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Agricultural Production Efficiency and Differentiation of City Clusters along the Middle Reaches of Yangtze River under Environmental Constraints

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Abstract: The improvement of overall agricultural efficiency in the city clusters along the middle reaches of the Yangtze River is crucial for promoting stable regional agricultural production and ensuring food security. This study employs the SBM (slack-based measure) model with the unexpected environmental output, including agricultural surface pollution and agricultural carbon emissions, and the SFA (stochastic frontier approach) model to investigate the overall agricultural efficiency and its influencing factors in 31 prefecture-level cities in the middle reaches of the Yangtze River urban agglomeration from 2008 to 2021. The research findings indicate the following: (1) Without eliminating the impact of environmental variables, the overall agricultural efficiency in the middle reaches of the Yangtze River city clusters shows a rise–fall–stability trend and limited level. The scale of production input is relatively reasonable, but there is inefficiency in the utilization of factor resources. (2) The SFA model reveals that economic development, urbanization construction, industrial structure, and government influence have significant but different impacts on agricultural production factor input. Accelerating economic development is helpful for reducing excessive inputs of agricultural capital, labor, planting area, agricultural film, and irrigation. Increasing the level of urbanization can promote the efficient allocation of planting area and effective irrigation area. The improvement of industrialization level pushes the rational input of planting area and agricultural film, but it may also lead to excessive input of agricultural capital, labor, pesticides, and effective irrigation area. Expanding government influence can restrain the excessive use of pesticides. (3) After eliminating environmental variables, there is a low and slow declining trend of the overall agricultural efficiency over time. Neither production scale efficiency nor pure technical efficiency reached optimal levels; the former one is significantly lower than the latter. In terms of spatial distribution, there exists a “higher in the west and lower in the east” feature, with obvious and expanding regional efficiency differences and high-efficiency areas gradually concentrating in the Wuhan urban circle. In summary, this article puts forward the following suggestions: optimize the structure of the government’s support for agriculture, focusing on the construction of agricultural infrastructure and the support for green production in agriculture; improve the research and development and promotion of green production technology and encourage the establishment of the use of resources and recycling; and absorb the population of farmers who have been transferred to urban areas reasonably and orderly under the adjustment of industrial structure.

Keywords: city clusters along the middle reaches of Yangtze River; environmental constraints; heterogeneous analyses; overall agricultural efficiency; unexpected output SBM model; SFA model



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1. Introduction

The city clusters along the middle reaches of Yangtze River, connecting east and west as well as north and south, play an indispensable role in the pattern of regional development in China. In April 2015, the State Council approved the implementation of the

“Development Plan for City Clusters along the Middle Reaches of Yangtze River” [1]. The city clusters along the middle reaches of Yangtze River have become a new growth pole for China’s economic development. The urban agglomeration in the middle reaches of the Yangtze River is also one of China’s main grain-producing areas, and it plays a strategic role in China’s food security, but there exists an increasing gap between the region’s agricultural and economic development. The urban—rural dual structure has led to serious phenomena such as the massive loss of rural labor and the encroachment of agricultural resources by urban development [2]. Taking the secondary city clusters along the middle reaches of the Yangtze River—the urban agglomeration around Changsha-Zhuzhou-Xiangtan—as an example, in 2018, the rural labor force in the region decreased by about 0.19 million people, and the arable land decreased by about 4.3 thousand hectares. The massive loss of agricultural production factors is a serious threat to the region’s stable agricultural production and food security. Under the rigid constraints of production factors, it is necessary to study the agricultural production efficiency in the region and explore how to promote the effective allocation of production factors and enhance agricultural production efficiency. The mismatch of agricultural capital, labor, and land hinder the improvement of agricultural production efficiency to a large extent [3]. Therefore, it is of great significance to study the overall efficiency of agricultural production and analyze the driving factors in the city clusters along the middle reaches of Yangtze River under the decreasing production factors. For example, agricultural labor helps promote the improvement of the regional agricultural production efficiency and guarantee food security.

Agricultural production efficiency has always been a hot topic for scholars. Some scholars have tried to analyze the level of agricultural production efficiency through the construction of evaluation index system qualitatively and quantitatively. Previous studies evaluated the level of China’s agricultural development in terms of resource-saving utilization, environmental protection, and production supply capacity [4]. Some scholars constructed an evaluation index system to analyze the level of China’s agricultural development [5]; to set evaluation standards for the level of low-carbon agricultural development [6]; and to evaluate the level of sustainable agricultural development in China [7]. Although scholars try to construct a comprehensive index system of agricultural production efficiency as best they can and fully consider the factors of ecological environment, the conventional evaluation index system can only be suitable in the overall situation to evaluate the level of agricultural production, while it cannot facilitate a good response to the efficiency of regional agricultural production. Regarding the measurement of efficiency, scholars generally use the data envelopment model (DEA), and this model is also widely used in the study of agricultural production efficiency. The DEA model was formally proposed by Charnes in 1978 [8], followed by scholars such as Restuccia and Vollrath, who used this model to analyze the problem of agribusiness efficiency in the world [9,10]. Ruttan used this model to explore the regional agricultural production efficiency under the factor constraints of environment, resources, and scientific and technological innovation [11]. In recent years, Chinese scholars have also used the DEA model to measure agricultural production efficiency. Scholars utilized the method to measure interprovincial agricultural total factor productivity in China [12]. Xing [13] discussed the influencing factors based on the efficiency measure using the Tobit model. DEA models are divided into radial and non-radial models. The radial DEA model assumes that input and output vary proportionally, while the non-radial model relaxes this assumption, allowing them to vary disproportionately. Moreover, the traditional radial model usually underestimates the directional distance function of the model when evaluating the input–output efficiency of agricultural production, which is unfavorable for reflecting the actual efficiency of each decision unit [14]. In order to overcome this problem, the non-radial data envelopment model has been gradually applied in the evaluation of agricultural production efficiency. It can be used to study the comprehensive efficiency of agricultural production in counties of Hebei Province [15]. The efficiency of agricultural production in Heilongjiang Reclamation Area was evaluated, with which scholars further analyzed the influencing factors by using

the FGLS (feasible generalized least squares) model [16]. The traditional DEA model cannot eliminate the interference of management and stochastic factors on the efficiency, so some scholars have introduced the stochastic frontier method (SFA) to propose the three-phase DEA model, taking environmental variables into account, and applied the three-stage DEA model to study the efficiency of agricultural production in 2008 [17]. Urbanization level, industrial development level, transportation status, financial support, and other factors have been taken as environmental variables in the studies [18–20].

Ecological environmental protection has raised increasing attention in society, and more and more scholars have begun to explore the problem of environmental pollution generated in agricultural production. Environmental pollution is a non-desired output of agricultural production, and ignoring this output in the measurement of agricultural production efficiency will inevitably lead to biased results [21]. The previous DEA model could not analyze the efficiency measurement including non-expected outputs, so some scholars proposed the SBM model with environmental pollution non-expected outputs [22]. Pan and Lv incorporated the agricultural non-point source pollution into non-desired outputs to measure the level of agricultural production efficiency [23,24]. A few studies have measured the agricultural environmental efficiency and agricultural green total factor productivity by applying the SBM model with carbon emission as the non-expected output [25–27]. In addition, some scholars adopted the nitrogen surplus of agricultural land and agricultural non-point source pollution as the non-desired outputs of agricultural production [28,29]. Some scholars have taken the Yellow River Basin and the Yangtze River Economic Belt as objectives to explore the problem of agricultural production efficiency with the negative externalities of production [30,31].

Nowadays, there are many studies focusing on agricultural production efficiency, but they still have some shortcomings. Firstly, the existing studies are mostly focused on the macro level of the country or the province, and the practical guiding significance of the conclusions and recommendations is limited. Secondly, there is a relative lack of studies based on the micro level of the municipal area; most of the studies are limited to a single province, so there is a lack of inter-regional coordinated analysis. In addition, the existing studies mainly take capital, labor, and land into consideration. They lack consideration of non-desired outputs such as environmental pollution of agricultural production, which results in an inaccurate result of real overall agricultural production efficiency of the region.

