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An Innovative TOPSIS–Mahalanobis Distance Approach to Comprehensive Spatial Prioritization Based on Multi-Dimensional Drought Indicators

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Abstract: This research explores a new methodological framework that blends the TOPSIS (technique for order of preference by similarity to ideal solution) and Mahalanobis Distance methods, allowing for the prioritization of nine major watersheds in China based on the integration of multi-dimensional drought indicators. This integrated approach offers a robust prioritization model by accounting for spatial dependencies between indices, a feature not commonly addressed in traditional multi-criteria decision-making applications in drought studies. This study utilized three drought indices—the Standardized Precipitation Evapotranspiration Index (SPEI), Vegetation Health Index (VHI), and Palmer Drought Severity Index (PDSI). Over years of significant drought prevalence, three types of droughts occurred simultaneously across various watersheds in multiple years, particularly in 2001, 2002, 2006, and 2009, with respective counts of 16, 17, 19, and 18 concurrent episodes. The weights derived from Shannon's entropy emphasize the importance of the Potential Drought Severity Index (PDSI) in evaluating drought conditions, with PDSI-D (drought duration) assigned the highest weight of 0.267, closely followed by VHI-D (Vegetation Health Index under drought conditions) at 0.232 and SPEI-F (drought frequency) at 0.183. The results demonstrated considerable spatial variability in drought conditions across the watersheds, with Watersheds 1 and 4 exhibiting the highest drought vulnerability in terms of meteorological and agricultural droughts, while Watersheds 6 and 3 showed significant resilience to hydrological drought after 2012. In particular, the severe meteorological drought conditions at Watershed 1 highlight the urgent need for rainwater harvesting and strict water use policies, and in contrast, the conditions at Watershed 4 show the need for the modernization of irrigation to mitigate agricultural drought impacts. This integrated framework allows for targeted drought management solutions that directly relate to the specific contexts of the watersheds, while being more conducive to planning and prioritizing resource allocations for regions facing the highest drought vulnerability.

Keywords: drought vulnerability; drought mitigation strategies; MCDA; remote sensing; climate resilience planning

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1. Introduction

Drought, an ongoing and multi-faceted natural force, has wide-ranging and pervasive effects across Earth's varying regions. Drought is commonly classified into three primary categories: meteorological, hydrological, and agricultural drought. However, additional classifications, such as socio-economic drought—which impacts human activities and economies—and ecological drought—which affects ecosystems and biodiversity—are increasingly recognized in the drought literature, as well [1,2]. Each emergence comes with a multitude of challenges, such as meteorological droughts being defined or characterized by scarce precipitation, and hydrological droughts experiencing limited water supply in lakes, rivers, and reservoirs [3,4]. Additionally, of all droughts, agricultural drought can have the most widespread impact on food availability, because it refers to crops that have limited access to soil moisture [5]. Around the globe, the economic consequences of drought have been staggering, with the World Bank estimating that the costs of drought have been economically greater than USD 124 billion over the past decade [6]. Meanwhile, for China, the economic effects of drought were even more far-reaching when, in 2010 to 2011, drought impacted 35 million hectares of cropland, and the resultant losses were valued at over USD 7 billion [7]. Droughts are driven by natural climate variability and human activity, highlighting the need for adaptable and robust drought mitigation systems [8].

Globally, over the years, drought has been studied and defined in numerous ways, from different angles, by innumerable scholars. Around the world, much work and progress have been made in understanding drought mechanisms, impacts, and mitigation measures. Researchers have created multiple drought indices that quantify the severity of drought events based on precipitation and temperature data using multiple methodologies, such as the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index (SPI) [9,10]. Drought indices are used to assess and predict meteorological drought conditions all over the world [11,12]. However, often, drought indices do not incorporate or develop any additional dimensions of agricultural or hydrological drought, which limits the use of drought indices in complex scenarios [13]. For example, SPI does not include groundwater depletion or aquifer recharge, even though this is critical in understanding hydrological drought in water-scarce areas, such as Northern China [14]. Furthermore, some researchers have developed and used analysis models to prioritize areas based on the severity of drought, examples of which can be found in studies across Iran, India, and Spain that employ fuzzy logic, AHP (Analytic Hierarchy Process), and other integrated MCDM methodology types to rank areas based on vulnerability to drought [15–19].

With climate change and population growth, monitoring drought patterns and impacts has become more essential than ever. Fortunately, the tools that we are able to use for drought monitoring and management have fundamentally shifted—from Remote Sensing (RS) and Geographic Information Systems (GISs), advancing the process of simply looking at droughts as a static ground measurement, to measuring drought and utilizing analyses in real time and at the place of drought occurrence [20,21]. RS provides the opportunity to snapshot the vast regions that are experiencing limited or no access to water, revealing the spatial extent of drought and relationships in time [22]. In addition, with the availing of MCDM (multi-criteria decision-making) concepts, as embedded in TOPSIS (technique for order preference by similarity to ideal solution), analytics and findings from RS/GIS categorically situate Earth observation evidence in decision-relevant international systems for evaluating water management, the allocation of resources, or preparedness for other emergencies [23]. Of course, with precarious and critical agricultural regions and watersheds throughout China, the advantages gained from the use of these technologies can serve to greatly enhance water scarcity monitoring [24]. However, utilizing the accessible data from these advanced technologies can present some challenges. One is integrating the evidence from technology-based spatial analysis data into a full-scale, usable, and operational strategy across vast areas, like in China [25].

In China, previous research on drought has primarily focused on the examination of spatial and temporal trends [26–31], as well as the provision of early warning systems to help promote aspects of preparedness for water shortage [32–34]. However, drought studies have relied heavily on meteorological data, which do not consolidate or consider the intertwined nature of different drought types. A lack of systematic integration of aggregated meteorological, hydrological, and agricultural datasets has often resulted in piecemeal drought management techniques that do not always help tackle the issue [35]. Yang et al. (2020) have aptly pointed out that hydrological droughts in larger river basins like the Yellow and Yangtze Rivers have received less focus than meteorological drought [36].

Meanwhile, agricultural drought has largely been overlooked for consideration in China, but food security hinges on water efficiency, so it should be of paramount importance [37]. In comparison, globally, the work of the Multivariate Standardized Drought Index (MSDI) derived by Hao and AghaKouchak (2013, 2014) elaborated a trend to consolidate multiple dimensions of drought [13,38]. However, the ability to use this method is relatively uncommon, as the complex impacts of drought in a country like China lead to a need for combined approaches that include subjective elements [39]. Another, rather subtle oversight in the literature is that the integration of multi-criteria models and advanced technology, such as RS and GIS, has been inadequately considered, with only a few examples within academia and policy [40–42].

This research intends to address these gaps by presenting a novel methodology that employs the TOPSIS and the Mahalanobis Distance to prioritize major watersheds of China with respect to multi-faceted drought indicators. Although this combined approach has been successfully utilized to simplify decision-making processes for other natural hazards, such as floods and landslides [43], its application in droughts has not yet been explicitly studied. Through the integration of drought indicators (i.e., meteorological, hydrological, and agricultural) into one holistic decision-making structure, this study will enhance our understanding of drought vulnerability encountered by watersheds across China. This multi-faceted structure is particularly important as China faces increasing pressures on its water resources, enabling a targeted and strategic approach to resource allocation and mitigation measures [44–46]. More importantly, as an emergent methodology combining the strengths of TOPSIS with Mahalanobis Distance, this research is not identified as place- or hazard-specific so that the methodology can be used in other regions or for other natural hazards.

The overarching goal of this study is to prioritize watersheds in China according to a full suite of drought indicators. Specifically, it will (1) provide a robust decision-making framework that integrates multiple dimensions of drought conditions, (2) examine the differentiation of drought severity spatial patterns within China's major watersheds, and (3) generate drought management insights that are useful to policymakers and resource managers. Our study design has the ability to fill an important gap in the drought research literature and also serves to advance the global body of knowledge regarding drought management by adapting the suggested framework for other regions facing similar circumstances. The designed methodology attempts to enhance the accuracy of drought prioritization by incorporating spatial dependencies within a multi-dimensional framework. This approach is particularly innovative in drought studies because it provides a cohesive prioritization of watersheds, thereby addressing an identified gap in studies using single-dimensional or meteorological-only indicators. The following sections detail how this method builds upon prior MCDM work in natural hazard assessment.

2. Materials and Methods

2.1. Study Area

China has a vast and diverse topography that ranges from coastal plains to towering mountain ranges, such as the Himalayas and the Kunlun Mountains. The western part of the country is characterized by rugged terrain, including the Tibetan Plateau, the world's highest and largest plateau, often referred to as the "roof of the world". In contrast, the eastern regions consist of fertile plains and river basins like the Yangtze and Yellow Rivers, which support a significant portion of the country's agriculture and population. This variety in landscapes creates unique environmental conditions across different watersheds. China's climate is as varied as its topography, shaped by the monsoon system and ranging from tropical in the south to subarctic in the northeast. The eastern and southern parts of the country experience humid, subtropical climates with distinct wet and dry seasons, while the western regions face a more arid desert climate. The interplay of these climatic conditions makes China highly susceptible to different types of droughts, including meteorological, hydrological, and agricultural droughts. Monsoon variability often exacerbates drought events, particularly in northern China, where water resources are already limited due to less frequent rainfall [47–51].

Droughts in China have profound impacts on agriculture, water resources, and socio-economic development. The country's reliance on rain-fed agriculture in many regions, particularly in the northern and northwestern provinces, means that even slight changes in precipitation patterns can lead to severe agricultural droughts. Hydrological droughts are also a concern, especially in watersheds fed by glaciers and snowmelt in the western regions, where shifts in temperature due to climate change affect water availability. Moreover, human activities, such as land use changes, deforestation, and intensive irrigation, have further aggravated the frequency and severity of droughts in many areas. These factors, combined with China's ongoing urbanization and industrial growth, put additional pressure on water resources, especially at the northern watersheds, where over-extraction has led to significant groundwater depletion.

