

Analysis of Arain Production Efficiency in 30 Provinces in China Based on DEA-Malmquist Index Model

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Abstract:

Provincial panel data from 2011 to 2021 (excluding Tibet) were selected, the DEA model was used to measure the grain production efficiency of 30 provinces across the country, and the Malmquist index method was used to further analyze the changes and characteristics of grain production efficiency in each province. The results show that my country's grain production efficiency has not reached effective levels in 2011, 2016 and 2021, and has shown an overall trend of declining first and then rising; the total factor productivity of grain production has increased overall from 2011 to 2021, but the growth rate fluctuates less, and technical efficiency is the main factor affecting grain production efficiency. It is necessary to strengthen agricultural infrastructure construction and upgrade agricultural irrigation technology to improve food production efficiency.

Keywords:

DEA Model, Malmquist Index Method, Grain Production Efficiency, Grain Yield

1. Introduction

Food security is the cornerstone of national security and the fundamental guarantee for economic and social development [1]. As a country with a large population, China has always placed food security at the top of its agenda [2]. However, with the rapid advancement of industrialization and urbanization, practical challenges such as tighter constraints on cultivated land resources, structural shortages of agricultural labor, and increasing pressure on the ecological environment have become increasingly prominent. The traditional development model that relies on large-scale investment in resource factors to ensure food production is no longer sustainable. In this context, improving food total factor productivity (TFP) and achieving “connotative” growth in food production through technological progress and efficiency improvements have become the fundamental way out and strategic choice to break resource and environmental constraints and ensure national food security.

Currently, China's grain production faces severe challenges: on the one hand, agricultural resource endowments, especially cultivated land and water resources, are

increasingly tight, and the ecological environment's carrying capacity is facing bottlenecks [3]; on the other hand, domestic grain demand maintains a rigid growth trend due to population growth and consumption structure upgrades, and international grain market fluctuations have intensified imported risks [4]. This contradiction between the rigid growth of demand and the rigid constraints of resources urgently requires my country's grain production to shift from expansionary development that mainly relies on resource input to intensive development that relies more on scientific and technological progress and efficiency improvements. Therefore, scientific quantification and dynamic analysis of grain production efficiency and its evolution are of great theoretical and practical significance for identifying growth bottlenecks, optimizing resource allocation, and accurately formulating policies.

In the field of efficiency measurement research, data envelopment analysis (DEA) and its derived Malmquist index model have become a powerful tool for measuring total factor productivity (TFP) and its dynamic changes because it can handle complex systems with multiple inputs and multiple outputs, without preset production function forms, and can separate changes in technical efficiency and contributions from technological progress [5]. This model has been widely used in research on agricultural, especially grain production efficiency. It can clearly reveal whether efficiency growth is due to the "catch-up effect" or the "growth effect" and provides a micro-level entry point for policy regulation [6]. However, existing applied research still has shortcomings: first, multi-focused static cross-sectional efficiency analysis, few systems track the inter-temporal dynamic evolution characteristics of my country's grain productivity, especially spatial differentiation; second, comprehensive research based on inter-provincial panel data and comprehensive use of the DEA-Malmquist model to deeply examine the efficiency-driving mechanisms in different regions across the country is relatively scarce; third, the depth of the deep structural and spatial causes behind efficiency changes at the inter-provincial level needs to be improved.

This article aims to use the DEA-Malmquist index method to build a system framework and empirically examine the dynamic evolution of grain production efficiency in 30 provinces in China (excluding Hong Kong, Macao, Taiwan and Tibet, where data is seriously missing). The specific objectives include: first, quantitatively measure the total factor productivity of grain in each province and its decomposition index, and analyze its overall growth trend and dynamic evolution characteristics during the investigation period; second, deeply analyze the differences in the driving mechanisms of efficiency growth in different regions, and reveal the leading role of efficiency improvement or technological frontier advancement; third, combine the perspective of spatial heterogeneity and macro-environmental evolution to deeply explore the key structural factors that affect inter-provincial efficiency changes, such as the degree of land scale management, mechanization level, irrigation facilities, agricultural science and technology investment, policy support, etc. By describing the inter-provincial differences, dynamic trajectories and driving sources of my country's grain production efficiency, this study will help deepen the understanding of the efficiency characteristics of the national grain production system, and provide solid decision-making reference and academic support for optimizing regional agricultural policies, promoting high-quality development of the grain industry, and building a solid barrier to national food security.

