sustainability

MDPI

Article

Can Mechanization Promote Green Agricultural Production? An Empirical Analysis of Maize Production in China

Yakun Wang [1], Jingli Jiang [1], Dongqing Wang [2] and Xinshang You [1,*]

[1] School of Economics and Management, Hebei University of Science and Technology, Shijiazhuang 050018, China
[2] Bozhou Power Supply Company, Anhui Electric Power Co., Ltd., Bozhou 236000, China
* Correspondence: youxinshang@hebust.edu.cn

Abstract: This study systematically analyzes the impact of China's maize Green Total Factor Productivity (GTFP) and mechanization on GTFP, providing a reference for reasonably playing the role of mechanization and improving China's agricultural GTFP. Based on the difference in crop types and regional applicability of agricultural mechanization, this study selects maize as the research crop to analyze the impact of agricultural mechanization level on GTFP. In this study, the SBM-ML model is used to measure China's maize GTFP, reveal the temporal and regional change characteristics of maize GTFP, and clarify the optimization direction of maize GTFP from the perspective of regional differences and resource endowment differences. This study uses the threshold regression model to systematically analyze the impact of agricultural mechanization on GTFP and its mechanism. Results are given as follows: (1) The growth of China's maize production GTFP fluctuates greatly in each year, and the growth of maize GTFP depends on the alternate promotion of technical efficiency and technical progress. Greenhouse gas emissions have a significant impact on GTFP. Excessive use of pesticides and fertilizers is the biggest obstacle to the improvement of maize GTFP. (2) There are also specific regional differences in the factors that affect the improvement of maize GTFP efficiency in different regions. The impact of mechanization on agricultural GTFP varies among regions. (3) The development level of agricultural mechanization at different stages has different promotion effects on maize GTFP. Agricultural mechanization has a two-way effect on maize GTFP. The factors of land type and land area will not limit the promotion of agricultural mechanization to maize GTFP. (4) Agricultural financial investment, environmental pollution control efforts, agricultural science and technology expenditure and other factors play a positive role in improving GTFP. (5) In future production, we should pay attention to the combination of agricultural mechanization and regional production characteristics, optimize the allocation of agricultural machinery, and strengthen the coordination between agricultural mechanization and moderate scale operation. The findings of our study provide useful policy implications for the promotion and development of agriculture in China.

Keywords: agricultural mechanization; green total factor productivity; SBM-ML model; threshold effect

check for updates

Citation: Wang, Y.; Jiang, J.; Wang, D.; You, X. Can Mechanization Promote Green Agricultural Production? An Empirical Analysis of Maize Production in China. *Sustainability* **2023**, *15*, 1. https://doi.org/10.3390/su15010001

Academic Editors: Margarita Maria Brugarolas Molla-Bauza and Laura Martinez-Carrasco

Received: 5 November 2022
Revised: 12 December 2022
Accepted: 14 December 2022
Published: 20 December 2022

1. Introduction

Agriculture is the foundation of the national economy. China is a large agricultural country, and the development of agriculture is related to the food security of more than one billion Chinese people. With advances in technology and productivity, China's agriculture has made great progress, but there are still many problems in the process of development. China's agriculture has been undergoing extensive growth for a long time, with prominent constraints on agricultural resources and worsening environmental problems. China has recognized the fragility of agricultural development. The 19th National Congress of the Communist Party of China proposed promoting the construction of an ecological civilization. The 20th CPC National Congress of the Communist Party of China made it clear that we should adhere to sustainable development. Agricultural Total Factor Productivity

(TFP) measures the ability of a production unit to convert agricultural inputs into outputs. Agricultural TFP is a theoretical and statistical indicator for comprehensive measurement of agricultural economic efficiency [1,2]. However, studies on the measurement of agricultural TFP mainly consider capital, labor and other factors, and rarely involve the factors of agricultural green development [3,4]. In the traditional TFP accounting framework system, the resource and environmental constraint variables are fully considered, and the measured TFP is defined as the Green Total Factor Productivity (GTFP). GTFP takes into account production efficiency and ecological protection and is an important indicator to measure the quality of agricultural green growth. The accurate measurement of agricultural GTFP and analysis of the factors and mechanisms that promote its growth are key to achieving sustainable agricultural development.

Agricultural mechanization is an important material basis for the construction of modern agriculture, and also an important symbol of realizing agricultural modernization [5]. According to the statistical scope of the China Statistical Yearbook, China's agricultural machinery holdings include large tractors (including supporting agricultural tools) and small tractors. In 2021, the comprehensive mechanization rate of cultivation and harvest of staple grain crops in China exceeded 80%. As an advanced means of labor, agricultural machinery can replace labor force, reduce labor input [6], and optimize the allocation of agricultural production factors [7]. At the same time, scholars have noticed the effect of the agricultural mechanization level on agricultural production. Only when agricultural mechanization reaches a certain level can agricultural labor force be completely removed from agricultural production [8,9]. In addition, with the continuous improvement in agricultural mechanization, the marginal utility of agricultural GTFP promoted by technological progress has shown a declining trend [10]. The economic structure of small farmers with farmers as the unit can not produce an increasing marginal return mechanism with technological innovation and knowledge spillover as the "medium" [11]. Areas with important ecological microzones should be left fragmented [12].

As one of the important grain crops in China, maize plays a pivotal role in the country's agricultural development. In 2021, China's grain-planting region reached 117.63 million hectares; the maize planting region reached 43.32 million hectares, accounting for 36.83%. Under the influence of natural and socioeconomic conditions, agricultural production in the southern and northern parts of China exhibits great differences in terms of the farming system, type and scale of cultivated land, mechanization and other aspects, and maize production also shows great regional differences. Agriculture is an ecological complex formed by crops and the growth environment. There are differences in agricultural production conditions between regions, differences in the applicability of mechanization between crop types and differences in the applicability of mechanization between regions. Therefore, in this study, considering the heterogeneity of crop types and the applicability of agricultural mechanization in production regions, maize was selected as the research crop to investigate the effects of agricultural mechanization level on GTFP of the same crop in different regions. This study defines the mechanical level according to the standards of China Statistical Yearbook.

This study measures maize GTFP in China using the Slack Based Measure-Malmquist-Luenberger (SBM-ML) model, reveals the temporal and regional variation characteristics of maize GTFP, and identifies the optimization direction of maize GTFP according to the causes of factor loss. The threshold regression model is applied to systematically analyze the influence degree and mechanism of agricultural mechanization level on maize GTFP from the perspective of regional and resource endowment differences. Compared with previous studies, the innovative angle of this study is mainly in the following aspects: based on considering the applicability of crop mechanization from the perspective of a single crop category, the SBM-ML method is first used to measure the GTFP of maize production. The effects of mechanization on GTFP production are systematically verified from regional differences and land scale differences.

The rest of this article is structured as follows: Section 2 reviews the relevant literature and analyzes the mechanism of the influence of mechanization on agricultural GTFP. Section 3 describes the sources of the methods and data. Section 4 presents the empirical results, Section 5 analyzes them, and Section 6 summarizes our findings.

2. Literature Review and Mechanism Analysis

2.1. Calculation of Agricultural GTFP

Agricultural GTFP emphasizes the trade-off among input, expected output and non-expected output in agricultural production. It considers economic benefits (expected output) and negative environmental impacts (unexpected output) while analyzing the development of agricultural production [13,14]. There are two main types of calculation methods for GTFP in academic circles: one is parametric methods, including stochastic frontier analysis (SFA), Cobb–Douglas (C-D) function, transcendental logarithmic function, etc.; the other is nonparametric, mainly calculated by using data envelopment analysis (DEA) in combination with exponents. The FSA method needs to set the probability distribution from the random error term, and the frontier production function is easily affected by individual regions [15,16]. The DEA method has relatively loose requirements for production forms and does not need to set specific production functions. It is applicable to the boundary production function of multi-input and multi-output [17,18]. For example, Wang et al. [19] used DEA to calculate the GTFP index of Chinese provinces from 2004 to 2015. Liu et al. [4] calculated the GTFP of Chinese agriculture by using provincial panel data. Since the Malmquist index of the traditional DEA method cannot measure the part containing the unexpected output, some scholars use the Malmquist–Luenberger (ML) index to measure the agricultural GTFP [20]. When calculating agricultural GTFP, input variables generally include labor, land, and capital, while output variables include expected output and non-expected output. The output yield and value of agriculture are generally regarded as the expected output, while unexpected outputs usually include greenhouse gas emissions [4,21,22] and agricultural non-point source pollution [22].

2.2. Influencing Factors of Agricultural GTFP

With the continuous improvement of measurement methods, scholars have begun to pay attention to the influencing factors of GTFP. For example, Zhan et al. [23] found that the input of agricultural science and technology and labor capital had a positive impact on the growth of agricultural productivity. Liu et al. [24] determined that labor force, machinery, pesticides and agricultural film are important factors affecting agricultural productivity. Liu et al. [25] tested the significant double-threshold effect between human capital and agricultural GTFP under different levels of agricultural material capital and agricultural economic development. Fang et al. [26] found that agricultural insurance had a significantly positive impact on GTFP. In summary, the factors influencing agricultural GTFP can be divided into two categories: agricultural factor endowments (internal factors) and regional characteristics (external factors). Agricultural factor endowments (internal factors) include the agricultural economic development level, agricultural production structure, agricultural technology level, planting structure, land management, mechanization level, natural conditions, and other factors [27–29]. Regional characteristics (external factors) include the regional economic development level, urbanization level, regional openness, financial factors and other factors [30,31].

2.3. Impact of Mechanization on Agricultural GTFP

There is consensus that mechanization is an important factor influencing agricultural production. Many scholars have confirmed the importance of agricultural mechanization from the perspectives of production quality [32–36], economic benefits [37–43], ecological benefits [44–49] and social benefits [50,51]. Some scholars have noticed that the effect of mechanization on agricultural production is different. Xue et al. [8] and Zhang et al. [9] believe that only when the level of agricultural mechanization reaches a certain level can the agricultural labor force be completely released from production. Lv et al. [10] believe that, with the continuous improvement of the level of agricultural mechanization, there is a trend of diminishing marginal utility in the improvement of agricultural production efficiency through the path of technological progress. In addition, agricultural production conditions, including terrain characteristics and agricultural land management scale, will also affect the effect of machinery. Xue et al. [52] believe that terrain conditions affect agricultural GTFP by affecting the feasibility of agricultural machinery operation. It is considered that machinery requires a lot of land [53–55].

2.4. Research Assumptions

Agricultural mechanization will affect factor input and utilization efficiency. Agricultural mechanization improves agricultural GTFP by optimizing the allocation of agricultural production factors. As an advanced means of labor, agricultural machinery can replace labor and reduce labor input [5,6]. Substitution of agricultural machinery for manual operations in agricultural production can alleviate the negative impact of agricultural labor transfer on agricultural production, maintain a weak labor force, and improve agricultural production efficiency [56]. Agricultural mechanization can improve the efficiency of agricultural technology. Technical efficiency improvement is critical for improving total factor productivity [57]. Agricultural mechanization can improve agricultural productivity [58,59]. According to the essential role of agricultural mechanization, the productivity of land and the labor efficiency of farmers will be improved [33]. Agricultural mechanization runs through the whole process of agricultural production by promoting standardization and normalization [60]. Through the introduction of technology, advanced agricultural machinery is introduced into the production chain to improve efficiency [61].

