# The Impact of Dams on Water Scarcity: A Case Study of the Zayandehrood River Basin

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**Abstract:**

Although dams are designed to regulate water extraction in river basins, environmental experts contend that excessive and poorly managed dam development can result in more harm than benefit. While dams can offer some benefits, the scale of dam construction in Iran has far exceeded what is considered sustainable. The widespread modification of river systems through damming and associated infrastructure far surpasses the water management objectives set by the Ministry of Energy, revealing a disconnect between the magnitude of infrastructure development and the effective management of water resources. This study proposes the development of a multivariate metric to evaluate the severity of sustained water stress, integrating alternative water supply sources in engineered sub-basins. The proposed index is based on entropy theory and is compared with conventional water stress indices, with key differences highlighted. Remotely sensed vegetation data are used as an independent validation tool to assess the new index. The results demonstrate that in sub-basins with minimal artificial water sources, the proposed index aligns closely with traditional drought metrics. However, in areas where engineered water supplies are present, the index provides a more accurate representation of water stress, as reflected by its ability to support vegetation growth. The results revealed that, in the upstream basin of the dam, the precipitation-based index and the combined index yielded identical outcomes in all years except for 1998. In contrast, in the downstream basin, the two indices showed divergent results in 66% of the water years analyzed.

**Keywords:**

Dam, Entropy, Multivariate Index, Precipitation, Surface Water.

## 1. Introduction

Drought and water scarcity are persistent challenges in Iran, often lasting for several consecutive years. To address these issues, the country has relied on dam construction and watershed management projects aimed at conserving groundwater and controlling surface water flows. Large dams serve multiple purposes, including securing drinking water, preventing floods, supplying water for industrial and agricultural use, and generating hydroelectric power. However, environmental experts argue that excessive and uncontrolled dam-building has caused more harm than good. With numerous large dams already in operation, concerns are growing that continued expansion could lead to irreversible depletion of critical water resources, destruction of river ecosystems, and the flooding of villages, agricultural lands, and pastures. Even if the necessity of some dams is acknowledged, their current scale has far exceeded reasonable limits. The water management goals set by the Ministry of Energy do not align with sustainable water resource management, leading to an imbalance between infrastructure development and long-term water security [1-2].

One of the key consequences of excessive water extraction and mismanagement is water stress. This occurs when water demand exceeds available supply or when poor water quality limits its usability. Water stress encompasses two critical factors: the quantity and quality of water. Over-extraction of groundwater, depletion of aquifers, and drying rivers reduce water availability, while pollution from agricultural runoff, industrial waste, and salinity intrusion degrades water quality. These issues not only threaten ecosystems but also pose significant risks to human health and food security. Water stress is often measured by the ratio of water withdrawals to available surface and groundwater resources, highlighting the need for effective water conservation strategies [3].

Climate change has further intensified water stress by increasing drought frequency and severity. Throughout Earth's history, the climate has undergone natural fluctuations, including seven major cycles of glacial advance and retreat over the past 650,000 years. The most recent ice age ended roughly 7,000 years ago, coinciding with the rise of human civilization. While past climate shifts were largely driven by natural variations in Earth's orbit, the current warming trend is primarily the result of human activities. Scientific evidence suggests with over 95% certainty that greenhouse gas emissions have been the dominant driver of global warming since the mid-20th century. The consequences of climate change, such as altered precipitation patterns, rising temperatures, and increased evaporation rates, directly affect water availability, exacerbating existing drought conditions [4].

Drought, a prolonged period of deficient rainfall, is one of the most devastating consequences of climate change and water mismanagement. A lack of precipitation can lead to widespread agricultural losses, drinking water shortages, and severe economic and social crises. Prolonged droughts can trigger forced displacement, resource conflicts, and even famine. Unlike sudden natural disasters such as hurricanes or earthquakes, droughts develop gradually, making them difficult to predict. However, their impacts can be long-lasting and far-reaching. Since 1900, droughts have claimed more than 11 million lives and affected over 2 billion people worldwide. They also rank among the most costly natural disasters—California, for instance, has suffered at least $2 billion in annual economic losses due to drought conditions since 2014 [5].

