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Economic Evaluation of Drought Resistance Measures for Maize Seed Production Based on TOPSIS Model and Combination Weighting Optimization

Chao Liang [1,2], Shouchao Yu [1], Hengjia Zhang [1,2,*], Zeyi Wang [2] and Fuqiang Li [2]

[1] College of Agronomy and Agricultural Engineering, Liaocheng University, Liaocheng 252059, China
[2] College of Water Conservancy and Hydropower Engineering, Gansu Agricultural University, Lanzhou 730070, China
* Correspondence: zhanghj@gsau.edu.cn

Abstract: In order to optimize the appropriate drought resistance measures in the implementation of high-efficiency and intensive production of maize seed, in 2018 and 2019, maize cultivation experiments with different drought resistance measures were carried out in the arid area of northwest China, including water retention agent (SA), white plastic film mulch (WF), black plastic film mulch (BF), straw mulch (SM), and open ground flat seed as control (CK). A total of five treatments were conducted. Ten specific indicators contained four types of attributes, namely the yield, quality, water use efficiency (WUE), and economic benefit of maize seed production, aimed at constructing a multilevel evaluation system. To improve the reliability of evaluation results, subjective and objective weights of indexes were calculated using the analytic hierarchy process (AHP) and entropy weight method (EWM), respectively. Then, based on the integrated weighting method of game theory (GT), the combined weights of subjective and objective unity were obtained. Finally, with the help of the technique for order preference by similarity to ideal solution (TOPSIS), a comprehensive benefit evaluation model was established to screen out the optimal drought resistance measures. Compared with CK, different drought resistance measures significantly improved the grain quality of seeds-production corn, and the average annual yield and WUE of black and white film treatments were improved by 49.57% and 42.97% and by 65.67% and 58.21%, respectively. This proved that black film mulching (BF) could significantly increase the yield and WUE of maize seed production and effectively improve grain quality, which could be used as the best drought-resistant cultivation mode for maize seed planting in Hexi and similar areas.

Keywords: maize seed production; drought resistance; TOPSIS model; combination weight optimization; comprehensive evaluation

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1. Introduction

In China, a country with a large agricultural industry and population, grain output has an essential role. However, the grain export yield of China is lower than in other countries [1]. Maize is one of the main grain crops in China, ranking 14th in average yield per unit area. By 2020, the planting area of maize reached around 38.4667 million, the unit price of commercial seeds was close to 36.75 RMB/kg [2], and the average maize yield was 5167 kg/ha, 45.4% lower than that of the United States. Providing more than two-thirds of the province's commodity grain, the Hexi Oasis Region is the main base of commodity grain in Gansu province and even the northwest region. Zhangye, located in the middle of the Hexi corridor, has become one of the main bases of maize seed production in China because of its unique climatic resources and superior irrigation conditions. However, the water demand of maize seed production is mainly supplemented by irrigation because the precipitation in this region is extremely scarce, with an average of only 130 mm annually. Due to the intense evaporation of precipitation, it is difficult to effectively store the limited rainfall as plant irrigation water, which seriously affects crop yield and the quality of maize seed production. Therefore, it is necessary to identify the optimal drought resistance measures for maize seed production.

The optimal drought resistance measures depend on crop type, variety characteristics, climatic conditions, planting patterns, and other factors [3–5]. Currently, mulching and adding super-absorbent resin have become important measures for soil water storage and preservation, as well as efficient water saving of farmland soil in inhibiting water evaporation [6]. Considerable studies showed that appropriate drought resistance measures could significantly improve farmland agroecological microclimate [7], promote crop root differentiation and growth [8], and increase leaf area index as well as dry matter accumulation [9], ultimately improving yield, water use efficiency [10], fruit appearance, and nutritional quality [11]. Therefore, the primary objective is to choose the appropriate drought resistance measures in fulfilling the large-scale, intensive, and standard construction of the maize seed production industry.

The confirmation of every index weight in the evaluation system is key to comprehensive quality evaluation. Many scholars put forward various index weight calculation models based on the related mathematical theory, such as the expert scoring method, weighing method, entropy value method, standard deviation method, etc. [12]. However, due to different information angles and emphases, these single evaluation method-based studies have their defects, including remarkable data fluctuations and difficulties in finding typical distribution rules, which greatly limit the accuracy of the evaluation results. The weights of crop growth, physiological nutrient uptake, yield, quality, evapotranspiration, water use efficiency, and other indexes of oilseed rape were acquired based on the gray relevancy analysis and entropy weight method (EWM) according to Du et al. [13], and the comprehensive evaluation of oilseed rape planting patterns was conducted using principal component analysis, ideal solution, and sequence preference similarity of dynamic technology. The subjective weight of evaluation indexes was determined by Li et al. [14] using the analytic hierarchy process (AHP) in establishing the evaluation model of the impact of drought on winter wheat yield, and the comprehensive weight of evaluation indexes was obtained, combined with the variation coefficient method, which greatly improved the reliability of the evaluation model. Thus, with full consideration of both the advantages and disadvantages of subjective and objective weighting methods, AHP and EWM were selected to determine the subjective and objective weight of evaluation indicators, respectively. In order to avoid the one-sidedness of a single weighting method caused by the limitations of subjective and objective weights, the combination weighting method of game theory (GT) was adopted to unify the subjective and objective weights from multiple sources of information, making the comprehensive decision analysis more reasonable and reliable.

Rational evaluation of agricultural production is a crucial way to promote scientific agricultural production. The TOPSIS model evaluates the merits of samples by calculating the relative distance of samples from positive and negative ideal solutions. It has no special requirements for sample size, and is not disturbed by the selection of reference sequences, which ensures the robustness of the evaluation effect. The application of TOPSIS in basic agricultural science mainly focuses on agricultural cultivated land quality evaluation [15,16], agricultural ecological environment evaluation [17,18], integrated management of water and fertilizer [19,20], irrigation water allocation and automatic network management [21,22], and agricultural economic benefit evaluation [23,24], confirming the evaluation effect of the TOPSIS model. Wang et al. [25] used the TOPSIS model to evaluate the yield and quality of radix isatidis under water deficit irrigation (WDI), revealing that continuous application of mild water deficit during the vegetative growth period and fleshy root growth period improved root quality, and the yield was not greatly reduced. The TOPSIS model was also used in a comprehensive analysis of planting priority planning of corn, rape, and soybean crops, and the three methods indicated significant difference at the probability level of 0.05 [26]. According to the grades assigned by the priority model, corn crop was superior to other plants. The comprehensive benefits of the rice planting model were evaluated by adopting the TOPSIS model [27]. The input and output of rice under different planting models were analyzed comprehensively, and an evaluation system with three first-level indicators and eight second-level indicators was established, with the final evaluation results showing that the direct sowing model of rice had the highest comprehensive benefits. Wang et al. [28] used the TOPSIS model to evaluate the management of different water and fertilizer amounts under drip irrigation in silty loam. Therefore, the TOPSIS method has been extensively applied to evaluate crop irrigation patterns, planting systems, and water and fertilizer applications, but the comprehensive evaluation research on crop drought resistance measures is still scarce, especially in the crop seeds-production industry in northwest China. The application of TOPSIS in crop evaluation mainly focuses on measured data collection, including yield, growth index, and irrigation amount. We introduce GT to improve the TOPSIS evaluation method, combining the subjective weight and objective weight, and putting maize seed yield, quality, water use efficiency, and economic benefits into full consideration. Therefore, our drought resistance evaluation is conducted based on multiple categories and indexes, which will provide a theoretical basis for drought resistance measures in selecting the most suitable maize seed production system in northwest China.

