Evaluating Agricultural Production Efficiency in Jiangsu and Anhui Provinces: A Three-Stage DEA and Malmquist Index Approach

Abstract: This study assesses the agricultural production efficiency of Jiangsu and Anhui Provinces from 2018 to 2022, with a focus on the impact of the Yangtze River Delta Regional Integration Development Plan. Utilizing a three-stage Data Envelopment Analysis (DEA) model and the Malmquist index, the research controls for environmental factors and analyzes efficiency changes dynamically. The results indicate that Jiangsu achieved a higher rate of technological progress, with an average annual growth rate of 1.0066, which drove its overall productivity gains. In contrast, Anhui demonstrated substantial potential in scale efficiency, reflecting opportunities for future productivity improvements through optimized resource allocation. The regional integration plan appears to have played a pivotal role in advancing agricultural productivity in Jiangsu by facilitating technology-driven improvements. Findings suggest that while Jiangsu should continue to enhance its technological capabilities, Anhui could focus on harnessing its scale efficiency potential to bridge the productivity gap between the two provinces. These insights underscore the significance of regional integration policies in fostering balanced agricultural development, promoting both technological progress and scale efficiency across different regional contexts.

Keywords: agricultural production efficiency; Three-stage DEA model; Malmquist index; environmental factors

Introduction:

With the implementation of the Yangtze River Delta Regional Integration Development Plan, economic cooperation among provinces and cities within the region has significantly strengthened, deepening collaboration in scientific and technological innovation and promoting coordinated regional development. This integration has driven agricultural modernization, fostered balanced regional growth, and improved infrastructure and public services—all essential factors for enhancing agricultural production efficiency. Su et al. (2024) evaluated the level of regional integration within the Yangtze River Delta Urban Agglomeration (YRDUA) from 2005 to 2019, highlighting the critical role of integration in ensuring food security. Additionally, scholars have used the super-slacks-based measure (SBM) model to assess rural development efficiency (RDE) at the county level in the region from 2012 to 2021 (Wu & Chen, 2024).

Despite these advancements, limited research specifically examines how regional integration policies impact agricultural efficiency in the Yangtze River Delta, leaving questions about the tangible effects of integration on agricultural productivity. Jiangsu and Anhui Provinces, as key agricultural contributors within the delta, provide valuable case studies for this exploration. Known as the “land of fish and rice,” Jiangsu is a vital agricultural hub, while Anhui plays a significant role as a primary agricultural base. Both provinces thus offer substantial research value in assessing how regional integration policies may enhance agricultural efficiency across different contexts within the delta.

The study of agricultural production efficiency has a long-standing history, and many scholars, both domestically and internationally, have utilized various methodologies to assess agricultural efficiency. Among these, the Data Envelopment Analysis (DEA) model is widely used for measuring agricultural efficiency. The DEA approach dates back to Farrell's 1957 study on British agriculture (Farrell, 1957). Since then, numerous scholars have applied the DEA model and its extensions to investigate agricultural production efficiency. Coluccia et al. (2020) employed traditional DEA to assess the eco-efficiency of Italy's agricultural sector, highlighting regional disparities. Kalli et al. (2024) used DEA to evaluate farmers' productivity through technical efficiency (TE). The super-efficiency DEA model, an extension of traditional DEA, allows some decision-making units (DMUs) to surpass an efficiency score of 1. Ma et al. (2021) used this model to analyze agricultural efficiency in China. The Malmquist index complements DEA by enabling dynamic efficiency analysis, addressing the limitation of traditional DEA, which is limited to static evaluations. Le and Mishra, among others, integrated the DEA model with the Malmquist index to conduct both dynamic and static analyses of agricultural production efficiency (L. & Mishra, 2022; Le et al., 2019). Shah et al. (2024) employed DEA and the Malmquist index to analyze the dynamic relationship between agricultural technological innovation and total-factor agricultural water usage efficiency (TFAWUE) across Chinese provinces between 2000 and 2020, assessing overall water use efficiency. Zhang et al. (2024) further combined the super-efficiency DEA model with the Malmquist index to examine agricultural production efficiency. The three-stage DEA model has also been widely applied in agricultural efficiency studies, as it eliminates the influence of external environmental factors, thereby improving the accuracy of results. S. Yao and Wu (2022) utilized the three-stage DEA model to analyze the impact of green agricultural technology innovation on rural revitalization in Anhui Province. Yang and Shang (2020) applied the three-stage DEA to examine the agricultural efficiency of conservation tillage implementers, investigating the effects of environmental factors. Pan et al. (2022) integrated the three-stage DEA model with the Malmquist index to study agricultural production efficiency in the Yangtze River Economic Belt from 2010 to 2019 from both dynamic and static perspectives.

In summary, while the study of agricultural efficiency is well-established, there is a noticeable gap in comparative research on the agricultural production efficiency of Jiangsu and Anhui provinces using the three-stage DEA model and the Malmquist index within the context of the Yangtze River Delta regional integration. Given that the three-stage DEA model eliminates the interference of external environmental factors and the Malmquist index allows for dynamic analysis, this study will combine these two approaches to evaluate and compare the agricultural efficiency of Jiangsu and Anhui provinces. By removing external factors, the study will provide an accurate assessment of agricultural efficiency in both provinces. Furthermore, this research will explore how agricultural production efficiency in Jiangsu and Anhui has been affected by the implementation of the Yangtze River Delta Regional Integration Development Plan. Based on the evaluation results, this study will also identify the key issues in the current agricultural development of both provinces, offering recommendations to enhance agricultural efficiency.

1. Research Methods

1.1 Three-stage DEA model

Fried et al. (2002) proposed an innovative evaluation model to effectively filter out the influence of environmental factors and other unintended random variables—excluding scale, technology, and management factors—on the assessment of production efficiency. This model, known as the three-stage Data Envelopment Analysis (DEA) model, introduced a significant methodological advancement in efficiency measurement. The core innovation of this model lies in its use of the slack variables inherent in the standard DEA model to adjust input values. This adjustment allows for the comparison of decision-making units (DMUs) under a hypothetical uniform external environment. Following this adjustment, the conventional DEA model is re-applied to re-estimate the technical efficiency of each DMU. Through this process, the model effectively eliminates the distorting effects of environmental factors, providing a more accurate and reliable depiction of the inherent efficiency characteristics of each decision-making unit.

