applied sciences

MDPI

*Article*

# Improved Evaluation of Cultivation Performance for Maize Based on Group Decision Method of Data Envelopment Analysis Model

**Wei Huang [1,†], Han Li [2,*,†], Kaifeng Chen [3], Xiaohua Teng [3,4], Yumeng Cui [2], Helong Yu [5], Chunguang Bi [5], Meng Huang [3] and You Tang [3,5,*]**

1 Economic and Management School, Jilin Agricultural Science and Technology University, Jilin 132101, China
2 School of Science, Northeast Electric Power University, Jilin 132012, China
3 Electrical and Information Engineering College, Jilin Agricultural Science and Technology University, Jilin 132101, China
4 College of Animal Science and Technology, Northeast Agricultural University, Harbin 150030, China
5 College of Information Technology, Jilin Agricultural University, Changchun 132101, China
* Correspondence: hl_2022@neepu.edu.cn (H.L.); tangyou@jlnku.edu.cn (Y.T.)
† These authors contributed equally to this work.

**Abstract:** Maize cultivation performance, including the efficiency of the input and output of maize, which reflect the allocation and utilization of resources in the process of maize cultivation, is crucial for evaluating and improving maize cultivation. This paper adopts the method of quadratic regression orthogonal rotation combination experimental design to explore the effects of four main cultivation measures (planting density, nitrogen fertilizer, phosphorus fertilizer and potassium fertilizer) on maize yield at five levels (−2, −1, 0, 1; 2). The CCR (A. Charnes, W. Cooper and E. Rhodes) model, which is the basic model of data envelopment analysis (DEA), was used to evaluate the 36 groups of cultivation measures. The results show that 9 groups are CCR-effective cultivation measures, but the performance of these cultivation measures cannot be further evaluated. To improve the evaluation of cultivation performance, a novel method termed as the group decision method of DEA (GDM-DEA) is proposed to detect the improvement of evaluation performance and is tested using the measurements of maize cultivation. The results suggest that the GDM-DEA method can classify and sort the performance of all the cultivation measures, which is more sensitive and accurate than the CCR method. For the effective cultivation measures that meet the requirements of GDM-DEA, the optimal cultivation measures could be determined according to the ranking of yield. This method determined the most effective cultivation measure. Further independent validation showed that the final optimal cultivation measures fall in the range of the expected cultivation measures. The GDM-DEA model is capable of more effectively evaluating cultivation performance.

**Keywords:** CCR model; improved DEA model; optimal cultivation measures; production efficiency of maize; quadratic regression orthogonal rotation combination experimental design

check for updates

**Citation:** Huang, W.; Li, H.; Chen, K.; Teng, X.; Cui, Y.; Yu, H.; Bi, C.; Huang, M.; Tang, Y. Improved Evaluation of Cultivation Performance for Maize Based on Group Decision Method of Data Envelopment Analysis Model. *Appl. Sci.* **2023**, *13*, 521. https://doi.org/10.3390/app13010521

Academic Editor: Habib Hamam

Received: 1 December 2022
Revised: 23 December 2022
Accepted: 26 December 2022
Published: 30 December 2022

**Copyright:** © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

## 1. Introduction

Maize (*Zea mays* L.) is one of the most widely planted cereal crops in the world, which is used as grain, animal feed, and industrial raw material to ensure the security of national food, animal husbandry, and the corn processing industry [1,2]. In the past 20 years, the maize planting area has continuously increased in China [3]. The yield of kernel is a consequence of the coordinated development between the source and sink, which could be adjusted by fertilizer and planting density [4]. Therefore, it is of great significance to explore the effects of different cultivation measures, including nitrogen, phosphorus, potassium fertilizer, and density, on source–sink properties, and also to reveal the formation characteristics of a high-yield kernel yield [5,6]. However, a high yield does not mean the

high production efficiency of maize. Increases in planting density or the excessive use of chemical fertilizers are often used to achieve a high yield. However, the increases in sowing density and fertilization may cause the waste of resources, soil hardening, and environmental pollution [7]. Many studies have focused on how efficient fertilization can result in a high maize yield [8–11].

Some studies have developed statistical methods to evaluate the input–output efficiency of different cultivation measures [12–15]. The following four types of methods are commonly used to study productivity: the least square method, price/quantity index method, stochastic frontier analysis (SFA) and data envelopment analysis (DEA). Among these, DEA is the most popular method for performance evaluation [16–18]. DEA is a non-parametric method. The efficiency of DEA evaluation refers to the ratio of the productivity of the evaluated object to the productivity of the evaluated object on the production boundary. The production boundary is found by means of mathematical programming (generally linear programming). The evaluated object located on the production boundary can be solved by DEA. Its technical efficiency value is 1, and other evaluated objects are compared with it [16,18].

Pritpal Singh studied wheat cultivation efficiency under rice wheat and cotton wheat cropping systems in northwest India using the DEA method [19] and proved that rice residue management (RRM) affects the sustainability of the ecosystem, due to changes in the energy use, carbon footprint (CF) and net carbon budget (NECB) of the ecosystem [20]. At the same time, a non-parametric production function (data encapsulation analysis) of DEA was also applied to optimize the energy utilization of rice, which clarified the efficiency of 20 decision-making units (DMUs), while half of them were classified as inefficient [21]. Gurdeep Singh and Pritpal Singh studied the resource use efficiency (RUE) for reduced energy footprints in wheat production using non-parametric measures viz. the Cobb–Douglas production function (CDPF) and DEA approaches and based benchmarking helped in reducing the energy input of wheat by 1953.4 $\pm$ 46.9 MJ ha$^{-1}$ (~7.2%) [22]. In addition, they used the DEA method to improve the carbon and energy budget of the net ecosystem of cotton planting in northwest India [23]. Mohammadi, A. et al. used DEA to improve the energy efficiency and input cost in kiwi production [24]. A non-parametric method of DEA was used to estimate the energy efficiencies of soybean producers based on eight energy inputs, including human labor, diesel fuel, machinery, fertilizers, chemicals, water for irrigation, electricity and seed energy, and the single output of the grain yield. The study also helps to rank efficient and inefficient farmers and to identify optimal energy requirements and wasteful uses of energy [25]. Nabavi-Pelesaraei applied the DEA approach to improve energy efficiency and reduce greenhouse gas emissions from rice production [26], and they proposed a non-parametric method of DEA and MOGA (multi-objective genetic algorithm) to estimate the energy efficiency of wheat farmers and the reduction in greenhouse gas emissions in the Ahvaz county of Iran [27]. Snehasish Bhunia used the DEA approach by considering two models, namely BCC and CCR models, with 15 decision-making units and the research results show that energy budgeting and optimization were carried out for rice–wheat–green gram cultivation in three different tillage systems, viz. conservation tillage, reduced tillage, and zero tillage, along with five different residue and fertilizer doses.

The DEA method is not only used in agriculture, but also used to evaluate the utilization rate of medical and other social resources. For example, Mirpouya Mirmozaffari used the DEA method to evaluate the average technical efficiency assessment in public hospitals during and following the COVID-19 pandemic [28]. Mirpouya, M. et al. developed a novel integrated generalized DEA method to evaluate hospitals that provided stroke care services [29], and Pejman Peykani used DEA to evaluate the dynamic performance assessment of hospitals [30]. Zhou. X. used the DEA method to study the spatio-temporal characteristics of the intensive use of cultivated land (CLIU), carbon emission efficiency (CEE), and carbon emissions from cultivated land (CLCE) in the Yellow River basin of China, as well as the spatial correlation between CLIU and CEE [31]. Nabavi-Pelesaraei,

A. et al. optimized the energy required by orange producers and greenhouse gas emissions using DEA [32].

Some performance evaluation methods combine DEA with other methods, such as the joint use of the life cycle assessment (LCA) and DEA, known as the LCA + DEA methodology, which is an expanding area of research in this quest. Mohammadi, A. et al. studied the potential greenhouse gas emission reductions in soybean farming [33] and the benchmarking of environmental impacts in rice paddy production [34]. Payandeh, Z. et al. used this method to improve the energy efficiency of barley production [35]. Zhang X. Y. used the LCA/time-series DEA method to evaluate the eco-efficiency of complex forestry enterprises [36]. Mirpouya, M. et al. proposed a novel machine learning approach that combined the K-means algorithm with optimization models for eco-efficiency evaluation [37]; at the same time, Mirpouya, M. et al. compared the machine learning tools and algorithms of another new artificial intelligence method, and used this method to evaluate eco-efficiency [38].

