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Technical Efficiency of Maize Production and Its Influencing Factors in the World's Largest Groundwater Drop Funnel Area, China

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Abstract: Improving the efficiency of maize production is of great significance for global food security and the effective supply of agricultural products. Based on the survey data of 381 rural households, this study uses a stochastic frontier analysis to estimate the efficiency value and empirically analyze the factors affecting the technology efficiency of maize production in the Hengshui area of the North China Plain. First, higher costs were found to be related to extensive production methods of fertilization, pesticide application, and irrigation. Second, the results showed that there was an inverted U-shaped relationship between the irrigation cost and maize output. Specifically, when the irrigation cost was about 938 yuan/hectare, the maize output per unit area was optimal. Third, there was also an inverted U-shaped relationship between the fertilizer cost and maize output, and the loss of technical efficiency of maize output was minimal when the fertilizer cost is 2547 yuan/hectare. In addition, the findings of the inefficiency influencing factor model suggested that temperature and humidity were all positively associated with the non-efficiency of maize production. These findings can provide empirical support for improving the efficiency of maize production in North China or arid and semi-arid regions around the world.

Keywords: maize production; technical efficiency; stochastic frontier analysis; Hebei province

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1. Introduction

Food is an important basis for national development, and food security is related to the harmony and stability of society [1]. Maize production is fundamental for the global food system and has great potential for yield increase, and is currently widely grown worldwide. It has become an indispensable source of food, feed, and industrial raw materials [2]. Therefore, the sustainable production of maize is of great significance to ensure national and global food security, and for the effective supply of agricultural products.

Maize, of all food crops, has the greatest potential for production increase, and the growth in demand has become irreversible in China [3]. In 2020, China's maize-sown area was 41.26 million hectares, with an output of 261 million tons, accounting for 38.94% of China's grain yield, ranking second in the world [4]. Maize in China is mainly cultivated in the northeast, north, southwest, and northwest, roughly forming a long oblique planting belt from northeast to southwest. Northeast and North China contribute 70% of the country's maize production (Figure 1) [5]. However, China's maize development is inefficient and still struggles with duplication of efforts, especially in smallholder agriculture [6]. This is closely related to China's long-term output-oriented food policy, including the excessive application of fertilizers and pesticides [7]. Such extensive production and management methods endanger sustainable agriculture and rural development in China. These challenges in China's maize production remind policymakers to balance production and productivity, which necessitates an in-depth analysis of how to improve the efficiency of maize production.

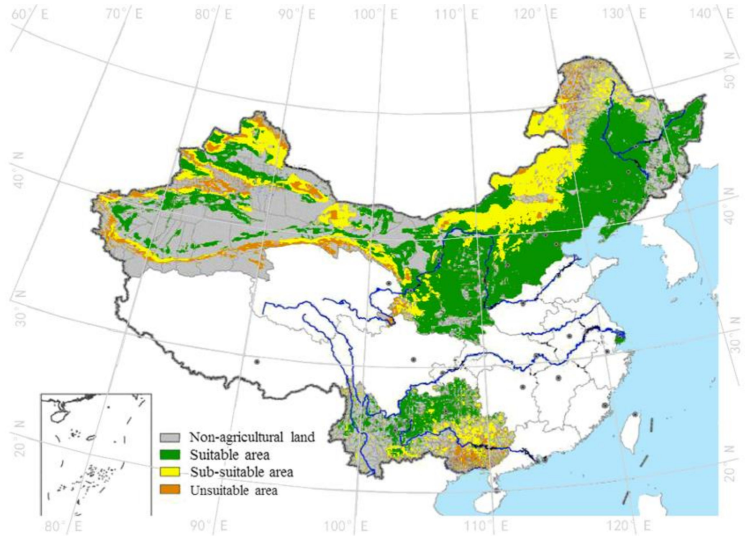

Figure 1. China's maize planting area and suitability assessment. Source: China Meteorological Administration.

Drought is the main constraint factor for crop production in rain-fed systems around the world [8]. However, global freshwater supplies are facing unprecedented challenges and risks [9], which seem to be more serious in China because of China's uneven distribution of water and its water pollution crisis. Meanwhile, agricultural irrigation is the largest water-use sector, accounting for about 70% of global water withdrawals and nearly 90% of consumptive water use [10]. Existing studies have provided evidence on the close relationship between water use and maize production. For example, Cao et al. explored spatiotemporal patterns of water use efficiency and found it played an important role in maize production [11]. Zheng et al. found that water productivity on a regional scale is useful for identifying and managing inefficiencies in crop production systems [12]. The North China Plain is one of the most seriously over-exploited groundwater areas, with a 13.92 million km^2 land area of a distributed groundwater-level drawdown funnel group, and a funnel area of more than 9700 km^2 [13,14]. In our research area, Hengshui city, the groundwater has been used as a water source for drinking water and for intensive agriculture activities for many years, which has resulted in the over-exploitation of typical groundwater in the Hengshui area.

