture, forestry, animal husbandry and fishery.
	Land	X_2	Planting area of crops (khm^2)	Statistical Yearbook queries
	Chemical fertilizer	X_3	Fertilizers consumption ($\times 10^4$t)	Statistical Yearbook queries
	Pesticide	X_4	Pesticides usage (t)	Statistical Yearbook queries
	Agricultural film	X_5	Agricultural film consumption(t)	Statistical Yearbook queries
	Agricultural Machinery Power	X_6	Total power of agricultural machinery ($\times 10^4$kW)	Statistical Yearbook queries
	Irrigation	X_7	Effective irrigation area (khm^2)	Statistical Yearbook queries
Output index	Total output value of farm	Y	Total output value of farm ($\times 10^8$¥)	Statistical Yearbook queries
Bad output index	Carbon emission	U_1	Total carbon emissions from fertilizers, pesticides, agricultural membranes, agricultural diesel, agricultural irrigation and agricultural sowing ($\times 10^4$t)	Total carbon emissions = chemical fertilizer application×0.90 + pesticide use × 4.93 + agricultural film use× 5.18 + agricultural diesel use× 0.59 + effective irrigation area ×20.48 + total crop sown area×312.60
	Pollution emissions	U_2	Quantity of chemical fertilizer, pesticide, total residues of agricultural membrane ($\times 10^4$t)	Total pollution emission = chemical fertilizer application× 0.65 + pesticide use× 0.50 + agricultural film use× 0.10

previous research results (LU ZHANG et al., 2019; JIANDONG CHEN et al., 2018) and the actual situation of the agricultural production in China, the carbon emissions in agricultural production activities were considered to be the total carbon emissions from the chemical fertilizers, pesticides, agricultural films, agricultural diesel, agricultural irrigation, and agricultural sowing, and the method adopted was to multiply the corresponding indicator by the emission factor. For example, the carbon emissions from chemical fertilizers = the application of chemical fertilizer×the carbon emission coefficient of chemical fertilizers. The equations used to calculate the carbon emissions from other activities are similar. The emission coefficients used in this article were obtained from the First National Pollution Survey: Manual of Pesticide Loss Coefficient and Farmland Film Residue Coefficient issued by the Chinese government. The values used are as follows: chemical fertilizers 0.90 kg/kg, pesticides 4.93 kg/kg, agricultural films 5.18 kg/kg, diesel oil 0.59 kg/kg, agricultural irrigation 20.48 kg/hm2, and agricultural cultivation 312.60 kg/hm2.

Improper use of chemical fertilizers, pesticides, and agricultural films in agricultural production can cause agricultural pollution. With reference to the existing research (HUA LU, 2018; LILIN ZOU et al., 2020), in this study, the fertilizer pollution, pesticide pollution, and agricultural film residues were used to estimate the agricultural pollution caused by agricultural chemicals. The amount of chemical fertilizer pollution was calculated based on the data for the amount of chemical fertilizer used and the chemical fertilizer loss rate over the years—that is, amount of chemical fertilizer pollution = amount of chemical fertilizer applied × chemical fertilizer loss rate—and the equations used for the amount of pesticide pollution and the agricultural film residue rate were similar. According to the results of several domestic studies in China, a fertilizer loss rate of 65%, a pesticide pollution rate of 50%, and a film residue rate of 10% were used in this study.

Comprehensive evaluation index system of urbanization

Scholars have a different emphasis on the evaluation of urbanization. YANNICAO et al., (2021) defined urbanization from the perspective of land urbanization. YANG ZHOU et al., (2021) analyzed the problem of population urbanization. JIEYU WANG (2019) constructed an index system for the measurement of urbanization quality scores based on the four aspects of population, economy, society, and space. According to the existing research and the development of urbanization in China, this paper studies urbanization from three aspects: population urbanization, economic urbanization and land urbanization, so as to study the impact of urbanization on agricultural ecological efficiency more specifically. This article uses the urbanization rate of the population and the per capital disposable income of urban residents as alternative indicators of the urbanization status of the population to reflect the inflow of rural population into cities and the living standards of urban residents; Taking the urban economic density and the proportion of the secondary and tertiary industries in GDP as substitute indicators of economic urbanization to reflect the concentration of urban industries and the regional industrial structure; The proportion of built-up area and per capital built-up area are used as substitute indicators for land urbanization to reflect the expansion of urban land and the availability of urban services to individuals. The specific indicators are set in table 2 below.

