MEASUREMENT OF AGRICULTURAL TECHNICAL EFFICIENCY IN CHINA AND ITS INFLUENCING FACTORS

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Abstract. Using stochastic frontier analysis and the transcendental logarithmic production function, this study measures changes in agricultural technical efficiency and the factors affecting it based on panel data for 13 major grain-producing regions in China from 2007 to 2018. The results show the following. (1) The average agricultural technical efficiency of the studied areas shows a gradually increasing trend, from 0.369 in 2007 to 0.675 in 2018. (2) Dividing the production areas reveals differences in the agricultural technical efficiency of rice-, wheat-, and corn-production areas. The efficiency values for rice- and wheat-production areas are at the same level while those for corn-production areas are the lowest. (3) Agricultural machinery purchase subsidies, rural power generation, and urbanization factors have significant positive effects on agricultural technical efficiency; however, the proportion of the grain crop area structure has a negligible relationship with agricultural technical efficiency. Based on the findings, policy suggestions are made to adjust the input–output structure, improve the level of agricultural intensification, and avoid development that disregards environmental consequences.
Keywords: *agricultural technical efficiency, influencing factor, major grain-producing region, stochastic frontier analysis*

Introduction

Achieving high-quality agricultural development and rural revitalization requires improving the technical efficiency of agriculture. Limited by resource shortages, China has long been dominated by smallholder farming, and the process of agricultural modernization has been slow. Extensive input and output are the main obstacles impeding the improvement of agricultural technical efficiency. In recent times, although large number of factor inputs have stimulated agricultural output, they have also brought about a serious waste of resources, the spread of nonpoint source pollution, and a decrease in land fertility (Yang and Liu, 2021). In 2019, China’s Ministry of Agriculture and Rural Affairs and Ministry of Finance issued the “Notice on Doing a Good Job in the Implementation of Agricultural Production Development and Other Projects.” This included improving the quality of agricultural development, resource-allocation efficiency, and promoting new progress in rural revitalization. Then, in 2020, the CPC Central Committee and the State Council issued the “Opinions on Focusing on Key Work in the Areas of Agriculture, Rural Areas, and Farmers to Ensure the Realization of an Overall Well-Off Society on Schedule.” This called for promoting resource utilization, further reducing the use of pesticides and fertilizers, expanding agricultural investment, and giving more policy support to major grain-producing regions.

As an important area of economic research, efficiency measurement aims to help operators use lower costs to obtain a higher output. In the context of high-quality economic development, sustainable agricultural growth requires not only the continued

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expansion of inputs but also improved production technology efficiency to obtain higher returns. In traditional economic efficiency studies, total-factor productivity (TFP) includes the efficiency of all economic variables. Aside from factor endowment, it also considers the influence of various social factors. As a separate concept from TFP, technical efficiency (TE) focuses on the measurable economic output of inputs such as labor, capital, and land.

Current methods for measuring TE include the DEA–Malmquist index, DEA–GML index, and stochastic frontier analysis (SFA) (Battese, 1992; Rezitis et al., 2002). Existing studies of agricultural TE mainly focus on two categories. One is the measurement of agricultural TE, focusing on environmental pollution constraints. Liang et al. (2012) estimated the average agricultural TE in China from 1997 to 2009. They found that in the first stage, from 1997 to 2000, the efficiency of agricultural environmental technology showed a downward trend, from 0.699 to 0.625. The second stage was from 2001 to 2003, and the efficiency of agricultural environmental technology was relatively stable, and the average value of this stage was 0.627. The third stage is from 2004 to 2009, during this stage, the efficiency of agricultural environmental technology showed a rapid increase trend, in 2004 it was 0.690, an increase of 0.058 over 2003, and increased to 0.794 in 2009, an average annual increase of 0.018, economic level, agricultural structure and land resources are the main factors affecting the change of agricultural TE.