2. Literature Review

2.1. Research Methods for Food Production

Many scholars have conducted research on China's grain production efficiency from different angles and using different methods, and the research subjects cover provinces across the country. Xiao Hongbo et al. [7] used the DEA model to measure China's grain production efficiency from 2000 to 2009, and found that the average comprehensive technical efficiency and pure technical efficiency of grain production were both low. Yang Lin et al. [8], Ding Wenbin [9] and others used the input- and output-oriented BBC model to measure the grain production efficiency of the country and Hubei Province respectively, and found that increasing factor inputs can improve grain production efficiency. In order to make up for the shortcomings of the traditional DEA model assumptions that are inconsistent with the actual situation, scholars have improved the DEA model. Wang Qian et al. [10] used the Malmquist-DEA method to measure the total factor efficiency of grain production at the county level in Hebei Province, and explained the spatial differentiation and trend characteristics of grain production efficiency within the province. Zeng Fusheng et al. [11] used the SBM-Tobit model to calculate China's grain production efficiency in 2009 and found that grain production efficiency is closely related to factors such as fertilizer usage and grain sowing area. Zhang Liguang et al. [12] used DEA-Malmquist index and fixed effects model to analyze the spatiotemporal evolution and driving factors of grain total factor productivity in China's main grain-producing areas from 2001 to 2012. In order to make up for the neglect of spatial effects in the study of grain production efficiency, Gao Ming et al. [13] used the DEA-Moran's I-Theil Index model to analyze the spatial autocorrelation of grain production technical efficiency and its regional differences. Yang Lixia et al. [14] used ESDA and geographically weighted regression models to conclude that grain production and its driving factors are spatially heterogeneous. Yang Chun et al. [15] used a spatial econometric model to conclude that China's grain production has strong spatial dependence.

Existing research results on the spatial variation characteristics of grain production efficiency are relatively few, and there is a lack of exploration into the influencing factors of grain production efficiency. This study uses system supply constraints and environmental constraints as constraints to avoid overestimation or underestimation of efficiency measurement due to the influence of a special decision-making unit [16]. It builds a dynamic DEA calculation model of grain production efficiency based on DDF to measure China's grain production efficiency from 2011 to 2019, and adopts Using the ESTDA model proposed by Rey et al. [17], with the help of LISA time path and space-time transition analysis methods, combined with geographical detectors, the dynamic changing characteristics of the spatial pattern of grain production efficiency and its influencing factors are analyzed, with a view to providing a decision-making reference for improving China's grain production efficiency and ensuring food security.

2.2. Selection of Indicators for Grain Production

When Chinese scholars study the factors affecting the development of the grain economy, they usually conduct analyzes based on relevant domestic data. Research by Yang Ren et al. [18] found that domestic scholars divide the influencing factors into four types: land resources, capital investment, human resources, and natural disasters. Xiao Haifeng et al. [19] studied the 15-year historical data from 1990 to 2004 and

concluded that land resources and funds played the greatest role in the development of the domestic grain economy, and provided relevant suggestions for the growth of the domestic grain economy. Xin Liangjie et al. [20] pointed out that in addition to the impact of grain sown area and grain output on the development of the grain economy, the impact of different regions is also significant. With the development of technology and in-depth research, Gao Ming et al. [21] studied the differences in production efficiency in the development of the grain economy from a spatial and functional perspective, and pointed out that to promote the development of the grain economy, agricultural machinery should be used in more areas, and advanced production technologies should be promoted to more areas. Zhang Xiaoyan et al. [22] combed through the data from 1949 to 2020 and analyzed that the sown area, the total power of effective irrigation agricultural machinery, the amount of chemical fertilizer application and the amount of pesticide use have a significant impact on grain production efficiency. Xiang Sheng et al. [23] concluded through empirical testing that factors such as grassroots agricultural technology extension, social capital and land management scale have a significant impact on the technical efficiency of grain production. Research by Huan Meili et al. [24] found that farming methods, planting scale and irrigation methods have a significant positive impact on grain production efficiency.

