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Analysis of the Evolution Characteristics and Impact Factors of Green Production Efficiency of Grain in China

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Abstract: Ensuring sufficient food production and guaranteeing the safety and quality of food are crucial aspects of food security, how to achieve the balance between food production efficiency and environmental protection is an urgent problem and challenge to be solved. This study introduced an assessment system for the green production efficiency of grain, and measured China's green production efficiency of grain by using the slacks-based measurement (SBM) model, kernel density estimation, and Tobit regression model. The findings show the following: (1) From 2000 to 2019, China's green production efficiency of grain showed an overall upward trend, while in different regions it was shrinking. The central region has the fastest growth rate, the western region and the northeast region have the same growth rate, and the eastern region has the slowest growth rate. (2) According to the kernel density estimation, China's green production efficiency of grain increased year by year, and the national development was relatively balanced from 2000 to 2104. However, there are obvious regional differences from 2014 to 2019; the eastern and northeastern regions are relatively balanced, and the central and western regions have further expanded over time. (3) From the perspective of whole country, the regional financial support for agriculture and the urbanization rate have a significant positive impact on the green production efficiency of grain, while the crop disaster affected area and agricultural output value have a significant negative impact on green production efficiency. (4) From the regional perspective, the impact of different factors on the level of green production efficiency of grain varies.

Keywords: food security; green production efficiency of grain; SBM model; time-series; impact factors

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1. Introduction

Global food security has long been one of the major issues in global development. Currently, the world is facing the challenges of the COVID-19 pandemic, climate change and regional conflicts resulting in immense challenges and difficulties for global food security. Food security not only refers to the assurance of food production but, more importantly, to the guarantee of food quality and safety. Specifically, food security is a state where all individuals have physical, social, and economic access to sufficient, safe, and nutritious food to meet their dietary needs for an active and healthy life. Green and healthy food refers to food that is free from harmful substances and non-toxic to human health. For example, during the cultivation process, toxic pesticides and chemical fertilizers should not be used to ensure that harmful substances are not present in food. Simultaneously, adhering to environmental protection principles during food production and reducing the environmental impact are essential aspects of food security. Food security not only affects the health of each individual but also the health and stability of the entire society. Therefore, ensuring food security requires not only guaranteeing the production but also emphasizing the safety of green and healthy food. Effectively promoting coordinated development between food production and ecological protection and fundamentally changing the traditional resource-dependent food production method has become an urgent practical issue to address [1]. Green food production efficiency reflects the output-to-input ratio of food production, including environmental impacts. The greater the value, the stronger the green food production efficiency, making it the "key pulse" of the green development of the food industry. Actively implementing the concept of green development in food production necessitates transforming and adjusting the existing resource-intensive and environmentally damaging food production methods to achieve a higher level of green food production efficiency. Thus, scientifically measuring China's green grain production efficiency and examining the spatiotemporal differentiation characteristics and influencing factors of China's green grain production efficiency are of great significance for ensuring China's food security, improving green grain production, alleviating poverty [2], and stabilizing the world's food supply.

Scholars' research on food production efficiency mainly focuses on measurement methods, regional differences, and influencing factors. In terms of efficiency measurement research, various methods and models have been employed. Some scholars have conducted institutional diagnostics for food security in Africa, proposing effective solutions to food security from a technological perspective [3]. Originating from the water–energy nexus, the DEA model is primarily utilized to measure grain production efficiency [4,5]. In China, Zheng used the stochastic frontier approach (SFA) model to measure grain production efficiency [6], while Sun employed the super-efficiency model, investigating the coupling relationship between water and food resources to measure China's grain production efficiency [7]. Bao analyzed the green total factor productivity of grain in the Poyang Lake Basin [8]. Regarding regional differences in grain production efficiency, some Chinese scholars have studied variations in grain production efficiency levels across different regions. For example, Liu investigated the crop production level and potential in the northwest region of China from a water resources perspective [9,10]. Yu examined the differences in grain production between the northern and southern regions of China [11]. Other scholars have studied the differences in grain production efficiency within various river basins, such as the study on agricultural green production efficiency and input–output efficiency in Yangtze river [12,13]. In terms of research on factors influencing grain production, different scholars have adopted diverse perspectives when studying countries and regions at different developmental levels. Research on developing countries primarily focuses on traditional influencing factors. For instance, some scholars have investigated the impact of climatic conditions on grain production in Bangladesh [14,15]. In India and Bangladesh, land fragmentation has resulted in low land intensification, which is an important reason for the low grain production efficiency in these regions [16,17]. In South Africa and Iran, the low utilization and high consumption of water resources poses potential crises for grain production in these areas [18,19]. Research on developed countries mainly concentrates on higher-level factors such as agricultural intensification [20], public participation [21], environmental effects [22], water resources planning [23], and the relationship between water, energy, food, land, and climate [24]. Some scholars have focused on the influence of traditional factors on grain production efficiency, such as water resources [25], climate change [26], and fertilizer use [27]. Others have considered new influencing factors, such as external connections [28] and urban factors [29]. Additionally, some scholars have begun to recognize the spatial spillover effects of grain production efficiency and have used spatial econometric models to study their influencing factors [30,31].