A line of literature, most related to our work, studies a certain set of factors affecting agricultural productivity. The theoretical and empirical literature acknowledge that determinants of agricultural productivity can be categorized into three types: crop production management (e.g., irrigation), socioeconomic factors (e.g., farmers' education level), and climatic factors (e.g., precipitation). In terms of crop production management, the most direct impact on maize production is inseparable from the various field management methods such as breeding, fertilization, weeding, and irrigation, and the focus should be on the effects of these management factors on crop yield [15–18]. In terms of socioeconomic factors, previous studies have found that the education level of the farmers is positively related to agricultural productivity [19,20]. The underlying reason is that education enhances the farming skills and productive capabilities of the farmers and enables them to follow written instructions regarding the application of adequate and recommended doses of chemicals and other inputs [20]. In another study, Guo et al. found that elderly farmers, who do not intend to abandon farming, had higher agricultural outputs compared to other farmers, suggesting that a farmer's age may also have a positive effect on agricultural productivity [21]. On the other hand, agricultural productivity may be reduced as a result of aging farmers' physical deficiencies. In terms of climatic factors, empirical studies have found that agricultural productivity is significantly affected by certain climate variables, including precipitation, humidity, and temperature [22]. Under unfavorable climatic conditions, such as water deficits and temperature extremes, the reproductive phase of plant growth will be influenced, and in cereals, flower initiation and inflorescence are negatively affected by water stress [23].

Furthermore, this paper is closely related to other studies on different measurements of grain productivity. In general, the most used tools for analyzing agricultural production efficiency include data envelopment analysis (DEA) and SFA, which are frequently used on a global level across different issues [24–27]. The SFA is a parametric technique involving the estimation of a specific parameterized efficient frontier with a composite error term, while the DEA is a non-parametric linear programming methodology that quantifies the relative efficiency of multiple similar entities or decision-making units (DMUs) [28]. One major drawback of the DEA is that derived TFP often draws inconsistent conclusions, partly because it cannot distinguish productivity from measurement errors and white noise [29–31]. The SFA allows for the separation of inefficiency from random shocks or measurement errors [32], thus presenting an advantage over other parametric and non-parametric methods [33]. With these advantages, the SFA has gained popularity for measuring agricultural productivity.

Although existing studies have provided theoretical foundations and empirical findings on agricultural productivity and its influencing factors, most of them measured the efficiency at the intranational or interprovincial scale [34]. However, agriculture is a remarkably diverse industry that is greatly affected by differences in farmers' attributes and field environments [35]. These studies are mainly macro-level analyses using aggregated data, which cannot reflect the circumstances of individual villages and farmers, and the implications obtained tend to be vague. To relieve the estimated bias resulting from such regional heterogeneity, especially the uneven distribution of water resources, more research is needed on the grain production efficiency at the county level. The significance of this research is that it can lead to concrete policy recommendations by analyzing from a micro-level perspective based on in-depth interviews with farmers. The study area itself is another point of significance in this study: Hengshui, of Heibei province, is the largest overdraft area and is an important region for maize production in the North China Plain. The findings of this study are expected to clarify ways in which the efficiency of maize production in North China or in other arid and semi-arid regions around the world, can be improved.

Given the above background, the objectives of this study are twofold. (i) The first is to use the SFA to estimate the efficiency of maize production in Hengshui based on the cost-benefit analysis. To investigate the potential nonlinear relationship between the maize output and certain inputs, the quadratic term of irrigation costs and chemical fertilizer use were incorporated into the stochastic frontier production function, which followed the form of the Cobb–Douglas function. (ii) The second objective is to identify the key determinants triggering inefficiency in maize productivity. The influencing factors of maize inefficiency mainly included temperature, precipitation, humidity, average years of school attainment of farmers, and the farmers' age. This analysis could shed new light on improving the efficiency of maize production from the perspective of socioeconomic and climatic indicators.

2. Materials and Methods

2.1. Study Area and Sampling Procedure

The surveyed area, Hengshui, is in the southeast of Hebei Province, with a total area of 8815 km^2. It is one of the largest emerging cities in the flat diluvial and alluvial terrain of the North China Plain. The city belongs to the continental monsoon region with a semi-arid climate, of which the highest temperature reaches 42.7 °C, and the lowest temperature −23 °C [36]. Groundwater in this area has been used as a water source for both drinking water and intensive agriculture activities for many years, resulting in the over-exploitation of the typical groundwater in Hengshui.