1.1.1 The first stage

This stage is the initial efficiency measurement stage of the DEA model, which obtains the initial technical efficiency value through the unadjusted efficiency. In 1978, Charnes et al. (1978) introduced the CCR model, which operates under the assumption of constant returns to scale (CRS). Building on this, in 1984, Banker et al. (1984) proposed the BCC model, which relaxes the constant returns to scale assumption to allow for variable returns to scale (VRS). The mathematical formulation of these models can be expressed as:

$$TE = SE \times PTE \qquad (1)$$

TE stands for technical efficiency; SE stands for scale efficiency; PTE stands for pure technical efficiency.

1.1.2 The second stage

This stage adjusts the impact of environmental and random factors on efficiency to obtain more accurate efficiency results. By establishing a similar Stochastic Frontier Analysis (SFA) model, the slack variables obtained in the first stage are decomposed into three components: external environmental factors, random factors, and management factors. Traditional DEA models do not differentiate between these three factors, making it difficult to determine the cause of inefficiency. However, through a second-stage SFA-like regression, the interference from external environmental and random factors can be filtered out, thus isolating their influence on efficiency scores. The corresponding expression is as follows:

$$s_{ik} = f^{i}\left(z_k;\beta^{i}\right) + v_{ik} + \mu_{ik} \qquad (2)$$

In the formula, i = 1,2,⋯,m; k = 1,2,⋯,n; $\bar{v}_{ik}$ is the estimated value of the random interference term

1.1.3 The third stage

This stage is to use DEA to measure efficiency again after adjusting for environmental and random factors to determine the true technical efficiency. The efficiency value obtained in this stage is regarded as the final efficiency value after adjustment. The input variables obtained after the second-stage SFA regression are used to replace the original input variables, and the original output of the first stage is still used as the output variable to perform the DEA-BCC model operation to obtain a more realistic efficiency value after eliminating external factors.

1.2 Malmquist Index

The Malmquist index can analyze the changes in comprehensive efficiency, technical efficiency and technological progress from a dynamic perspective (G. Zhou et al., 2024). The corresponding expression is as follows:

$$M(x_{t+1}, y_{t+1}, x_t, y_t) = \left[\frac{D_t(x_{t+1}, y_{t+1})}{D_t(x_t, y_t)} \times \frac{D_{t+1}(x_{t+1}, y_{t+1})}{D_{t+1}(x_t, y_t)}\right]^{\frac{1}{2}} (3)$$

(x,y)represent input variables and output variables respectively;D_t和D_{t+1} represent the distance equations at period t and period t+1 respectively.

The Malmquist index analysis model can decompose total factor productivity (TFPCH) into technological progress (TECCH) and technical efficiency (TECH).

$$TFPCH_t^{t+1} = TECCH_t^{t+1} \times TECH_t^{t+1} \qquad (4)$$

2. Research Area and Evaluation Indicators

2.1 Research area and data sources

Jiangsu Province consists of 13 prefecture-level cities, while Anhui Province includes 16 prefecture-level cities, for a total of 29 cities. This study utilizes data from these 29 cities covering the period from 2018 to 2022. To ensure consistency, all data used in this research are sourced from the Jiangsu Statistical Yearbook and the respective statistical yearbooks of its prefecture-level cities, the Anhui Statistical Yearbook and the respective statistical yearbooks of its prefecture-level cities, as well as the EPS database.

2.2 Indicator system

This study employs the three-stage DEA model and the Malmquist index to analyze agricultural production efficiency from both static and dynamic perspectives. Therefore, it is necessary to define the relevant input indicators, output indicators, and environmental variables. Drawing on previous studies and considering factors such as the exogeneity of environmental variables, data availability, and representativeness, this study ultimately identifies a set of 2 output indicators, 4 input indicators, and 3 environmental variables as the indicator system for the analysis (see Table 1 for details)(Guo et al., 2023; Hsu et al., 2023; Zhou R. et al., 2023).

2.2.1 Input and output indicators

When conducting Data Envelopment Analysis (DEA), four key principles are generally followed: First, there should be no linear relationship between input and output indicators. Second, the number of decision-making units (DMUs) should be at least twice the sum of the input and output indicators. Third, the selected input and output indicators must be both available and representative(Yao F. & Zhu, 2019). Based on these principles and a review of relevant literature, this study selects total agricultural output value and grain production as output indicators. For the input indicators, four dimensions are considered: labor input, capital input, technology input, and land input. Specifically, rural population represents labor input, expenditures on agriculture, forestry, and water affairs represent capital input, total power of agricultural machinery represents technology input, and total sown area of crops represents land input.

2.2.2 Environmental variables

The selection of environmental variables should adhere to the principle of exogeneity, meaning that the chosen variables should influence agricultural production efficiency without being subject to the control of the decision-making units. Based on the review of relevant literature and guided by principles such as exogeneity and data availability, this study considers three dimensions of environmental factors: farmers' living standards, urbanization level, and transportation accessibility. Specifically, the per capita net income of rural residents represents farmers' living standards, the proportion of the urban population reflects the level of urbanization, and the total road mileage serves as a proxy for transportation accessibility. To ensure comparability and eliminate the impact of differing measurement units, all environmental variables were standardized for analysis.