Existing research has systematically investigated the content and themes related to the green production efficiency of grain, providing crucial theoretical and empirical support for further study in this area. However, research on the green efficiency of grain production remains insufficient. Scholars have not taken into account environmental consumption during the grain production process and have used traditional methods to measure grain production efficiency, which does not adequately consider green factors [32]. Although some researchers have noted regional differences, they lack a grasp of the long-term trends of these differences. This paper aims to fill these gaps in the following ways: (1) This study focuses on utilizing the knowledge of the undesirable output SBM model and Tobit model for measurement while incorporating carbon emission-related knowledge to construct a green efficiency evaluation system for grain production. (2) From a macro perspective, the undesirable output SBM model is employed to investigate the green efficiency of provincial-level grain production in China. (3) The panel fixed-effects Tobit model is applied to analyze and explore the driving effects of external factors on the green efficiency of grain production in China. This approach can provide new insights for improving China's grain production green efficiency and can guide the transformation and upgrading of the world's grain production.

2. Data Sources

2.1. Selection of Measurement Indicators

In the face of global warming and the threat of various uncertain events, only by accelerating the green, ecological, and sustainable development of society and the economy can we guarantee food security. The green production of grain mainly considers how pollutants and carbon emissions in the production process, such as pesticides, fertilizers, and machinery inputs, should be reasonably controlled to guide green and low-carbon development. Based on the reality of in China, we construct the index system of grain green production efficiency, as shown in Table 1. In terms of input indicators, this paper selected land, fertilizer, machinery, pesticides, and water resources for measurement. In terms of expected output, this paper selected total grain production for measurement, and in terms of non-expected output, we selected total carbon emissions and total pollution emission outputs as representative values. The total carbon emissions were calculated from irrigated, fertilizer use, pesticide use, agricultural film use, and diesel fuel; the formula for measuring carbon emissions is as follows:

$$E = \sum E_i = \sum (G_i \times \delta_i) \tag{1}$$

Table 1. Green grain production efficiency evaluation index system.

Primary Indicators	Secondary Indicators	Variables and Descriptions
Inputs	Labor input	[Number of rural population × (total agricultural output value/total agricultural, forestry, animal husbandry and fishery output value)]/10,000 people
	Land input	Grain sown area/khm^2
	Fertilizer input	Fertilizer application/million tons
	Mechanical input	Total power of agricultural machinery/million tons
	Pesticide input	Pesticide use/million tons
	Water input	Water input volume/million tons
Expected output	Total grain production	Total grain production/million tons
Non-expected output	Carbon output	Total carbon emissions/million tons
	Pollution emission output	Total pollution emissions/million tons

In Equation (1), E represents the total carbon emissions in grain production; E_i represents the carbon emissions of the first carbon source; G_i represents the original amount for each carbon emission source; and δ_i is the carbon emission coefficient of the above carbon emission sources. The emission coefficients of the above carbon emission sources are as follows: pesticide, 4.3941 kg/kg; fertilizer, 0.8956 kg/kg; agricultural film, 5.18 kg/kg; tillage, 3.126 kg/km^2; agricultural machinery power, 0.18 kg/kW; and irrigation, 266.48 kg/hm^2.

Pollution emissions mainly refer to the surface source pollution in the process of grain production, especially in the excessive use and residual pollution of agricultural chemicals, such as fertilizers, pesticides, agricultural films, etc. In this paper, we use the amount of nitrogen fertilizer, phosphorus fertilizer, pesticides, and agricultural films lost to characterize the pollution emission of arable land used for grain production, and measure the carbon emissions by means of the following formula:

$$W = \sum W_i = \sum (H_i \times \theta_i) \quad (2)$$

In Equation (2), W is the total pollution emission of grain production; W_i is the pollution emission of the first source;H_i is the original amount for each pollution emission source; and θ_i is the pollution emission coefficient. The pollution emission coefficient refers to the "National Pollution Source Census Production and Emission Coefficient Manual".

2.2. Construction of Impact Factor Indicators

Based on the reality of grain production in China, this paper considers the effects on the green production efficiency of grain in terms of rural residents' living standards, the natural conditions of agricultural production, local government financial support policies for agriculture, the regional economic structure, and the urbanization level [33]. The level of the living standards of rural residents is significantly related to grain production, while the living standard of rural residents depends largely on income. In particular, the higher the wage income of rural residents, the more farmers tend to engage in non-farm production, and non-farm production activities may cause the abandonment of arable land, which is detrimental to agricultural production. The ratio of wage income to the per capita disposable income of rural residents is thus chosen as the influence factor and expressed as WI. In terms of the natural conditions of agricultural production, grain production is significantly constrained by the natural environment, especially the threat of natural disasters such as waterlogging and drought, which seriously affects grain production efficiency. The share of crop disaster affected area was chosen as the impact factor and expressed as CAA. In terms of the government's financial support policies for agriculture, financial support policies directly stimulate the input of agricultural production factors and affect the development efficiency of agriculture, and so the proportion of the expenditure on agriculture in the general budget of regional finance is chosen as the influence factor and expressed as RAF. In terms of regional economic structure, regional economic development is the basis of agricultural development, leading to the improvement of grain production capacity, and so the proportion of the total output value of agriculture was chosen as the impact factor and expressed as TOVA. In terms of the urbanization rate, urbanization regulates the resources needed for grain production through land, labor, capital, and other factors, and changes the traditional agricultural organization system by adjusting the structure of grain production, thus changing grain cultivation as well as green production methods. At the same time, the transfer of rural labor, the "non-grain" use of arable land, and the emission of pollutants from towns and industries accompanying urbanization will also have a negative impact on grain production, so the urbanization rate was chosen as the impact factor and expressed as UR.