2. Materials and Methods

2.1. Description of the Experimental Site

The experiment was carried out at the comprehensive demonstration site (100°6′–100°52′ E, 38°32′–39°24′ N) of maize seed production by the integration of water and fertilizer in 2018 and 2019 in Tianjiazha Village, Ganzhou District of Gansu Province. The test area belongs to a temperate continental climate zone, with an altitude of 1474 m, annual average temperature of 7.25 °C, annual average precipitation of 130 mm, sunshine duration of 2975 h, and frost-free period of 157 days. The tested soil was sandy loam with medium fertility, the maximum field water capacity was 26.8%, the wilting coefficient was 7.3%, and the soil bulk density was 1.38 g/cm^3. The soil pH value within the 0–40 cm surface layer was 8.35, the organic matter content was 16.30 g/kg, and the soil available phosphorus, nitrogen, and potassium contents were 15.80, 45.32, and 125.36 mg/kg, respectively. The rainfall in 2018 was 118.2 mm and the evaporation was 1898.5 mm; in 2019, the rainfall was 207.5 mm and the evaporation was 1736.9 mm.

2.2. Experimental Design and Field Management

Maize seed (*Zea Mays* L.) was used as the test material, and the maize variety was NC242. It was provided by Gansu Zhongzhong International Seeds Co., Ltd. Zhangye City, China, with the planting density of 8.0 × 104/ha. The experiment was designed with white mulching film (WF), black mulching film (BF), straw mulching (SM), and open-ground seeds (CK) (Table 1) with three replications. There were 15 plots in total with the plot area of 132 m^2 (6 m × 22 m), and the split plot design was adopted. A drip irrigation belt produced by DAYU Water-Saving Group Co., Ltd. Jiuquan City, China was paved on the soil surface. In the first experimental year, the female seeds were sown on 17 April 2018, and the male seeds were sown in the first and second phases on 26 and 30 April, respectively, while the crops were harvested on 30 September 2018. In the second experimental year, the female seeds were sown on 12 April 2019, and the male seeds were sown in the first and second phases on 19 and 24 April, respectively, while the crops were harvested on 15 September 2019. The planting row ratio of parents was 1:4, with 1 line of father plants and 4 lines of mother plants oriented east–west. The female seeds were sown in wide-narrow rows with row spacing of 0.45 m and plant spacing of 0.2 m, while the male seeds were sown in the middle 2 lines of female parents with row spacing of 1.35 m and plant spacing of 0.2 m. Each plot was laid with 5 lines of film, and 2 lines of seeds were sown on each film. Basal fertilizer application was urea of 105 kg/ha, with P_2O_5 of 138 kg/ha and K_2O of 75 kg/ha, and the nitrogen topdressing dosage was 345 kg/ha. The topdressing was carried out at maize jointing, silking, and filling, with a topdressing ratio of 3:4:3. Drip irrigation was adopted with water and fertilizer coupling. During the growth period of maize seed in 2018, irrigation was carried out 7 times on the 51st, 65th, 73rd, 90th, 98th, 108th, and 116th day after sowing, with the irrigation quota of 400, 450, 450, 450, 500, 500, and 400 m^3/ha, respectively, for a total of 3150 m^3/ha. In 2019, the maize seed was irrigated 6 times during the growth period on the 46th, 62nd, 82nd, 95th, 101st, and 120th day after sowing, with the irrigation quota of 400, 550, 500, 400, 550, and 550 m^3/ha, respectively, for a total of 2950 m^3/ha.

Table 1. Experimental design.

Number	Treatment	Description of Treatments
SA	water retention agents	Forestry water retention agent (long-term) was selected from Gansu Hai Ruida Ecological Environmental Science and Technology Co., Ltd. Lanzhou, CN. The arable layer soil was turned over 30 cm before sowing and mixed with seed manure of 45.0 kg/ha and depth of 10–15 cm. Then, the drip irrigation belt was paved. Planter dibbling was used to sow female seeds first, and male seeds were sown in different stages.
WF	white mulching film	The arable layer soil was turned over 30 cm before sowing. Enough fertilizer was applied, and the drip irrigation belt was paved. A 120 cm wide white mulch film was used to cover, purchased from Shanxi Dongqing Agricultural Film Co., Ltd. Datong City, CN.No space was left between the films, and the films overlapped each other by about 5 cm. Soil was compacted at the interface. Planter dibbling was used to sow female seeds first, and male seeds were sown in different stages.
BF	black mulching film	Soil preparation, fertilizing, and drip irrigation belt pavement were the same as the WF treatment before covering the ground. A 120 cm wide black mulch film was used to cover, purchased from Shanxi Dongqing Agricultural Film Co., Ltd. No space was left between the films, and the films overlapped each other by about 5 cm. Soil was compacted at the interface. Planter dibbling was used to sow female seeds first, and male seeds were sown in different stages.
SM	straw mulching	Soil preparation, fertilizing, and drip irrigation belt pavement were the same as the WF treatment before covering the ground. The corn straw was crushed into 5–10 cm long sections by machinery, and evenly covered the bare ground between rows totaling 3500 kg/ha after the emergence of seedlings. Planter dibbling was used to sow female seeds first, and male seeds were sown in different stages.
CK	open-ground seed	Planter dibbling was used to sow female seeds first, and male seeds were sown in different stages without covering.