The severity of a drought depends on regional precipitation patterns, making its definition highly variable. In regions with high average rainfall, such as Atlanta, Georgia, which receives approximately 127 cm (50 inches) of rain annually, even a slight reduction can lead to water shortages. Conversely, in arid regions like the American Southwest, where annual rainfall is typically less than 25 cm (10 inches), a drought may last much longer before its impacts become apparent. Identifying the onset and conclusion of a drought is particularly challenging. Unlike storms, which have clear start and end points, droughts evolve slowly over weeks, months, or even years. A brief rain shower may provide temporary relief, but long-term droughts require sustained precipitation to restore normal water levels, making recovery a complex process [6].

Droughts typically arise when disruptions in weather patterns interrupt the natural water cycle. Changes in atmospheric circulation can cause storm tracks to shift or stall, reducing precipitation over extended periods. Wind pattern shifts can also limit moisture absorption, worsening drought conditions. One well-documented example of such climatic disruptions is El Niño, a phenomenon characterized by warmer-than-normal sea surface temperatures in the central Pacific Ocean. This warming influences global storm patterns and is associated with drought conditions in regions such as Indonesia, Australia, and northeastern South America. Climate scientists predict that El Niño events occur approximately every two to seven years, highlighting the need for better forecasting and preparedness strategies to mitigate drought impacts [6-7].

By understanding the interplay between dam construction, water stress, climate change, and drought, policymakers can develop more sustainable water management strategies. Iran, like many other drought-prone regions, must balance infrastructure development with environmental conservation to ensure long-term water security [5-6].

Many researchers have developed water stress indices to better understand and manage drought conditions. For example, Smith and Maidment introduced the Integrated Drought Information System in the United States, which provides a comprehensive overview of drought conditions by integrating data from different types of droughts [8]. Similarly, Karamouz et al. employed three key indices—the Standardized Precipitation Index (SPI) for meteorological droughts, the Palmer Drought Severity Index (PDSI) for agricultural droughts, and the Surface Water Supply Index (SWSI) for hydrological droughts. Their study in Iran's Zayandehrood Basin introduced a novel method for quantifying drought impacts by analyzing drought-related damages. These indices play a crucial role in improving drought prediction and water resource management, helping policymakers develop strategies to mitigate water shortages and protect vulnerable regions [9].

Pandey et al. introduced the Drought Vulnerability Index (DVI), which incorporates seven key parameters: basin slope, land use, soil type, groundwater availability, surface water availability, water demand/consumption, and precipitation deviation [10]. In 2012, Pandey et al. also applied a spatial geoinformatics method for assessing agricultural, meteorological, and hydrological drought risks in the Palamu region [11]. Liu et al. reconstructed historical drought events and evaluated future drought risks in Oklahoma, a drought-prone basin, under climate change scenarios using the Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), and Standardized Runoff Index (SRI) [12].

Hao and Aghakouchak presented a multivariate drought index approach based on the concept of copulas. Their model, the Multivariate Standard Drought Index (MSDI), probabilistically combines the Standard Precipitation Index (SPI) and the Standard Soil Moisture Index (SSI) to describe drought conditions [13]. Similarly, Rajsekhar et al. introduced the Multivariate Drought Index (MDI), which integrates variables related to meteorological, hydrological, and agricultural droughts to present a more comprehensive picture of drought [14].

Safavi et al. developed an integrated drought index that incorporates key drought factors, using the Zayandehrood basin as a study area due to its hydrological significance within the central plateau of Iran [15]. In 2015, Huang et al. introduced the Integrated Drought Index (IDI), which combines meteorological, hydrological, and agricultural drought indices in the Yellow River Basin [16]. That same year, Wasim et al. developed the Composite Drought Index (CDI), which accounts for variables related to all three types of drought [17]. Khoshoei et al. designed and implemented a drought monitoring system for the Zayandehrood basin, based on various drought-related factors [18].

Faiz et al. introduced a new composite drought index (CDI) by integrating potential and actual evapotranspiration, climatic water balance, and precipitation. This CDI was assessed by comparing it with various drought indicators such as soil moisture, the Palmer Drought Severity Index (PDSI), scaled crop yield index (sCYI), the evaluation integrated drought index (EIDI), and the standardized runoff index (SRI) in China [19]. Shah and Mishra developed an Integrated Drought Index (IDI) that combines meteorological, hydrological, and agricultural drought responses, also factoring in groundwater storage [20]. Jing Zhang and colleagues evaluated different drought indices for monitoring drought conditions using remote sensing data [21]. Li et al. compared drought conditions across China using remote sensing, focusing on different drought indices from 2017 [22]. Zhou et al. included the climate anomaly index in a drought model to study the impacts of the El Niño-Southern Oscillation (ENSO) and the Madden-Julian Oscillation (MJO) on drought across various eco-geographic zones of China [23]. Heidarizadi et al. utilized twelve remotely sensed indices from MODIS and DEM to monitor drought between 2000 and 2018, with the Standardized Precipitation Index (SPI) as a reference, employing machine learning techniques to model the relationship between the indices and SPI at various time scales [24]. These diverse indices and technologies enhance drought prediction and water resource management, helping policymakers develop more effective strategies for mitigating water scarcity.