Given this complex environmental backdrop, the nine major watersheds analyzed in this study span a wide range of climatic zones and topographical features, providing a holistic understanding of how drought impacts differ across the country. This research centers on prioritizing major watersheds in China with respect to drought indices (Figure 1). An annual time step was used to derive the drought indices, highlighting variability in drought duration and frequency. The watersheds selected for analysis were purposely chosen based on their agricultural significance and their consequential effects on water management for other beneficial uses and the challenges involved [52–58].

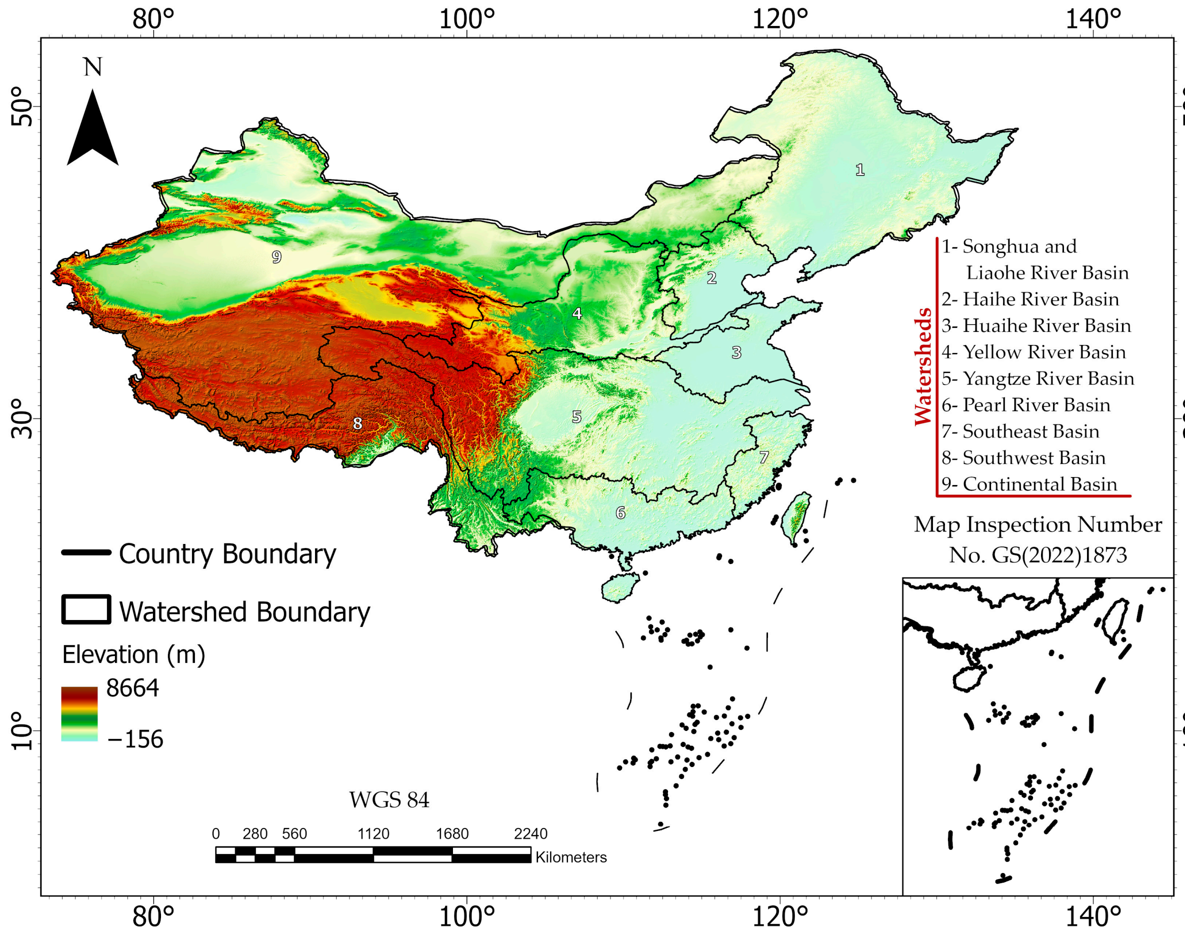

Figure 1. Location map of the study area and the nine major watersheds.

2.2. Data Sources and Processing

The methodological framework adopted in this research is depicted in Figure 2 and discussed further below.

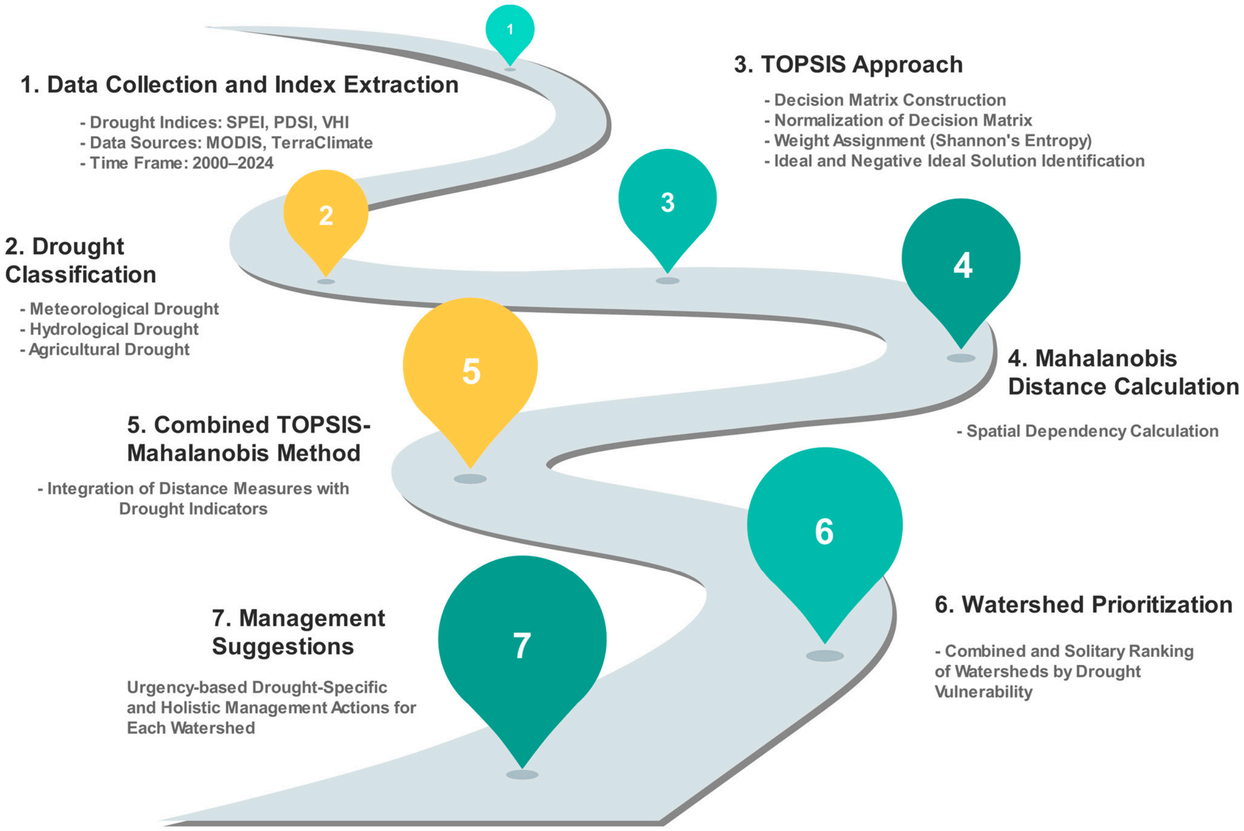

Figure 2. Methodological flowchart adopted in this study.

2.2.1. Drought Indices

Three different drought indices were utilized to summarize the overall meteorological, hydrological, and agricultural drought types in the major watersheds of China. The drought indices were extracted from MODIS and TerraClimate data for a time frame of twenty-four years (2000–2024). The temporal scale of monitoring and derivation was singularly designated to an annual scale. Table 1 provides descriptive information on the derived indices.

Table 1. Descriptive information on the derived drought indices across China.

Drought Category	Index		Constituents	Satellite/ Dataset	Spatial Resolution (km)	Adopted Temporal Resolution (Month)	Temporal Range (Year)
Meteorological	SPEI		Precipitation Evapotranspiration	SPEIbase	55.5	24	2000–2024
Hydrological	PDSI		Precipitation Evapotranspiration Runoff	TerraClimate	4.5		
Agricultural	VHI	VCI	NDVI (Normalized Difference Vegetation Index)	MODIS (MOD13Q1 product)	1		
		TCI	LST (Land Surface Temperature)	MODIS (MOD11A2 product)	1		

Meteorological Drought Indices: Standardized Precipitation Evapotranspiration Index (SPEI)

In our study, we utilized the Global SPEI database (SPEIbase), as summarized in Table 1, a product available through Google Earth Engine (GEE), which provides comprehensive and long-term information on drought conditions at a global scale with a 0.5-degree pixel size and monthly cadence. The SPEIbase employs the FAO-56 Penman–Monteith method for estimating potential evapotranspiration, which is recognized as a superior approach compared to other methods, such as the Thornthwaite estimation used in the SPEI Global Drought Monitor. This distinction enhances the reliability and applicability of the SPEI values derived from this dataset. We chose the SPEIbase not only for its methodological rigor but also for its capacity to provide standardized SPEI values that can be easily compared across different regions and time periods. The reference period for calculating SPEI in the SPEIbase corresponds to the entire study period, ensuring that the index accurately reflects deviations from long-term climatic balances in our specific analysis of drought conditions across the major watersheds in China [19,59]. SPEI is classified into nine standard classes, as detailed in Table 2, in which values below −0.5 represent the onset of meteorological drought conditions [60].