The second category of research investigates the interaction between agricultural TE and other factors. Latruffe and Desjeux (2016), for example, suggested that financial support for agriculture funds and farmers' funds can promote agricultural TE. Nowak et al. (2015), meanwhile, surveyed farmers and found a positive effect of socialized service in rice planting on agricultural TE. Some factors have also been found to have negative effects on agricultural TE. For example, using a DEA Tobit model to study the effects of rural labor force aging and other environmental variables on agricultural TE, Yang et al. (2014) found that labor force aging had a significant negative effect on TE and scale efficiency. Other studies, meanwhile, have investigated the interaction between agricultural TE and other factors. For example, Uaiene (2008) and Zamanian et al. (2013) and Liu et al. (2016) verified, respectively, the effects of urbanization, rural financial support, and farmland transfer on agricultural TE.

The above-mentioned studies reveal that research on agricultural TE is relatively mature. However, owing to differences in measurement methods and input–output elements, the conclusions are often quite different. Some studies do not extend the research period to the latest year. Moreover, although some studies focus on the factors affecting agricultural TE, there are blind spots regarding the relationship between certain other factors and agricultural TE. This study, therefore, focuses on the following questions. First, with increasing investment in agricultural elements, what is the current level of agricultural TE in China? Second, as agricultural TE is the common result of the input-output of many agricultural elements, are there other factors that promote the improvement of agricultural TE? Unlike previous studies, this study measures the change in agricultural TE in China based on 13 major grain-producing regions. Moreover, purchase subsidies for agricultural machinery are introduced as the main variables to analyze the factors affecting agricultural TE, thus expanding the research scope to a certain extent.

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Empirical design and data

There are currently 13 major grain producing regions in China, including Heilongjiang, Henan, Shandong, Anhui, Jilin, Inner Mongolia, Hebei, Jiangsu, Sichuan, Hunan, Hubei, Liaoning, and Jiangxi. There are 7 northern provinces and 6 southern provinces. In recent years, the grain production of 13 major grain producing areas has accounted for a proportion of the total national production, and overall, it has been continuously increasing, maintaining over 78% for many consecutive years. This study uses panel data for 13 main grain-producing regions in China from 2007 to 2018. First, an input-output model is constructed using the transcendental logarithmic production function, and SFA is used to measure changes in agricultural TE. Second, panel regression is used to verify the effects of agricultural machinery purchase subsidies and other factors on agricultural TE. Further, different areas of grain production are divided to consider regional heterogeneity.

Data sources

The data are derived from the Agricultural Mechanization Statistical Annual Report, Rural Statistical Yearbook, and EPS Agriculture and Forestry Database of each province from 2008 to 2019. *Table 1* shows the descriptive statistics of the variables. Among them, the sown area of crops, the amount of chemical fertilizer application, the total power of agricultural machinery, and employees in the primary industry are the input variables of agricultural TE. The total output value of agriculture is the output variable of agricultural TE. Purchase subsidies for agricultural machinery, rural power generation, the proportion of grain crop area structure, urbanization rate, and the proportion of the rural elderly population are the factors affecting agricultural TE.

Table 1. *Descriptive statistics of the variables*

Variable	Unit	Maximum value	Minimum value	Mean value	Standard deviation
Total output value of agriculture	Hundred billion yuan	9549.63	1276.44	4427.87	1954.33
Sown area of crops	Hectare	2,881,868	648	358,479	721,536
Fertilizer application rate	Ten thousand tons	716.09	123.2	295.36	140.43
Primary industry practitioners	Ten thousand people	2920	508	1342.32	662.248
Total power of agricultural machinery	Ten thousand kilowatts	13,353	1678.33	5368.03	3073.94
Agricultural machinery purchase subsidies	Hundred million yuan	19.5	0.52	8.39	4.73
Rural power generation	Ten thousand kilowatts	4,354,130	616	586,979	1,011,198
Proportion of food crop structure	%	0.957	0.509	0.719	0.106
Urbanization rate	%	0.677	0.343	0.511	0.078
Proportion of rural elderly population	%	0.173	0.069	0.109	0.023

Methods

(1) The transcendental logarithmic production function is chosen as the basic model for efficiency measurement. Compared with other types of production functions, it has better estimation and inclusiveness (Chiristensen et al., 1973). The transcendental logarithmic production function with logarithms on both sides is usually written as

$$\ln\mathrm{Y} = \beta_0 + \sum_{n=1}^{N}\beta_n lnX_n + 1/2\sum_{n=1}^{N}\sum_{m=1}^{N}\beta_{mn} lnX_n lnX_m \qquad \text{(Eq.1)}$$