However, different stages of agricultural mechanization have different effects on the improvement of agricultural total factor productivity. Only when agricultural mechanization reaches a certain level can agricultural labor be completely removed from agricultural production [8,9]. From the perspective of improving agricultural technical efficiency, when agricultural mechanization is at a low level, the improvement of agricultural mechanization has a greater effect on the improvement of GTFP. The reason is that, when the level of agricultural mechanization is low, the use of agricultural machinery in agricultural production is lower. Farmers choose agricultural machinery that can effectively reduce the input of factors or improve the output, and the effect of the technological progress brought about by agricultural mechanization is relatively large. With the continuous improvement in the level of agricultural mechanization, there is a trend of diminishing marginal utility in the promotion of agricultural GTFP through technological progress [10]. Agricultural production conditions include terrain characteristics, agricultural land management scale, etc. Terrain conditions affect agricultural GTFP by affecting the feasibility of agricultural machinery operation [53–55]. Agricultural machinery has certain requirements for the "intensiveness" and "scale" of land [11]. The popularization of agricultural machinery and equipment must involve proper planning and layout. Small parcels of scattered arable land are not conducive to the large-scale operation of agricultural machinery [62]. If agricultural machinery is to be operated on a small area of land, the operating costs of machinery and equipment (including labor and fuel) will increase, and machinery cost will increase significantly [63,64]. Land fragmentation will hinder farmers from adopting agricultural machinery technology [12], and cause diseconomies of scale in the use of agricultural machinery.

According to the abovementioned analysis, agricultural mechanization can improve agricultural GTFP. However, in different stages of agricultural mechanization development, the level of agricultural mechanization has different effects on the improvement of agricultural GTFP. Factors such as terrain features and land management scale will also affect the rational use of agricultural machinery power, resulting in uncertainty about the role of agricultural mechanization in improving the agricultural GTFP in different regions. Finally, the following hypotheses are proposed:

H1. *Agricultural mechanization has the effect of increasing the GTFP of maize. There are differences in the promotion effect of the agricultural mechanization level on maize GTFP at different stages.*

H2. *Compared with plains areas, agricultural mechanization has less effect on the GTFP of maize in hilly and mountainous areas with undulating terrain.*

H3. *The larger the scale of land management, the more significant the effect of agricultural mechanization on GTFP of maize; on the contrary, the smaller the scale of land management, the smaller the effect of agricultural mechanization on GTFP of maize.*

The research framework of this study is shown in Figure 1.

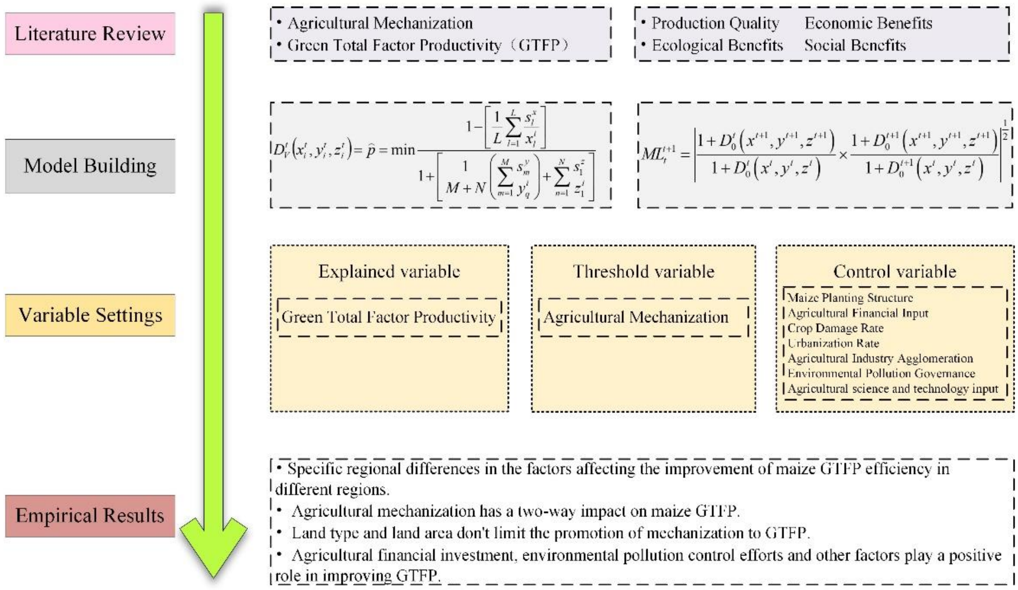

Figure 1. Research framework of this study.

3. Materials and Methods

3.1. Methods

3.1.1. Super-Efficient SBM

This study uses a Super SBM model to calculate China's maize production GTFP. The Super-SBM model is a DEA model that combines super efficiency with the SBM model. The Super-SBM model can reflect the relaxation improvement in the efficiency measurement, and can also compare the efficiency values between the effective decision-making units [65,66]. This study uses the nonradial and nonangular super-efficiency SBM model combined with the ML index to calculate the efficiency value and its growth rate. The SBM-ML model can evaluate the effective decision-making unit (efficiency value = 1) and analyze the slack problem of production factors.

Each major maize-producing province is regarded as a decision-making unit (DMU); each DMU has L inputs $X = \{x_1, x_2, x_3, \ldots, x_L\} \in R_L^+$ and produces M expected output $Y = \{y_1, y_2, y_3, \ldots, y_M\} \in \mathrm{R}_M^+$ and N kinds of undesired outputs $Z = \{z_1, z_2, z_3, \ldots, z_N\} \in \mathrm{R}_N^+$, thus constructing the SBM function expression of a province in year t containing both expected and undesired outputs:

$$D_V^t\left(x_i^t, y_i^t, z_i^t\right) = \widehat{p} = \min \frac{1 - \left[\frac{1}{L}\sum\limits_{l=1}^{L}\frac{s_i^x}{x_l^i}\right]}{1 + \left[\frac{1}{M+N}\left(\sum\limits_{m=1}^{M}\frac{s_m^y}{y_m^i} + \sum\limits_{n=1}^{N}\frac{s_n^z}{z_n^i}\right)\right]} \tag{1}$$

$$s.t.\begin{cases} \sum_{i=1}^{I} u_i^t y_{i,m}^t - s_m^y = y_{i,q}^t = 1,2\cdots,M; \\ \sum_{i=1}^{I} u_i^t x_{i,l}^t - s_l^x = x_{i,l}^t = 1,2,\cdots,L; \\ \sum_{i=1}^{I} u_i^t z_{i,n}^t - s_n^z = z_{i,n}^t = 1,2,\cdots,N; \\ \sum_{i=1}^{I} u_i^t = 1, u_i^t \geq 0, s_m^y \geq 0, s_l^x \geq 0, s_n^z \geq 0, i = 1,2,\cdots,I \end{cases} \quad (2)$$

D_V^t means the directional distance function under variable returns to scale.x_i^t, y_i^t, z_i^t represents the input–output collection of provinces. The objective function $\hat{p}$ represents the overall efficiency of the decision-making unit. The numerator and denominator of the expression represent the average distance between the actual production of the decision-making unit and the production frontier. The inefficiency of input and output are expressed by the numerator and denominator of the expression. The closer $\hat{p}$ gets to 1 decision unit, the more efficient the production is. When $\hat{p} = 1$, the decision unit is at the frontier of production, and there is no shortage of input and output. s_l^x, s_m^y, s_n^z means the slack variables of input, expected output, and undesired output; u_i^t means the weight vector of each decision-making unit.

3.1.2. Malmquist–Luenberger Index

The Malmquist index measures the growth rate of total factor productivity and is an indicator of dynamic changes in efficiency. A directional distance function that includes bad output is applied in the Malmquist index, called the Malmquist–Luenberger index [20]. This study uses the geometric mean of the two ML indices to obtain the change in total factor productivity from period t as the base period to the $t+1$ period. We decomposed the measurement results into technological progress and technological efficiency through the ML index. The study uses the ML index to analyze the changing trend of maize GTFP in each province. The ML index from period t to period $t+1$ is:

$$ML_t^{t+1} = EC_t^{t+1} + TC_t^{t+1} = \left| \frac{1 + D_0^t\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}{1 + D_0^t(x^t, y^t, z^t)} \times \frac{1 + D_0^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}{1 + D_0^{t+1}(x^t, y^t, z^t)} \right|^{\frac{1}{2}} \quad (3)$$

$$EC_t^{t+1} = \left| \frac{1 + D_0^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}{1 + D_0^t(x^t, y^t, z^t)} \right| \quad (4)$$

$$TC_t^{t+1} = \left| \frac{1 + D_0^t\left(x^t, y^t, z^t\right)}{1 + D_0^{t+1}(x^t, y^t, z^t)} \times \frac{1 + D_0^t\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}{1 + D_0^{t+1}(x^{t+1}, y^{t+1}, z^{t+1})} \right|^{\frac{1}{2}} \quad (5)$$

In the formula, EC means technical efficiency and TC means technological progress. $ML_t^{t+1} = 1$ means that there is no change in productivity from period t to period $t+1$. A value greater than 1 indicates an increase in productivity. EC_t^{t+1} means the technical efficiency change index. EC_t^{t+1} measures the degree of production technology change of production system from period t to period $t+1$. EC_t^{t+1} greater than 1 indicates that the technical efficiency has improved; otherwise, the technical efficiency has decreased. TC_t^{t+1} means the technology change index. TC_t^{t+1} measures the degree of production technology change of the production system from t to $t+1$. TC_t^{t+1} is greater than 1, indicating that the production technology has progressed; otherwise, the production technology has regressed.

3.1.3. Threshold Regression

This study analyzes the possible nonlinear effects of agricultural mechanization on the GTFP of maize. Based on Hayes and Andrew's research methods [67], the study applied the panel threshold regression model proposed by Hansen to verify the threshold effect of agricultural mechanization on each maize production area. The model uses logarithmic variables to reduce heteroscedastic data. The sample interval is divided according to the data characteristics and the estimated threshold value. The single-threshold panel threshold regression model constructed in this study is:

$$\ln GTFP = u_1 + a_0 + a_1 \ln MECH \times 1(\ln MECH \leq c) + a_2 \ln MECH \times 1(\ln MECH > c) + b \ln x \quad (6)$$

$\ln GTFP$ represents the green total factor productivity of maize. u_1 denotes the random error term. a_0 represents the individual effect. The value is 1 when the conditions in the parentheses are satisfied. According to whether the agricultural mechanization ($\ln MECH$) is greater than the threshold value (c), the sample interval is divided into two zones. The two zones are distinguished by slope values a_1 and a_2. x represents the control variable.

Considering that there may be multiple threshold values in the model, taking the double threshold model as an example:

$$\begin{aligned} &\ln GTFP = u_1 + \alpha_0 + \alpha_1 \ln MECH \cdot 1(\ln MECH \leq c_1) + \alpha_2 \ln MECH \cdot 1(c_1 \leq \ln MECH \leq c_2) \\ &+\alpha_3 \ln MECH \cdot 1(\ln MECH \geq c_2) + \beta \ln x \end{aligned} \quad (7)$$

3.2. Definition of Variables

3.2.1. GTFP Measurement: Input and Output Variables

This study follows the traditional literature to select inputs and outputs for the model [4,19,20]. The input variables select labor input and material data input. The labor index selects the number of working days; seeds are the foundation, and chemical fertilizers and pesticides are the main factors for increasing maize production. Machinery plays a significant role in improving maize production efficiency. In order to reduce the calculation error of pesticide costs and mechanical action costs, this study uses the input and output factor data per unit area as indicators.

