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Evaluation of Cropland Utilization Eco-Efficiency and Influencing Factors in Primary Grain-Producing Regions of China

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Abstract: Under the backdrop of the "double-carbon" target, the primary grain-producing regions in China are confronted with the tasks of mitigating pollution and carbon emissions and ensuring food security. This paper explores the eco-efficiency of cropland utilization and the factors influencing the primary grain-producing regions in China, utilizing panel data from 13 provinces spanning the period from 2000 to 2019. The analysis employs three models: the super-efficiency SBM model, the Malmquist index model, and the random-effect panel Tobit model. The findings suggest the following: (1) Although the eco-efficiency of cropland utilization in China's primary grain-producing regions did not reach the production frontier during the period of 2000–2019, it exhibited a high level with an overall upward trend. The limiting factor inhibiting the growth of total factor productivity is lower technical efficiency. (2) There is evident spatial variation in the eco-efficiency of cropland utilization across China, displaying a dynamic evolution from northeast > western > central > eastern to northeast > western > eastern > central. Total factor productivity in each province demonstrates an upward trend, with the east > northeast > west > central ranking. (3) Regarding the influencing factors, the utilization of agricultural production chemicals exerts a negative influence, while the proportion of government financial input, labor input, and irrigation index have a positive impact.

Keywords: cropland utilization; eco-efficiency; super-efficient SBM model; influencing factors; primary grain-producing regions

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1. Introduction

The realization of double-carbon targets, as one of the important means of promoting sustainable development, is accelerating the leading of a comprehensive green low-carbon transformation of the economy and society. Arable land serves as a foundational resource in ensuring food security and has significant potential for carbon sequestration [1,2]. In the context of the "double-carbon" target, the green low-carbon utilization of arable land is an essential way to achieve sustainable agricultural development and guarantee food security. However, the sustained, intense use of cropland, coupled with excessive reliance on agrochemicals, has presented serious challenges to the ecological security of these land resources. These practices have weakened the soil and vegetation's capacity to sequester carbon and have increased carbon inputs in the food production process [3]. Thus, the imperative for a green low-carbon transformation of China's cultivated land utilization has become increasingly apparent. The principal grain-producing regions of China have abundant cropland resources, with the "China Statistical Yearbook (2019)" indicating that these areas account for 70% of the nation's cultivated land while contributing to more than two-thirds of its grain production. Consequently, safeguarding cultivated land resources and promoting its green low-carbon utilization directly contribute to national food security and cultivated land ecological security. This paper aims to comprehensively evaluate the eco-efficiency of cropland utilization and analyze the factors influencing it within the main grain-producing areas. By doing so, this research provides a solid theoretical foundation and decision-making reference for facilitating the green low-carbon transformation of cropland utilization in China.

Schaltegger and Stum were the first to coin the term eco-efficiency, which alludes to the efficiency of ecological resources in meeting human needs [4]. The objective is to achieve a harmonious equilibrium between the preservation of the environment and the advancement of economic activities and to maximize economic growth while minimizing environmental costs. The eco-efficiency of cropland use serves as an indicator to measure the reasonableness and effectiveness of inputs [5]. Various research methods are employed to analyze eco-efficiency, including the modeling method, such as the widely used data envelopment analysis (DEA) model [6], the economic/environmental ratio method (EERM) [7], the life cycle approach (LCA) [8], the stochastic frontier analysis (SFA) [9], and the ecological footprint analysis method [10,11]. Initially, research on land eco-efficiency primarily focused on urban areas [12–14]. However, as China began to prioritize food security, cultivated land security, and green development, scholars shifted their focus toward the utilization of cropland. Currently, scholarly investigations pertaining to the ecological efficiency of cropland use primarily focus on measuring and evaluating its efficiency in land utilization [15]. Additionally, it involves analyzing the spatiotemporal patterns [16,17] and the elements that impact eco-efficiency [18–20]. The scale of research in this field varies, ranging from the micro-scale of farmers [21] to the provincial scale [22], national scale [23], regional scale [24,25], and city scale [26]. In terms of geographical focus, the study areas primarily revolve around the Yangtze River Economic Belt, the Yellow River Basin, and Northeast China [27–29]. In the realm of eco-efficiency research pertaining to cropland utilization, scholars have made noteworthy contributions. However, the existing literature suffers from several deficiencies. Firstly, the majority of studies tend to concentrate on urban land use eco-efficiency, neglecting the equally important aspect of cropland utilization. Secondly, the research conducted on cropland use eco-efficiency primarily focuses on a national level or specific regions, limiting the overall understanding of the principal grain-producing regions within China. Finally, current eco-efficiency research primarily employs static DEA efficiency analysis, disregarding the significance of dynamic total factor productivity analysis. These shortcomings highlight the need for further investigation and a more comprehensive approach to the topic.

The possible marginal contribution of this paper lies in three aspects: (1) this paper takes cropland utilization eco-efficiency as the object of study, which makes up for the inadequacy of the existing studies that focus excessively on urban land utilization eco-efficiency; (2) this paper measures cropland utilization eco-efficiency of 13 provinces in China's main grain-producing areas, which can reveal more comprehensively the overall level and inter-provincial differences of China's main grain-producing areas; (3) this paper employs the super-efficiency SBM model and Malmquist index model to analyze the temporal and spatial characteristics of the eco-efficiency of cropland utilization in the main grain-producing areas from the static and dynamic perspectives, which can more accurately reflect the trend of the eco-efficiency of cropland utilization and its heterogeneity compared with the previous studies. The above analysis helps to clarify the spatial and temporal characteristics and driving factors of the eco-efficiency of cropland utilization in China's main grain-producing areas, thus expanding the scope and depth of the study on eco-efficiency of cropland utilization and providing policy references for the formulation of policies on the green low-carbon utilization of cropland.