This research aims to investigate water stress in two distinct types of watersheds: a natural watershed located upstream of the dam and an engineered watershed situated downstream of the dam. The natural watershed refers to the area where water flow and distribution are governed by natural hydrological processes without significant human intervention. In contrast, the engineered watershed downstream has been altered by the presence of the dam, which influences water flow, storage, and distribution through artificial means such as controlled releases and infrastructure modifications. By comparing these two types of watersheds, the study seeks to evaluate the dam's influence on water availability, distribution, and drought resilience. Specifically, the research will examine how the dam impacts water stress in both regions, considering variables such as changes in surface and groundwater levels, shifts in agricultural water use, and the overall alteration of the hydrological cycle. Additionally, the study will assess the dam's effect on drought conditions, including the frequency and severity of drought events in the downstream basin, compared to the natural flow conditions upstream. This comparative analysis will help elucidate the extent to which dams, as a form of human intervention, mitigate or exacerbate water stress and drought in different watershed environments. The findings are expected to provide insights into the broader implications of dam construction on regional water resources, ecosystem health, and long-term sustainability, offering valuable information for water management and policy-making in regions facing similar challenges.

## 2. Methodology

Drought indicators are commonly defined based on several key variables, specifically in meteorological, hydrological, and agricultural contexts. These indicators serve as measurable factors that help identify the onset, severity, and duration of drought conditions. Drought triggers, on the other hand, are threshold values for each indicator; once these thresholds are reached, they signal different stages of drought intensity and dictate the timing for implementing drought management actions. Establishing and formalizing these indicators and triggers involves understanding their spatial and temporal relevance, their consistency over time and across locations, and ensuring statistical alignment. This alignment includes the coherence of triggers with one another and with the conditions marking the start and end of drought events.

In the field of information theory, entropy serves as a metric for the average amount of information required to describe the probability distribution of a random variable. Essentially, it gauges the level of uncertainty inherent in a system or process. By quantifying this uncertainty, entropy provides insight into a system's potential to generate information from existing data, a feature that makes it widely applicable across various fields. Since drought patterns are inherently random and difficult to predict, entropy theory proves useful in modeling drought characteristics. Here, we aim to capture drought conditions driven by limited water availability from diverse sources. Entropy theory facilitates this by enabling the integration of these varied, random water sources that contribute to the overall water supply. Through an entropy-based weighting approach, we can effectively combine these inputs, creating a composite measure that better represents the unpredictability and impact of drought.

To quantify drought, various sources of information are considered based on different factors, such as precipitation levels, surface water storage, and other relevant indicators. Entropy weighting helps determine the importance or "weight" of each factor, allowing a more accurate representation of each indicator's contribution to drought assessment. In this approach, we introduce a matrix with mmm rows and n columns to estimate these weights, where mmm represents the number of indicators, and m corresponds to the number of evaluation objects—typically sample data points from a time series for each indicator. This structure results in an original indicator value matrix, which serves as the foundation for calculating the entropy weights and provides a comprehensive view of the data distribution across all selected indicators.

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \tag{1}$$

In this study, ($x_{ij}$) represents the $j_{th}$ evaluation object corresponding to the $i_{th}$ indicator data. The indicators for the X matrix examined in this research include precipitation and surface water storage, which will be detailed in the subsequent sections. The matrix mentioned above can be normalized as follows:

$$R = (r_{ij})_{m\times n} \tag{2}$$

Here, ($r_{ij}$) denotes the $j_{th}$ evaluation object of the normalized data for the $i_{th}$ indicator, where ($r_{ij}$) falls within the range of [0, 1]. Each term is defined as follows:

$$r_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{3}$$

The calculation for the $i_{th}$ evaluation metric is as follows:

$$E_i = -k\sum_{j=1}^{n} f_{ij}\ln(f_{ij}) i = 1, 2, 3, \ldots.., n \tag{4}$$

Where $f_{ij}$ and $k$ are defined as follows:

$$f_{ij} = r_{ij} / \sum_{j=1}^{n} r_{ij} \tag{5}$$

$$k = 1/\ln(n) \tag{6}$$

where $f_{ij}$ denotes the frequency associated with the $j_{th}$ evaluation object and the $i_{th}$ indicator, except when if $f_{ij} = 0$ then $f_{ij}\, ln\left(f_{ij}\right) = 0$