The middle reaches of the Yangtze River, as an important grain-producing area in China, are endowed with unique agricultural resources. According to statistics, in 2021, the grain output of the middle reaches of the Yangtze River accounted for 11.76% of the national total production, making a great contribution to China's food security. However, due to the long history of agriculture and dense population in the region, there is a trend of shrinking proportion and increasing fragmentation of arable land. This helps increase application of agrochemicals, surface source pollution, and agricultural carbon emission, and other problems are becoming more and more prominent. The middle reaches of the Yangtze River are now facing the challenge of sustainable development of agriculture. Based on this, this paper takes 31 prefecture-level cities in the middle reach of the Yangtze River from 2008 to 2021 as an example, using the SBM model and the SFA model with the undesired outputs of the environment to analyze the overall agricultural production efficiency with the hope of finding the influencing factors from both macro and micro perspective and paths of agricultural efficiency under environmental constraints. Moreover, the study aims to provide new ideas for the city clusters along the middle reaches of Yangtze River, improve the overall efficiency of agriculture, and guide the transformation and upgrading of regional agricultural production. This article clarifies the correlation between environmental factors, management factors, and agricultural production efficiency, enriching the theoretical foundation of agricultural environmental governance. At the same time, the applicability of SBM model and SFA model is expanded, which provides useful supplements to the governance factors in current agricultural production.

2. Model

2.1. Stage 1: SBM Modeling of Undesired Outputs

This paper constructs the most optimal production frontier for each year for the 31 prefectural cities in the middle reaches of the Yangtze River as a decision unit. Assume that each decision unit has m input terms and s_1 desired output terms with s_2 non-desired output terms; the matrix form can be expressed, respectively, as $X = [x_1 \cdots x_{31}] \in R^{m \times 31}$; $Y^g = [y_1^g \cdots y_{31}^g] \in R^{s_1 \times 31}$; $Y^b = [y_1^b \cdots y_{31}^b] \in R^{s_2 \times 31}$; $X > 0$, $Y^g > 0$, $Y^b > 0$; the production possibility frontier of the resulting decision unit P can be expressed as follows:

$$P = \left\{ (x, y^g, y^b) \mid x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, \lambda \geq 0 \right\} \quad (1)$$

In Equation (1), $\lambda \in R^{31}$ is the intensity vector that assigns weights to each observation when constructing the production set, assuming constant returns to scale since no constraints are imposed on their sum. In the case of constant returns to scale, it can improve the stability of the research in this paper, and assuming constant returns to scale is a common situation in applying the SBM model, so this paper assumes constant returns to scale. To bring the decision unit under the condition of non-desired outputs, $DMU_1(x_1, y_1^g, y_1^b)$ is efficient to reach the optimal frontier; then, its input–output term needs to satisfy the following conditions: $x_1 \leq x$, $y_1^g \geq y^g$, $y_1^b \leq y^b$, and $(x, y^g, y^b) \in P$. Therefore, the non-expected output SBM model constructed in this paper is specified as follows:

$$\rho = \min \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{io}}}{1 + \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{ro}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{ro}^b} \right)} \quad (2)$$

$$\begin{cases} x_o = X\lambda + s^- \\ y_o^g = Y^g\lambda - s^g \\ y_o^b = Y^b\lambda + s^b \\ s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0 \end{cases} \quad (3)$$

where the vector $s^- \in R^m$ and $s^b \in R^{s_2}$ denote the excess of the decision unit input term and the undesired output term, respectively. $s^g \in R^{s_1}$ denotes the amount of shortfall in the desired output of the decision unit, while $0 < \rho \leq 1$. Under the non-desired output condition, when $\rho = 1$, $s^- = 0$, $s^g = 0$, and $s^b = 0$, the production efficiency of the decision unit reaches the optimal frontier; when $0 < \rho < 1$, the optimal frontier is not reached, which means that the production efficiency can be improved by optimizing the input–output structure of the decision unit.

2.2. Stage 2: Similarity SFA Analytical Model

The efficiency values obtained from the non-expected SBM model in the first stage are affected by the external environment, random errors, and internal management factors. The influence of these three factors can be eliminated by using the similar SFA analysis model as follows:

$$S_{mn} = f(z_n; \beta^m) + v_{mn} + u_{mn}a \quad (4)$$

where $m = 1, 2, \dots$ denotes the first m input; $n = 1, 2, \dots$ indicates the first n input; S_{mn} indicates the first n decision unit and m the slack variables for the inputs; z_i and β^m denote the environment variables and parameters to be estimated, respectively; $f(z_n; \beta^m)$ denotes the effect of environmental variables on the redundant variables S_{mn} . As scholars usually do, in this study, we chose to use $f(z_n; \beta^m) = z_n * \beta^m$. Equation (4) $v_{mn} + u_{mn}$ is the composite error term. $v_{mn} \sim N(0, \delta_{vm}^2)$ reflects the effect of statistical noise, and $u_{mn} \geq 0$ reflects managerial inefficiencies. We assume that u_{mn} obeys a half-normal distribution $\mu_{mn} \sim N^+(0, \delta_{um}^2)$, and v_{mn} and u_{mn} are independent of each other and of

the environment variables. It is a good idea to make $\gamma = \delta_{um}^2 / \delta_{um}^2 + \delta_{vm}^2$; when γ tends to 1, managerial factors have the greatest influence in the inefficient decision-making unit; when γ tends to 0, random interference factors have the greatest influence.

Using the measurements of Equation (3), the input and output data of each decision-making unit were adjusted as shown in Equation (5):

$$\begin{aligned} x_{mn}^A &= x_{mn} + [\max_n \{z_n \hat{\beta}^m\} - z_n \hat{\beta}^m] + [\max_n \{\hat{v}_{mn}\} - \hat{v}_{mn}], n = 1, 2, \dots; m = 1, 2, \dots, \\ y_{mn}^{gA} &= y_{mn}^g + [\max_n \{z_n \hat{\beta}_{mn}^g - z_n \hat{\beta}_{mn}^g\}] + [\max_n \{\hat{v}_{mn}^g\} - \hat{v}_{mn}^g] \\ y_{mn}^{bA} &= y_{mn}^b + [\max_n \{z_n \hat{\beta}_{mn}^b - z_n \hat{\beta}_{mn}^b\}] + [\max_n \{\hat{v}_{mn}^b\} - \hat{v}_{mn}^b] \end{aligned} \quad (5)$$

where x_{mn}^A denotes the input-adjusted values, and y_{mn}^{gA} and y_{mn}^{bA} denote the adjusted desired and non-desired output values, respectively.

2.3. Stage 3

The input–output efficiencies were estimated again by applying the non-desired output SBM model in conjunction with the adjusted input and output volumes. The input–output efficiencies were estimated to eliminate the effects of environmental variables and random errors this time.

3. Data and Indicators

3.1. Data Sources

Based on the “Development Plan for City Clusters along the Middle Reaches of the Yangtze River”, this paper takes 31 prefecture level cities in the Middle Reach of the Yangtze River as objective and divides them into three sub-city clusters: (1) Wuhan city group (urban agglomeration around Wuhan in Hubei Province): Wuhan City, Huangshi City, Jingzhou City, Yichang City, Xiangyang City, Ezhou City, Jingmen City, Xiaogan City, Huanggang City, Xianning City, Xiantao City, Tianmen City, and Qianjiang City; (2) Chang-Zhu-Tan city group (the Changsha-Zhuzhou-Xiangtan city group in Hunan Province): Changsha City, Zhuzhou City, Xiangtan City, Hengyang City, Yueyang City, Changde City, Yiyang City, and Loudi City; and (3) Poyang Lake city group (clusters around Poyang Lake in Jiangxi Province): Nanchang City, Jingdezhen City, Pingxiang City, Jiujiang City, Xinyu City, Yingtan City, Ji'an City, Yichun City, Fuzhou City, and Shangrao City. Among these, Huanggang City, Xianning City, Xiantao City, and Ezhou City were excluded due to serious missing data. The geographical location of the city clusters along the middle reaches of the Yangtze River in China is shown in Figure 1. The data of input–output variables and external influencing factors of agricultural production in this paper come from “Statistical Yearbook of Hubei Province”, “Statistical Yearbook of Hunan Province”, “Statistical Yearbook of Jiangxi Province”, and “Statistical Yearbook and Statistical Bulletin of Prefecture-level Municipalities” in 2009–2022 [32–35]. For the missing data, this paper uses quadratic exponential smoothing to supplement them and prevent model-run failures caused by 0 values in the raw data.