2.3. Measurements and Calculations

2.3.1. Soil Moisture Content

During the growth period, soil samples were randomly collected from the middle position of two maize plants every 15 days, and soil water content was determined to select the drying method. The soil depth was 100 cm with a gradient of 20 cm.

$$\theta = \mathrm{m}_a - m_b/m_b \tag{1}$$

where θ is the soil moisture content (%), m_a is the weight of a fresh soil sample (g), and m_b is the dry soil sample weight (g).

2.3.2. Plant Yield

The maize was harvested separately according to plot after maturity, and the grain was threshed and calculated after natural air drying. Three to five days before maize harvest, 20 maize plants with uniform growth were randomly selected from each plot to determine ear diameter, ear length, number of grains per ear, grain weight per ear, and 100-grain weight per plant.

2.3.3. Water Consumption and Water Use Efficiency

The water balance equation was used to calculate the water consumption of maize seed during the crop growth season:

$$ET = P + W_1 - W_2 + I + K - R \quad (2)$$

where ET is the total water consumption during the growth period (mm), P is the rainfall during the growth period, W_1 is the soil water storage capacity (mm) in the 0–100 cm soil layer after harvest, W_2 is the soil water storage capacity (mm) in the 0–100 cm soil layer at sowing time, I is the irrigation amount (mm), K is the inland water replenishment amount (mm) during the time period, and R is the surface runoff (mm) during the time period. The field capacity of this experiment was 26.8%.

Water use efficiency was calculated according to grain yield and water consumption during the growth period:

$$WUE = Y/ET \quad (3)$$

where Y is the grain yield of maize seed, and WUE is the water use efficiency (kg/m^3).

2.3.4. Quality

The contents of starch and soluble sugar were determined by the anthrone colorimetric method [29], the crude fat content was determined by the residual method [30], the crude protein content was determined by the Kjeldahl nitrogen determination method [31], and the crude fiber content was determined by the filter bag method [31].

2.3.5. Determination of Weights

Analytic hierarchy process (AHP) is an unstructured decision theory proposed by American operations research expert T.L. Saaty [32] that can help decision makers decompose complex problems into several levels and elements. The weight coefficients of different factors are generally obtained by simple comparison, judgment, and calculation of the factors. The specific steps are as follows:

(1) Establishment of the declining hierarchical structure. The relationship and affiliating among every factors were divided into multiple levels, including criterion layer, target layer, and scheme layer, according to the different characteristics of factors.
(2) Construction of pairwise judgment matrix. Pairwise comparison of factors in the criterion layer was carried out to construct a pairwise comparison matrix among factors, and a nine-point scale method was adopted (Table 2). Then, a pairwise comparison judgment matrix was formed from the quantization results $O - C = \left(\mathrm{a}_{ij}\right)_{n\times n}$.
(3) Calculation of the relative weight of the factors. The relative weight of the factors was calculated by the judgment matrix, and the weight of all the elements in this layer in the upper layer was calculated and further synthesized by the calculation results of the weight of a single layer. By weight sorting, the optimal scheme was selected and the consistency of the judgment matrix was tested to ensure the scientific and reliable calculation.

The next step is the calculation of the normalized weight coefficient. In previous papers, while using the AHP method to solve practical problems, one of the methods was used to derive the weight, leading to the deviation of the results. In this work, we used the arithmetic average method, geometric average method, and feature vector method to calculate the weight of each index.

Table 2. Judgment matrix scale definition.

Scaling	Meaning
1	Equally important
3	Slightly important
5	Obviously important
7	Strongly important
9	Extremely important
2, 4, 6, 8	The median of the above two adjacent judgments
reciprocal	A is compared to B if the scale is 3, then B is 1/3 compared to A

a. Arithmetic average method

$$\omega_i = \frac{1}{n}\sum_{j=1}^{n}\left(a_{ij}\Big/\sum_{k=1}^{n}a_{jk}\right) \quad (\mathrm{i} = 1,\ 2, \ldots\ldots,\ n) \tag{4}$$

b. Geometric average method

$$\omega_\mathrm{i} = \left(\prod_{j=1}^{n}a_{ij}\right)^{\frac{1}{n}}\Big/\sum_{k=1}^{n}\left(\prod_{j=1}^{n}a_{ij}\right)^{\frac{1}{n}} \quad (\mathrm{i} = 1,\ 2, \ldots\ldots,\ n) \tag{5}$$

c. Feature vector method

The maximum eigenvalue of the matrix $\lambda_{\max}$ and the corresponding eigenvector were calculated, and the processing was normalized to obtain the weight ω_i. The judgement matrix is $O - C = (a_{ij})_{n\times n}$, and the steps for checking consistency are as follows:

a. Calculation of consistency indicators (CI):

$$CI = (\lambda_{\max} - n)/(n-1) \tag{6}$$

b. Calculation of the corresponding average random consistency index (RI) (Table 3).
c. Calculation of consistency ratio CR:

$$CR = CI/RI \tag{7}$$

Table 3. Average random consistency index.

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
RI	0	0	0.52	0.89	1.12	1.24	1.36	1.41	1.46	1.49	1.52	1.54	1.56	1.58	1.59

If $CR < 0.1$, the consistency of the matrix is acceptable; otherwise, it should be modified.

The entropy weight method (EWM) was used to assign index weight depending on the discreteness of data [33], and the specific steps are as follows:

(1) The indexes to be calculated are formed into a numerical matrix to judge whether there is a negative number in the input matrix. If so, it should be re-normalized to a non-negative range to ensure that every element is a non-negative number to form a positive matrix $X = (X_\mathrm{ij})_{n\times m}$.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \cdots & \cdots & \cdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix} \tag{8}$$

So, the normalized matrix polar Z is:

$$z_{ij} = x_{ij} / \sqrt{\sum_{i=1}^{n} x_{ij}^2} \tag{9}$$

If there are negative numbers in the Z-matrix, another normalization method needs to be used for X.