2. Methods

2.1. Super-Efficient SBM Model

Data envelopment analysis (DEA) is frequently employed in the assessment of eco-efficiency in land use. Among the various models used within the field, the super-efficient SBM (Slacks-based measure) model has gained significant popularity. In 2001, Tone introduced the SBM model with non-expected outputs [30]. This model effectively addresses the issue of input factor "slackness" or "crowding" arising from the conventional DEA in both radial and angular directions. Nevertheless, the SBM model exhibits a similar limitation to the traditional DEA model in that it lacks the capability to accurately differentiate between decision-making units that possess an efficiency value of 1. To overcome this limitation, Tone suggests a potential solution known as the super-efficient SBM model [31], which allows for the effective differentiation of decision-making units at the forefront. The subsequent section presents the construction of the model as follows:

$$\mathrm{Min}\rho = \frac{\frac{1}{m}\sum_{i=1}^{m}\left(\frac{\overline{x}}{x_{ik}}\right)}{\frac{1}{r_1+r_2}\left(\sum_{s=1}^{r_1}\frac{\overline{y}^d}{y_{sk}^d}+\sum_{q=1}^{r_2}\frac{\overline{y}^u}{y_{qk}^u}\right)} \tag{1}$$

$$\overline{x} \geq \sum_{j=1,\neq k}^{n} x_{ij}\lambda_j; \overline{y}^d \leq \sum_{j=1,\neq k}^{n} y_{sj}^d\lambda_j; \overline{y}^d \geq \sum_{j=1}^{n} y_{dj}^d\lambda_j; \tag{2}$$

In the above equation, $\overline{x} \geq x_k; \overline{y}^d \leq y_k^d; \overline{y}^u \geq y_k^u; \lambda_j \geq 0, i = 1,2,\ldots,m; j = 1,2,\ldots,n, j \neq 0; s = 1,2,\ldots,r_1; q = 1,2,\ldots,r_2$

In this model, it is postulated that there exist n decision-making units (DMUs). The input variables are denoted as m, while the desired outputs are represented by r_1. Conversely, the undesired outputs are denoted as r_2. The elements in the input matrix, desired output matrix, and non-desired output matrix are represented by x, y^d, and y^u, respectively. Additionally, ρ represents the eco-efficiency value.

2.2. Malmquist Exponential Model

The Malmquist model was proposed by Malmquist in 1953 in the process of analyzing consumption to study the change in consumption in different periods. In 1994, Färe et al. [32] established the Malmquist exponential model (TFP) based on Malmquist model, which basically uses the ratio of distance function to calculate the efficiency value between inputs and outputs. Since then, the Malmquist index (TFP) has been widely used in the field of production analysis because of its advantage of being able to analyze the internal change of production efficiency from two perspectives, such as technological change and technological efficiency change, and at the same time, it is not subject to the conditions of minimum cost, maximum profit, and price information and has been widely used in the field of production analysis. In this paper, the Malmquist index is introduced to dynamically analyze the time evolution characteristics of eco-efficiency, and the efficiency of technological progress of cropland utilization (Techch) can reflect the degree of technological progress in the process of cropland production and utilization; the efficiency of pure technology of cropland utilization (Pech) can reflect the degree of technological reform in the process of cropland production and utilization; and the efficiency of scale (Sech) can reflect the level of utility of scale production in the process of cropland production and utilization. The principle of the formula is that by setting t as the base period, the change in eco-efficiency in the period of t + 1 can be expressed as follows:

$$tfpch = \left[\frac{D_c^t(x^{t+1}, y^{t+1})}{D_c^t(x^t, y^t)} \times \frac{D_c^{t+1}(x^{t+1}, y^{t+1})}{D_c^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \tag{3}$$

In this study, the notation (x^t, y^t) denotes the input and output vectors during period t, while (x^{t+1}, y^{t+1}) denotes the input and output vectors during period t + 1. The output distance function in period t with constant returns to scale (CRS) is denoted as $D_c^t(x^t, y^t)$. Under this assumption, it is possible to decompose the total factor productivity index (*tfpch*) into two separate indices: the index of technical efficiency change (*effch*) and the index of technical progress (*techch*).

$$effch = \left[\frac{D_c^{t+1}(x^{t+1}, y^{t+1})}{D_c^t(x^t, y^t)} \right]^{\frac{1}{2}} \tag{4}$$

$$techch = \left[\frac{D_c^t(x^{t+1}, y^{t+1})}{D_c^{t+1}(x^t, y^t)} \times \frac{D_c^t(x^t, y^t)}{D_c^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \tag{5}$$

The index of technical efficiency change (*effch*) can be decomposed into the index of pure technical efficiency change (*pech*) and the index of scale efficiency change (*sech*), considering variable returns to scale (VRS).

$$pech = \frac{D_v^{t+1}(x^{t+1}, y^{t+1})}{D_v^{t+1}(x^t, y^t)} \tag{6}$$

$$sech = \frac{D_v^{t+1}(x^t, y^t)}{D_v^{t+1}(x^{t+1}, y^{t+1})} \times \left[\frac{D_c^{t+1}(x^{t+1}, y^{t+1})}{D_c^t(x^t, y^t)} \right]^{\frac{1}{2}} \tag{7}$$

$$Tfpch = Effch \times Tech = (Pech \times Sech) \times Tech \tag{8}$$

A Malmquist index above 1 signifies enhanced efficiency, and below 1 signifies diminished efficiency.

2.3. Tobit Model

The Tobit model was first proposed by James Tobit to solve the problem of statistical analysis in the presence of truncated data. The Tobit model is able to transform truncated data into a probabilistic model, which can then be used to statistically analyze the truncated data. In order to select an appropriate model for analyzing the factors that influence eco-efficiency, the Tobit model proves effective in addressing the impact of eco-efficiency with non-negative truncation characteristics. However, for panel data, obtaining consistent and unbiased estimates with a fixed-effect Tobit model is often challenging. Therefore, this study chooses the random-effect panel Tobit model to examine the factors that influence eco-efficiency in cropland utilization in the primary grain-producing regions. The model is shown below as follows:

$$Y_{it} = \lambda_0 + \sum_j \lambda_j X_{j,it} + \mu_i + \varepsilon_{it} \tag{9}$$

The formula includes various variables: Y_{it} represents the eco-efficiency value of cropland utilization in province i during year t. The intercept term is denoted as λ_0, while λ_j represents the coefficient to be estimated. X_j is the influencing factor, μ_i represents the individual effect, and ε_{it} denotes the random error term.