3.2. Selection of Indicators

3.2.1. Input–Output Indicators

Based on the data availability and consistency of statistical caliber, the total output value of agriculture, forestry, animal husbandry, and fishery in municipalities was selected as the desired output variable, and the agricultural carbon emissions and agricultural non-point source pollution were selected as the non-desired output variables [36]. Considering the inflation and taking 2008 as the base period, the gross output value of agriculture, forestry, animal husbandry, and fishery was converted by the index of their gross output value, and the converted gross output value was used as the desired output variable.

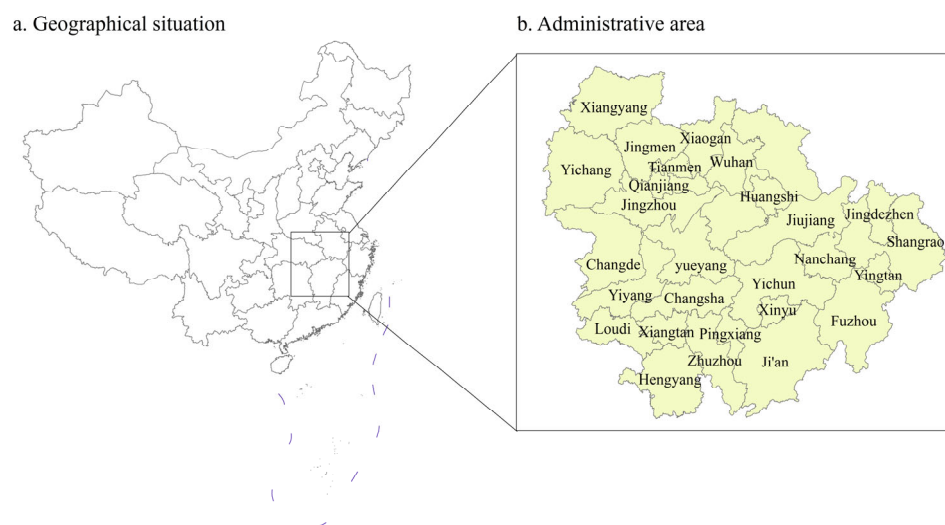


Figure 1. The geographical location of the city clusters along the middle reaches of the Yangtze River in China.

Agricultural production cannot exist without factors such as agricultural capital, labor, land, fertilizer, pesticide, agricultural film, and irrigation. Due to the lack of statistical data on agricultural capital, the degree of agricultural electrification, i.e., the total power of agricultural machinery, was selected as a proxy variable for capital input. Labor force was selected as the labor input of agriculture, forestry, animal husbandry, and fishery in each municipality. Since the shifting and abandonment of cultivation in different regions, the cultivated area cannot represent the land input situation, so the sown area of crops in different regions was adopted as the land input. Effective irrigation area can reflect the degree of hydration of agricultural production and the drought-resistance ability of arable land, so effective irrigation area was taken as one of the input factors. Agricultural fertilizer can improve soil fertility and is also an important measure to increase the yield of crops per unit area, so it was selected as an input indicator of agricultural production. Pesticides can prevent diseases, insects, grass, and other hazards to crops and are indispensable agricultural production materials. Agricultural film is conducive to crop germination and seedling emergence, which improves the soil's ability to retain water and fertilizer. As an important factor in stable and high agricultural production, it was used as an input element.

With reference to the earlier studies [15,37,38], when measuring the total agricultural carbon emissions in each city combined with the selection of input indicators, the study estimated the carbon emissions from agricultural farming and irrigation, pesticides, agricultural films, agricultural fertilizer use, agricultural electrification, etc. Due to the diversity and complexity of agricultural carbon emission sources, the formula constructed for calculating the total agricultural carbon emissions is as follows:

$$E_t = \sum E_{ti} = \sum S_{ti}\theta_i \quad (6)$$

where E_t is the total carbon emissions from agricultural production; E_{ti} denotes t city and i carbon emissions from the carbon source category; S_{ti} denotes t city i amount of inputs from the class of carbon sources; θ_i denotes the number of i carbon emission coefficients for each type of carbon source. The carbon emission coefficients for each type of carbon source are shown in Table 1. During analysis, CO_2 and N_2O were uniformly converted to standard carbon.

Agricultural non-point pollution was calculated with reference to the previous studies [39], which use the equal weight assignment method (each weight was 0.25), and measured by the weighted value of the average input of fertilizer, pesticide, and agricultural film.

Table 1. Carbon emission factors for major carbon sources.

Carbon Source	Emission Factor	Reference Source
Agricultural tillage and irrigation	579.0800 kg/hm ²	ORNL (Oak Ridge National Laboratory, USA)
Pesticide	4.9341 kg/kg	ORNL (Oak Ridge National Laboratory, USA)
Agricultural film	5.1800 kg/kg	IREEA (Institute of Agricultural Resources and Ecology, Nanjing Agricultural University)
Fertilizer use	0.8956 kg/kg	[40]
Agricultural electrification	Average carbon emission factor of electricity kg/kWh	[41]

3.2.2. Description of Indicators of External Environmental Factors of Overall Agricultural Efficiency

Based on the availability of data and the related literature [42–45], this study hypothesized that the external drivers of overall agricultural efficiency in the city clusters along the middle reaches of the Yangtze River are mainly divided on the following four aspects:

(1) Economic development: This paper uses per capita GDP to measure the level of regional economic development. The level of economic development is a key factor affecting a region's technology level, environmental protection inputs, etc., which will impose greater impact on the overall efficiency of regional agriculture;

(2) Urbanization development: The proportion of the urban population to the total population stands for the level of urbanization development. In the process of urbanization expansion, the agricultural population will migrate to cities, making it easier to consolidate the fragmented arable land, thus promoting the large-scale operation of agricultural production, which will finally affect the overall agriculture efficiency within the region;

(3) Industrial structure: The proportion of the secondary industry is used to indicate the factors of regional industrial structure. Most of the existing studies found that industrial structure plays an important role in the resource utilization, such as the stage and mode of regional industrial development. Whether the type of industry is highly water-consuming or high-polluting or not, it will affect the overall efficiency of regional agriculture;

(4) Government influence: This paper uses the government's expenditure budget on agriculture, forestry, and water affairs to measure the influence of regional governments. The government's investment in the construction of water infrastructure, guidance for industrial transformation, and related environmental policies all play an important role in the overall efficiency of regional agriculture.

The selection and interpretation of indicators for measuring agricultural production efficiency in the city clusters along the middle reaches of the Yangtze River are shown in Table 2.

Table 2. Categories of Indicator Selection and Interpretation.

Indicator	Variables	Variables Interpretation
Inputs	Agricultural capital X_1	Total power of agricultural machinery (billion watts)
	Agricultural labor force X_2	Number of people employed in agriculture, forestry, animal husbandry, and fishery (10,000 people)
	Land X_3	Area sown with crops (thousands of hectares)
	Fertilizer X_4	Fertilizer use (million tons)
	Pesticides X_5	Pesticide use (tons)
	Agricultural film X_6	Agricultural film use (hundred tons)
	Irrigation X_7	Effective irrigated area (thousand hectares)
Output	Expected output Y_1	Agriculture forestry, livestock, and fisheries GDP (billion yuan)
	Undesired output Y_2	Total carbon emissions from agriculture (tons) Agricultural surface source pollution (tons)

Table 2. Cont.

Indicator	Variables	Variables Interpretation
External Environment	Economic development E_1	Per capita GDP (million yuan)
	Urbanization development E_2	Share of urban population in total population
	Industrial structure E_3	Share of secondary industry
	Government influence E_4	Government expenditure on agriculture, forestry, and water resources (ten thousand yuan)

Based on the previous analysis, the theoretical relationship between factor allocation, external environment, and agricultural production efficiency can be seen in Figure 2.