Accordingly, the weight of the $i_{th}$ indicator can be determined using the following formula:

$$w_i = \frac{1 - E_i}{(m - \sum_{i=1}^{m} H_i)} \quad (7)$$

where $0 \le w_i \le 1$ and $\sum_{i=1}^{\mathrm{m}} w_i = 1$.

In this study, we applied entropy weighting theory to construct a multivariate drought index. This index is calculated as the weighted sum of the entropy values linked to each indicator. Specifically, we selected precipitation and surface water storage as the two key indicators (where m=2), representing meteorological and hydrological drought conditions, respectively. By focusing on these indicators, the multivariate drought index provides a composite measure that reflects the combined impact of both precipitation patterns and water storage levels. The final weight for each indicator was derived through entropy calculations, producing a comprehensive drought index as follows:

$$CDI = w_p \times [precipitation] + w_{sws} \times [Runoff] \quad (8)$$

The relationship between precipitation weight and surface runoff weight is established through a pre-calculated matrix that represents the respective weights. These matrices are then multiplied by the corresponding precipitation and surface runoff data to facilitate the computation of weighted values. Specifically, the matrix for rainfall weight is multiplied with the rainfall data, and the matrix for surface runoff weight is multiplied with the surface runoff data. This process ensures that the respective weights are appropriately applied to the observed precipitation and runoff values, enabling more accurate modeling and analysis of hydrological processes.

## 3. Case Study

The Zayandehrood basin ranks among the country's key population centers, yet it has increasingly struggled with water shortages driven by rapid industrial development and a growing population, largely due to migration from other provinces. This rising demand for water has widened the gap between supply and consumption. Historically, water transfer initiatives were introduced to mitigate shortages in this basin, but escalating demand—especially from desert regions beyond the basin—suggests that the supply-demand imbalance will likely worsen in the coming years. This challenge underscores the urgent need to assess both the supply and demand dynamics within the basin.

To address this issue, comprehensive studies on water resources and usage patterns in the Zayandehrood basin are essential. Such studies must also examine atmospheric contributions to water availability across different years, assessing how rainfall and other climate factors influence the region's overall water resources. Covering an area of 26,917 square kilometers, the Zayandehrood basin not only supports its immediate population and industries but also encompasses much of the Gavkhoni wetland watershed. This wetland forms part of the greater watershed of Iran's central desert, which further complicates water management efforts, given the basin's interconnected water needs across desert and urban regions.

The Zayandehrood River, spanning 350 kilometers, is a critical resource in its basin, supporting agriculture, industry, domestic water supply, and numerous economic activities with its natural annual flow averaging around 900 million cubic meters (MCM). The Zayandehrood Dam, the primary surface water reservoir in the region with a storage capacity of 1,450 MCM, has been operational since 1971. During winter and spring, seasonal runoff allows the dam to release regulated flows into the river.

The basin's upper area consists of mountainous highlands with relatively low water demand, whereas its central and lower regions are arid to semi-arid, with sedimentary plains, moderate slopes, and dry beds. In this setup, the Chelgerd sub-basin, situated upstream, is a natural area where flows are largely unaffected by human intervention. In contrast, the Esfahan-Borkhar sub-basin downstream is engineered, where water distribution is managed by the Zayandehrood Dam. Figure (1) shows the locations of the natural, upstream Chelgerd sub-basin and the managed, downstream Esfahan-Borkhar sub-basin.

This study uses precipitation and surface water storage as key indicators to evaluate drought susceptibility and to develop a multivariate drought index. Data collection involves 145 precipitation measurement stations across the Zayandehrood River basin. Daily surface water flow data, provided by the Isfahan

Regional Water Authority, was collected from two stations to determine surface water storage. For flow modeling in each sub-basin, we used data from one hydrometric station.

