Agricultural Vulnerability Assessment of High-Temperature Disaster in Shaanxi Province of China

Yining Ma1,2,3, Suri Guga1,2,3, Jie Xu1,2,3, Yulin Su1,2,3, Xingpeng Liu1,2,3, Zhijun Tong1,2,3 and Jiquan Zhang1,2,3,*

1 School of Environment, Northeast Normal University, Changchun 130024, China; mayn818@nenu.edu.cn (Y.M.); surgg146@nenu.edu.cn (S.G.); xuj463@nenu.edu.cn (J.X.); suyl686@nenu.edu.cn (Y.S.); liuxp912@nenu.edu.cn (X.L.); gis@nenu.edu.cn (Z.T.)
2 State Environmental Protection Key Laboratory of Wetland Ecology and Vegetation Restoration, Northeast Normal University, Changchun 130024, China
3 Key Laboratory for Vegetation Ecology, Ministry of Education, Changchun 130024, China
* Correspondence: zhangjq022@nenu.edu.cn; Tel.: +86-135-9608-6467

Abstract: The negative impact of high-temperature disaster on agricultural production is becoming more and more serious, and reducing the vulnerability to high-temperature disaster is fundamental to achieving sustainable agricultural development. This study is mainly focused on the vulnerability to agricultural high-temperature disaster in Shaanxi Province, China. Firstly, 15 indicators were selected from the perspectives of exposure, sensitivity, and adaptability. Secondly, the combined weighting method (Critic-G1 model) was used to determine the weight of each index. Based on the aforementioned procedures, the Kullback–Leibler (KL)-distance-improved TOPSIS model was utilized to evaluate the vulnerability. Lastly, the obstacle model was used to analyze the influencing factors and to make recommendations for disaster prevention and mitigation. The results show that: (1) The improved TOPSIS model was closer to the results of the synthetical index method. (2) The northern and southern area of Shaanxi is more vulnerable to high-temperature disaster, especially in Ankang and Tongchuan. Low values are distributed in the Guanzhong Plain. (3) Sensitivity is the biggest obstacle to reducing the vulnerability to high-temperature disaster. Among the influencing factors, the meteorological yield reduction coefficient of variation, multiple cropping index and per capita net income of rural residents of the obstacle are high. Decreasing sensitivity should be accompanied by increasing adaptability to improve regional disaster preparedness and mitigation. The results of this study can provide a basis for the development of agricultural high-temperature disaster mitigation and loss reduction strategies and provide new ideas for future research.

Keywords: improved TOPSIS model; multiple-criteria decision-making (MCDM); vulnerability assessment; obstacle analysis; G1-Critic; agricultural high-temperature disaster

1. Introduction

Climate change is one of the most important environmental problems facing mankind in the 21st century [1–3]. Among the 12 warmest years since 1850, the warming trend in the past 12 years has been 0.74 °C, which is 0.6 °C higher than the trend predicted in the AR3 of the IPCC. Over the past 50 years, the warming trend has been 0.13 °C per decade, almost double the rate over the past 100 years. The AR6 of the IPCC stated that the global surface temperature has increased by about 1.1 °C compared to 1850–1900, a level of warming not seen since 125,000 years ago [4–6]. Undoubtedly, global warming caused by climate change will trigger more frequent and intense extreme high-temperature events [7–10]. China has a vast territory, complicated topography and changeable weather system, which makes it vulnerable to meteorological disasters [11–13]. In the wave of extreme high-temperature weather caused by global warming, China, as a large agricultural country, will face serious adverse threats and have a serious impact on agricultural ecosystem and...
national economic security [14–17]. Strategic measures to prevent and mitigate disasters in agriculture are of great importance for maintaining sustainable, healthy and stable economic development [18]. Therefore, the causes of agricultural high-temperature disaster vulnerability were analyzed and the methods to reduce vulnerability were found out. Exploring ways to prevent and mitigate the risk of high-temperature disaster has become an urgent task.

In recent years, scholars have carried out considerable research on agricultural vulnerability assessment [19–22]. Shahid and Behrawan [23] selected seven indicators to evaluate drought vulnerability in Bangladesh in terms of both socio-economic and physical/infrastructural factors. Zhang et al. [24] used a fuzzy variable set model for a comprehensive assessment of agricultural drought risk in Liaoning Province, China, starting from the direction of hazard, exposure, vulnerability, and drought resilience. Zhou et al. [25] combined the entropy principle and fuzzy pattern recognition method to analyze agricultural drought vulnerability in Bengbu, China. Ma et al. [26] conducted a comprehensive risk assessment of high-temperature disaster in kiwifruit in Shaanxi Province based on natural disaster system theory. Wirehn et al. [27] considered the synthetical index method to be a simple and effective method of vulnerability assessment. Nam et al. [28] evaluated the adaptive capability and irrigation vulnerability of agricultural reservoirs in South Korea built on a concept of probability theory and reliability analysis. Sahana et al. [29] used seven methods to evaluate drought vulnerability in India. The results showed that the TOPSIS model was the most robust for drought vulnerability assessment. However, few of these studies have addressed the evaluation of vulnerability to high-temperature disaster in agriculture. Therefore, it is necessary to explore the index system and evaluation method suitable for the vulnerability evaluation of agricultural high-temperature disaster.

Due to the complexity and comprehensiveness of agricultural high-temperature disaster, the realization of vulnerability assessment has been turned into a problem of multi-criteria decision analysis (MCDA) [30,31]. Currently, there are many MCDA methods, such as AHP, ANP, VIKOR, TOPSIS, MOORA, etc. [32–38]. The technique for Order Preference by Similarity to Ideal Solution (TOPSIS) proposed by C.L. Hwang and K. Yoon in 1981 is widely used [39,40]. The basic principle is tantamount to ranking the evaluation objects by detecting the proximity between the positive ideal solution and negative ideal solution [41,42]. Alternatives that are closest to the positive ideal solution and farthest from the negative ideal solution are considered to be given priority [43]. TOPSIS methods are widely used, such as national energy development [44–46], soil and water resources assessment [47], ecological and environmental risk assessment [48–51], and vulnerability assessment [52–56]. However, there are currently no scholars using the TOPSIS model to evaluate agricultural high-temperature disaster vulnerability and for generating decision support options. Therefore, we have attempted to combine the TOPSIS model with natural disaster theory to evaluate the vulnerability to high-temperature disaster in agriculture.

This study seeks to improve the TOPSIS model and apply it to the study of agricultural high-temperature disaster vulnerability assessment. Our aims consisted of the following: (1) Vulnerability assessment indicators are selected in terms of exposure, sensitivity, and adaptability. (2) To obtain the weights for each indicator, we combined a subjective weight method (G1 method) with an objective weight method (critic based on an improved entropy weighting method). (3) We used the improved TOPSIS model and the traditional TOPSIS model to evaluate the vulnerability to agricultural high-temperature disaster in Shaanxi Province. (4) We use the synthetical index method to verify the rationality of the evaluation results of two TOPSIS models. (5) Using an obstacle model to analyze the causes of vulnerability to high-temperature disaster in different regions and to make appropriate recommendations for disaster prevention and mitigation.

2. Study Area and Data Sources

Shaanxi Province is located inland in the northwest (31°42′–39°35′ N, 105°29′–111°15′ E), in the marginal zone of the summer monsoon (Figure 1). With its complex and variable
underlying surface and diverse climate types, it is part of the sensitive areas in terms of global climate change response. Bounded by the Beishan Mountains and the Qinling Mountains, the province consists of three major landform areas: the northern Shanbei Plateau, the Guanzhong Plain, and the Qinba Mountains. The special geographical conditions make Shaanxi province straddle the northern temperate and subtropical zones, with four distinct seasons and hot summer. In recent years, extreme high-temperature events occur frequently in summer, which has a serious impact on local agricultural production.

Figure 1. Geographical location of the study area.