For maize yield, Gutiérrez analyzed the production efficiency of organic agriculture in Spain using the two-stage DEA model and found that the low efficiency of the organic production model stems from insufficient output [39]. Patrick V. Ndlovu and Bempomaa used the DEA model to evaluate the technical efficiency and maize production efficiency of planting in different agro-ecological areas of Zimbabwe and Ghana [40,41]. Aye and Ogundari employed the DEA model to evaluate the technical efficiency, the economies of scale, and cost-effectiveness of small-scale corn production in Nigerian traditional planted maize and hybrid corn [42,43]. Mwambo used an improved DEA model (the EM-DEA model) to evaluate the resource utilization efficiency and sustainability of the corn production system in northern Ghana [44]. In some studies, the DEA model was combined with other methods to conduct the evaluation [45,46]. Nevertheless, these studies used DEA methods to evaluate the economic or technical efficiency of maize planting in a certain area, but they did not evaluate the performance of cultivation measures, which could guide farmers to achieve maximum efficiency. Orthogonal experiments and statistical analysis are often used to determine the optimal cultivation measures [47,48]. However, whether it is a quadratic orthogonal rotation combination experiment [49,50] or a quadratic positive traffic combination experiment [51,52], the final results include the range of planting density and nitrogen, phosphorus and potassium fertilizer application, but not specific cultivation measures.

In this study, an evaluation method called the group decision method of DEA (GDM-DEA) model, as an improved version of the CCR model, was proposed to evaluate the maize cultivation efficiency. The comparison between the DEA model and GDM-DEA reported here showed the improvement of the evaluation for field experiments of maize. Additionally, independent validations were implemented in two groups of publicly available experimental datasets that have the same experimental environments and design. This study demonstrated that GDM-DEA is a better evaluation method for an optimized crop cultivation measure.

## 2. Materials and Methods

### 2.1. Experimental Design

A JLASTU experiment was conducted in the experimental field affiliated with Jilin Agricultural Science and Technology University. The experimental field is located at 43°97′ N, 126°48′ E, and 200 m above the sea level. It belongs to the northeast China corn belt, one of the three golden corn belts in the world, which is an alluvial plain. The soil is a dark brown sandy loam.

The maize variety Zhengdan 958 is used in this study. The maize planting density ($x_1$), nitrogen application rate ($x_2$), phosphorus application rate ($x_3$), and potassium application rate ($x_4$) are selected as the decision variables that mainly affect maize yield ($y$). The effects of these four main cultivation measures at five levels (−2, −1, 0, 1, and 2) were explored using the method of quadratic regression orthogonal rotation combination experimental

design. In the experiment, direct seeding was used. The amount of nitrogen, phosphorus, and potassium was pre-calculated and applied to a single cell according to our cultivation experience. The amount of precipitation was the average precipitation value in the past ten years, and the control of pests and weeds in the local high-yield practices [53]. The test factors and level codes are shown in Table 1.

**Table 1.** Decisive variety $x$ and linear coded data.

| Variable ($X_i$) | Changes in Pitch | Design Level ($r$) | | | | |
|---|---|---|---|---|---|---|
| | | −2 | −1 | 0 | 1 | 2 |
| Density ($X_1$) | 1 (10,000 plants/ha) | 5 | 6 | 7 | 8 | 9 |
| N ($X_2$) | 40 (kg/ha) | 160 | 200 | 240 | 280 | 320 |
| $P_2O_5$ ($X_3$) | 20 (kg/ha) | 80 | 100 | 120 | 140 | 160 |
| $K_2O$ ($X_4$) | 30 (kg/ha) | 60 | 90 | 120 | 150 | 180 |

### 2.2. Experimental Data

The sowing time of maize was between 20 April 2006 and 22 April 2006. The sampling days at the harvest stage were from 20 September 2006 to 1 October 2006. The precipitation and other climatic conditions of that year met the normal level recorded in previous years. After natural air drying, the samples were measured in the laboratory from 20 October 2006 to 25 October 2006. The weight of the kernels was adjusted to the standard moisture content and then calculated as kilograms of the yield per hectare.

The cultivation measures of the JLATSU experiment, including yield production, are shown in Table 2. The cultivation measures of group codes 25–36 in the table are the control group and the others are the experimental groups.

### 2.3. Independent Validation

If the same crops are planted on the same land every year, the soil will become less fertile. Therefore, secondary rotation combination design experiments are rarely continuously conducted in the same experimental field to determine the best cultivation measures of corn. Two groups of public experimental data with the same experimental location and experimental design as the JLASTU experiment were selected to verify the GDM-DEA method. The experiments were named the Anshun Pan experiment and the Anshun Tang experiment, respectively [54,55]. The cultivation measures and yield production are shown in Tables S1–S4. As is the case with the JLASTU experiment, the two experiments also have twelve control groups.

The Chifeng Zheng experiment [56] with different regions and experimental designs was also selected for verification. The experimental data were collected with the four-factor five-level quadratic general rotation combination design method in the experimental site of Chifeng Academy of agricultural and animal husbandry sciences (Table S5). In contrast to the quadratic regression orthogonal rotation combination design method, the quadratic general rotation combination design method has 31 experimental groups in this study. In the Chifeng Zheng experiment, the cultivation measures of group codes 25–31 are the control group. The cultivation measures, as well as the yield production of the Chifeng Zheng experiment can be found in Table S6.

Figure 1 is the flow chart of the full text, which is divided into the following two parts: the corn planting experiment and corn production performance evaluation. The experiment adopts the quadratic regression orthogonal rotation combination design, and the evaluation method adopts the CCR model that can evaluate the relative effectiveness of multiple decision-making units. Based on this model, a new evaluation model is proposed, which is easier to determine the optimal cultivation measures in corn from the evaluation results.

**Table 2.** Experiment structural matrix of the JLASTU experiment.

| Group Code | $x_1$ | $x_2$ | $x_3$ | $x_4$ | Production (kg/ha) |
|---|---|---|---|---|---|
| 1 | −1 | −1 | −1 | −1 | 11,486.7 |
| 2 | −1 | −1 | −1 | 1 | 10,538.1 |
| 3 | −1 | −1 | 1 | −1 | 11,886.9 |
| 4 | −1 | −1 | 1 | 1 | 11,243.8 |
| 5 | −1 | 1 | −1 | −1 | 11,059.9 |
| 6 | −1 | 1 | −1 | 1 | 11,430.5 |
| 7 | −1 | 1 | 1 | −1 | 12,093.7 |
| 8 | −1 | 1 | 1 | 1 | 12,895.3 |
| 9 | 1 | −1 | −1 | −1 | 12,043.9 |
| 10 | 1 | −1 | −1 | 1 | 12,043.4 |
| 11 | 1 | −1 | 1 | −1 | 12,006.4 |
| 12 | 1 | −1 | 1 | 1 | 12,246.6 |
| 13 | 1 | 1 | −1 | −1 | 12,738.7 |
| 14 | 1 | 1 | −1 | 1 | 13,001.6 |
| 15 | 1 | 1 | 1 | −1 | 12,063.6 |
| 16 | 1 | 1 | 1 | 1 | 13,641.3 |
| 17 | −2 | 0 | 0 | 0 | 10,151.1 |
| 18 | 2 | 0 | 0 | 0 | 12,383.8 |
| 19 | 0 | −2 | 0 | 0 | 12,997.4 |
| 20 | 0 | 2 | 0 | 0 | 13,007.9 |
| 21 | 0 | 0 | −2 | 0 | 11,758.3 |
| 22 | 0 | 0 | 2 | 0 | 12,823.3 |
| 23 | 0 | 0 | 0 | −2 | 10,720.7 |
| 24 | 0 | 0 | 0 | 2 | 11,864.9 |
| 25 | 0 | 0 | 0 | 0 | 11,442.4 |
| 26 | 0 | 0 | 0 | 0 | 11,969.2 |
| 27 | 0 | 0 | 0 | 0 | 12,208.1 |
| 28 | 0 | 0 | 0 | 0 | 11,911.5 |
| 29 | 0 | 0 | 0 | 0 | 11,801.6 |
| 30 | 0 | 0 | 0 | 0 | 12,032.9 |
| 31 | 0 | 0 | 0 | 0 | 11,783.5 |
| 32 | 0 | 0 | 0 | 0 | 11,682.2 |
| 33 | 0 | 0 | 0 | 0 | 12,082.6 |
| 34 | 0 | 0 | 0 | 0 | 11,994.8 |
| 35 | 0 | 0 | 0 | 0 | 11,576.7 |
| 36 | 0 | 0 | 0 | 0 | 11,835.9 |