Four counties (Shenzhou, Zaoqiang, Wuyi, and Wuqiang) with different levels of economic development in Hengshui were selected, which helped to ensure that the sample has strong external validity in relation to the target population (Figure 2). In each county, two villages were chosen for the survey. Then, 15–20 households were randomly selected to conduct a face-to-face interview in each village. These surveyed farmers were given a small gift, like a bottle of edible oil or a package of washing powder, to enhance their participation enthusiasm. The questionnaire had a series of closed-ended questions with multiple choice answers and was divided into two main sections: the socioeconomic profile of the interviewees (e.g., gender, age, education level, and a number of family members) and details of the household's maize production chain (e.g., fertilizer use, irrigation cost, and yields). The final sample included 24 villages and 381 households.

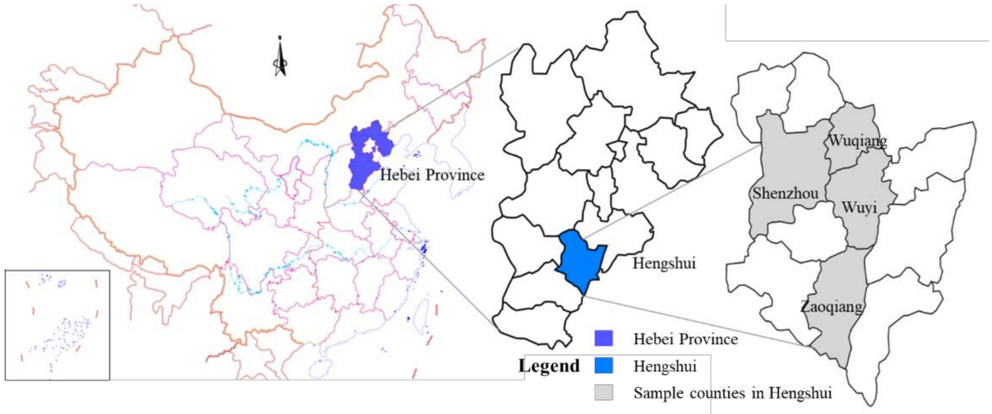

Figure 2. Location of sample counties in Hengshui prefecture of Hebei Province, China.

2.2. Variable Design and Econometric Model

2.2.1. Variable Design

Maize is harvested with a high moisture content, and to ensure safe storage the moisture content must be reduced to 12–14% [37]. Most farmers choose to dry their harvested produce for increased maize production value. However, nearly one-third of farmers in the survey sold fresh maize with high moisture content at lower prices. Therefore, the data on the value-added maize production were used to represent the maize output, which could reduce the estimation bias resulting from differences in weight measurements between maize green ears and maize kernels. The maize output is the output variable (dependent variable). For factors affecting the maize production, this paper includes seven key inputs: irrigation cost, fertilizer cost, pesticide cost, labor cost, machinery cost, planting areas, and the number of family laborers working in agriculture (core independent variable). In addition, farmer's age, education level, and some climate factors (temperature, humidity, and precipitation) were incorporated as determinants affecting the technical inefficiency of the maize production (other independent variables). The irrigation cost was calculated based on the electricity consumed for pumping the irrigation water. The fertilizer cost includes basal fertilizer and top dressing. The cost of pesticides includes the use of herbicides and insecticides. The cost of labor was measured by the combined cost of hired labor and household labor in the whole production process. Finally, the cost of machinery refers to the service fee of rented machinery and fuel.

2.2.2. Econometric Model

Stochastic frontier analysis (SFA) has been widely used to study the technical efficiency of agricultural production [38]. SFA is a parametric technique with an advantage over other parametric and non-parametric methods [33]. Following Liu et al., the Cobb–Douglas production frontier was used in this paper as the stochastic frontier production function [39]. The SFA model was set as follows:

$$Y_i = F(X_i, \beta)exp(v_i - u_i) \quad (1)$$

where Y_i is the maize output of farmer i; X_i is a vector of input quantities; β is a vector of parameters; v_i is the random error term, which follows the distribution of N (0, σ_v^2); and u_i is the term for technical inefficiency, which is assumed to follow a truncated normal distribution.

It is worth noting that X_i includes two key inputs—irrigation costs and chemical fertilizer use. Some empirical literature has reported that there is a nonlinear relationship between the above two inputs and agriculture production [40,41]. Therefore, quadratic terms of irrigation costs and chemical fertilizer use were incorporated into the analysis.

Maize productivity was measured by technical efficiency, which was calculated by the SFA. Technical efficiency was defined as the ratio of actual output to potential output. In the model, the technical efficiency was estimated as

$$TE_i = \frac{E(Y_i|-u_i, X_i)}{E(Y_i|u_i = 0, X_i)} = exp(-u_i) \qquad TE_i \in (0, 1) \quad (2)$$

where TE_i is technical inefficiency of the ith maize growers and E is the maize output of farmer i. For Y_i, X_i, v_i, and u_i, see Equation (1) for their meanings.