Meteorological data that included daily observations of the maximum temperature from 37 meteorological stations in Shaanxi Province were collected from the National Meteorological Information Center (http://data.cma.cn/ accessed on 26 May 2021) for the period from 1960 to 2020. Data that are abnormal or missing longer time series were removed to ensure the integrity of the data for that time period. Historical disaster data were obtained from the statistical yearbooks of Shaanxi, and the China Meteorological Disaster Dictionary-Shaanxi Volume. The data on agricultural production conditions and socio-economics in Shaanxi Province is from the 1990–2019 Statistical Yearbook of Shaanxi, China Rural Statistical Yearbook, and China Statistical Yearbook for Regional Economy.

3. Methodology
3.1. Collection of Evaluation Indexes

Vulnerability, as an important component of risk assessment, characterizes the degree of disaster suffered [57–59]. The IPCC defines vulnerability as the degree to which a system is vulnerable or unable to cope with the adverse effects of climate change [60]. With the advancement of vulnerability research, vulnerability is considered to be the combined result of exposure, sensitivity and adaptability (Figure 2) [61,62].
3.1.1. Exposure (XE)

1. Frequency of light heat events (XE1): Daily maximum temperature ≥ 35 °C for 3 days. Positive Indicator. Unit: % [26,63–65].
2. Frequency of moderate heat events (XE2): Daily maximum temperature ≥ 35 °C for 5 days. Positive Indicator. Unit: %.
3. Frequency of heavy heat events (XE3): Daily maximum temperature ≥ 35 °C for 7 days. Positive Indicator. Unit: %.
4. Arable land cover (XE4): It is the ratio of the total area of arable land to the total area of the region, reflecting the extent of arable land use. Positive Indicator. Unit: %.
5. Multiple cropping index (XE5): It is the ratio of the total area of crops sown in an area to the area of arable land in that area. Positive Indicator. Unit: %.

3.1.2. Sensitivity (XS)

1. Meteorological yield reduction rate (XS1): Reflects the average level of yield reduction when a crop is threatened by a natural disaster. Positive Indicator. Unit: % [8].
2. Meteorological yield reduction coefficient of variation (XS2): Reflects the degree of dispersion of crop negatively relative to meteorological yield. Positive Indicator. Unit: / [66].
3. Share of the agricultural population (XS3): The share of the agricultural population in the population of the whole region. Positive Indicator. Unit: % [67,68].
4. Per capita farmland area (XS4): Reflects the amount of pressure that the population exerts on the land. Negative Indicator. Unit: hm²/person [26,37].
5. Agricultural GDP share (XS5): Reflects the extent to which the region relies on agricultural production. Positive Indicator. Unit: % [69].

3.1.3. Adaptability (XA)

1. Per capita net income of rural residents (XA1): It is the total final consumption expenditure and savings available to rural residents. Negative Indicator. Unit: yuan [26,37,70].
2. Total agricultural machinery power (XA2): Reflects the occurrence of high-temperature disaster, through irrigation to reduce the capacity of temperature mitigation. Negative Indicator. Unit: kW.
3. Number of people with junior high school education or above (XA3): Reflects the population’s level of awareness of high-temperature disaster and ability to cope with disasters. Negative Indicator. Unit: person.
4. Total agricultural insurance premiums (XA4): To protect against the economic losses caused by natural disasters and accidents in the process of agricultural production. Negative Indicator. Unit: yuan.
3.2. Vulnerability Assessment Model and Weighting Calculation

3.2.1. Traditional TOPSIS Method

With \( n \) evaluation objects and \( m \) evaluation indexes, and the raw data could be written as matrix \( X = (X_{ij})_{n \times m} \). For high optimal (the larger the better) Equation (1) and low optimal (the smaller the better) Equation (2), index was normalized change [56,71,72]:

\[
Z_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{n} X_{ij}^2}} \quad (1)
\]

\[
Z_{ij} = \frac{1}{X_{ij}} \sqrt{\sum_{i=1}^{n} \left( \frac{1}{X_{ij}} \right)^2} \quad (2)
\]

The normalized matrix \( Z = (Z_{ij})_{n \times m} \) is obtained, and the best and worst vectors formed by the maximum and minimum values of each column are, respectively, recorded as follows:

\[
Z^+ = (Z_{\max 1}, Z_{\max 2}, \cdots, Z_{\max m}) \quad (3)
\]

\[
Z^- = (Z_{\min 1}, Z_{\min 2}, \cdots, Z_{\min m}) \quad (4)
\]

The distance of every observation from the positive ideal solution and the negative ideal solution is calculated, respectively, by Equations (5) and (6):

\[
S^+_i = \sqrt{\sum_{j=1}^{m} (Z_{\max j} - Z_{ij})^2} \quad (5)
\]

\[
S^-_i = \sqrt{\sum_{j=1}^{m} (Z_{\min j} - Z_{ij})^2} \quad (6)
\]

The relative closeness of the \( i \)-th evaluation object to the optimal solution is:

\[
C_i = \frac{S^-_i}{S^+_i + S^-_i} \quad (7)
\]

The evaluation object is ranked according to the value of the relative degree of approximation. The bigger the value is, the better the evaluation object is.

3.2.2. Improved TOPSIS Method

The traditional TOPSIS method has a weight that is too subjective [73]. When judging the degree to which the scheme is close to the ideal solution by Euclidean distance, the problem that the distances of the positive ideal solution and the negative ideal solution are equal appears [74,75]. Moreover, the method is currently less commonly applied in agro-meteorological disaster vulnerability assessment [76].

To address these two shortcomings, we used the combined weight method to determine the indicator weight. Subsequently, the Kullback–Leibler (KL) distance was used instead of the Euclidean distance to calculate the posting schedule for the ideal solution. Thus, the ranking of the advantages and disadvantages of the scheme is obtained. The method can be taken as the following steps:

Step 1: Develop a decision matrix

Consider that there are \( m \) cities and \( n \) assessment indicators, and the original matrix \( Z_{ij} \) is calculated by Equation (8):
\[ Z_{ij} = \begin{bmatrix}
C_1 & C_2 & C_3 & C_4 \\
M_1 & Z_{11} & Z_{12} & \cdots & Z_{1n} \\
M_2 & Z_{21} & Z_{22} & \cdots & Z_{2n} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
M_m & Z_{m1} & Z_{m2} & \cdots & Z_{mn}
\end{bmatrix} \tag{8} \]

Step 2: Normalized decision-making matrix
As the initial data have different magnitudes and orders of magnitude, to make them comparable, the initial decision-making matrix needs to be normalized by the following formula:

\[ r_{ij} = \frac{z_{ij}}{\sqrt{\sum_{m=1}^{m} z_{ij}^2}}, \quad i = 1, 2, \ldots, m \quad j = 1, 2, \ldots, n \tag{9} \]

Step 3: Determine the weight of each indicator
We combined the Critic method with the G1 method to determine the weight of each indicator.

(1) Subjective weight
The G1 method, otherwise known as order relation analysis, is an improved analytic hierarchy process [77]. No consistency requirements of the judgment matrix [78,79]. The method can be taken as the following steps:

1⃝ Determining the order relation between indicators.
Determine the order of the assessment indicators \(X_1, X_2, X_3, \ldots, X_n\) concerning a criteria layer \(X_1 > X_2 > \cdots > X_{j-1} > X_j > \cdots > X_n\) according to the evaluation system.

2⃝ Judge the relative importance of each adjacent indicator.
\[ \frac{w_j^{s+1}}{w_j^s} = r_j, \quad j = n, n-1, n-2, \ldots, 3, 2 \tag{10} \]

where \(w_j^{s+1}\) and \(w_j^s\) denote the weight coefficients of assessment indicators \(X_{j-1}^s\) and \(X_j^s\), respectively, \(r_j\) indicates the relative importance of the \(j-1\)-th indicator to the \(j\)-th indicator, and the values are shown in Table 1.