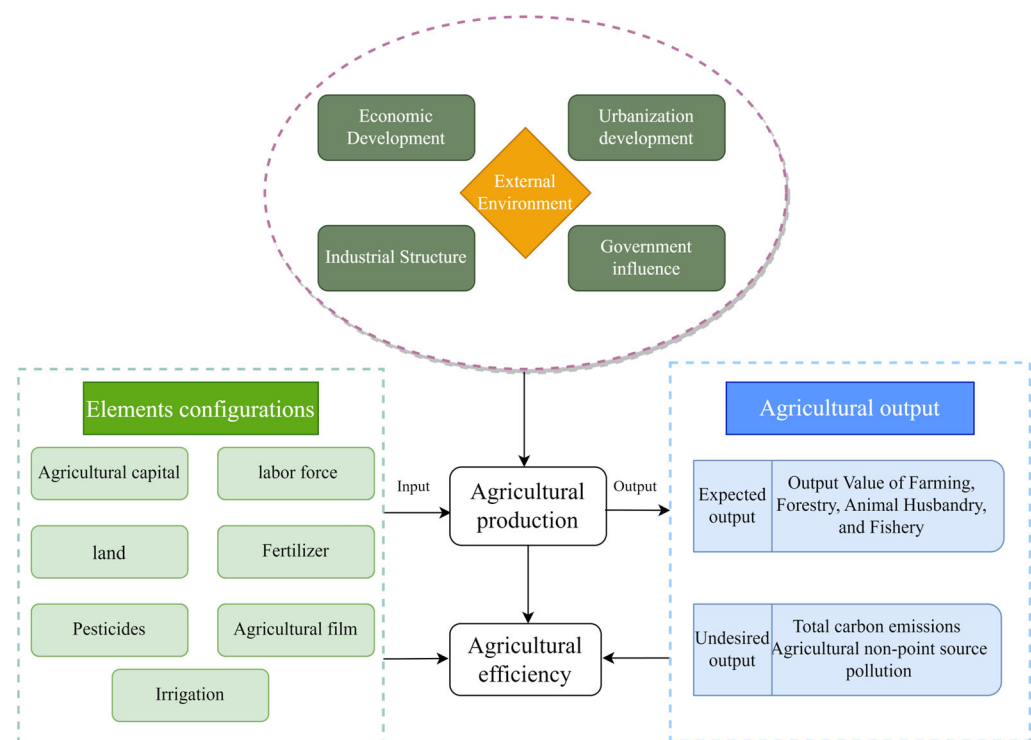


Figure 2. Theoretical framework of factor allocation, external environment, and agricultural production efficiency.

4. Empirical Analysis

4.1. Phase 1: SBM Model Analysis of Non-Expected Outputs

Based on the input–output indicator system of agricultural production and the SBM model of non-expected output, the measurement results of the comprehensive agricultural efficiency value and the characteristics of time variation of the city clusters along the middle reaches of the Yangtze River from 2009–2021 are shown in Figure 3.

Overall agricultural efficiency shows an upward–declining–steady trend, with obvious stage changes in efficiency. The comprehensive efficiency of agriculture sharply declined from 0.744 in 2008 to 0.486 in 2021. The first turning point appeared in 2009, which reached the highest point of 0.825, then showed a decreasing trend year by year after 2009; the second turning point appeared in 2013, and the comprehensive efficiency of agricultural production declined to the relative low point of 0.466. The scale effects of agricultural green production are good; the level of pure technical efficiency is lower than scale efficiency. As a whole, the average value of comprehensive efficiency in the city clusters along the middle reaches of the Yangtze River in 2008–2021 is 0.609, which is not a high level. The average level of scale efficiency is 0.820, and the average level of pure technical efficiency is 0.736.

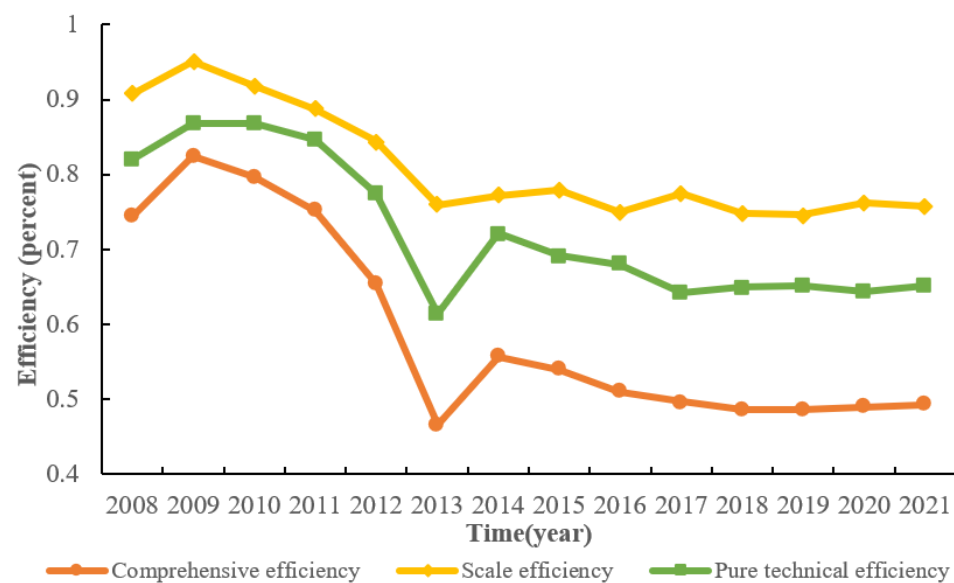


Figure 3. Decomposition of Agricultural Comprehensive Efficiency and Temporal Characteristics in the City Clusters along the Middle Reaches of the Yangtze River from 2008 to 2021.

The first stage of efficiency measurement contains the influence of environmental variables and random factors, which cannot truly reveal the actual situation of agricultural production efficiency in the city clusters along the middle reaches of the Yangtze River; it was therefore necessary to further eliminate the interference of exogenous variables.

4.2. Stage 2: SFA Model Analysis

The redundancy value of each input variable in the first stage SBM model was used as an explanatory variable, and the external environmental factors of agribusiness efficiency were used as explanatory variables. The paper uses Frontier 4.1 software for SFA regression, whose results are shown in Table 3.

Table 3. Stage 2: SFA regression results.

Slack Variables	Capital X_1	Labor X_2	Land X_3	Fertilizer X_4	Pesticides X_5	Agricultural Film X_6	Irrigation X_7
The constant term	−7041.21 ***	−139.722 ***	6133.37 *	−10.454	−8.921	−228.61 *	304.701 ***
Economy E_1	−0.316 ***	−0.0001 **	−0.1251 **	0	0.323	−0.17435 *	−0.0006 ***
Town E_2	1515.33 ***	1.710 ***	−1368.23 ***	−0.037	5.257 ***	−0.8291	−2.318 ***
Industry E_3	52,660.75 ***	67.183 **	−2735.98 *	15.108	47.543 **	−218.258 **	101.266 **
Government E_4	0.016 *	0.0001 ***	161.13	0.000017 ***	−0.011 **	149.24	0.00015 ***
σ^2	1.34×10^9 ***	3273.3 ***	484,373.1 ***	136.555 ***	2765.43 ***	4543.251 **	17,433.86 ***
γ	0.751 ***	0.893 ***	0.81 ***	0.534 ***	0.732 ***	0.825 ***	0.951 ***
Log likelihood function	3432.010	−1634.953	−3370.60	−1105.50	−448.59	−1438.36	−1482.714
LR test of the one-sided error	179.820	168.75	151.80	12.132	61.37	66.37	254.261
Mean	2.939	89.244	481.559	15.84	0.665	75.489	217.548
Variance	417.639	3200.977	104,447.353	95.478	2710.607	1,581,073.334	17,826.701

Note: *, **, and *** indicate significant at 10%, 5%, and 1% significance levels, respectively; numbers in parentheses are the corresponding estimated t -statistic variables.

The log likelihood function value from SFA regression results (log likelihood) and likelihood ratio test (LR test) show a good estimation effect. Most coefficients of each environmental variable on the input variables can pass the test of significance, which indicates that the external environmental variables have a significant influence on redundant value for each input variable. It can also be seen that each of the agricultural input slack variable's

γ values pass the test at a 1% level of significance, indicating that management factors play a dominant role in agricultural inputs, and it is necessary to strip out environmental and stochastic factors.