In this paper, the panel data of 31 provinces in China from 2000 to 2019 were used as the sample, and the data for evaluation indicators and impact factors were obtained from "China Rural Yearbook" and "China Statistical Yearbook" from 2001 to 2020. The descriptive statistics of impact factor variables are shown in Table 2.

Table 2. Impact factor system and descriptive statistics.

Impact Factor	Variable Description	Average Value	Standard Deviation	Maximum Value	Minimum Value
WI	Wage income/disposable income per rural resident (%)	0.373	0.143	0.791	0.062
CAA	Crop-affected area/crop sown area ratio (%)	0.231	0.161	0.936	0
RAF	Regional agricultural finance/local financial expenditure (%)	0.097	0.040	0.279	0.009
TOVA	Total output value of agriculture/regional GDP (%)	0.204	0.102	0.602	0.076
UR	Urbanization rate (%)	0.506	0.157	0.896	0.209

3. Methods

3.1. Super-Efficient SBM Model

We used the super-efficient slacks-based measurement (SBM) model to measure the efficiency of the green production of grain [34]. The super-efficient SBM model combines the advantages of the SBM model and the super-efficient data envelopment analysis (DEA) model, which can incorporate non-desired outputs into the model while differentiating and comparing effective decision units, thus avoiding the loss of information on effective decision units. The formulas for the super-efficient SBM model incorporating non-desired outputs are as follows:

$$\rho^* = \min \frac{1 + \frac{1}{m} \sum_{i=1}^{m} \frac{D_i^-}{x_{ih}}}{1 - \frac{1}{s_1+s_2} \left(\sum_{r=1}^{s_1} \frac{D_r^g}{y_{rh}^g} + \sum_{k=1}^{s_2} \frac{D_k^b}{y_{kh}^b} \right)} \tag{3}$$

$$s.t. \begin{cases} x_{ik} \geq \sum_{j=1, j \neq h}^{n} \lambda_j x_{ij} - D_i^-, i = 1, \cdots, m \\ y_{rh}^g \geq \sum_{j=1, j \neq h}^{n} \lambda_j y_{ij}^g + D_r^g, r = 1, \cdots, s_1 \\ y_{kh}^b \geq \sum_{j=1, j \neq h}^{n} \lambda_j y_{kj}^b - D_k^b, k = 1, \cdots, s_2 \\ 1 - \frac{1}{s_1+s_2} \left(\sum_{r=1}^{s_1} \frac{D_r^g}{y_{rh}^g} + \sum_{k=1}^{s_2} \frac{D_k^b}{y_{kh}^b} \right) > 0 \\ D^- \geq 0, D^g \geq 0, D^b \geq 0 \end{cases} \tag{4}$$

In the formulas, ρ^* is the green grain production efficiency index, there are n decision units in the grain production process, m represents the input elements, s_1 represents the desired outputs, s_2 represents the non-desired outputs, and there are three sets of vectors, with $x \in R^m$ being inputs, $y^g \in R^{s_1}$ being expected outputs, and $y^b \in R^{s_2}$ being non-expected outputs. Additionally, we define the matrix $X = [x_1, \cdots, x_n] \in R^{m \times n}$ as slack variables for inputs,$Y^g = \left[y_1^g, \cdots, y_n^g\right] \in R^{s_1 \times n}$ *as* slack variables for desired outputs, and $Y^b = \left[y_1^b, \cdots, y_n^b\right] \in R^{s_2 \times n}$ as slack variables for non-desired outputs. D^-, D^g, andD^b are weight vectors.

3.2. Kernel Density Estimation

Kernel density estimation is a nonparametric method for estimating probability density functions, which has the advantage of not requiring any parametric model assumptions and being able to describe the distribution pattern and evolution characteristics of random variables with continuous density profiles [35]. The functional equation is as follows:

$$f(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x_i - x}{h}\right) \tag{5}$$

The dominant Gaussian kernel function in academia estimates the time-series dynamic evolution of production efficiency. The position of the center of gravity of the curve can portray the evolution characteristics of the size of efficiency values, the height of the main peak of the curve can portray the evolution characteristics of the difference of efficiency values, the number of peaks of the curve can portray the evolution characteristics of the multi-polarity of efficiency values, the length of the trailing curve can portray the evolution characteristics of efficiency values in the high (low)-efficiency value area, and the thickness of the trailing curve can portray the evolution characteristics of the percentage of high (low)-efficiency values.

3.3. Panel Tobit Regression Model

Due to the calculation of green grain production efficiency values in this study being based on truncated data, ranging from 0 to 1, directly using the efficiency values measured by the undesirable output SBM model as explanatory variables in constructing a least squares model may not yield consistent estimates. Therefore, when studying green grain production efficiency, it is more appropriate to use the Tobit model, which is suitable for censored or segmented dependent variables, to empirically test the external driving factors [36]. Consequently, this study establishes a panel Tobit regression model to empirically analyze the influencing factors of regional differences in green grain production efficiency. The model is as follows:

$$y_{it} = c + \delta_1 WI_{it} + \delta_2 CAA_{it} + \delta_3 RAF_{it} + \delta_4 TOVA_{it} + \delta_5 UR_{it} + \varepsilon_{it} \tag{6}$$

where: y_{it} is the explained variable; x_{it} is the explanatory variable; δ_k is the regression coefficient of each explanatory variable; c is the constant term; and ε_{it} is the random error term that obeys the distribution.

To better understand the process of this study, we drew a technical flowchart of the research methodology, as show Figure 1.