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Four variables are selected as agricultural technical input elements, expressed by crop-planting area (A), fertilizer application amount (F), the total power of agricultural machinery (M), and primary industry practitioners (L). The output variable of TE is the generalized gross output value of agriculture (Y). The transcendental logarithmic production function can be written as

$$\begin{aligned} \ln Y = \beta_0 + \beta_A lnA + \beta_F lnF + \beta_L lnL + \beta_M lnM \\ +1/2\left[\beta_{AA}(lnA)^2 + \beta_{FF}(lnF)^2 + \beta_{LL}(lnL)^2 + \beta_{MM}(lnM)^2\right] + \\ \beta_{AF} lnAlnF + \beta_{AL} lnAlnL + \beta_{AM} lnAlnM + \beta_{FL} lnFlnL + \beta_{LM} lnLlnM \end{aligned} \quad \text{(Eq.2)}$$

(2) In the stochastic frontier model the main methods for measuring TE include parametric and nonparametric methods. In this study, parametric SFA is used to measure agricultural TE. SFA can describe the production process and perform inspection and inference through measurement. Early SFA did not consider the effect of time change on TE. Here, we refer to Battese and Coelli's (1995) SFA of time-varying TE:

$$Y_{it} = f(X_{it}, \beta) * exp(v_{it} - \mu_{it}) \quad \text{(Eq.3)}$$

$$\mu_{it} = \mu_i * exp\left[-\eta(t - T)\right] \quad \text{(Eq.4)}$$

where i and t are region and period number, respectively; Y_{it} is the total agricultural output of region i during period t; X_{it} represents the input of various factors during period t in region I; and $f(X_{it}, \beta)$ is the deterministic output part of the production frontier model. The error term includes two parts—systematic random error v_{it} and technical invalid random error μ_{it} -which are independent of each other in *Equation 3.* v_{it} is the accumulation of errors caused by uncontrollable factors, $v_{it} \sim N(0, \sigma_v^2)$; μ_{it} represents the controllable technical invalid error, which follows the nonnegative tail-breaking normal distribution of $N^+(\mu, \sigma_\mu^2)$. In addition, in *Equation 4*, the μ_{it} function describes the error caused by time change, and parameter η reflects the change degree of technical inefficiency. When $\eta > 0$, the corresponding exp value decreases at an increasing rate; when $\eta < 0$, the corresponding exp value increases at an increasing rate. The logarithm of both sides of *Equation 3* can be obtained as follows:

$$\ln Y_{it} = lnf(X_{it}, \beta) + v_{it} - \mu_{it} \quad \text{(Eq.5)}$$

Combined with the transcendental logarithmic production function, the complete SFA model can be written as

$$\begin{aligned} \ln Y = \beta_0 + \beta_A lnA_{it} + \beta_F lnF_{it} + \beta_L lnL_{it} + \beta_M lnM_{it} + \\ 1/2\left[\beta_{AA}(lnA_{it})^2 + \beta_{FF}(lnF_{it})^2 + \beta_{LL}(lnL_{it})^2 + \beta_{MM}(lnM_{it})^2\right] \\ +\beta_{AF} lnA_{it} lnF_{it} + \beta_{AL} lnAlnL_{it} + \beta_{AM} lnAlnM_{it} \\ +\beta_{FL} lnF_{it} lnL_{it} + \beta_{LM} lnL_{it} lnM_{it} + v_{it} - \mu_{it}. \end{aligned} \quad \text{(Eq.6)}$$

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The model parameter γ value $\gamma = \sigma_\mu^2 / \sigma_v^2 + \sigma_\mu^2$ estimated by the maximum likelihood method can be used to test whether there is technical inefficiency. The closer the γ value is to 1, the more the technical error of inefficiency is controllable. Technical efficiency is $TE_{it} = exp(-\mu_{it})$; that is, the calculated efficiency value. To measure technical efficiency, we use Frontier 4.1 software, which can estimate the stochastic frontier cost model and the stochastic frontier production model using the maximum likelihood method.