The impact of the level of economic development, urbanization level, industrial structure, and government influence on the redundancy value of each agricultural input was examined through the SFA model. When the coefficient of SFA regression is positive, it indicates a positive impact of environmental variables on inputs, which will increase the input redundancy value and the waste of resources; when the coefficient is negative, the environmental variables will reduce the input redundancy value, which is conducive to the saving of agricultural inputs. The SFA regression results are shown in Table 3.

(1) Level of economic development: The level of economic development has a significant negative impact on the slack variables of agricultural capital, agricultural labor, sown area, agricultural film, and irrigation, which means as the economy develops, the redundancy leading to the above five agricultural inputs will decrease. The level of economic development reflects, to a certain extent, the service management capability of the region. Agricultural trusteeship services were increasingly recognized and accepted by farmers; the mechanized operation of agricultural trusteeship occupied the form of farmers' self-purchased mechanical operations, which promoted the effective allocation of agricultural capital; the outsourcing of nursery services also reduced the overuse of agricultural film to a certain extent. With the development of the economy, there are more employment opportunities to absorb surplus agricultural workers. This promotes the rational allocation of land in different industries, making inefficient and even idle arable land being utilized. However, the effect of the level of economic development on the slack variable of agricultural fertilizer use is not significant, indicating that there is no significant relationship between the economic development and agricultural fertilizer use;

(2) Level of urbanization: The level of urbanization has a significant positive effect on the slack variables of agricultural capital, agricultural labor, and pesticides and a significant negative effect on the slack variables of sown area and effective irrigated area. With the increase of urbanization, the above five factors show an over-input problem, and resources are not effectively allocated. The urbanization expansion has promoted the outflow of rural labor. The women and children left in the rural area have pushed for the popularization of mechanized operations. It was found in the surveys that, although farmers household their own agricultural machinery and equipment, the usage rate is generally low. At present, the traditional fine and intensive operation of agriculture is still an important mode of production, coupled with the rural "home-based care" model for elderly people. Agricultural workers are "locked up", preventing the orderly flow of rural labor. Over all, the rural labor force is on the outflow trend, and the reduction of a young and strong labor force promotes the use of chemicals to eliminate pests and diseases, resulting in excessive pesticide inputs. Urbanization has promoted the construction of high-standard farmland and better allocation of land resources, improving the effective use of arable land;

(3) Industrial structure: The level of industrialization development has a significant positive effect on the slack variables of agricultural capital, agricultural labor, pesticides, and effective irrigation area and a significant negative effect on the slack variables of sown area and agricultural film. Accompanied by the development of industry, the feeding effect of industry on agriculture is more obvious, promoting the application of science and technology in agricultural production. Machinery and equipment have been popularized among farmers so as to liberate the labor force gradually, but there are many obstacles to the rational flow of excess labor. Scientific and technological progress has led to the development of water conservancy, improving the irrigation capacity of farmland water conservancy facilities, but some land did not bring considerable output with limited condition. Pesticides have become an important means of preventing and controlling pests and diseases; agricultural science and technology have enhanced the use effectiveness of pesticide, and coupled with increasing consumers' demand on agricultural products' quality, this has led to excessive use of pesticides. The development of industrialization

is inseparable from the demand for land, which, to a certain extent, has optimized the allocation of land between industry and agriculture. The recycling of agricultural films also benefits from the development of industrialization, thus reducing the excessive use of agricultural films;

(4) Government influence: Government influence mainly reflects the support for agriculture, which has a significant positive effect on the slack variables of agricultural capital, agricultural labor, fertilizer and effective irrigated area and a significant negative effect on the pesticide slack variable. The government's agricultural machinery subsidy policy is one of the key factors contributing to the redundancy of agricultural capital, while the possession of further complete agricultural machinery and equipment by farmers leads to the redundancy of labor. Expenditures on agriculture, forestry, and water affairs are also used for water conservancy expenditures and fertilizer subsidies, resulting in overuse of fertilizers and over-irrigation. Pesticide subsidies are now mainly for large grain farmers or those who purchase green pesticides. Farmers can purchase pesticides in accordance with the relevant guidelines, reducing the blindness of purchases and promoting the rational use of pesticides.

It can be seen that environmental variables have an important impact on agricultural factor inputs, which further affects agricultural production efficiency. Therefore, it is necessary to adjust the original input variables and then eliminate the impact of environmental variables to examine the level of agricultural production efficiency.

4.3. Stage 3: Adjusted Unexpected Output SBM Empirical Results

According to Equation (5), the original input variables were adjusted, and the adjusted input variables and the original output variables were introduced into the SBM model for efficiency measurement to obtain the actual situation of agricultural production efficiency in the city clusters along the middle reaches of the Yangtze River in the third stage.

4.3.1. Characteristics of Time Evolution of Comprehensive Agricultural Efficiency

Figure 4 shows the value of overall agricultural efficiency and the evolutionary trend over time in the city clusters along the middle reaches of the Yangtze River.

(1) The comprehensive agricultural efficiency is low, with a slowly decreasing trend. From 2008 to 2021, the average value of the comprehensive efficiency of agricultural production in the city clusters along the middle reaches of the Yangtze River was 0.51. It was reduced from 0.530 in 2008 to 0.436 in 2021, and the decline was not obvious. One of the reasons for the low comprehensive efficiency of agricultural production in the city clusters along the middle reaches of the Yangtze River is the low scale efficiency, which has been below 0.6 for a long period of time, while the continuous decline in pure technical efficiency has led to a slow decline in comprehensive efficiency. In 2013, there was the H7N9 avian influenza epidemic; poultry farming suffered an unprecedented damage, and the expected output of agriculture declined, resulting in a value of agricultural production efficiency below 0.5. In recent years, the growth of food production in the middle reaches of the Yangtze River has been obviously weak. The construction of the urban agglomeration occupied a large amount high-quality arable land, which is also one of the reasons for the continued decline in comprehensive efficiency, with the 2021 comprehensive efficiency falling to 0.436. Despite the rising agricultural GDP in the city clusters along the middle reaches of the Yangtze River, excessive inputs of production materials such as fertilizers, pesticides, and agricultural machinery have led to an increase in non-desired outputs. This accelerated the continued decline in the comprehensive efficiency of agricultural production. The agricultural production efficiency after the adjustment of input variables changed more gently than before the adjustment, indicating that environmental variables have a non-negligible impact on agricultural production efficiency. Under such low agricultural comprehensive efficiency conditions, due to the relatively developed industry in the urban agglomeration of the middle reaches of the Yangtze River, the loss of rural labor force will be more severe;

(2) The scale efficiency of agricultural production basically maintains a stable trend, and the level of pure technical efficiency shows a slow downward trend. The average level of scale efficiency is only 0.567, and the average level of pure technical efficiency is 0.912. Scale efficiency reflects the impact of the expansion of production scale on productivity. The scale efficiency of agricultural production in the city clusters along the middle and lower reaches of the Yangtze River is low; the scale effect is not obvious, which is also an important factor contributing to the low comprehensive efficiency of agriculture in the region. Most of the urban agglomerations in the middle reaches of the Yangtze River are in developed areas. The development of cities devours agricultural land and, coupled with China's small per capita arable land area, makes it difficult to realize the scale of land in the region, and the inputs of other factors of production make it difficult to realize economies of scale. Pure technical efficiency reflects the comprehensive management level of agricultural production and the impact of technological upgrading on productivity. The level of pure technical efficiency in this region is high compared to the level of scale efficiency, both above 0.8, but showing a slow downward trend in 2008–2021. The high level of pure technical efficiency in the city clusters along the middle and lower reaches of the Yangtze River is due to the advantages of technological innovation and promotion; the developed industrial development has provided technological support for agricultural production, and the effect of industry feeding agriculture has gradually appeared [46]. However, the enthusiasm of farmers for technology acceptance is not high. Correspondingly, research and development institutions lack the motivation for research and development. The promotion of the role of technology in agricultural production has not been fully realized, and the inhibitory effect on agricultural production has become more and more obvious.