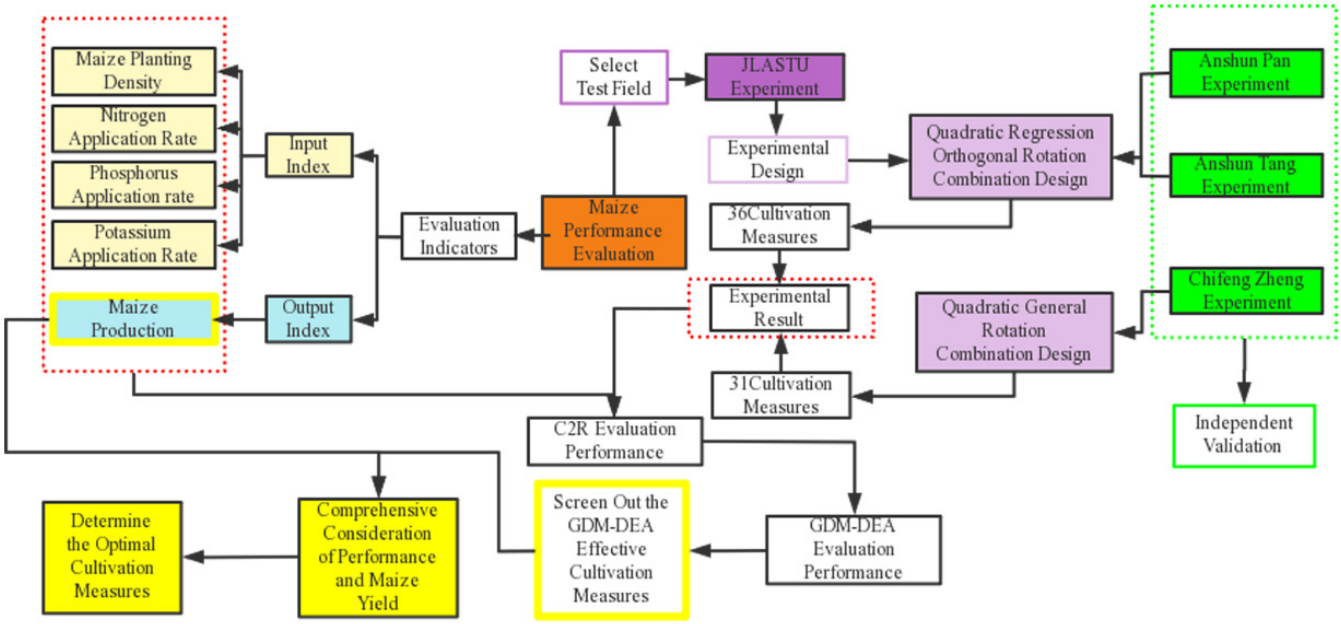



**Figure 1.** Research workflow.

The current research methods used to determine the efficiency mainly include the parametric method and non-parametric method. The parametric method includes the deterministic parameter method and non-deterministic parameter method. The deterministic parameter method has some defects with no explicit assumption for the error term. Thus, the non-deterministic parameter method has received increasing attention. At present, the probability frontier construction method and stochastic frontier analysis are the most common methods. The non-parametric method originates from production frontier research methods based on the relative measurement of economic efficiency proposed by Farrell. It does not limit the shape of the efficiency frontier and does not require a clear definition for the basic production function but locates relatively efficient points on the production frontier based on the observation of a large number of actual data and particular production effectiveness standards. Currently, the most popular non-parametric method is the DEA Method.

DEA is an efficiency evaluation method based on the concept of relative efficiency. At present, research that uses the DEA method mainly concentrates on economic system evaluation and analysis, human resource management, technology innovation and technical progress, financial analysis, financial management, banking management, logistics and supply chain management and many other fields. The decision-making unit (DMU) is the most important unit in the DEA model. Each DMU represents some economic significance, and its basic characteristic involves the possession of certain inputs and outputs. It tries to achieve its own decision-making goals in the process of transforming inputs into outputs. The DEA model can not only be used in time-series analysis in which each period is a decision-making unit, but can also be used in horizontal analysis, in which every individual is a decision-making unit.

DEA is a method used in the evaluation of the relative efficiency of decision-making units. This method uses a mathematical programming model for the estimation of the production frontier of economic systems with multi-inputs and multi-outputs, and judges whether the observation data of DMU are DEA-effective based on the production frontier. By the use of DEA in DMU efficiency evaluation, we can obtain a significant amount of management information with profound meaning and background in economics, which can provide decision-makers with important management decision information.

### 2.4. Models and Tools

#### 2.4.1. CCR Model

The CCR model was the first DEA model proposed by Charnes, Cooper, Rhodes and some other scholars in 1978 [37], which is widely used to evaluate the relative effectiveness of the same type of departments or units. The CCR model is a method that is used to study the relationship between input and output based on the production function. It extends the efficiency concept of a single input and single output to the effectiveness evaluation system of similar decision-making units with multiple inputs and multiple outputs.

Assuming that there are $n$ DMUs, each having $m$ types of "input" (denoting the "resource" consumption of the DMU) and $s$ types of "output" (they are some indexes of "effectiveness" after the consumption of "resources" by the DMU), the input and output data of each DMU are as follows:

$x_{ij}$ denotes the $i$th input of the $j$th DMU, $y_{rj}$ denotes the $r$th output of the $j$th DMU, $v_i$ represents the corresponding weight of $x_{ij}$, $u_r$ represents the corresponding weight of $y_{rj}$; $x_{ij_0}$ and $y_{rj_0}$ denote the input and output vectors of the DMU under evaluation, respectively. Therefore, the CCR model can be expressed as follows:

$$\max \frac{\sum_{r=1}^{s} u_r y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}} = V_{j_0}^{CCR}$$
$$(P_{CCR})\ s.t. \begin{cases} \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \\ v_i \ge 0,\ i = 1, 2, \cdots, m \\ u_r \ge 0,\ r = 1, 2, \cdots, s \\ j = 1, 2, \cdots, n \end{cases} \quad (1)$$

The objective function of the CCR model is to find the optimal efficiency value of the $j_0$th DMU-$V_{j_0}^{CCR}$, and the variables are the weights $v_i$ ($i$ = 1, 2, ... , $m$) of the input index and weights $u_r$ ($r$ = 1, 2, ... , $s$) of the output index. The DMU was evaluated using the CCR model. With the optimum weight, the evaluation result can achieve the best efficiency. If $V_{j_0}^{CCR} = 1$, the $j_0$th DMU is CCR-effective; otherwise, the $j_0$th DMU is not CCR-effective.

The weights used in the CCR model are all optimal weights, which are not necessarily equal to the actual weights, so they suggest a certain level of idealization. When evaluating corn production performance, the CCR model can only distinguish which kind of cultivation measures are effective or ineffective and cannot compare or rank the production performance of cultivation measures. Therefore, based on the CCR model, the GDM-DEA (group decision method of DEA) model is proposed.

The GDM-DEA model can not only ensure that the obtained GDM-DEA-effective cultivation measures are CCR-effective but can also reduce the number of effective cultivation measures, reduce the workload of the actual calculation, and select environment-friendly cultivation measures on the premise of ensuring the effectiveness and high yield of the cultivation measures.

#### 2.4.2. GDM-DEA Method

GDM-DEA adds a new DMU average decision unit $j_{n+1}$, by taking the average value of each input and output of $n$ evaluated DMUs as the input and output value of $j_{n+1}$. If the evaluated cultivation measures $j_0$ are removed, the remaining $n-1$ original cultivation measures and mean cultivation measures $j_{n+1}$ can form a new group with $n$ evaluated cultivation measures.

If $j_0$ has a great influence, the efficiency of the new group will change greatly after removing $j_0$; otherwise, it will not change or will change very little. In short, the removal and retention of $j_0$ can reflect the degree of its impact on the efficiency of new groups, and can also reflect the role of $j_0$.