The output variables include expected output and undesired output, and the maize yield per unit area of each province is taken as the expected output, which represents the positive effect in the maize production process. According to FAO statistics, agricultural production has become the second-largest source of greenhouse gas emissions in the world. Fertilizer application, chemical oxygen demand and greenhouse gas emissions are important sources of agricultural pollution. This study follows the traditional literature to select greenhouse gas emissions in agricultural production as the unexpected output [21,22]. The CO_2 emissions are calculated according to the formula $C = \sum E_i \times \theta_i$ to calculate the total carbon emissions in the maize production process, with E_i representing the number of θ_i carbon emission sources and the coefficient of carbon emission sources. The carbon emission coefficients of fertilizers, pesticides and diesel refer to Oak Ridge National Laboratory (2009), China Agricultural University College of Biological Sciences and the IPCC (Intergovernmental Panel on Climate Change). N_2O is the main greenhouse gas emitted by agricultural activities. The radiation intensity of N_2O is 298 times that of CO_2 of the same mass. The direct emission of N_2O from agricultural land mainly comes from nitrogenous fertilizers and straw returning to the fields. The indirect emission of N_2O mainly comes from atmospheric nitrogen deposition and nitrogen leaching runoff loss. The direct emission of N_2O has an absolute position. The direct emission of N_2O is calculated by reference to Zhang [68], by summing the products of various nitrogen sources and N_2O direct emission factors. Specific variables are described in Table 1.

3.2.2. Influence Factor Variables

The level of agricultural mechanization is used as the threshold variable and the core explanatory variable. The ratio of the total power of agricultural machinery to the total sown area of crops is used to measure the level of agricultural mechanization. This study follows the traditional literature to select the factors that affect maize GTFP [23–31]. Seven control variables are added to the model: maize planting structure, agricultural financial input, crop disaster rate, urbanization rate, agricultural industry agglomeration, environmental pollution control, and agricultural science and technology input. The maize planting structure uses the ratio of maize sown area to total crop sown area. The agricultural financial input is measured by the ratio of agriculture, forestry, and water affairs expenditure to the total financial expenditure. The disaster rate of maize is measured by the ratio of the affected area of crops to the total sown area of crops. The urbanization rate is measured by the ratio of the urban population to the total population. The proportion of environmental pollution control investment in GDP is assessed for environmental pollution control. The study uses the proportion of agricultural science and technology expenditure to the total fiscal expenditure to measure the agricultural science and technology input. The location entropy index is used to measure the level of agricultural industry agglomeration, calculated by the formula $AGGL = (x_{ij}/x_i)/(x_j/x)$, where x_{ij} and x_i represent the total agricultural output value and regional GDP of i, and x_j and x represent the national agricultural output value and the national GDP, respectively. The greater the value calculated by the formula, the higher the degree of agricultural industry aggregation. Specific variables are described in Table 2.

Table 1. Description of input–output variables.

	Variable Category	Variable Description	Unit
Output	Expected	Main product yield	kg/hm^2
	Undesired	CO_2 emissions	kg/hm^2
		N_2O emissions	kg/hm^2
Input	Labor	Working days	D/hm^2
	Material data	Seed dosage	kg/hm^2
		Amount of chemical fertilizer	kg/hm^2
		Pesticide cost	Yuan/hm^2
		Mechanical work fee	Yuan/hm^2

Table 2. Description of influential factor variables.

Variable Category	Variable Name	Variable Symbol
Explained variable	GTFP of maize	GTFP
Threshold variable	Level of agricultural mechanization	MECH
Control variable	Maize planting structure	STRU
	Agricultural financial input	FINA
	Crop damage rate	DISA
	Urbanization rate	URBA
	Agricultural industry agglomeration	AGGL
	Environmental pollution governance,	ENVI
	Agricultural science and technology input	SCTE

3.3. Samples and Data Sources

This study divides the regions according to the distribution of maize planting ecological zones in China. The northern spring sowing region includes Heilongjiang, Jilin, Liaoning, Inner Mongolia and Ningxia. The Huang–Huai–Hai summer sowing region includes Hebei, Shanxi, Jiangsu, Anhui, Shandong, Henan and Hubei. The southwest mountain sowing region includes Guangxi, Sichuan, Guizhou, Yunnan and Chongqing. The northwest irrigation sowing region includes Shaanxi, Gansu, and Xinjiang.

The four maize-growing regions have different characteristics. In the northern spring sowing region, the terrain is flat, the soil layer is deep, and the light and heat resources are rich. The maize production region in this area is concentrated, and the land management scale is large. The Huang–Huai–Hai summer sowing region is the largest concentrated maize production area in China. The Huang–Huai–Hai Plain is flat and generally less than 50 m above sea level. In this area, the temperature is high, the evaporation is large, the rainfall is concentrated, and the natural conditions are very favorable to the growth of maize. More than 90% of the land in the southwest mountain sowing region is hilly and plateau, and the degree of land use is low. The northwest irrigation sowing region is located in the diluvial impact plains area, with flat terrain and fertile soil, which is convenient for cultivation and large-scale agricultural land management.

The time span was from 2001 to 2020. The data on the number of working days, the amount of seeds, the amount of chemical fertilizer, the cost of pesticides and the cost of mechanical action were from the "National Agricultural Product Cost and Benefit Data Compilation (2001–2021)." The missing data were filled in by interpolation. The total power data of agricultural machinery come from the China Agricultural Machinery Industry Yearbook (2001–2021). The total crop sown area, maize sown area, expenditure on agriculture, forestry and water affairs, total financial expenditure, urban population, total population, GDP data and agricultural science and technology input data come from the China Statistical Yearbook (2001–2021). The crop disaster area comes from the China Rural Statistical Yearbook (2001–2021). Environmental pollution control investment data come from the China Environmental Statistical Yearbook (2001–2021).

4. Empirical Results

4.1. Measurement Results of GTFP of Maize

4.1.1. Characteristics of GTFP of Maize

Figure 2 shows the measurement results of GTFP of maize using MAX-DEA software. ML represents the growth rate of maize GTFP between adjacent years. EC means the growth rate of technical efficiency, and TC means the growth rate of technological progress. On the whole, the growth rate of GTFP growth of maize production in China varies greatly in different years. The growth of GTFP of maize depends on the alternating promotion of technical efficiency and technological progress.

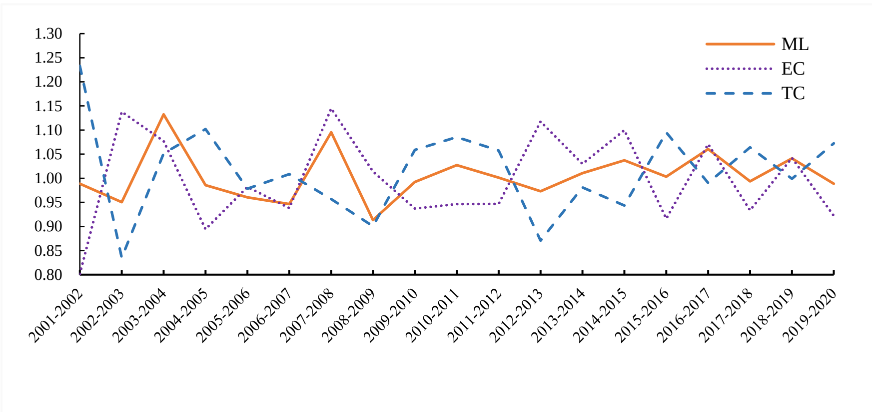

Figure 2. Growth rate and decomposition trend of China's GTFP of maize 2001–2020.

Table 3 shows the values of maize GTFP in each province and region of China. The GTFP of maize in China has the characteristics of regional imbalance, and the efficiency values of the four regions are quite different. From the perspective of the overall level of maize GTFP in each region, the southwest mountain sowing region (1.002) > the northern spring sowing region (0.957) > the Huang–Huai–Hai summer sowing region (0.943) > the northwest irrigation sowing region (0.917).

From the perspective of provinces, the GTFP gap among provinces was large. The average efficiency of six provinces reached the effective level, accounting for 30% of the total main producing provinces, namely Shanxi, Xinjiang, Sichuan, Ningxia, Inner Mongolia and Guangxi. Shanxi had the best maize production situation, with an average efficiency of 1.23. The efficiency of 11 provinces was lower than the average level of the main maize-producing regions in China, and most of them were distributed in the "Sickle Bay area".

Table 3. Measurement results of maize GTFP in various provinces and regions in China.

Area		2001	2005	2010	2015	2020	Average
The northern springsowing region	Heilongjiang	0.805	1.220	1.141	1.005	0.915	0.983
	Jilin	1.007	0.887	0.895	0.915	0.991	0.874
	Liaoning	1.094	1.027	0.705	0.744	0.828	0.859
	Inner Mongolia	1.064	1.018	1.068	1.009	1.064	1.023
	Ningxia	1.101	1.047	1.020	1.013	1.019	1.048
	Average	1.014	1.040	0.966	0.937	0.963	0.957
The Huang-Huai-Hai summer sowing region	Hebei	0.779	0.752	0.811	0.907	0.871	0.868
	Shanxi	1.249	1.001	1.427	1.347	1.073	1.230
	Jiangsu	0.828	0.790	0.909	0.955	0.859	0.818
	Anhui	1.066	0.917	0.880	1.009	0.970	0.940
	Shandong	0.923	0.740	0.795	0.883	0.814	0.854
	Henan	0.805	1.034	1.003	1.137	1.011	0.997
	Hubei	0.935	1.036	1.033	0.809	0.921	0.893
	Average	0.941	0.896	0.980	1.007	0.931	0.943
The southwest mountain sowing region	Guangxi	0.796	1.293	1.038	1.230	0.979	1.007
	Sichuan	1.067	1.556	0.731	1.108	0.734	1.192
	Guizhou	0.719	1.004	1.140	0.794	1.037	0.902
	Yunnan	1.164	0.624	1.035	0.679	0.627	0.965
	Chongqing	0.727	1.009	0.842	0.779	0.931	0.945
	Average	0.895	1.097	0.957	0.918	0.862	1.002
The northwest irrigation sowing region	Shaanxi	1.011	1.012	0.879	0.820	1.000	0.787
	Gansu	0.735	0.830	0.723	0.833	0.917	0.770
	Xinjiang	1.091	1.122	1.076	1.142	1.258	1.195
	Average	0.946	0.988	0.893	0.932	1.058	0.917

4.1.2. Optimization of GTFP of Maize

This study regards provinces with efficiency values lower than the average level of the main producing areas as relatively ineffective. A total of 11 provinces are relatively ineffective. From Table 4, it can be seen that the relatively ineffective area has different degrees of redundancy in terms of input and undesired output, and the CO_2 emissions and N_2O emissions redundancy rates are both high. Therefore, greenhouse gas emissions have a significant impact on GTFP. Among the input elements, pesticides and fertilizers have the highest redundancies. The redundancy of pesticide cost reaches −27.328%. The provinces with the highest redundancy are Gansu, Shaanxi, Jiangsu and Shandong. These four provinces are located in different maize-producing areas. There are differences in the influencing factors restricting the improvement of efficiency in different regions.