3. Selection of Indicators and Data Sources

3.1. Construction of Evaluation Index System for Eco-Efficiency of Cropland Utilization

Drawing upon the connotation of eco-efficiency and considering the carbon dioxide emissions associated with cropland utilization, this research constructs a system of eco-efficiency indicators for the utilization of cropland. According to existing scholarly research [33–35], it is believed that carbon emissions from agricultural land activities come from four main sources: (1) carbon emissions directly or indirectly triggered by the inputs of pesticides, fertilizers, and agricultural films during the process of cropland utilization; (2) carbon emissions from diesel fuel consumed by the use of agricultural machinery; (3) loss of organic carbon due to the destruction of the top layer of soil by tilling in the process of agricultural production; (4) carbon emissions from the consumption of electrical energy in the process of agricultural irrigation. Six input indicators are selected: the sowing area of grain crops (instead of the plowing area) [36], fertilizer use, pesticide use, agricultural diesel use, agricultural film use, and the irrigated area of agricultural land. The regional gross agricultural product and food production are chosen as the desired output indicators. Additionally, the aggregate quantity of carbon dioxide emissions has been designated as a non-desired output indicator (Table 1). There is also the focus of this research on the narrower concept of agriculture, i.e., the plantation industry.

Table 1. Evaluation index system for ecological efficiency in utilizing cultivated land.

Type of Indicator	Indicator Elements	Indicator Name	Indicator Unit
Input indicators		Plowed Area	Thousand hectares
		Labor Input	Ten thousand people
		Fertilizer Use	Tons
		Pesticide Use	Tons
		Agricultural Diesel Use	Tons
		Agricultural Film Use	Tons
		Cropland Irrigated Area	Thousand hectares
Output indicators	Expected outputs	Regional Gross Agricultural Product	Billions
		Grain Production	Tons
	Non-expected outputs	Carbon Emissions	Tons

The quantification of carbon emissions resulting from cropland utilization for non-desired outputs is accomplished through the application of a designated mathematical equation [33].

$$E = \sum E_\mathrm{i} = \sum T_\mathrm{i} \times \delta_\mathrm{i} \tag{10}$$

In this study, E denotes the carbon emissions resulting from cropland utilization. The variable E_i denotes the specific carbon emissions associated with each type of carbon source, while T_i represents the quantity of input from each carbon emission source. δ_i symbolizes the carbon emission coefficient linked to each carbon source. Based on a comprehensive review of research conducted both domestically and internationally, it was found that the carbon emission coefficient for plowing [37] is 312.6 kg·km^{-2}. Furthermore, the carbon emission factor for chemical fertilizers [38] is 0.8956 kg·kg^{-1}, and for pesticides [39], it is 4.9341 kg·kg^{-1}. Additionally, the carbon emission coefficients for diesel fuel and agricultural film [40] are 0.5927 kg·kg^{-1} and 5.18 kg·kg^{-1}, respectively, while the carbon emission coefficient for agricultural irrigation is 25 kg·Cha^{-1} [41]. The realization process is shown in Figure 1.

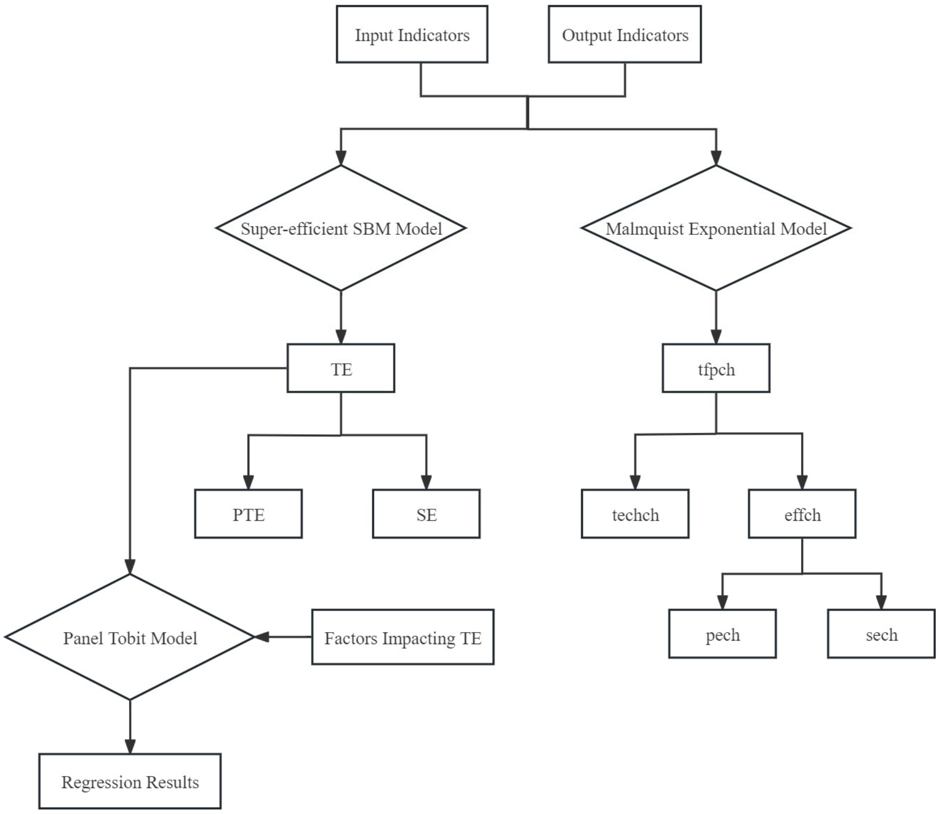

Figure 1. Flowchart of the method.

3.2. Construction of the Index System for Factors Influencing the Eco-Efficiency of Cropland Utilization

The eco-efficiency of cropland utilization is influenced by various elements. This study draws upon the research conducted by relevant scholars [42–44] and identifies eight main categories of influential indicators from the realms of resource endowment, economic and technological development, and agricultural production inputs (refer to Table 2). The following section provides a detailed description of these influencing factors.

Table 2. Factors impacting the eco-efficiency of cropland utilization in primary grain-producing regions.

Level 1 Indicators	Secondary Indicators	Description of Variables	Impact
Resource Endowment	Labor Input per Unit Area	Agricultural Labor Inputs/Sown Area (persons/ha)	Uncharted
	Labor Force Quality	Rural per Capita Years of Schooling (years)	Forward
Economic and technological development	Disposable Income per Capita	Per Capita Disposable Income of Rural Residents (thousand CNY/person)	Negative Direction
	Machinery Density	Total Power of Agricultural Machinery/Area Sown (kW/ha)	Uncharted
Agricultural Production Inputs	Chemical Input per Unit Area	Agrochemical Inputs/Sown Area (tons/ha)	Uncharted
	Multiple Cropping Index	Grain Crop Planting Area/Cultivated Land Area (%)	Uncharted
	Irrigation Index	Irrigated Area/Total Sown Area of Crops (%)	Uncharted
	Government Financial Input Proportion	Government Expenditure on Agriculture, Forestry, and Water/Total Expenditure (%)	Forward

3.2.1. Impact Forecast of Resource Endowment

Resource endowment: In this study, two characterization indicators are selected for resource endowment: labor input per unit area and labor quality. Labor input can influence farming methods and improve farming efficiency, leading to increased desired output. However, excessive labor input may result in inefficient operation scale and hinder technological improvement and efficiency [45]. Therefore, the predicted impact of labor input on ecological efficiency is unknown. On the other hand, higher levels of education among the labor force are likely to promote the modernization and greening of agricultural operations, suggesting a positive impact.