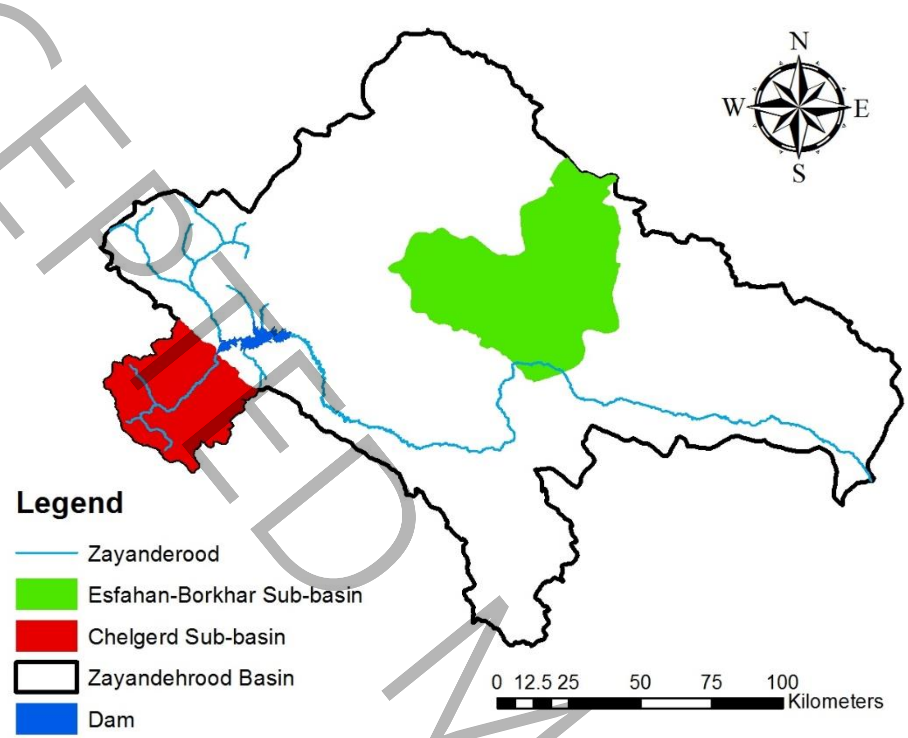


Figure 1: Zayandehrood river basin, situation of engineered and non-engineered sub-basins, Zayandehrood river and Zayandehrood Dam.

Average precipitation levels for both the upstream and downstream sub-basins were determined by analyzing data collected from various precipitation monitoring stations. Significant fluctuations were observed throughout the study period, which spanned from 1991 to 2020, as illustrated in Figure (2). This figure clearly shows that the upstream sub-basin receives more precipitation on average compared to its downstream counterpart, highlighting a notable difference in hydrological conditions between the two areas.

Additionally, Figure (3) displays the annual variations in surface water volume, measured in million cubic meters, for two key monitoring stations: Ghale-Shahrokh, located in the upstream sub-basin, and Pole Khajo, situated in the downstream sub-basin. The data depicted in this figure further emphasizes the discrepancies in water availability between the upstream and downstream regions throughout the years under review. These variations in surface water volume and precipitation patterns are critical for understanding the overall hydrological dynamics of the Zayandehrood basin and can provide valuable insights into water management and drought vulnerability assessments in the area. Overall, the results underscore the importance of continuous monitoring and analysis of precipitation and surface water resources to address future water challenges effectively.