Table 1 Agricultural production efficiency research indicator system

Indicator Type	Indicator Name	Indicator Meaning	Unit
Input Indicators	Grain production	Food production level	10,000 tons
	Total agricultural output value	Direct agricultural production level	100 million yuan
	Total sown area of crops	Land input	Thousand hectares
Output Indicators	Total power of agricultural machinery	Technology input	10,000 kilowatts
	Rural population	Labor input	10,000 people
	Agriculture, forestry and water affairs expenditure	Capital input	100 million yuan
	The per capita net income of rural residents	Farmers' living standards	Yuan
Environmental variables	The proportion of the urban population	Urbanization level	%
	The total road mileage	Transportation accessibility	Kilometer

2.3 Pearson correlation coefficient test

In the three-stage DEA model, an increase in input variables should not lead to a decrease in output variables, a requirement known as the "principle of isotonicity." DEA uses linear programming to measure efficiency, while the Pearson correlation coefficient is used to assess the linear relationship between variables(Song & Ma, 2024). Accordingly, this study employs Pearson correlation tests using Stata 17.0 software to examine the relationships between the input and output variables (see Table 2). As shown in the table, all correlation coefficients between input and output variables are positive and statistically significant at the 1% level, confirming that the variables meet the “isotonicity” principle.

Table 2 Pearson correlation coefficient test

	Grain production	Total agricultural output value	Total sown area of crops	Total power of agricultural machinery	Rural population	Agriculture, forestry and water affairs expenditure
Grain production	1.000					
Total agricultural output value	0.758***	1.000				
Total sown area of crops	0.968***	0.756***	1.000			
Total power of agricultural machinery	0.887***	0.676***	0.888***	1.000		
Rural population	0.779***	0.612***	0.854***	0.684***	1.000	
Agriculture, forestry and water affairs expenditure	0.478***	0.739***	0.480***	0.427***	0.520***	1.000

Note:*indicates significance at the 10% level,**indicates significance at the 5% level,***indicates significance at the 1% level, and the same below.

3. Results and Analysis

3.1 Analysis of DEA results in the first stage

The original input and output variables for the 29 prefecture-level cities in Jiangsu and Anhui provinces from 2018 to 2022 were entered into DEAP 2.1 software to calculate their technical efficiency, pure technical efficiency, and scale efficiency in the first-stage DEA analysis. Due to space constraints, this paper only presents data for 2018 and 2022, as shown in Table 3.

On the whole, the average technical efficiency, pure technical efficiency, and scale efficiency of Jiangsu Province in 2018 were 0.972, 0.975, and 0.996, respectively, and in 2022, these values increased to 0.979, 0.984, and 0.996, respectively. In contrast, for Anhui Province, the average technical efficiency, pure technical efficiency, and scale efficiency in 2018 were 0.805, 0.912, and 0.889, respectively, and in 2022, they had changed to 0.801, 0.884, and 0.911, respectively. These results indicate that from 2018 to 2022, Jiangsu consistently outperformed Anhui in terms of technical efficiency, pure technical efficiency, and scale efficiency. Moreover, the gap in technical and pure technical efficiency between the two provinces widened over this period, while the gap in scale efficiency narrowed.

At the city level, in 2018, eight cities in Jiangsu achieved a technical efficiency score of 1, indicating DEA efficiency, while the remaining five cities had scores above 0.83, indicating relatively high efficiency. By 2022, ten cities in Jiangsu achieved DEA efficiency, with only Suzhou, Suqian, and Nantong falling short, though their efficiency scores still exceeded 0.87, indicating relatively high efficiency. In terms of scale efficiency, the number of cities in Jiangsu with decreasing returns to scale decreased from three in 2018 to two in 2022, while the number of cities with increasing returns to scale fell from two to one.

In Anhui Province, only Huainan and Bozhou achieved DEA efficiency in 2018, with the lowest technical efficiency score at 0.581 in Anqing. By 2022, only Bozhou achieved DEA efficiency, and the lowest score was still Anqing, though it had improved to 0.594. Regarding scale efficiency, four cities in Anhui experienced decreasing returns to scale in 2018, but by 2022, all cities except Bozhou exhibited increasing returns to scale, suggesting significant growth potential. Despite fewer cities in Anhui achieving DEA efficiency and generally lower technical efficiency scores compared to Jiangsu, the majority of cities in Anhui showed increasing returns to scale, indicating substantial future development potential.

Conclusion:

In conclusion, the first-stage DEA results indicate that from 2018 to 2022, Anhui lagged behind Jiangsu in terms of technical efficiency, pure technical efficiency, and scale efficiency. Jiangsu had a significantly higher number of cities achieving DEA efficiency. However, many cities in Anhui demonstrated increasing returns to scale, reflecting significant potential for agricultural development. It is important to note that these initial results may be influenced by external environmental factors and random disturbances, which may distort the true efficiency. Therefore, the next step in this study will involve analyzing the slack variables to remove the effects of external factors and random disturbances.

Table 3 Agricultural production efficiency of cities in Jiangsu and Anhui provinces in the first phase from 2018 to 2022

		2018				2022			
Province	City	Technical efficiency	Pure technical efficiency	Scale efficiency	Scale efficiency characteristic	Technical efficiency	Pure technical efficiency	Scale efficiency	Scale efficiency characteristic
Jiangsu Province	Xuzhou	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Huaian	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Yancheng	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Lianyungang	0.972	0.983	0.988	irs	1.000	1.000	1.000	-
	Suqian	0.899	0.900	0.998	drs	0.907	0.912	0.995	irs
	Nanjing	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Suzhou	0.929	0.944	0.985	drs	0.948	0.972	0.975	drs
	Wuxi	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Changzhou	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Zhenjiang	0.996	1.000	0.996	irs	1.000	1.000	1.000	-
	Yangzhou	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Taizhou	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Nantong	0.836	0.848	0.986	drs	0.877	0.902	0.972	drs
Average value of Jiangsu Province		0.972	0.975	0.996		0.979	0.984	0.996	
Anhui Province	Suzhou	0.777	0.799	0.973	drs	0.801	0.803	0.998	irs
	Huaibei	0.877	1.000	0.877	irs	0.924	1.000	0.924	irs
	Bengbu	0.989	1.000	0.989	irs	0.942	0.980	0.961	irs
	Fuyang	0.823	0.824	0.998	drs	0.870	0.874	0.996	irs
	Huainan	1.000	1.000	1.000	-	0.903	0.941	0.960	irs
	Bozhou	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Hefei	0.734	0.735	0.998	irs	0.730	0.749	0.975	irs
	Luan	0.793	0.795	0.998	drs	0.790	0.796	0.993	irs
	Chuzhou	0.914	1.000	0.914	drs	0.956	0.966	0.989	irs
	Anqing	0.581	0.618	0.940	irs	0.594	0.621	0.956	irs
	Huangshan	0.650	1.000	0.650	irs	0.686	1.000	0.686	irs
	Wuhu	0.739	0.859	0.860	irs	0.700	0.763	0.918	irs
	Maanshan	0.873	1.000	0.873	irs	0.758	0.943	0.804	irs
	Tongling	0.711	1.000	0.711	irs	0.773	1.000	0.773	irs
	Xuancheng	0.770	0.963	0.800	irs	0.739	0.805	0.918	irs
	Chizhou	0.650	1.000	0.650	irs	0.653	0.898	0.727	irs
Average value of Anhui Province		0.805	0.912	0.889		0.801	0.884	0.911	

Note: irs means increasing returns to scale, drs means decreasing returns to scale, - means constant returns to scale, the same below.