4.2. Threshold Effect of Agricultural Mechanization on GTFP of Maize

4.2.1. Stationarity Test

Due to the existence of unit root process instability in the series, there may be spurious regression in the regression analysis. In this study, all variables were tested by a unit root test, and the stationarity of variables was tested by the same root test (LLC) and a different root test (IPS). According to the p-value judgment stationarity of data, if the p-value is greater than 0.1, the panel data are not stable. The results are shown in Table 5. The variables all directly passed the unit root test, except that the maize planting structure ($LnSTRU$) and agricultural science and technology expenditure ($LnSCTE$) were stable after the first difference. Therefore, all variables in the model are stationary.

Table 4. Input-output redundancy ratio of provinces and regions.

Province	Input Redundancy Rate (%)					Output Redundancy Rate (%)		
	Employment Quantity	Seed Dosage	Pure Fertilizer Consumption	Mechanical Fee	Pesticide Cost	Product Yield	CO_2 Emissions	N_2O Emissions
Jilin	−6.650	−1.410	−14.125	−6.140	−34.951	0	−19.838	−42.825
Liaoning	−9.347	−14.476	−16.369	−0.324	−30.137	0	−29.197	−45.401
Hebei	−11.658	−9.983	−4.266	−4.143	−35.871	0	−37.583	−45.564
Chongqing	−2.216	1.975	−3.233	−17.587	−6.264	0	−4.538	−4.291
Jiangsu	−15.139	−12.998	−23.771	−1.624	−37.601	0	−29.971	−35.086
Anhui	−2.397	−9.898	−7.130	10.602	−21.035	0	−12.272	−32.899
Shandong	−10.397	−9.932	−14.612	1.979	−39.913	0	−30.158	−3.229
Hubei	−0.452	−10.275	−13.368	−2.973	−26.303	0	−27.809	−23.411
Guizhou	−12.158	−8.521	−13.369	−2.948	−12.465	0	−8.049	−21.390
Shaanxi	−25.684	−30.560	−21.119	−4.249	−25.013	0	−31.999	−8.568
Gansu	−36.292	−12.828	−18.894	−15.975	−31.059	0	−19.161	−7.885
The northern springsowing region	−7.999	−7.943	−15.247	−3.232	−32.544	0	−24.518	−44.113
The Huang-Huai-Hai summer sowing region	−8.009	−10.617	−12.629	0.768	−32.145	0	−27.559	−28.038
The southwest mountain sowing region	−7.187	−3.273	−8.301	−10.268	−9.3645	0	−6.2935	−12.8405
The northwest irrigation sowing region	−30.988	−21.694	−20.007	−10.112	−28.036	0	−25.580	−8.227
Mean	−12.035	−10.810	−13.660	−3.944	−27.328	0	−22.780	−24.595

Note: Redundancy rate = Redundancy/Original input.

Table 5. Variable unit root test results.

	The Northern Spring Sowing Region		The Huang-Huai-Hai Summer Sowing Region		The Southwest Mountain Sowing Region		The Northwest Irrigation Sowing Region	
variable	LLC	IPS	LLC	IPS	LLC	IPS	LLC	IPS
LnGTFP	0.0000	0.0234	0.0000	0.0002	0.0000	0.0824	0.0264	0.0005
LnSTRU	0.0597	0.0474	0.1139	0.0232	0.4954	0.0943	0.0710	0.2417
LnFINA	0.0016	0.0040	0.0000	0.0735	0.0146	0.0120	0.0098	0.0052
LnDISA	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0001	0.0106
LnURBA	0.0000	0.0069	0.0000	0.0650	0.0275	0.0938	0.0060	0.0006
LnAGGL	0.0070	0.0304	0.0733	0.0133	0.0181	0.0465	0.0912	0.0898
LnENVI	0.0104	0.0461	0.0004	0.0002	0.0000	0.0000	0.0000	0.0809
LnSCTE	0.0273	0.0296	0.4167	0.0347	0.2750	0.0559	0.2769	0.4226
LnMECH	0.0001	0.0250	0.0031	0.0000	0.0000	0.0019	0.0015	0.0032

4.2.2. Threshold Effect Test Results

Table 6 shows the test results of 1000 times repeated sampling by Stata 14.0 (College Station, KSAT, USA) software. The threshold effect is judged by the p-value. The level of agricultural mechanization had a threshold effect on the GTFP of four maize ecological regions, which indicated that agricultural mechanization had a nonlinear effect on GTFP. The effect of the agricultural mechanization development level was different at different stages on maize GTFP. For the northern spring sowing region, the F statistic was significant at least at 0.05 in the two-threshold model. If the p-value is less than 0.10, there are two threshold values in the model. For the Huang–Huai–Hai summer sowing region, it is significant at the 0.01 level. There are two threshold variables in the Huang–Huai–Hai summer sowing region. For the southwest mountain sowing region, there are at least two threshold variables at the 0.10 significance level. For the Northwest Irrigation sowing region, there is one threshold variable at the 0.01 significance level.

4.2.3. Threshold Estimation Results

The threshold estimation results are shown in Table 7. The effect of agricultural mechanization on GTFP of maize varies by region. Except for the northwest irrigation sowing region, which is a single-threshold type, the other three regions are all double-threshold types. There are differences in the threshold values of different regions. For the northern spring sowing region, the double-threshold values of the maize mechanization level are 1.3420 and 1.4600. In the Huang–Huai–Hai summer sowing region, the double-threshold values of mechanization level are 1.3473 and 1.3570. In the southwest mountain sowing region, the double-threshold values of maize mechanization level are 0.8575 and 1.8374. In the northwest irrigation sowing region, the single-threshold value of mechanization level is 1.7335. Figures 3–6 show the likelihood ratio function of the estimated threshold value under the 0.95 confidence interval for the four regions. The lowest point of the LR statistic is the corresponding real threshold value and the dotted line represents the critical value. Since the critical value is significantly larger than the threshold value, the threshold values of each area passed the LR test. Therefore, the above thresholds are true and valid.

Table 6. Test results of threshold effect in each region.

Region	Number of Thresholds	F Value	p Value	0.10	0.05	0.01
The northern spring sowing region	1	10.96	0.022	8.1148	9.3548	14.1804
	2	8.03	0.018	5.5991	6.8230	8.6451
	3	3.01	0.8050	13.4942	15.8945	18.9082
The Huang-Huai-Hai summer sowing region	1	14.10	0.0710	12.7956	15.2795	20.4469
	2	25.77	0.0020	14.0010	16.8625	20.5256
	3	8.28	0.3940	20.1435	25.7562	36.9362
The southwest mountain sowing region	1	17.65	0.0110	11.9043	13.4385	17.4857
	2	14.19	0.0630	11.7045	16.1474	24.2509
	3	5.58	0.3540	10.0470	14.6726	28.7893
The northwest irrigation sowing region	1	21.90	0.0000	5.8738	7.1177	7.1177
	2	4.90	0.1800	5.8803	7.2234	8.2222
	3	1.87	0.9370	7.0788	7.2442	8.3924

Table 7. Estimated results of threshold values in each region.

Region	Threshold Type	Threshold
The northern spring sowing region	double threshold	1.3420 1.4600
The Huang-Huai-Hai summer sowing region	double threshold	1.3473 1.3570
The southwest mountain sowing region	double threshold	0.8575 1.8374
The northwest irrigation sowing region	single threshold	1.7335

4.2.4. Threshold Regression Results

The parameter estimation results obtained by panel threshold regression are shown in Table 8. The study judged whether it passed the significance test according to the $|P| > t$ value. The regression results of the southwest mountain sowing region and the Northwest Irrigation sowing region confirm hypothesis H1. For the southwest mountain sowing region, the level of agricultural mechanization had a positive effect on GTFP of maize. With the increasing level of mechanization in the southwest mountain sowing region, the effect of maize GTFP weakened. When the level of mechanization was less than 0.8575, the coefficient was 1.6265. When the level of mechanization was between 0.8575 and 1.8374, the regression coefficient was 1.0159. When the maize mechanization level crossed the second threshold of 1.3570, the coefficient weakened to 0.1226. The above regression coefficient passed the significance test at the 0.10 level. For the northwest irrigated area, agricultural mechanization had a significant effect on the GTFP of maize. Agricultural mechanization effectively relieved the agro-ecological pressure in the process of maize production in the Northwest Irrigation sowing region. When the level of mechanization was lower than the first threshold value (<1.7335), the regression coefficient was 0.3297. When the level of maize mechanization crossed the first threshold, the regression coefficient weakened to 0.0805.

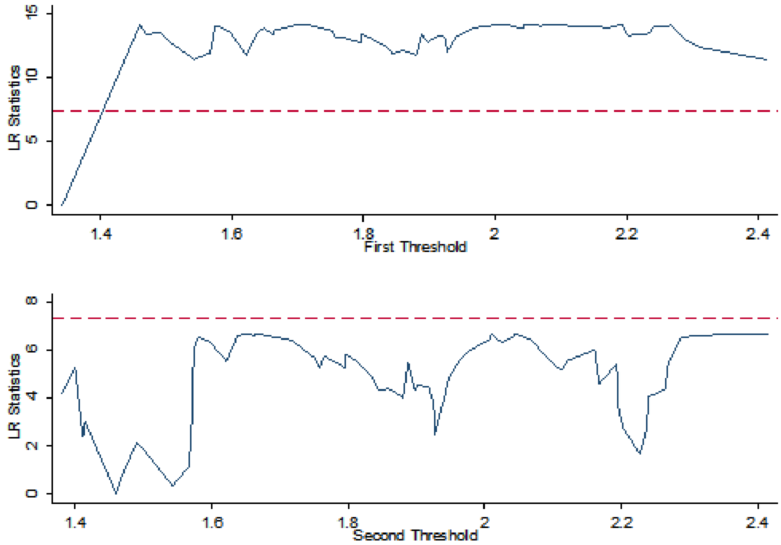

Figure 3. Likelihood ratio function diagram of the northern spring sowing region.

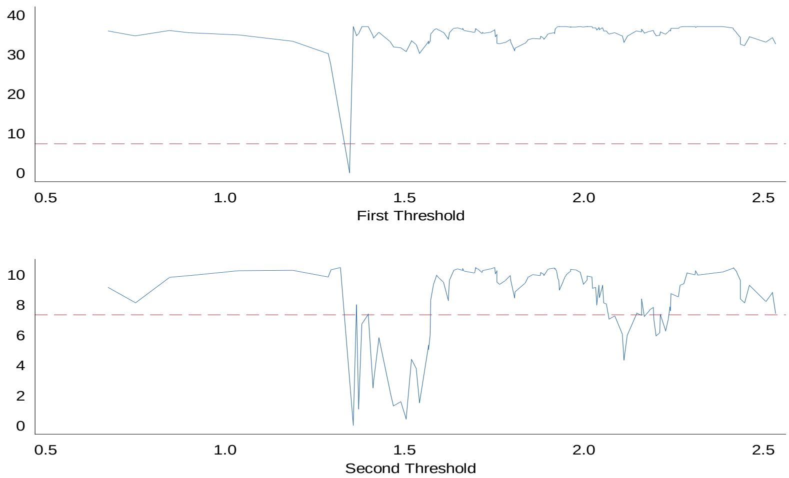

Figure 4. Likelihood ratio function diagram of the Huang-Huai-Hai summer sowing region.