Each DMU also has $m$ kinds of "input" and $n$ kinds of "output"; $x_{ij}$ denotes the $i$th input of the $j$th DMU; $x_{ij_0}$ denotes the $i$th output of the $j_0$th DMU; $v_i$ represents the corresponding weight of $x_{ij}$; $y_{rj}$ denotes the $r$th output of the $j$th DMU; $y_{rj_0}$ denotes the $r$th output of the $j_0$th DMU; $u_r$ represents the corresponding weight of $y_{rj}$. For $n$ DMUs, $\overline{x_i}$ denotes the average value of the $i$th input, and $\overline{y_r}$ denotes the average value of the $r$th output. $E_{j_0}$ represents the GDM-DEA efficiency of $j_0$. The below expression represents the GDM-DEA model used for calculating the GDM-DEA efficiency value of the $j_0$th DMU.

$$(P_{GDM})\text{s.t.}\begin{cases} \max \sum_{r=1}^{s} u_r \overline{y_r} \\ \sum_{i=1}^{m} v_i x_{ij} \geq \sum_{r=1}^{s} u_r y_{rj}\ j = 1, 2, \cdots, n, j \neq j_0 \\ \sum_{i=1}^{m} v_i \overline{x_i} = 1\ i = 1, 2, \cdots, m \\ v_i, u_r \geq 0\ r = 1, 2, \cdots, s \\ \overline{x_i} = \frac{1}{n}\sum_{j=1}^{n} x_{ij}, \overline{y_r} = \frac{1}{n}\sum_{j=1}^{n} y_{rj} \end{cases} \tag{2}$$

$$E_{j_0} = \frac{\sum_{r=1}^{s} u_r y_{rj_0}}{\sum_{i=1}^{s} v_i x_{ij_0}}\ (j_0 = 1, 2, \cdots, n) \tag{3}$$

Firstly, taking the optimal efficiency of the average decision unit $j_{n+1}$ as the goal, and the efficiency of the $j$th DMU ($j$ = 1, 2, … , $n$, but $j \neq j_0$) as the constraint condition, $P_{GDM}$ should be solved to obtain weights $v_i$ and $u_r$. Then, the weights can be regarded as the weights of the corresponding input and output indicators of $j_0$. Lastly, the GDM-DEA efficiency value of $j_0$—$E_{j_0}$ can be calculated. If $E_{j_0} \geq 1$, the $j_0$th DMU is effective in the GDM-DEA model; otherwise, the $j_0$th DMU is ineffective in the GDM-DEA model.

#### 2.4.3. Min–Max Standardization

To compare the yield and production performance of maize cultivation, the min–max standardization method is used to standardize the kernel yield. The min–max standardization method is used to linearly transform the original data. The formula is as follows:

$$x^* = \frac{x - Min\ A}{Max\ A - Min\ A} \tag{4}$$

where *Min A* and *Max A* represent the minimum and maximum values of attribute *A*, respectively. Using this formula, we can map an original value $x$ of $A$ onto the value $x$* in the interval [0, 1] through min–max standardization.

#### 2.4.4. Orthogonal Design

Quadratic orthogonal rotation combination design and quadratic general combination design belong to the field of orthogonal design, which is an experimental design method used to study multiple factors. In multi-factor experiments, the number of treatment combinations will increase sharply with the increase in the number of experimental factors and levels. For example, there will be $4^4$ = 256 treatment combinations in a test with 4 factors and 4 levels, and $4^5$ = 1024 treatment combinations in a test with 4 factors and 5 levels. It is quite difficult to fully implement such a large experiment. Therefore, D. J. Finney proposed a partial experimental method [57]. In addition, many Japanese scholars prefer to use the orthogonal style to design the experiments, which are called orthogonal experiments.

The results of quadratic orthogonal experiments are expressed, analyzed, simulated, predicted and controlled by the quadratic polynomial regression model. Therefore, the quadratic polynomial regression analysis model is widely used in the optimal design of

scientific experiments [58]. The structure of the multivariate quadratic polynomial model is as follows:

$$y = b_0 + \sum_{i=1}^{m} b_i x_i + \sum_{i=1}^{m} b_{ii} x_i^2 + \sum_{i=1}^{i<j} b_{ij} x_x x_j \quad (5)$$

where, $x_i$ represents the independent variable, $y$ represents the dependent variable and $b_0$, $b_1$, . . . , $b_m$, $b_{11}$, $b_{22}$, . . . , $b_{mm}$, $b_{12}$, $b_{13}$, . . . , and $b_{m-1,m}$ are the regression coefficients. In this experiment, $m$ = 4, $x_1$ represents the maize planting density, $x_2$ represents the nitrogen application rate, $x_3$ represents the phosphorus application rate, $x_4$ represents the potassium application rate, and $y$ represents the maize yield. According to the experimental design scheme and the experimental results, each regression coefficient in the quadratic polynomial regression equation is estimated.

#### 2.4.5. Solution Software

For the JLASTU experiment, the Data Processing System (DPS) v18.10 [59] was used to calculate the quadratic regression orthogonal rotation combination design. Lingo 18.0 [60] was selected to solve the CCR and GDM-DEA models.

## 3. Results

### *3.1. Generalized Summary of JLASTU Experiment*

When determining the optimal cultivation measures, the high-yield frequency analysis method is usually used to determine the high-yield standard of the quadratic regression orthogonal rotation combination design test, and the average yield of 36 groups of cultivation measures is used as the high-yield standard. DPS v18.10 was used to obtain the best combination of cultivation techniques and measures for a high yield in the JLASTU experiment. The planting density was 74,300–77,000 plants/ha; the nitrogen application rate was 235.64–248.75 kg/ha; the phosphorus application rate was 121.56–127.81 kg/ha; and the potassium application rate was 123.47–131.44 kg/ha.

### *3.2. Comparative Analysis with CCR Model and GDM-DEA Method for JLASTU Experiment*

The CCR model and GDM-DEA method were used for the performance comparison of the data collected from the JLASTU experiment. The results were obtained and are listed in Table 3.

**Table 3.** GDM-DEA efficiency value of the JLASTU experiment cultivation measures.

| **Group Code** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CCR efficiency value | 1.000 | 0.917 | 1.000 | 0.944 | 0.963 | 0.995 | 1.000 | 1.000 | 1.000 | 0.973 | 0.997 | 0.815 |
| GDM-DEA efficiency value | 1.045 | 0.917 | 0.961 | 0.878 | 0.956 | 0.952 | 0.938 | 1.064 | 0.852 | 0.852 | 0.799 | 0.792 |
| **Group Code** | **13** | **14** | **15** | **16** | **17** | **18** | **19** | **20** | **21** | **22** | **23** | **24** |
| CCR efficiency value | 1.000 | 0.941 | 0.887 | 0.877 | 0.951 | 0.852 | 1.000 | 0.962 | 1.000 | 0.919 | 1.000 | 0.878 |
| GDM-DEA efficiency value | 0.869 | 0.887 | 0.776 | 0.877 | 0.934 | 0.766 | 1.039 | 0.927 | 0.971 | 0.890 | 0.793 | 0.878 |
| **Group Code** | **25** | **26** | **27** | **28** | **29** | **30** | **31** | **32** | **33** | **34** | **35** | **36** |
| CCR efficiency value | 0.846 | 0.885 | 0.903 | 0.881 | 0.873 | 0.890 | 0.872 | 0.864 | 0.894 | 0.887 | 0.856 | 0.876 |
| GDM-DEA efficiency value | 0.846 | 0.885 | 0.903 | 0.881 | 0.873 | 0.890 | 0.872 | 0.864 | 0.894 | 0.887 | 0.856 | 0.876 |

For the JLASTU experiment, the evaluation results of the CCR model indicated that the CCR model could only distinguish whether the group of cultivation measures was CCR-effective or not (Table 3). The CCR model could only divide the groups into two parts but could not classify or rank all the decision-making units. Roughly, half of the cultivation measures were CCR-effective, but the best cultivation measures could not be determined. In contrast, the results from the GDM-DEA model showed that if a cultivation measure is GDM-DEA-effective, it must be CCR-effective. Otherwise, it may not be true. The GDM-DEA model can classify and rank all the cultivation measures in the JLASTU experiment (Table 3). Therefore, the GDM-DEA model demonstrates better performance than the CCR model in evaluating the effectiveness of cultivation measures.

### *3.3. Cultivation Measure Selection*

The results of the yield were transformed by min–max normalization, and the output from the CCR and GDM-DEA efficiency values of the JLASTU experiment are represented in Figure 2.