3.2.2. Impact Forecast of Economic and Technological Development

Economic and technological development: This study utilizes per capita disposable income to measure the level of economic development and machinery density to measure the level of technological development. Among them, per capita disposable income can reflect the production stickiness of agricultural output to laborers, and the higher the per capita income level in agricultural production, the more likely it is for laborers to adopt a high-yield oil agricultural production mode. Therefore, the predicted impact of per capita disposable income on ecological efficiency is negative. Green technological innovation can significantly mitigate carbon emissions associated with cropland utilization [46]. The level of technological development is measured by agricultural machinery density. On one hand, higher agricultural machinery density enables more efficient production. On the other hand, excessively high agricultural machinery density consumes more petroleum-based fossil resources and subsequently creates pressure on the ecosystem, thus affecting the unknown prediction.

3.2.3. Impact Forecast of Agricultural Production Inputs

Agricultural production inputs. This study examines three characterization indicators: agricultural chemical inputs per unit area, multiple cropping index, irrigation index, and government financial input ratio. Agricultural chemical inputs per unit area, which include pesticides, fertilizers, and agricultural films, can increase desired output to some extent. However, they can also have negative effects, including leading to elevated carbon emissions from agriculture and highlighted environmental pollution. Consequently, the precise estimation of these impacts remains uncertain. The multiple cropping index and irrigation index have the potential to enhance agricultural output. However, the process of plowing cultivated land during multiple cropping can lead to the destruction of the soil's organic carbon pool, resulting in significant carbon emissions into the air [47]. Additionally, the irrigation process consumes electricity and indirectly contributes to carbon emissions by consuming fossil fuels [48]. Consequently, the impact prediction for these indicators is also uncertain. On the other hand, a higher proportion of government financial input can encourage producers to adopt green production technology and tools, facilitating the adoption of ecologically sustainable practices. Thus, the impact of government financial input is expected to be positive.

3.3. Data Sources

3.3.1. Regional Overviews

China's main grain-producing areas include 13 provinces, including Heilongjiang, Henan, Shandong, Anhui, Jilin, Hebei, Jiangsu, Inner Mongolia, Sichuan, Hunan, Hubei, Liaoning, and Jiangxi (Figure 2), which is located at longitude 97°12″~135°05″ E and latitude 24°29″~53°33″ N. Calculations from the data in the China Statistical Yearbook 2019 show that the grain sown in the area The total area is 88,568 square kilometers, and the annual grain output of each province reaches 2 million tons, totaling more than 500 million tons, accounting for about 78.8% of the country's total grain output, providing a solid guarantee for China's food security. Agricultural production in the region is relatively developed, with significant negative externalities. In terms of farming methods, the region mainly adopts modern agricultural farming methods, such as mechanical farming, precision fertilizer application, and drone plant protection, in order to improve the efficiency of agricultural production; however, the use of fertilizers, pesticides, and agricultural films and other agricultural materials in the region exceeds 70% of the nation's agricultural material use, and agricultural carbon emissions are significantly higher than those of other provinces in China. This suggests that agricultural production in the region has a greater impact on the environment and requires effective management measures to achieve sustainable development of agricultural production.

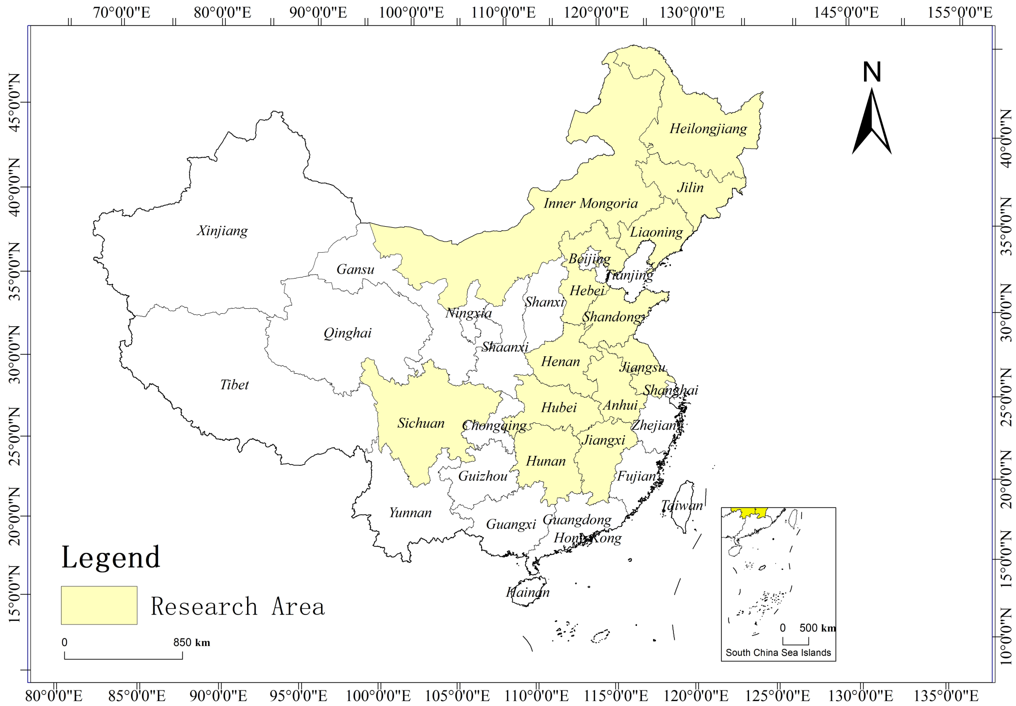

Figure 2. Overview of the research area.