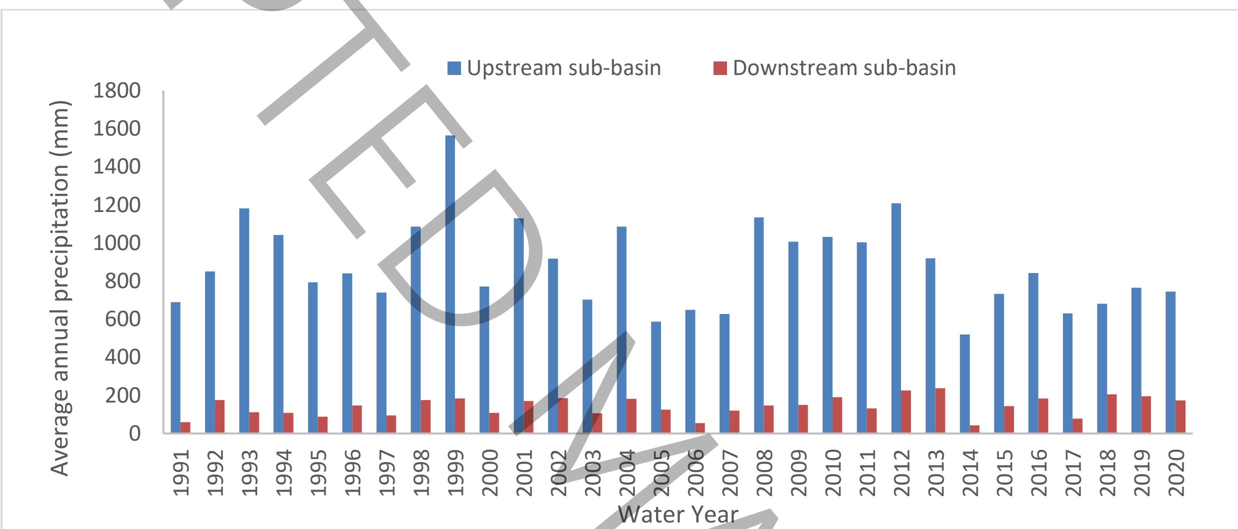


Figure 2: The average yearly precipitation for sub-basins located upstream and downstream over the 1991-2020 water years.

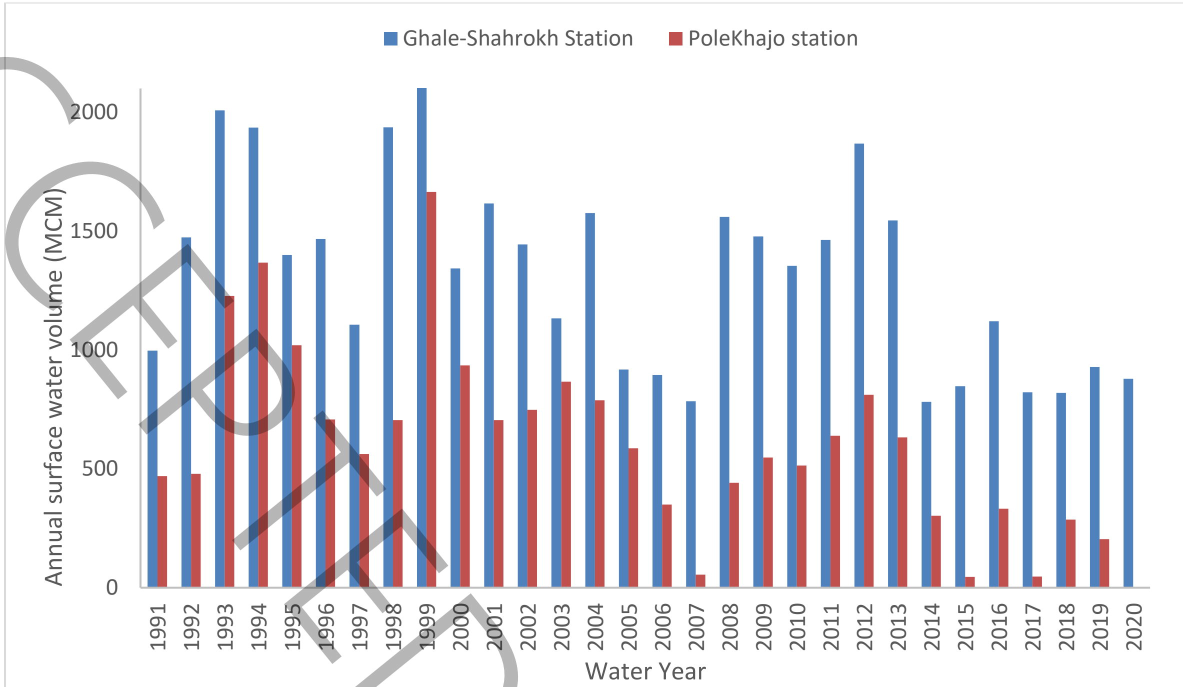


Figure 3: Yearly surface water volume (MCM) recorded at Ghale-Shahrokh station (located in the upstream, natural sub-basin) and at PoleKhajo station (situated in the downstream, engineered sub-basin).