Table 2. SPEI categories.

Categorization	SPEI Values
Extremely wet	2.00 and above
Severely wet	1.50 to 1.99
Moderately wet	1.00 to 1.49
Mildly wet	0.49 to 0.99
Normal	0.50 to −0.50
Mild drought	−0.49 to −0.99
Moderate drought	−1.00 to −1.49
Severe drought	−1.50 to −1.99
Extreme drought	−2.00 and below

Our SPEI classification scheme encompasses a wider range of categories than the WMO standard, offering greater resolution in drought condition analysis. This enhanced granularity allows us to detect subtle differences in drought impacts across diverse watersheds, providing a more comprehensive understanding of hydrological dynamics amid regional climate variability. With additional categories, we are better equipped to inform water resource management and develop drought mitigation strategies that address the specific needs of each region.

Hydrological Drought Indices: Palmer Drought Severity Index (PDSI)

The Potential Drought Severity Index (*PDSI*) is arguably the most common indicator for assessing long-term drought situations using water supply and demand. It is calculated from a soil moisture model using precipitation, evapotranspiration, and runoff, as follows:

$$PDSI = \frac{Z}{K} \tag{1}$$

where Z represents the moisture anomaly and K is a calibrated climatic parameter. *PDSI* is intended primarily to assess hydrological (drought) conditions at large spatial scales (sub-regional and greater) [61]. PDSI is classified into eleven standard classes, in which values below −0.5 represent the onset of hydrological drought conditions (Table 3).

Table 3. PDSI categories.

Categorization	SPEI Values
Extremely wet	4.00 and above
Very wet	3.00 to 3.99
Moderately wet	2.00 to 2.99
Slightly wet	1.00 to 1.99
Incipient wet spell	0.50 to 0.99
Near normal	0.49 to -0.49
Incipient dry spell	−0.50 to −0.99
Mild drought	−1.00 to −1.99
Moderate drought	−2.00 to −2.99
Severe drought	−3.00 to −3.99
Extreme drought	−4.00 and below

Agricultural Drought Indices: Vegetation Health Index (VHI)

The Vegetation Health Index (*VHI*) is a remote sensing index that measures vegetation health and is used to identify drought. The *VHI* is calculated from satellite observations and is a combination of the vegetation condition index (*VCI*) and the thermal condition index (*TCI*) [62]. The *VHI* is used to estimate crop conditions and anticipated yields (Equation (3)).

$$VHI = a \times VCI + (1 - a) \times TCI \tag{2}$$

where a determines the contributions of *VCI* and *TCI* to *VHI*, which varies depending on the environment of the study area [63].

The *VCI* (Vegetation Condition Index) is extracted from the *NDVI* (Normalized Difference Vegetation Index) to indicate drought-driven vegetation stress factors. It is calculated by normalizing the *NDVI* values (Equation (3)).

$$VCI = \frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \times 100 \tag{3}$$

where $NDVI_i$ is the current NDVI, and $NDVI_{min}$ and $NDVI_{max}$ are the minimum and maximum *NDVI* values over the study period. By quantifying vegetation stress, the *VCI* serves as a suitable portal for agricultural drought conditions [64].

The *TCI* complements the *VCI* by measuring the thermal stress experienced by vegetation, which is particularly useful in identifying heat-induced drought conditions (Equation (4)).

$$TCI = \frac{LST_{max} - LST}{LST_{max} - LST_{min}} \times 100 \tag{4}$$

where *LST* represents the land surface temperature. The *TCI* addresses extreme temperature impacts on agricultural droughts, providing complementary information on drought intensity [65]. A decrease in the *VHI* would, for example, indicate relatively poor vegetation conditions and warmer temperatures, signifying stressed vegetation conditions, and, over a longer period, would be indicative of drought. The *VHI* is classified into five standard classes, in which values below 40 represent the onset of agricultural drought conditions (Table 4).

Table 4. VHI categories.

Categorization	SPEI Values
Extreme drought	10 and below
Severe drought	9 to 19
Moderate drought	20 to 29
Light drought	30 to 39
No drought	40 and above

2.3. TOPSIS Stages

The TOPSIS ranking method is based on comparing alternatives (watersheds) with respect to their theoretical distance from the positive ideal and negative ideal solutions. What follows are the mathematical stages for prioritizing the alternatives attributed by multiple criteria (drought indices) [66].

2.3.1. Decision Matrix Construction

The decision matrix D is constructed, where each element X_{ij} represents the performance of watershed i concerning drought indices j:

$$D = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_j \\ \vdots \\ A_m \end{array} \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1j} & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2j} & \cdots & X_{2n} \\ \vdots & \vdots & & \vdots & & \vdots \\ X_{i1} & X_{i2} & \cdots & X_{ij} & \cdots & X_{in} \\ \vdots & \vdots & & \vdots & & \vdots \\ X_{m1} & X_{m2} & \cdots & X_{mj} & \cdots & X_{mn} \end{bmatrix} \tag{5}$$

2.3.2. Decision Matrix Normalization

Each element of the decision matrix is normalized to obtain dimensionless values, following Equation (6).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{6}$$

2.3.3. Creating a Weighted Normalized Decision Matrix

The normalized decision matrix is weighted by multiplying each element by the corresponding weight ω_j assigned to each index:

$$v_{ij} = \omega_j r_{ij} \tag{7}$$

We used Shannon's entropy method to assign weights to different drought metrics and indices (i.e., the frequency and duration of the *SPEI*, *VHI*, and *PDSI*). This method is completely data-driven and calculates the weights of criteria (indices) based on the inherent information and variability in the dataset. It does not rely on subjective judgments, making it suitable for situations where human bias needs to be avoided in decision-making. This mathematical procedure behind this method is provided further below.

2.3.4. Ideal and Negative-Ideal Solution Identification

The ideal solution A^+ and negative-ideal solution A^- are determined by selecting the best (Equation (8)) and worst (Equation (9)) values for each index:

$$\begin{array}{c} A^+ = \left\{\max\left(v_{ij}\right) \middle| j = 1, 2, \ldots, n\right\}, \\ A^- = \left\{\min\left(v_{ij}\right) \middle| j = 1, 2, \ldots, n\right\} \end{array} \tag{8}$$

$$\begin{array}{c} A^+ = \left\{\min\left(v_{ij}\right) \middle| j = 1, 2, \ldots, n\right\}, \\ A^- = \left\{\max\left(v_{ij}\right) \middle| j = 1, 2, \ldots, n\right\} \end{array} \tag{9}$$

2.3.5. Separation Measure Calculation

The Euclidean distance between each alternative and the ideal solutions is calculated as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - A_j^+\right)^2}$$
$$D_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - A_j^-\right)^2} \tag{10}$$

2.3.6. Calculating the Relative Closeness to the Ideal Solution

The relative closeness C_i of each watershed to the ideal solution is computed as follows:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{11}$$

Watersheds are then ranked based on their relative closeness.

2.4. Weighting the Drought Indices Using Shannon's Entropy Method

In the multi-criteria decision-making process, it is essential to assign appropriate weights to each criterion to reflect its importance in the overall prioritization. For this study, Shannon's entropy method was employed to calculate the weights of the drought indices used in the TOPSIS model. Shannon's entropy is a widely used objective weighting technique that evaluates the degree of uncertainty or randomness in a dataset. A lower entropy value indicates higher information content, leading to a higher weight for that criterion. The following steps outline the process of calculating the weights using Shannon's entropy [67,68].

2.4.1. Normalizing the Decision Matrix

Let the original decision matrix be denoted by $X = [x_{ij}]$, where x_{ij} represents the value of the i-th alternative (watershed) for the j-th criterion (drought index). The decision matrix is first normalized to ensure all values are comparable. The normalization formula used is as follows:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{12}$$

where r_{ij} is the normalized value, x_{ij} is the original value for watershed i and criterion j, and m is the total number of watersheds.

2.4.2. Calculating the Entropy Value for Each Criterion

The entropy E_j for each criterion j is calculated using the normalized values r_{ij} as follows:

$$E_j = -k\sum_{i=1}^{m} r_{ij}.\ln(r_{ij}) \tag{13}$$

where E_j is the entropy of the j-th criterion, $k = \frac{1}{\ln(m)}$ is a constant that ensures E_j falls between 0 and 1, and r_{ij} is the normalized value for the i-th alternative and j-th criterion. If $r_{ij} = 0$, then $r_{ij}\ln(r_{ij})$ is defined as 0 to avoid undefined operations.

2.4.3. Calculating the Degree of Diversification for Each Criterion

The degree of diversification d_j for each criterion j is then calculated as follows:

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

This reflects the variation in the data; a higher degree of diversification means that the criterion provides more useful information for prioritization.

2.4.4. Calculating the Weights

The weight ω_j for each criterion j is obtained by normalizing the degree of diversification values:

$$\omega_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{15}$$

where ω_j is the weight for the j-th criterion, d_j is the degree of diversification for the j-th criterion, and n is the total number of criteria (drought indices).

2.5. Mahalanobis Distance

The Mahalanobis Distance is calculated as follows:

$$MD = \sqrt{(X - \mu)^T \Sigma^{-1} (X - \mu)} \tag{16}$$

where X is the vector of drought indices, μ is the mean vector, T is the transposed matrix, and Σ is the covariance matrix [69].