And use the entropy method to calculate the weight of each indicator for the six indicators, and then get the comprehensive urbanization index to more comprehensively reflect the overall development of urbanization.

Variable setting

Explained variable: Agricultural ecological efficiency is reflected by the efficiency value measured by the undesired output SBM model.

Core explanatory variable: The first group: Comprehensive Urbanization Evaluation Index .The second group: Population urbanization rate, Per capital disposable income of urban residents, Urban economic density, Proportion of secondary and tertiary industries in GDP Proportion of built-up area, Per capital Built-up area

Control variables: In the selection of control variables, this article refers to existing research (WAGAN et al., 2018; ZHOU & KONG, 2019) and combines the actual development of China's agriculture to select agricultural disaster rate, agricultural machinery density, The level of regional financial support for agriculture and the level of regional industrialization are the control variables for the analysis of the impact of urbanization development on agricultural ecological efficiency.

The agricultural disaster rate reflects the impact of natural disasters on agricultural production, and its calculation formula is: agricultural disaster rate = disaster area of crops/total sown area of crops (%).

The density of agricultural machinery reflects the input of agricultural machinery per unit area of agriculture, and its calculation formula is: agricultural machinery density = total power of agricultural machinery/total sown area of crops (kw/ha).

Table 2 - Evaluation index system of comprehensive index of urbanization.

Target level index	System-level index	Evaluating index	symbol	Computational method
urbanization	Population urbanization	Population urbanization rate	C1	Statistical Yearbook queries
		Per capita disposable income of urban residents	C2	Statistical Yearbook queries
	Economic urbanization	Urban economic density	C3	The output value of secondary and tertiary industries under its jurisdiction/Land area of jurisdiction
		Proportion of secondary and tertiary industries in GDP	C4	The output value of secondary and tertiary industries under its jurisdiction / Jurisdiction GDP
	Land urbanization	Proportion of built-up area	C5	Built-up area/Area of administrative land
		Per capita Built-up area	C6	Built-up area//Total population of jurisdiction

The level of regional financial support for agriculture reflects the strength of local governments' support for agriculture. The calculation formula is: regional financial support for agriculture = local financial expenditure on agriculture, forestry and water affairs/local financial general budget expenditure (%).

The regional industrialization level reflects the development of the regional supply industry, and its calculation formula is: regional industrialization level = industrial added value / regional gross product (%).

The regression analysis variable settings of urbanization on agricultural ecological efficiency are shown in table 3 below.

RESULTS AND DISCUSSION

Measurement results of agricultural ecological efficiency

The study uses the SBM model that considers undesired output combined with the input-output indicator system of agricultural ecological efficiency to calculate agricultural ecological efficiency. The DEA-SLOVER PRO software is used to measure the agricultural ecological efficiency of 30 provinces and cities in China from 2009 to 2018, as shown in Appendix 1.

In order to more clearly see the changes in the average value of agricultural ecological efficiency in China's 30 provinces and cities from 2009 to 2018, based on the measurement results of agricultural ecological efficiency in China's 30 provinces and cities, a map was made to obtain figure 1.

As can be seen from figure 1, the average agricultural ecological efficiency of 30 provinces and cities in China was 0.439 in 2009, reaching 0.730 in 2018, with an increase of 0.290 in 10 years, which reflects that China's agricultural ecological environment policy has played a good role and the overall agricultural ecological environment has been improved. And it is obvious from figure 1 that the average agricultural ecological efficiency of 30 provinces and cities in China is accelerating, especially the average agricultural ecological efficiency in 2018 is 0.087 higher than that in 2017,

Table 3 - Regression analysis variable setting of urbanization on agricultural ecological efficiency.

Variable type	Variable name	symbol	Calculation formula
Explained variable	Agricultural ecological efficiency	AEE	SBM model and calculation of agricultural ecological efficiency index system based on considering undesired output
Core explanatory variables	Urbanization Comprehensive Evaluation Index	UI	Calculation based on entropy method and comprehensive evaluation index system of urbanization
	Population urbanization rate	C1	Statistical Yearbook queries
	Per capita disposable income of urban residents	C2	Statistical Yearbook queries
	Urban economic density	C3	The output value of secondary and tertiary industries under its jurisdiction/Land area of jurisdiction
	Proportion of secondary and tertiary industries in GDP	C4	The output value of secondary and tertiary industries under its jurisdiction / Jurisdiction GDP
	Proportion of built-up area	C5	Built-up area/Area of administrative land
	Per capita Built-up area	C6	Built-up area//Total population of jurisdiction
Control variable	Agricultural disaster rate	DR	Agricultural disaster rate = disaster area of crops/total sown area of crops (%)
	Agricultural machinery density	JX	Agricultural machinery density = total power of agricultural machinery/total sown area of crops (kw/ha)
	Regional financial support for agriculture	CZ	Regional financial support for agriculture = local financial expenditure on agriculture, forestry and water affairs/local financial general budget expenditure (%)
	Regional industrialization level	GY	Regional industrialization level = industrial added value/regional gross product (%)