The Z-matrix is obtained after the normalization of matrix X, and its standard formula is:

$$Z_{\mathrm{ij}} = \frac{x_{ij} - \min\{x_{1j}, x_{2j}, \ldots, x_{nj}\}}{\max\{x_{1j}, x_{2j}, \ldots x_{nj}\} - \min\{x_{1j}, x_{2j}, \ldots x_{nj}\}} \tag{10}$$

(2) The non-negative matrix Z is obtained through normalization, and the proportion of the ith sample in the jth index is calculated, which is regarded as the probability used in relative entropy calculation:

$$Z = \begin{bmatrix} z_{11} & \cdots & z_{1m} \\ \cdots & \cdots & \cdots \\ z_{n1} & \cdots & z_{nm} \end{bmatrix} \tag{11}$$

Calculation of the probability matrix P, with the calculation formula of each element P_{ij} in P, is as follows:

$$p_{ij} = z_{ij} \Big/ \sum_{i=1}^{n} z_{ij} \tag{12}$$

(3) Calculations of the information entropy of each indicator, the information utility value, and the entropy weight of each indicator through normalization were conducted as follows:

$$e_{\mathrm{j}} = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln(p_{ij}) \quad (j = 1, 2, \ldots, m) \tag{13}$$

$$d_j = 1 - e_j \tag{14}$$

$$W_{\mathrm{j}} = d_j \Big/ \sum_{j=1}^{m} d_j \quad (j = 1, 2, \ldots, m) \tag{15}$$

Index weight plays an important role in the comprehensive evaluation of a multi-factor system. The advantages of subjective and objective weight assignment were taken into full consideration, and the GT clustering model was used to combine the indexes to achieve the balance and unity of subjective and objective weight. The specific steps are as follows:

(a) Use different weighting methods (L kinds) to weight the participating indicators and construct the basic weight vector set.

$$u_k = \{u_{k1}, u_{k2}, \ldots, u_{kn}\} \quad (\mathrm{k} = 1, 2, \ldots, L) \tag{16}$$

(b) Construction of the linear combination q of weight vectors. The linear combination of the above L vectors is:

$$u = \sum_{k=1}^{L} \alpha_k u_k^T \quad \left(\alpha_k > 0, \sum_{\mathrm{k}=1}^{\mathrm{L}} \alpha_{\mathrm{k}}\right) \tag{17}$$

(c) where u is the weight set after linear combination, and α_k is the coefficient of linear combination. In order to minimize the deviation with each, the equilibrium idea of GT is used to optimize α_k, i.e.,

$$\min\left\|\sum_{j=1}^{L}\alpha_j u_j^T - u_i\right\|_2 \quad (i = 1, 2, \ldots, L) \tag{18}$$

According to the first derivative of Equation (18), the equivalent linear equations can be obtained:

$$\begin{bmatrix} u_1 \cdot u_1^T & u_1 \cdot u_2^T & \cdots & u_1 \cdot u_L^T \\ u_2 \cdot u_1^T & u_2 \cdot u_2^T & \cdots & u_2 \cdot u_L^T \\ \vdots & \vdots & \vdots & \vdots \\ u_L \cdot u_1^T & u_L \cdot u_2^T & \cdots & u_L \cdot u_L^T \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_L \end{bmatrix} = \begin{bmatrix} u_1 \cdot u_1^T \\ u_2 \cdot u_2^T \\ \vdots \\ u_L \cdot u_L^T \end{bmatrix} \tag{19}$$

(d) After obtaining the optimal linear combination coefficient $(\alpha_1, \alpha_2, \ldots \alpha_L)$ according to Equation (19), it is processed with the improved normalization formula [34], i.e.,

$$\alpha_k^* = |\alpha_k| \Big/ \sum_{k=1}^{L} |\alpha_k| \tag{20}$$

(e) By applying GT, the comprehensive weight vector is obtained by combining AHP and EWM:

$$u^* = \sum_{k=1}^{L} \alpha_k^* u_k^T \tag{21}$$

2.4. TOPSIS Model Evaluation Method

TOPSIS is a method for ranking finite evaluation schemes according to their proximity to idealized schemes, and it belongs to one of the multi-attribute decision-making methods [35,36]. The basic principle is to calculate the optimal solution and the worst solution, and then, according to the distance between each optimal solution and the optimal solution and the worst solution, if the evaluation scheme is closest to the optimal solution and furthest from the worst solution, it is the optimal solution. The calculation procedure is as follows:

(1) Construct the weighted evaluation matrix.

$$\tilde{Z}_{ij} = w_j \times z_{ij} = \begin{bmatrix} \tilde{z}_{11} & \tilde{z}_{12} & \tilde{z}_{12} & \tilde{z}_{1m} \\ \tilde{z}_{21} & \tilde{z}_{22} & \tilde{z}_{12} & \tilde{z}_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{z}_{n1} & \tilde{z}_{n2} & \cdots & \tilde{z}_{nm} \end{bmatrix} \tag{22}$$

(2) Determine positive and negative ideal solutions. First, the weighting matrix was forward—that is, the benefit index—and then the matrix Z was obtained by normalizing and removing the dimension. Finally, the positive ideal solution set was formed by the maximum value of each participating index in the scheme, and the negative ideal solution set was formed by the minimum value.

The maximum value of each column was regarded as the optimal vector: $Z^+ = (Z_1^+, Z_2^+, \cdots, Z_m^+)$

$$= \left(\max\left\{\tilde{z}_{11}, \tilde{z}_{21}, L, \tilde{z}_{n1}\right\}, \max\left\{\tilde{z}_{12}, \tilde{z}_{22}, L, \tilde{z}_{n2}\right\}, L, \max\left\{\tilde{z}_{1m}, \tilde{z}_{2m}, L, \tilde{z}_{nm}\right\}\right)$$

The minimum value of each column was regarded as the worst vector: $Z^- = (Z_1^-, Z_2^-, \cdots Z_m^-)$

$$= \left(\min\left\{\tilde{z}_{11}, \tilde{z}_{21}, L, \tilde{z}_{n1}\right\}, \min\left\{\tilde{z}_{12}, \tilde{z}_{22}, L, \tilde{z}_{n2}\right\}, L, \min\left\{\tilde{z}_{1m}, \tilde{z}_{2m}, L, \tilde{z}_{nm}\right\}\right)$$

(3) Calculate Euclidean distance. For each evaluation scheme, the distance to the positive ideal solution and the distance to the negative ideal solution were calculated as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{m}\left(\widetilde{Z}_j^+ - \widetilde{z}_{ij}\right)^2} \tag{23}$$

$$D_i^- = \sqrt{\sum_{j=1}^{m}\left(\widetilde{Z}_j^- - \widetilde{z}_{ij}\right)^2} \tag{24}$$

(4) Calculate the comprehensive score. According to Equation (25), the proximity Si of each scheme to the optimal scheme was first calculated, and then the comprehensive score of each evaluation scheme was obtained after normalization according to Equation (26):

$$S_{\text{i}} = D_i^- / \left(D_i^+ + D_i^-\right) \tag{25}$$

$$\widetilde{S}_i = S_i \bigg/ \sum_{i=1}^{n} S_i \tag{26}$$

2.5. Statistics Analysis

Duncan's multiple comparison method in SPSS (Version 19.0, Stanford University, Stanford, CA, USA) was used to compare the significance differences of data. Microsoft Excel 2010 (Microsoft 365) was used for data statistics and chart making, and MATLAB R2021b (MathWorks, Natick, MA, USA) was used for model solving.