2.6. Normalization Within the TOPSIS–Mahalanobis Framework:

In this study, the Mahalanobis Distance calculation inherently addresses normalization by using the covariance matrix to scale each index based on its variance and adjust for correlations between indices. This effectively places all drought indices (the *SPEI*, *VHI*, and *PDSI*) on a comparable scale without the need for explicit vector normalization as in traditional TOPSIS applications (i.e., Equation (6)). By leveraging the covariance structure in the Mahalanobis Distance method, we ensure that differences in units and value ranges do not affect the prioritization, as each index is inherently adjusted based on its natural variance and correlation with other indices. Consequently, while traditional TOPSIS requires a separate normalization step, the Mahalanobis Distance method in our combined framework performs this normalization intrinsically, streamlining the calculation and reducing potential redundancy.

2.7. Integrated TOPSIS–Mahalanobis Method

A combined application integrating TOPSIS (technique for order of preference by similarity to ideal solution) into the Mahalanobis Distance was used to rank the watersheds based on the six drought indices. The coupled TOPSIS and Mahalanobis Distance method exceeds standalone multi-criteria prioritization methods by considering the inherent independence among the spatiotemporal patterns of environmental (drought) indices. This approach combines the distance measures of TOPSIS and the correlation-sensitive Mahalanobis Distance to incorporate the multivariate context of drought data. The equations can be integrated as follows:

$$MD_i^+ = \sqrt{\left(A_j^+ - r_i\right)^T \Omega^T \Sigma^{-1} \Omega \left(A_j^+ - r_i\right)} \tag{17}$$

$$MD_i^- = \sqrt{\left(r_i - A_j^-\right)^T \Omega^T \Sigma^{-1} \Omega \left(r_i - A_j^-\right)} \tag{18}$$

$$\Omega = diag\left(\sqrt{W_1}, \sqrt{W_2}, \ldots, \sqrt{W_n}\right) \tag{19}$$

$$C_i^* = \frac{MD_i^-}{MD_i^+ + MD_i^-} \tag{20}$$

where Ω is the square root of the elements of the weight vector on the diagonal matrix. This approach, following the cadence of the integrated methodology, helps us to achieve more robust spatial prioritization because it better incorporates the relative closeness notion with spatial correlation between the indices, resulting in a more cohesive decision-making process when combined with prior drought planning efforts.

2.8. Decision Matrix and Prioritization

The nine major watersheds in China collectively revealed specific vulnerabilities to meteorological, agricultural, and hydrological droughts. The overall vulnerability of these watersheds was calculated and prioritized using a multi-criteria decision-making (MCDM) method, the TOPSIS–Mahalanobis Distance method, forming a 9×6 decision matrix. Each matrix included two indicators for each drought type (frequency and average duration). These indicators used data from the Standardized Precipitation Evapotranspiration Index (SPEI) to represent meteorological droughts, from the Vegetation Health Index (VHI) to depict agricultural droughts, and from the Palmer Drought Severity Index (PDSI) for hydrological droughts. In total, six metrics (i.e., the frequency and duration of three indices) were weighted using Shannon's entropy.

These weights were then applied to the TOPSIS–Mahalanobis method. In sum, these indicators established an adequate overview of drought spatiotemporal conditions. As such, overall drought risk (RC) was determined for the pools of watersheds using a combined multi-criteria decision-making (MCDM) method (coupled TOPSIS and Mahalanobis Distance). Together with overall drought risk rank (RC), watersheds were ranked for individual vulnerability to each type of drought: meteorological (RM), agricultural (RA), and hydrological (RH). The combined drought risk rank (RC) depicts the overall susceptibility of the pooled watersheds, while the individual ranks represent the specific vulnerabilities of each watershed. This analysis enables the development of practices/responses to reduce the overall drought risk and/or practices/responses tailored to meet specific vulnerabilities to conserve threatened supply. The drought vulnerability of each watershed was assessed separately in a 9×2 matrix (with combinations of available drought frequency and duration in each specific index), yet overall drought was assessed for all watersheds concurrently. Overall, this method yields an expansive prioritization of watersheds, though it simultaneously increases the complexity of managing multiple types of droughts at once. Further, multiple indicator data do not always convey specific drought patterns. For example, watersheds that show a high vulnerability range to meteorological drought may not necessarily show high vulnerability to agricultural or hydrological drought, indicating the complex interplay of local conditions, water management practices, and temporal dynamics.

3. Results and Discussion

3.1. Decision Matrix and Distance from Ideal Solutions

The decision matrix, shown in Table 5, consolidates the various drought indicators for each watershed. Each row represents a watershed, while the columns indicate the different criteria assessed, including meteorological, hydrological, and agricultural drought metrics. To quantify the performance of each watershed, we calculated the Mahalanobis distances (MDs) from the ideal solutions. These distances indicate how far each watershed is from the best possible conditions (MD−) and the worst possible conditions (MD+). The calculations for MD− and MD+ are detailed in Table 6, respectively, following the formulations provided in Equations (17) and (18).

Table 5. Decision matrix containing the alternatives (nine major watersheds) and drought F-D (frequency–duration) variables derived from multi-dimensional drought indices.

Alternative	*SPEI-F*	*SPEI-D*	*PCI-F*	*PCI-D*	*VHI-F*	*VHI-D*
1	12	6.00	18	4.75	5	1.50
2	14	3.50	20	7.00	2	3.00
3	5	2.50	14	1.00	4	1.67
4	13	4.33	17	3.60	6	7.00
5	5	2.50	16	8.00	9	2.50
6	8	2.67	13	4.33	5	2.50
7	4	2.00	11	1.83	3	3.00
8	5	1.25	12	2.40	6	1.50
9	15	5.00	9	2.25	6	1.75

Table 6. Mahalanobis Distances from the best and worst solutions.

Alternative	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
MD+	4.53	3.92	3.37	4.83	4.54	2.30	1.53	3.64	3.84
MD−	4.13	5.03	5.19	2.63	3.52	4.14	5.13	5.28	4.77

3.2. Temporal Variability in Drought Indicators: Comparative Insights Across Watersheds

The temporal variability in drought indicators across the nine watersheds provides an understanding of the relative drought dynamics of the watersheds (Figure 3). The Vegetation Health Index (VHI), indicative of agricultural drought conditions, shows an overall upward trajectory at most watersheds from 2011 to 2023. Watersheds 1 and 2 demonstrate consistently positive trajectories in VHI, indicative of reduced agricultural drought impacts on vegetation health. The positive trajectory is likely due to improved water resource management or more favorable climate variability in the past. Watersheds 4 and 9 exhibited some of the largest variability in VHI, especially in the early 2000s and after 2015, indicating less stability in the vegetation response to moisture levels than other watersheds, possibly due to inconsistent precipitation patterns or other anthropogenic factors, such as land use changes.

The Standardized Precipitation Evapotranspiration Index (SPEI) exhibits an interesting pattern, where, compared to other watersheds, watersheds 1, 5, and 7 appear to have experienced greater and longer meteorological droughts between 2005 and 2010. This period coincides with some of the significant drought events impacting East Asia [70,71]. However, in 2012, it appeared that a distinct recovery period began for most watersheds, as shown by watershed 5, as the values were approaching the mean within the normal range for the SPEI, indicating improved conditions related to moisture. Meanwhile, the Palmer Drought Severity Index (PDSI) indicated that a moderate but notably stable trend of hydrological drought recovery occurred for most watersheds and particularly after 2012. Watersheds 6 and 3 displayed a unique pattern of resilience and stability, indicated by moderate PDSI values, along with a recovery trajectory post-2012. Watershed 4 demonstrated a comparatively consistent lower but recurring PDSI, which appeared to indicate hydrologic stress post-2015, potentially because of the watershed geographies and topography.

Comparing the watersheds, we can observe that Watersheds 1, 3, and 6 appear to have improved generally across all three indices of interest, showing either effective drought management or more favorable weather conditions. On the other hand, Watersheds 4 and 9 appear to have variable drought indices across all indices, especially the VHI and PDSI. These watersheds may require more targeted drought management to buffer against the impacts of hydrological and agricultural drought. This supports the need for adaptive drought management strategies that are specific to watershed contexts, as well as potential long-term climate resilience in specific watersheds. Watersheds that show variations in drought indices (including indices that are agriculture-related) should warrant further investigation to understand the environmental or anthropogenic causes of variability.