(3) Panel regression model. Panel data are used to track the same individual data within a period. This can not only obtain the sample's cross-sectional information (n individuals) but also measure the sample's time information (t periods). A panel data model can provide more information about the dynamic behavior of individuals and demonstrate the effect between variables on time nodes (Mwalupaso et al., 2019). After measuring agricultural TE, this study constructs a panel regression model to analyze the factors affecting agricultural TE:

$$y_{it} = \mu + X_{it}^{'}\beta + Z_i^{'}\delta + \varepsilon_{it} \quad \text{(Eq.7)}$$

where i represents an individual, and t represents time. All of the explanatory variables can be divided into individual characteristic x that changes with time and individual characteristic z that does not change with time. The disturbance term can be further divided as follows:

$$y_{it} = \mu + X_{it}^{'}\beta + Z_i^{'}\delta + \alpha_i + \lambda_t + \upsilon_{it} \quad \text{(Eq.8)}$$

where α_i is the unobstructed individual difference that does not change with time in the disturbance term-specifically, the individual effect. λ_t is the unobtrusive time difference that does not vary with individuals in the disturbance term-specifically, the time effect. υ_{it} is the remaining part of the perturbation term, which is assumed to satisfy spherical perturbation variance and other assumptions.

Variable selection

Referring to Kuang and Yang (2018) and Peng (2020), the following variables are selected to improve the econometric regression model.

(1) Explained variable: agricultural technical efficiency (TE), which reflects the proportion between actual input and maximum output. The final efficiency value is calculated using SFA.

(2) Core explanatory variable: agricultural machinery purchase subsidy. This study focuses on the factors that affect agricultural TE, and the agricultural machinery purchase subsidy is an important project set up by the Treasury. Subsidies can mobilize farmers' machine purchasing power, and the overall level of agricultural mechanization plays an important role in agricultural improvement. Subsidies for the purchase of agricultural machinery are different from financial input for the purchase of agricultural machinery and mainly cover two levels: central and local subsidies. Central subsidies account for the vast majority of subsidies in various regions and are usually distributed in two batches every year.

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(3) Other control variables: rural power generation, the proportion of grain crop area structure, urbanization rate, and the proportion of the rural elderly population are selected as other influencing factors. Rural power generation reflects the infrastructure of agricultural production and life. The better the rural power facilities, the more conducive to agricultural production and to improve agricultural efficiency. The structural proportion of grain crop area refers to the proportion of the sown area of grain crops to the total sown area of crops, reflecting the structural efficiency of agricultural production. This is included because the richer the product structure, the more obvious the effect of technology diffusion, which might promote the improvement of agricultural TE. Urbanization rate refers to the proportion of the permanent urban population in the total permanent population. Urbanization typically leads to the crowding of agricultural land, which affects normal agricultural production. Urbanization also causes a large amount of the rural labor force to enter urban employment, which might prompt the redistribution of rural land, labor force, and various resource factors, thus affecting agricultural TE. The proportion of rural elderly refers to the proportion of the rural population aged 65 and above in the total population. The labor factor has always been a key factor in agricultural production, and the increasingly serious problem of population aging is a major issue facing China's agricultural economy. The increase in rural elderly might have a negative effect on agricultural production but might also improve agricultural TE to some extent.

Division of study regions

Thirteen major grain-producing regions are selected as samples. To measure the specific TE and influencing factors of different regions, grain-production areas are divided into rice-, wheat-, and corn-production areas, following the "Guiding Opinions of the State Council on the Establishment of Functional Grain Production Zones and Important Agricultural Production Reserves," issued by the State Council in 2017 (*Table 2*). Rice-production areas include nine provinces (e.g., Sichuan, Hunan, Hubei). Wheat-production areas include Shandong, Henan, Hebei, and 10 others. Corn-production areas include six provinces (e.g., Heilongjiang, Jilin, and Liaoning).