3. Results

3.1. Selection of Evaluation Indicators

Ten specific indexes reflecting four attributes of maize seed yield, quality, water use efficiency, and economic benefit under different drought resistance measures were selected as the participating indexes. A comprehensive evaluation of drought resistance measures was carried out at different crop growth and physiology levels. Table 4 shows the effects of different drought resistance measures on maize yield, WUE, water consumption, output value, output value of one cubic meter of water, starch, crude protein, crude fat, and soluble sugar in seed production in 2018 and 2019.

Different drought resistance measures in both years had significant ($p < 0.05$) effects on water consumption, yield, water use efficiency, and crop quality during the whole growth period of maize seed (Table 4). Based on the data of 2018 and 2019, it was found that different drought resistant measures could significantly reduce the water consumption of maize seed during the whole growing period. Among them, water consumption is greatly reduced in the SM, which was 659.51 m^3/ha less than conventional open-field planting CK. Compared with CK, the WF, BF, and SA also reduced the water consumption during the whole growth period, and the decreases were 14.07%, 9.67%, 9.60%, and 9.13%, respectively. The WUE in CK was the lowest, with only 1.34 kg/m^3, and the WUE was significantly increased by 36.37–65.49% by adding drought resistance measures. The WUE in BF was the highest, with 2.22 kg/m^3, followed by WF, SA, and SM, which were significantly increased by 65.49%, 58.60%, and 42.11%, and 36.37%, respectively, compared with CK.

Table 4. Experimental results of the indicators for a comprehensive evaluation system.

Year	Treatment	Yield (kg/ha)	Starch (%)	Crude Protein (mg/g)	Crude Fat (%)	Soluble Sugar (%)	Crude Fiber (%)	Water Consumption (m^3/ha)	WUE (kg/m^3)	Output Value (RMB/ha)	Output Value of One Cubic Meter of Water (RMB/m^3)
2018	SA	8280.75 bc	67.57 a	9.08 ab	1.49 ab	13.28 ab	6.75 a	4211.35 ab	1.97 b	31301.24 bc	9.94 bc
	WF	9075.44 ab	64.96 ab	9.12 ab	1.33 bc	12.04 c	4.83 c	4027.18 bc	2.25 a	34305.16 ab	10.89 ab
	BF	9431.62 a	68.69 a	9.66 a	1.55 a	12.91 bc	4.53 c	4111.46 ab	2.29 a	35651.52 a	11.32 a
	SM	7566.39 c	67.90 a	9.14 ab	1.61 a	14.75 a	3.87 d	3985.60 c	1.90 b	28600.95 c	9.08 c
	CK	6229.51 d	62.78 b	8.47 b	1.15 c	10.37 d	5.61 b	4529.03 a	1.38 c	23547.55 d	7.48 d
2019	SA	7915.08 b	66.98 ab	8.92 bc	1.31 cd	12.76 ab	6.29 a	4305.71 bc	1.84 bc	28098.53 b	9.52 b
	WF	8845.55 a	65.11 ab	8.45 c	1.42 bc	11.84 bc	4.37 b	4439.24 ab	1.99 ab	31401.70 a	10.64 a
	BF	9317.17 a	70.18 a	10.58 a	1.84 a	12.15 b	4.46 b	4360.85 bc	2.14 a	33075.95 a	11.21 a
	SM	7128.76 c	68.14 ab	9.61 ab	1.51 b	13.66 a	5.90 a	4067.93 c	1.75 c	25307.10 c	8.58 c
	CK	6305.24 d	63.10 b	7.79 c	1.22 d	11.03 c	4.51 b	4843.51 a	1.30 d	22383.60 d	7.59 d

Note: Within each column, different letters after the values indicate significant differences at $p < 0.05$ according to Duncan's test.

Different drought resistance measures significantly ($p < 0.05$) increased maize seed yield (Table 4). Based on the analysis of the average data in 2018 and 2019, we found that the yield of BF treatment was marked the highest with 9374.40 kg/ha^2, followed by WF treatment and SA treatment with 8960.50 and 8097.92 kg/ha^2, respectively. Compared with CK, the yield of these three treatments was significantly increased by 49.57%, 42.97%, and 29.21%, respectively. Although the increase rate of straw mulching treatment was lower than in other drought resistance measures, the rate was still notably increased by 17.24% compared with CK. The effect of different drought resistance measures on output was consistent with the change in yield and could significantly increase the water output by 1.30–3.74 RMB/m^3, among which BF and WF treatment were the most significant, with increases of 3.74 RMB/m^3 and 3.24 RMB/m^3, which were 49.57% and 42.97% higher than CK. Although the increase rate of SA and SM treatment was lower than that of plastic film mulching, it was still increased by 2.20 RMB and 1.30 RMB/m^3 compared with CK, which was significantly increased by 29.20% and 17.23%. Different drought resistance measures had different effects on quality components of maize seed production. BF treatment significantly increased starch content of maize seed, followed by SM, which was significantly increased by 10.32% and 8.07% compared with CK. Although starch content in SA and WF treatments increased by 6.89% and 3.33%, there was no significant difference ($p > 0.05$). The crude protein and crude fat contents of maize seed were greatly increased by different drought resistance measures, among which the BF was the highest, with 10.12 mg/g and 1.70%, respectively, followed by SM, SA, and WF. Compared with CK, the crude protein and crude fat contents in all the treatments were significantly increased by 24.48%, 15.31%, 10.70%, and 8.06% and 43.04%, 31.65%, 18.14%, and 16.03% respectively. Different drought resistance measures were beneficial to the accumulation of soluble sugar content in maize seed, among which the accumulation effect of SM was the best, with 14.21%, followed by SA, BF, and WF, which were significantly increased by 32.76%, 21.68%, 17.10%, and 11.59% compared with CK. The application of a water retaining agent could significantly increase the crude fiber content of maize seed by 28.85%, while plastic film mulching and straw mulching were not suitable for the accumulation of crude fiber content.

Compared with CK, the grain crude fiber content in BF treatment decreased the most (11.17%), followed by WF treatment (9.09%), and the difference was significant. The grain crude fiber content in SM treatment decreased the least (3.46%), and the difference was not significant.