3.3.2. Data Sources

Based on the present state of cropland utilization in China, this research focuses on measuring and analyzing the eco-efficiency of cultivated land utilization in the primary grain-producing regions from 2000 to 2019, taking into consideration the availability and timeliness of data. The data used for analysis include the following variables: area dedicated to grain crops, the extent of irrigation in cultivated land, the utilization of agricultural fertilizers, grain output, regional agricultural GDP, and labor inputs [49]. Information on employees in the primary industry is calculated by multiplying the number of employees in the primary sector by the agricultural output value divided by the gross output value of agriculture, forestry, animal husbandry, and fishery. Data on pesticide use, agricultural diesel, and agricultural plastic film are obtained from the China Rural Statistical Yearbook. The data on employees in the primary industry are sourced from the statistical yearbooks of provinces and cities, whereas the data on cropland region are gathered from the China Statistical Yearbook, bulletins issued by provincial departments of natural resources, and statistical yearbooks of provinces. For the period of 2011–2013, data on Heilongjiang are sourced from the "Prospect Database".

4. Results

4.1. Static Analysis of the Super-Efficient SBM Model

This section conducts a static analysis of the super-efficient stochastic frontier analysis (SFA) method to measure the eco-efficiency value of cropland utilization in China's primary grain-producing regions from 2000 to 2019. The analysis places emphasis on the indicators related to input and output. By organizing the measurement results, the efficiency value of cultivated land use for each year and sub-region is obtained, and the comprehensive efficiency is decomposed into total efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE), as illustrated in Table 3.

Table 3. Mean eco-efficiency in China's primary grain-producing regions, 2000–2019.

Year	Technical	Pure Technical Efficiency	Scale Efficiency
2000	0.839	0.974	0.862
2001	0.805	0.946	0.851
2002	0.760	0.941	0.807
2003	0.687	0.895	0.768
2004	0.778	0.927	0.839
2005	0.732	0.903	0.811
2006	0.740	0.901	0.822
2007	0.811	0.938	0.864
2008	0.812	0.930	0.873
2009	0.863	0.943	0.916
2010	0.843	0.932	0.904
2011	0.833	0.932	0.894
2012	0.837	0.912	0.917
2013	0.788	0.880	0.896
2014	0.798	0.853	0.935
2015	0.798	0.857	0.932
2016	0.818	0.878	0.932
2017	0.819	0.879	0.932
2018	0.839	0.891	0.942
2019	0.836	0.891	0.939
20-year average	0.801	0.910	0.880

4.1.1. Overall Summary of Ecological Efficiency

Overall, from 2000 to 2019, the average eco-efficiency value of cultivated land utilization in China's primary grain-producing regions was 0.801. The eco-efficiency values for each year were less than 1, indicating that they were unable to attain the production frontier. However, the average annual eco-efficiency values exhibited a slight upward trajectory (Figure 3). This suggests that the eco-efficiency of cropland utilization in China's primary grain-producing regions is at a comparatively high level and in a positive development trend. There is still potential for further enhancement in the coordination between the economy and the environment.

4.1.2. Overview of the Temporal Evolution of Ecological Efficiency

From a temporal perspective (Figure 3), the eco-efficiency of cropland utilization in China's primary grain-producing regions was categorized into three distinct stages during the study period. The years 2000–2003 experienced a period of decline, characterized by a significant downward trend in the eco-efficiency of cropland utilization. The decline might be attributed to the limitations in agricultural production levels and the extensive mode of agricultural management prevalent during that time. The period from 2003 to 2013 witnessed fluctuations in the utilization of cropland, characterized by a general upward trajectory. In 2003, China officially introduced the concept of "green agriculture" at the International Symposium on the Construction of Market Channels for Green Food and Organic Agriculture in the Asia–Pacific Region, signaling increased attention to the sustainable development of agriculture. As green agriculture was in its exploratory stage, the eco-efficiency of cropland utilization showed fluctuating growth. The period from 2013 to 2019 saw a stable and consistent increase in the eco-efficiency of China's primary grain-producing regions. The primary reason for this steady growth can be attributed to the 18th CPC National Congress prioritizing the construction of eco-civilization and introducing it as a strategic objective throughout economic and social development. Additionally, the central government's No.1 document gradually emphasized the construction of rural eco-civilization, further promoting the green development of agriculture and the concept of green land utilization [50]. Against this backdrop, the eco-efficiency of cropland utilization has demonstrated steady improvement.

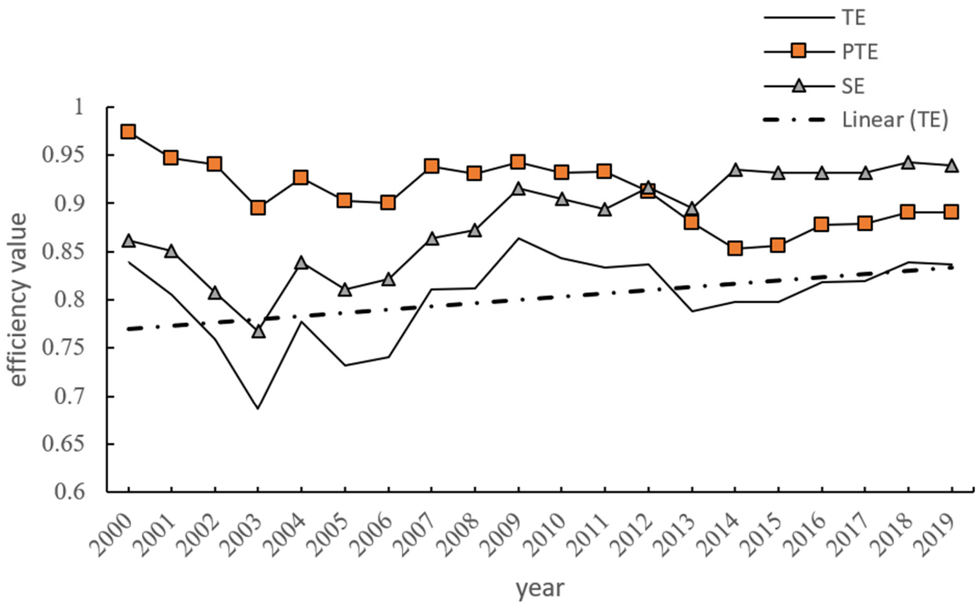

Figure 3. Trends in eco-efficiency of cropland utilization in China's primary grain-producing regions, 2000–2019.