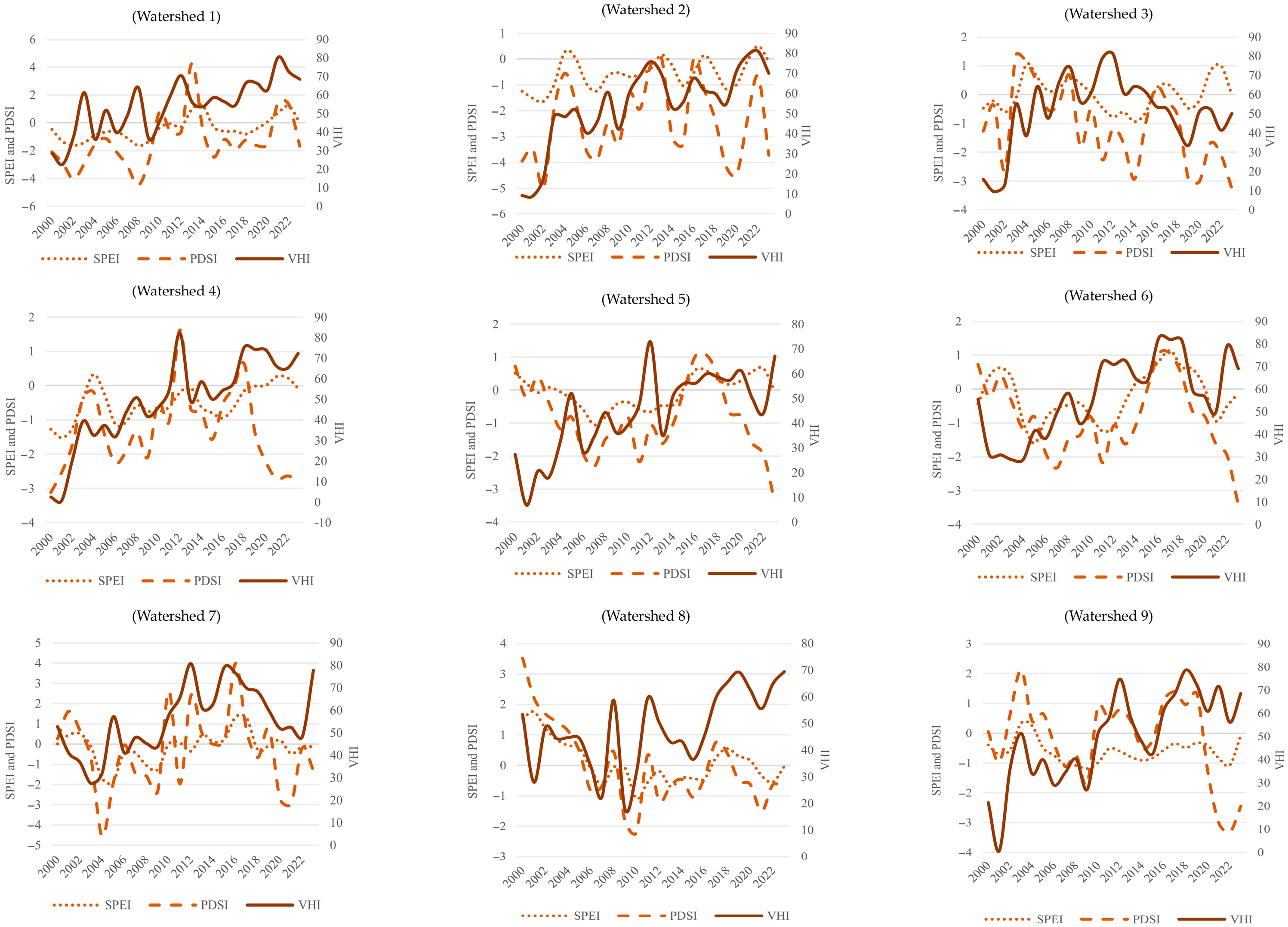

Figure 3. Temporal variability in drought indicators across major watersheds of China.

The differences observed among the SPEI, VHI, and PDSI indices across watersheds reflect the unique drought dimensions that each index captures and the diverse environmental characteristics of the watersheds studied. The SPEI primarily captures meteorological drought, which responds quickly to atmospheric variability. The VHI, an agricultural drought index, indicates vegetation health and soil moisture stress, which can vary sharply in watersheds with high agricultural reliance. The PDSI, as a hydrological index, reflects long-term soil and groundwater conditions, often responding more gradually to precipitation changes. These distinctions lead to varying patterns in drought severity across watersheds, as shown in Figure 3, where each watershed's drought response is shaped by both the chosen index and the watershed's unique environmental features.

Research indicates that the performance and suitability of drought indices can vary significantly across China's diverse regions due to distinct climatic and environmental characteristics. For example, the SPEI, which accounts for evapotranspiration, is particularly responsive in regions with high temperature and precipitation variability, such as southern China, where it captures short-term meteorological drought effectively. However, in colder northern regions with lower evapotranspiration rates, SPEI may not fully represent drought conditions, and the Palmer Drought Severity Index (PDSI), with its focus on long-term soil moisture, may be more appropriate for assessing drought severity [72,73]. Additionally, indices like the Vegetation Health Index (VHI), which reflects vegetation stress, are crucial in agriculturally intensive regions such as eastern and southeastern China, where rapid soil moisture depletion impacts crop health. Conversely, in arid northwestern regions, where water scarcity is a major concern, PDSI serves as a more stable indicator for hydrological drought, highlighting the importance of selecting indices based on regional environmental contexts [72,74–76]. Notably, recent climate anomalies between 2020 and 2022, including intensified monsoon events in the south and persistent aridity in the north, may account for some of the observed divergence in drought indices during this period. These events likely caused rapid shifts in drought conditions that were captured differently by each index depending on the local context [47–51]. These regional discrepancies underscore the importance of using multiple drought indices to capture the nuanced impact of drought across varied environmental landscapes, particularly in a large country like China.

3.3. Spatiotemporal Distribution of Drought Events Across Watersheds

Table 7 and Figure 4 summarize the incidence of drought types (0 to 3) on a yearly basis from 2000 to 2023, across nine major watersheds (1–9). These values correspond to how many types of droughts (meteorological, agricultural, hydrological) occurred in a given watershed per year. The number of drought types observed per watershed ranged from 0 (no droughts) to 3 (all three types of drought). Throughout years of high drought prevalence, three drought types occurred simultaneously across several watersheds in multiple years, notably in 2001, 2002, 2006, and 2009, representing a period of considerable and extended drought exposure. In particular, in 2002, all three drought types were observed at Watersheds 1, 2, 3, and 4, demonstrating the exceptional severity and expanse of drought across these four watersheds. In contrast, during the relatively low-drought years 2010, 2013, 2014, and 2017, much less exposure to droughts across watersheds was discerned, with large areas experiencing no droughts at all (e.g., Watershed 8 had no droughts recorded in 2013 and 2014). Remarkably, Watershed 2 had the highest occurrence of severe droughts, with multiple years recorded as showing three drought types (e.g., 2001, 2002, 2006, and 2009). On the other hand, Watershed 6 had relatively few severe drought occurrences overall, with years usually only recording drought type 0 or 1 for the various years surveyed. Watersheds 1 and 4 also had higher exposure to two or more drought types, particularly in the years 2001–2009, which suggests a high vulnerability in these regions, as they were exposed to two or more droughts simultaneously. In 2001 and 2002, there were several watersheds that had all three drought types occurring simultaneously, which marks another key time period for drought intensity; this was then followed by a relatively calmer year in 2003, but more severe drought exposure re-emerged again in

2006 and 2009. For better interpretation, these oscillations are plotted in Figure 4. It is noteworthy that the drought pattern shown in Figure 4 does not follow a clear temporal trend and may be driven by complex, irregular factors rather than a consistent progression over time. Additionally, the impacts of recent drought events may have been amplified by socio-economic pressures such as increased water demand from population growth, urban expansion, and intensified agricultural activities. These factors deplete water resources more rapidly, heightening vulnerability to drought impacts even when drought intensity is moderate.

Table 7. Incidence of drought types (0 to 3) on a yearly basis from 2000 to 2023 across nine major watersheds (1–9) (the light-yellow-to-brown color palette signifies the watershed experiencing zero drought to multiple drought types).

Year	Watershed ID									Sum
	1	2	3	4	5	6	7	8	9	
2000	2	3	2	3	1	0	0	0	1	12
2001	3	3	1	3	1	1	0	1	3	16
2002	3	3	3	3	1	1	1	0	2	17
2003	2	2	0	1	1	2	2	0	0	10
2004	3	1	1	1	2	3	3	0	1	15
2005	2	1	0	2	1	2	2	0	0	10
2006	3	2	1	3	3	3	0	2	2	19
2007	2	2	0	2	3	2	1	3	3	18
2008	2	2	0	2	2	1	2	0	2	13
2009	3	2	1	2	2	1	2	2	3	18
2010	0	2	0	1	2	2	0	3	1	11
2011	1	2	1	2	2	2	1	1	1	13
2012	1	0	2	0	2	2	0	1	1	9
2013	0	0	2	1	2	0	0	2	1	8
2014	0	1	2	2	1	0	0	0	2	8
2015	1	2	2	2	0	0	0	2	1	10
2016	2	1	0	2	0	0	0	0	1	6
2017	2	1	0	1	0	0	0	0	0	4
2018	2	1	1	0	0	0	1	0	0	5
2019	1	2	2	1	1	0	0	1	0	8
2020	1	2	1	1	1	1	1	1	1	10
2021	0	1	1	1	1	2	1	1	2	10
2022	0	1	1	1	1	0	0	2	2	8
2023	1	1	1	1	1	1	1	1	1	9

Additionally, the years 2001 and 2006 were selected as examples to display the spatial distribution of different drought types using three examined indices (i.e., the SPEI, VHI, and PDSI) in Figure 5. In both 2001 and 2006, large areas of China were impacted by drought, with each drought type (as represented by the SPEI, VHI, and PDSI indices) affecting significant portions of the country's land area. According to the SPEI, 55.52% of the area (approximately 532.8 M·km^2) experienced drought in 2001, which increased to 59.55% (571.4 M·km^2) in 2006. The VHI showed more highly drought-affected areas, with 63.85% (612.7 M·km^2) in 2001 and 65.05% (624.2 M·km^2) in 2006, indicating widespread agricultural drought conditions. The PDSI results similarly demonstrated extensive drought coverage, with affected areas rising from 61.36% (588.8 M·km^2) in 2001 to 66.52% (638.3 M·km^2) in 2006. However, an analysis of multi-year data from 2000 to 2023 reveals that there is no clear, linear worsening trend over time; rather, drought conditions fluctuate, underscoring the complex and variable nature of droughts across China. This multi-dimensional assessment highlights the importance of monitoring drought through different lenses—meteorological, agricultural, and hydrological—to capture the full scope of drought impacts in different regions and years.