Table 2. *Division of study regions*

Grain-production area	Provinces
Rice-production areas	Heilongjiang, Jilin, Liaoning, Sichuan, Hunan, Hubei, Jiangsu, Anhui, Jiangxi
Wheat-production areas	Shandong, Henan, Hebei, Sichuan, Inner Mongolia, Hunan, Hubei, Jiangxi, Jiangsu, Anhui
Corn-production areas	Heilongjiang, Jilin, Liaoning, Shandong, Henan, Hebei

Measurement of agricultural technical efficiency

Model estimation results

The maximum likelihood estimation results of the model parameters are obtained based on the stochastic frontier production function of *Equations 2–6. Table 3* shows the estimated coefficients of each input variable and its interaction terms. Except for the interaction coefficients of β_{AF} (land and fertilizer) and β_{AM} (land and machinery), the parameter estimates of the output intercept term and other input variables all pass the significance level test below 5%. Input variables that are significantly positively correlated with the measurement of agricultural TE include β_L, β_M, β_{AA}, β_{AL}, β_{FL}, and

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β_{FM} . Input variables with significant negative correlations are β_A , β_F , β_{FF} , β_{LL} , β_{MM} , and β_{LM} . In SFA, greater inputs for each factor are not more helpful for TE. An input variable with a negative coefficient indicates that the input is no longer helpful for efficiency output, and there might be spillover effects (e.g., the sown area of crops and the amount of fertilizer applied). In addition, the total variance σ^2 is 0.055, and the γ value $\gamma = \sigma_\mu^2 / \sigma_v^2 + \sigma_\mu^2$ is 0.940, indicating the objective existence of technical inefficiencies. Controllable technical inefficiencies are 94.08%, and random technical inefficiencies account for 5.92%. The parameter is 0.076 and greater than 0, indicating that probability μ_{it} decreases at an accelerated rate of 0.076 over time. Thus far, the estimation results demonstrate the suitability of the original model and that the SFA method is feasible.

Table 3. *Stochastic frontier production function estimation results*

Parameter	Coefficient	Standard error	T-value	Parameter	Coefficient	Standard error	T-value
β_0	56.066***	1.160	48.311	β_{AM}	−0.404	0.390	−1.037
β_A	−2.771***	0.178	−12.764	β_{FL}	0.823***	0.330	2.488
β_F	−5.219**	2.519	−2.071	β_{FM}	2.166***	0.340	6.354
β_L	5.488***	1.786	3.071	β_{LM}	−0.048***	0.227	−4.614
β_M	7.113***	1.513	4.701	σ^2	0.055***	0.008	6.272
β_{AA}	1.681**	0.759	2.215	γ	0.940***	0.016	58.353
β_{FF}	−4.081***	0.790	−5.163	μ	0.455***	0.071	6.353
β_{LL}	−2.001***	0.406	−4.922	η	0.076***	0.005	14.988
β_{MM}	−1.015***	0.234	−4.324				
β_{AF}	0.520	0.678	0.767	Logarithmic likelihood function		150.376	
β_{AL}	1.872***	0.425	4.404	Unilateral likelihood ratio test		280.670	

***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively

Agricultural technical efficiency in major grain-producing regions

Figure 1 shows the average value of agricultural TE from 2007 to 2018. During the 12 years, the average value of agricultural TE in the 13 major grain-producing regions is 0.510, showing an overall trend of a gradual rise from 0.369 in 2007 to 0.675 in 2018. This indicates that the actual agricultural output gradually approaches the theoretical maximum output, which is conducive to the development of the agricultural economy. In general, the agricultural input–output efficiency of the 13 major grain-producing regions is not high, and there is still much room for improvement. Compared with the national agricultural TE measured by Barros and Dieke (2008) and Porcelli (2009), there are both similarities and differences. First, in the measurement period, it is noteworthy that agricultural TE is on the rise with the development of the agricultural economy. Second, imbalances between provinces have existed for a long time, and the vast majority of research samples are still below the production frontier. The reasons for the slowly rising trend in agricultural TE are as follows. First, the total amount of input-output factors keeps increasing. Except for the primary industry labor factor, the sown area of crops, the amount of chemical fertilizer application, the total power of machinery, and the total agricultural output value increased steadily over the 12-year study period, reaching the maximum values in 2017 and 2018. This is basically consistent with the trend of efficiency. Second, the structure of agricultural input–output

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in major grain-producing regions has been stable for a long time. For various reasons, the high agricultural input in the highest-producing areas does not result in the rapid growth of the gross agricultural product, leading to a low overall agricultural TE. This phenomenon is not easily changed in the short term.