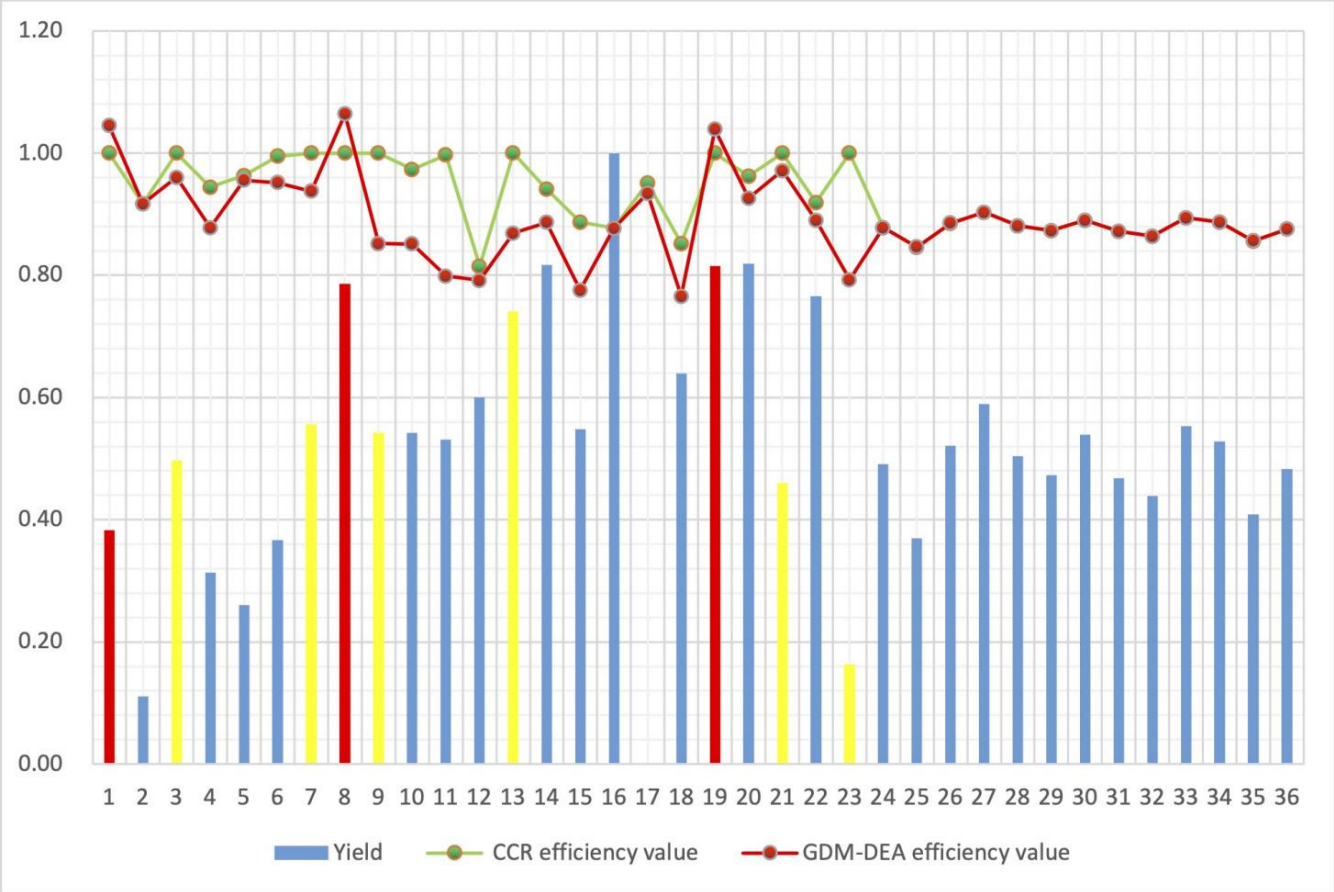



**Figure 2.** Output and efficiency analysis for the JLASTU experiment.

In Figure 2, the red bar represents that the yield corresponds to the cultivation measures that are both CCR-effective and GDM-DEA-effective. The yellow bar represents that the yield corresponds to the cultivation measures that are CCR-effective only. The red broken line indicates the efficiency trend of GDM-DEA, and each broken point represents the efficiency value of GDM-DEA. The green broken line represents the efficiency trend of CCR, and each broken point represents the CCR efficiency value.

The values of $V^{C^2R}$ were all 1s in groups 1, 3, 7, 8, 9, 13, 19, 21, and 23. Groups 1, 8, and 19 were both CCR-effective and GDM-DEA-effective (Figure 2). The order of yield for these three groups of cultivation measures from high to low is as follows:

19 (12,997.4 kg/ha) > 8 (12,895.3 kg/ha) > 1 (11,486.7 kg/ha). To determine the optimal cultivation measures, the cultivation measures of the three groups need to be contrastively analyzed.

The planting density and the amount of nitrogen, phosphorus, and potassium applied for group 1 were all at the −1 level, which was lower than the previous planting density and fertilization rate in this area. It not only reduces the investment in the economy, but also reduces the negative impact on the soil and other environments due to the reduction in the fertilization rate. However, the yield of group 1 was also lower than the average yield of the 36 groups of cultivation measures in the JLASTU experiment. Therefore, group 1 has a high production efficiency, but is not a high-yield cultivation measure.

The planting density of group 8 was at the -1 level, which was lower than the previous planting density standard in the region, and the amount of fertilization was at the level of 1, which was higher than the previous fertilization standard in the region. Although the yield under this cultivation measure exceeded the average yield of the 36 groups of cultivation measures in the JLASTU experiment, it was still not the best cultivation measure because excessive fertilization will lead to soil hardening and environmental pollution. Consequently, group 8 is a high-performance and high-yield measure, but not an environment-friendly cultivation measure.

If only considering the perspective of high yield, group 16 (yield: 13,641.3 kg/ha) should be selected as the optimal cultivation measure, but its planting density and the amount of nitrogen, phosphorus, and potassium application for this cultivation measure were all at the +1 level, which was much higher than the previous standard level in this area.

The planting density and the amount of phosphorus and potassium applied in group 19 were the same as the previous standard level in the region, while the nitrogen application rate was at the −2 level, which was far lower than the standard level. Although its yield was not the highest one among the 36 groups of cultivation measures, it was much higher than the average yield. Thus, group 19 is the most environment-friendly cultivation measure with a high production efficiency and high yield, and also the best cultivation measure of the JLASTU experiment.

### 3.4. Independent Validation

The publicly available experimental data previously generated from the same location with same experimental design [54–56] were used to validate the GDM-DEA model. The yield data of three independent experiments were processed by min–max normalization. Lingo 18.0 was used to solve the CCR and GDM-DEA efficiency values of each cultivation measure in the three independent experiments. It was found that groups 12, 15, 19, and 35 met the criteria of CCR and GDM-DEA effectiveness. Among those, group 35 had the highest yield (Table S7 and Figure S1).

The published results of the Anshun Pan experiment used the average yield of 36 groups (10,527.15 kg/ha) as the high-yield standard [54,55]. Obviously, group 35 was the best cultivation measure, which met the standards of high performance and high yield. In the Anshun Pan experiments, the cultivation measures of groups 25–36 were the same. Except for groups 25 and 35, the efficiency value and GDM-DEA efficiency value of the other 10 groups were close to 1, and the yield was much higher than the standard high-yield value. The explanation for the differences between the Anshun Pan and JLASTU experiment in performance and yield may be that the effects of previously grown crops, environmental effects and/or the edge row could affect the experimental data.

Groups 6, 12, 14, 16, 20, and 24 were CCR-effective only, and groups 15 and 35 were both CCR-effective and GDM-DEA-effective. Taking CCR and GDM-DEA effectiveness as the standard, the yield was reported as follows: 35 (13,502.1 kg/ha) > 15 (12,471.6 kg/ha).

The experimental sites and design of the Anshun Tang experiment and the Anshun Pan experiment were the same, so the same cultivation measure in the two independent experiments had a similar performance and yield. This published research took 12,000 kg/ha as the high-yield standard of maize in the Anshun Tang experiment [54,55]. Consider-

ing GDM-DEA efficiency and the yield, group 35 was the best cultivation measure in our analysis.

The 12th, 16th, 18th, and 20th cultivation measures were all CCR-effective, while the CCR efficiency value of the 14th, 22nd, and 24th cultivation measures were both CCR-effective and GDM-DEA-effective. The yield of the shared three groups was ranked as 22 (14,222.85 kg/ha) > 14 (13,147.05 kg/ha) > 24 (12,652.35 kg/ha).

In contrast to the first two independent experiments, in the Chifeng Zheng experiment, we used DPS software to determine that the high-yield standard was 12,134.98 kg/ha. Groups 14, 22, and 24 all met the high-yield standard. The amount of nitrogen, phosphorus, and potassium fertilizer applied in group 22 was at level 0, and the planting density was level−2. The input of group 22 was lower than the other two groups, and the yield was larger than the other two groups, so it was the best cultivation measure.

Here, the optimal cultivation measures from the GDM-DEA model and other statistical methods were compared (Table 4). The Anshun Pan experiment and Anshun Tang experiment used the high-yield frequency analysis method to obtain the optimal combination scheme of agronomic measures with a higher yield than the average yield. This scheme only determined the range of planting density, nitrogen application rate, potassium application rate, and phosphorus application rate, but did not give the best cultivation measure. In the Chifeng Zheng experiment, DPS was used to process the data and regression analysis results. Finally, the optimal solution of the quadratic regression model was obtained, and the highest yield cultivation measures were obtained at the theoretical level.