3. Research Methods and Indicator Selection

3.1. research methods

3.1.1. DEA model

Data envelopment analysis (DEA) is a data processing method for studying economic production boundaries and operations research. Because it does not contain specific function assumptions and weights, it can measure the static efficiency of multiple decision-making units (Decision making units, DMU) while studying multiple input and output variables at the same time. Data envelopment analysis is divided into a model with constant returns to scale and a model with variable returns to scale. The model with constant returns to scale is mainly used to measure comprehensive technical efficiency including scale efficiency, while the model with variable returns to scale is mainly used to measure pure technical efficiency excluding the impact of scale efficiency.

The pure technical efficiency in the grain crop planting and production process is calculated through the DEA model, and the scale efficiency is derived by using the relationship between comprehensive technical efficiency and pure technical efficiency in the DEA model. Pure technical efficiency refers to the efficiency of input and output of each decision-making unit under study when it reaches the optimal scale, and can represent the efficiency of the use of input factors. Scale efficiency refers to whether the ratio of input and output of each decision-making unit studied is appropriate. The higher the value, the more suitable the current scale is and the greater its productivity. Data envelopment analysis (DEA) is an efficiency evaluation method in which each model has two forms: output-oriented and input-oriented. The model can be set to return a constant in proportion and a variable in proportion. Taking into account factors such as the agricultural production policy environment and other related social internal conditions, as well as related natural conditions and external environment factors such as weather, the returns to scale will change to a certain

extent: only humans can control the input factors, and the output factors will not change according to people's subjective wishes. Therefore, the BCC model with variable returns to scale was finally chosen.

If it is assumed that the decision-making system contains n DMUs, there are m input factors and s output factors. Define $x=(x_{ij}) \in R^{m \times n}$ to represent the input variable, $y=(y_{ij}) \in R^{s \times n}$ to represent the output, and $x > 0$, $y > 0$. Select a model with variable returns to scale, and the specific settings are as follows.

$$\rho = \min \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{S_i^-}{x_{i0}}}{1 + \frac{1}{s} \sum_{r=1}^s \frac{S_r^+}{y_{r0}}} \quad (1)$$

$$\text{S.T.} \begin{cases} x_0 = X\lambda + S^- \\ y_0 = Y\lambda - S^+ \\ S^-, S^+, \lambda \geq 0 \end{cases} \quad (2)$$

In the formula, λ is the weight variable, S^+ is excessive input, S^- is insufficient output, ρ is the efficiency value of DMU, and $0 < \rho < 1$. When $\rho = 1$, it indicates that the DMU is invalid.

3.1.2. Malmquist index

The concept of Malmquist index was originally proposed by Malmquist [25]. Caves [26] and others developed it into a theory for measuring productivity changes. Fre [27] and others combined it with DEA theory. The Malmquist index is mainly used to study the dynamic analysis of industrial efficiency. Hou Xuhua [28] et al. used the DEA model and the Malmquist index model to measure and analyze the financing efficiency of the industry as a whole and at the subdivision level from a static and dynamic perspective respectively. Chen Jie [29] et al. applied the three-stage DEA model and the Malmquist index model to measure China's agricultural green water resource utilization efficiency. It can be seen that the Malmquist index model is widely used in research on measuring efficiency. According to the specific research objectives, the Malmquist index of the i -th DMU from t to $t+1$ is expressed as follows.

$$M_i(x_t, y_t, x_{t+1}, y_{t+1}) = \frac{1}{2} \left[\frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)} \times \frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^{t+1}(x^t, y^t)} \right] \quad (3)$$

In the formula, (x, y) represents the input and output variables in each period; D_t and D_{t+1} respectively represent the technology in period t as a reference. The distance equation between period t and period $t+1$. If the measured value is less than 1, it means that the resource utilization efficiency from t to $t+1$ period is reduced; if the measured value is greater than 1, it means that the resource utilization efficiency from t to $t+1$ period is increased.