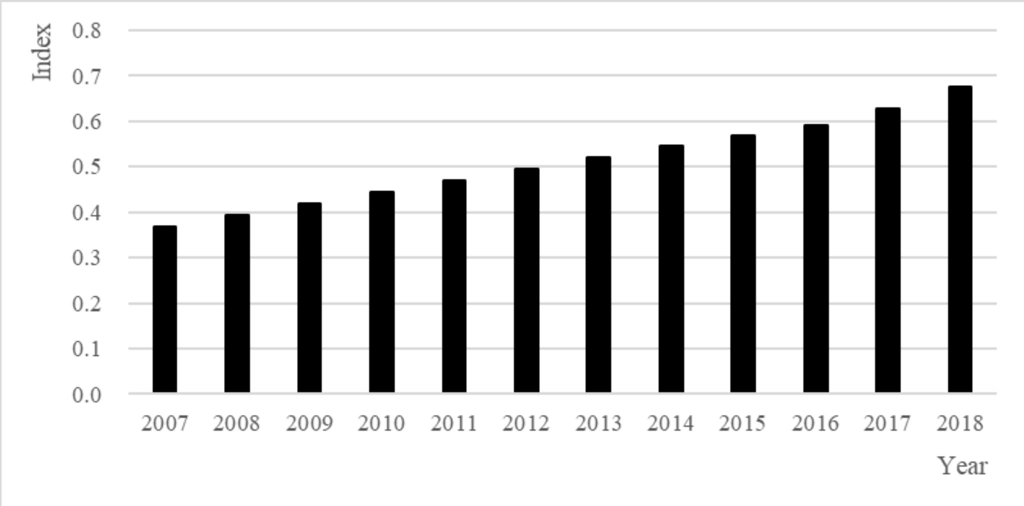

Figure 1. *Average agricultural technical efficiency in major grain-producing regions, 2007–2018*

Agricultural technical efficiency of different grain-production areas

Grain-production areas are divided into rice-, wheat-, and corn-production areas. *Table 4* shows the average agricultural TE of these different grain-production areas. First, the TE values of the rice-, wheat-, and corn-production areas significantly improve during the study period. The rice-production area increased from 0.385 in 2007 to 0.650 in 2018, the wheat-production area increased from 0.405 in 2007 to 0.666 in 2018, and the corn-production area increased from 0.325 in 2007 to 0.605 in 2018. However, the agricultural TE of these production areas is similar to that of the 13 major grain-producing regions. Second, comparing the values of the three production areas, we can see that the efficiency values of the rice- and wheat-production areas are almost on the same curve. The TE value of the wheat-production area is slightly higher than that of the rice-production area while that of the corn-production area is the lowest. This indicates that the input and output effect of wheat planting is relatively better. At present, the rice and wheat industries are no longer different in the north and south; most areas of China can grow these types of crops. In the main grain-producing regions, many areas have two or more production tasks.

Factors affecting agricultural technical efficiency

Baseline regression results

Hausman’s test is used to identify the individual effects of the panel model. Based on *Equations 7* and *8*, the factors affecting agricultural TE are analyzed by adding the control variables step by step. *Table 5* includes five regression models that fit the results according to the Hausman test, including two random-effect and three fixed-effect

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models. The obtained Wald chi-square value (or F-value) indicates that the model has a good effect. The core explanatory variable of agricultural machinery purchase subsidies has a significant positive effect on agricultural TE and passes the 1% significance test. With the addition of other independent variables, the regression coefficient of agricultural machinery purchase subsidies shows a decreasing trend, and the coefficient in the final model V is 0.077. The greater the intensity of agricultural machinery purchase subsidies, the more conducive it is to improving agricultural TE. As a special fund set up by the central government to promote agricultural production, this policy can be considered beneficial for agricultural development.