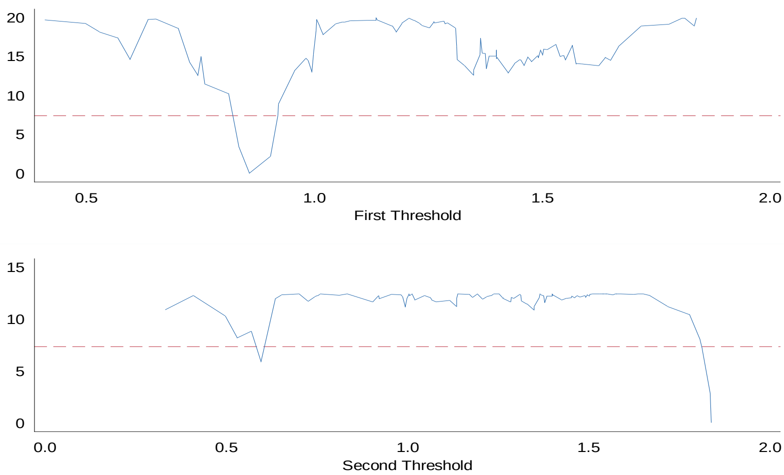

Figure 5. Likelihood ratio function diagram of the southwest mountain sowing region.

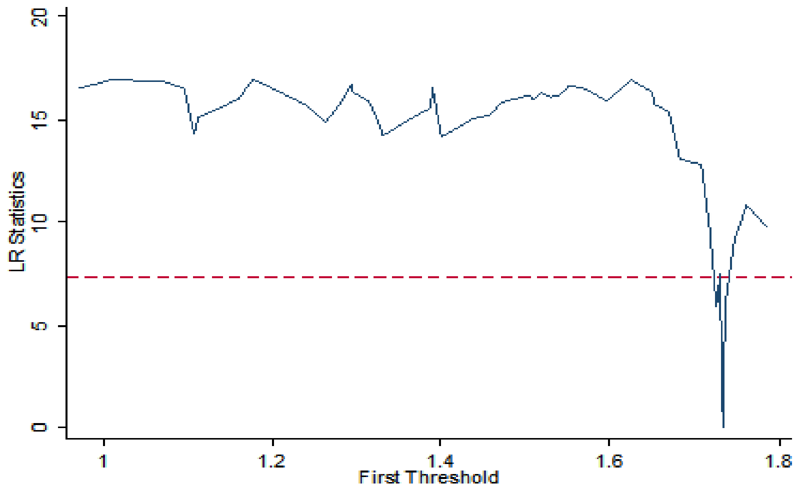

Figure 6. Likelihood ratio function diagram of the northwest irrigation sowing region.

Table 8. Estimated results of regression parameters for each region.

The Northern Spring Sowing Region		**The Huang-Huai-Hai Summer Sowing Region**		**The Southwest Mountain Sowing Region**		**The Northwest Irrigation Sowing Region**	
Variable	**Return Coefficient**	**Variable**	**Return Coefficient**	**Variable**	**Return Coefficient**	**Variable**	**Return Coefficient**
LnSTRU	−0.1826	LnSTRU	−0.3601 **	LnSTRU	−0.2366	LnSTRU	0.3375 *
LnFINA	0.2715 **	LnFINA	0.1641 **	LnFINA	0.1552	LnFINA	0. 2018
LnDISA	−0.1515 ***	LnDISA	−0.0869 ***	LnDISA	−0.1067 **	LnDISA	0.1028 **
LnURBA	−0.2872	LnURBA	−0.0543	LnURBA	−0.1710 ***	LnURBA	0.0878
LnAGGL	0.0263	LnAGGL	−0.2180	LnAGGL	−0.5137	LnAGGL	0.0913
LnENVI	0.1508 ***	LnENVI	0.0973 **	LnENVI	0.0221	LnENVI	0. 1272 ***
LnSCTE	0.0501	LnSCTE	0.0239	LnSCTE	0.4236 ***	LnSCTE	0.0929
LnMECH ≤ 1.3420	0.3655 *	LnMECH ≤ 1.3473	0.2856 **	LnMECH ≤ 0.8575	1.6265 ***	LnMECH ≤ 1.7335	0.3297 ***
1.3420 < LnMECH ≤ 1.4600	−0.0654	1.3473 < LnMECH ≤ 1.3570	−0.5533 ***	0.8575 < LnMECH ≤ 1.8374	1.0159 ***	LnMECH > 1.7335	0.0805 ***
LnMECH > 1. 4600	0.0798	LnMECH > 1.3570	0.1226	LnMECH > 1.8374	0.7072 ***		

Note: ***, ** and * represent passing the significance test at the 0.01, 0.05 and 0.10 levels, respectively, judged by value $|P| > t$.

For the northern spring sowing region, when the level of mechanization was low ($lnMECH < 1.3420$), there was a positive effect on the GTFP of maize with a coefficient of 0.3655. The result passed the significance test at the 0.10 level. When the level of mechanization was between the two thresholds, the regression coefficient was −0.0654. The level of agricultural mechanization between the two thresholds had a negative impact on GTFP. However, the results did not pass the significance test, so the inhibitory effect of agricultural mechanization on GTFP has not been highlighted. When the level of maize mechanization was high ($lnMECH > 1.4600$), there was a positive effect on GTFP with a coefficient of 0.0798. The Huang–Huai–Hai summer sowing region has a high level of agricultural mechanization, and agricultural technology is fully utilized. When the level of mechanization was less than 1.3473, it had a positive impact on GTFP of maize. The regression coefficient was 0.2856. The result passed the significance test at the 0.05 level. When the mechanization level was between 1.3473 and 1.3570, the regression coefficient was −0.5533. Agricultural mechanization had a negative effect on the GTFP of maize, and the effect increased. The model passed the significance test at the 0.10 level. When the level of agricultural mechanization crossed the second threshold, for every 0.01 increase in the level of agricultural mechanization, maize GTFP increased significantly by 0.1226%. The regression results of the northern spring sowing region and the Huang–Huai–Hai summer sowing region were contrary to hypothesis H1. The effect of agricultural mechanization on maize GTFP has two sides. Agricultural mechanization has an inhibitory effect on maize GTFP in specific regions.

In terms of terrain characteristics and the agricultural land management scale, the southwest mountainous area has a high altitude, and the terrain conditions are mainly plateau, basin, and mountain, with a high degree of land fragmentation and a small area of cultivated land. The northwest irrigation area is characterized by small topographic relief, sparsely populated land and a large scale of agricultural land management. The regression results show that agricultural mechanization has the largest role in improving the GTFP of maize in the southwest mountain area, and the empirical results are contrary to hypotheses H2 and H3.

According to the estimation results of the control variables, agricultural financial input ($lnFINA$), environmental pollution control intensity ($lnENVI$) and agricultural science and technology expenditure ($lnSCTE$) have a significantly positive effect on the GTFP of maize. The policy of regional financial support for agriculture can optimize maize production and play a positive role in improving GTFP. The urbanization rate ($lnURBA$) and crop damage rate ($lnDISA$) have inhibitory effects on maize GTFP.

4.2.5. Robustness Test

In order to ensure the robustness of the study results, we conducted tests shortening the sample period and replacing the independent variable.

The sample period selected in this study was 2001–2020, but some data of crop disasters before 2005 are missing. Although the missing data were supplemented by the interpolation method in the study, in order to avoid the interference of the processed data with the empirical results, the sample was adjusted to 2006–2020 and the threshold effect test was conducted again.

According to Tables 9 and 10, the threshold effect test and threshold value estimation results showed that, after shortening the sample period, the level of agricultural mechanization still had the threshold effect on GTFP in the four maize-producing regions. The number of threshold values in the northern spring sowing region, the Huang–Huai–Hai summer sowing region and the northwest irrigation sowing region did not change. The southwest mountain sowing region has changed from double threshold type to single threshold type. The ecological environment of the southwest mountain sowing region is relatively fragile. It is affected by earthquakes, typhoons and heavy rainfall from time to time. Therefore, the number of crop disasters and the GTFP fluctuate greatly in different periods, which leads to great differences in the impact of agricultural mechanization level on GTFP in different years, so the test results have changed. According to the estimation results (Table 11), the direction and significance of the estimation coefficient of agricultural mechanization level in each region have not changed significantly. At the same time, the direction of estimation coefficients of all control variables has not changed significantly. In general, the test results are consistent with the above, the results are robust.

The level of agricultural mechanization in this study was measured by the mechanical dynamics. Agricultural machinery costs cover all machinery used in the process of agricultural production (expenditure and consumption). Generally speaking, the higher the level of agricultural mechanization in a region, the greater the expenditure of farmers on agricultural machinery. At the same time, based on the data availability, this study took the mechanical action cost of planting maize per hectare as the explained variable to re-test the threshold characteristics of the model.

Table 9. Test results of threshold effect after shortening the sample period.

Region	Number of Thresholds	F Value	p Value	0.10	0.05	0.01
The northern spring sowing region	1	2.90	0.0900	11.2122	12.2836	19.1482
	2	13.13	0.0500	10.6846	12.6891	22.1712
	3	2.65	0.7100	8.3258	9.6570	13.7519
The Huang-Huai-Hai summer sowing region	1	10.77	0.0200	7.8744	9.7850	11.0032
	2	3.23	0.0900	7.8848	8.5515	11.6286
	3	8.70	0.2600	11.6234	14.2047	22.3868
The southwest mountain sowing region	1	15.28	0.0100	8.9966	11.2299	14.4563
	2	3.03	0.6300	8.0172	9.4800	13.1324
	3	2.66	0.7100	8.6024	9.8323	15.5177
The northwest irrigation sowing region	1	14.83	0.0000	6.1892	6.4056	7.5565
	2	3.96	0.3900	7.7704	7.9938	8.2403
	3	1.36	0.8300	9.3622	10.4846	11.9482

Table 10. Estimated results of threshold values after shortening the sample period.

Region	Threshold Type	Threshold	Region	Threshold Type	Threshold
The northern Springsowing region	double threshold	1.6005 1.6749	The southwest mountain sowing region	single threshold	1.4251
The Huang-Huai-Hai summer sowing region	double threshold	1.6218 1.7581	The northwest irrigation sowing region	single threshold	1.7335

Table 11. Estimated results of regression parameters after shortening the sample period.