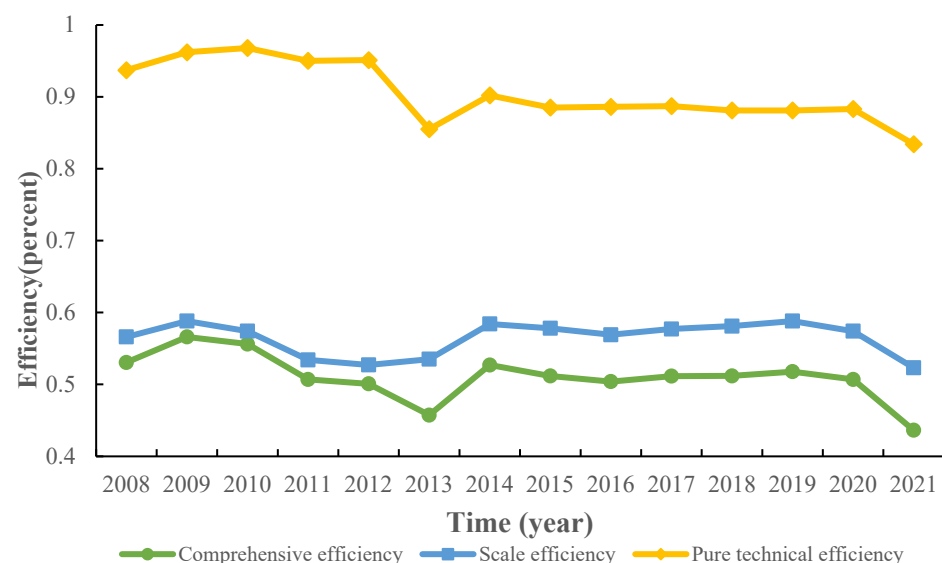


Figure 4. Comprehensive Agricultural Comprehensive Efficiency and Its Decomposition in the City Clusters of the Middle Reaches of the Yangtze River from 2008 to 2021.

4.3.2. Characteristics of Spatial Distribution of Comprehensive Agricultural Efficiency

(1) The comprehensive agricultural efficiency of the city clusters along the middle reaches of the Yangtze River shows a distribution of “high in the west and low in the east”. During the period of 2008–2021, the comprehensive agricultural efficiency of the urban agglomeration in the middle reaches of the Yangtze River has decreased from the west to the east generally, and in the dynamic change period of the comprehensive agricultural efficiency of the three major sub-city clusters, the regional agricultural production efficiency was relatively stable in general, but the difference between them increased. The average comprehensive efficiency level of agricultural production in the Wuhan city group is the highest, reaching 0.636. The average comprehensive efficiency level of the city cluster around Changsha city, Zhuzhou city, and Xiangtan city (Chang-Zhu-Tan city group) is

the second highest at 0.599; and the average comprehensive efficiency of agricultural production in the city cluster around Poyang Lake is the lowest at only 0.343. As can be seen from Figure 5, the Wuhan city group has the fastest growth rate in comprehensive agricultural production efficiency and has been overtaking the agricultural production efficiency of the Chang-Zhu-Tan city group since 2011. This may stem from the leading role of the Wuhan city group in the region, whose high-quality technological resources provide vitality to agricultural production. Figure 6 also shows that the pure technological efficiency of the Wuhan city group is significantly higher than that of the urban agglomeration around Poyang Lake and the urban agglomeration around Chang-Zhu-Tan, but the pure technological efficiency of the three regions has not significantly improved over time. The reason for this result may be the insufficient promotion of agricultural technology and the low transformation rate of agricultural science and technology. The difference in the pure technology efficiency of the three regions has gradually increased. In 2008, the pure technical efficiency was highest in the Chang-Zhu-Tan city group (0.97), followed by the Wuhan city group (0.938), and the city cluster around Poyang Lake is the lowest (0.909). Although none of the three reaches the pure technical efficiency optimum, they are all closer to 1. After 2008, the pure technical efficiency of the city cluster around Chang-Zhu-Tan continued to decline, reaching its lowest value in 2013, and then stayed at 0.8–0.9. The pure technical efficiency of the urban agglomeration around Poyang Lake is in a declining trend, but the rate of decline is slower than that of the urban agglomeration around Chang-Zhu-Tan, causing it to surpass the urban agglomeration around Chang-Zhu-Tan in 2013. The scale efficiency of all three regions is low, and the scale efficiency value does not even reach 0.8; the scale efficiency of the Poyang Lake city group is much lower than that of the other two regions, while there is not much difference between the scale efficiency of the Wuhan city group and the Chang-Zhu-Tan city group. Due to the low scale efficiency of the city cluster around Poyang Lake, the comprehensive efficiency of agricultural production in this region is the lowest compared with the other two regions. See Figure 7 for details. The average comprehensive agricultural productivity and its decomposition in all these cities above can be found in Figure 8. It can be seen that the non-scale of land is one of the important factors constraining the improvement of agricultural productivity;

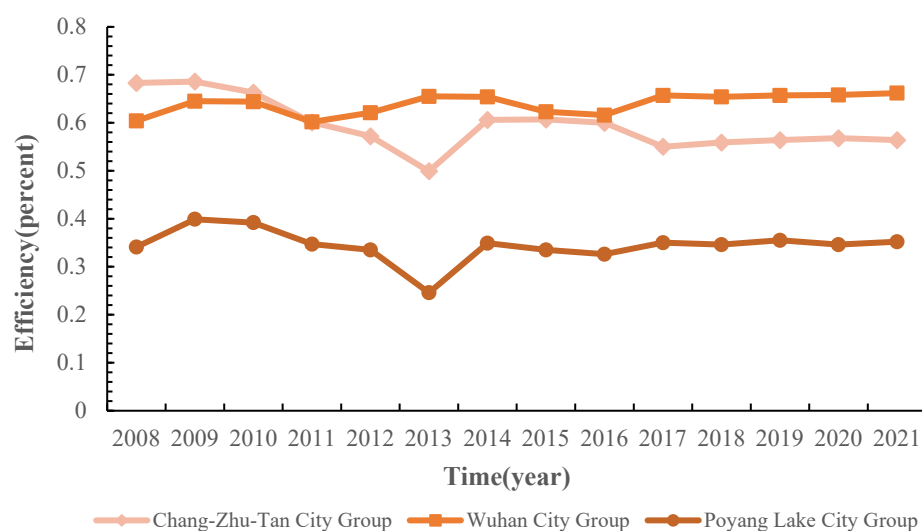


Figure 5. Evolutionary trend of comprehensive agricultural efficiency in urban agglomerations in the middle reaches of the Yangtze River, 2008–2021.

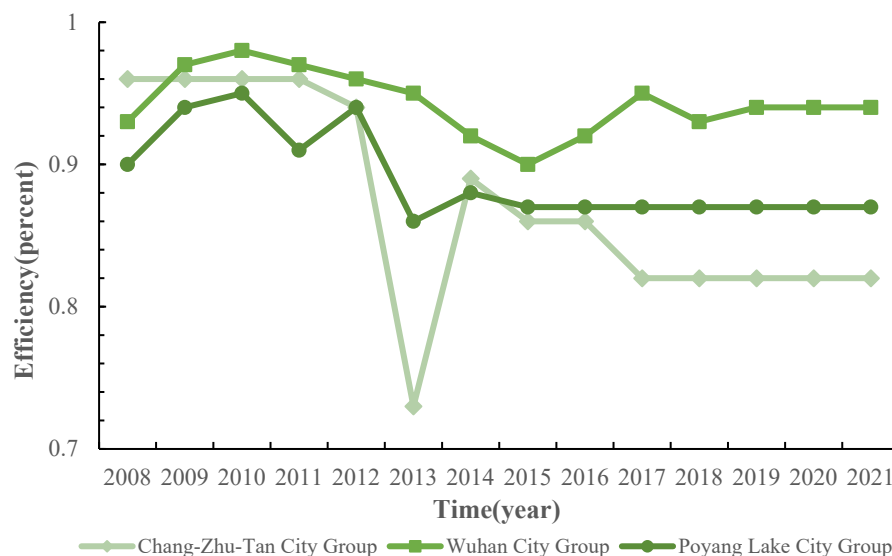


Figure 6. Evolutionary trend of pure technical efficiency in agriculture in the city cluster in the middle reaches of the Yangtze River, 2008–2021.