4.1.3. Spatial Distribution of Ecological Efficiency

The spatial distribution of eco-efficiency in the primary grain-producing regions of China is divided into five intervals on the basis of the eco-efficiency value of the provinces. These intervals are (0, 0.6], (0.6–0.7], (0.7–0.8], (0.8, 1), and [1, 1.28], representing the low-efficiency zone, lower-efficiency zone, medium-efficiency zone, higher-efficiency zone, and high-efficiency zone, respectively. For the convenience of presentation, this paper classifies them into grades I to V in descending order of magnitude. Due to space limitations, this paper selects three representative year nodes for analysis (Figure 4).

In terms of provincial characteristics, the quantity of provinces situated within the level I efficiency zone has shown a steady increase. In 2003, only Jilin belonged to the level I efficiency zone. By 2013, Liaoning, Heilongjiang, and Sichuan were added, and Jiangsu was added by 2019. The number of provinces within the level II efficiency zone has been growing and gradually moving towards the level I efficiency zone. In 2003, it included Liaoning and Sichuan. By 2019, both provinces had transformed to the level I efficiency zone. As of 2019, four provinces (Jiangxi, Shandong, Hubei, and Hunan) belonged to the level II efficiency zone. The quantity of provinces within the level III efficiency zone tends to decrease as they gradually move toward the higher efficiency zone. In 2003, four provinces (Inner Mongolia, Heilongjiang, Jiangxi, and Hunan) were in this zone, which was reduced to two provinces (Shandong and Hunan) by 2013. By 2019, all provinces apart from Inner Mongolia had achieved a leap towards a higher level of efficiency zone. The quantity of provinces within the level IV efficiency zone initially increases and then decreases. In 2003, it included three provinces (Jiangsu, Shandong, and Hubei), which increased to include Inner Mongolia, Jiangxi, and Henan by 2013 and decreased to only two provinces (Inner Mongolia and Henan) by 2019. The quantity of provinces within the level V efficiency zone tends to stabilize. In 2003, it included three provinces (Hebei, Anhui, and Henan). In 2013 and 2019, it still included two provinces (Hebei and Anhui).

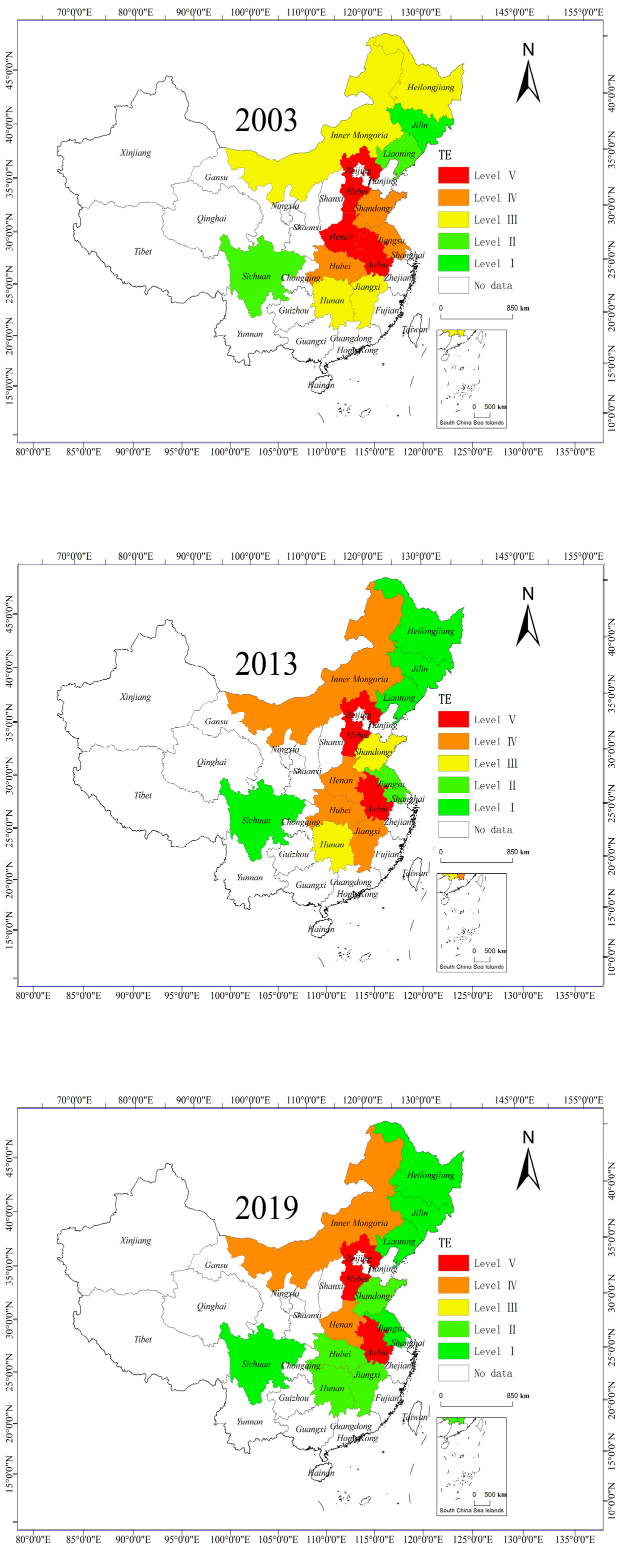

Figure 4. Distribution of eco-efficiency of cropland utilization by provinces in the primary grain-producing regions.

Considering the overall regional characteristics and in order to facilitate observation, this paper divides the main grain-producing regions into the eastern region (Hebei, Jiangsu, and Shandong), the central region (Anhui, Jiangxi, Henan, Hubei, and Hunan), the western region (Inner Mongolia and Sichuan), and the northeastern region (Heilongjiang, Jilin, and Liaoning), in accordance with the criteria of the National Bureau of Statistics (NBS) on the division of the economic zones. The eco-efficiency of cropland utilization in China's primary grain-producing regions in 2003, 2013, and 2019 showed high efficiency at both ends and lower efficiency in the middle. Cultivated land utilization eco-efficiency levels III~V are predominantly situated within the eastern and central regions of China, while levels I~II are primarily concentrated within the regions of northeastern and western. The ecological efficiency exhibited a shift in characteristics from 2003, with the pattern of Northeast > West > Central > East, to 2019, where it transformed to the pattern of Northeast > West > East > Central.

4.2. Dynamic Analysis of the Malmquist Index

The Malmquist index has the capability to effectively depict the dynamic trend of changes in ecological efficiency. This paper builds upon the previous analysis of eco-efficiency in cropland utilization in the primary grain-producing regions to examine the total factor productivity of eco-efficiency from 2000 to 2019 and decompose its components. The aim is to assess the trends and heterogeneity in eco-efficiency changes.