The Northern Spring Sowing Region		The Huang-Huai-Hai Summer Sowing Region		The Southwest Mountain Sowing Region		The Northwest Irrigation Sowing Region	
Variable	Return Coefficient	Variable	Return Coefficient	Variable	Return Coefficient	Variable	Return Coefficient
LnSTRU	−0.3448	LnSTRU	−0.0245	LnSTRU	−0.1180	LnSTRU	−0.2460 *
LnFINA	0.3158 **	LnFINA	0.4447 ***	LnFINA	0.6014 **	LnFINA	0.1365
LnDISA	−0.1002 ***	LnDISA	−0.0714 **	LnDISA	−0.0049	LnDISA	−0.0430 **
LnURBA	−0.6276 *	LnURBA	−0.2598	LnURBA	−0.0419 **	LnURBA	−0.4481
LnAGGL	0.5658 ***	LnAGGL	−0.1162	LnAGGL	−0.1245	LnAGGL	−0.2778
LnENVI	0.0536	LnENVI	0.0778 **	LnENVI	0.1418 *	LnENVI	0.0796 ***
LnSCTE	0.0815	LnSCTE	0.1770 **	LnSCTE	0.4112 **	LnSCTE	0.0638
LnMECH ≤ 1.6005	0.2160	LnMECH ≤ 1.6218	0.0923 *	LnMECH ≤ 1.4251	0.6508 **	LnMECH ≤ 1.7335	0.4718 ***
$1.6005 <$ LnMECH ≤ 1.6749	−0.5743 ***	$1.6218 <$ LnMECH ≤ 1.7581	−0.0817 **	LnMECH > 1.4251	0.4702 *	LnMECH > 1.7335	0.6461 ***
LnMECH > 1.6749	0.1980	LnMECH > 1.7581	0.0026				

Note: ***, ** and * represent passing the significance test at the 0.01, 0.05 and 0.10 levels, respectively, judged by value $|P| > t$.

According to the threshold effect test and threshold value estimation results (Tables 12 and 13), the number of threshold values in the four regions did not change after replacing the independent variable. According to the regression parameters estimation results (Table 14), the influence direction of agricultural mechanization level on GTFP is basically consistent with the above, and the significance level has been improved. Although the influence of control variables on GTFP is different from the above, the direction of influence is basically the same. Therefore, this model is robust.

Table 12. Test results of threshold effect after replacing the independent variable.

Region	Number of Thresholds	F Value	p Value	0.10	0.05	0.01
The northern springsowing region	1	2.90	0.0900	11.2122	12.2836	12.1988
	2	13.13	0.0500	10.6846	12.6891	14.7445
	3	2.65	0.7100	8.3258	9.6570	10.8404
The Huang-Huai-Hai summer sowing region	1	4.71	0.0540	9.2488	10.0097	13.0876
	2	16.72	0.0100	11.2332	13.6044	16.2485
	3	15.16	0.9800	10.5395	11.3675	14.0178
The southwest mountain sowing region	1	5.83	0.0400	8.7593	10.7098	14.4831
	2	4.25	0.0400	7.6933	9.8916	12.5103
	3	2.55	0.6500	7.1737	8.9246	13.5153
The northwest irrigation sowing region	1	16.85	0.0160	8.0472	9.6753	10.6076
	2	14.00	0.4100	6.2956	9.8986	9.8986
	3	11.73	0.8800	10.6925	10.0396	10.2984

Table 13. Estimated results of threshold values after replacing the independent variable.

Region	Threshold Type	Threshold	Region	Threshold Type	Threshold
The northern Springsowing region	double threshold	5.7728 6.8735	The southwest mountain sowing region	double threshold	3.8199 4.0110
The Huang-Huai-Hai summer sowing region	double threshold	5.5102 6.0740	The northwest irrigation sowing region	single threshold	7.4187

Table 14. Estimated results of regression parameters after replacing the independent variable.

The Northern Spring Sowing Region		The Huang-Huai-Hai Summer Sowing Region		The Southwest Mountain Sowing Region		The Northwest Irrigation Sowing Region	
Variable	Return Coefficient	Variable	Return Coefficient	Variable	Return Coefficient	Variable	Return Coefficient
LnSTRU	−0.3516 *	LnSTRU	−0.0447 **	LnSTRU	−0.3503	LnSTRU	−0.3583 **
LnFINA	0.1410	LnFINA	0.1194 **	LnFINA	0.1025	LnFINA	0.1679
LnDISA	−0.1029 ***	LnDISA	−0.1318 ***	LnDISA	−0.0218	LnDISA	−0.0939 **
LnURBA	−0.0889	LnURBA	−0.0626	LnURBA	−1.3480 ***	LnURBA	−0.5048
LnAGGL	0.2601 ***	LnAGGL	−0.1891	LnAGGL	−0.3376	LnAGGL	−0.1793
LnENVI	0.0468	LnENVI	0.1187 **	LnENVI	0.0215	LnENVI	0.0834 *
LnSCTE	0.0599	LnSCTE	0.1025	LnSCTE	0.4196 ***	LnSCTE	0.0669
LnMECH $\leq$ 5.7728	0.3702 ***	LnMECH $\leq$ 5.5102	0.2081 **	LnMECH $\leq$ 3.8199	0.0716 *	LnMECH $\leq$ 7.4187	0.3221 ***
5.7728 < LnMECH $\leq$ 6.8735	−0.3822 ***	5.5102 < LnMECH $\leq$ 6.0740	−0.2357 ***	3.8199 < LnMECH $\leq$ 4.0110	0.1033 ***	LnMECH > 7.4187	0.3483 **
LnMECH > 6.8735	−0.3448 ***	LnMECH > 6.0740	0.2185	LnMECH > 4.0110	0.0700 ***		

Note: ***, ** and * represent passing the significance test at the 0.01, 0.05 and 0.10 levels, respectively, judged by value $|P| > t$.

5. Discussion

The annual fluctuation and regional differences in maize GTFP in different regions are large, and the effect of agricultural mechanization on agricultural GTFP in different regions is different. Agriculture is the industry most directly affected by nature, so the annual fluctuation and regional differences in maize GTFP in different regions are large. The conclusions that the overall level of GTFP in the northwest irrigation area is the lowest and that GTFP fluctuates greatly during natural disasters in the southwest mountainous area confirms that agriculture is an industry with strong dependence on natural resources and the environment and is greatly affected by natural disasters. The differences in agricultural development, economic development, industrial structure and natural conditions in different regions are objective realities, which make the production of the same crop vary greatly in different regions. At the same time, the development level of mechanization in each region is also different, so the impact of mechanization on agricultural GTFP in each region is different.

According to the redundancy rate of inputs and outputs of each province, the redundancy rate of CO_2 emissions, N_2O emissions, pesticide application, fertilizer consumption and labor quantity is at a high level. From the regional perspective, the redundancy rate of CO_2 emissions and N_2O emissions in each region is at a high level, and the greenhouse gas emissions have a significant impact on GTFP. The issue of greenhouse gas emissions in agricultural production needs urgent attention. The "dual carbon strategy" of reaching the peak of carbon by 2030 and achieving carbon neutrality by 2060 will involve profound economic and systemic social changes, and green low-carbon agriculture will become the future development direction. In terms of input factors, pesticide redundancy is the highest, followed by fertilizer consumption. By spraying pesticides, human beings have greatly reduced the threat of diseases and pests, making it possible to stabilize agricultural production. Through the use of chemical fertilizers, the photosynthetic capacity of crops has been greatly improved, which means that we can fully tap the crop yield potential, making high yields possible. Pesticides and chemical fertilizers are a double-edged sword. On the one hand, they have greatly improved the crop yield; on the other hand, they have dramatically exacerbated the adverse impact of agriculture on the environment. In addition, due to farmers' scientific, technological and cultural level of blind drug use, dealers oversell pesticides, attach importance to chemical prevention, and reject agricultural, physical and biological prevention and other factors, resulting in pesticides being the most redundant input. The problem of redundant labor quantity is obvious in northwest China, and can be attributed to the replacement of the agricultural labor force by agricultural machinery. In addition, the promotion and application of new agricultural science and technology, such as chemical herbicides and sprinkler irrigation technology, can save a lot of agricultural labor.

The results for the southwest mountainous area and northwest irrigation area confirmed that agricultural mechanization can improve maize GTFP, and the improvement effect of the agricultural mechanization development level on maize GTFP is different at different stages. When the degree of mechanization is low, the use of mechanization in planting production is relatively small. With the improvement of the mechanization level, a large part of the labor force is liberated from the planting sector before the replacement effect of machinery on labor increases. The improvement of the standardization of mechanical operation leads to the professional division of labor and industrial aggregation of planting production, which leads to the emergence of the effectiveness of mechanized element allocation and the scale effect. That is, with the improvement in the mechanization level, the role of improving agricultural GTFP is increasingly significant. The role of machinery in agricultural GTFP starts to decline when the scale effect reaches the stage of scale decline. The regression results of the spring sowing areas in the north and the summer sowing areas in the Huang–Huai–Hai region are contrary to hypothesis H1. This can be attributed to the impact of agricultural mechanization on the environment. The agricultural mechanization level in the northern spring sowing area and the Huang–Huai–Hai summer sowing area is relatively high. The large-scale application of agricultural mechanization has brought about energy consumption and environmental pollution problems, reduced the use of organic fertilizer and other low-carbon elements, and, after the aging of agricultural machinery, will inhibit the maize GTFP. The results for the spring sowing area in the north and the summer sowing area in the Huang–Huai–Hai area were contrary to those of the southwest mountainous area and the northwest irrigation area, which conformed the law of the difference of the influence of mechanization on agricultural GTFP.

In terms of the impact of land type and land area on the role of agricultural mechanization on maize GTFP, the empirical results are contrary to hypotheses H2 and H3. In terms of terrain characteristics and agricultural land management scale, the southwest mountainous area has a high altitude, and the terrain conditions are mainly plateau, basin and mountains, with a high degree of land fragmentation and a small area of cultivated land. The northwest irrigation area is characterized by small topographic relief, sparsely populated land and large agricultural land management scale. The regression results show that agricultural mechanization plays the largest role in improving the GTFP of maize in the southwest mountainous area. That is to say, compared with the plains with a large area of flat land, and the mountainous and hilly area with finely fragmented farmland, agricultural mechanization plays a more significant role in improving maize GTFP. The effect of agricultural mechanization on maize GTFP is not restricted by land area or type. At present, the land policy of household contract responsibility system will exist for a long time, and the miniaturization of agricultural machinery is in line with this situation. The per capita income level of farmers is not high, and there is a certain pressure on the burden of large-scale machinery, while the purchase of small machinery can be borne. In recent years, small agricultural machinery in China has developed rapidly to meet the realistic demand. Based on the current situation of agricultural mechanization in China, the field management depends on small agricultural machinery. In plains areas where large-scale agricultural machinery is highly popular, field management still relies on small-scale agricultural machinery. In mountainous, hilly and other areas not suitable for the use of large agricultural machinery, small agricultural machinery must be promoted to save manpower. Agriculture in mountainous and hilly areas basically relies on small machinery or manual agricultural production. In mountainous and hilly areas, there are not only single products, but also many kinds of special agriculture. Small agricultural machinery can better play its role according to local conditions, saving labor and greatly improving efficiency. This is consistent with the fact that most maize planting in Xinjiang involves small-scale intensive farming, and the GTFP efficiency is excellent.