A number of control variables related to maize production were included. Irrigation costs and chemical fertilizer use were two important inputs for maize production, especially in dry Hengshui. Pesticide use and labor cost were also included as two inputs. The machinery costs for maize production were related to a farm's technical equipment, on which maize production largely depends. In their study, Mcfadden et al. found that maize production was positively associated with farmer numbers and planting areas. These two variables were also added to the control variables [42].

The influencing factors (denoted by "*zi*") of maize output value and maize inefficiency were estimated by the one-step method. The one-step method specifies both the stochastic frontier and the way in which u_i depends on zi, and can be estimated in a single step. The one-step method is more robust, compared with the "two-step" procedure which will produce biased results [43]. For factors (zi) affecting inefficiency (u_i), we included the farmer's average years of school attainment and the farmer's age. In addition, climatic features pose significant effects on crop production [44]. Therefore, the counties' yearly temperature, precipitation, and humidity were also incorporated.

3. Results and Discussion

3.1. Descriptive Statistics

Table 1 shows the summary statistics of the variables. The sample data show that the standard deviation of the maize output, labor cost, machinery cost, irrigation cost, and fertilizer cost variables are high, indicating that these data are spread out. This is the result of different production cognitions, farming experience, and other aspects of maize growers. In face-to-face interviews, the local farmers were found to rely too much on their farming experience, without receiving much crop cultivation training. This has resulted in a considerable disparity in inputs and outputs among maize growers.

Table 2 shows that 80% of the surveyed farmers were male. People over 60 years of age account for nearly 50%, and 48% were middle-aged (between 41 and 59 years old), indicating that the aging problem among maize growers is very serious. Most of the surveyed farmers were at the education level of primary school or junior high school, accounting for about 80%, suggesting that the surveyed maize growers had relatively low education levels.

Figure 3 shows the cost-benefit analysis of maize production. The cycle of controlling diseases and pests is long with a lower mechanization level, so it accounts for the highest proportion of labor costs. Unified mechanized production can be used for sowing and harvesting maize, which makes the mechanical costs relatively high. The fertilizer and irrigation costs accounting for the highest proportion of the material costs also need attention. With the fixed cost given, the variable cost of the maize production totals 8807.52 yuan·ha^{-1}. The gross and the net income of maize are 16,921.4 yuan·ha^{-1} and 813.88 yuan·ha^{-1}, respectively.

Table 1. Variable settings and descriptive Statistics.

Code	Variable	Variable Definition	*N* = 381		
			Unit	**Mean**	**SD**
Opt	Output	The output value of maize, maize output = yield × price	RMB·ha^{-1}	16,921.40	3558.96
Irr	Irrigation cost	Electricity bills that need to be paid for irrigating maize	RMB·ha^{-1}	1198.93	692.74
Fer	Fertilizer cost	The material costs such as farm manure and nutrients	RMB·ha^{-1}	1841.80	373.03
Pes	Pesticide cost	Insecticides and herbicides used to control pests and weeds	RMB·ha^{-1}	711.22	414.41
Mac	Machinery cost	Costs of renting machinery and fuel in the production process	RMB·ha^{-1}	2827.23	480.73
Lab	Labor cost	The costs of farmers' own labor force and hired force	RMB·ha^{-1}	1403.55	314.84
Num	Farmer number	The number of family members engaged in maize production	Pcs·household^{-1}	2.22	0.88
Pla	Planted area	Maize planted area per household	ha^{-1}	1.21	1.82
Edu	Education	Farmer's education level	years	8.73	2.08
Age	Age	Farmer's age	years	59.45	8.91
Tem	Temperature	The annual average temperature of a county	°C	13.96	0.27
Pre	Precipitation	Average annual precipitation of a county	mm	506.25	33.44
Hum	Humidity	The annual average humidity of a county	%	60.64	0.66

Note: "RMB" refers to Chinese yuan, 1 RMB = 0.1587 USD (as of 22 February 2022); the data of "Temperature, Precipitation, Humidity" come from the China Meteorological Administration.

Table 2. Basic characters of surveyed farmers.

Variables	Classification	Obs.	Proportion
Sex	Male	307	80.58%
	Female	74	19.42%
Age	≤40	10	2.62%
	41–59	181	47.51%
	≥60	190	49.87%
Education	Below grade 6, primary school or illiteracy	109	28.61%
	Between grades 6 and 9, middle school	198	51.97%
	Between grades 9 and 12, high school	73	19.16%
	College level or above	1	00.26%