3.2. Indicator selection

In order to eliminate the impact of changes in grain selling prices in different years, all indicators are expressed in physical quantities during the selection process. When analyzing grain efficiency, panel data from 30 provinces in China (excluding Tibet) from 2011 to 2021 were selected for research. The total grain production of each province is used as the output indicator, and the effective irrigation area, the reduced amount of agricultural fertilizer application, the crop sown area, and the total power of agricultural machinery are selected as the input indicators. The data comes from the "China Statistical Yearbook" from 2011 to 2021.

4. Empirical Analysis

4.1. Analysis of grain production efficiency by province

Using Deap2.1 software, the DEA model was used to statically calculate the grain production efficiency of 30 provinces across the country (excluding Tibet) from 2011 to 2021 at five-year intervals. The results are shown in Table 1.

4.1.1. Comprehensive efficiency

As can be seen from Table 1, the national grain production efficiency averages in 2011, 2016, and 2021 are 0.638, 0.6, and 0.67 respectively, which have not reached the effective state. Overall, the top three in comprehensive efficiency in 2011, 2016 and 2021 have always been Jilin, Heilongjiang and Liaoning. Among them, the grain production efficiency of Jilin and Heilongjiang is at the optimal production frontier in 2011, 2016, and 2021, that is, the grain production in these two places is in the optimal configuration state, and the grain production efficiency is maximized; and Jilin and Heilongjiang provinces have achieved comprehensive efficiency, pure technical efficiency, and scale efficiency at the same time, and agricultural production input and output have reached the optimal state. They are veritable grain-producing provinces, while other provinces have not reached the optimal state, and there is still a lot of room for improvement in grain production efficiency. Among them, Hainan Province has the lowest comprehensive efficiency in 2011, 2016, and 2021. Its comprehensive efficiency is 0.386, 0.292, and 0.327 respectively, which are quite different from the national average. The comprehensive efficiency of Beijing and Guangxi showed a downward trend, Tianjin, Shanxi, Inner Mongolia, and Gansu showed an upward trend. The comprehensive efficiency of Hebei, Liaoning, Jiangsu, Anhui, Shandong, Henan, Guizhou, Yunnan, and Qinghai showed a fluctuation trend that first decreased and then increased. The fluctuations in Zhejiang, Jiangxi, Hubei, Hunan, Guangdong, Sichuan, Shaanxi, Ningxia, and Xinjiang were not obvious.

4.1.2. Pure technical efficiency

From Table 1, we can see that the national average pure technical efficiency will decrease from 0.734 in 2011 to 0.694 in 2016, and then rise to 0.74 in 2021. In 2011 and 2016, the pure technical efficiency of Beijing, Jilin Province, Heilongjiang Province, Shanghai, and Qinghai has reached effective levels; by 2021, with the addition of Tianjin, six places will have effective pure technical efficiency. Among them, the province with the lowest pure technical efficiency in 2011 was Zhejiang Province, with a pure technical efficiency of 0.527, followed by Guizhou with a pure technical efficiency of 0.547; the province with the lowest pure technical efficiency in 2016 was Guangxi, with a technical efficiency of 0.423, followed by Guangdong at 0.432. The province with the lowest pure technical efficiency in 2021 was 0.413, followed by Guangdong at 0.495, which is far from the national average. During the study period, except for the pure technical efficiency of a few provinces that reached the optimal level, the technical level of five provinces: Tianjin, Liaoning, Shandong, Henan, and Chongqing was relatively high, Inner Mongolia, Anhui, Jiangxi, and Gansu increased, and the pure technical efficiency of Jiangsu, Guizhou, and Yunnan The efficiency showed a fluctuating upward trend, while Fujian, Hunan, Guangxi, Hainan, Shaanxi, Ningxia, and Xinjiang showed a downward or fluctuating downward trend. The technical efficiency of Hebei, Shanxi, Hubei, Guangdong, and Sichuan changed slightly but was generally relatively stable.