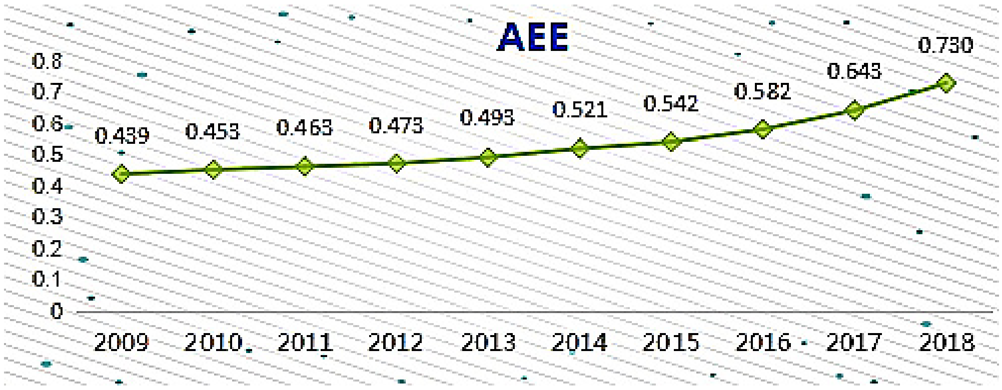

Figure 1 - the change trend of agricultural ecological efficiency (AEE) in 30 provinces and cities of China from 2009 to 2018.

which shows that the improvement speed of China's agricultural ecological environment is accelerating.

Based on the measurement results, plot the spatial distribution of agricultural ecological efficiency in 2009 and 2018, and get figure 2 and figure 3.

It can be seen from figure 2(a) that the overall agricultural ecological efficiency of China's 30 provinces and cities in 2009 was low. Most provinces and cities had $AEE \leq 0.4$, and only a few economically developed areas such as Beijing, Shanghai, and Guangdong had $AEE \geq 0.6$. From figure 3 (b) , it can be seen that the overall agricultural ecological efficiency of China has improved in 2018. Among the 30 provinces and cities, the agricultural ecological efficiency of 12provinces and cities had $AEE \geq 0.8$,. In terms of spatial distribution, in 2009

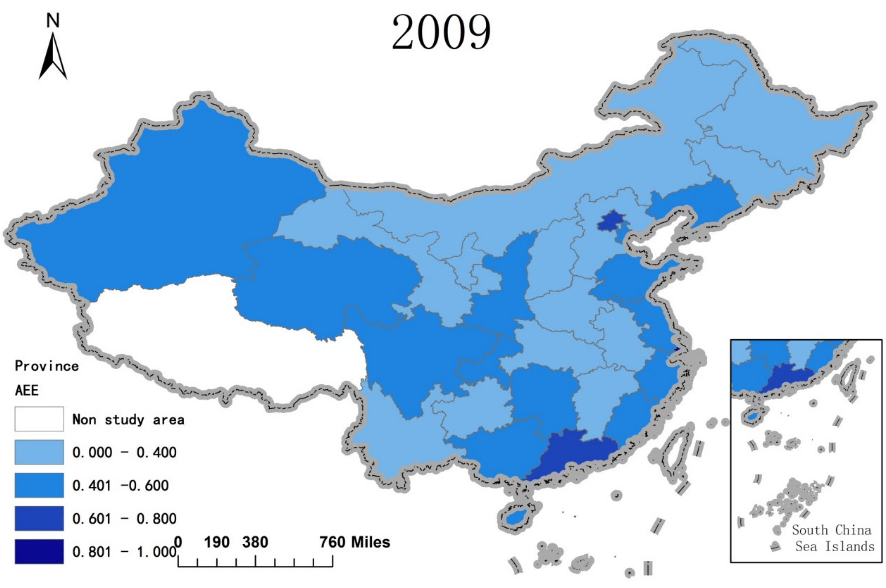

Figure 2 - The spatial distribution of agricultural ecological efficiency in 30 provinces and cities in China in 2009 and 2018(a).