In recent years, the degree of mechanization and information technology has greatly improved the external unfavorable production conditions of uneven rainfall and heat. However, farmers still bear higher production costs in maize production and their input pattern is rough, mainly in the following ways: (1) the mechanization degree of production links such as fertilization, application, and irrigation is still not high—the level of production specialization is low and factors such as land fragmentation restrict the large-scale production of maize. (2) Farmers' awareness of chemical yield-booming methods such as applying fertilizers, pesticides, nutrients, etc. is low. Most farmers believe that "the more investment, the more gains", so the level of water and fertilizer input is still high. (3) There is no rational behavior in the production process to calculate the production cost. Production inputs follow empirical practices—there is "blindness" and "blind following" in planting investment. This may be related to the operating background of the smallholder land contract responsibility system in China, the fragmentation of plots, the stereotypical way of thinking due to the low level of education, the seriously aging rural population and its low cognition of new things, etc. At the micro level, they cause problems such as a reduced willingness of farmers to plant and an unstable income. At the macro level, they result in the waste of water and soil resources, agricultural non-point source pollution, and food security problems. They are not conducive to the sustainable development of maize growing. Therefore, it is necessary to estimate the factors affecting the efficiency and non-efficiency of agricultural production. Only when the causes of non-efficiency are understood can policy recommendations be rightly given.

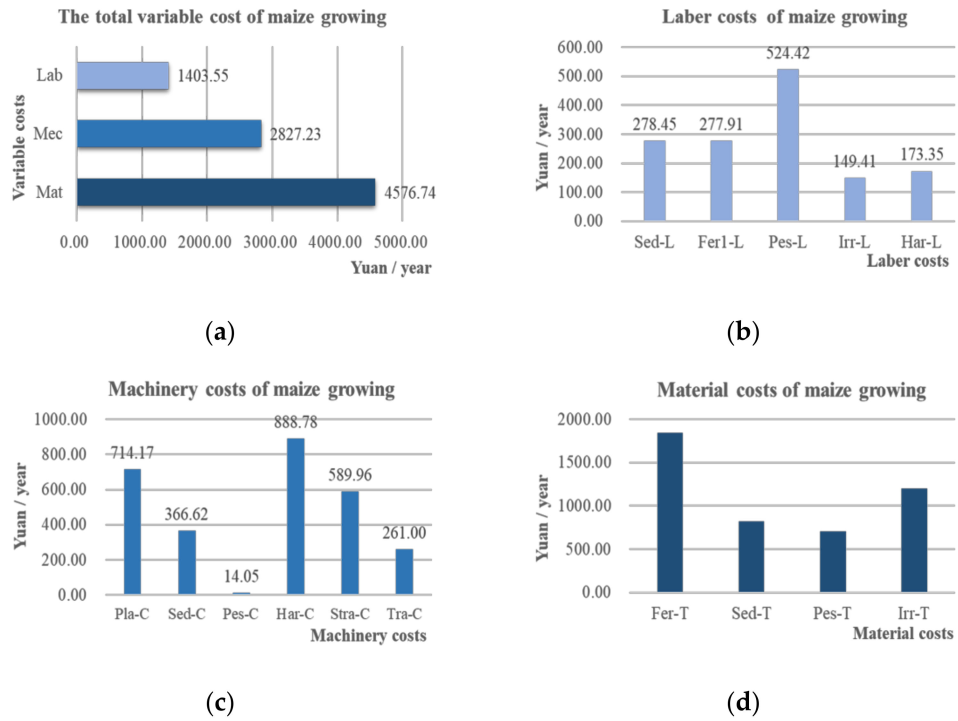

Figure 3. Composition of maize planting costs in Hengshui, Hebei Province, China. (**a**) Lab, Mec, and Mat represent labor costs, machinery costs, and material costs, respectively; (**b**) Sed-L, Fer1-L, Pes-L, Irr-L, Har-L are respectively the labor costs paid in sowing, fertilizing, pest control, irrigation, and harvesting, with household and hired labor included; (**c**) Pla-C, Sed-C, Pes-C, Har-C, Str a-C, Tra-C respectively indicate the use of machines to plow the land, sowing, spraying pesticides, harvesting, crushing straw, and transporting maize; (**d**) Sed-T, Fer-T, Pes-T, Irr-T respectively refer to the cost from purchasing seeds, fertilizers, pesticides, and irrigation.

3.2. Stochastic Frontier Model

The regression results of the stochastic frontier and influencing factors of the technical inefficiency model are shown in Table 3. STATA software was used to conduct empirical estimation with the data being logarithmically transformed. LR test results, reported at the bottom of Table 3, reject the null hypothesis of "Sigma u = 0", indicating that the inefficiency term is significant, and the model error is mainly due to input inefficiency. That is, the stochastic frontier model constructed in this study is reasonable.

Empirical literature has found that there is a nonlinear relationship between the irrigation and fertilizer inputs, and agriculture production. The estimated coefficient of the quadratic term of irrigation cost is negative and significant at the 1% level, suggesting that there is an inverted "U" relationship between irrigation cost and maize output. The function of the relationship between irrigation cost and maize production is

$$y_i = ax_i^2 + bx_i + c \tag{3}$$

where y_i is the maize output of farmer i; x_i is the irrigation input quantities of farmer i; a is the coefficient of the quadratic term ((ln Irr)2, (ln Fer)2) in Table 3; b is the coefficient of the linear term (ln Irr, ln Fer) in Table 3; and c is Constant in Table 3.