Table 4. *Average agricultural technical efficiency of grain-production areas, 2007–2018*

Year	Rice-production area	Wheat-production area	Corn-production area
2007	0.385	0.405	0.315
2008	0.409	0.430	0.341
2009	0.434	0.455	0.369
2010	0.459	0.479	0.396
2011	0.484	0.504	0.423
2012	0.508	0.528	0.449
2013	0.532	0.551	0.476
2014	0.556	0.574	0.502
2015	0.579	0.597	0.528
2016	0.602	0.619	0.553
2017	0.626	0.643	0.579
2018	0.650	0.666	0.605

Table 5. *Estimated results of the panel regression model*

Variable	Model I	Model II	Model III	Model IV	Model V
Agricultural machinery purchase subsidy	0.171^{***} (14.69)	0.166^{***} (14.65)	0.165^{***} (14.59)	0.082^{***} (5.39)	0.077^{***} (5.91)
Rural power generation		0.070^{***} (3.00)	0.094^{***} (3.58)	0.095^{***} (4.31)	0.100^{***} (5.22)
Proportion of grain crop area			0.858^{*} (1.72)	0.688 (1.64)	0.244 (0.66)
Urbanization rate				1.178^{***} (7.00)	0.554^{***} (3.14)
Proportion of rural elderly					0.619^{***} (6.26)
Constant term	-1.114^{***} (−11.27)	-1.277^{***} (−10.92)	-1.043^{***} (−6.13)	−0.145 (−0.76)	0.663^{***} (3.15)
R^2	0.648	0.678	0.680	0.768	0.830
F value/Wald chi-square value	215.78	241.54	83.46	101.22	116.15
Effect of individual	Re	Re	Fe	Fe	Fe
Observed value	156	156	156	156	156

***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively

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The increase in rural power generation and urbanization rate variables also have a significant positive effect on agricultural TE. In the main model V, the regression coefficients of the two variables reach 0.100 and 0.554. This highlights the role of rural infrastructure construction and shows that urbanization promotes the allocation of rural land, labor force, and other factors. However, the structural proportion of grain crops has a negligible relationship with agricultural TE. There is a significant positive correlation between the proportion of rural elderly and agricultural TE, which means that the larger the rural elderly population, the higher the agricultural TE. Silva et al. (2022) found that the aging society is not conducive to agricultural TE, but there are also studies showing technical inefficiency in China's agricultural production. The aging of the rural labor force does not reduce the efficiency of food production (Xu and Zhang, 2014). The present study suggests that increases in the elderly population increase dependence on agricultural machinery and encourage farmers to use more machinery, which can, in turn, improve agricultural efficiency. In rural China, a large number of farmers have had concurrent jobs for a long time. Compared with young and middle-aged people, the elderly is better able to devote themselves to agricultural production.

Subregional regression results

To explore the specific effects of selected factors on agricultural TE and reflect regional differences, this study further carries out subregional regression for rice-, wheat-, and corn-production areas and directly selects panel regression based on solid effects. *Table 6* shows the results. In the three estimation models, agricultural machinery purchase subsidy variables are positively correlated with agricultural TE. The regression coefficients of the rice-, wheat-, and corn-production areas are 0.078, 0.032, and 0.091, respectively, at the 1% significance level. This verifies the benchmark accuracy of the regression model and affirms the same conclusion: the higher the agricultural machinery purchase subsidy, the higher the agricultural TE value. Other factors have different effects on agricultural TE. First, rural power generation in the three models has a positive effect on the dependent variables, and the regression coefficient of the wheat-production area is relatively higher than that of rice- and corn-production areas, which highlights the importance of infrastructure for agricultural TE. Second, the urbanization rate of wheat-production areas is one factor for improving TE, indicating that an increase in the urbanization rate can help increase the efficiency value. Regarding the relationship between the proportion of elderly and TE, the rice-and corn-production areas have a positive promoting effect. Meanwhile, the structural proportion of grain crops has no obvious relationship with the agricultural TE value of the three areas of grain production.

Robustness test

To verify the reliability of the econometric regression and check whether the results are stable under different conditions, the 12-year study period is divided into four stages for robustness testing. As shown in *Table 7*, in the multiperiod panel regression, agricultural machinery purchase subsidies and rural power generation in the four time periods all pass the significance test and have a positive effect on agricultural TE. Meanwhile, urbanization rate and population factors can also promote an increase in agricultural TE to a certain extent. Thus, the estimations are consistent with the main model, and the measurement results are robust.