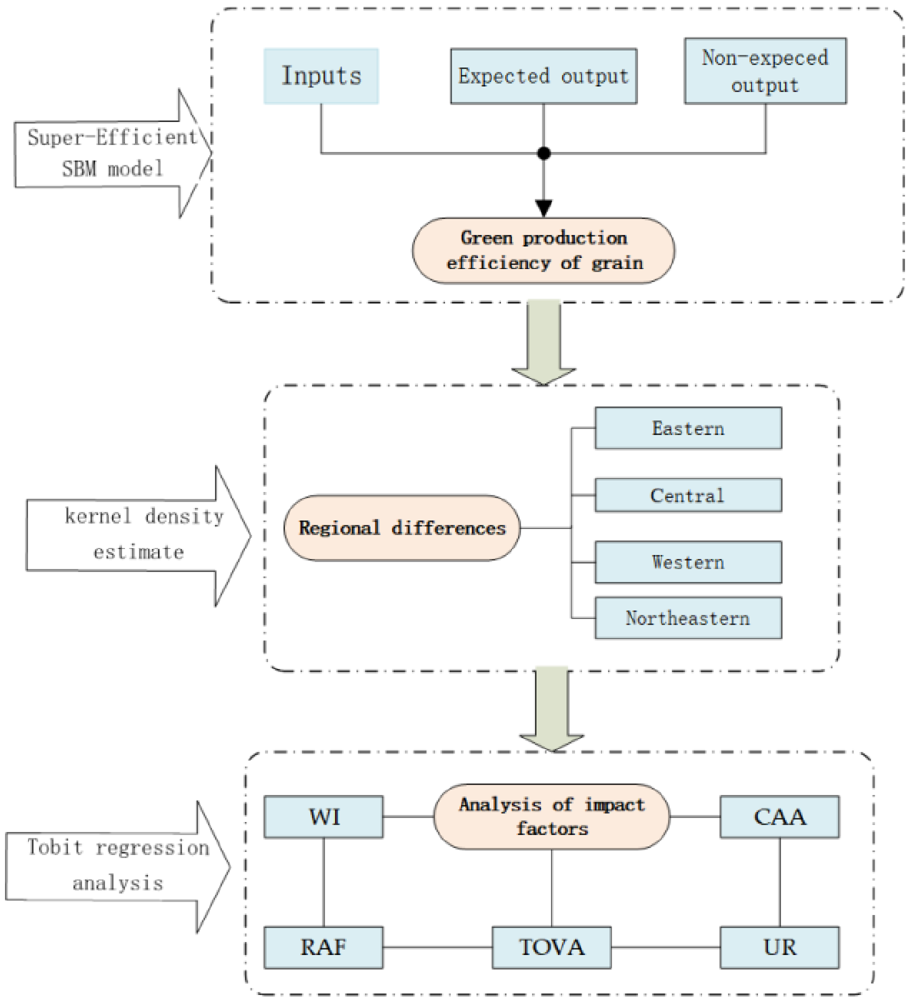

Figure 1. Research technical flowchart.

4. Results

4.1. Measurement Results of Green Production Efficiency

We calculated the green grain production efficiency of all provinces in China. As shown in Table 3, Beijing, Shanghai, Hainan, Chongqing and Qinghai are at a high level, with an average annual green grain production efficiency greater than 0.9, while Hebei, Shandong and Henan are at a low level, with an average annual green grain production efficiency lower than 0.3, and the rest of the provinces have an average annual green grain production efficiency between 0.4 and 0.8. Overall, there are obvious differences in green grain production efficiency among the three provinces, but the differences in neighboring provinces are gradually narrowing.

Table 3. Provincial green production efficiency of grain from 2001 to 2019.