4.1.3. Scale efficiency

Judging from the results in Table 1, the overall national average scale efficiency dropped from 0.885 in 2011 to 0.881 in 2016. In 2021, the national average scale efficiency increased again to 0.915. Specifically, the provinces with optimal scale efficiency in 2011 were Jilin, Heilongjiang and Anhui; the only provinces with optimal scale efficiency in 2016 were Jilin and Heilongjiang; the only provinces with optimal scale efficiency in 2021 are Jilin and Heilongjiang. In 2011, the province with the lowest scale efficiency was Hainan, with a scale efficiency of 0.439, followed by Qinghai with 0.46; the two provinces with lower scale efficiency in 2016 were also Hainan and Qinghai, with scale efficiencies of 0.505 and 0.412 respectively; the province with the lowest scale efficiency in 2021 is Beijing, with a scale efficiency of only 0.491, which is quite different from the national average. During the study period, except for Jilin and Heilongjiang, which have always maintained the best, other provinces have fluctuated to varying degrees. The scale efficiency of Beijing and Sichuan shows a gradually declining trend. The scale efficiency of Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang shows a fluctuating or rising trend. The scale efficiency of Shanghai and Jiangxi is declining amid fluctuations. Overall, the scale efficiency of most identities across the country shows a rising trend.

Table 1. Grain production efficiency and composition of 30 provinces across the country from 2011 to 2021.

area	2011			2016			2021		
	overall efficiency	pure technical efficiency	scale efficiency	overall efficiency	pure technical efficiency	scale efficiency	overall efficiency	pure technical efficiency	scale efficiency
Beijing	0.668	1	0.668	0.53	1	0.53	0.491	1	0.491
Tianjin	0.604	0.825	0.732	0.66	0.811	0.814	0.878	1	0.878
Hebei	0.662	0.679	0.976	0.653	0.653	0.999	0.737	0.738	0.999
Shanxi	0.588	0.617	0.952	0.607	0.63	0.963	0.756	0.771	0.981
Inner Mongolia	0.675	0.685	0.986	0.735	0.738	0.996	0.834	0.838	0.995
Liaoning	0.87	0.883	0.986	0.835	0.848	0.985	0.973	0.979	0.994
Jilin	1	1	1	1	1	1	1	1	1
Heilongjiang	1	1	1	1	1	1	1	1	1
Shanghai	0.85	1	0.85	0.684	1	0.684	0.803	1	0.803
Jiangsu	0.733	0.753	0.973	0.677	0.679	0.998	0.764	0.764	0.999
Zhejiang	0.489	0.525	0.932	0.424	0.455	0.932	0.482	0.507	0.951
Anhui	0.592	0.592	1	0.67	0.67	0.999	0.734	0.734	0.999
Fujian	0.503	0.548	0.918	0.45	0.49	0.919	0.47	0.5	0.939
Jiangxi	0.727	0.743	0.978	0.763	0.773	0.987	0.751	0.778	0.966
Shandong	0.715	0.878	0.814	0.691	0.819	0.843	0.786	0.875	0.899
Henan	0.654	0.862	0.758	0.637	0.912	0.699	0.682	0.86	0.793