Agricultural financial investment, environmental pollution control efforts and agricultural science and technology expenditure can optimize the agricultural production environment and play a role in improving GTFP. The effect of agricultural fiscal expenditure on GTFP growth can be divided into two aspects: one is the impact on desirable agricultural economic output, and the other is the impact on undesirable environmental pollutant emissions. Financial support for agriculture can improve agricultural production conditions and the environment. For example, an agricultural machinery purchase subsidy policy can produce an income effect, substitution effect and multiplier effect. Through the use and popularization of agricultural machinery, the combination of labor force, land and other elements can be optimized to improve the efficiency of resource allocation. The urbanization rate has an inhibitory effect on maize GTFP. The expansion of cities and towns has led to a reduction in cultivated land and the transfer of the rural labor force to cities, and the reduction in the labor force has a negative impact on maize production. As an industry greatly affected by natural disasters, the disaster rate of crops has an inhibitory effect on maize GTFP.

6. Conclusions and Implications

6.1. Conclusions

This study examined 20 major maize-producing provinces in China from 2001 to 2020. Specifically, we measured China's maize GTFP using the SBM-ML model and revealed the time and regional variation characteristics of maize GTFP. Secondly, we clarified the optimization direction of maize GTFP according to the loss reasons of regional factors. Finally, we applied the threshold regression model to analyze the impact and mechanism of agricultural mechanization level on maize GTFP from the perspective of regional differences and resource endowment differences.

The main conclusions include:

The growth in China's maize production GTFP fluctuates greatly year by year, and depends on the alternate promotion of technical efficiency and technical progress. Greenhouse gas emissions have a significant impact on GTFP. Excessive use of pesticides and fertilizers is the biggest obstacle to the improvement in maize GTFP. Agricultural mechanization plays a significant role in improving maize GTFP. Due to objective differences in agricultural development and natural conditions in each region, the impact of mechanization on agricultural GTFP in each region is different. The development level of agricultural mechanization at different stages has different promotion effects on maize GTFP. Agricultural mechanization has a two-way impact on maize GTFP. The factors of land type and land area will not limit the promotion of agricultural mechanization to maize GTFP. In addition to agricultural factors, agricultural financial investment, environmental pollution control efforts, agricultural science and technology expenditure and other factors can play a positive role in improving GTFP.

6.2. Policy Implications

Based on the conclusions of this study, the following policy recommendations can be made:

First, the relationship between agricultural mechanization and maize green production should be comprehensively examined. The rational allocation of agricultural machinery should be optimized, and the coordination between agricultural mechanization and moderate-scale operation should be strengthened. The development of agricultural machinery should be promoted to intelligent so as to facilitate the transformation and development of agricultural machinery to green and high-end. Strengthening the actual operation level of agricultural machinery causes the correlation between agricultural mechanization and GTFP to reach a higher level.

Secondly, green agriculture requires increasing the protection of the environment, the full use of agricultural ecological data resources in production, and promoting the development of agricultural mechanization from replacing manual labor to coordinating resource utilization. For example, when reducing maize carbon emissions, intermittent irrigation techniques can be used to control greenhouse gas emissions. Each region should strengthen research and development and the promotion of suitable agricultural machinery. All departments should consider the specific needs of different types of food crops for agricultural machinery. For example, maize has certain problems in the process of returning straw to the field and mechanical tillage, and the straw cannot be used after being crushed. Therefore, each region should strengthen relevant technologies and equipment to break through the weak links of maize production, so as to provide support for the realization of refined maize cultivation.

Third, promoting agricultural mechanization should combine regional characteristics and agricultural machinery with the appropriate scale and terrain. For example, the southwest region is mainly mountainous and hilly, and the use of large agricultural machinery is not convenient, so the promotion and publicity of small agricultural machinery should be strengthened. The northwest irrigation region should increase the research and development of water-saving irrigation equipment to promote agricultural production.

6.3. Research Limitations

This study enriches related research on the effect of agricultural mechanization in maize green production. However, limited by personal ability and objective conditions, this study has the following deficiencies:

First of all, the research scale of this study is at the provincial level, taking a single maize crop as the sample, so statistical data on the relevant indicators required are difficult to obtain. In this study, impact factor indicators such as disaster rate, environmental pollution control efforts and scientific and technological expenditure cannot encapsulate the data of individual maize crops, and it may affect the accuracy of the model if we replace them with the overall agricultural data.

Secondly, because the level of agricultural mechanization is used to measure the state of the development of agricultural mechanization in a region as a whole, using the ratio of the total power of agricultural machinery to the total sown area of crops to measure the level of agricultural mechanization is not comprehensive. In a follow-up study, it is necessary to add indicators that objectively reflect the level of agricultural mechanization.

Finally, the internal mechanism of the influence of agricultural mechanization on regional maize green production is complex. This study analyzes from the perspective of resource endowment, while this study only considers differences in regional topography and land management scale and does not consider the moderating effect of climate conditions. Therefore, the research results have certain limitations.

Author Contributions: Conceptualization, Y.W., J.J., D.W. and X.Y.; methodology, Y.W. and J.J.; software, Y.W. and J.J.; validation, Y.W., J.J. and X.Y.; formal analysis, Y.W. and X.Y.; investigation, Y.W., J.J. and D.W.; resources, Y.W., J.J. and D.W.; data curation, Y.W.; writing—original draft preparation, Y.W., J.J. and X.Y.; writing—review and editing, Y.W., J.J. and X.Y.; visualization, Y.W. and J.J.; supervision, Y.W. and X.Y.; project administration, Y.W., and X.Y.; funding acquisition, Y.W. and X.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Social Science Foundation of Hebei Province, grant number HB22YJ045.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: These data were derived from the following resources available in the public domain: (1) "National Agricultural Product Cost and Benefit Data Compilation". (The data on the number of working days, the amount of seeds, the amount of chemical fertilizer, the cost of pesticides, and the cost of mechanical action.); (2) "China Agricultural Machinery Industry Yearbook". (The data on total agricultural machinery power); (3) "China Statistical Yearbook". (The data on crop sown area, maize sown area, expenditure on agriculture, forestry and water affairs, total financial expenditure, urban population, total population, GDP data, agricultural science and technology input); (4) "China Rural Statistical Yearbook". (The data on crop disaster area); (5) "China Environmental Statistical Yearbook". (The data on environmental pollution control investment). All data included in this study are available upon request by contact with the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

GTFP	Green Total Factor Productivity
SBM-ML	Slack Based Measure-Malmquist-Luenberger
MECH	Level of Agricultural Mechanization
STRU	Planting Structure of Maize
FINA	Agricultural Financial Input
DISA	Crop Damage Rate
URBA	Urbanization Rate
AGGL	Agricultural Industry Agglomeration
ENVI	Environmental Pollution Governance
SCTE	Agricultural Science and Technology Input

References

1. Johnson, D.G. Agriculture and the wealth of nations. *Am. Econ. Rev.* **1997**, *87*, 1–12.
2. Xia, F.; Xu, J. Green total factor productivity: A re-examination of quality of growth for provinces in China. *China Econ. Rev.* **2020**, *62*, 101454. [CrossRef]
3. Zhou, R.M. Technical progress, technical efficiency, and productivity growth of China's agriculture. *J. Quant. Technol. Econ.* **2009**, *26*, 70–82.
4. Liu, D.D.; Zhu, X.Y.; Wang, Y.F. China's agricultural green total factor productivity based on carbon emission: An analysis of evolution and influencing factors. *J. Clean. Prod.* **2020**, *278*, 123692. [CrossRef]
5. Martin, P.L.; Olmstead, L. The Agricultural mechanization controversy. *Science* **1985**, *227*, 601–606. [CrossRef]
6. Rodolfo, T.L. Agricultural mechanization, work and subjectivity: The theory of social representations as a resource for understanding the changes occurred in Brazilian sugarcane fields. *Rev. Colomblana Sociol.* **2021**, *44*, 73–96.

7. Alanoud, A.; Farrukh, N. A review of applications of linear programming to optimize agricultural solutions. *Int. J. Inf. Eng. Electron. Bus.* **2021**, *13*, 11–21.
8. Xue, C.; Shi, X.Y.; Zhou, H. Influence path of agricultural mechanization on total factor productivity growth in planting industry. *J. Agrotech. Econ.* **2020**, *10*, 87–102.
9. Zhang, J.H.; Zheng, F.Y.; Gao, D. The impact of China's labor transfer on total factor productivity growth. *Chin. J. Popul. Sci.* **2020**, *6*, 29–40+126–127.
10. Lv, N.; Zhu, L.Z. Study on China's agricultural environmental technical efficiency and green total factor productivity growth. *J. Agrotech. Econ.* **2019**, *4*, 95–103.
11. Deng, H.T.; Cui, B.M. The nature of the property right of the Chinese agricultural land during institution change: The angle of view of the history. *Nankai Econ. Stud.* **2007**, *6*, 118–141.
12. Bentley, J.W. Economic and ecological approaches to land fragmentation: In defense of a Much-Maligned Phenomenon. *Annu. Rev. Anthropol.* **1987**, *16*, 31–67. [CrossRef]
13. Ismael, M.; Srouji, F.; Boutabba, M.A. Agricultural technologies and carbon emissions: Evidence from Jordanian economy. *Environ. Sci. Pollut. Res. Int.* **2018**, *25*, 10867–10877. [CrossRef] [PubMed]
14. Akbar, U.; Li, Q.; Akmal, M.A.; Shakib, M.; Iqbal, W. Nexus between agro-ecological efficiency and carbon emissions transfer: Evidence from China. *Environ. Sci. Pollut. Res. Int.* **2021**, *28*, 18995–19007. [CrossRef] [PubMed]
15. Aigner, D.; Lovell, C.K.; Schmidt, P. Formulation and estimation of stochastic frontier production function models. *J. Econom.* **1977**, *6*, 21–37. [CrossRef]
16. Lin, B.Q.; Wang, X.L. Exploring energy efficiency in China's iron and steel industry: A stochastic frontier approach. *Energy Policy* **2014**, *72*, 87–96. [CrossRef]
17. Fare, R.; Grosskopf, S.; Norris, M.; Zhang, Z. Productivity growth, technical progress and efficiency change in the industrialised countries. *Am. Econ. Rev.* **1994**, *84*, 66–83.
18. Tugcu, C.T.; Tiwari, A.K. Does renewable and/or non-renewable energy consumption matter for total factor productivity (TFP) growth? Evidence from the BRICS. *Renew. Sustain. Energy Rev.* **2016**, *65*, 610–616. [CrossRef]
19. Wang, X.L.; Sun, C.Z.; Wang, S.; Zhang, Z.; Zou, W. Going green or going away? A spatial empirical examination of the relationship between environmental regulations, biased technological progress, and green total factor productivity. *Int. J. Environ. Res. Public Health* **2018**, *15*, 1917. [CrossRef]
20. Chung, Y.H.; Färe, R.; Grosskopf, S. Productivity and undesirable outputs: A directional distance function approach. *J. Environ. Manag.* **1997**, *51*, 229–240. [CrossRef]
21. Xu, X.C.; Huang, X.Q.; Huang, J.; Gao, X.; Chen, L. Spatial-temporal characteristics of agriculture green total factor productivity in China, 1998–2016: Based on more sophisticated calculations of carbon emissions. *Int. J. Environ. Res. Public Health* **2019**, *16*, 3932. [CrossRef] [PubMed]
22. Chen, Y.F.; Miao, J.F.; Zhu, Z.T. Measuring green total factor productivity of China's agricultural sector: A three-stage SBM-DEA model with non-point source pollution and CO_2 emissions. *J. Clean. Prod.* **2021**, *318*, 128543. [CrossRef]
23. Zhan, J.T.; Tian, X.; Zhang, Y.Y.; Yang, X.; Qu, Z.; Tan, T. The effects of agricultural R&D on Chinese agricultural productivity growth: New evidence of convergence and implications for agricultural R&D policy. *Can. J. Agric. Econ. /Rev. Can.* **2017**, *65*, 453–475.
24. Liu, J.X.; Dong, C.R.; Liu, S.T.; Rahman, S.; Sriboonchitta, S. Sources of total-factor productivity and efficiency changes in China's agriculture. *Agriculture* **2020**, *10*, 279. [CrossRef]
25. Liu, F.; Lv, N. The threshold effect test of Human capital on the growth of agricultural green total factor productivity: Evidence from China. *Int. J. Electr. Eng. Educ.* **2021**, *in press*. [CrossRef]
26. Fang, L.; Hu, R.; Mao, H.; Chen, S.J. How crop insurance influences agricultural green total factor productivity: Evidence from Chinese farmers. *J. Clean. Prod.* **2021**, *321*, 128977. [CrossRef]
27. Gao, F. Evolution trend and internal mechanism of regional total factor productivity in Chinese agriculture. *J. Quant. Technol. Econ.* **2015**, *5*, 3–19,53.
28. Liu, Z. Analysis on the dynamic and influencing factors of agricultural total factor productivity in China. *Chin. J. Agric. Resour. Reg. Plan.* **2018**, *39*, 104–111.
29. Ge, P.F.; Wang, S.J.; Huang, X.L. Measurement for China's agricultural green TFP. *China Popul. Resour. Environ.* **2018**, *28*, 66–74.
30. Song, M.L.; Li, H. Total factor productivity and the factors of green industry in Shanxi Province, China. *Growth Change* **2020**, *51*, 488–504. [CrossRef]
31. Kajol, R.; Akshay, K.K.; Keerthan, K.T. Automated agricultural field analysis and monitoring system using IOT. *Int. J. Inf. Eng. Electron. Bus.* **2018**, *10*, 17–24.
32. Devkota, R.; Pant, L.P.; Gartaula, H.N.; Patel, K.; Gauchan, D.; Hambly-Odame, H.; Thapa, B.; Raizada, M.N. Responsible agricultural mechanization innovation for the sustainable development of Nepal's hillside farming system. *Sustainability* **2020**, *12*, 374. [CrossRef]
33. Zhou, X.S.; Ma, W.L. Agricultural mechanization and land productivity in China. *Int. J. Sustain. Dev. World Ecol.* **2022**, *29*, 530–542. [CrossRef]
34. Yukichi, M.; Kazushi, T.; Keijiro, O. Mechanization in land preparation and agricultural intensification: The case of rice farming in the Cote d'Ivoire. *Int. J. Sustain. Dev. World Ecol.* **2020**, *51*, 899–908.