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Table 6. *Panel regression estimation results for different production areas*

Variable	Rice-production area	Wheat-production area	Corn-production area
Agricultural machinery purchase subsidy	0.078*** (5.06)	0.032** (1.96)	0.091*** (6.73)
Rural power generation	0.233*** (5.11)	0.078*** (3.98)	0.065*** (3.95)
Proportion of grain crop area	0.104 (0.23)	0.288 (0.71)	−0.561 (−1.15)
Urbanization rate	0.289 (1.39)	1.365*** (5.82)	0.343 (1.54)
Proportion of rural elderly	0.621*** (5.29)	0.108 (0.74)	0.829*** (8.20)
Constant term	−0.062*** (−0.20)	0.351 (1.33)	0.858*** (4.10)
R^2	0.825	0.838	0.921
F value	71.97	88.49	114.65
Effect of individual	Fe	Fe	Fe
Observed value	108	120	72

***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively

Table 7. *Estimated results of the time-segmented panel regression model*

Variable	2007–2009	2007–2012	2007–2015	2007–2018
Agricultural machinery purchase subsidy	0.069*** (4.95)	0.077*** (6.11)	0.074*** (5.46)	0.077*** (5.91)
Rural power generation	0.078** (2.14)	0.203*** (4.53)	0.170*** (5.35)	0.100*** (5.22)
Proportion of grain crop area	−0.093 (−0.24)	0.639 (1.57)	0.855** (2.05)	0.244 (0.66)
Urbanization rate	0.369 (1.14)	0.531** (2.06)	0.695*** (3.14)	0.554*** (3.14)
Proportion of rural elderly	0.092 (0.41)	−0.011 (−0.06)	0.327** (2.19)	0.619*** (6.26)
Constant term	−0.778 (−1.25)	−0.940** (−2.16)	0.131 (0.42)	0.663*** (3.15)
R^2	0.823	0.834	0.828	0.830
F value/Wald chi-square value	123.39	60.32	83.25	116.15
Observed value	39	78	117	156

***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively

Discussion

Our empirical research has found that there is still considerable room for improvement in agricultural TE in most grain producing areas in China. Furthermore, the agricultural economy needs to adjust its input-output structure, improve the level of agricultural intensification, and avoid development that disregards environmental consequences. Secondly, since its establishment in 2004, the subsidy for purchasing

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agricultural machinery has shown an increase in farmers' enthusiasm for production. Therefore, it is suggested that the government continue to expand the scope of agricultural machinery subsidies and enhance the influence of policies. In addition, in the past decade, the Chinese government has introduced a series of agricultural environmental regulation policies, which also require the protection of the agricultural ecological environment to create more favorable conditions for agricultural production and achieve sustainable development.

Conclusion

In this study, SFA was used to measure changes in agricultural TE in 13 major grain-producing regions and specific production areas in China during 2007-2018. A panel data regression model was built to explore the effects of agricultural machinery purchase subsidies and other factors on agricultural TE. The conclusions were as follows. (1) During the 12-year study period, the average agricultural TE in the 13 major grain-producing regions was 0.510, showing a gradual upward trend, from 0.369 in 2007 to 0.675 in 2018. In general, the agricultural input–output efficiency in the 13 major grain-producing regions was not high, and there was still much room for improvement. (2) There were some differences in the agricultural TE of rice-, wheat-, and corn-production areas. The rice-production area increased from 0.385 in 2007 to 0.650 in 2018, and the wheat-production area increased from 0.405 in 2007 to 0.666 in 2018. The efficiency of the corn-production area increased from 0.325 in 2007 to 0.605 in 2018, and its efficiency was the lowest. (3) Agricultural machinery purchase subsidies had a significant positive effect on agricultural TE. The five regression models showed that the results had high robustness. In addition, increases in rural power generation, urbanization rate, and the proportion of rural elderly also contributed to the improvement of agricultural TE. However, the structural proportion of food crops had a negligible relationship with agricultural TE.

Author contributions. FZ contributed to the motivation, the interpretation of the methods, the data analysis and results, and provided the draft versions and revised versions, references. QH provided the data and results, the revised versions and references.

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Data availability statement. The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

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