As a key industry, it is important to select the best drought resistance measures for maize seed production to increase WUE and grain quality on the basis of yield increase. In this study, the important nutrients contained in seeds such as seed coating, embryo, endosperm, etc., comprised the grain quality index, the yield was selected as the yield index, the output value and the water output were selected as the economic benefit index, and the water consumption and use efficiency during the whole growth period were selected as the water use status index. Taking 10 indexes of the four attributes into consideration, the drought resistance measures with high quality, high yield, and high efficiency of maize seed in the semi-arid area of northwest China were evaluated by mathematical statistics.

3.2. Determination of the Weight of Indices in the Evaluation System

3.2.1. The Analytic Hierarchy Process

Analytic hierarchy process (AHP) is a combination of qualitative and quantitative, systematic and hierarchical analysis methods, which can reflect decision makers' experience in different indicators. Based on a certain scale, a coherent hierarchical relationship was constructed according to the importance of the indexes, and the index weighting number was obtained. The main steps of the subjective weighting method were as follows:

(1) Establishment of a hierarchy. In order to find suitable drought resistance measures for maize seed production in northwest China, the evaluation index system was constructed considering the concepts of yield, water use efficiency, quality, and economic benefits and the principles of scientific, representativeness, and consistency. In addition, an index decomposition was conducted to the four dimensions that were needed in the study of drought resistance measures. The comprehensive hierarchical evaluation model was constructed by using the principle of the analytic hierarchy process (Figure 1).

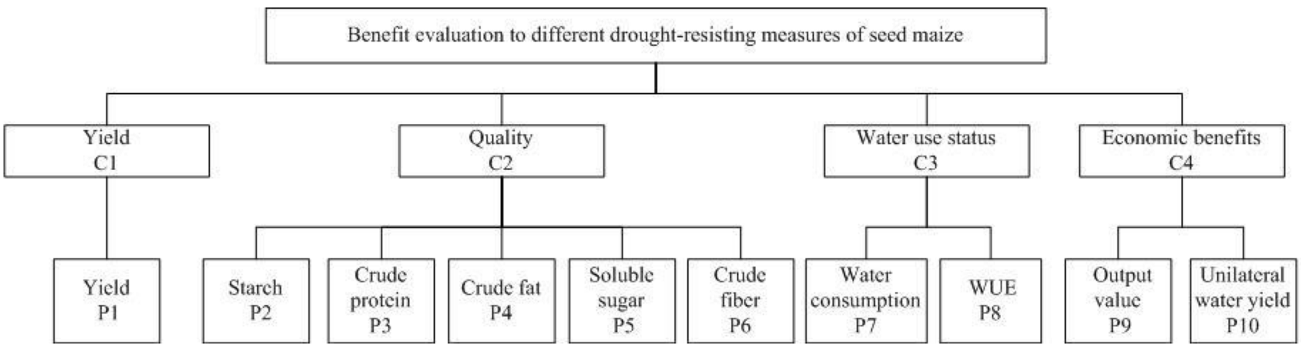

Figure 1. Hierarchical structure diagram.

(2) Construction of a judgment matrix. The weight was calculated by constructing the judgment matrix $O - C = (a_{ij})n \times n$ according to the 1–9 ratio scale method (Table 5).

Table 5. Judgment matrix $O - C$.

O	C1	C2	C3	C4
C1	1	2	3	5/3
C2	1/2	1	7/3	2
C3	1/3	3/7	1	2
C4	3/5	1/2	1/2	1

(3) Calculation of the subjective weights using the judgment matrix (wsj). In order to ensure the rationality of the results, the arithmetic average method, geometric average method, and feature vector method were adopted in this study to calculate the weights.

The calculation results of MATLAB software are shown in Table 6 with CR = 0.0796 < 0.10. Therefore, the judgment matrix $O-C$ had acceptable consistency. The weight coefficients calculated by the arithmetic average method, geometric average method, and eigenvector method were basically the same. Finally, feature vectors were selected as the subjective weight coefficients of each evaluation index, and the weights of each index layer were as follows (Table 7).

Table 6. The weight coefficients of the judgment matrix $O-C$.

Method	C1	C2	C3	C4	λ_{max}	CI	CR
Average method	0.4023	0.2754	0.1731	0.1493	4.2124	0.0708	0.0796
Geometric means method	0.4071	0.2830	0.1674	0.1425			
Eigenvector method	0.4070	0.2774	0.1699	0.1456			

Table 7. Subjective weight of evaluation index (AHP).

Target Layer	Criterion Layer (Weights)	Indicator Layer			Comprehensive Weight
		Index		Weights	
Benefit evaluation of different drought resistance measures of maize seed	Yield C1 (0.4070)	Yield	P1	1	0.4070
	Quality C2 (0.2774)	Starch	P2	0.1161	0.0322
		Crude protein	P3	0.2502	0.0694
		Crude fat	P4	0.1269	0.0352
		Soluble sugar	P5	0.4047	0.1123
		Crude fiber	P6	0.1021	0.0283
	Water use status C3 (0.1699)	Water consumption	P7	0.2500	0.0425
		WUE	P8	0.7500	0.1274
	Economic benefits C4 (0.1456)	Output value	P9	0.3333	0.0485
		Output value of one cubic meter of water	P10	0.6667	0.0971

3.2.2. Entropy Weight Method

EWM is an objective weighting method which can avoid the unweighted overlapping calculation of evaluation factors and artificial subjective interference. The information entropy theory is used to determine the index weight according to the amount of information provided by the observation value of each index.

According to the data in Table 4, the constructed matrix X was obtained after standardization, and the objective weight of the evaluation index was calculated by using Equations (8)–(15). The calculation results were as follows in Table 8.

Table 8. Objective weight of evaluation indicators (EWM).

Year	Yield P1	Starch P2	Crude Protein P3	Crude Fat P4	Soluble Sugar P5	Crude Fiber P6	Water Consumption P7	WUE P8	Output Value P9	Output Value of One Cubic Meter of Water P10
2018	0.10168	0.10385	0.09884	0.10204	0.10440	0.10151	0.09055	0.09372	0.10168	0.10173
2019	0.09960	0.09652	0.10856	0.13416	0.09894	0.10630	0.07871	0.07796	0.09960	0.09963

3.2.3. Combination Weights

The subjective weight obtained by AHP and the objective weight obtained by EWM were optimized and combined with the GT, and the combined weight values of each index were obtained according to Equations (16)–(21) (Table 9).

Table 9. The weight of each index in the evaluation system.