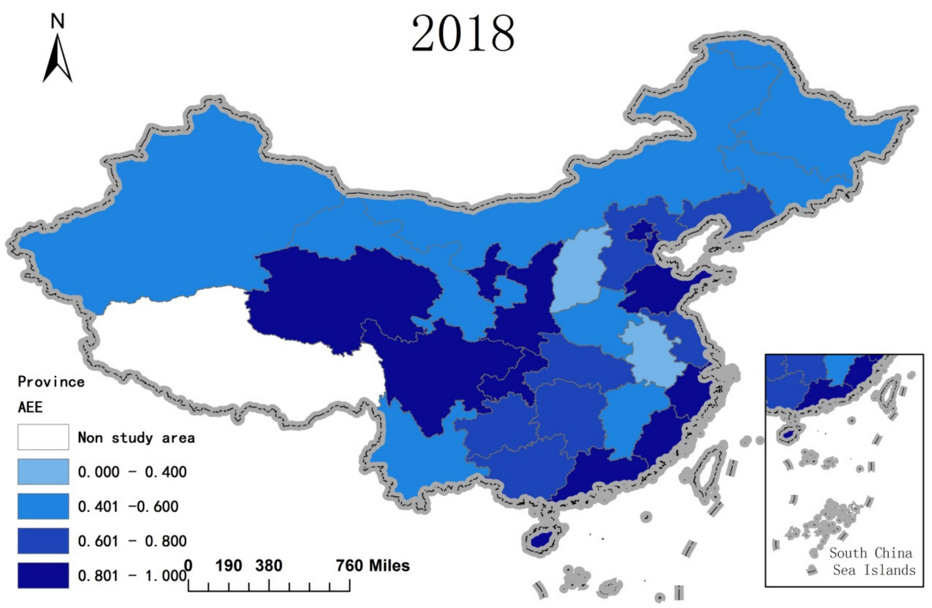

Figure 3 - The spatial distribution of agricultural ecological efficiency in 30 provinces and cities in China in 2009 and 2018(b).

and 2018, the eastern and western regions of China had higher agricultural ecological efficiency, while the central and northeastern regions had relatively lower. This may be due to the relatively developed economy and advanced agricultural production technology in the eastern coastal areas of China, so the total agricultural output value in the eastern region is relatively high, and because the local government has realized the environmental problems in agricultural production earlier, it has strengthened the pollution control in the regional agricultural activities; The higher agricultural ecological efficiency in Northwest China is mainly due to less pollution emissions from agricultural activities; Relatively speaking, the total agricultural output value of the central and northeast regions is higher than that of the western regions, but they rely more on resource input in agricultural activities, which aggravates environmental pollution.

Urbanization comprehensive index measurement

The study uses the entropy method combined with the comprehensive urbanization evaluation index system to measure the comprehensive urbanization index. Using the entropy method, the weights of urbanization indicators are:C1=0.081;C2=0.145;C3=0.398;C4=0.034 ;C5=0.220;C6=0.122 . Combining the weights measured by the entropy method and the basic data of various indicators of urbanization, the comprehensive urbanization index of China's 30 provinces and cities from 2009 to 2018 is calculated, as shown in Appendix 2. Based on the comprehensive urbanization index obtained from the measurement, calculate the average value of the comprehensive urbanization index from 2009 to 2018, and plot it to get figure 4.

It can be seen from figure 4 that from 2009 to 2018, the comprehensive urbanization index is constantly improving, from 0.147 in 2009 to 0.276 in 2018, with an increase of 0.129, reflecting the rapid development of urbanization in China.

Based on the comprehensive urbanization index of 30 provinces and cities in China, the article plots the spatial distribution of the comprehensive urbanization index in 2009 and 2018, and we get figure 5 and figure 6.