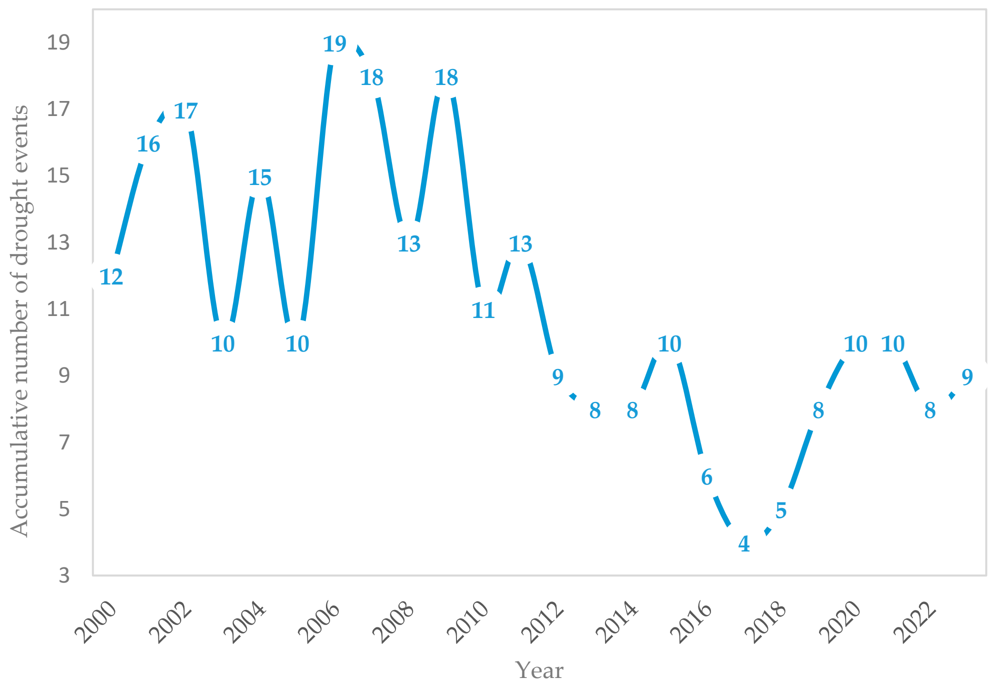

Figure 4. The total number of meteorological, agricultural, and hydrological drought events experienced across China over the years.

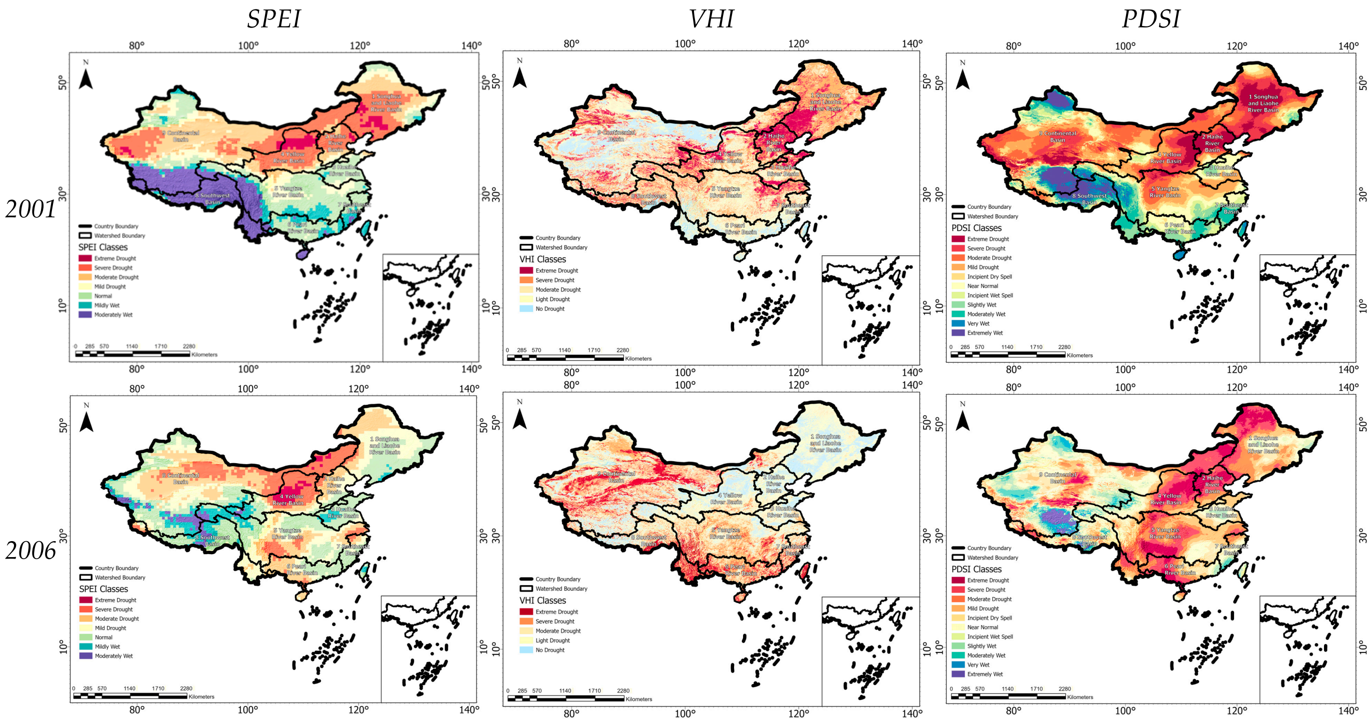

Figure 5. Spatial patterns of the SPEI, VHI, and PDSI indices, representing meteorological, agricultural, and hydrological droughts, respectively, across China during two notably severe years: 2001 and 2006.

In exploring the temporal variability and spatiotemporal distribution of drought indicators across watersheds, Sections 3.2 and 3.3 offer complementary insights into the complexities of drought phenomena. Section 3.2 delves into the temporal variability of drought indicators, highlighting how the Vegetation Health Index (VHI), Standardized Precipitation Evapotranspiration Index (SPEI), and Palmer Drought Severity Index (PDSI) reveal different dynamics across watersheds. For instance, while Watersheds 1, 3, and 6 demonstrate resilience through consistent improvement across indices, Watersheds 4 and 9 indicate a need for targeted drought management due to the observed variability in their responses. This underscores the significance of tailoring adaptive management strategies to specific watershed characteristics and historical drought impacts. Then, Section 3.2 emphasizes the spatiotemporal occurrence of drought types, illustrating how simultaneous occurrences of meteorological, agricultural, and hydrological droughts—particularly in years of high prevalence such as 2002—expose vulnerabilities in multiple watersheds. The analysis indicates that Watershed 2 experienced the highest frequency of severe droughts, reinforcing the idea that cumulative drought impacts can exacerbate regional vulnerability and stress on water resources. Integrating insights from both sections enhances our understanding of drought management. The interplay between temporal and spatial drought dynamics underscores the necessity for a cohesive narrative that informs management strategies. By recognizing how different drought types can converge and affect watersheds simultaneously, we can develop more comprehensive and targeted drought management approaches. These strategies should not only address immediate drought conditions but also consider long-term resilience planning in the context of ongoing climatic change and socio-economic pressures, which compound drought effects.

3.4. Overview of Watershed Drought Vulnerabilities

The nine major watersheds in China collectively revealed specific vulnerabilities to meteorological, agricultural, and hydrological droughts. The results of our analysis, as presented in Table 8, indicate the weights assigned to the various drought metrics derived from Shannon's entropy, which were utilized for watershed prioritization through the TOPSIS–Mahalanobis method. The weights highlight the significance of the Potential Drought Severity Index (PDSI) in assessing drought conditions, with PDSI-D (drought duration) receiving the highest weight of 0.267, followed closely by VHI-D (Vegetation Health Index during drought conditions) at 0.232 and SPEI-F (drought frequency) at 0.183. This suggests that both the severity and frequency of drought conditions, particularly as reflected by the PDSI, are critical in understanding drought dynamics, while vegetation health also plays a substantial role.

Table 8. Shannon's entropy-derived weights assigned to drought metrics used for watershed prioritization using the TOPSIS–Mahalanobis method.

Metrics	PDSI-D	VHI-D	SPEI-F	SPEI-D	VHI-F	PDSI-F
Weights (Largest to Smallest)	0.267	0.232	0.183	0.155	0.117	0.045

In Table 9, the ranking of the watersheds based on their combined ranks reveals varying degrees of vulnerability to different types of droughts. Watershed 4 emerges as the most critically vulnerable, marked by severe agricultural drought issues and high meteorological stress, necessitating immediate intervention. In contrast, Watershed 7 shows the least vulnerability, with lower ranks across all drought types. Notably, Watershed 2, despite experiencing high hydrological drought stress, exhibits less urgency for immediate action regarding meteorological and agricultural droughts. This differentiation underscores the importance of tailored water resource management strategies that address the specific vulnerabilities and drought dynamics of each watershed, reflecting the nuanced insights gained from the multi-faceted approach of our analysis.

Table 9. Combined and drought-specific ranking of China's major watersheds.

Watershed ID	RC (Combined Rank)	RM (Meteorological Rank)	RA (Agricultural Rank)	RH (Hydrological Rank)	General Status
1	3	1	6	3	Watershed 1 faces critical meteorological drought. Hydrological conditions are under moderate stress, while agricultural systems are relatively stable.
2	5	4	9	1	Watershed 2 has high hydrological drought stress, with less immediate concerns for meteorological and agricultural drought.
3	7	5	8	6	Watershed 3 is moderately impacted across all drought types, with meteorological drought being a higher concern than hydrological and agricultural drought.
4	1	3	1	4	Watershed 4 is the most vulnerable overall, with severe agricultural drought issues, high meteorological stress, and moderate hydrological concerns.
5	2	5	2	2	Watershed 5 faces significant agricultural and hydrological drought conditions, requiring urgent action in these areas.
6	8	7	5	5	Watershed 6 has moderate vulnerabilities across all areas, but its situation is less critical compared to others.
7	9	8	7	9	Watershed 7 is the least vulnerable, with lower ranks across all drought types, requiring minimal interventions.
8	6	9	4	7	Watershed 8 shows moderate agricultural vulnerability, with minimal concern for meteorological drought.
9	4	2	3	8	Watershed 9 experiences high meteorological and agricultural drought stress, with less concern for hydrological drought.