Table 3. Parametric regression results of the stochastic frontier model.

Variable Name	Parameter Estimates	Standard Error
	stochastic frontier model	
ln Irr	0.876 ***	0.326
(ln Irr)2	−0.064 ***	0.024
ln Fer	4.135 **	1.666
(ln Fer)2	−0.264 **	0.11
ln Mac	0.033	0.057
ln Lab	−0.041	0.054
Ln pes	−0.040 **	0.019
ln Pla	0.030 **	0.014
ln Num	−0.051 *	0.028
Year (virtual)	Controlled	
Constant	−8.822 ***	6.495
	Influencing Factors of technical inefficiency model	
Pre	−3.207	3.191
Tem	329.3 **	134.9
Hum	550.5 **	235.1
ln Age	0.58	0.746
ln Edu	−0.494	0.446
Constant	−3112.4 **	1321.7
σ_v	0.138 ***	0.013
σ_u	0.213 ***	0.025
Log likelihood	97.119	
LR test of σ_u	0	chibar2(01) = 6.44
N	381	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The inflection point value $MaxPt$ of the "U" relationship can be calculated as

$$MaxPt = -(b/2a) \tag{4}$$

As shown in Table 3, $a = -0.063$, $b = 0.865$, and the inflection point value of the curve is 6.843 (Figure A1). The actual value of the inflection point ($MaxPt$) is 938 after an exponential transformation. This finding indicates that the maize output shifted from an upward trend to a downward trend when the irrigation cost was at 938 yuan·ha^{-1}—that is, the output value rose with irrigation cost when the irrigation cost was less than 938 yuan·ha^{-1} and decreased with irrigation cost when the irrigation cost was more than 938 yuan·ha^{-1}. By referring to the *Agricultural Irrigation Water Quota and Agricultural Water Quota Standard of Hebei Province* [45], the optimal interval of maize irrigation in Hengshui is between 750 m^3·ha^{-1} and −1800 m^3·ha^{-1}. Given that the price of agricultural water in Hengshui is 0.73 yuan·(m^3)$^{-1}$, the optimal interval of irrigation cost for maize production should be between 547 and 1314 yuan·ha^{-1}. Therefore, the estimated inflection point of the SFA model is within the optimal range, demonstrating the validity of our results.

The coefficient of the fertilizer cost is positive, and the coefficient of the quadratic term is negative, both of which are significant at the 5% level. This suggests that there is also an inverted "U" relationship between the fertilizer cost and maize output. The estimated inflection point value ($MaxPt$) is 7.843 (Figure A1), and the actual value of the inflection point is 2518.552 after an exponential transformation. This means that the output value will rise with fertilizer cost when the fertilizer cost is less than 2518.552 yuan·ha^{-1} and decrease with fertilizer cost when the fertilizer cost is more than 2518.552 yuan·ha^{-1}. Compared with the data of the average fertilizer cost of maize in China in 2019, which was 2326.2 yuan·ha^{-1}, the fertilizer cost in the survey area is higher than at the national level [46]. In addition to the geographical factors, it is highly related to the soft soil of the North China Plain, the dense summer rainfall, and the irrigation methods of flood irrigation that most farmers still use. Previous studies pointed out that excessive irrigation aggravated the loss of nutrient elements, including chemical fertilizers, pesticides, and other substances [47], so the demand for fertilization in the North China Plain is higher than the national level.

For other control variables, the relationship between maize output and sown areas was positive and statistically significant at a 5% level. The coefficient indicates that a 1% increase in planted areas would bring about a 2.94% increase in maize output. Many studies have shown that the productivity of large-scale production is higher than that of fragmented production, and the expansion of the planting scale can reduce the planting cost by promoting mechanization in maize planting [48], which is also in agreement with the current situation of maize planting in North China. The coefficients of pesticide cost and the number of household farmers were -0.026 and -0.051, respectively. Both were significant at the 5% level, indicating that excessive investment in pesticides and excessive participation of family members have a negative impact on farmers' maize output. For every 1% increase in pesticide costs, the farmer's maize output dropped by 2.64%, and for every 1% increase in the number of household farmers, the farmer's maize output decreased by 5.06%. Excessive use of pesticides not only increased the cost for farmers but also adversely affected the maize yield. Meanwhile, personnel redundancy also led to inefficiency.