Province	2001	2003	2005	2007	2009	2011	2013	2015	2017	2019	Average
Beijing	0.88	0.90	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.98	0.94
Tianjin	0.77	0.80	0.84	0.86	0.89	0.91	0.92	0.94	0.95	0.96	0.88
Hebei	0.01	0.03	0.06	0.10	0.15	0.22	0.29	0.36	0.44	0.51	0.20
Liaoning	0.70	0.75	0.79	0.82	0.85	0.88	0.90	0.92	0.93	0.94	0.84
Shanghai	0.91	0.92	0.94	0.95	0.96	0.97	0.97	0.98	0.98	0.98	0.95
Jiangsu	0.21	0.28	0.36	0.43	0.51	0.57	0.64	0.69	0.74	0.78	0.51
Zhejiang	0.37	0.44	0.51	0.58	0.64	0.70	0.75	0.79	0.82	0.85	0.63
Fujian	0.59	0.65	0.70	0.75	0.79	0.83	0.86	0.88	0.90	0.92	0.78
Shandong	0.03	0.05	0.09	0.14	0.20	0.27	0.34	0.42	0.49	0.56	0.24
Guangdong	0.36	0.44	0.51	0.58	0.64	0.70	0.74	0.79	0.82	0.85	0.63
Hainan	0.90	0.92	0.93	0.94	0.95	0.96	0.97	0.97	0.98	0.98	0.95
Shanxi	0.38	0.45	0.53	0.59	0.65	0.71	0.75	0.79	0.83	0.86	0.64
Jilin	0.65	0.70	0.75	0.79	0.83	0.86	0.88	0.90	0.92	0.93	0.81
Heilongjiang	0.51	0.58	0.64	0.70	0.75	0.79	0.82	0.85	0.88	0.90	0.73
An Hui	0.10	0.16	0.22	0.29	0.37	0.44	0.52	0.58	0.65	0.70	0.39
Jiangxi	0.57	0.63	0.68	0.73	0.78	0.81	0.85	0.87	0.89	0.91	0.76
Henan	0.05	0.09	0.14	0.20	0.27	0.35	0.42	0.50	0.57	0.63	0.31
Hubei	0.39	0.47	0.54	0.60	0.66	0.72	0.76	0.80	0.84	0.86	0.65
Huanan	0.28	0.36	0.43	0.50	0.57	0.64	0.69	0.74	0.78	0.82	0.57
Guangxi	0.30	0.38	0.45	0.52	0.59	0.65	0.71	0.75	0.79	0.83	0.58
Inner Mongolia	0.69	0.73	0.78	0.81	0.85	0.87	0.89	0.91	0.93	0.94	0.83
Chongqing	0.85	0.88	0.90	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.93
Sichuan	0.41	0.48	0.55	0.62	0.68	0.73	0.77	0.81	0.84	0.87	0.66
Guizhou	0.65	0.70	0.75	0.79	0.82	0.85	0.88	0.90	0.92	0.93	0.81
Yunnan	0.27	0.34	0.42	0.49	0.56	0.63	0.68	0.73	0.78	0.81	0.56
Tibet	0.76	0.80	0.84	0.86	0.89	0.91	0.92	0.94	0.95	0.96	0.88
Shanxi	0.40	0.48	0.55	0.61	0.67	0.72	0.77	0.81	0.84	0.87	0.66
Gansu	0.47	0.54	0.60	0.66	0.72	0.76	0.80	0.83	0.86	0.89	0.70
Qinghai	0.93	0.94	0.95	0.96	0.97	0.98	0.98	0.98	0.99	0.99	0.97
Ningxia	0.79	0.82	0.85	0.88	0.90	0.92	0.93	0.94	0.95	0.96	0.89
Xinjiang	0.52	0.59	0.65	0.70	0.75	0.79	0.83	0.86	0.88	0.90	0.74

In terms of the time-series evolution of national green grain production efficiency, as we can see in Table 4 and Figure 2, China's overall green grain production efficiency has steadily increased from 0.4808 in 2000 to 0.8673 in 2019, with an average annual growth rate of 1.93%. The green production efficiency of grain in the eastern region increased from 0.4820 in 2000 to 0.8106 in 2019, with an average annual growth rate of 1.75%. The central region increased from 0.2657 in 2000 to 0.7642 in 2019, with an average annual growth rate of 2.45%. The efficiency in the western region increased from 0.5864 in 2000 to 0.9008 in 2019, with an average annual growth rate of 1.75%. That of the northeast region increased from 0.5914 in 2000 to 0.9102 in 2019, with an average annual growth rate of 1.59%. It can be seen that the central region has the fastest growth in green grain production efficiency, the western and eastern regions have comparable growth, and the increase rate in northeast region ranks the last. In terms of the disparity between regions, green grain production efficiency increased more significantly in the western region. It can be seen that the green production efficiency of grain in the whole country and different regions is improving year by year, and the gap between regions is narrowing year by year.

Table 4. National and regional green production efficiency of grain from 2000 to 2019.

Year	National	Eastern	Central	Western	Northeast
2000	0.4808	0.48201903	0.265736971	0.586434755	0.591456067
2001	0.507	0.50253171	0.296820571	0.6136397	0.621470267
2003	0.5588	0.52318008	0.328835	0.640023664	0.650087
2004	0.5841	0.54392558	0.361516071	0.6654594	0.677231467
2005	0.6089	0.56472724	0.394594443	0.689844409	0.702858967
2006	0.6331	0.58553822	0.427802814	0.713100718	0.726950833
2007	0.6565	0.6063036	0.4608827	0.735173391	0.749510967
2008	0.6793	0.62695943	0.4935905	0.756028918	0.7705619
2009	0.7011	0.64743344	0.525702943	0.775653009	0.7901412
2010	0.7221	0.66764658	0.5570209	0.7940481	0.808298567
2011	0.7422	0.68751598	0.5873725	0.811230827	0.8250924
2013	0.7793	0.70695802	0.616614229	0.827229591	0.840587633
2014	0.7964	0.7258915	0.644631457	0.842082236	0.8548535
2015	0.8126	0.74424083	0.671337629	0.855833864	0.867961367
2016	0.8277	0.76193836	0.696672614	0.868534873	0.879983733
2017	0.8418	0.77892645	0.720600686	0.880239327	0.890992433
2018	0.855	0.79515837	0.743107629	0.891003509	0.9010582
2019	0.8673	0.81059913	0.764198243	0.900884645	0.9102495