Hubei	0.548	0.562	0.976	0.517	0.519	0.994	0.569	0.572	0.995
Hunan	0.659	0.663	0.994	0.602	0.608	0.991	0.617	0.62	0.995
Guangdong	0.493	0.507	0.971	0.421	0.432	0.973	0.486	0.495	0.981
Guangxi	0.506	0.554	0.913	0.381	0.423	0.899	0.378	0.413	0.915
Hainan	0.386	0.879	0.439	0.292	0.577	0.505	0.327	0.541	0.604
Chongqing	0.859	0.984	0.873	0.689	0.803	0.858	0.738	0.835	0.884
Sichuan	0.729	0.731	0.996	0.686	0.693	0.989	0.746	0.754	0.989
Guizhou	0.481	0.547	0.88	0.618	0.668	0.926	0.602	0.654	0.92
Yunnan	0.556	0.595	0.934	0.443	0.476	0.93	0.639	0.65	0.983
Shaanxi	0.53	0.593	0.893	0.446	0.505	0.883	0.518	0.533	0.972
Gansu	0.532	0.576	0.923	0.534	0.587	0.91	0.622	0.67	0.929
Qinghai	0.46	1	0.46	0.412	1	0.412	0.678	1	0.678
Ningxia	0.522	0.66	0.791	0.497	0.592	0.841	0.538	0.583	0.924
Xinjiang	0.566	0.574	0.986	0.455	0.465	0.979	0.514	0.522	0.986
Average Value	0.638	0.734	0.885	0.6	0.694	0.881	0.67	0.74	0.915

4.2. Measurement of dynamic efficiency of grain production in each province based on Malmquist index model

In order to further analyze the dynamic trends of grain production efficiency and technical level in various provinces across the country during the research period, the Malmquist index model in Deap2.1 software was used to further decompose and analyze the grain production efficiency of 30 provinces in the country from 2011 to 2021. The results are shown in Table 2 and Table 3.

4.2.1. Analysis of time differences in national grain production efficiency from 2011 to 2021

As can be seen from Table 2, the national grain production efficiency showed an overall upward trend from 2011 to 2021. During the study period, only the total factor productivity of grain production showed a declining trend in 2013-2014 and 2016-2017. The total factor productivity in other time periods was greater than 1.000, indicating that total factor productivity showed an upward trend during these time periods. Among them, the total factor productivity in 2018-2019 has a larger increase, with an increase of 1.3%; the total factor productivity in 2020-2021 has the largest increase, with an increase of 1.6%. The technical efficiency value fluctuated greatly during the study period. It decreased in six time periods and increased in four time periods. The technical efficiency increased the most from 2017 to 2018, reaching 11.8%, and the average value increased by 0.4%. The technical efficiency of grain production nationwide showed an overall upward trend. The value of technological progress increased in 6 time periods and decreased in 4 time periods, with the average value increasing by 0.2%. Pure technical efficiency shows a state of constant fluctuation in a small range, with an average value of just 1.000. The scale efficiency value fluctuated in a small range in the first six time periods, with some rising and falling, and some rising while falling. However, it showed an upward trend in the last four time periods, with an absolute value increase of 0.4%. Overall, the main factor in improving the total factor productivity of grain production across the country is that

technical efficiency, technological progress and scale efficiency jointly promote the improvement of total factor productivity.

Table 2. National grain production efficiency and its decomposition from 2011 to 2021.

Year	Technical efficiency	Technical progress	Pure technical efficiency	Scale efficiency	Total factor productivity
2011-2012	0.989	1.028	0.994	0.995	1.016
2012-2013	0.94	1.08	0.939	1.001	1.016
2013-2014	1.014	0.973	1.016	0.998	0.987
2014-2015	0.999	1.009	0.999	1	1.008
2015-2016	0.987	1.015	0.989	0.998	1.002
2016-2017	1.013	0.986	1.017	0.996	0.998
2017-2018	1.118	0.903	1.076	1.039	1.009
2018-2019	0.979	1.035	0.978	1.001	1.013
2019-2020	1.033	0.969	1.022	1.01	1.001
2020-2021	0.979	1.037	0.977	1.002	1.016
Average Value	1.004	1.002	1	1.004	1.006