3.2 Analysis of SFA results in the second stage

The second stage primarily involves using Stochastic Frontier Analysis (SFA) regression to decompose environmental factors, management inefficiency, and random error terms, thus eliminating external environmental factors to obtain new input variables. In this stage, the slack variables obtained from the first-stage DEA are used as dependent variables, while the standardized rural per capita net income, urbanization rate, and road mileage are selected as independent variables representing environmental factors. The SFA regression is conducted using Frontier 4.1 software, allowing for the removal of external environmental influences.

As shown in Table 4, most of the regression coefficients pass the 10% significance level in the t-test, indicating that the environmental variables selected in this study have a significant impact on the slack variables of the input factors. This confirms that the selected environmental variables are appropriate for the analysis. Moreover, the one-sided likelihood ratio (LR) tests all pass the 1% significance level, further validating the use of the SFA model for the second-stage regression. Additionally, the gamma values in Table 2 are all close to 1 and pass the 1% significance test, indicating that management inefficiency plays a dominant role in explaining the slack in the input variables. This suggests that management inefficiency is the primary cause of the observed input redundancies, making it essential to use the SFA model to separate the impact of external environmental factors and random disturbances on agricultural production efficiency.

A positive regression coefficient for an environmental variable implies that an increase in this variable tends to lead to greater input inefficiency, whereas a negative coefficient suggests that higher values of the environmental variable are conducive to improving agricultural production efficiency.

(1) Rural Per Capita Net Income: This variable represents the living standards of rural residents. It has passed the significance test for most of the slack input variables, with all coefficients being positive. As farmers' living standards and income levels increase, they are likely to invest more human and material resources into agricultural production, potentially leading to input redundancy, which may hinder improvements in agricultural production efficiency.

(2) Urbanization Rate: The urban population ratio represents the level of urbanization. It did not pass the significance test for the slack input variables related to rural labor and expenditures on agriculture, forestry, and water resources. However, it did pass for the slack variables of total sown area and total agricultural machinery power. Additionally, the coefficients for all four slack variables are negative. This indicates that higher levels of urbanization can enhance resource allocation capabilities and optimize input levels, thereby improving agricultural production efficiency.

(3) Road Mileage: Road mileage serves as a proxy for the convenience of transportation. It passed the significance test for all four slack input variables, and the coefficients are negative. This suggests that an increase in road mileage improves transportation convenience in rural areas, significantly reducing the time and costs associated with transporting agricultural products. As a result, it has a positive impact on agricultural production efficiency.

In summary, the environmental variables have a significant impact on the input variables, as confirmed by the likelihood ratio (LR) tests, all of which pass the 1% significance level. Additionally, the gamma values are close to 1 and have passed the 1% significance test, indicating that management inefficiency plays a dominant role. Therefore, it is essential to adjust the input variables for the 29 prefecture-level cities in Jiangsu and Anhui provinces from 2018 to 2022, placing them under the same external environmental conditions and stochastic influences. This adjustment aims to obtain more accurate and reliable estimates of agricultural production efficiency.

Table 4 Second-stage SFA estimation results

	Total sown area of crops	Total power of agricultural machinery	Rural population	Agriculture, forestry and water affairs expenditure
Constant	-11.394***(-2.745)	-12.747**(-2.588)	-6.955*** (-2.776)	-2.310** (-2.019)
The per capita net income of rural residents	11.131***(4.608)	11.239***(3.629)	3.806** (2.422)	0.608(0.759)
The proportion of the urban population	-10.627***(-4.025)	-10.533***(-3.132)	-2.555(-1.502)	-1.110(-1.268)
The total road mileage	-5.538***(-3.072)	-4.524*(-1.952)	-2.651** (-2.329)	-1.401** (-2.228)
sigma-squared	14237.060***(3689.933)	10428.977***(10236.809)	6899.519*** (27.144)	1156.076*** (3.063)
gamma	0.977(326.900)	0.949***(148.481)	0.980*** (315.866)	0.964*** (69.091)
Log value	-679.129	-705.028	-614.458	-511.222
LR test	305.355***	213.020***	329.295***	170.600***

Note:The corresponding estimated t-statistics are in brackets

3.3 Analysis of DEA results in the third stage

After inputting the adjusted input variables and the original output variables for the 29 prefecture-level cities in Jiangsu and Anhui provinces from 2018 to 2022 into DEAP 2.1, we obtained the adjusted technical efficiency, pure technical efficiency, and scale efficiency values in the third stage of the DEA analysis. The results are shown in Table 5.

First, from an overall perspective, the adjusted mean technical efficiency for Jiangsu Province in 2018 was 0.975, the pure technical efficiency was 0.984, and the scale efficiency was 0.990. In 2022, the adjusted mean technical efficiency was 0.983, with pure technical efficiency at 0.989 and scale efficiency at 0.994. Compared to the pre-adjustment results, technical efficiency increased over the 2018-2022 period, with a notable rise in pure technical efficiency, while scale efficiency showed a slight decline. For Anhui Province, the adjusted mean technical efficiency, pure technical efficiency, and scale efficiency in 2018 were 0.769, 0.925, and 0.840, respectively, while in 2022, they were 0.786, 0.913, and 0.867, respectively. In contrast to Jiangsu, Anhui's technical efficiency decreased post-adjustment over the same period, despite a rise in pure technical efficiency, as scale efficiency declined. These results indicate that, while both provinces experienced improvements in pure technical efficiency, the differences in the rate of change in technical and scale efficiencies led to an increase in Jiangsu's overall technical efficiency, while Anhui's overall technical efficiency declined. Notably, the efficiency gap between the two provinces widened post-adjustment, with Jiangsu continuing to outperform Anhui in technical efficiency, pure technical efficiency, and scale efficiency. Although the pure technical efficiency gap narrowed, the scale efficiency gap expanded.