3.5. Link Between Drought Metrics and Management Practices

The choice of metrics (the SPEI, VHI, and PDSI) was instrumental in capturing a range of drought vulnerability aspects. This combination enables a multi-layered understanding of drought conditions, providing nuanced insights into regional variations in drought impacts across watersheds. The SPEI measures meteorological drought, incorporating precipitation and evapotranspiration to assess water balance. It quantifies short- and long-term precipitation anomalies and how these anomalies contribute to drought emergence. Watersheds that are highly vulnerable in the SPEI (e.g., Watershed 1) experienced prolonged periods of below-average precipitation. Even though lower temperatures help reduce moisture loss in certain watersheds, if precipitation is consistently below average, this can still lead to drought conditions. Essentially, lower temperatures mitigate some impacts of drought by retaining moisture, but they do not address the underlying issue of insufficient rainfall. Thus, even with reduced moisture loss, the lack of adequate precipitation compounds vulnerability to drought incidents. In other words, prolonged below-average precipitation can overshadow the effects of temperature on drought conditions. A watershed's rank in the SPEI, therefore, establishes a basal need for urgent interventions like rainwater harvesting, cloud seeding, or emergency water use restrictions in order to provide immediate relief from shortages. The VHI, on the other hand, reflects agricultural drought, which tabulates meteorological anomalies with vegetation health and vigor and is a natural choice for agronomic drought monitoring. High VHI ranks are obtained by watersheds such as Watershed 4, which require modern irrigation practices and drought-resistant crop cultivars to counter the effect of low soil moisture on vegetation health. Lastly, the PDSI serves as a measure of hydrological drought to assess long-term water availability in surface water bodies and groundwater. It normally lags behind precipitation accumulation and is often invoked to evaluate longer-term drought conditions. High PDSI ranks are therefore obtained by watersheds that experience long-term needs, such as Watershed 2, requiring actions such as reservoir deposition, aquifer recharging efforts, and long-term water management plans to ensure that water meets residential, industrial, and ecological needs. Each of these indices performs a distinct transformation that captures the initiation and duration of a separate, specific drought type. When these indices are combined into one decision matrix together with their combined rankings, they provide metrics to rank watersheds in order of their overall drought vulnerability while also enabling an understanding of the drought-type-specific impacts on the study region in more detail.

The observed variance in drought indices across the different watersheds can be attributed to a combination of climatic conditions, hydrological characteristics, and human activities. Climatically, factors such as regional temperature patterns, precipitation variability, and seasonal shifts play a crucial role in determining drought severity. For instance, watersheds located in areas with consistently low precipitation and high evapotranspiration rates, like Watershed 1, tend to experience more severe drought conditions. Conversely, watersheds benefiting from more stable rainfall patterns may exhibit lower drought vulnerability. Hydrological characteristics, including soil type, land cover, and watershed morphology, further influence how moisture is retained or lost. For example, watersheds with well-drained soils may experience quicker runoff, leading to reduced water availability during dry spells. Additionally, human activities, such as agricultural practices and urbanization, can significantly impact local hydrology and water demand. Increased water extraction for irrigation, industrial use, and residential needs can exacerbate drought conditions, especially in watersheds already under stress, as seen in Watershed 5. These multi-faceted interactions highlight the complexity of drought dynamics and underscore the need for tailored management strategies that account for both natural and anthropogenic influences.

3.6. Advantages and Challenges of Using the Combined 9 × 6 Decision Matrix

The combined 9 × 6 matrix has provided many worthwhile benefits in determining which watersheds are most vulnerable. The benefits include that the value of the combined matrix is holistic in assessing the drought condition because it consists of the frequency and duration of each drought type over each watershed. More precisely, using the SPEI, VHI, and PDSI captured a multi-dimensional aspect of drought and prioritized it more holistically than a single-dimensional threat. In addition, this method allows for management opportunities that directly or indirectly consider vulnerability to combined drought types and how to expedite the management response for watersheds with the most extreme and sustained droughts. However, this approach can complicate the process to various degrees. Managing all indicators simultaneously can obscure specific patterns unique to a drought type. For instance, a watershed being ranked highly overall could be due primarily to one drought type (e.g., meteorological drought), while the consideration of other drought types (i.e., agricultural drought or hydrological drought) has been overstated. Furthermore, the possibility of complex relationships across drought types (i.e., meteorological drought triggering agricultural drought) can be lost in the combined matrix. Watersheds being ranked highly due to one particular drought could potentially mask the urgency of further drought-specific interventions.

3.7. Augmenting the Analysis of Separate Drought Types and the Phase-Based Relationship

To address the limitations associated with the combined matrix, individual assessments were conducted and the methodology from the earlier approach was enhanced using matrices populated with 9 × 2 indices. By doing so, a more targeted management strategy was developed for each type of drought within each watershed, allowing for actionable interventions when needed. An important consideration is that there is often a sequential temporal association tied to the different drought types, but this will not always be evident in the rankings generated. Generally, meteorological drought tends to be the first drought type to occur, with the effects of precipitation deficits impacting the evaporation process over land and, subsequently, the surface moisture of soils and flows in river systems. Following meteorological drought is the occurrence of agricultural drought in the water cycle, where notable cessation or declining soil moisture impacts agricultural crop growth and plant health. This is evident in the watersheds directly tied to VHI vulnerabilities, where early intervention for meteorological drought could prevent transition to a more significant agricultural drought. Hydrologic drought tends to occur last, as the depletion of water bodies and aquifer reserves occurs more slowly. It generally lags behind meteorological drought, as it is always slower to experience a downward trend, and management approaches require more complex models. Based on these premises, such a temporal association demonstrates potential value in conveying a phased approach. For example, an early preventive intervention for meteorological drought (e.g., Watershed 1) could reduce the likelihood of it transitioning into an agricultural drought at that particular watershed.

3.8. Rank-Dependent Drought Management Strategies

A crucial element of this evaluation has been the creation of rank-dependent management options based on the extent and severity of drought conditions encountered by each watershed. These options are proposed in a logical order from most immediate/urgent (first rank) to least, with nine overall ranks (Tables 9 and 10). This method allows for the effective use of limited available resources by focusing on the most impactful level of drought conditions while also pursuing options in less affected watersheds. For example, the most impacted watershed was Watershed 1 due to its high ranking for meteorological drought, which entails active rainwater harvesting practices and strict water usage regulations. Comparably, Watershed 7 ranked lower for all three drought types and could benefit from proper monitoring and readiness if a drought occurred.

3.9. Solitary Rank-Dependent Management Strategies

Solitary rank-dependent drought-specific management strategies for each watershed are summarized in Table 10 and discussed below; these are designed to signify the level of urgency in each watershed.

3.9.1. Meteorological Drought: An Immediate Concern

According to Table 10, meteorological drought (RM) represents deficits in precipitation and their immediate effects on available supply. Watershed 1 has the most extreme precipitation deficits, which need immediate remediation. Interventions such as rainwater harvesting, cloud seeding, and stringent water use restrictions should be initiated immediately to mitigate the impacts of meteorological droughts on hydrological and agricultural systems where applicable. In comparison, Watershed 8 was ranked ninth, with the least number of major precipitation deficits, indicating that it is relatively stable with regard to precipitation amounts. This watershed may not be an immediate priority, but the standard monitoring of precipitation trends should be maintained to detect any possible shifts in rainfall patterns in the future.

3.9.2. Agricultural Drought: Water-Efficient Farming Systems

Ranked first in agricultural drought (RA), Watershed 4 has an urgent need to modernize its irrigation system to adapt to biophysical constraints and soil moisture, as well as to reduce the strain on water resources. Therefore, the promotion of drought-resistant crops and a rapid shift towards smart irrigation systems are necessary to recover from chronic water scarcity. Conversely, Watershed 2 is ranked ninth in this domain. Strategies should focus on maintaining this advantage, as biophysical constraints limit the area under irrigation. Sustainable, water-efficient agricultural practices such as rainfed farming could still be promoted at this watershed.

Table 10. Rank-based drought-specific management strategies for major watersheds in China. Management strategies are categorized into four urgency levels, color-coded as (1) green, low priority; (2) gray, supportive; (3) orange, moderate; and (4) red, urgent.

Watershed ID	Meteorological Drought Management	Agricultural Drought Management	Hydrological Drought Management
1	**Urgent**: Implement rainwater harvesting, strict water use restrictions, and cloud seeding.	**Supportive**: Promote drought-tolerant crops and irrigation efficiency.	**Moderate**: Invest in infrastructure upgrades and monitor water withdrawal practices.
2	**Moderate**: Use weather forecasting systems and water conservation campaigns.	**Low priority**: Maintain current practices but monitor for changes.	**Urgent**: Prioritize reservoir replenishment and upgrade aquifer recharge systems.
3	**Moderate**: Install early-warning systems and improve the awareness of climate impacts.	**Low priority**: Monitor agricultural systems. No immediate interventions needed.	**Supportive**: Ensure long-term water storage improvements. But no urgent actions required.
4	**Moderate**: Enhance rainwater collection and weather modification strategies.	**Urgent**: Implement modern irrigation and promote drought-resistant crops.	**Moderate**: Monitor water table levels and prepare storage infrastructure.
5	**Moderate**: Focus on rainfall prediction systems and water-saving campaigns.	**Urgent**: Implement advanced irrigation technologies and water-efficient farming practices.	**Urgent**: Upgrade water reservoirs and improve groundwater management.
6	**Low priority**: Monitor rainfall patterns. No immediate interventions needed.	**Moderate**: Promote efficient irrigation practices to prevent stress.	**Moderate**: Continue strengthening water storage systems and focus on higher-ranked watersheds.
7	**Low priority**: Routine monitoring. No urgent interventions needed.	**Low priority**: Perform routine monitoring. No large-scale actions needed.	**Low priority**: Routine monitoring. No urgent interventions needed.
8	**Low priority**: Routine checks. No immediate interventions needed.	**Moderate**: Implement crop diversification and water-efficient irrigation practices.	**Low priority**: Water storage systems appear stable; monitor them regularly.
9	**Urgent**: Implement emergency water use restrictions, rainwater harvesting, and cloud seeding.	**Moderate**: Equip farming communities with drought-resistant crops and efficient irrigation.	**Low priority**: Maintain current water management practices. No urgent actions needed.