**Table 1.** The values of \(r_j\).

| \(r_j\) | Inscription |
|--------|-------------|
| 1.0    | \(X_{j-1}^s\) is as important as \(X_j^s\) |
| 1.2    | \(X_{j-1}^s\) is slightly more important than \(X_j^s\) |
| 1.4    | \(X_{j-1}^s\) is more important than \(X_j^s\) |
| 1.6    | \(X_{j-1}^s\) is much more important than \(X_j^s\) |
| 1.8    | \(X_{j-1}^s\) is extremely more important than \(X_j^s\) |
| 1.1, 1.3, 1.5, 1.7 | The middle value of the above two adjacent judgements |

Based on the values of \(r_j\), we can obtain the weight of the \(n\)-th factor \(w_n^s\) by Equation (11):

\[ w_n^s = \left( 1 + \sum_{j=2}^{n} \prod_{k=j}^{n} r_k \right)^{-1} \tag{11} \]

(4) To get the rest weights, we can use the following equation:

\[ w_{j-1}^s = r_j w_j^s \tag{12} \]

From this, the subjective weight (\(w_{sj}\)) for each indicator can be obtained.
(2) Objective weight

As an objective weighting method, the Critic method, takes into account not only the impact of index variation on weight, but also the conflict between indicators [80]. It is able to reflect the degree of correlation of several indicators at the same time, but there is the absence of research on the existence of discrete relationships among such indicators. If it is associated with the entropy method, the discreteness of each indicator can be comprehensively analyzed, and a more accurate weight can be obtained [81,82], calculated as follows:

1. Calculate the standard deviation of $X_j$

\[ \sigma_j = \sqrt{\frac{1}{m-1} \sum_{i=1}^{m} (x_{ij} - \bar{x}_j)^2} \]  

(13)

where \( \sigma_j \) is the standard deviation of the assessment indicator $X_j$, and $\bar{x}_j$ is the mean of indicator $X_j$ across the $m$ schemes.

2. Calculate the correlation coefficient matrix for the $n$ assessment indicators:

\[ R = \begin{pmatrix} r_{ij} \end{pmatrix}_{m \times n} \]

3. Calculate the entropy value of each indicator

\[ e_j = -\frac{1}{\ln(m)} \sum_{i=1}^{n} (Q_{ij} \times \ln Q_{ij}) \]  

(14)

\[ Q_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \]  

(15)

where $e_j$ is the entropy value of indicator $j$, and $Q_{ij}$ is the proportion of the $i$-th evaluated object under the $j$-th indicator.

Determine the entropy method weight of indicator $j$ using the standardized data:

\[ w_{oj}^2 = \frac{1 - e_j}{\sum_{j=1}^{n} (1 - e_j)} \]  

(16)

4. The combination of the Critic-entropy method results in Equation (17):

\[ w_{oj} = \frac{(\sigma_j + e_j) \sum_{j=1}^{n} (1 - s_{ij})}{\sum_{j=1}^{n} (\sigma_j + e_j) \sum_{j=1}^{n} (1 - s_{ij})} \]  

(17)

(3) Combined weights method

\[ W_j = \frac{w_{oj} - w_{sj}}{\sum_{j=1}^{n} w_{oj} \cdot w_{sj}} \]  

(18)

where $w_{oj}$ is the objective weight of the $j$-th indicator, and $w_{sj}$ is the subjective weight of the $j$-th indicator. The final combined weight is $W = \{ W_1, W_2, \cdots, W_n \}$.

Step 4: Construction of weighted normalized decision-making matrix

Multiply $r_{ij}$ and each assessment indicator weight $W = \{ W_1, W_2, \cdots, W_n \}$ to obtain the normalized decision-making matrix $X = (X_{ij})_{m \times n}$

Step 5: Determination of positive ideal solutions ($X^+ = \{ X^+_1, X^+_2, \cdots, X^+_n \}$) and negative ideal solutions ($X^- = \{ X^-_1, X^-_2, \cdots, X^-_n \}$)

Step 6: Distance calculation

\[ S^+_j = \sum_{j=1}^{n} \left( X^+_j \frac{X^+_j}{X_{ij}} + (1 + X^+_j) \frac{1 - X^+_j}{1 - X_{ij}} \right) \]  

(19)
\[ S_i^- = \sum_{j=1}^{n} \left\{ X_j^- \log_j + \left( 1 - X_j^- \right) \log_1 \left( 1 - X_j^- \right) \right\} \]  

(20)

Step 7: Computing the closeness between the evaluation object and the ideal solution

The distance between alternative and positive ideal solutions, calculated as follows:

\[ C_i = \frac{S_i^-}{S_i^+ + S_i^-} \]  

(21)

The larger the \( C_i \) is, the closer it is to the positive ideal solution, indicating that the vulnerability to agricultural high-temperature disaster is higher.

3.3. Validation of Vulnerability Assessment Results—Synthetical Index Method

The rationality of the synthetical index method of the comprehensive risk assessment of agricultural heat damage in Shaanxi Province has been verified by scholars [19]. We compared the results with two TOPSIS results to verify the applicability and accuracy of the TOPSIS model for the assessment of vulnerability to high-temperature disaster in agriculture [83,84]. The vulnerability of the study area is:

\[ V = E \times S \times A = \sum_{i=1}^{n} W_{Ei}X_{Ei} \times \frac{\sum_{i=1}^{n} W_{Si}X_{Si}}{\sum_{i=1}^{n} W_{Ai}X_{Ai}} \]  

(22)

where \( V \) denotes the agricultural high-temperature disaster vulnerability index for Shaanxi Province. The greater the value, the greater the vulnerability of regional agricultural high-temperature disaster, and the greater the potential loss. \( E \) indicates exposure and reflects the degree of risk to which the system is exposed to external influences. \( S \) indicates sensitivity and reflects the degree of instability of the system itself. \( A \) indicates adaptability, which is the ability of the system to self-adjust, recover and adapt. \( X_{Ei}, X_{Si} \) and \( X_{Ai} \) denote indicators of exposure, sensitivity and adaptability, respectively. Additionally, \( W_{Ei}, W_{Si} \) and \( W_{Ai} \) denote the weight of the \( i \)-th indicator, respectively.

3.4. Vulnerability Impact Factor Identification—Obstacle Analysis

For the study of agricultural vulnerability, it is not only necessary to evaluate the vulnerability level of high-temperature disaster in different regions. What is more important is to clarify the factors that affect the vulnerability and the degree of influence. To prevent and develop policies accordingly. We used the obstacle model [85] to obtain the indicator obstacle by calculating the factor contribution and the indicator deviation [86,87]. The calculation formula is as follows:

\[ F_j = w_j \times z_j \]  

(23)

where \( F_j \) is the factor contribution, \( w_j \) is the weight of the \( j \)-th factor, and \( z_j \) is the weight of the \( i \)-th sub-goal to which the \( j \)-th factor belongs.

\[ I_j = 1 - R_{ij} \]  

(24)

where \( I_j \) is the indicator deviation and \( R_{ij} \) is the value of a single indicator after standardization.

\[ P_{ij} = \frac{F_{ij} \cdot I_{ij}}{\sum_{j=1}^{n} (F_{ij} \cdot I_{ij})} \times 100\% \]  

(25)

Based on the obstacle degree of every single indicator, we calculate the obstacle degree of every criterion layer to the vulnerability to agricultural high-temperature disaster. The formula is:

\[ P_{ij} = \sum P_{ij} \]  

(26)
3.5. Standard Deviation Classification Method

The mean value (V) and standard deviation (B) of vulnerability index obtained by the synthetical index method and TOPSIS model were calculated, respectively. The study area has been classified into four classes (Table 2). The zoning maps of exposure, sensitivity, adaptability and vulnerability to agricultural high-temperature disaster were drawn by ArcGIS 10.2.

### Table 2. Standard deviation grading method grading.

| Rank | I    | II   | III  | IV   |
|------|------|------|------|------|
| Threshold | (0, V - B) | (V - B, V) | (V, V + B) | (V + B, 1) |

4. Results

4.1. Vulnerability Assessment Indicators Weight

The G1 method was used to determine the subjective weights, and the calculation steps are described in the Supplementary Material (Tables S1–S3). The weight of the indicators is shown in Table 3.