As shown in Figure 1, post-adjustment, most cities in Jiangsu either maintained or improved their technical efficiency from 2018 to 2022, with a few experiencing declines. However, the downward trend observed in 2018 improved by 2022. In Anhui, technical efficiency declined in most cities after adjustment, with only a few maintaining or improving efficiency levels, though this downward trend also showed signs of improvement in 2022. As shown in Table 5, in 2018, after adjustments, seven cities in Jiangsu achieved DEA efficiency, with Changzhou no longer DEA-efficient compared to the pre-adjustment results. The remaining cities had technical efficiency values above 0.89, indicating improvement. In 2022, nine cities in Jiangsu were DEA-efficient post-adjustment, with Changzhou again falling short of DEA efficiency. However, all other cities had technical efficiency values above 0.91, an improvement over pre-adjustment levels. For Anhui, the number of DEA-efficient cities remained unchanged, with only Huainan and Bozhou achieving efficiency in 2018, while the city with the lowest technical efficiency was still Anqing at 0.517, a decline compared to the pre-adjustment results. In 2022, only Bozhou maintained DEA efficiency, with the lowest technical efficiency shifting from Anqing to Huangshan at 0.609, marking an improvement over 2018. Furthermore, from 2018 to 2022, the number of cities with increasing returns to scale in Jiangsu shifted from four to two, while those with decreasing returns dropped from two to one. Meanwhile, in Anhui, the number of cities exhibiting increasing returns to scale rose, while the number of cities with decreasing returns to scale declined, indicating greater agricultural production potential.

Overall, the adjusted results for 2018-2022 reveal that agricultural production efficiency in Jiangsu continues to outperform Anhui, though Anhui has demonstrated increasing returns to scale, indicating growing agricultural development potential. The adjustments also show that pure technical efficiency increased for both provinces, while scale efficiency generally declined. Due to varying degrees of change in pure technical and scale efficiencies, Jiangsu's technical efficiency improved post-adjustment, while Anhui's declined. Moreover, the changes in agricultural production efficiency across cities in both provinces underscore the significance of external environmental factors and stochastic disturbances, which were isolated in the second stage through the SFA regression. This further validates the necessity of removing external environmental influences and highlights that both provinces, especially Anhui, have considerable room for improvement in scale efficiency.

In conclusion, the post-adjustment results indicate that Jiangsu Province's agricultural production efficiency continues to surpass that of Anhui Province. Additionally, the results from the second stage of the SFA regression reveal inefficiencies in resource allocation in both provinces, with varying degrees of input redundancy and resource waste across cities. This underscores the importance of improving not only pure technical efficiency but also scale efficiency to enhance overall agricultural production efficiency.

Table 5 Adjusted agricultural production efficiency of cities in Jiangsu and Anhui provinces from 2018 to 2022

		2018				2022			
Province	City	Technical efficiency	Pure technical efficiency	Scale efficiency	Scale efficiency characteristic	Technical efficiency	Pure technical efficiency	Scale efficiency	Scale efficiency characteristic
Jiangsu Province	Xuzhou	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Huaian	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Yancheng	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Lianyungang	0.974	0.996	0.978	irs	1.000	1.000	1.000	-
	Suqian	0.917	0.920	0.996	irs	0.910	0.925	0.984	irs
	Nanjing	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Suzhou	0.979	0.979	0.999	drs	0.984	0.986	0.999	drs
	Wuxi	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Changzhou	0.966	1.000	0.966	irs	0.948	1.000	0.948	irs
	Zhenjiang	0.941	1.000	0.941	irs	1.000	1.000	1.000	-
	Yangzhou	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Taizhou	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Nantong	0.894	0.898	0.996	drs	0.931	0.941	0.989	drs
Average value of Jiangsu Province		0.975	0.984	0.990		0.983	0.989	0.994	
Anhui Province	Suzhou	0.872	0.873	0.999	drs	0.833	0.843	0.987	irs
	Huaibei	0.811	1.000	0.811	irs	0.827	1.000	0.827	irs
	Bengbu	0.909	1.000	0.909	irs	0.915	0.990	0.924	irs
	Fuyang	0.827	0.834	0.992	irs	0.896	0.910	0.986	irs
	Huainan	1.000	1.000	1.000	-	0.902	0.966	0.933	irs
	Bozhou	1.000	1.000	1.000	-	1.000	1.000	1.000	-
	Hefei	0.732	0.744	0.985	irs	0.750	0.789	0.951	irs
	Luan	0.789	0.794	0.993	irs	0.800	0.815	0.981	irs
	Chuzhou	0.959	1.000	0.959	drs	0.961	0.975	0.986	irs
	Anqing	0.589	0.663	0.889	irs	0.622	0.668	0.932	irs
	Huangshan	0.517	1.000	0.517	irs	0.609	1.000	0.609	irs
	Wuhu	0.690	0.912	0.756	irs	0.722	0.835	0.865	irs
	Maanshan	0.716	1.000	0.716	irs	0.740	0.980	0.755	irs
	Tongling	0.592	1.000	0.592	irs	0.624	1.000	0.624	irs
	Xuancheng	0.730	0.983	0.742	irs	0.747	0.869	0.859	irs
	Chizhou	0.574	1.000	0.574	irs	0.628	0.971	0.647	irs
Average value of Anhui Province		0.769	0.925	0.840		0.786	0.913	0.867	