**Table 4.** Comparison of two kinds of results from the statistical method and GDM-DEA method.

| Independent Experiment | | Planting Density (Plants/ha) | Nitrogen Fertilizer (kg/ha) | Phosphate Fertilizer (kg/ha) | Potash Fertilizer (kg/ha) | Yield (kg/ha) |
|---|---|---|---|---|---|---|
| Anshun Pan experiment | Results obtained by statistical method | 52,830–55,170 | 160.5–187.5 | 142.5–157.5 | 154.5–175.5 | ≥10,527.15 |
| | GDM-DEA optimal cultivation measures | 54,000 | 174 | 150 | 165 | 11,943 |
| Anshun Tang experiment | Results obtained by statistical method | 63,000–65,055 | 245.55–351.3 | 187.65–244.5 | 278.4–340.5 | ≥12,000 |
| | GDM-DEA optimal cultivation measures | 64,035 | 360 | 240 | 240 | 13,502.1 |
| Chifeng Zheng experiment | Results obtained by statistical method | 52,500 | 750 | 375 | 187.5 | 16,072.35 |
| | GDM-DEA optimal cultivation measures | 52,500 | 600 | 225 | 150 | 14,222.85 |

In the Anshun Pan experiment and Anshun Tang experiment, the optimal cultivation measures selected by the GDM-DEA model concorded with the range of optimal cultivation measures given in the experiment. The Chifeng Zheng experiment demonstrated the cultivation measures with the maximum theoretical yield. Compared with the best cultivation measure calculated by the GDM-DEA model, the maximum theoretical yield is necessary to increase the fertilization amount of nitrogen, phosphorus, and potassium, which negatively impacts the environment and soil. At the same time, from an economic point of view, it increases investment, but its economic benefit has not been greatly improved.

In the JLASTU experiment, there are nine groups of CCR-effective cultivation measures and three groups of GDM-DEA-effective cultivation measures. In the validation experiment, the Anshun Pan experiment has 11 groups of CCR-effective cultivation measures and 4 groups of GDM-DEA-effective cultivation measures; the Anshun Tang experiment has 8 groups of CCR-effective cultivation measures and 2 groups of GDM-DEA-effective cultivation measures; there are 7 groups of CCR-effective cultivation measures and 3 groups

of GDM-DEA-effective cultivation measures in the Chifeng Zheng experiment. The number of effective cultivation measures of GDM-DEA is 1/4–3/7 of the CCR model. Therefore, the calculation efficiency of the GDM-DEA model is 2–4-times higher than the CCR model when determining the best cultivation measures for maize.

## 4. Discussion

In this study, we proposed and applied a new model named GDM-DEA model for the evaluation of cultivation measures in maize. We also compared the performance of the GDM-DEA model with other models.

Taking the JLASTU experiment as an example, nine groups of CCR-effective maize cultivation measures can be determined by the CCR model. Three groups of effective cultivation measures can be selected by the GDM-DEA model, and the three groups of cultivation measures meet the desired level of CCR effectiveness. Only by analyzing the cultivation measures and yield of the three groups, it could be determined that group 19 is the best cultivation measure for the JLASTU experiment, which has an unchanged yield, planting density and phosphorus, and potassium application at the previous standard level in the same region, while its nitrogen application is at the $-2$ level. The optimal cultivation measures are the same as the measures that were determined by the CCR model. Therefore, the evaluation results of the GDM-DEA model and CCR model are the same, but they can reduce the workload of determining the optimal cultivation measures.

As demonstrated in the JLASTU experiment and the three independent experiments, the GDM-DEA model outperforms the CCR model when determining an optimized estimation. Therefore, the GDM-DEA model is good enough for predicting the maize yield output under different cultivation measures. It also may be applicable for other crops, although it needs to be tested in the future.

The CCR model is commonly used to evaluate performance. However, the CCR model can give only a general range of planting density and fertilization data but not specific planting guidance. The CCR model is only dependent on the original data and analyzes the data objectively. In the CCR model, each DMU selects the subjective weights that are propitious to their own. It means that a DMU only needs the original data of the input index and output index when the CCR model evaluates the DMU. The solution results of the model include both the efficiency value of the DMU and the corresponding weight of each input and output index. When evaluating a group of cultivation measures, in view of the "uncertain weight" of the CCR model, the cultivation measures will choose a weight to maximize their own efficiency. In other words, when evaluating a group of cultivation measures of four indicators, the greater the input, the smaller the index weight, and the smaller the input, the greater the index weight, so that this group of cultivation measures will achieve the maximum efficiency value. Therefore, when evaluating maize cultivation performance, it should be noted that there are many CCR-effective cultivation measures, and the cost of calculation will be relatively high in the process of determining the optimal cultivation measures.

GDM-DEA could solve the above problems. The principle of this model is to add an average decision unit as the "control group". When calculating the GDM-DEA efficiency value of a group of cultivation measures, the group of cultivation measures should be removed from the model, and the remaining original cultivation measures and mean cultivation measures will form a new group. If the removed cultivation measure has a great influence, the efficiency of the average decision unit will change greatly and vice versa. In short, the removal and retention of the removed cultivation measure could reflect the degree of its impact on the efficiency of new groups, which could also reflect the role of the removed cultivation measure. Therefore, by optimizing the index composition of the average decision unit in the new evaluation set, and then taking the sum of the optimal weighting coefficient of the average decision unit as the standard for the evaluated cultivation measures, we can not only establish a relationship between the average cultivation measures and the evaluated cultivation measures, but also make the evaluation results

more reasonable. Meanwhile, the effective cultivation measures of GDM-DEA must meet the effectiveness of CCR, but the opposite is not necessarily true. Therefore, the GDM-DEA model could reduce the workload of determining the optimal cultivation measures.

During the comparison among the cultivation measures, a high yield should not be the only criterion used to determine the cultivation performance. The optimal cultivation measures not only have high performance in production, but also have high yield with minimal environment impacts. In this way, the problems of resource waste and environmental pollution caused by high investment could be avoided, and the planting efficiency could be improved from an economic point of view. Using the CCR model to evaluate performance, the cultivation measures could only be preliminary classified as effective or ineffective. At the same time, many effective cultivation measures were obtained. Although the cultivation measure of CCR is effective and demonstrates a high yield, it negatively impacts the environment. The evaluation of the GDM-DEA model not only ensures that the obtained GDM-DEA-effective cultivation measures are CCR-effective, but also reduces the number of effective cultivation measures. At the same time, we could also choose environment-friendly cultivation measures on the premise of ensuring the effectiveness and high yield of the cultivation measures.

In addition, as an improved performance evaluation model, GDM-DEA may be used to evaluate not only the production performance of grains such as wheat and sorghum, but also the production performance of other crops. However, this needs to be tested in future experiments. The current conclusion was based on one-year field data, and more experimental data from additional years will be needed for a practice purpose.

GDM-DEA also has shortcomings. If the GDM-DEA efficiency value is $E_{j_0} \geq 1$, the $j_0$th DMU is GDM-DEA-effective. However, when the GDM-DEA model evaluates the removed cultivation measure, the removed cultivation measure could reflect the degree of its impact on the efficiency of new groups, and it will select the subjective weights that are propitious to its own. Although the GDM-DEA model is more objective than the CCR model, it cannot completely eliminate the influence of the "self-interest" of the DEA performance evaluation model. For the follow-up study of the DEA model in evaluating maize cultivation performance, we will conduct a more objective evaluation of the performance of each evaluated cultivation measure as a further research goal.

## 5. Conclusions

Through the specific cultivation measures and corresponding yields of the four groups of experiments, as well as the performance evaluation results, it can be observed that a high yield should not be the only criterion to determine the cultivation performance when guiding the actual production of crops. The selection of optimal cultivation measures should take high efficiency, high yield and environmental friendliness as the criteria to determine the optimal cultivation measures through experiments, which can avoid the problems of resource waste and environmental pollution caused by high investment, and improve the planting benefits from an economic point of view.

Using the CCR model to evaluate performance, we can only preliminarily classify cultivation measures as effective or ineffective. There are many effective cultivation measures, and the situation of "effective cultivation measures and high yield, but not friendly to the environment" will appear when evaluating these measures. The evaluation of the GDM-DEA model can not only ensure that the obtained GDM-DEA-effective cultivation measures are CCR-effective, but can also reduce the number of effective cultivation measures, reduce the workload of the actual calculation, and select environment-friendly cultivation measures on the premise of ensuring the effectiveness and high yield of the cultivation measures.

The GDM-DEA model has the following two advantages over the CCR model: (1) the GDM-DEA model can rank all cultivation measures; (2) combined with a high yield and GDM-DEA efficiency value greater than 1, the optimal cultivation measures can be determined, and the amount of calculation can be reduced in the calculation process.