### Table 3. Weight of indicators and factors used to calculate the vulnerability of study regions.

| Criteria Layer | Code | Critic Method | G1 Method | Combined Method |
|----------------|------|---------------|-----------|-----------------|
| Exposure       | XE1  | 0.0762        | 0.0623    | 0.0625          |
|                | XE2  | 0.0451        | 0.0521    | 0.0516          |
|                | XE3  | 0.0637        | 0.0562    | 0.0571          |
|                | XE4  | 0.0839        | 0.0749    | 0.0794          |
|                | XE5  | 0.0475        | 0.0534    | 0.0565          |
|                | XS1  | 0.0662        | 0.0912    | 0.1827          |
|                | XS2  | 0.0829        | 0.0753    | 0.0781          |
|                | XS3  | 0.0624        | 0.0585    | 0.0571          |
|                | XS4  | 0.0512        | 0.0603    | 0.0594          |
|                | XS5  | 0.0684        | 0.0553    | 0.0583          |
|                | XA1  | 0.0762        | 0.0622    | 0.0662          |
|                | XA2  | 0.0632        | 0.0728    | 0.0715          |
| Sensitivity    | XA3  | 0.0658        | 0.0727    | 0.0792          |
|                | XA4  | 0.0721        | 0.0717    | 0.0669          |
|                | XA5  | 0.0752        | 0.0811    | 0.0735          |
| Adaptability   | XA3  | 0.0658        | 0.0727    | 0.0792          |
|                | XA4  | 0.0721        | 0.0717    | 0.0669          |
|                | XA5  | 0.0752        | 0.0811    | 0.0735          |

4.2. Regional Classification

We use the standard deviation classification method, which will be exposure, sensitivity, adaptability, and vulnerability divided into four levels (Table 4).

### Table 4. Classification of criteria layer ranks.

| Method          | Criteria Layer | I                  | II                  | III                 | IV                  |
|-----------------|----------------|--------------------|--------------------|--------------------|--------------------|
| Improved TOPSIS method | Exposure        | (0, 0.3612)        | (0.3612, 0.4086)   | (0.4086, 0.5714)   | (0.5714, 1)        |
|                 | Sensitivity     | (0.3584, 0.4332)   | (0.4332, 0.5079)   | (0.5079, 1)        |                    |
|                 | Adaptability    | (0.5231, 0.6885)   | (0.6885, 0.8539)   | (0.8539, 1)        |                    |
|                 | Vulnerability   | (0.2941, 0.4327)   | (0.4327, 0.5714)   | (0.5714, 1)        |                    |
| Traditional TOPSIS method | Exposure        | (0.0647, 0.2186)   | (0.2186, 0.3725)   | (0.3725, 1)        |                    |
|                 | Sensitivity     | (0.1551, 0.3276)   | (0.3276, 0.5001)   | (0.5001, 1)        |                    |
|                 | Adaptability    | (0.4598, 0.6373)   | (0.6373, 0.8148)   | (0.8148, 1)        |                    |
|                 | Vulnerability   | (0.2941, 0.4229)   | (0.4229, 0.5514)   | (0.5514, 1)        |                    |
| Synthesitical index method | Exposure        | (0.2920, 0.4605)   | (0.4605, 0.6291)   | (0.6291, 1)        |                    |
|                 | Sensitivity     | (0.3339, 0.4808)   | (0.4808, 0.6277)   | (0.6277, 1)        |                    |
|                 | Adaptability    | (0.3954, 0.5539)   | (0.5539, 0.7124)   | (0.7124, 1)        |                    |
|                 | Vulnerability   | (0.0071, 0.0104)   | (0.0104, 0.0138)   | (0.0138, 1)        |                    |
4.3. Exposure Analysis

Figure 3 shows the spatial distribution of high-temperature disaster exposure in Shaanxi Province. The improved TOPSIS model shows that all regions have an exposure level of II, except for Yulin and Yangling, which are at level III. The results have some similarities to the traditional TOPSIS model, the traditional TOPSIS model shows Yulin and Yangling in level IV. Yulin is located in the temperate semi-arid continental monsoon climate zone and is one of the high-value sunshine areas in China. Hot summers with high exposure are influenced by continental air masses and the westward and northward extension of subtropical high pressure [88]. Studies have shown that the large-scale development of energy and minerals in northern Shaanxi has brought great pressure to the fragile agricultural ecological environment [89,90]. Agriculture modernization, production efficiency and multiple cropping index continue to improve, increasing the regional exposure [91].

4.4. Sensitivity Analysis

From Figure 4, the spatial distribution of sensitivity is similar for both TOPSIS models. Higher sensitivity is present in northern and southern Shaanxi. In the improved TOPSIS model, Xianyang, Ankang, and Yulin are all at a sensitivity level of IV. Xi’an and Hanzhong areas are at level III. In addition to the Tongchuan and Yangling in level I, the rest of the region is at level II. In the traditional TOPSIS model, Yulin is in level IV. Xianyang, Xi’an, and Ankang are in level III, while the rest of the region is in level II. Sensitivity is mainly related to socio-economic, demographic and agricultural situations. Crop yield fluctuations in more sensitive areas are susceptible to adverse meteorological factors resulting in yield and economic losses [26].

4.5. Adaptability Analysis

Figure 5 shows the spatial distribution of high-temperature disaster adaptability in Shaanxi Province. The higher the level of adaptability, the less able the area is to adapt and recover from disasters. In the improved TOPSIS model, the Yulin and Xi’an regions are at level I. The two areas of disaster prevention and mitigation capacity are stronger. The Guanzhong Plain is at a high level of agricultural modernization, at level II. So, given the strong ability of a disaster, the disaster reduction effect is relatively on time. Overall, the agricultural production and development of Yangling, Tongchuan, and Shangluo are all
highly vulnerable to high-temperature disaster. Adaptability showed a spatial distribution of high in the central region, followed by the southern region and weakest in northern Shaanxi. This was in line with the findings of He et al. [92] and Wu et al. [93].

**Figure 4.** Spatial distribution of sensitivity in the study area.

**Figure 5.** Spatial distribution of adaptability in the study area.

### 4.6. Vulnerability Assessment

The distribution of vulnerability shows clear regional differences (Figure 6). The grade is higher in northern and southern Shaanxi, and the low-value area is located in the Guanzhong Plain. In the improved TOPSIS model, Tongchuan and Ankang are the most vulnerable. These two regions are under a continental monsoon climate with a large difference in the geographical distribution of temperatures. Compared with other regions, its agricultural system is more vulnerable to the threat of high-temperature disaster. It
should be a key concern for resilience and the mitigation of agricultural high-temperature disaster in Shaanxi Province. Yulin, Yan’an, Yangling, and Shangluo are also greatly affected by monsoon circulation. Shangluo, in particular, is subject to the combined effects of the winter and summer monsoons and the Qinghai-Tibet Plateau circulation, as well as the blockage of warm and humid air currents from the south by the Qinling Mountains, resulting in four distinct seasons and extremely hot summers in the region. Xiangyang and Hanzhong have a lower vulnerability rating. These two regions have a mild climate and are rich in light, heat, and water resources, which are conducive to agriculture, forestry, animal husbandry, and fishery development. Baoji, Xi’an, and Weinan have relatively flat terrain and a high level of agricultural modernization. As a result, vulnerability is lowest, which is at the heart of the development of the agricultural industry in Shaanxi Province. There are some differences between the traditional TOPSIS results and the improved TOPSIS method, with Yulin being the most vulnerable.

Figure 6. Spatial distribution of vulnerability in the study area.

(a) Improved TOPSIS method  (b) Traditional TOPSIS method

The vulnerability of each area is the result of a combination of exposure, sensitivity, and adaptability, as shown in Figure 7. For the improved TOPSIS model, Tongchuan (0.578) is the most vulnerable region, followed by Ankang (0.572), Yulin (0.566), and Shangluo (0.557). The composition of vulnerability varies considerably from region to region. Overall, adaptability shows the greatest difference. The maximum value is in Xi’an (0.989). The minimum value is in Yangling (0.406). For exposure, the regions ranged between 0.37 and 0.525. The sensitivity was high in most areas, especially the Yulin (0.564). Yangling (0.312) had the lowest sensitivity. Low-vulnerability areas often have higher adaptability.