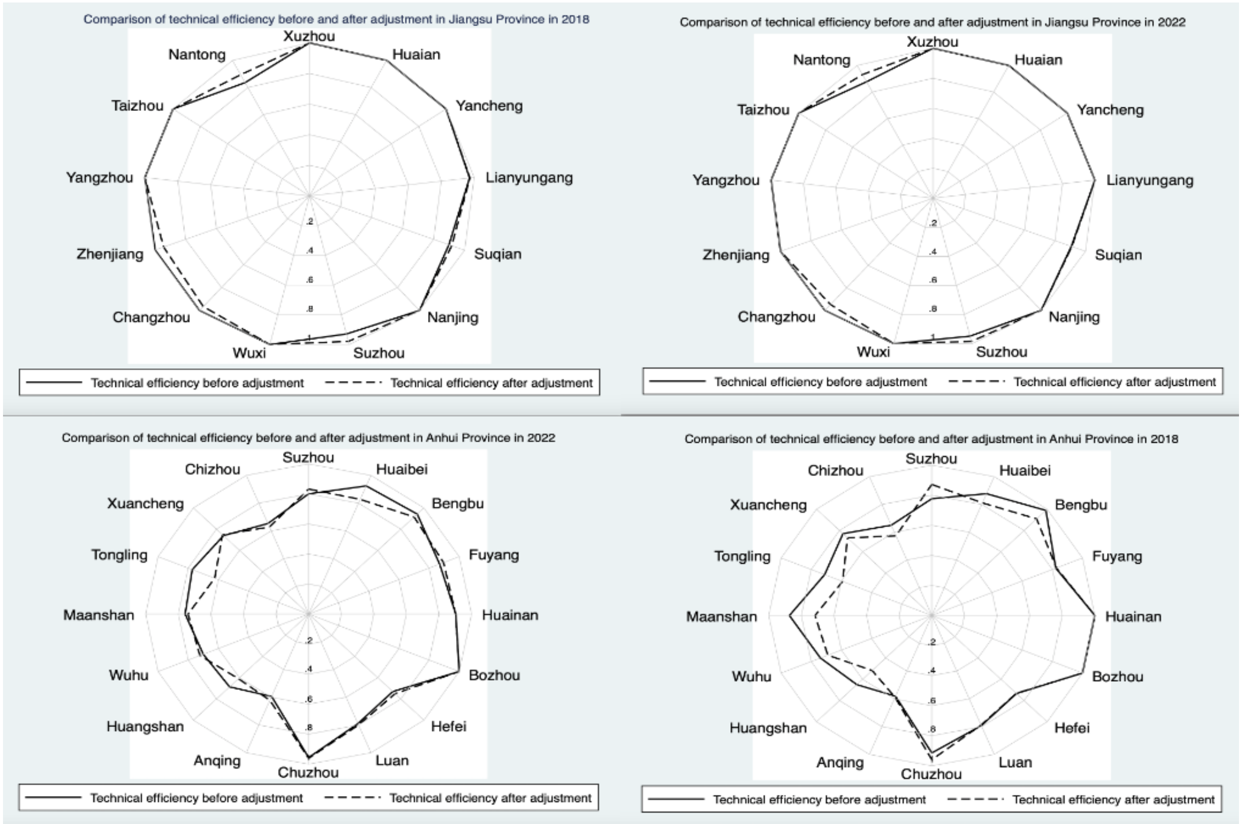

Figure 1 Comparison of agricultural production efficiency of 29 prefecture-level cities in Jiangsu Province and Anhui Province before and after the adjustment from 2018 to 2022

3.4 Malmquist Index Results Analysis

Since the three-stage DEA model only provides a static analysis of agricultural production efficiency, this study employs the Malmquist Index model using DEAP 2.1 software to calculate the total factor productivity (TFP) for Jiangsu and Anhui provinces from 2018 to 2022. The adjusted input variables from the second stage and the original output variables are used. The calculated TFP (TFPCH) is further decomposed into technological progress (TECH) and technical efficiency change (TECCH) to conduct a dynamic analysis of agricultural production efficiency in both provinces. If the calculated TFP is less than 1, it indicates a decline in productivity from period t to t+1, whereas a value greater than 1 indicates an increase in productivity.

As shown in Table 6 and Figure 2, during the 2018-2022 period, the average TFP, technical efficiency, and technological progress for Jiangsu Province were 1.0087, 1.0022, and 1.0066, respectively. This indicates that Jiangsu's agricultural TFP increased by 0.87% over this period, with technical efficiency and technological progress contributing increases of 0.22% and 0.66%, respectively. Although the overall improvement was modest, both technical efficiency and technological progress played roles in driving TFP growth. On a year-by-year basis, the largest increase in TFP occurred between 2019 and 2020, with a value of 1.0363, while a decline occurred between 2018 and 2019, primarily due to a drop in technological progress. In other years, Jiangsu's agricultural TFP showed consistent improvement.

In contrast, Anhui Province's average TFP, technical efficiency, and technological progress values during the same period were 0.994, 1.0081, and 0.9922, respectively, indicating a slight decline in TFP, mainly driven by a decrease in technological progress. While Anhui's agricultural TFP improved in most years, a decline was observed between 2019 and 2020. Overall, except for the 2018-2019 period, Jiangsu consistently outperformed Anhui in TFP, as shown in Table 6 and Figure 2. In terms of technical efficiency, the gap between the two provinces was small, with Anhui even surpassing Jiangsu during 2021-2022. However, Jiangsu maintained a significant advantage in technological progress throughout the period, except in 2018-2019. This suggests that Jiangsu's higher TFP is largely attributable to its superior technological progress compared to Anhui.

Additionally, both provinces saw increases in TFP in all years except for Jiangsu in 2018-2019 and Anhui in 2019-2020. A key driver of these improvements was the implementation of the Yangtze River Delta Regional Integration Development Plan in 2019, which promoted agricultural integration in the region and contributed to higher TFP in both Jiangsu and Anhui from 2020 to 2022.