Indicator		Subjective Weight	Objective Weight		Combined Weights	
			2018	2019	2018	2019
Yield	P1	0.4070	0.10168	0.09960	0.4082	0.3845
Starch	P2	0.0322	0.10385	0.09652	0.0319	0.0369
Crude protein	P3	0.0694	0.09884	0.10856	0.0693	0.0723
Crude fat	P4	0.0352	0.10204	0.13416	0.0350	0.0425
Soluble sugar	P5	0.1123	0.1044	0.09894	0.1123	0.1113
Crude fiber	P6	0.0283	0.10151	0.10630	0.0280	0.0340
Water consumption	P7	0.0425	0.09055	0.07871	0.0423	0.0452
WUE	P8	0.1274	0.09372	0.07796	0.1275	0.1238
Output value	P9	0.0485	0.10168	0.09960	0.0483	0.0523
Output value of one cubic meter of water	P10	0.0971	0.10173	0.09963	0.0971	0.0973

3.3. Integrated Evaluation Model Based on the Improved TOPSIS Method

The TOPSIS method is an evaluation model for approximating ideal solutions, proposed by Hwang and Yoon in 1981. Its calculation basis is derived from objective data with appropriate objectivity and the results can accurately reflect the gap between various evaluation schemes, being suitable for the comparison and selection of multiple schemes [35]. Based on the improved TOPSIS method, the comprehensive evaluation models of different drought resistance measures were established (Figure 2). The calculation results are shown in the figures below.

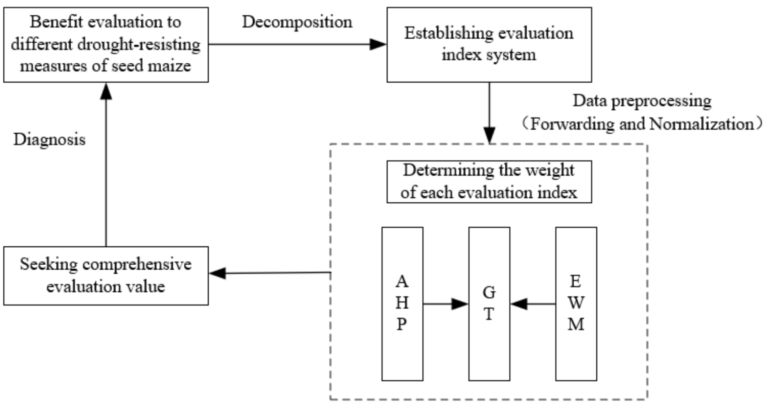

Figure 2. Construction process of comprehensive evaluation model.

According to the initial evaluation data of each drought resistance measure, the cost index in the judgment matrix was further processed, followed by normalized treatment. Among them, crude fiber P6 and water consumption P7 were selected as cost indexes, while others were selected as benefit indexes. Normalized treatment was carried out for five drought resistance treatment indexes, and the standardized weighted matrix $\widetilde{Z} = \left(\widetilde{Z}_{ij}\right)_{10\times 5}$ (Equation (22)) was constructed by using the comprehensive weight determined by GT. The positive and negative ideal solutions are presented in Table 10.

Table 10. The weighted matrix of each standardized evaluation indicator.

Year	Treatment Number	Yield	Starch	Crude Protein	Crude Fat	Soluble Sugar	Crude Fiber	Water Consumption	WUE	Output Value	Output Value of One Cubic meter of Water
2018	SA	0.1844	0.0145	0.0309	0.0162	0.0523	0.0000	0.0148	0.0566	0.0218	0.0439
	WF	0.2021	0.0140	0.0311	0.0145	0.0474	0.0126	0.0234	0.0646	0.0239	0.0481
	BF	0.2101	0.0148	0.0329	0.0169	0.0508	0.0146	0.0195	0.0658	0.0249	0.0500
	SM	0.1685	0.0146	0.0311	0.0176	0.0581	0.0189	0.0253	0.0546	0.0199	0.0401
	CK	0.1387	0.0135	0.0288	0.0125	0.0408	0.0075	0.0000	0.0396	0.0164	0.0330
	Optimal vector	0.2101	0.148	0.0329	0.0176	0.0581	0.0000	0.0000	0.0658	0.0249	0.0500
	Worst vector	0.1387	0.135	0.0288	0.0125	0.0408	0.0189	0.0253	0.0396	0.0164	0.0330
2019	SA	0.1706	0.0166	0.0316	0.0169	0.0516	0.0000	0.0214	0.0558	0.0232	0.0432
	WF	0.1906	0.0161	0.0300	0.0183	0.0478	0.0203	0.0161	0.0603	0.0259	0.0482
	BF	0.2008	0.0174	0.0375	0.0237	0.0491	0.0193	0.0192	0.0649	0.0273	0.0508
	SM	0.1536	0.0168	0.0341	0.0194	0.0552	0.0041	0.0309	0.0530	0.0209	0.0389
	CK	0.1359	0.0156	0.0276	0.0157	0.0446	0.0188	0.0000	0.0394	0.0185	0.0344
	Optimal vector	0.2008	0.0174	0.0375	0.0237	0.0552	0.0000	0.0000	0.0649	0.0273	0.0508
	Worst vector	0.1359	0.0156	0.0276	0.0157	0.0446	0.0203	0.0309	0.0394	0.0185	0.0344

3.4. Results Analysis

The higher the comprehensive evaluation value Si, the better the comprehensive benefit. The rank of different drought resistance measures according to the calculated value of normalized score $\tilde{S}_i$ (Equation (26)) is shown in Table 11. The rank of comprehensive evaluation value was BF > WF > SM > SA > CK in 2018 and BF > WF > SM > SA > CK in 2019. The decision evaluation of the TOPSIS method using GT to optimize weight was the same in the two-year experiment, and BF was the best drought resistance measure in the two growing seasons, followed by WF, with S_i values of 0.8195, 0.7772, and 0.7806, 0.6773, respectively. The worst evaluation in the two years was CK, with S_i values of 0.1729 and 0.3232, respectively. The worst drought resistance measure in both years was CK, with S_i values of 0.1729 and 0.3232, respectively. After two years of the field experiment, different drought resistance measures were tested, such as functional polymer materials, biology, physics, and so on, which proved that BF had practicability in improving maize seed yield and efficiency, and had an overall effect on high quality, high yield, and high efficiency, and thus could be used as the best drought resistance strategy in arid areas of northwest China.

Table 11. Sequencing and calculation of the progress of each test process.