4.2.2. Analysis of spatial differences in national grain production efficiency from 2011 to 2021

It can be seen from Table 3 that, except for Beijing, Heilongjiang, Shanghai, Jiangxi, Guangdong, Guangxi, Hainan, Chongqing, Ningxia, and Xinjiang, the total factor productivity of grain production in the 30 provinces in the country increased from 2011 to 2021. The total factor productivity of grain production in other provinces increased to varying degrees. Among them, the increases in Qinghai and Tianjin were larger, with increases of 4.9% and 4.6% respectively. During the study period, the technical efficiency, technological progress, pure technical efficiency and scale efficiency values of 11 provinces including Tianjin, Hebei, Jilin, Jiangsu, Anhui, Shandong, Henan, Guizhou, Yunnan, Gansu and Qinghai were all ≥ 1.000 . This shows that the total factor productivity of the above 11 provinces is promoted by the four indexes, agricultural production input is relatively scientific and reasonable, and technical efficiency plays the greatest role in total factor productivity, effectively promoting the improvement of grain production efficiency. Further analysis shows that in provinces with total factor productivity < 1.000 , their technical efficiency is basically < 1.000 , indicating that, and. In addition, in provinces with technical efficiency < 1.000 , their pure technical efficiency is basically < 1.000 , indicating that low technical efficiency is mainly caused by low pure technical efficiency. The level of grain production in these places is low. Improving the level of agricultural technology production is an effective way to improve the total factor productivity of grain production. Overall, technical efficiency and technological progress are the main factors affecting grain production efficiency.

Table 3. Grain production efficiency and its breakdown by provinces across the country.

Area	Technical efficiency	Technical progress	Pure technical efficiency	Scale efficiency	Total factor productivity
Beijing	0.970	1.007	1.000	0.970	0.976
Tianjin	1.038	1.007	1.019	1.018	1.046
Hebei	1.011	1.008	1.008	1.002	1.019
Shanxi	1.026	0.996	1.022	1.003	1.022

Inner Mongolia	1.021	0.992	1.020	1.001	1.013
Liaoning	1.011	0.997	1.010	1.001	1.008
Jilin	1.000	1.001	1.000	1.000	1.001
Heilongjiang	1.000	0.997	1.000	1.000	0.997
Shanghai	0.994	0.972	1.000	0.994	0.967
Jiangsu	1.004	1.007	1.001	1.003	1.011
Zhejiang	0.999	1.008	0.997	1.002	1.006
Anhui	1.022	1.007	1.022	1.000	1.029
Fujian	0.993	1.007	0.991	1.002	1.000
Jiangxi	1.003	0.988	1.005	0.999	0.991
Shandong	1.010	1.008	1.000	1.010	1.017
Henan	1.004	1.007	1.000	1.004	1.011
Hubei	1.004	0.998	1.002	1.002	1.001
Hunan	0.993	1.009	0.993	1.000	1.003
Guangdong	0.999	0.997	0.998	1.001	0.995
Guangxi	0.971	1.018	0.971	1.000	0.989
Hainan	0.983	1.010	0.953	1.032	0.993
Chongqing	0.985	1.012	0.984	1.001	0.997
Sichuan	1.002	1.010	1.003	0.999	1.012
Guizhou	1.023	1.008	1.018	1.004	1.030
Yunnan	1.014	1.002	1.009	1.005	1.016
Shaanxi	0.998	1.004	0.989	1.009	1.002
Gansu	1.016	1.011	1.015	1.001	1.027
Qinghai	1.040	1.009	1.000	1.040	1.049
Ningxia	1.003	0.996	0.988	1.016	0.999
Xinjiang	0.990	0.982	0.991	1.000	0.973
Average Value	1.004	1.002	1.000	1.004	1.006