It can be seen from figure 5(a) that in 2009, the comprehensive urbanization index of China's provinces and cities was at a relatively low level, and only Beijing, Jiangsu, Shanghai, Tianjin, and Zhejiang had UI ≥ 0.2. From figure 6(b), it can be seen that the comprehensive urbanization index of China's provinces and cities has increased to a certain extent in 2018, and the number of provinces and cities with UI ≥ 0.2 has increased to 22. From

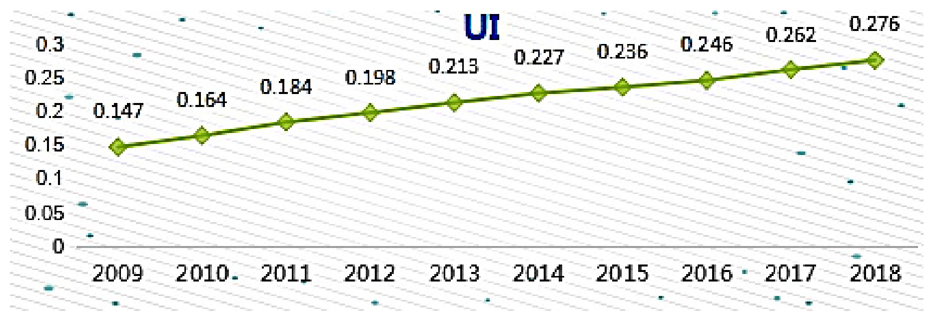

Figure 4 - comprehensive urbanization index (UI) of 30 provinces and cities in China from 2009 to 2018.

the perspective of spatial distribution, the distribution of China's urbanization comprehensive index in 2009 generally showed a trend of gradually decreasing from east to west. In 2018, China's urbanization comprehensive index is still higher in the eastern region, and the urbanization level of the central region has been improved rapidly in the past 10 years, and its urbanization comprehensive index is second only to the eastern region, and the comprehensive urbanization index of the western region and northeast region is relatively low. The eastern region has benefited from the rapid development of the economy and relatively complete urban facilities and public services to attract people from other regions, so the comprehensive index of urbanization in the eastern region has a long-term advantage; The central region has a good agricultural foundation and agricultural surplus labor force. In recent years, with the rising prices of labor force, land and other factors in eastern China, some industries have been transferred to central provinces

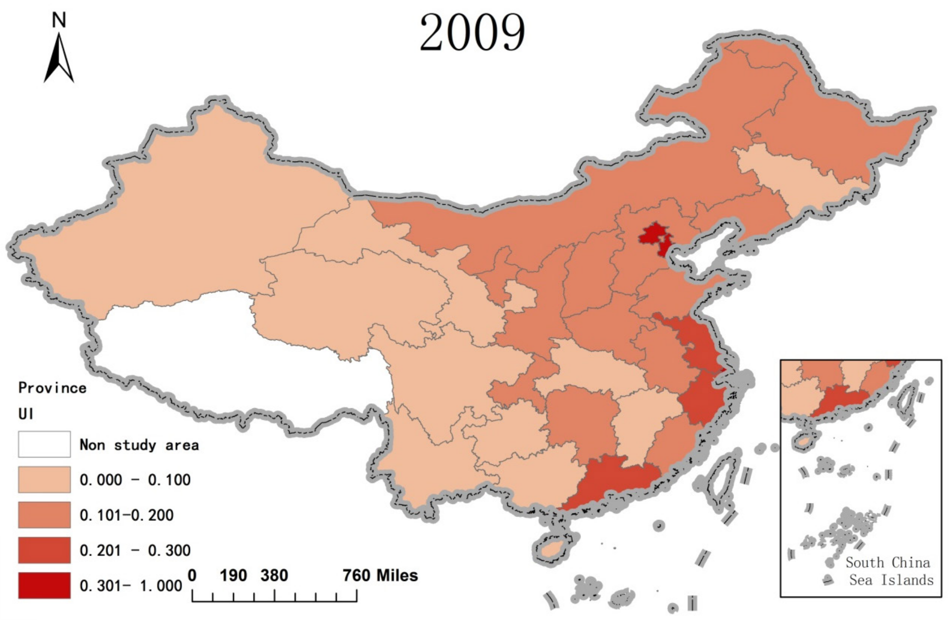

Figure 5 - The spatial distribution of the comprehensive urbanization index of 30 provinces and cities in China in 2009(a).