In conclusion, the analysis reveals that Jiangsu's agricultural TFP exhibited overall improvement from 2018 to 2022, with balanced progress in both efficiency and technological advancement. In contrast, Anhui experienced a decline in TFP, primarily due to a downward trend in technological progress. The comparative analysis between Jiangsu and Anhui indicates that Jiangsu's advantage in TFP is primarily driven by its superior technological progress during this period. To improve its agricultural TFP, Anhui should focus not only on enhancing technical efficiency but also on fostering technological progress by investing more resources in innovation. Finally, the implementation of the Yangtze River Delta Regional Integration Development Plan has had a significant positive impact on agricultural production efficiency in the region, as evidenced by the increase in TFP in both provinces from 2020 to 2022, underscoring the role of policy support in driving agricultural production efficiency growth.

Table 6 Total factor productivity of Jiangsu Province and Anhui Province from 2018 to 2022

Year	Province	Total Factor Productivity	Technical efficiency	Technological advancement
2018-2019	Jiangsu Province	0.945	1.002	0.943
	Anhui Province	1.021	1.025	0.997
2019-2020	Jiangsu Province	1.036	1.010	1.026
	Anhui Province	0.958	0.996	0.962
2020-2021	Jiangsu Province	1.033	0.993	1.040
	Anhui Province	1.018	0.991	1.029
2021-2022	Jiangsu Province	1.021	1.004	1.017
	Anhui Province	1.001	1.021	0.981
Average value	Average value of Jiangsu Province	1.009	1.002	1.007
	Average value of Anhui Province	0.999	1.008	0.992

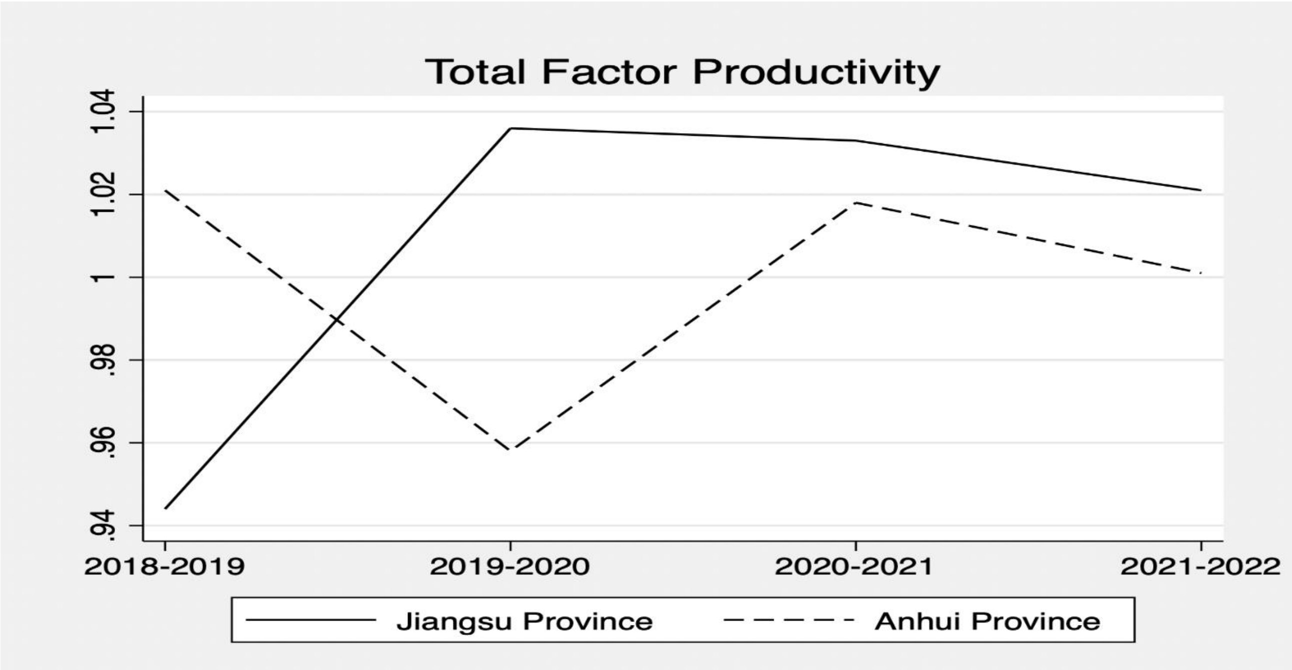

Figure 2 Total factor productivity of Jiangsu and Anhui provinces from 2018 to 2022

4. Discussion and Recommendation

4.1 Discussion and Outlook

Firstly, this paper applies a three-stage DEA model to study agricultural production efficiency in 29 prefecture-level cities in Jiangsu and Anhui, two key agricultural provinces, from 2018 to 2022. By eliminating external environmental factors and random disturbances, the study places these cities in the same external environment and adjusts for luck factors, leading to more accurate measurements of agricultural production efficiency. The results show that Jiangsu consistently outperformed Anhui in agricultural production efficiency, whether in the initial stage or after removing external environmental factors in the third stage. Specifically, Jiangsu surpassed Anhui in terms of technical efficiency, pure technical efficiency, and scale efficiency. This is largely due to Jiangsu’s status as an economically developed province in eastern China, which enables it to attract advanced technologies, talent, and stronger policy support, giving it an overall advantage in agricultural production efficiency. The third-stage results further reveal that after adjusting for external factors, both Jiangsu and Anhui saw improvements in pure technical efficiency, while scale efficiency declined. However, the differing degrees of change in pure technical efficiency and scale efficiency between the two provinces led to an increase in adjusted technical efficiency for Jiangsu and a decline for Anhui. Moreover, in both provinces, the increase in the number of cities exhibiting increasing returns to scale, coupled with a reduction in cities showing decreasing returns to scale, suggests a positive shift in the production potential across these regions. This trend indicates that an increasing number of cities are operating at a level where output can grow more than proportionally to input expansions, highlighting the efficiency gains that could be achieved through optimized resource allocation and scale adjustments. The reduction in cities with decreasing returns to scale further underscores the potential for enhanced agricultural productivity, as fewer regions face inefficiencies related to overextension or suboptimal scaling, paving the way for strategic improvements in agricultural output across Jiangsu and Anhui. These findings affirm the appropriateness of employing SFA regression to control for external factors, while also highlighting the significant potential for further improvement in scale efficiency in both provinces.