Figure 8 displays the ranking of exposure, sensitivity, adaptability, and vulnerability of each region. For the improved TOPSIS model, Yan’an, Tongchuan, and Baoji are more exposed. These regions have larger cultivating areas and planting areas, and suffer greater threats and losses when adverse weather events strike. Areas of high sensitivity are Yulin, Ankang, and Xianyang. Sensitivity is mainly related to socio-economic, population structure, and agricultural situations. Crop yield fluctuations in these areas are vulnerable to adverse meteorological factors, resulting in reduced yields and economic losses. The regions with higher adaptability are Xi’an, Yulin, and Baoji. The vulnerable areas are Tongchuan, Ankang, and Yulin. Although Yulin has a good capacity for disaster prevention and mitigation, it has high sensitivity and therefore a high vulnerability.
Comparing the two TOPSIS models, in terms of ranking, the two models are more consistent in their calculations of adaptability. Differences in sensitivity rankings are mostly concentrated in Yangling and Ankang. The differences in exposure rankings are Ankang, Shangluo, and Yan’an. Additionally, the results of the two models of vulnerability are more consistent.

5. Discussion
5.1. Validation of Evaluation Results

To further verify the accuracy of the evaluation results, the results of the two TOPSIS models were spatially compared with the synthetical index method (Figure 9). The overall exposure level in Shaanxi Province is at level II, with higher exposure in Yulin and central Yan’an. Sensitivity shows a higher spatial distribution in northern and southern Shaanxi
and lowers in the Guanzhong Plain. Shaanxi province has good ability in disaster prevention and mitigation, low scattered in Yulin’s borders with Ningxia and Inner Mongolia. The spatial distribution of agricultural high-temperature disaster vulnerability in Shaanxi Province is high in the north and south and low in the center. The vulnerability level of the Guanzhong Plain is low, and these areas are relatively flat and have a good economic level and well-developed agricultural infrastructure, which is conducive to agricultural development [26,94].

We further verified the applicability of two TOPSIS models. According to the synthetic index method, the results show that there is a linear correlation between the equations, and the results pass the F test of $\alpha = 0.05$ (Improved TOPSIS method: $r = 0.75$, $\rho < 0.05$, Traditional TOPSIS method: $r = 0.61$, $\rho < 0.05$). The assessment results of the two models reached a significant level, which proved that the agricultural vulnerability assessment of high-temperature disaster using the two models was reasonable. Meanwhile, the improved TOPSIS method was found to be more robust than the traditional TOPSIS method.

![Figure 9](image)

**Figure 9.** Distribution of exposure (a), sensitivity (b), adaptability (c), and vulnerability (d) based on the synthetical index method.

5.2. Obstacle Analysis
5.2.1. Analysis of Obstacle Factor in the Criteria Layer

Overall, sensitivity indicators have the greatest hindering effect on reducing vulnerability to high-temperature disaster in agriculture, while adaptability indicators have a lesser hindering effect (Figure 10). Sensitivity represents the state that agriculture is prone to high-temperature disaster under certain external conditions [70,95]. Adaptability, on the other hand, responds to the ability of agricultural systems to recover after high-temperature disaster [96]. The maximum value of the exposure barrier is in Yulin with 57.53% and the minimum value is in Hanzhong (29.17%). The maximum value of the sensitivity barrier is in Shangluo (64.37%) and the minimum value is in Yulin (16.74%). Adaptability has a positive effect on reducing vulnerability to high-temperature disaster and therefore has a low barrier level. The maximum and minimum values are Xi’an (28.33%) and Tongchuan (1.28%), respectively. This is because of the range of impacts of high temperatures on agricultural systems, such as yield variation, planting northern boundaries and planting inputs [97–99]. The key to reducing the vulnerability to agricultural high-temperature disaster is lower sensitivity and improving disaster prevention and mitigation capacity [100].
5.2.2. Analysis of the Obstacle Factors in the Index Layer

Table 5 shows the degree of influence of each indicator on reducing vulnerability to agricultural high-temperature disaster. Specifically, in Ankang and Shangluo regions, the factors with greater obstacles were the frequency of moderate heat events and the meteorological yield reduction coefficient of variation, respectively. Unfavorable meteorological conditions have a greater impact on crop yields in these two regions, and monitoring and early warning of high-temperature disaster should be actively strengthened [26,37]. Strengthening the construction of disaster monitoring facilities can be achieved by expanding the coverage of the network of detection stations, increasing the number and type of stations, and improving the means of information processing. Baoji, Yangling, and Yulin are similar, with a greater obstacle to per capita net income of rural residents. What is different is that the per capita farmland area is the largest in Baoji with an obstacle of 44.92%. For regions that are slightly behind economically, the government should actively support regional agriculture. Efforts to upgrade agricultural technology should be increased in order to achieve increased income generation for farmers to reduce the dependence of the region’s agriculture on the economic level. In Xi’an, the larger obstacle factors are the multiple cropping index and the number of people with junior high school education or above. The higher the multiple cropping index, the greater the number of crops grown on the same area of arable land, and the greater the vulnerability to reduced yields due to meteorological disaster [26,70]. In Xianyang, the larger obstacle factors are the frequency of moderate heat events and the number of people with junior high school education or above. The governments of these two regions should improve the system of socialized agricultural services and, in particular, improve the knowledge base of farmers. In Yan’an and Weinan, the government should improve the level of agricultural machinery in the region by deploying funds and professional technicians. In Tongchuan, the government should make overall planning for agricultural subsidies in various regions, and appropriately carry out some financial transfers, to make the more backward and developed areas develop coordinately. Hanzhong should limit the rapid population growth and centralized distribution in the process of disaster prevention and resistance, and continue to increase investment in agricultural water conservancy construction. Increasing the effective irrigated area and improving the level of technological agricultural production. At the same time, choose a reasonable water-saving irrigation mode to improve agricultural water utilization and increase the proportion of irrigated land [101–103].
Table 5. Indicator layer obstacle degrees (%).

|       | Xi’an | Tongchuan | Baoji | Xianyang | Weinan | Yangling | Hanzhong | Ankang | Shangluo | Yan’an | Yulin |
|-------|-------|-----------|-------|----------|--------|----------|----------|--------|----------|--------|-------|
| XE<sub>1</sub> | 3.55  | 2.27      | 2.65  | 3.85     | 2.18   | 0.65     | 2.18     | 4.46   | 2.5      | 1.09   | 2.36  |
| XE<sub>2</sub> | 0.36  | 0.23      | 0.19  | 40.03    | 0.19   | 2.96     | 0.55     | 33.17  | 21.48    | 0.21   | 0.84  |
| XE<sub>3</sub> | 0.54  | 1.02      | 0.48  | 0.79     | 0.69   | 2.57     | 0.31     | 4.29   | 0.76     | 1.78   | 18.51 |
| XE<sub>4</sub> | 4.66  | 3.99      | 3.43  | 5.26     | 3.18   | 1.2      | 3.82     | 6.22   | 3.99     | 3.85   | 2.78  |
| XE<sub>5</sub> | 33.18 | 29.55     | 7.05  | 0.42     | 24.54  | 11.96    | 2.23     | 0.79   | 4        | 28.78  | 1.23  |
| XS<sub>1</sub> | 5.54  | 5.13      | 4.19  | 6.51     | 3.56   | 6.95     | 3.11     | 7.99   | 4.3      | 4.68   | 2.2   |
| XS<sub>2</sub> | 12.65 | 2.45      | 2.29  | 2.55     | 42.36  | 4.59     | 4.36     | 21.53  | 51.83    | 46.72  | 1.92  |
| XS<sub>3</sub> | 2.96  | 4.32      | 1.79  | 2.38     | 1.72   | 5.04     | 3.74     | 5.15   | 4.05     | 2.17   | 4.35  |
| XS<sub>4</sub> | 3.82  | 1.86      | 44.92 | 3.09     | 1.62   | 4.24     | 22.31    | 3.37   | 2.34     | 1.53   | 1.5   |
| XS<sub>5</sub> | 4.41  | 47.89     | 2.28  | 1.26     | 2.3    | 18.71    | 1.19     | 3.06   | 1.85     | 1.79   | 6.77  |
| XA<sub>1</sub> | 5.11  | 0.55      | 24.47 | 7.16     | 6.45   | 31.12    | 2.65     | 1.81   | 0.22     | 4.59   | 31.98 |
| XA<sub>2</sub> | 2.21  | 0.21      | 1.61  | 2.71     | 3.75   | 3.8      | 1.29     | 2.45   | 0.24     | 1.15   | 8.66  |
| XA<sub>3</sub> | 14.64 | 0.26      | 1.33  | 14.69    | 1.95   | 1.12     | 1.29     | 1.61   | 0.91     | 0.84   | 5.22  |
| XA<sub>4</sub> | 4.11  | 0.21      | 1.84  | 6.57     | 2.07   | 1.5      | 1.28     | 1.72   | 1.12     | 0.53   | 5.49  |
| XA<sub>5</sub> | 2.26  | 0.06      | 1.48  | 2.73     | 3.44   | 3.59     | 49.69    | 2.78   | 0.41     | 0.29   | 6.19  |