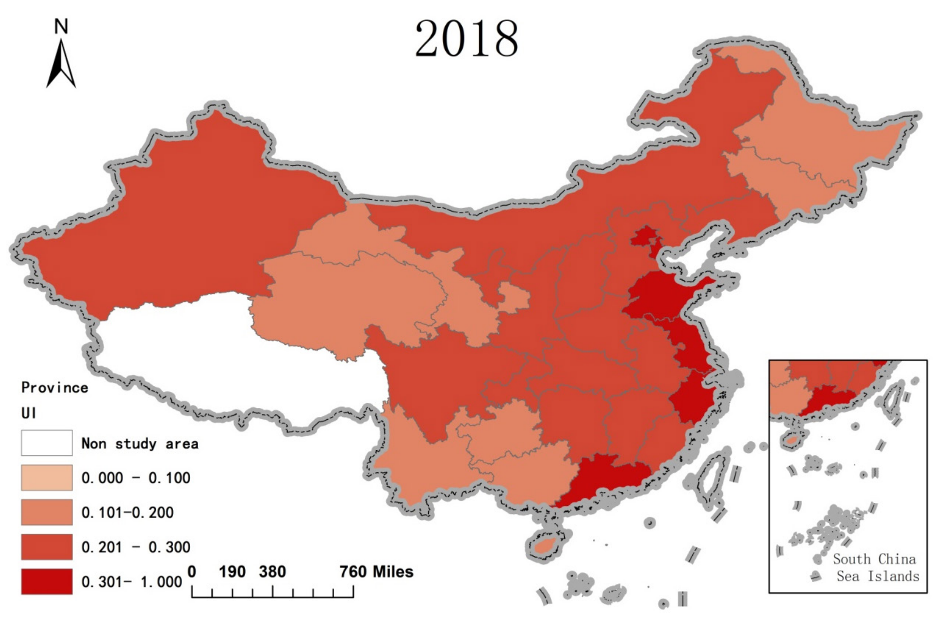

Figure 6 - The spatial distribution of the comprehensive urbanization index of 30 provinces and cities in China in 2009(b).

and cities, the industrial agglomeration effect of cities and towns in the central region has been improved, and a large number of rural labor force in the central region has chosen to be employed nearby, which has to some extent promoted the rapid increase of urbanization in the central region; The population in the western and northeastern regions is relatively small, the development of industry and service industries is relatively slow, and urban development is restricted.

Analysis of the impact of urbanization on agricultural ecological efficiency

The Tobit model was used to analyze the impact of urbanization comprehensive index and urbanization indicators on agricultural ecological efficiency. Stata software was used for analysis and Tobit regression was performed twice. In the first analysis, the explanatory variable was set as agricultural ecological efficiency , the explanatory variable was urbanization comprehensive index, and the control variables were agricultural disaster rate, agricultural machinery density, regional financial support for agriculture, and regional industrialization level. In the second analysis, the explanatory variables and control variables are set. The same as the first analysis, the explanatory variables are population urbanization rate, per capita disposable income, urban economic density, the proportion of secondary and tertiary industry in GDP , the proportion of built-up area and per capita built-up area. In order to further verify the robustness of the analysis results, this article uses Stata software to perform Ols estimation after Tobit regression, and its variable settings are consistent with Tobit regression. The first Tobit regression and its Ols estimation results are shown in table 4, and the second estimation results are shown in table 5.

It can be seen from table 4 that the coefficients and significance of Tobit estimation and Ols estimation in the first analysis are relatively consistent, indicating that the estimation results are robust. From the Tobit estimation results, Log likelihood = 123.379, and Prob > chi2 = 0.000, it can be seen that the goodness of fit of the model is good, and the core explanatory variables and most control variables are significant at the statistical level of 1%, indicating that the selection of model variables is reasonable. The UI coefficient is 0.639, which means that the urbanization comprehensive index can positively affect the agricultural ecological efficiency, and when the urbanization comprehensive

Table 4 - Tobit and Ols estimation results (a).

	--------------------------------Tobit----------------------------------				---------------------------------Ols---------------------------------			
AE	Coef.	Std. Err.	t	P>|t|	Coef.	Std. Err.	t	P>|t|
UI	0.639	0.106	6.010	0.000	0.530	0.095	5.550	0.000
DR	-0.212	0.054	-3.930	0.000	-0.216	0.052	-4.190	0.000
JX	-0.029	0.039	-0.740	0.460	-0.015	0.036	-0.420	0.674
CZ	-0.247	0.062	-4.010	0.000	-0.248	0.058	-4.260	0.000
GY	-0.283	0.045	-6.240	0.000	-0.272	0.043	-6.370	0.000
_cons	0.770	0.068	11.350	0.000	0.778	0.064	12.160	0.000
/sigma	0.143	0.006			---------------------------Prob>F=0.000-------------------------			
	------------------------Log likelihood =123.379--------------------							
	-------------LR chi2(5)=214.060（Prob>chi2=0.000)-----------							

index is increased by 1, the agricultural ecological efficiency can be increased by 0.639. Therefore, the development of urbanization as a whole can promote the improvement of agricultural ecological efficiency.