Secondly, the study utilizes the Malmquist Index model to calculate total factor productivity (TFP) for Jiangsu and Anhui from 2018 to 2022, based on the adjusted input variables from the second stage and the original output variables. The results indicate that, during this period, Jiangsu experienced improvements in TFP, technological progress, and changes in technical efficiency, whereas Anhui saw a decline in TFP, primarily due to a decrease in its rate of technological progress. Jiangsu's superior rate of technological progress allowed it to maintain an overall advantage in TFP over Anhui. Jiangsu, as an economically advanced region, benefits from substantial investments in agricultural research and development, robust institutional support, and access to modern infrastructure, which collectively enhance its capacity for adopting innovative farming techniques and maintaining steady improvements in productivity. In contrast, Anhui's comparatively limited financial resources and infrastructural development restrict its access to new technologies and innovations, hindering its ability to advance at a similar pace. This resource and support disparity ultimately contributes to the observed differences in technological progress and efficiency changes between the two provinces, solidifying Jiangsu's TFP advantage over Anhui during the study period. Furthermore, the study finds that while both provinces experienced TFP values below 1 in some of the earlier years, indicating declines in productivity, from 2020 to 2022, their TFP values exceeded 1, signaling growth in overall productivity levels. This improvement suggests that the implementation of initiatives such as the Yangtze River Delta Regional Integration Development Plan in 2019 played a pivotal role in promoting coordinated agricultural development across Jiangsu and Anhui. By fostering closer regional collaboration, enhancing resource-sharing mechanisms, and creating a more supportive policy environment, this plan effectively addressed some of the systemic barriers that had previously hindered agricultural productivity in the region. As a result, both provinces saw significant advancements in their agricultural sectors, which not only boosted production efficiency but also contributed to a more balanced and sustainable model of agricultural development across the Yangtze River Delta.

In summary, Jiangsu consistently outperformed Anhui in agricultural production efficiency from 2018 to 2022 due to its higher levels of technological progress and overall resource advantages. Additionally, regional policy initiatives aimed at promoting integration and collaboration, such as the Yangtze River Delta Regional Integration Development Plan, played a crucial role in boosting agricultural production efficiency in both provinces, particularly in the latter years of the study period. From a practical standpoint, the results emphasize the need for tailored strategies in improving agricultural efficiency. For Jiangsu, with its already high efficiency, the focus should be on sustaining and enhancing technological progress and fine-tuning scale efficiency. Anhui, in contrast, should prioritize technological innovation and infrastructure improvements to close the efficiency gap with Jiangsu. The Yangtze River Delta Regional Integration Development Plan has evidently contributed positively to these efforts by facilitating resource sharing and collaboration across provinces, a policy whose influence is reflected in the observed efficiency improvements from 2020 onwards.

Despite these contributions, the study has some limitations. First, while the three-stage DEA model addresses environmental influences, it may not fully capture the complexities of policy impact and economic interactions within the Yangtze River Delta. Second, our reliance on historical data from 2018 to 2022, though recent, may not reflect ongoing changes or the long-term effects of current policies. In addition, the study's scope is limited to two provinces, and future research could benefit from a broader dataset encompassing more regions within Yangtze River Delta to enhance the generalizability of the findings. Therefore, future research could explore these limitations by examining the effects of specific regional policies on agricultural efficiency over a longer period, potentially through the integration of other econometric or spatial analysis models. Additionally, investigating the role of digital agriculture and precision farming in enhancing efficiency could be beneficial, particularly in regions like Anhui, where there is significant room for growth. As technological advancements continue to reshape agriculture, further research on their impact in different economic contexts could provide more targeted recommendations for policy and resource allocation across varying levels of economic development.

4.2 Related suggestions

(1) Optimizing Resource Allocation and Reducing Waste: The second-stage SFA regression reveals varying degrees of input redundancy in Jiangsu and Anhui, indicating inefficient resource allocation. Improving agricultural production efficiency does not solely rely on increasing inputs; rather, enhancing resource use efficiency is critical. By optimizing the allocation of land, labor, and capital, both provinces can achieve higher outputs with reduced inputs, thereby improving overall agricultural production efficiency.

(2) Promoting Land Transfer and Agricultural Scale Efficiency: The third-stage DEA analysis shows a decline in scale efficiency for the majority of cities in Jiangsu and Anhui after accounting for external factors, suggesting significant room for improvement in scale efficiency. Promoting rational land transfer to facilitate large-scale agricultural operations can improve scale efficiency, enabling more efficient production systems and better utilization of resources.

(3) Increasing Technological Investment and Advancing Both Technological Progress and Technical Efficiency: The Malmquist Index analysis highlights fluctuations in both technological progress and technical efficiency in Jiangsu and Anhui during different years, with the lag in Anhui's technological progress being a key factor behind its lower total factor productivity (TFP) compared to Jiangsu. To address this, both provinces should focus on enhancing technological progress and technical efficiency, while increasing investment in agricultural technology to boost productivity.

(4) Leveraging Policy and Geographical Advantages: The research findings suggest that the implementation of the Yangtze River Delta Regional Integration Development Plan has driven improvements in agricultural production efficiency in the region. Under the framework of Yangtze River Delta integration, Jiangsu and Anhui should fully leverage their geographical advantages and regional policy support. By integrating regional resources, adjusting the agricultural industrial structure, and attracting skilled labor, both provinces can foster further improvements in agricultural production efficiency.

In conclusion, optimizing resource allocation, promoting agricultural scale efficiency, investing in technological advancement, and capitalizing on policy and geographical advantages are all essential strategies for enhancing agricultural production efficiency in Jiangsu and Anhui.

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Author(s) hereby declare that generative AI technologies such as Large Language Models, etc. have been used during the writing or editing of manuscripts. This explanation will include the name, version, model, and source of the generative AI technology and as well as all input prompts provided to the generative AI technology

Details of the AI usage are given below:

1. I hereby declare that during the writing of this paper, I only used ChatGPT-4 for translation and polishing purposes, and did not use it for any other purposes.

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