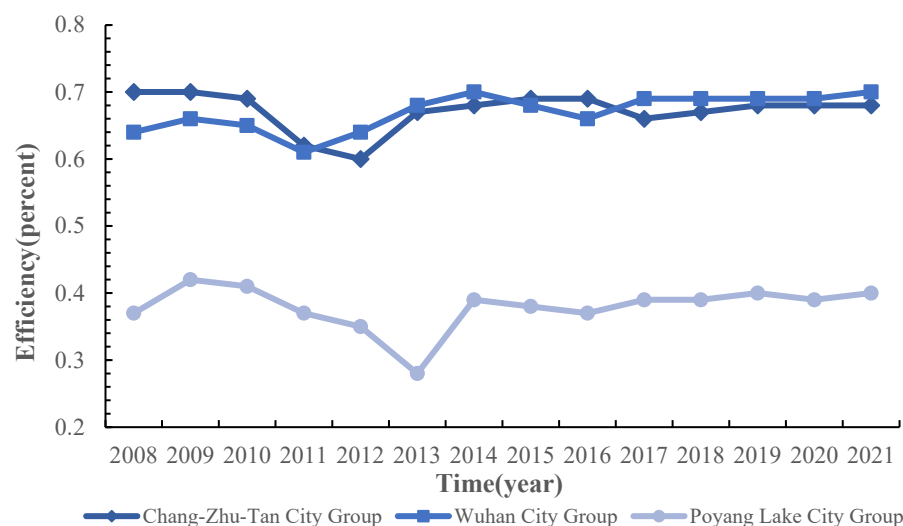


Figure 7. Evolutionary trend of agricultural scale efficiency in urban agglomerations in the middle reaches of the Yangtze River, 2008–2021.

(2) The inter-regional efficiency differences in comprehensive agricultural efficiency in the middle reaches of the Yangtze River sub-city cluster are obvious, and the gap is gradually increasing. Referring to the related study [47], the comprehensive efficiency of agricultural green production in the city clusters along the middle reaches of the Yangtze River is classified into four types, that is, the high-efficiency level ($0.8E \leq 1$), the medium-high-efficiency level ($0.6E \leq 0.8$), medium-low-efficiency level ($0.4E \leq 0.6$), and the low-efficiency level ($0.4 \leq E$) (see Figure 9). From the micro level, the cities with higher comprehensive efficiency of agricultural production are mainly in the Wuhan city group, in which Wuhan, Yichang, Xiangyang, and other places have higher comprehensive efficiency of agriculture, belong to the high-efficiency type, and have the “continuation effect” of high efficiency of agricultural green production. The cities with low efficiency of agricultural production are mainly in the Chang-Zhu-Tan city group and the Poyang Lake city group. The low-efficiency cities of agricultural production are mainly gathered in the city group around Chang-Zhu-Tan and the city group around Poyang Lake, in which the high-efficiency areas in the city group around Chang-Zhu-Tan are gradually reduced to

medium–high-efficiency areas, and there is a tendency of increase in the low-efficiency areas. Overall, with the passage of time, the high-efficiency area of agricultural green production gradually concentrated to the Wuhan city group, and the high-efficiency area gradually decreased, showing the trend of sinking to low efficiency.

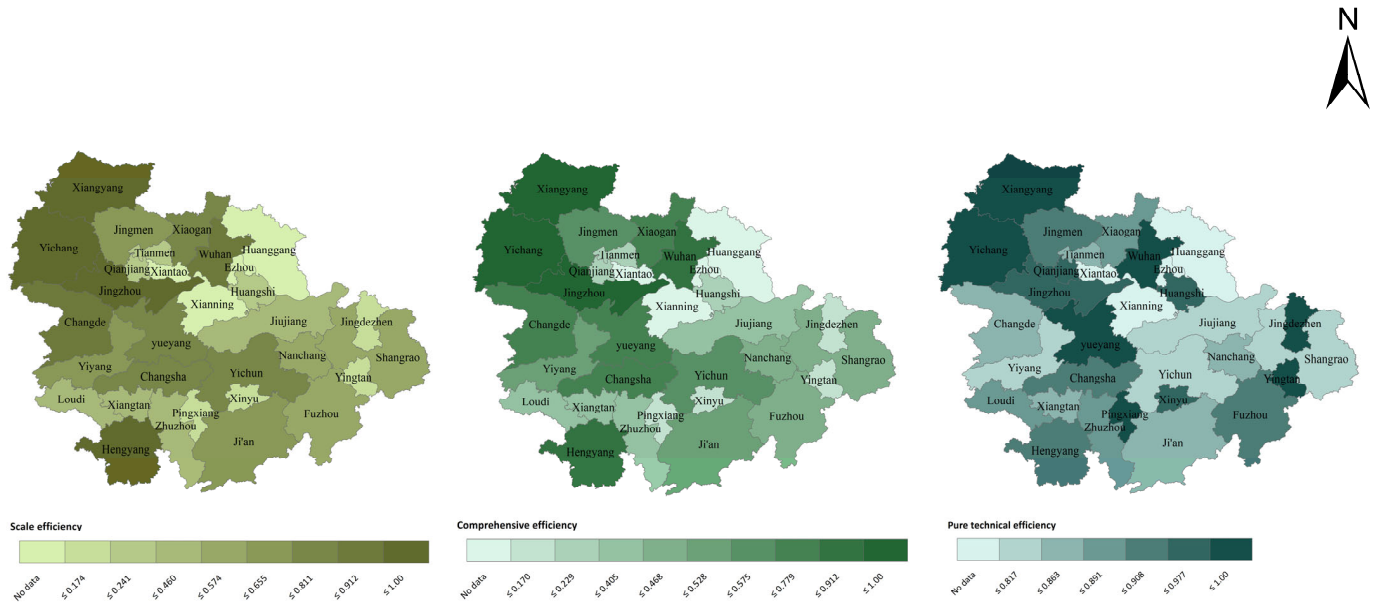


Figure 8. Average Comprehensive Agricultural Productivity and its Decomposition in Cities of the City Cluster in the Middle Reaches of the Yangtze River, 2008–2021.

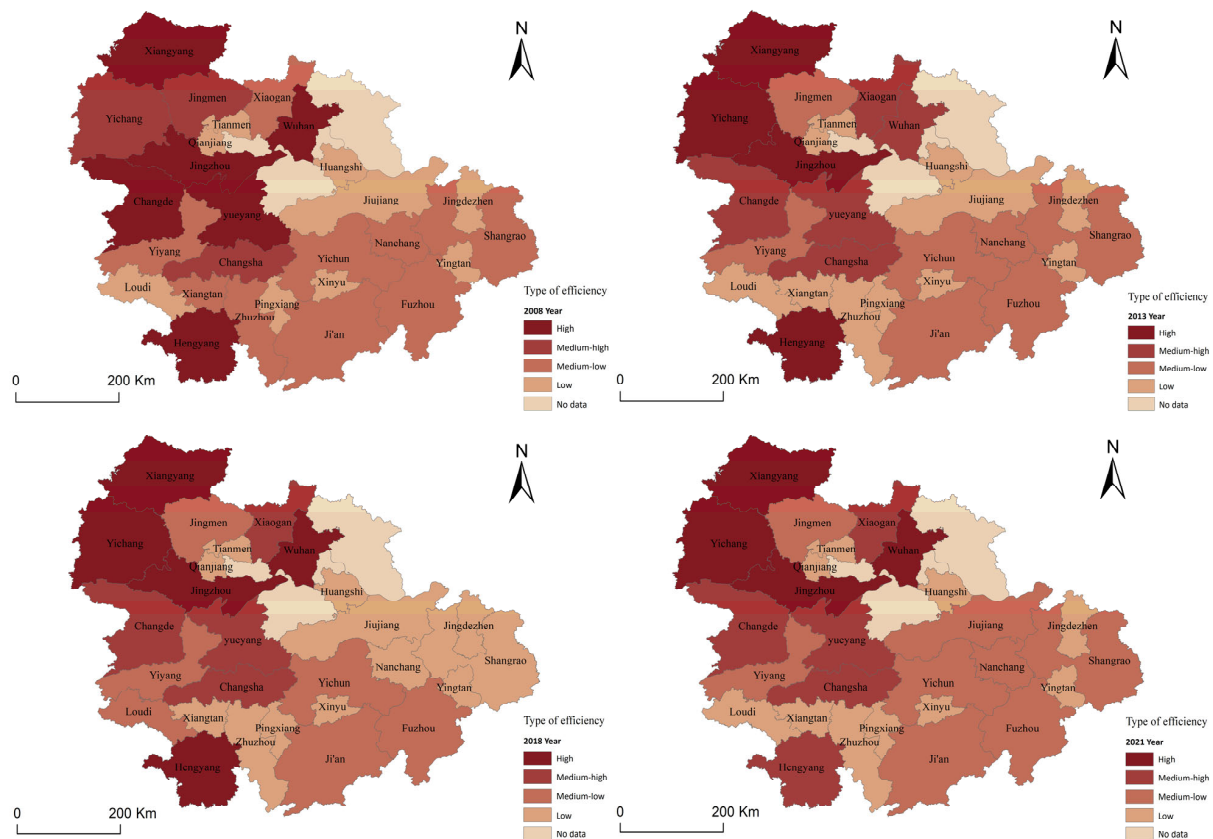


Figure 9. Clustering of comprehensive agricultural efficiency in cities of the city cluster in the middle reaches of the Yangtze River in 2008–2021.