**Supplementary Materials:** The following are available online at https://www.mdpi.com/article/10.3390/app13010521/s1.

**Author Contributions:** Y.T. and H.L. conceived and designed the study. K.C. designed and completed the JLASTU experiment, W.H., Y.C. and C.B. completed the sorting of the independent verification experimental data. H.L. proposed the GDM-DEA model and performed the data analysis. M.H., X.T. and H.Y. helped to review the results and manuscript. H.L. and W.H. drafted the manuscript. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by [the Science and Technology Development Plan Project of Jilin Province] grant number [YDZJ202201ZYTS692].

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The data sets used for analysis in this study can be found in Supplementary Material section (Tables S1–S9).

**Acknowledgments:** We would like to thank the reviewers for their constructive comments on the manuscript.

**Conflicts of Interest:** The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## References

1. Benz, B.F. Archaeological evidence of teosinte domestication from Guilá Naquitz, Oaxaca. *Proc. Natl. Acad. Sci. USA* **2001**, *98*, 2104–2106. [CrossRef] [PubMed]
2. Wang, H.; Nussbaum-Wagler, T.; Li, B.; Zhao, Q.; Vigouroux, Y.; Faller, M.; Bomblies, K.; Lukens, L.; Doebley, J.F. The origin of the naked grains of maize. *Nature* **2005**, *436*, 714–719. [CrossRef] [PubMed]
3. FAO. *FAO Statistical Pocketbook 2015: World Food and Agriculture*; Food and Agriculture Organization of the United Nations: Rome, Italy, 2015.
4. Qi, R.; Ma, Y.; Hu, B.; de Reffye, P.; Cournède, P.-H. Optimization of source–sink dynamics in plant growth for ideotype breeding: A case study on maize. *Comput. Electron. Agric.* **2010**, *71*, 96–105. [CrossRef]
5. Chen, X.P.; Zhang, F.S.; Cui, Z.L.; Li, F.; Li, J.L. Optimizing Soil Nitrogen Supply in the Root Zone to Improve Maize Management. *Soil Sci. Soc. Am. J.* **2010**, *74*, 1367–1373. [CrossRef]
6. Cui, Z.; Zhang, F.; Mi, G.; Chen, F.; Li, F.; Chen, X.; Li, J.; Shi, L. Interaction between genotypic difference and nitrogen management strategy in determining nitrogen use efficiency of summer maize. *Plant Soil* **2009**, *317*, 267–276. [CrossRef]
7. Xu, X.; He, P.; Pampolino, M.F.; Johnston, A.M.; Qiu, S.; Zhao, S.; Chuan, L.; Zhou, W. Fertilizer recommendation for maize in China based on yield response and agronomic efficiency. *Field Crop. Res.* **2014**, *157*, 27–34. [CrossRef]
8. Du, X.; Wang, Z.; Lei, W.; Kong, L. Increased planting density combined with reduced nitrogen rate to achieve high yield in maize. *Sci. Rep.* **2021**, *11*, 358. [CrossRef]
9. Yang, Y.; Xu, W.; Hou, P.; Liu, G.; Liu, W.; Wang, Y.; Zhao, R.; Ming, B.; Xie, R.; Wang, K.; et al. Improving maize grain yield by matching maize growth and solar radiation. *Sci. Rep.* **2019**, *9*, 3635. [CrossRef]
10. Xu, X.; He, P.; Qiu, S.; Pampolino, M.F.; Zhao, S.; Johnston, A.M.; Zhou, W. Estimating a new approach of fertilizer recommendation across small-holder farms in China. *Field Crop. Res.* **2014**, *163*, 10–17. [CrossRef]
11. Xu, X.; He, P.; Pampolino, M.F.; Chuan, L.; Johnston, A.M.; Qiu, S.; Zhao, S.; Zhou, W. Nutrient requirements for maize in China based on QUEFTS analysis. *Field Crop. Res.* **2013**, *150*, 115–125. [CrossRef]
12. Wang, G.; Chen, J.; Zhou, Q.; Chu, X.; Zhou, X. Modelling analysis of water-use efficiency of maize in Heihe River Basin. *Phys. Chem. Earth Parts A/B/C* **2016**, *96*, 50–54. [CrossRef]
13. Ku, Y.G.; Kang, D.H.; Lee, C.K.; Lee, S.Y.; Ryu, C.S.; Kim, D.E.; Polovka, M.; Namieśnik, J.; Gorinstein, S. Influence of different cultivation systems on bioactivity of asparagus. *Food Chem.* **2018**, *244*, 349–358. [CrossRef] [PubMed]
14. Färe, R.; Lovell, C.K. Measuring the technical efficiency of production. *J. Econ. Theory* **1978**, *19*, 150–162. [CrossRef]
15. Bertocco, M.; Basso, B.; Sartori, L.; Martin, E. Evaluating energy efficiency of site-specific tillage in maize in NE Italy. *Bioresour. Technol.* **2008**, *99*, 6957–6965. [CrossRef] [PubMed]
16. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
17. Tone, K. A slacks-based measure of super-efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2002**, *143*, 32–41. [CrossRef]
18. Brožová, D.; Emrouznejad, A.; Cooper, W.W.; Seiford, L.M.; Tone, K. *Data Envelopment Analysis*, 2nd ed.; Policy; Springer: Berlin/Heidelberg, Germany, 2007.
19. Singh, P.; Singh, G.; Sodhi, G. Applying DEA optimization approach for energy auditing in wheat cultivation under rice-wheat and cotton-wheat cropping systems in north-western India. *Energy* **2019**, *181*, 18–28. [CrossRef]