Treatment Number	2018					2019				
	D^+	D^-	S_i	$\tilde{S}_i$	Ranking	D^+	D^-	S_i	$\tilde{S}_i$	Ranking
SA	0.1365	0.1266	0.4812	0.1632	4	0.1406	0.1318	0.4839	0.1719	4
WF	0.0555	0.1935	0.7772	0.2636	2	0.0860	0.1804	0.6773	0.2405	2
BF	0.0443	0.2013	0.8195	0.2779	1	0.0581	0.2068	0.7806	0.2772	1
SM	0.0822	0.1900	0.6979	0.2367	3	0.1321	0.1619	0.5508	0.1956	3
CK	0.2139	0.0447	0.1729	0.0586	5	0.2135	0.1020	0.3232	0.1148	5

4. Discussion

4.1. Analysis and Evaluation of Measured Values Based on Indicators

The results show that the yield of maize seed is considerably improved by implementing drought resistance measures. Compared with CK, BF, WF, SA, and SM were significantly increased by 47.77–51.40%, 40.29–45.68%, 25.53–32.93%, and 13.06–21.46%, respectively. It could be seen that the yield of BF was the highest, followed by WF, SA, and SM, while there was no significant difference between BF and WF. Zhao [37], Zhang [38], and Jin et al. [39] concluded that drought resistance measures such as plastic film mulching, SA, and SM could all improve maize yield, consistent with our experimental conclusions, but there were some slight differences in the yield-increase effect, which may be caused by crop varieties, experimental area environments, and irrigation quotas. At the same time, it was found that the drought resistance measures could also significantly improve WUE. Compared with CK, BF and WF significantly increased the WUE by 64.12–66.78%, 47.77–51.40% and 53.06–63.84%, 40.29–45.68%, respectively. The increase rates of the SA and SM were lower than that of mulching with plastic film. It could be seen that plastic film mulching was more conducive to improving WUE, and black plastic film mulching was more advantageous. The same conclusion was also confirmed in the study of Sun et al. [40].

In addition, previous studies showed that crop quality could be improved and the output could also be increased at the same time under the drought resistance measures [41,42]. It was found that different drought resistance measures had different effects on quality components of maize seed. The contents of starch, crude protein, ether extract, and soluble sugar in maize seed grains increased by 9.41–11.22%, 14.05–35.82%, 34.78–50.82%, and 10.15–24.49%, respectively, compared with no mulching. Although the WF, SA, and SM could also improve the quality index content of maize seed, the improvement range was lower than that of the BF, which was not beneficial to the improvement of comprehensive quality. Wang et al. [43] found that black plastic film mulching could improve crop quality, which is consistent with this conclusion.

It could be seen that the response characteristics and degree of different evaluation indexes to drought resistance measures were not consistent, and a single index could not be reasonably evaluated. Therefore, it was necessary to establish a comprehensive evaluation model with multiple factors and layers.

4.2. CW of Evaluation Indicators

Weight is a value used to measure the effect of each statistical item on the whole. It represents the importance of an index item in the system [44]. At present, there are many methods to determine the weight of indicators, which are generally divided into subjective and objective weight determination methods [45]. Since the measures of drought resistance evaluation were not "absolutely" optimal and the interaction mechanism was also relatively complex, problems existed in each index and the subjective evaluation process. GT, namely empowerment methods, can be used to seek coordination or compromise among various "conflicts" to achieve the optimal decision [46]. This study fully considered the limitations and one-sidedness of subjective and objective weighting methods. Firstly, AHP and EWM were used to obtain the subjective and objective weights of evaluation indicators, respectively, and then the combined weights based on GT were constructed, which could make the weight results better reflect the advantages of various weighting methods and overcome the limitations of a single weighting method. A more ideal index weight value was obtained for evaluating drought resistance measures of maize seed production.

However, faced with different research objects and environments, weight definition and allocation become more difficult because the mathematical analysis and derivation are cumbersome, with poor operability and applicability. Therefore, in future research and applications, computer programming, machine learning, model training, and other techniques should be combined. The samples' properties and the regional environment should also be put into consideration. In addition, it is necessary to test the consistency of indicators at all levels and check the "conflict" of various weighting methods, so as to avoid the blindness of combination and further improve the rationality and reliability of evaluation results.

4.3. Comprehensive Evaluation Results of Drought Resistance Measures

A comprehensive evaluation method refers to a method that evaluates multiple indicators and units simultaneously in a systematic and standardized way [47]. Su et al. [48] performed a comprehensive evaluation of different drought-resistant cultivation measures of cassava based on principal component analysis, and obtained adequate evaluation results. In this study, the TOPSIS comprehensive evaluation model by combination weighting was used to evaluate the yield, quality, water use status, and economic benefits of maize seed in northwest China. According to the results, BF treatment achieved the unity of high quality, high yield, and high efficiency, in agreement with the measured results. This is similar to the analysis and evaluation conclusions of Xiao et al. [49] on different drought resistance measures of maize seed production under the combined application of bacterial fertilizers. Therefore, this model not only realized the optimization and screening of drought resistance measures to a certain extent, but also provides the possibility of selecting a rational crop evaluation model in arid areas.

Due to the condition limitations, there are still some deficiencies in this work. The experiment only gave comprehensive evaluation scores to five different drought resistance measures from 10 secondary evaluation standard level indicators. However, as the research object of the study was maize seed, the key points should not only be seed yield, quality, and storage, but seed germination, antioxidant enzyme activity, gene expression, and so on should also be subjected to experimental study, requiring germination tests and research on the maize seed harvest in order to filter and popularize it.

5. Conclusions

Ten different evaluation indexes were selected to construct the optimized evaluation index model considering the four aspects of maize seed yield, quality, water use status, and economic benefit. AHP and EWM were used to assign subjective and objective weights to the indexes. Making full use of the index information in the original data and then calculating the comprehensive weight of the two weighting methods by GT can avoid the one-sidedness of a single weighting method. In the comprehensive weight obtained from the two-year experimental data, the maximum weights of maize seed yield were 0.4082 (2018) and 0.3845 (2019). Considering five drought resistance measures put forward for maize seed in the arid areas of northwest China, the optimization model was established based on the TOPSIS theory of combination weighting to calculate the relative closeness degree of each scheme. The normalized scores of each scheme were 0.1632, 0.2636, 0.2779, 0.2367, and 0.0586, respectively, in 2018, and 0.1719, 0.2405, 0.2772, 0.1956, and 0.1148, respectively, in 2019. Black film mulching (BF) was determined to be the best drought resistance measure. During the practical production of maize seed, the optimized scheme is well adapted and is able to improve the output and water use efficiency to guarantee economic benefits. This study proved that the multi-attribute decision-making model of TOPSIS based on GT with combination weight is scientific and effective, providing a new mechanism of identifying the optimal choice.

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