6. Conclusions

In this study, we used the TOPSIS model to evaluate the vulnerability to agricultural high-temperature disaster and made two improvements to the model. The results show that vulnerability is higher in northern and southern Shaanxi. Especially in southern Shaanxi, the overall dependence on agricultural production is high, and once a major natural disaster occurs, the loss will be great. Sensitivity indicators have a great effect on reducing vulnerability. It is suggested that the government should establish a stable growth mechanism of financial investment and integrate and optimize the investment in enterprise construction. Continuously adjusting and optimizing agricultural subsidy policies will improve the ability to cope with disasters. There are many factors that affect the vulnerability to high-temperature disaster. Therefore, it is crucial to establish a scientific system of evaluation indicators. Although we have made some explorations, we are still limited by data. Moreover, we use natural risk theory to evaluate vulnerability and lack research on narrow vulnerability. Future research should further strengthen theoretical research and obtain data from various aspects. Meanwhile, the physical and chemical properties of crops and their resistance should be considered in the evaluation process. We provide an idea for a vulnerability assessment of agricultural high-temperature disaster. The selection of indicators and validation of the model can be carried out according to the actual situation in different regions, so as to achieve the ultimate goal of providing reference for decision makers in disaster prevention and mitigation.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agriculture12070980/s1, Table S1: Expert panel member information; Table S2: Ranking and assignment of criterion and indicator layers for evaluating the vulnerability agriculture high-temperature disaster in Shaanxi Province; Table S3: Statistical values of expert weights.

Author Contributions: Y.M.: Conceptualization, Writing—original draft. S.G.: Investigation, Data curation. X.L.: Conceptualization, Methodology, Resources. Z.T.: Writing—review and editing. Y.S.: Visualization, Supervision. J.X.: Conceptualization. J.Z.: Conceptualization, Writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This study is supported by the National Key Research and Development Program of China (2019YFD1002201); The National Natural Science Foundation of China (41877520, 42077443); The Science and Technology Development Planning of Jilin Province (20190303018SF); Key Research and Projects Development Planning of Jilin Province (2020040306SF); Industrial technology research and development project supported by Development and Reform Commission of Jilin Province(2021C044-5); The Science and Technology Planning of Changchun (19SS007).
Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author.

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

Abbreviations

- MCDM (multiple-criteria decision-making); K–L distance (Kullback–Leibler distance); AHP (analytic hierarchy process); ANP (analytic network process); VIKOR (VIseKriterijumska optimizacija toptomrisno rešenje); TOPSIS (technique for order of preference by similarity to ideal solution); MOORA (multi-objective optimization on the basis of ratio analysis); G1 (order relation analysis); IPCC (United Nations Intergovernmental Panel on Climate Change); AR3 (Third Assessment Report); AR6 (Sixth Assessment Report).