20. Singh, P.; Singh, G.; Sodhi, G.; Sharma, S. Energy optimization in wheat establishment following rice residue management with Happy Seeder technology for reduced carbon footprints in north-western India. *Energy* **2021**, *230*, 120680. [CrossRef]
21. Singh, P.; Singh, G.; Sodhi, G.P.S. Energy auditing and optimization approach for improving energy efficiency of rice cultivation in south-western Punjab, India. *Energy* **2019**, *174*, 269–279. [CrossRef]
22. Singh, G.; Singh, P.; Sodhi, G.; Tiwari, D. Energy auditing and data envelopment analysis (DEA) based optimization for increased energy use efficiency in wheat cultivation (*Triticum aestium* L.) in north-western India. *Sustain. Energy Technol. Assessments* **2021**, *47*, 101453. [CrossRef]
23. Singh, P.; Singh, G.; Sodhi, G.P.S. Data envelopment analysis based optimization for improving net ecosystem carbon and energy budget in cotton (*Gossypium hirsutum* L.) cultivation: Methods and a case study of north-western India. *Environ. Dev. Sustain.* **2021**, *24*, 2079–2119. [CrossRef]
24. Mohammadi, A.; Rafiee, S.; Mohtasebi, S.S.; Avval, S.H.M.; Rafiee, H. Energy efficiency improvement and input cost saving in kiwifruit production using Data Envelopment Analysis approach. *Renew. Energy* **2011**, *36*, 2573–2579. [CrossRef]
25. Mousavi-Avval, S.H.; Rafiee, S.; Jafari, A.; Mohammadi, A. Optimization of energy consumption for soybean production using Data Envelopment Analysis (DEA) approach. *Appl. Energy* **2011**, *88*, 3765–3772. [CrossRef]
26. Nabavi-Pelesaraei, A.; Abdi, R.; Rafiee, S.; Taromi, K. Applying data envelopment analysis approach to improve energy efficiency and reduce greenhouse gas emission of rice production. *Eng. Agric. Environ. Food* **2014**, *7*, 155–162. [CrossRef]
27. Nabavi-Pelesaraei, A.; Hosseinzadeh-Bandbafha, H.; Qasemi-Kordkheili, P.; Kouchaki-Penchah, H.; Riahi-Dorcheh, F. Applying optimization techniques to improve of energy efficiency and GHG (greenhouse gas) emissions of wheat production. *Energy* **2016**, *103*, 672–678. [CrossRef]
28. Mirmozaffari, M.; Yazdani, R.; Shadkam, E.; Khalili, S.M.; Tavassoli, L.S.; Boskabadi, A. A Novel Hybrid Parametric and Non-Parametric Optimisation Model for Average Technical Efficiency Assessment in Public Hospitals during and Post-COVID-19 Pandemic. *Bioengineering* **2021**, *9*, 7. [CrossRef] [PubMed]
29. Mirmozaffari, M.; Shadkam, E.; Khalili, S.M.; Yazdani, M. Developing a Novel Integrated Generalised Data Envelopment Analysis (DEA) to Evaluate Hospitals Providing Stroke Care Services. *Bioengineering* **2021**, *8*, 207. [CrossRef]
30. Peykani, P.; Memar-Masjed, E.; Arabjazi, N.; Mirmozaffari, M. Dynamic Performance Assessment of Hospitals by Applying Credibility-Based Fuzzy Window Data Envelopment Analysis. *Healthcare* **2022**, *10*, 876. [CrossRef]
31. Zhou, X.; Yu, J.; Li, J.; Li, S.; Zhang, D.; Wu, D.; Pan, S.; Chen, W. Spatial correlation among cultivated land intensive use and carbon emission efficiency: A case study in the Yellow River Basin, China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 43341–43360. [CrossRef]
32. Nabavi-Pelesaraei, A.; Abdi, R.; Rafiee, S.; Mobtaker, H.G. Optimization of energy required and greenhouse gas emissions analysis for orange producers using data envelopment analysis approach. *J. Clean. Prod.* **2014**, *65*, 311–317. [CrossRef]
33. Mohammadi, A.; Rafiee, S.; Jafari, A.; Dalgaard, T.; Knudsen, M.T.; Keyhani, A.; Mousavi-Avval, S.H.; Hermansen, J.E. Potential greenhouse gas emission reductions in soybean farming: A combined use of Life Cycle Assessment and Data Envelopment Analysis. *J. Clean. Prod.* **2013**, *54*, 89–100. [CrossRef]
34. Mohammadi, A.; Rafiee, S.; Jafari, A.; Keyhani, A.; Dalgaard, T.; Knudsen, M.T.; Nguyen, T.L.T.; Borek, R.; Hermansen, J.E. Joint Life Cycle Assessment and Data Envelopment Analysis for the benchmarking of environmental impacts in rice paddy production. *J. Clean. Prod.* **2015**, *106*, 521–532. [CrossRef]
35. Payandeh, Z.; Jahanbakhshi, A.; Mesri-Gundoshmian, T.; Clark, S. Improving Energy Efficiency of Barley Production Using Joint Data Envelopment Analysis (DEA) and Life Cycle Assessment (LCA): Evaluation of Greenhouse Gas Emissions and Optimization Approach. *Sustainability* **2021**, *13*, 6082. [CrossRef]
36. Zhang, X.; Xu, D. Assessing the eco-efficiency of complex forestry enterprises using LCA/time-series DEA methodology. *Ecol. Indic.* **2022**, *142*, 109166. [CrossRef]
37. Mirmozaffari, M.; Yazdani, M.; Boskabadi, A.; Dolatsara, H.A.; Kabirifar, K.; Golilarz, N.A. A Novel Machine Learning Approach Combined with Optimization Models for Eco-Efficiency Evaluation. *Appl. Sci.* **2020**, *10*, 5210. [CrossRef]
38. Mirmozaffari, M.; Shadkam, E.; Khalili, S.M.; Kabirifar, K.; Yazdani, R.; Gashteroodkhani, T.A. A novel artificial intelligent approach: Comparison of machine learning tools and algorithms based on optimization DEA Malmquist productivity index for eco-efficiency evaluation. *Int. J. Energy Sect. Manag.* **2021**, *15*, 523–550. [CrossRef]
39. Gutiérrez, E.; Aguilera, E.; Lozano, S.; Guzmán, G.I. A two-stage DEA approach for quantifying and analysing the inefficiency of conventional and organic rain-fed cereals in Spain. *J. Clean. Prod.* **2017**, *149*, 335–348. [CrossRef]
40. Ndlovu, P.V.; Mazvimavi, K.; An, H.; Murendo, C. Productivity and efficiency analysis of maize under conservation agriculture in Zimbabwe. *Agric. Syst.* **2014**, *124*, 21–31. [CrossRef]
41. Abdulai, S.; Nkegbe, P.K.; Donkoh, S.A. Assessing the technical efficiency of maize production in northern Ghana: The data envelopment analysis approach. *Cogent Food Agric.* **2018**, *4*, 1512390. [CrossRef]
42. Ogundari, K.; Ojo, S.; Ajibefun, I. Economies of Scale and Cost Efficiency in Small Scale Maize Production: Empirical Evidence from Nigeria. *J. Soc. Sci.* **2006**, *13*, 131–136. [CrossRef]
43. Aye, G.C.; Mungatana, E.D. Technical efficiency of traditional and hybrid maize farmers in Nigeria: Comparison of alternative approaches. *African J. Agric. Res.* **2010**, *5*, 2909–2917. [CrossRef]
44. Mwambo, F.M.; Fürst, C. A Holistic Method of Assessing Efficiency and Sustainability in Agricultural Production Systems. *J. Environ. Account. Manag.* **2019**, *7*, 29–45. [CrossRef]

45. Rybaczewska-Błażejowska, M.; Masternak-Janus, A. Eco-efficiency assessment of Polish regions: Joint application of life cycle assessment and data envelopment analysis. *J. Clean. Prod.* **2018**, *172*, 1180–1192. [CrossRef]
46. Ullah, A.; Perret, S.R. Technical- and Environmental-Efficiency Analysis of Irrigated Cotton-Cropping Systems in Punjab, Pakistan Using Data Envelopment Analysis. *Environ. Manag.* **2014**, *54*, 288–300. [CrossRef]
47. Sun, Y. A study on the yield function model of corn applied main cultural practices. *J Jilin Agric Univ.* **1987**, *9*, 11–14.
48. Yu, G. Study on the mathematical model of agriculture integrated measures for high yield of corn in dry land. *Maize Sci.* **1999**, *7*, 35–39. [CrossRef]
49. Qin, H.B.; Shi, C.Q.; Wang, B.; Yan, F.Y.; Tang, Y.Y.; Huang, A.X.; Zheng, J.X.; Huang, F.L. Effect of Different Density Fertilizer Combinations on the Yield of a New Corn Variety Zhaofeng 588 in Guangxi. *J Southern Agric.* **2014**, *45*, 1612–1615.
50. Wang, X.; Shen, L.; Qi, Y. Selection on varieties of glutinous maize and its cultivation technique for high yield. *Guizhou Agric. Sci.* **2005**, *5*, 35–77.
51. Nilahyane, A.; Islam, M.A.; Mesbah, A.O.; Garcia, A.G.Y. Effect of Irrigation and Nitrogen Fertilization Strategies on Silage Corn Grown in Semi-Arid Conditions. *Agronomy* **2018**, *8*, 208. [CrossRef]
52. Yin, Z.C.; Guo, W.Y.; Liang, J.; Xiao, H.Y.; Hao, X.Y.; Hou, A.F.; Zong, X.X.; Leng, T.R.; Wang, Y.J.; Wang, Q.Y. Effects of multiple N, P, and K fertilizer combinations on adzuki bean (Vigna angularis) yield in a semi-arid region of northeastern China. *Sci. Rep.* **2019**, *9*, 19408. [CrossRef]
53. Zhao, J.; Li, K.; Wang, R.; Tong, Z.; Zhang, J. Yield Data Provide New Insight into the Dynamic Evaluation of Maize's Climate Suitability: A Case Study in Jilin Province, China. *Atmosphere* **2019**, *10*, 305. [CrossRef]
54. Tang, G. Study on super high yield cultivation techniques of a new hybrid maize variety Shundan 6 in medium and high altitude areas—I preliminary study on the effects of density and nitrogen, phosphorus and potassium on yield and main economic characters. *Seed* **2009**, *28*, 119–122.
55. Pan, Z. Study on high yield cultivation techniques of new hybrid maize variety Jin Guidan No.3 in the central part of Gui Zhou province. *China Seed Ind.* **2020**, 39–41. [CrossRef]
56. Zheng, W.; Zhang, L. Effect analysis of combined application of nitrogen, phosphorus and potassium and density on maize yield. *Jiangsu Agric. Sci.* **2015**, *43*, 67–69.
57. Finney, K.; Fenton, N. Evaluating the effectiveness of Z: The claims made about CICS and where we go from here. *J. Syst. Softw.* **1996**, *35*, 209–216. [CrossRef]
58. Liu, X. Intirety D-Optimal Designs for Partial Linear-Quadratic Mixture Models. *J. Northeast Univ. Nat. Sci.* **1997**, *18*, 197–200.
59. Tang, Q.-Y.; Zhang, C.-X. Data Processing System (DPS) software with experimental design, statistical analysis and data mining developed for use in entomological research. *Insect Sci.* **2012**, *20*, 254–260. [CrossRef]
60. Aviso, K.B.; Tan, R.R.; Foo, D.C.; Lee, J.-Y.; Ubando, A.T. Data set and model code on the optimal operating state of a negative emission polygeneration system. *Data Brief* **2020**, *29*, 105140. [CrossRef]


**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.