3.9.3. Hydrological Drought: Long-Term Water Security

Hydrological drought (RH) refers to effects on water bodies consisting of surface and groundwater supplies such as rivers, lakes, and aquifers. In terms of hydrological drought, Watershed 2 was highly ranked and classified as being at high risk due to low water availability over extended periods. Efforts to restock reservoirs and recharge aquifers should be more immediate, along with implementing policies to maximize water conservation. It is important to address these issues so that the water bodies in the watershed can meet human needs and environmental requirements during extended dry weather. In contrast, Watershed 9 (with the hydrological drought rank of 8) holds relatively constant water year-round. That said, it is important to continue adherence to current water management practices to avoid any degradation incurred by imminent shifts in the future.

3.10. Integrated Drought Management Strategies for Combined Vulnerabilities

The combined rank (RC) is essential when considering overall drought risks, as it provides consideration for all three drought types. Watershed 4, for example, had the highest overall vulnerability because it was ranked first in combined rank overall, signifying that it is experiencing severe level of stress from all three drought categories, which necessitates a holistic management strategy to concurrently mitigate cascading drought impacts. On the other end of the spectrum, Watershed 7 ranked ninth in overall combined rank, indicating that this watershed is the least vulnerable of all nine watersheds assessed, necessitating only baseline soil and water monitoring activities in the future and minimal management strategies across the three categories. In summary, exposure to a multitude of varied vulnerabilities and different drought rankings across watersheds necessitates developing adaptive and anticipatory management systems to target the particular problems at each watershed.

In conjunction with distinct management tactics for each drought type, it is also critical that we employ combined management methods that address the overall vulnerability of each watershed (Table 11). For Watershed 4, ranked first in RC, a comprehensive drought management plan should be created that integrates management plans across all sectors. For example, modern irrigation systems could go hand in hand with upgrades to water storage infrastructure to reduce agricultural and hydrological droughts. In the same way, an integrated water- and agriculture-based approach would be beneficial for Watershed 5, ranked second in RC. By combining modern irrigation technology with groundwater management, Watershed 5 could mitigate shortages of water for agricultural uses while ensuring long-term water supplies. Table 11 integrates the previous drought-specific management strategies into one holistic framework, aiming to achieve a combined goal. It is noteworthy that when it comes to developing management strategies, recognizing the temporal relationship between different drought types should be an important consideration. Meteorological drought is often a precursor to both agricultural and hydrological droughts; that is, interventions handling rainfall deficits (RM) should reduce the burden created by future agricultural and hydrological droughts (RA and RH). For instance, in Watershed 1 (ranked first in RM), meteorological drought alleviation practices like rainwater harvesting can have downstream effects on both agricultural and hydrologic droughts. The upstream benefits of drought action, referred to as early and fast interventions, can mitigate the downstream impacts of a drought.

Table 11. Combined drought management methods addressing the overall drought vulnerability of major watersheds in China.

Watershed ID	Integrated Drought Management Strategy (Holistic Approach)
1	**Integrated water management**: Combine rainwater harvesting with irrigation system improvements to simultaneously reduce meteorological and hydrological drought impacts.
2	**Long-term water storage strategy**: Focus on reinforcing reservoirs and creating a drought-resilient water distribution network to mitigate future drought risks.
3	**Cross-sector drought monitoring**: Create a monitoring system that links rainfall predictions with water storage and agricultural planning.
4	**Comprehensive drought plan**: Develop an integrated management plan that addresses agricultural water use, rainwater collection, and water storage upgrades.
5	**Integrated water and agriculture strategy**: Link advanced irrigation with groundwater management, ensuring that water savings benefit both agriculture and water storage.
6	**Sustained drought resilience**: Maintain long-term drought resilience through efficient water use and gradual infrastructure improvements.
7	**Basic monitoring strategy**: Continue basic monitoring and ensure that emergency drought plans are ready if needed.
8	**Agriculture and water use strategy**: Focus on balancing agricultural needs with available water resources through crop diversification and irrigation control.
9	**Rainfall and agriculture linkage**: Combine rainwater harvesting with modern farming techniques to optimize water usage across sectors.

3.11. Temporal Lags and Local Characteristics in Watershed Rankings

The ranks of each watershed did not necessarily come out sequentially according to drought propagation. This is primarily a function of local parameters such as soil type, water holding capacity, and vegetation cover that impact how rapidly a basin will transition from a meteorological drought into an agricultural and hydrological one. For example, Watershed 1 placed first in meteorological drought (RM) and sixth in agricultural drought (RA), suggesting tremendous agricultural resistance to persistent dryness. This implies that intervention strategies should concentrate on rainwater harvesting and water usage regulations, and not so much on agricultural issues. For example, Watershed 2 ranks number one in hydrological drought (RH) but number nine in agricultural drought (RA), which shows that although the watershed is probably having tremendous issues with long-term water availability, its agricultural systems are not suffering too much, possibly because of an exceptional adaptive agricultural system, water-stress-resistant crops, and water resource management. But here, water storage structures should be the main concern, and not so much agricultural support. These findings emphasize the need to understand the uniqueness of local watershed conditions and use watershed-specific drought-type rankings in order to develop appropriate management strategies to address the distinctive sensitivities of each watershed.

3.12. Limitations and Future Works

This study acknowledges several limitations that may impact the robustness and applicability of the findings. Firstly, the variability in spatial scales of the input data poses a significant challenge. Different watersheds often encompass diverse environmental and climatic conditions, and the use of data at varying resolutions may lead to inconsistencies in drought assessment and management recommendations. Moreover, the reliance on historical drought indices may limit the ability to accurately predict future drought conditions, especially given the ongoing effects of climate change, which can alter precipitation patterns and increase the frequency of extreme weather events. Additionally, while the methodologies applied in this research offer valuable insights, they may require further refinement to enhance their applicability across different geographical and socio-economic contexts. In terms of future work, it would be beneficial for subsequent studies to incorporate real-time and high-resolution data to capture more immediate and localized drought impacts. Utilizing advanced modeling techniques, such as deep learning and remote sensing, could significantly improve the predictive accuracy of drought assessments and foster adaptive management strategies. Furthermore, engaging with local stakeholders and incorporating socio-economic variables into future analyses would also enhance the relevance of research findings, ultimately guiding effective drought mitigation efforts in diverse contexts. By addressing these limitations and exploring new research directions, researchers in this field can better navigate the complexities of drought management in the face of changing environmental conditions.

4. Conclusions

This research represents a significant advancement in applying multi-criteria decision-making (MCDM) frameworks to drought management, particularly through the integration of the TOPSIS (technique for order preference by similarity to ideal solution) and Mahalanobis distance methods. The key findings of this study can be summarized as follows:

- *Integration of Drought Dimensions:* The study effectively combines three dimensions of drought into a coherent decision matrix, allowing for a comprehensive vulnerability assessment at the watershed level.
- *Identification of Vulnerable Watersheds:* Watersheds 1, 4, and 5 are identified as the most vulnerable across all three selected indices, highlighting the urgent need for strategic interventions.
- *Targeted Mitigation Measures:*
    - For Watershed 1, implementing meteorological drought mitigation measures such as rainwater harvesting and establishing strict groundwater abstraction regulations is imperative.
    - For Watershed 4, updating irrigation technologies and cultivating drought-resistant crops are crucial steps to combat agricultural drought.

- *Consideration of Spatial Dependencies:* This novel application of the coupled TOPSIS and Mahalanobis distance method accounts for spatial dependencies in drought indicators, enhancing the robustness of the prioritization process. The TOPSIS–Mahalanobis approach provides actionable insights that can support drought response planning and promote resilience across other drought-prone regions.
- *Adaptive Drought Management:* An adaptive approach to drought management that respects local specificities is essential. Understanding the sequenced nature of drought types allows for proactive measures, where addressing meteorological drought can mitigate the risks of them transitioning to agricultural and hydrological droughts. This study highlights the fact that Watersheds 1, 4, and 5 face heightened drought risks, calling for a combination of rainwater harvesting, aquifer recharge, and modernized irrigation to mitigate drought impacts. Policymakers are encouraged to prioritize resource allocation in these regions, adapting the proposed solutions to local needs to ensure water security.
- *Phased Relationship Insights:* The analysis for Watershed 1 illustrates that timely integrated water conservation actions can prevent subsequent agricultural drought impacts.
- *Scalable Prioritization Tool Development:* A significant achievement of this study is the creation of a scalable prioritization tool, applicable to various multi-dimensional natural hazards, providing valuable insights for water decision-makers and managers.
- *Future Research Directions:* Future studies should incorporate climate change impacts and social variables, aiming to adapt the framework to ensure water availability to allow regions to transition from vulnerability to resilience, despite evolving drought types.

This research not only contributes to the theoretical framework of drought management but also offers practical recommendations for real-world applications in resource management and decision-making.

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