References

1. Raupach, M.R.; Marland, G.; Ciais, P.; Quere, C.L.; Canadell, J.G.; Klepper, G.; Field, C.B. Global and regional drivers of accelerating CO₂ emissions. *Proc. Natl. Acad. Sci. USA* 2007, 104, 10288–10293. [CrossRef] [PubMed]
2. Fischer, G.; Shah, M.; Tubiello, F.N.; Velthuizen, H.V. Socio-economic and climate change impacts on agriculture: An integrated assessment. *Philos. Trans. R. Soc. B* 2005, 360, 2067–2083. [CrossRef]
3. Schmidhuber, J.; Tubiello, F.N. Global food security under climate change. *Proc. Natl. Acad. Sci. USA* 2007, 104, 19703–19708. [CrossRef] [PubMed]
4. Tollefson, J. IPCC climate report: Earth is warmer than it’s been in 125,000 years. *Nature* 2021, 596, 171–172. [CrossRef] [PubMed]
5. Panday, P.K.; Thibeault, J.; Frey, K.E. Changing temperature and precipitation extremes in the Hindu Kush-Himalayan region: An analysis of CMIP3 and CMIP5 simulations and projections. *Int. J. Climatol.* 2015, 35, 3058–3077. [CrossRef]
6. Alexender, L.L.V.; Zhang, X.; Peterson, T.C.; Caesar, J.; Gleason, B.; Tank, A.M.G.K.; Haylock, M.; Collins, D.; Trewin, B.; Rahimzadeh, F. Global observed changes in daily climate extremes of temperature and precipitation. *J. Geophys. Res. Atmos.* 2006, 111, 1042–1063. [CrossRef]
7. Gornall, J.; Betts, R.; Burke, E.; Clark, R.; Camp, J.; Willett, K.; Wiltshire, A. Implications of climate change for agricultural productivity in the early twenty-first century. *Philos. Trans. R. Soc. Lond. B. Biol. Sci.* 2010, 365, 2973–2989. [CrossRef]
8. Zhang, Y.; Wang, Y.; Niu, H. Effects of temperature, precipitation and carbon dioxide concentrations on the requirements for crop irrigation water in China under future climate scenarios. *Sci. Total Environ.* 2019, 656, 373–387. [CrossRef]
9. Lieth, H.; Box, E. Evapotranspiration and primary productivity: C. W. Thornthwaite memorial model. *Publ. Climatol.* 1972, 25, 37–46.
10. Mon, D.L.; Cheng, C.H.; Lin, J.C. Evaluating weapon system using fuzzy analytic hierarchy process based on entropy weight. *Fuzzy Sets Syst.* 1994, 62, 127–134. [CrossRef]
11. Asseng, S.; Spänkuch, D.; Hernandez-Ochoa, I.M.; Laporta, J. The upper temperature thresholds of life. *Lancet Planet. Health* 2021, 5, e378–e385. [CrossRef] [PubMed]
12. Ishimaru, T.; Xaiyalath, S.; Nallathambi, J.; Santishraj, R.; Yoshimoto, M.; Phoudalay, L.; Samson, B.; Hasegawa, T.; Hayashi, K.; Arumugam, G.; et al. Quantifying rice spikelet sterility in potential heat-vulnerable regions: Field surveys in Laos and southern India. *Field Crop. Res.* 2016, 190, 3–9. [CrossRef]
13. Parker, L.E.; McElrone, A.J.; Ostoja, S.M.; Forrestel, E.J. Extreme heat effects on perennial crops and strategies for sustaining future production. *Plant Sci.* 2020, 295, 110397. [CrossRef] [PubMed]
14. Parry, M.L.; Rosenzweig, C.; Iglesias, A.; Livermore, M.; Fischer, G. Effects of climate change on global food production under SRES emissions and socio-economic scenarios. *Glob. Environ. Change Hum. Policy Dims.* 2004, 14, 53–67. [CrossRef]
15. Hattfield, J.L.; Boote, K.J.; Kimball, B.A.; Ziska, L.H.; Izaaurralde, R.C.; Ort, D.; Thomson, D.W. Climate impacts on agriculture: Implications for crop production. *Agron. J.* 2011, 103, 351–370. [CrossRef]
16. Sharma, A.; Anandhi, A. Temperature based indicators to develop adaptive responses for crop production in Florida, USA. *Ecol. Indic.* 2021, 121, 107064. [CrossRef]
17. Zhang, Y.; Qu, H.; Yang, X.; Wang, M.; Qin, N.; Zou, Y. Cropping system optimization for drought prevention and disaster reduction with a risk assessment model in Sichuan Province. *Glob. Ecol. Conserv.* 2020, 23, e011095. [CrossRef]
18. Ashutosh, K.; Dario, S.; Nitin, B.V.; Ashish, D. Critical Exploration of Indian Economic Reforms of 1991: A lesson for Developing Economies. *Int. J. Eng. Adv. Technol.* 2019, 8, 490–500. [CrossRef]
19. Challinor, A.J.; Koehler, A.K.; Ramirez-Villegas, J.; Whitfield, S.; Das, B. Current warming will reduce yields unless maize breeding and seed systems adapt immediately. *Nat. Clim. Chang.* 2016, 6, 954–958. [CrossRef]
| Page | Reference |
|------|-----------|
| 20. | Polsky, C.; Neff, R.; Yarnal, B. Building comparable global change vulnerability assessments: The vulnerability scoping diagram. *Glob. Environ. Chang.* 2007, 17, 472–485. [CrossRef] |
| 21. | Song, Z.; Jiang, S.; Jin, J.; Zhang, M. Comprehensive assessment of agricultural drought vulnerability based on improved cloud similarity: A case study of Bengbu city. *Hydro-Sci. Eng.* 2017, 3, 56–63. [CrossRef] |
| 22. | Wang, Y.; Wang, J.; Yao, Y.; Wang, J. Evaluation of drought vulnerability in southern China based on principal component analysis. *Ecol. Environ. Sci.* 2014, 23, 1897–1904. (In Chinese) |
| 23. | Shahid, S.; Behrawan, H. Drought risk assessment in the western part of Bangladesh. *Nat. Hazards* 2008, 46, 391–413. [CrossRef] |
| 24. | Zhang, D.; Wang, G.; Zhou, H. Assessment on agricultural drought risk based on variable fuzzy sets model. *Chin. Geogr. Sci.* 2011, 21, 167. [CrossRef] |
| 25. | Zhou, R.; Jin, J.; Cui, Y.; Ning, S.; Bai, X.; Zhang, L.; Zhou, Y.; Wu, C.; Tong, F. Agricultural drought vulnerability assessment and diagnosis based on entropy fuzzy pattern recognition and subtraction set pair potential. *Alex. Eng. J.* 2022, 61, 51–63. [CrossRef] |
| 26. | Ma, Y.; Guga, S.; Xu, J.; Zhang, J.; Tong, Z.; Liu, X. Comprehensive Risk Assessment of High Temperature Disaster to Kiwifruit in Shaanxi Province, China. *Int. J. Environ. Res. Public Health* 2021, 18, 10437. [CrossRef] |
| 27. | Wiren, L.; Danielsson, A.; Neson, T.S. Assessment of composite index methods for agricultural vulnerability to climate change. *J. Environ. Manag.* 2015, 156, 70–80. [CrossRef] |
| 28. | Nam, W.; Choi, J.; Hong, E. Irrigation vulnerability assessment on agricultural water supply risk for adaptive management of climate change in South Korea. *Agri. Water Manag.* 2015, 152, 173–187. [CrossRef] |
| 29. | Sahana, V.; Mondal, A.; Sreekumar, P. Drought vulnerability and risk assessment in India: Sensitivity analysis and comparison of aggregation techniques. *J. Environ. Manag.* 2021, 299, 113689. [CrossRef] |
| 30. | Seyed, H.M.; Aliereza, S.A. A comprehensive MCDM-based approach using TOPSIS, COPRAS and DEA as an auxiliary tool for material selection problems. *Mater. Des.* 2017, 121, 237–253. [CrossRef] |
| 31. | Ustaoglu, E.; Sisman, S.; Aydinoglu, A.C. Determining agricultural suitable land in peri-urban geography using GIS and Multi Criteria Decision Analysis (MCDA) techniques. *Ecol. Model.* 2021, 455, 109610. [CrossRef] |
| 32. | Chang, H.; Liou, J.; Chen, W. Protection priority in the coastal environment using a hybrid AHP-TOPSIS method on the Miaoli coast. *Taiwan J. Coast. Res.* 2012, 28, 369–374. [CrossRef] |
| 33. | Mosadeghi, R.; Warnken, J.; Tomlinson, R.; Mirfenderesk, H. Comparison of Fuzzy-AHP and AHP in a spatial mul-ti-criteria decision making model for urban land-use planning. *Comput. Environ. Urban Syst.* 2015, 49, 54–65. [CrossRef] |
| 34. | Janssen, J.A.E.B.; Krol, M.S.; Schielen, R.M.J.; Hoekstra, A.Y. The effect of modelling expert knowledge and uncertainty on multicriteria decision making: A river management case study. *Environ. Sci. Policy* 2010, 13, 229–238. [CrossRef] |
| 35. | Liang, X.; Chen, T.; Ye, M.; Lin, H.; Li, Z. A hybrid fuzzy BWM-VIKOR MCDM to evaluate the service level of bike-sharing companies: A case study from Chengdu, China. *J. Clean. Prod.* 2021, 298, 126759. [CrossRef] |
| 36. | Brodny, J.; Tutak, M. Assessing sustainable energy development in the central and eastern European countries and analyzing its diversity. *Sci. Total Environ.* 2021, 801, 149745. [CrossRef] |
| 37. | Ma, Y.; Guga, S.; Xu, J.; Liu, X.; Tong, Z.; Zhang, J. Assessment of Maize Drought Risk in Midwestern Jilin Province: A Comparative Analysis of TOPSIS and VIKOR Models. *Remote Sens.* 2022, 14, 2399. [CrossRef] |
| 38. | Janssen, M.A.; Schoon, M.L.; Ke, W.; Börner, K. Scholarly networks on resilience, vulnerability and adaptation within the human dimensions of global environmental change. *Glob. Environ. Chang.* 2006, 3, 240–252. [CrossRef] |
| 39. | Hwang, C.L.; Yoon, K. *Multiple Attribute Decision Making-Methods and Applications*; Springer: Berlin/Heidelberg, Germany, 1981. |
| 40. | Chen, W.; Shen, Y.; Wang, Y. Evaluation of economic transformation and upgrading of resource-based cities in Shaanxi province based on an improved TOPSIS method. *Sustain. Cities Soc.* 2018, 37, 224–240. [CrossRef] |
| 41. | Behzadian, M.; Otaghsara, S.K.; Yazdani, M.; Ignatius, J. A state-of-the-art survey of TOPSIS applications. *Expert Syst. Appl.* 2012, 39, 13051–13069. [CrossRef] |
| 42. | Dymova, L.; Sevastjanov, P.; Tikhoncnko, A. A direct interval extension of TOPSIS method. *Expert Syst. Appl.* 2013, 40, 4841–4847. [CrossRef] |
| 43. | Azadeh, A.; Kor, H.; Hatiei, S.M. A hybrid genetic algorithm-TOPSIS-computer simulation approach for optimum operator assignment in cellular manufacturing systems. *J. Chin. Inst. Eng.* 2011, 34, 57–74. [CrossRef] |
| 44. | Yuan, J.; Luo, X. Regional energy security performance evaluation in China using MTGS and SPA-TOPSIS. *Sci. Total Environ.* 2019, 696, 133817. [CrossRef] [PubMed] |
| 45. | Zhao, D.; Li, C.; Wang, Q.; Yuan, J. Comprehensive evaluation of national electric power development based on cloud model and entropy method and TOPSIS: A case study in 11 countries. *J. Clean. Prod.* 2020, 277, 123190. [CrossRef] |
| 46. | Zhu, B.; Tang, J.; Wang, P. Examining the risk of China’s pilot carbon markets: A novel integrated approach. *J. Clean. Prod.* 2021, 328, 129408. [CrossRef] |
| 47. | Liu, D.; Qi, X.; Fu, Q.; Li, M.; Zhu, W.; Zhang, L.; Faiz, M.A.; Khan, M.I.; Li, T.; Cui, S. A resilience evaluation method for a combined regional agricultural water and soil resource system based on Weighted Mahalanobis distance and a Gray–TOPSIS model. *J. Clean. Prod.* 2019, 229, 667–679. [CrossRef] |
| 48. | Li, X. TOPSIS model with entropy weight for eco geographical environmental carrying capacity assessment. *Microprocess. Microsystems.* 2021, 82, 103805. [CrossRef] |
| 49. | Xu, X.; Zhang, Z.; Long, T.; Sun, S.; Gao, J. Mega-city region sustainability assessment and obstacles identification with GIS–entropy–TOPSIS model: A case in Yangtze River Delta urban agglomeration, China. *J. Clean. Prod.* 2021, 294, 126147. [CrossRef] |
50. Yang, T.; Zhang, Q.; Wan, X.; Li, X.; Wang, Y.; Wang, W. Comprehensive ecological risk assessment for semi-arid basin based on conceptual model of risk response and improved TOPSIS model—-a case study of Wei River Basin, China. *Sci. Total Environ.* 2020, 719, 137502. [CrossRef]