1. Overall Dynamic Efficiency Analysis

From the perspective of overall efficiency changes (refer to Table 4), the mean value of whole factor productivity of China's eco-efficiency in cultivated land utilization from 2000 to 2019 was 1.0525, indicating a growth trend with a rate of 5.25%. Throughout the 10-year study period, the total factor productivity of eco-efficiency in the primary grain-producing regions remained above 1. The lowest growth rate was observed during the time period of 2013–2014, with a rate of 0.34%, while the highest growth rate occurred in 2018–2019, with a rate of 13.75%. These findings indicate a steady increase in eco-efficiency in cultivated land utilization.

Table 4. Malmquist index and decomposition of cultivated land utilization in China, 2000–2019.

Year	Technical Effectiveness Rate Change	Technological Progress	Purely Technical Efficiency Rate of Change	Scale Efficiency Rate of Change	Total Factor Productivity
2000–2001	0.9593	1.0671	0.9721	0.9869	1.0237
2001–2002	0.9434	1.1054	0.9939	0.9493	1.0428
2002–2003	0.9048	1.0671	0.9510	0.9514	0.9655
2003–2004	1.1317	1.0000	1.0361	1.0922	1.1316
2004–2005	0.9411	1.0990	0.9743	0.9659	1.0342
2005–2006	1.0117	1.0346	0.9976	1.0142	1.0467
2006–2007	1.0946	0.9417	1.0412	1.0513	1.0308
2007–2008	1.0018	1.1113	0.9921	1.0098	1.1133
2008–2009	1.0633	0.9251	1.0135	1.0491	0.9837
2009–2010	0.9762	1.1161	0.9882	0.9879	1.0895
2010–2011	0.9886	1.1310	1.0005	0.9881	1.1182
2011–2012	1.0040	1.0619	0.9786	1.0259	1.0662
2012–2013	0.9420	1.1432	0.9643	0.9768	1.0768
2013–2014	1.0123	0.9912	0.9693	1.0444	1.0034
2014–2015	1.0003	1.0584	1.0042	0.9961	1.0587
2015–2016	1.0251	0.9975	1.0248	1.0003	1.0226
2016–2017	1.0013	1.0401	1.0015	0.9998	1.0415
2017–2018	1.0247	1.0057	1.0133	1.0112	1.0305
2018–2019	0.9967	1.1413	0.9997	0.9970	1.1375
2000–2019 Average	0.9998	1.0527	0.9953	1.0045	1.0525

Regarding values for the whole factor productivity decomposition, the average technological progress was found to be 1.0527, with a growth rate of 5.27%. In the past 10 years, there have been eight periods where the value of technological progress exceeded 1. Furthermore, technological efficiency reached 1.143 in 2018–2019, significantly higher than the average value. These results highlight the steady growth of technological progress and its significant role in improving eco-efficiency in cropland utilization in China. However, the average value of technological efficiency change was only 0.9998, indicating that the potential of new technology in cropland utilization in the primary grain-producing regions has not been fully realized. It is crucial to enhance coordination among various resource elements to fully unlock the potential of established technology levels.

In terms of technical efficiency change decomposition, the average scale efficiency rate of change in the technical efficiency decomposition value was 1.0045. Conversely, the average pure technical efficiency rate of change was 0.9953, consistently lower than the rate of change in scale efficiency. This finding suggests that the decline in pure technical efficiency is the main factor contributing to the overall decline in technical efficiency.

2. Regional Analysis of Dynamic Efficiency

Concerning provincial efficiency changes (Table 5), during the period spanning from 2000 to 2019, the average total factor productivity of eco-efficiency of cropland utilization in the 13 primary grain-producing regions of China was all greater than 1. This indicates that the eco-efficiency of cropland utilization in China's main grain-producing regions has been continuously improving, and the advancement of green cropland utilization has been consistently progressing well. Among these regions, Heilongjiang had the highest growth rate at 7.7%, while Anhui had the lowest at 3.75%.

Table 5. Total factor productivity of cultivated land utilization and ranking by region, 2000–2019.

Provinces	Technical Efficiency Changes	Technological Progress	Purely Technical Efficiency Rate of Change	Scale Efficiency Rate of Change	Total Factor Productivity	Total Factor Productivity Ranking
Hebei	0.9980	1.0509	0.9907	1.0074	1.0488	8
Inner Mongolia	0.9853	1.0608	0.9762	1.0093	1.0452	10
Liaoning	1.0096	1.0541	0.9991	1.0105	1.0642	2
Jilin	1.0018	1.0577	1.0014	1.0004	1.0596	3
Helongjiang	1.0121	1.0641	1.0092	1.0028	1.0770	1
Jiangsu	1.0089	1.0499	0.9994	1.0095	1.0592	4
Anhui	0.9929	1.0449	0.9859	1.0071	1.0375	13
Jiangxi	0.9936	1.0529	0.9887	1.0049	1.0462	9
Shandong	1.0058	1.0463	0.9983	1.0075	1.0523	6
Henan	1.0007	1.0434	1.0005	1.0002	1.0441	12
Hubei	1.0002	1.0491	1.0002	1.0000	1.0494	7
Hunan	0.9889	1.0559	0.9889	1.0000	1.0442	11
Sichuan	1.0005	1.0553	1.0009	0.9996	1.0558	5
Eastern China	1.0127	1.1544	0.9884	1.0245	1.1690	1
Western China	0.9928	1.0581	0.9885	1.0044	1.0505	3
Central China	0.9953	1.0492	0.9929	1.0024	1.0442	4
Northeastern	1.0078	1.0586	1.0032	1.0046	1.0669	2
Average Value by Region	0.9998	1.0527	0.9953	1.0045	1.0525	-

The elevation in cropland eco-efficiency in each province is primarily attributed to technological progress and changes in technological efficiency, with technological progress being the dominant factor. However, Hebei, Inner Mongolia, Anhui, Jiangxi, and Hunan face constraints due to technological efficiency changes. Consequently, these regions should actively allocate resources to harmonize their utilization, promote the adoption of advanced technologies, and harness the potential of their technological advancements. On the other hand, the remaining regions benefit from both technological progress and changes in technical efficiency, but the latter is much lower than the former. Therefore, simply investing in technological development is insufficient; the regions must also focus on transforming technological achievements.