It can also be seen from the data in table 5 that the coefficients and significance of Tobit estimation and OLS estimation in the second analysis are consistent, indicating that the estimation results are robust.

From the Tobit estimation results, Log likelihood = 168.085 and Prob > chi2 = 0.000, which also shows that the model has good goodness of fit, and most of the explanatory variables at the statistical level of 1% significantly reflect that the selection of variables is more reasonable.

Population urbanization rate and per capital disposable income of urban residents have a positive impact on agricultural ecological efficiency at a significant level of 1%, with coefficients of 0.330 and 0.655, indicating that the increase of urban population proportion and the increase of per capital disposable income of urban residents are conducive to the improvement of agricultural ecological efficiency. The increase of population urbanization rate is the performance of population concentration to cities. The increase of urban population can promote regional economic growth and technological development, while regional economic growth and scientific and technological development can improve agricultural output, and the development of cleaner production

Table 5 - Tobit and OLS estimation results (b).

y	Coef.	Std. Err.	t	P>|t|	Coef.	Std. Err.	t	P>|t|
C1	0.330	0.079	4.210	0.000	0.329	0.075	4.380	0.000
C2	0.655	0.080	8.190	0.000	0.621	0.076	8.190	0.000
C3	-0.245	0.193	-1.270	0.205	-0.242	0.182	-1.330	0.183
C4	-0.184	0.079	-2.330	0.021	-0.185	0.076	-2.450	0.015
C5	0.032	0.181	0.180	0.860	-0.007	0.172	-0.040	0.968
C6	-0.158	0.049	-3.260	0.001	-0.155	0.047	-3.340	0.001
DR	-0.118	0.049	-2.400	0.017	-0.126	0.047	-2.660	0.008
JX	-0.062	0.036	-1.730	0.084	-0.057	0.034	-1.680	0.095
CZ	-0.172	0.075	-2.300	0.022	-0.178	0.072	-2.470	0.014
GY	-0.043	0.051	-0.840	0.402	-0.033	0.048	-0.690	0.490
_cons	0.571	0.077	7.430	0.000	0.580	0.074	7.860	0.000
/sigma	0.122	0.005			--------------------------Prob> = 0.0000--------------------------			
---------------------Log likelihood =168.085----------------------								
-----------LR chi2(10)=303.470 （Prob > chi2 =0.000)---------								

technology can improve the agricultural ecological environment. The increase of per capital disposable income of urban residents will promote the upgrading of residents' consumption level, and the upgrading of residents' consumption level may increase the demand for green agricultural products. The increase of green consumption can provide huge market space for the development of green agricultural industrialization, thus making farmers pay attention to the protection of agricultural ecological environment and reduce the use of chemical products such as chemical fertilizers and pesticides.

The proportion of the secondary and tertiary industries in GDP has a negative impact on the agricultural ecological efficiency at a significant level of 1%, with a coefficient of 0.184, indicating that the development of the secondary and tertiary industries will reduce the agricultural ecological efficiency. The development of industry can enrich the means of agricultural production, thus reducing the use cost of chemical fertilizer, pesticide and agricultural film, resulting in an increase in the use of chemical fertilizer and other agricultural means of production, and causing adverse effects on the agricultural ecological environment; In addition, the development of secondary and tertiary industries will reduce the input of agricultural land and labor force to a certain extent, which will have a negative impact on agricultural output.

The per capital built-up area has a negative impact on the agricultural ecological efficiency at a significant level of 1%, with a coefficient of 0.158, indicating that the increase in the per capital built-up area will reduce the agricultural ecological efficiency. As the built-up area expands, the agricultural ecological efficiency will decline. The reason may be that the expansion of urban land will encroach on agricultural land, and as agricultural land decreases, agricultural production will be affected. On the one hand, the lack of agricultural land directly leads to a decline in agricultural output, on the other hand, it may also cause more chemical products to be used, thereby exacerbating agricultural ecological environmental pollution. According to the index coefficients, although the proportion of the secondary and tertiary industry in GDP and the per capital built-up area have a significant negative impact on the agricultural ecological efficiency, the two indicators of population urbanization, population urbanization rate and per capital disposable income of urban residents have a significant positive impact on agricultural ecological efficiency, and the coefficient is relatively large. Therefore, the overall urbanization index has a significant positive impact on agricultural ecological efficiency.