5. Conclusions and Recommendations

5.1. Conclusions

Based on the input–output index system of agricultural green production, this paper uses the non-expected output SBM model and SFA model to measure the comprehensive agricultural efficiency and the external factors of the 31 prefectural-level cities in the middle reaches of the Yangtze River city clusters in the years 2008–2021. The paper draws the overall trend and distribution characteristics of agricultural comprehensive efficiency in the region and identifies important factors affecting agricultural production factor inputs. The specific conclusions are as follows:

(1) Without eliminating the influence of environmental variables, the comprehensive efficiency of agriculture in the city clusters along the middle reaches of the Yangtze River shows an upward–declining–steady trend, with obvious stage changes. The scale effect of green agricultural production is good, and the level of pure technical efficiency is lower than the scale efficiency. As a whole, the comprehensive efficiency level of the city cluster in the middle reaches of the Yangtze River is not high. The scale of production factor inputs such as agricultural land is more reasonable, but its pure technical efficiency level is low, and there exists inefficient utilization of factor resources;

(2) The results of the SFA model show that economic development, urbanization construction, industrial structure, and government influence have important impacts on agricultural production factor inputs. Accelerating economic development is conducive to reducing excessive inputs of agricultural capital, agricultural labor, sown area, agricultural film, irrigation, etc. Increasing the level of urbanization can promote the effective allocation of sown area and effective irrigated area but results in the redundancy of inputs of agricultural capital, agricultural labor, and pesticides. Increasing the level of industrial development can promote the reasonable inputs of sown area and agricultural film while also leading to the inputs of agricultural capital, agricultural labor, pesticides, pesticides, and effective irrigation area. Expanding the influence of the government can inhibit the excessive use of pesticides, but government subsidies make the input redundant in agricultural capital, labor, fertilizers, and effective irrigation area. It can be seen that environmental variables have an impact on the inputs of agricultural production factors and further affect the agricultural production efficiency. Therefore, it is necessary to eliminate environmental variables to examine the true level of production efficiency;

(3) The results after eliminating environmental variables show that, from the perspective of time evolution, the comprehensive efficiency of agriculture is low and presents an overall slow decline trend. The production scale efficiency and pure technical efficiency have not reached a better level, with the former significantly lower than the latter, and the low scale efficiency hinders the improvement of the comprehensive efficiency of agriculture. For the spatial distribution, the comprehensive efficiency of agriculture in the city cluster in the middle reaches of the Yangtze River shows the distribution of “high in the west and low in the east”. With the passage of time, there are obvious differences in the efficiency of the comprehensive efficiency of agriculture, and the gap between the regions is gradually increasing. The high-efficiency area is gradually gathering to the Wuhan city group and shows the trend of increasing to the low-efficiency area;

(4) The above research conclusions clarify the impact of various factors on the comprehensive efficiency of agriculture in the Yangtze River Basin, pointing out the direction for the sustainable development of agriculture in the region in the future. In the future, attention should be paid to the reasonable investment of agricultural labor, pesticides, telephone bills, etc., while meeting the needs of agricultural development and avoiding excessive investment.

5.2. Policy Recommendations

Based on the above conclusions, the following recommendations are put forward to improve the comprehensive efficiency of agriculture in the city clusters along the middle

reaches of the Yangtze River and guide the transformation and upgrading of regional agricultural production:

Firstly, decision makers must optimize the structure of government support for agriculture, focusing on agricultural infrastructure construction and agricultural green production support. The policy of financial support for agriculture can improve the conditions of farmland, water conservancy, production roads, and other infrastructures as well as strengthen the construction of agricultural production service teams, integrate agricultural production resources, improve the efficiency of resource utilization, and provide a strong guarantee for agricultural production. Financial support for agriculture should be appropriately tilted to the farmland fertility protection subsidies; decision makers should optimize the purchase of agricultural machinery subsidies, carry out training for agricultural professionals, etc., and subsidies should be concentrated to the advantageous production areas. We suggest increasing investments in scientific and technological research and development, supporting the construction of agricultural science and technology innovation centers, guiding farmers to gradually adopt new technologies, and improving the level of sustainable agricultural development. At the same time, it is necessary to strengthen the protection of agricultural ecological environment, promote the coordinated development of agriculture and ecological environment, implement agricultural ecological restoration projects, protect arable land resources, and reduce the negative impact of agricultural production on the environment.

Secondly, we suggest improving the research and development and popularization of green production technology and encouraging the establishment of resource use and recycling. Decision makers should vigorously develop water-saving irrigation techniques and green pest control techniques to reduce resource consumption and environmental pollution, improve the phenomenon of “heavy use, light recycling”, and reduce the cumulative effects of “reverse ecology”. Strengthening the construction of a multi-level agriculture ecological cycle linking the planting, animal husbandry, breeding, production and processing, and tourism industries and constructing an ecological cycle industry chain can help to realize a closed-loop flow of resources. We recommend strengthening the construction of ecological agriculture demonstration zones and promoting sustainable agricultural production models such as organic agriculture, ecological planting, and the utilization of agricultural waste resources. At the same time, decision makers should establish a sound ecological agriculture evaluation system, monitor and evaluate the ecological benefits of demonstration areas, promote successful experiences, form replicable and promotable models, and promote the development of ecological agriculture throughout the country.

Thirdly, under industrial restructuring, the population of farmers moving to urban areas should be absorbed in a rational and orderly manner. Through the establishment of a social security system and the formulation of appropriate supportive and preferential policies, problems such as social security for landless peasants will be solved, thereby promoting the flow of urban and rural factors, raising the level of intensification of agricultural production, promoting the industrialization of agriculture, and raising the level of agricultural production efficiency. But we cannot ignore the issue of rural development. We should strengthen the construction of rural infrastructure including roads, water supply, electricity, etc., to improve the living conditions of rural residents as well as strengthen rural education and training, improve the skill level of farmers, and enhance their ability to adapt to urban life.

5.3. Prospect

In future research, we will make improvements in variable selection to enhance the accuracy and rigor of the article. For example, currently, the calculation method for non-point source pollution is based on equal weight assignment, and suitable methods have not yet been found to measure the varying degrees of far-reaching effects caused by pesticides, agricultural films, and fertilizers. We will look for better ways to solve this problem in the future.

Next, we will continue to study the relevant issues of agricultural comprehensive efficiency and add cities in the Yellow River Basin as new research objects. Compared to the Yangtze River Basin, the Yellow River Basin itself has poor ecological conditions, high sediment content, and a poor ecological environment. One of the biggest obstacles to agricultural development is the shortage of water resources [48]. In addition, the urban agglomeration in the Yangtze River Basin is economically developed but has uneven development, with the phenomenon of industry feeding agriculture. However, the agricultural development in the Yellow River Basin lacks this advantage [49], and due to a series of factors such as terrain, cultural customs, policies, etc., the comprehensive efficiency of agriculture in the Yellow River region may present a completely different picture. Based on this, we can further explore the impact of mutual support between industry and agriculture on the comprehensive efficiency of agriculture.

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