3.3. Non-Efficiency Influencing Factors

The results for influencing factors of the non-efficiency in maize production are presented in the lower part of Table 3. It was found that temperature and humidity were all positive and statistically significant at a 5% level. That is, the non-efficiency of maize production increased with the temperature and humidity. It is evidence that rising temperatures have a negative effect on the yield and growth of the crops [49]. On one hand, from mid-June to early August, the historical meteorological data elucidated that high temperatures continued, subjecting maize to the dual stress of heat and drought [50]. While maize varieties and management measures remain unchanged, the increase in temperature leads to the advancement of the critical developmental period, shortens the reproductive period as a whole, and reduces the accumulation time of dry matter. Therefore, it is important to pay attention to the loss of maize production value in the context of global warming [51–53]. On the other hand, with the increase in humidity, the non-efficiency of maize production increases significantly. In general, increased temperature and humidity increase the spread of pests and diseases due to an increase in soil germs and molds [54]. It was found that high humidity is the pathogenic factor for maize brown spots, large and small spots, and rust in the Hengshui area of the North China Plain. Moreover, excessive humidity increases the incidence of pests such as stick insects, thrips, corn borers, and aphids.

The technical efficiency of maize production in four counties of Hengshui prefecture was obtained from the estimation results of the stochastic frontier analysis model (Table 4). The technical efficiency of all samples ranged between 0.629 and 0.973, and the average technical efficiency was 0.86. This suggests that about 85% of the potential output of the surveyed farmers can be obtained with existing combinations of production factors.

Table 4. Technical efficiency of maize production in each county.

Area	Shenzhou	Wuqiang	Wuyi	Zaoqiang
N	(101)	(86)	(88)	(106)
Mean	0.90	0.835	0.856	0.839
SD	0.041	0.081	0.073	0.081
Min	0.749	0.629	0.636	0.636
Max	0.956	0.969	0.973	0.968

3.4. Robustness Checks

In this subsection, this study performs a robustness check on the baseline results. Following Mulwa et al. and Miglietta et al.'s methodology, a non-parametric linear programming technique, DEA, was used to measure the technical efficiency. A Tobit regression model was then used to analyze the influencing factors of the non-efficiency in maize production [55,56].

For the measurement of each maize grower's technical efficiency, we consider k DMUs (growers), which utilize a vector of inputs, denoted by $x = x_i^k$, to produce a single non-negative output, denoted by $y = y^k$. Then the model takes the form of,

$$DF^L(x,y) = Min\varnothing_k^{VRS}\left\{\varnothing_k^{VRS} \geq 0\right\} \tag{5}$$

$$s.t.\ \sum_{k=1}^{K} \lambda^k y^k \geq y^* \tag{6}$$

$$\sum_{k=1}^{K} \lambda^k x_n^k \leq \varnothing_k^{VRS} x_n^*, n = 1, \ldots, N \tag{7}$$

$$\sum_{k=1}^{K} \lambda^k = 1, \lambda^k \geq 0, K = 1, \ldots, K \tag{8}$$

where DF^L is the Debreu–Farrell input-oriented efficiency measure. The inputs of the kth DMU are multiplied by parameter $\varnothing_k^{VRS}$ to scale them down by the smallest possible factor, subject to the constraint that these minimized inputs must still be able to produce the original output bundle. The VRS specification permits the technical efficiency measures devoid of scale inefficiencies.

This study also adopts the meta-frontier, which was proposed by Hayami and Ruttan [57]. The meta-technology can be defined as the totality of the regional technologies [55]. The meta-frontier is constructed by pooling all the observation units from the four counties (Shenzhou, Zaoqiang, Wuyi, and Wuqiang).

The results of the technical efficiency estimates are reported in Table 5.

Table 5. Technical efficiency of maize production estimated by DEA.

Area	Shenzhou	Wuqiang	Wuyi	Zaoqiang	Meta-Frontier
N	(101)	(86)	(88)	(106)	(381)
Mean	0.963	0.955	0.960	0.958	0.959
SD	0.028	0.028	0.027	0.298	0.028
Min	0.899	0.894	0.894	0.893	0.893
Max	1	1	1	1	1

Compared with the baseline result estimated by the SFA, the technical efficiency of maize production estimated by DEA shares the same pattern: Shenzhou ranks the first (96.3%), Wuyi the second (96.0%), Zaoqiang the third (95.8%), and Wuqiang the fourth (95.5%). The difference in the scale of the estimated efficiency is due to many factors such as statistical noise or data availability [58].

To determine the influencing factors of the non-efficiency in maize production, we follow Mulwa et al.'s methodology of using the Tobit model. The Tobit model takes the form of,

$$y_i^* = x_i^* \beta + \mu_i^* \tag{9}$$

where y_i^* is the technical inefficiency of the ith farmer, which is calculated as $1 - efficiency$; x_i^* is the inefficiency influencing factors, which are the same as that in the SFA; and μ_i^* is an independently distributed error term assumed to be normally distributed, with zero mean and constant variance.

The results for influencing factors of the non-efficiency in maize production are presented in Table 6. They share similar findings with the baseline result: the temperature and humidity were all positively correlated with inefficiency. This indicates that our baseline results are robust.

Table 6. Tobit model estimates for the inefficiency influencing factors.