CONCLUSION

Based on the measurement of the comprehensive index of agricultural ecological efficiency and urbanization, this paper uses the Tobit model to analyze the impact of urbanization on agricultural ecological efficiency. The main research conclusions are as follows:1) The agricultural ecological efficiency of 30 provinces and cities in China is on the increase trend from 2009 to 2018. The average value of agricultural ecological efficiency in 2009 was 0.439, while that in 2018 was 0.730. There was a gap between regions. The eastern region had the highest agricultural ecological efficiency, followed by the western region, and the central region and northeast region were relatively low; 2) From 2009 to 2018, the overall urbanization index of 30 provinces and cities in China has been continuously increasing, from 0.147 in 2009 to 0.276 in 2018. The urbanization level in the eastern region is the highest, the urbanization level in the central region is improving rapidly, and the urbanization level in the western region and Northeast China is relatively low; 3) As a whole, urbanization can promote the improvement of agricultural ecological efficiency, and the specific urbanization indicators have a complex impact on agricultural ecological efficiency. Therefore, to explore the impact of urbanization on agricultural ecological efficiency can not only be considered from a single aspect, but should be analyzed from multiple perspectives. According to the analysis, the comprehensive index of urbanization has a significant positive impact on agricultural ecological efficiency. From the perspective of each index, the urbanization rate of population and the per capital disposable income of urban residents have a significant positive impact on agricultural ecological efficiency. The proportion of output value of secondary and tertiary industries in GDP and the per capital built-up area have a significant negative impact on agricultural ecological efficiency.

According to the research, urbanization can improve the agricultural ecological efficiency as a whole, so we should further promote urbanization and constantly improve the quality of urbanization. To this end, we put forward the following suggestions, in order to provide some reference for the urbanization development of regions around the world.

(1) Stably promote the urbanization of the population, and effectively increase the income

level of residents. The development of population urbanization can promote the improvement of agricultural ecological efficiency. For this reason, it is necessary to gradually guide the transfer of surplus labor from rural areas to cities. In this process, attention should be paid to solving the housing, health, and children's education problems of the agriculturally transferred population. At the same time, we should actively promote the popularization and application of advanced agricultural technology, especially green agricultural technology, so as to reduce the negative impact of agricultural labor force on agricultural production. In addition, it can be seen from the research that the improvement of residents' disposable income can effectively improve the agricultural ecological efficiency. Therefore, we should improve the residents' disposable income by stabilizing employment, reducing tax burden, broadening investment channels for residents, and strengthening social security.

(2) Cleanly realize economic urbanization and effectively reduce industrial cluster pollution. From the study, we can see that the increase of the proportion of secondary and tertiary industries will have a negative impact on agricultural ecological efficiency. Therefore, in promoting the development of urban secondary and tertiary industries, we should strengthen the construction of industrial clean production capacity, and comprehensively consider the characteristics of industrial development and the spatial distribution of the cities and towns. Environmental problems caused by economic urbanization can be alleviated by improving cleaner production technology, strengthening waste recycling and optimizing the location of industrial parks.

(3) Appropriately develop land urbanization and promote the coordinated development of large and small towns. From the study, we can see that land urbanization will restrict the improvement of agricultural ecological efficiency. Therefore, we should promote the moderate development of land urbanization, and promote the construction of satellite cities and small towns according to local conditions. We should avoid the one-sided pursuit of urban scale and reduce the excessive squeezing of agricultural land in the process of land urbanization.

Based on the existing research results, this paper further expands the research on the influencing factors of agricultural ecological efficiency from the unique perspective of urbanization. However, there are still some areas that need to be improved and deepened, such as the optimization of urbanization index system, and the in-depth analysis of the impact path of various indicators of urbanization on agricultural ecological efficiency. It should be noted that since this article focuses on the impact of urbanization and its indicators on agricultural ecological efficiency, the impact of control variables on agricultural ecological efficiency is not discussed. The main reason is to focus with limited layout and research energy, and the control variables have been deeply discussed by predecessors. Therefore, it is of little value to analyze it.

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DECLARATION OF CONFLICT OF INTEREST

The authors declare no conflict of interest.

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