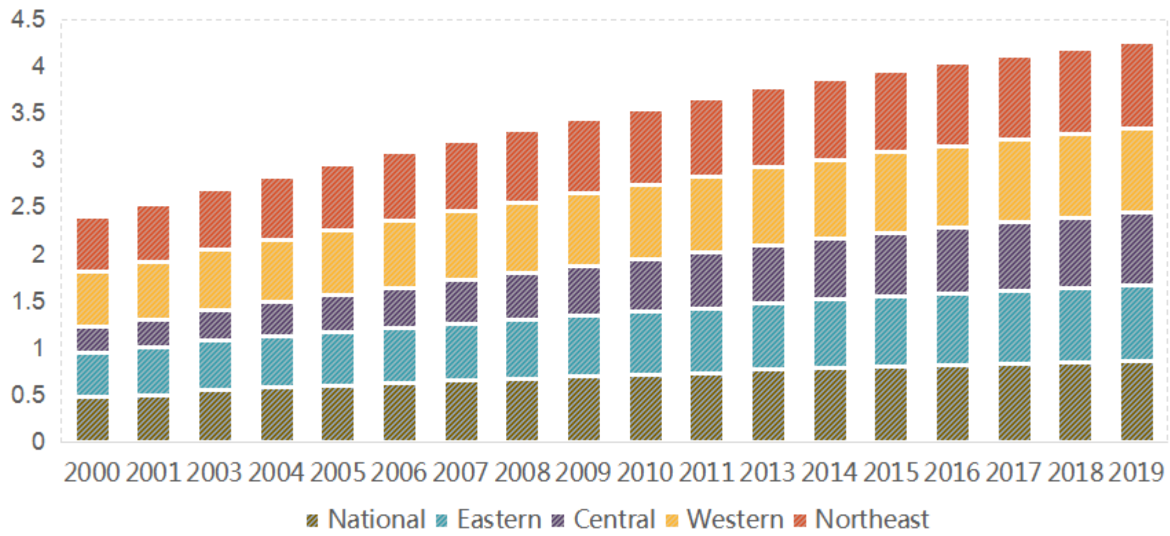

Figure 2. Time-series changes in green production efficiency of grain.

4.2. Analysis of Time-Series Dynamic Evolution Characteristics

The kernel density model can portray the time-series evolutionary characteristics of the national green production efficiency of grain, and the results are shown in Figure 2. As shown in Figure 3a, from the position of the center of gravity of the kernel density curve, it can be seen that it migrated to the right from 2004 to 2019, indicating that China's green grain production efficiency increased year by year during this period. In terms of the height of the curve crest, the crest rises slowly from 2004 to 2014, indicating that the inter-regional green grain production efficiency increased and the gap narrowed. The crest rises abruptly from 2014 to 2019, indicating that the inter-regional green grain production efficiency gap showed a tendency to widen. In terms of the number of peaks, there is one peak from 2004 to 2014, indicating that the national green grain production efficiency was in a roughly balanced state during this period; however, the two peaks from 2014 to 2019 indicate a polarization trend in green grain production efficiency. In terms of the degree of curve trailing, the left side of the curve trailing is larger than the right side, and the right side of the curve trailing shows a shortening trend, indicating that the provinces in the high-value area have improved their green grain production efficiency.