Variable Name	Parameter Estimates	Standard Error
Pre	−0.040	0.044
Tem	2.064 *	1.167
Hum	3.419 **	2.083
ln Age	−0.003	0.009
ln Edu	−0.008	0.006
Constant	−19.153 *	11.642
N	381	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4. Conclusions and Policy Implications

Maize has the greatest potential for production increase and the amplest room for growing consumer demand in China. However, China's maize development still struggles with high costs, poor benefits, and farmers' low enthusiasm for production. Based on the cross-sectional data of field investigation in the Hengshui area of the North China Plain, this study performed a detailed descriptive statistical analysis of the costs and benefits of the whole maize production process. A stochastic frontier model was then used to empirically analyze productivity and the factors related to the inefficiency of maize production.

Our findings from the cost-profit analysis suggest that in the process of maize planting, the modes of fertilization, pesticide application, and irrigation are still relatively extensive. This not only leads to the redundancy of production inputs to some extent but also results in the waste of water resources and non-point source pollution. The results of the stochastic frontier model show that there is an inverted U-shaped relationship between irrigation cost and maize output. Specifically, when the irrigation cost is about 938 yuan$\cdot$ha^{-1}, the maize output per unit area is optimal. The estimated inflection point is within the optimal range of *Agricultural Irrigation Water Quota and Agricultural Water Quota Standard of Hebei Province*, suggesting the validity of our results. In addition, there is also an inverted U-shaped relationship between fertilizer cost and maize output. When the fertilizer cost is 2547 yuan$\cdot$ha^{-1}, the loss of technical efficiency of maize output is minimal. The results of the inefficiency influencing factor model show that temperature and humidity are all positively associated with the non-efficiency of maize production.

The above research findings have important policy implications for the national maize production: first, farmers or cooperatives should monitor and calculate the cost of the whole process of maize production to avoid redundant inputs in the production process. Second, the government should upgrade the agricultural socialized service system to help farmers adopt new agriculture technology in modern farming. Policymakers should also provide professional guidance for fertilization and pesticide application, aiming to avoid excessive use of fertilizers and pesticides, and improve the efficiency of fertilizer and pesticide use. Third, innovating agricultural irrigation methods and promoting water-saving irrigation technology are effective measures for reducing irrigation costs. At the same time, technologies such as dry-land surface mulching, returning straw to the field, and subsoiling should be further developed to improve water use efficiency. Furthermore, the government, research institutions, and farmers should strengthen their cooperation to promote the sustainable development of China's maize production.

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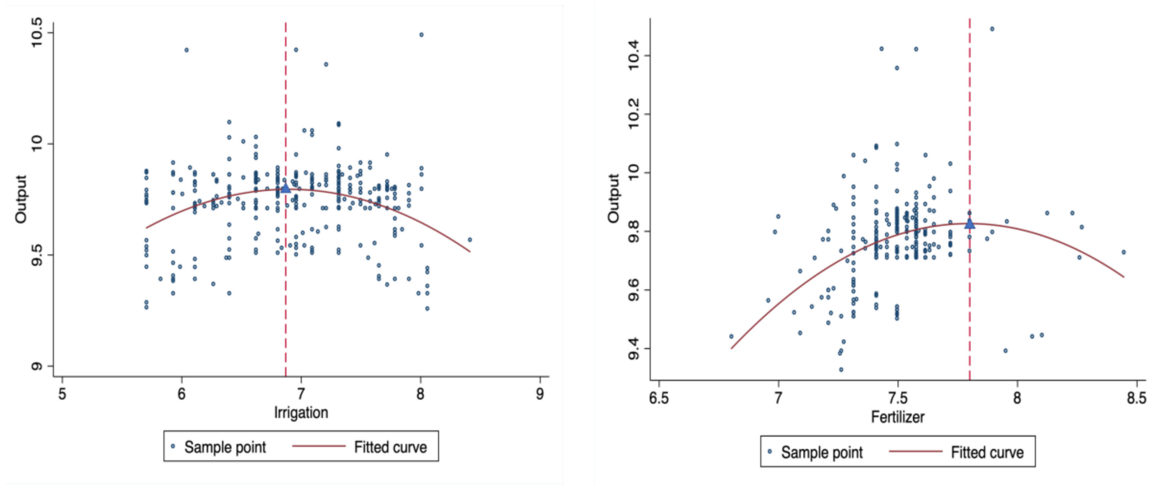
Appendix A

As the figures of the sample distribution show, there is a noticeable "U" relationship between the fertilizer and the maize output, and the irrigation and the maize output. The MaxPt point (the intersection of the Fitted curve and the dashed line in the figure), we have marked, is approximately around the estimated inflection point in the SFA model.



(**a**) (**b**)

Figure A1. "U" relationship between the fertilizer, irrigation and the maize output. (**a**) "U" relationship between the irrigation and maize output; (**b**) "U" relationship between the fertilizer and maize output.

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