51. Sadat, S.A.; Fini, M.V.; Hashemi-Dezaki, H.; Nazififard, M. Barrier analysis of solar PV energy development in the context of Iran using fuzzy AHP-TOPSIS method. *Sustain. Energy Technol. Assess.* 2021, 47, 101549. [CrossRef]

52. Amiri, M.; Pourghasemi, H.R.; Arabameri, A.; Vazirzadeh, A.; Yousefi, H.; Kafaei, S. Prioritization of flood inundation of maharloo watershed in Iran using morphometric parameters analysis and TOPSIS MCDM model. In *Spatial Modeling in GIS and R for Earth and Environmental Sciences*; Pourghasemi, H.R., Gokeceoglu, C., Eds.; Elsevier: Amsterdam, The Netherlands, 2019; pp. 371–390. [CrossRef]

53. Termeh, S.V.R.; Pourghasemi, H.R.; Alidadganfard, F. Flood inundation susceptibility mapping using analytical hierarchy process (AHP) and TOPSIS decision making methods and weight of evidence statistical model (case study: Jahanroo township, Fars Province). *J. Watershed Manag.* 2018, 9, 67–81. [CrossRef]

54. Yang, W.; Xu, K.; Lian, J.; Ma, C.; Bin, L. Integrated flood vulnerability assessment approach based on TOPSIS and Shannon entropy methods. *Ecol. Indic.* 2018, 99, 269–280. [CrossRef]

55. Ekmekciö˘ glu, Ö.; Koc, K.; Özger, M. Stakeholder perceptions in flood risk assessment: A hybrid fuzzy AHP-TOPSIS approach for Istanbul, Turkey. *Int. J. Disast. Risk Reduct.* 2021, 60, 102327. [CrossRef]

56. Sari, F. Forest fire susceptibility mapping via multi-criteria decision analysis techniques for Mugla, Turkey: A comparative tive analysis of VIKOR and TOPSIS. *Forest Ecol. Manag.* 2021, 480, 118644. [CrossRef]

57. Wilhelmi, O.; Hayden, M. Connecting people and place: A new framework for reducing urban vulnerability to extreme heat. *Environ. Res. Lett.* 2010, 5, 014021. [CrossRef]

58. Downing, J.; Bellis, M.A. Early pubertal onset and its relationship with sexual risk taking, substance use and anti-social behaviour: A preliminary cross-sectional study. *BMC Public Health* 2009, 9, 446. [CrossRef] [PubMed]

59. Birch, E.L. A Review of “Climate Change 2014: Impacts, Adaptation, and Vulnerability” and “Climate Change 2014: Mitigation of Climate Change”. *J. Am. Plan. Assoc.* 2014, 80, 184–185. [CrossRef]

60. IPCC. *Summary for Policy Makers*; IPCC Working Group II: Geneva, Switzerland, 2007.

61. Martens, P.; McEvoy, D.; Chang, C. The climate change challenge: Linking vulnerability, adaptation, and mitigation. *Curr. Opin. Environ. Sustain.* 2009, 1, 14–18. [CrossRef]

62. Turner, B.L.; Kasperson, R.E.; Matson, P.A.; McCarthy, J.J.; Corell, R.W.; Christensen, L.; Eckley, N.; Kasper, J.; Luers, A.; Martello, M.L.; et al. A framework for vulnerability analysis in sustainability science. *Proc. Natl. Acad. Sci. USA* 2003, 100, 8074–8079. [CrossRef]

63. Luo, Q. Temperature thresholds and crop production: A review. *Clim. Chang.* 2011, 109, 583–598. [CrossRef]

64. Teixeira, E.I.; Fischer, G.; Velthuizen, H.; Walter, C.; Ewert, F. Global hot-spots of heat stress on agricultural crops due to climate change. *Agric. Forest Meteorol.* 2013, 170, 206–215. [CrossRef]

65. Wheeler, T.R.; Craufurd, P.Q.; Ellis, R.H.; Porter, J.R.; Prasad, P.V. Temperature variability and the yield of annual crops. *Agric. Ecosyst. Environ.* 2000, 82, 159–167. [CrossRef]

66. Macholdt, J.; Hadasch, S.; Piepho, H.P.; Reckling, M.; Taghizadeh-Toosi, A.; Christensen, B. Yield variability trends of winter wheat and spring barley grown during 1932–2019 in the Askov Long-term Experiment. *Field Crop. Res.* 2021, 264, 108083. [CrossRef]

67. Carrão, H.; Naumann, G.; Barbosa, P. Mapping global patterns of drought risk: An empirical framework based on sub-national estimates of hazard, exposure and vulnerability. *Glob. Environ. Chang.* 2016, 39, 108–124. [CrossRef]

68. Meza, I.; Rezaei, E.E.; Siebert, S.; Ghazaryan, G.; Nouri, H.; Dubovyk, O.; Gerdener, H.; Herbert, C.; Kusche, J.; Popat, E.; et al. Drought risk for agricultural systems in South Africa: Drivers, spatial patterns, and implications for drought risk management. *Sci. Total Environ.* 2021, 799, 149505. [CrossRef]

69. Liu, Y.; Chen, J. Future global socioeconomic risk to droughts based on estimates of hazard, exposure, and vulnerability in a changing climate. *Sci. Total Environ.* 2021, 751, 142159. [CrossRef]

70. Zhang, J. Risk assessment of drought disaster in the maize-growing region of Songliao Plain, China. *Agric. Ecosyst. Environ.* 2004, 102, 133–153. [CrossRef]

71. Yoon, K.P.; Hwang, C.L. *Multiple Attribute Decision Making: An Introduction*; Sage Publications: Thousand Oaks, CA, USA, 1995; Volume 104.

72. Chakraborty, S.; Yeh, C.H. Comparison based group ranking outcome for multiattribute group decisions. In Proceedings of the UKSim 14th International Conference on Computer Modelling and Simulation, IEEE, Cambridge, UK, 27–29 March 2012.

73. Chakraborty, S.; Mandal, A. A novel TOPSIS based consensus technique for multiattribute group decision making. In Proceedings of the 2018 18th International Symposium on Communications and Information Technologies, ISCIT, IEEE, Bangkok, Thailand, 26–29 September 2018.

74. Bhadra, D.; Dhar, N.R.; Salam, M.A. Sensitivity analysis of the integrated AHP-TOPSIS and CRITIC-TOPSIS method for selection of the natural fiber. *Mater. Today* 2021, 10, 2429–2439. [CrossRef]

75. García-Cascales, M.S.; Lamata, M.T. On rank reversal and TOPSIS method. *Math. Comput. Model.* 2012, 56, 123–132. [CrossRef]

76. Belton, V.; Stewart, T. *Multiple Criteria Decision Analysis: An Integrated Approach*; Springer Science & Business Media: Berlin, Germany, 2002.
84. Xu, X.; Wang, L.; Sun, M.; Fu, C.; Bai, Y.; Li, C.; Zhang, L. Climate change vulnerability assessment for smallholder farmers in

89. Sun, S.K.; Li, C.; Wu, P.T.; Zhao, X.N.; Wang, Y.B. Evaluation of agricultural water demand under future climate change scenarios

87. Wang, Y.; Fang, X.; Yin, S.; Chen, W. Low-carbon development quality of cities in China: Evaluation and obstacle analysis.

100. Zhang, T.Y.; Huang, Y. Impacts of climate change and inter-annual variability on cereal crops in China from 1980 to 2008.

103. Kim, Y.; Chung, E.S. Fuzzy VIKOR approach for assessing the vulnerability of the water supply to climate change and variability in South Korea.

Agriculture 2022, 12, 980