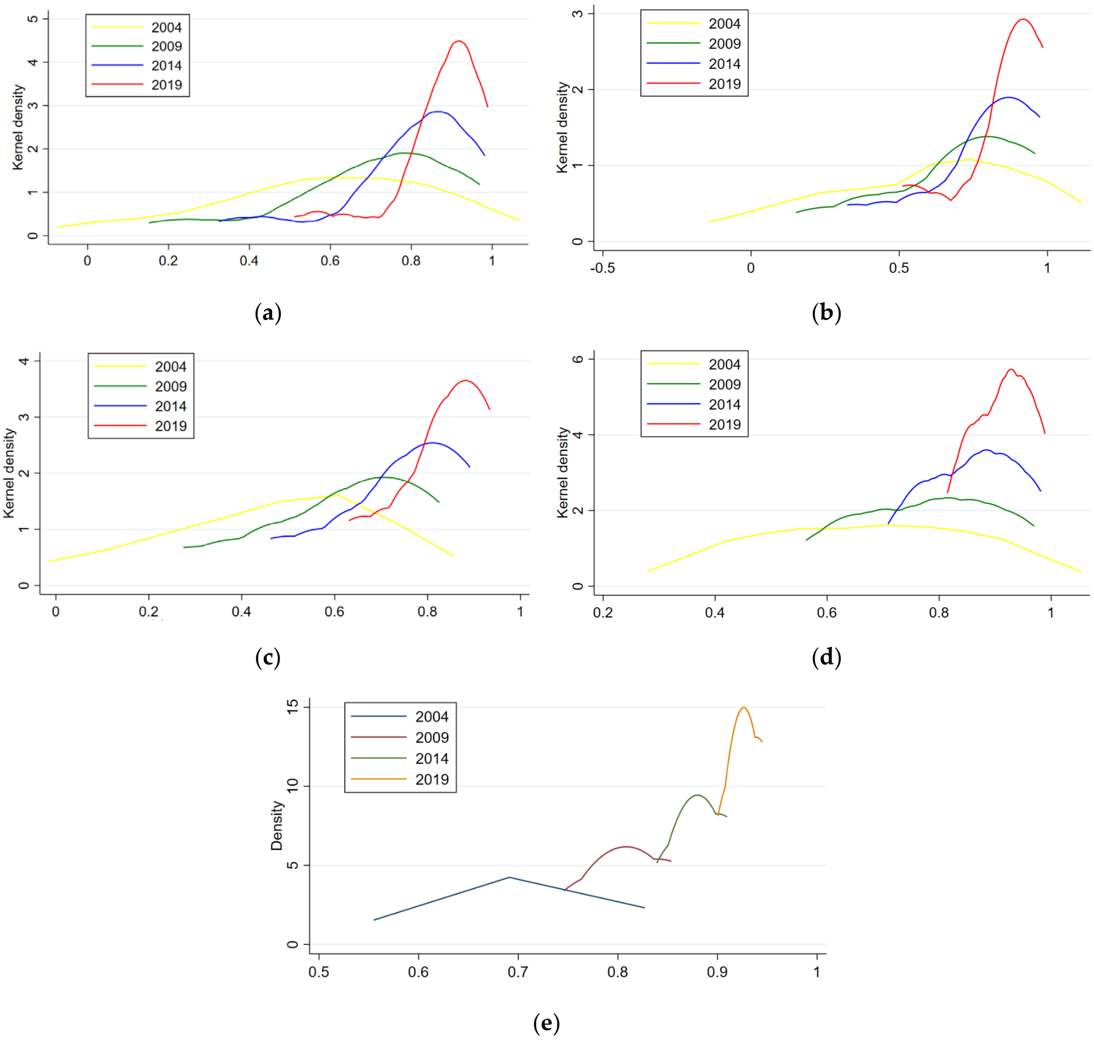

Figure 3. Estimation of kernel density of green grain production efficiency. (**a**) National kernel density estimates. (**b**) Eastern region kernel density estimates. (**c**) Central region kernel density estimates. (**d**) Western region kernel density estimates. (**e**) Northeastern region kernel density estimates.

Figure 3b–e show the kernel density estimation curves of green grain production efficiency in the eastern, central, western, and northeastern regions, respectively. The results show the following characteristics: (1) The position of the center of gravity of the curve shifted to the right from 2004 to 2019, indicating that the green grain production efficiency of all four regions improved year by year during this period. (2) From the height of the main crest of the curve, the crests of the central region, the western region and the northeastern region slowly increased from 2000 to 2019, indicating that the green grain production efficiency among these three regions increased. (3) In terms of the number of wave peaks, one wave peak appears in each region from 2004 to 2014, indicating that the national green grain production efficiency was in a roughly balanced state during this period. However, two wave crests appear in the western region from 2014 to 2019, indicating a polarization trend of green grain production efficiency in the western region. (4) In terms of the degree of curve trailing, the degree of trailing on the left side of the curve is greater than that on the right side in the central, western and northeastern regions, and the trailing on the right side shows a shortening trend, indicating that the green grain production efficiency improved in the high-value areas of these regions.

4.3. Regression Results

The results of the analysis of the impact factors were calculated using a panel Tobit regression model for green grain production efficiency, and the results are shown in Table 5. At the same time, the regression results were tested for the presence of individual effects to determine whether fixed effects or random effects estimation should be used. According to the LR test results, individual effects existed in the national and regional functional grain areas, so the random effects panel Tobit regression model was used. All Wald test results of the regressions passed the significance test ($p < 0.01$), indicating that the overall model fit was good.

Table 5. Panel Tobit regression results and tests.

Variables	National (1)	Eastern (2)	Central (3)	Western (4)	Northeastern (5)
WI	−0.00429 (0.0731)	−0.0963 (0.123)	0.338 ** (0.139)	0.211 ** (0.106)	0.878 *** (0.243)
CAA	−0.106 *** (0.0255)	−0.00938 (0.0434)	−0.0977 ** (0.0467)	−0.101 ** (0.0419)	−0.171 *** (0.0393)
RAF	1.303 *** (0.128)	0.559 *** (0.212)	1.124 *** (0.286)	0.756 *** (0.197)	1.778 *** (0.292)
TOVA	−0.791 *** (0.0825)	0.583 ** (0.282)	−1.229 *** (0.136)	−0.955 *** (0.131)	0.0525 (0.154)
UR	0.454 *** (0.0468)	1.475 *** (0.143)	0.679 *** (0.114)	0.246 *** (0.0701)	0.0723 (0.0782)
Cons	0.528 *** (0.0579)	−0.318 ** (0.159)	0.312 *** (0.101)	0.769 *** (0.0747)	0.391 *** (0.0728)
Wald Test	1295.63 ***	220.42 ***	1254.05 ***	496.69 ***	200.21 ***
LR Test	1056.37 ***	192.08 ***	205.95 ***	200.82 ***	17.27 ***
Number	620	200	120	240	60

Note: ** and *** denote 5% and 1% significance levels, respectively; numbers in parentheses are clustering robust standard errors.

4.4. Regression Analysis of Impact Factors

We used a panel Tobit regression model to analyze the impact factors on the green production efficiency of grain, and the results are shown in Table 5. Meanwhile, the regression results were tested for the presence of individual effects based on the test results to determine whether to use fixed effects or random effects for estimation. According to the LR test results, there are individual effects for the whole country as well as for each region, and thus the random effects panel Tobit regression model is used, and all regression results pass the Wald test of significance ($p < 0.01$), indicating a good overall fit of the model.

In terms of the national regression results, the coefficients of all variables pass the significance level test except for the wage income of rural residents (WI). Each percentage point increase in government financial support policies for agriculture (RAF) and urbanization rate (UR) has a positive effect by increasing the level of green production efficiency of grain by 1.303% and 0.454%, respectively. For each percentage point increase in the natural conditions of crop-affected area (CAA) and total output value of agriculture (TOVA), the level of green grain production efficiency decreases by 0.106% and 0.791%, respectively, playing a negative role.

The regression results from different regions in the east, central, west and northeast show in Table 5 that there are significant differences in the direction and degree of influence of different influencing factors on the efficiency of green production of grain.

(1) In terms of the wage income of rural residents (WI), the eastern region did not pass the significance test, while the central, western and northeastern regions passed the significance test at the 5% and 1% levels, respectively. The wage income of rural residents has a positive effect in the central, western, and northeastern regions, and the increase in wage income brings about an improvement in living standards, and farmers in these regions are more willing to invest in greening their grain production, which in turn promotes the level of green grain production in the region.