35. Daum, T.; Adegbola, Y.P.; Kamau, G.; Daudu, C.; Zossou, R.C.; Crinot, G.F.; Houssou, P.; Mose, L.; Ndirpaya, Y.; Wahab, A.A.; et al. Perceived effects of farm tractors in four African countries, highlighted by participatory impact diagrams. *Agric. Econ.* **2020**, *40*, 47. [CrossRef]
36. Jaleta, M.; Baudron, F.; Skoko, B.K.; Erenstein, O. Agricultural mechanization and reduced tillage: Antagonism or synergy? *Int. J. Agric. Sustain.* **2019**, *17*, 219–230. [CrossRef]
37. Takeshima, H.; Hatzenbuehler, P.L.; Edeh, H.O. Effects of agricultural mechanization on economies of scope in crop production in Nigeria. *J. Dev. Areas* **2020**, *177*, 102691. [CrossRef]
38. Qiu, T.W.; Boris, C.S.; Biliang, L. Is small beautiful? Links between agricultural mechanization services and the productivity of different-sized farms. *Appl. Econ.* **2022**, *54*, 430–442. [CrossRef]
39. Takeshima, H.; Yanyan, L. Smallholder mechanization induced by yield-enhancing biological technologies: Evidence from Nepal and Ghana. *Agric. Syst.* **2020**, *184*, 102914. [CrossRef]
40. Purba, T.; Helmi, H.; Sembiring, F.; Siagian, D.; Haloho, L.; Girsang, M.; Ramija, K. Measuring the effectiveness of agricultural mechanization performance on irrigated rice area in Batubara Regency. In Proceedings of the 1st International Conference on Sustainable Management and Innovation, ICoSMI 2020, Bogor, West Java, Indonesia, 14–16 September 2020.
41. Takeshima, H.; Kumar, A. Returns to scale and factor endowments induced specialization: Agricultural mechanization and agricultural transformation in Nepal. *J. Dev. Areas* **2021**, *55*, 133–145. [CrossRef]
42. Haryono, D.; Hudoyo, A.; Mayasari, I. The sustainable agricultural mechanization of rice farming and its impact on land productivity and profit in Lampung Tengah Regency. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *739*, 012056. [CrossRef]
43. Takeo, M.; Thanh, T.C.; Dung, L.C.; Kitaya, Y.; Maeda, Y. Transition of agricultural mechanization, agricultural economy, government policy and environmental movement related to rice production in the Mekong Delta, Vietnam after 2010. *AgriEngineering* **2020**, *2*, 649–675.
44. Emami, M.; Morteza, A.; Hossein, B.; Kalantari, I. Agricultural mechanization as the driver of reducing food loss and waste in developing countries: Evidence from Iran. *Russ. Agric. Sci.* **2021**, *47*, 530–535. [CrossRef]
45. Yutaka, K. Field work simulation for labor saving technologies in Japanese farms. *Inform. Stud.* **2021**, *7*, 58–61.
46. Kansanga, M.M.; Mkandawire, P.; Kuuire, V.; Luginaah, I. Agricultural mechanization, environmental degradation, and gendered livelihood implications in northern Ghana. *Land Degrad. Dev.* **2020**, *31*, 1422–1440. [CrossRef]
47. Guo, X.M.; Huang, S.; Wang, Y. Influence of agricultural mechanization development on agricultural green transformation in western China, based on the ML index and Spatial Panel Model. *Math. Probl. Eng.* **2020**, *2020*. [CrossRef]
48. Jiang, M.M.; Hu, X.J.; Chunga, J.; Lin, Z.; Fei, R. Does the popularization of agricultural mechanization improve energy-environment performance in China's agricultural sector? *J. Clean. Prod.* **2020**, *276*, 124210. [CrossRef]
49. Liu, Y.Q. An empirical research on contribution of agricultural mechanization to ecological protection and restoration in rural of China. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *742*, 012023. [CrossRef]
50. Kansanga, M.M.; Antabe, R.; Sano, Y.; Mason-Renton, S.; Luginaah, I. A feminist political ecology of agricultural mechanization and evolving gendered on-farm labor dynamics in northern Ghana. *Gend. Technol. Dev.* **2019**, *23*, 207–233. [CrossRef]
51. Lutz, D.; Rozel, F.C.; Pepijn, S.; Myint, T.; Islam, M.M.; Kundu, N.D.; Myint, T.; San, A.M.; Jahan, R.; Nair, R.M. When machines take the beans: Ex-Ante socioeconomic impact evaluation of mechanized harvesting of mungbean in Bangladesh and Myanmar. *Agronomy* **2021**, *11*, 925. [CrossRef]
52. Zhou, J.; Chen, Y.P.; Ruan, D.Y. The influence of terrain conditions on the regional imbalance of agricultural mechanization development: An empirical analysis based on county-level panel data in Hubei Province. *Chin. Rural Econ.* **2013**, *9*, 63–77.
53. Ullah, M.W.; Anad, S. Current status, constraints and potentiality of agricultural mechanization in Fiji. *Ama-Agric. Mech. Asia Afirca Lat. Am.* **2007**, *38*, 39–45.
54. Eunuch, M.L.; Hou, Y.X.; Lv, J. Agricultural mechanization service and technical efficiency in China's grains production: A met analysis. *J. Agric. For. Econ. Manag.* **2022**, *21*, 136–145.
55. Xu, Z.G.; Zheng, S.; Liu, X.Y. The impact of agricultural mechanism on high quality grain production and the heterogeneity of links—Based on the survey data of Heilongjiang, Henan, Zhejiang and Sichuan provinces. *J. Macro-Qual. Res.* **2022**, *10*, 22–34.
56. Benin, S. Impact of Ghana's agricultural mechanization services center program. *Agric. Econ.* **2015**, *46*, 103–117. [CrossRef]
57. Bernard, B.M.; Song, Y.; Hena, S.; Ahmad, F.; Wang, X. Assessing Africa's agricultural TFP for food security and effects on Human development: Evidence from 35 Countries. *Sustainability* **2022**, *14*, 6411. [CrossRef]
58. Sansen, K.; Wongboon, W.; Jairin, J.; Kato, Y. Farmer-participatory evaluation of mechanized dry direct-seeding technology for rice in northeastern Thailand. *Plant Prod. Sci.* **2019**, *22*, 46–53. [CrossRef]
59. Sarkar, A. Agricultural mechanization in India: A study on the ownership and investment in farm machinery by cultivator households across agro-ecological regions. *Millenn. Asia* **2020**, *11*, 160–186. [CrossRef]
60. Zhu, Y.Y.; Zhang, Y.; Piao, H.L. Does agricultural mechanization improve the green total factor productivity of China's planting industry? *Energies* **2022**, *15*, 940. [CrossRef]
61. Hu, Y.; Zhang, Z.H. The impact of agricultural machinery service on technical efficiency of wheat production. *Chin. Rural Econ.* **2018**, *5*, 68–83.
62. Sun, Y. The influence of labor mobility and land scale management on the development of agricultural modernization—Taking the county panel data in Jiangsu Province as an example. *Rural Econ. Sci.-Technol.* **2019**, *30*, 1–3.

63. Yang, Y.; Li, R.; Wu, M.F. The constraints of land fragmentation on farmers' agricultural machinery services purchase. *J. Agrotech. Econ.* **2018**, *10*, 17–25.
64. Gbadamosi, B.; Adeniyi, A.E.; Ogundokun, R.O.; Bunmi, O.B.; Precious, A.E. Impact of climatic change on agricultural product yield using K-Means and multiple linear regressions. *Int. J. Educ. Manag. Eng.* **2019**, *9*, 16–26.
65. Tone, K. A Slacks-based measure of super-efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2002**, *143*, 32–41. [CrossRef]
66. Zhou, Y.X.; Liu, W.L.; Lv, X.Y.; Chen, X.; Shen, M. Investigating interior driving factors and cross-industrial linkages of carbon emission efficiency in China's construction industry: Based on Super-SBM DEA and GVAR model. *J. Clean. Prod.* **2019**, *241*, 118322. [CrossRef]
67. Hayes, A.F. Beyond Baron and Kenny: Statistical mediation analysis in the New Millennium. *Commun. Monogr.* **2009**, *76*, 408–420. [CrossRef]
68. Zhang, X.Z.; Wang, J.Y.; Zhang, T.I.; Li, B.L.; Yan, L. Assessment of nitrous oxide emissions from Chinese agricultural system and low-carbon measures. *Jiangsu J. Agric. Sci.* **2021**, *37*, 1215–1233.