5. Conclusions, Countermeasures and Suggestions

5.1. Conclusion

This study shows that my country's grain production efficiency in 2011, 2016, and 2021 was all less than 1.000, and it was not effective. my country's grain production efficiency as a whole shows an evolutionary trajectory of "declining first and then rising". The scale efficiency value is systematically higher than the pure technical efficiency value, which reflects the structural contradiction between the significant economies of scale advantages and the redundancy of input factors in the current production system. This indicates that the policy focus should be on: giving priority to promoting precision technologies such as water-saving irrigation and precision fertilization in areas with technical shortcomings to improve factor utilization efficiency; while in areas with low scale efficiency, it is necessary to optimize and appropriately control the scale of production through the land transfer mechanism. From a time perspective, the total factor productivity of grain production in each province has generally increased from 2011 to 2021, with an average increase of 0.6%. From a spatial perspective, the technical efficiency, technological progress, pure technical efficiency and scale efficiency values of the 11 provinces of Tianjin, Hebei, Jilin, Jiangsu, Anhui, Shandong, Henan, Guizhou, Yunnan, Gansu and Qinghai are all ≥ 1.000 , indicating that their agricultural production factor configuration has system structure adaptability, the input-output combination has approached the frontier of the production possibility frontier, and agricultural production input is relatively scientific

and reasonable, while other provinces have a downward trend in some parameters. Among them, the total factor productivity of 10 provinces including Beijing, Heilongjiang, Shanghai, Jiangxi, Guangdong, Guangxi, Hainan, Chongqing, Ningxia, and Xinjiang has a downward trend, and technical efficiency is the main factor affecting total factor productivity. Therefore, this requires a shift in policy priorities, improving irrigation security rates through farmland water conservancy modernization projects, and relying on smart agricultural technology diffusion plans to optimize planting processes, thereby systematically breaking the negative constraints of technical efficiency on TFP growth. Based on the above conclusions, the following countermeasures and suggestions are put forward to optimize grain production efficiency and grain yield.

5.2. Suggestion

First, strengthen scientific and technological innovation and promotion to improve agricultural production technology. It is recommended that national and local governments increase investment in scientific and technological research and development related to grain production, especially core technologies that improve agricultural production efficiency and grain yields. Focus on supporting the cultivation of new varieties of food crops, the research and development and promotion of water-saving irrigation technology, precision agriculture and other technologies. Actively promote the construction of agricultural informatization, use big data, Internet of Things and other technologies to accurately manage agricultural production, reduce resource waste, and improve food production efficiency.

Second, areas with low grain production efficiency need to fully demonstrate their special advantages under the new development situation and continue to increase efforts to introduce high-level and high-level talents. Establish and improve a modern infrastructure system that is intensive, efficient, affordable, smart, green, safe and reliable, improve agricultural infrastructure, improve the ability to resist risks in the grain production process, reduce the impact of natural disasters on grain output, reduce agricultural production risks, and ensure farmers' income and food security.

Third, strengthen exchanges, coordination and deepen cooperation among various regions. Promote the construction of policies that benefit farmers and benefit farmers among various regions, stimulate the endogenous driving force for coordinated economic development in various regions, and promote the formation of synergy between policies and strengthen linkage between regions. Actively introduce international and domestic advanced agricultural production technologies and excellent agricultural management experience, thereby improving the development level of overall agricultural production.

Fourth, optimize the grain subsidy policy and increase the amount of subsidies for grain farmers. According to the actual situation, local governments can integrate farmers' direct subsidies, agricultural machinery purchase subsidies, improved seed subsidies and comprehensive agricultural input subsidies for grain-growing households, establish a direct grain compensation fund, and implement dynamic compensation to directly subsidize grain-growing farmers on the basis of comprehensive consideration of farmers' grain output, current CPI index levels, grain cost changes and other factors. The compensation items should be clarified to facilitate the operation of grassroots organizations in major grain crop production

areas, so that local farmers can understand the latest policies and measures, and follow the latest policy measures to make matching behavioral feedback in a timely manner.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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