(2) In terms of the crop disaster affected area (CAA), the eastern region did not pass the significance test, and the central region, the western region, and the northeast region all had significant negative effects. This may be due to the fact that the eastern region has good farmland water conservancy facilities and strong agricultural disaster resilience, which makes the effect on the green production efficiency of grain in this region not significant, while in the central, western and northeastern regions, the possibility of agricultural disaster is higher, and coupled with the general economic level of these regions, the agricultural disaster resilience is weak, which affects the green production efficiency of grain in these regions.

(3) From the perspective of financial support for agriculture (RAF), the regression coefficients of the four major regions are all positive and all passed the significance level test, indicating that financial support for agriculture has a positive contribution to the efficiency of green grain production. Financial support for agricultural production will stimulate a large amount of human, financial and material investment in agricultural production and promote the technological upgrading of green grain production, thus further optimizing the potential for improving the efficiency of green grain production. Among them, the coefficient is highest in Northeast China, probably because there is more state-owned farms in this region, which are more sensitive to the impact of financial support for agriculture.

(4) In terms of the share of total output value of agricultural (TOVA), it has a significant positive contribution in the eastern region, and shows a significant negative effect in both the central and western regions. The northeast region displays a positive significant effect, but did not pass the significance test. This indicates that the eastern region has a high proportion of secondary and tertiary industries, and the agricultural output value has a limited effect on the efficiency of its green grain production. The productivity level of the central and western regions is lower than that of the eastern regions, and the share of agricultural output value is higher, but its agricultural technology content is not high, thus producing a significant negative effect.

(5) In terms of urbanization rate (UR), it has a positive effect on all four regions, and all of them passed the significance test. Urbanization can cause the factors in the region to gather continuously and thus promotes the improvement of infrastructure, which helps to improve the level of green grain production.

5. Conclusions

5.1. Conclusions of the Study

Based on the panel data of 31 Chinese provinces from 2000 to 2019, this paper uses the super-efficient SBM model to measure the characteristics and regional differences of China's green grain production efficiency index and its influencing factors, and the results show the following:

Firstly, from 2000 to 2019, China's overall green production efficiency of grain showed an upward trend, but the performance of different regions varied. The central region had the fastest growth rate, followed by the western region, while the northeast region ranked between the central and western regions, and the eastern region had the lowest growth rate.

Secondly, the kernel density estimation results indicate that there are significant regional disparities in the green production efficiency of grain in China, with the eastern region being relatively balanced, and the central and western regions showing a further widening trend over time. Meanwhile, the northeast region displays relative equilibrium.

Thirdly, the regression results show that, for nationally, the financial support for agriculture and the urbanization rate has a significant positive impact on the efficiency of green production of grain, while the crop disaster affected area and the agricultural output have a significant negative impact. The rural residents' wage income shows no significant influence. For the regionally, the impact of various influencing factors on the green production efficiency of grain differs across different regions.

Finally, China's green production efficiency of grain has significant regional differences and can be improved through factor allocation, technology, and policy. The research results show that China's overall green production efficiency of grain is not high, and the regional differences are significant. Different regions can adopt different methods to improve their efficiency according to different influencing factors. There is room for improvement in China's grain production efficiency, and regions should strengthen communication and cooperation, promote the flow of factors, and continuously promote efficiency improvement.

This study has performed valuable explorations into measuring the efficiency of green grain production, but there are still many shortcomings that need to be further explored and discussed in future research. The green production efficiency of grain is dependent on climate conditions such as soil, water resources, and temperature, and neighboring regions have similar geographical environments; therefore, the green production efficiency of grain will show a significant spatial correlation. On the other hand, factors such as agricultural labor, technology, and capital exhibit spatial mobility, which will further strengthen the relationship between regional grain production. Therefore, in future research, it is necessary not only to analyze the differences between regions but also to consider the correlation between regions in order to provide more practical policy recommendations for improving the green efficiency of grain production and promoting sustainable food development.

5.2. Policy Recommendations

Based on the analysis of the current level of China's green grain production efficiency, the comparison of regional differences and the study of influencing factors, this study draws the following policy insights:

(1) To optimize the allocation of factors for grain production, it is necessary to promote the reasonable circulation of labor, science and technology, capital, and other resources in response to the natural conditions, agricultural disaster levels, and agricultural output of specific regional grain production areas. Continuous optimization of green and low-carbon grain production should be pursued by leveraging the complementary advantages between regions and innovating differentiated paths for the green production of grain with unique characteristics.

(2) Improving the design of relevant policy tools is also essential. Establishing a standardized evaluation system for "pollution and carbon reduction" in the use of farmland can provide institutional regulation and policy support for green and low-carbon use of farmland. Additionally, creating an agricultural carbon trading market can reflect the economic value of green and low-carbon agriculture and stimulate farmers' enthusiasm for the low-carbon use of farmland resources. Financial support for agriculture should also be focused on developing green and circular agriculture, reducing chemical fertilizer and pesticide use, and decreasing carbon emissions and arable land pollution. Finally, improving the ecological compensation mechanism for arable land can increase farmers' income and willingness to utilize arable land ecologically.

(3) To further strengthen the research and application of agricultural technologies, investment in and research and development of agricultural ecological technologies should be increased, especially in carbon sequestration and emission reduction on farmland and pollution control. Technological innovations in farmland governance should also be pursued. Additionally, big data platforms such as digital villages and smart agriculture

can promote the digital transformation of the whole process of arable land utilization and management.

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