Considering the overall regional efficiency changes, the average total factor productivity of eco-efficiency for cropland utilization in Eastern, Central, Western, and Northeastern China from 2000 to 2019 was 1.169, 1.0442, 1.0505, and 1.0669, respectively. These values demonstrate a trend of the eastern region > northeastern region > western region > central region, and the eco-efficiency of cropland utilization across all regions shows an upward trend. In addition to this, all four regions exhibit a technological progress index that surpasses a value of 1, implying a relatively deep adoption of new technologies and agricultural production methods. The technology efficiency change index in both the central and western areas is less than 1, indicating lower resource efficiency during the course of cropland utilization. This requires a focus on resource coordination and enhancement of land use management capabilities in cropland utilization, thereby enhancing technology efficiency change. The pure technical efficiency change rate index in the eastern region is less than 1, suggesting that the decrease in pure technical efficiency is a major factor restricting the technology efficiency change index.

5. Analysis of Influencing Factors

In this paper, the ecological efficiency of farmland utilization in major grain-producing areas was analyzed and evaluated by using the super-efficiency SBM model. To further investigate the factors that influence the eco-efficiency of land utilization, this research applies the Tobit model to analyze panel data spanning the years 2000 to 2019. The findings of the analysis are shown in Table 6.

Table 6. Panel Tobit regression results on factors influencing eco-efficiency of cropland in primary grain-producing regions.

Variables	Coefficient	Standard Deviation	*p*-Value	95% Confidence Interval	Significance
Labor input per unit	0.006	0.002	0.007	0.002~0.011	***
Quality of labor force	−0.024	0.023	0.287	−0.692~−0.021	
Per capita disposable income	−0.001	0.002	0.641	−0.005~0.003	
Mechanical density	0.007	0.005	0.144	−0.002~0.016	
Chemical inputs per unit area	−0.038	0.008	0.000	−0.053~−0.023	***
Multiple-crop index	0.028	0.041	0.49	−0.052~0.108	
Irrigation index	0.245	0.123	0.046	0.004~0.486	**
Proportion of government financial input	0.011	0.003	0.001	0.004~0.170	***
Constant	0.8677	0.177	0.000	0.523~1.213	***
Log likelihood = 271.20155				Prob ≥ chibar2 = 0.000	

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

The regression analysis confirms that the labor input per unit area, chemical input per unit area, irrigation index, and government financial input ratio have passed the significance test, thus warranting further analysis.

1. Impact Analysis of Labor Input per Unit Area

Tt is crucial to strengthen agricultural scientific and technological innovation and enhance the level of intensive land utilization. This can be achieved by actively promoting the use of new agricultural technologies and abandoning traditional rough farming methods. Technologies such as modern drip irrigation, soil improvement techniques, and uncrewed aerial vehicle spraying should be introduced to support the development of "intensive farming". The utilization of modern science and technology in agriculture will accelerate the green low-carbon transformation of the utilization of arable land and improve its ecological efficiency.

2. Explore Distinct Approaches to Reduce Regional Disparities

This study highlights significant variations in ecological efficiency across various regions within the primary grain-producing zones. Regions with high ecological efficiency should leverage their spillover effects to enhance the ecological efficiency of surrounding areas. Conversely, areas exhibiting low ecological efficiency values necessitate proactive exploration of low-carbon and efficient agricultural development models, accompanied by the formulation of corresponding countermeasures, an increase in policy support, and the enhancement of regional ecological efficiency.

3. Establishing the Concept of Green Production and Reducing the Utilization of Chemical Inputs in Agriculture

For one thing, this study provides agricultural producers with multi-level and multi-faceted training on new agricultural green technologies and ideological education in order to enhance farmers' awareness of green production. For another, this increases the input of green production elements. In diverse geographical areas, according to the actual conditions of cropland utilization, we should reduce or substitute the usage of agricultural chemical inputs, including fertilizers, pesticides, and plastic films.

6. Conclusions

On the basis of the panel data of 13 provinces in China's primary grain-producing regions spanning the years 2000 to 2019, this study examines the ecological efficiency of cultivated land utilization using the super-efficiency SBM model and the Malmquist index model to analyze static and dynamic changes, respectively. Additionally, this study employs the random-effect panel Tobit model to explore the factors that influence ecological efficiency. The key discoveries are as follows:

1. Overview of the Trend in Ecological Efficiency Changes

From the perspective of the trend in ecological efficiency values, the cultivation of land in China's primary grain-producing regions exhibited a high level of ecological efficiency from 2000 to 2019. Although the efficiency values did not reach the production frontier, they displayed an overall upward trend. The eco-efficiency experienced three periods: decline, fluctuation, and steady increase. Overall, China's cultivated land utilization eco-efficiency has shown significant progress, with ample room for further improvement. The average total factor productivity of ecological efficiency in these areas during the study period exceeded 1, indicating a positive growth trend. The analysis of the whole factor productivity decomposition reveals that the limitation on the growth of it can be attributed to a decline in the value of technology efficiency change. Therefore, attention should be given to the conversion rate of agricultural scientific and technological achievements and the unlocking of the potential of emerging technologies.

2. Significant Regional Differences in Ecological Efficiency of Cropland

Regional disparities in the eco-efficiency of cropland utilization are apparent in China. Considering ecological efficiency, the utilization of cropland in China's primary grain-producing regions demonstrates a distinct pattern characterized by high efficiency at the extremes and comparatively lower efficiency in the central areas. Provinces with high ecological efficiency are generally distributed in the northeast region. The regional differences, which were characterized by the northeast > west > central > east in 2003, have changed to the characteristics of the northeast > west > east > central in 2019. Analyzing total factor productivity, there is substantial variation among provinces, but all of them exhibit a growth trend, resulting in an overall pattern of East > Northeast > West > Central. Among them, the western and central regions experience a declining trend in technical efficiency change, which has become the main factor constraining the growth of ecological efficiency. The eastern region exhibits a downward trend in the rate of change of pure technical efficiency, which became the main reason limiting the growth of technological efficiency.

3. Diversity of Influencing Factors on Ecological Efficiency

Regarding the factors influencing eco-efficiency, different degrees of influence are observed in labor input per unit area, irrigation index, chemical input per unit area, and government financial input ratio for cultivated land use. In particular, chemical input per unit area has a negative effect, while labor input per unit area, irrigation index, and government financial input have a positive impact on eco-efficiency.

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