## 4. Result

The bivariate drought index relies on two primary data sources: precipitation and the volume of available surface water storage. These datasets are critical in assessing drought conditions and can be obtained through various monitoring stations, specifically rain gauge stations for measuring precipitation and hydrometric stations for tracking water storage levels. These stations provide valuable data on a monthly basis, which is essential for accurate drought assessments. The process of calculating the bivariate drought index begins with the estimation of a continuous 12-month time series for both precipitation and available surface water. This step is crucial for understanding long-term trends and variations in both factors, which are key indicators of drought severity.

In this study, the time frame under consideration spans from the water year 1985 to the water year 2014. The 12-month precipitation time series is derived by continuously calculating the average annual precipitation for a given basin. This approach helps create a robust dataset that captures seasonal and annual variations in precipitation. By using this continuous precipitation data, researchers are able to estimate the water availability and surface water storage for each month over the course of several years. This allows for a more precise understanding of how water resources fluctuate over time.

Once the continuous time series for both precipitation and surface water storage have been established, the next critical step is to calculate the weight coefficients for each input or variable in the bivariate drought index. These weight coefficients are fundamental in determining the relative importance of each variable when calculating the overall drought index. In this study, the weight coefficients for the second variable of the drought index are derived using a method known as entropy weighting, which helps to quantify the uncertainty and variability associated with each variable.

As described in the methodology section, entropy weighting is a statistical technique that assigns weights to variables based on the amount of information they contribute to the overall system. For the second variable of the bivariate drought index, which involves both precipitation and surface water storage, this technique ensures that each indicator is appropriately weighted according to its contribution to drought conditions. This method improves the accuracy of the drought index by ensuring that the most informative variables receive greater weight in the final calculation.

To further enhance the reliability of the bivariate drought index, two sub-basins within the Zayandehrood basin—Chalgerd and Esfahan Borkhar—were selected for this study. These two sub-basins serve as representative examples of natural and artificial basins, respectively. Chalgerd is considered a natural basin, while Esfahan Borkhar is an artificial basin that is influenced by human interventions, such as water management practices and infrastructure. By comparing these two types of basins, the study aims to provide a more comprehensive analysis of drought conditions, as natural and artificial basins may respond differently to precipitation and water storage fluctuations.

Table 1 in the study presents the calculated entropy weight values for both the Chalgerd and Esfahan Borkhar sub-basins. These values are critical in understanding how the variables—precipitation and surface water volume—are weighted in the drought index calculation. The variables used to assess the second variable of the drought index are precipitation and the volume of available surface water, both of which play a significant role in determining the severity of drought conditions. By combining these two indicators and applying the appropriate weight coefficients (Table 1), the bivariate drought index provides a more nuanced and accurate measure of drought severity, which is essential for effective water resource management and drought mitigation strategies.

By accurately measuring and assessing both precipitation and water storage levels, this index can help identify areas at risk of drought and guide decision-making processes to address water scarcity and ensure the sustainable management of water resources over time.

Table 1- Numerical value of entropy weight in Chalgerd and Esfahan-Borkhar sub-basins.

| Sub-Basin | Precipitation | Available Surface Water |
|---|---|---|
| Chelgerd (Upstream) | 0.716 | 0.284 |
| Esfahan-Borkhar (Downstream) | 0.206 | 0.794 |

Table 1 presents the modified entropy weights for the Chelgerd and Esfahan-Borkhar sub-basins. In the Chelgerd sub-basin, the modified entropy weight for precipitation is 0.716, while the weight for the available surface water volume is 0.284. This distribution is attributed to the relatively high precipitation in this sub-basin, which has a greater influence on the drought index compared to the downstream sub-basin near the Zayandehrood Dam. As a result, precipitation plays a more significant role in the calculation of the second variable index for Chelgerd.

On the other hand, in the Esfahan-Borkhar sub-basin, the modified entropy weight for precipitation is much lower, at 0.206, whereas the weight for surface water volume is significantly higher at 0.794. This is due to the greater importance of surface water storage in this engineered sub-basin, where the volume of water is controlled by regulatory dams. These dams play a central role in managing and regulating water availability, which makes surface water a more influential factor in calculating the second variable drought index for

Esfahan-Borkhar. Therefore, in this sub-basin, surface water volume is the dominant factor affecting the drought index, contrasting with the natural Chelgerd sub-basin, where precipitation has a more pronounced impact.

To determine the bivariate drought index, the next step involves calculating the integrated index values for the specified time intervals using Equation 8. As outlined, there are 360 time intervals available for analyzing both precipitation and surface water volume data. Following Equation 8, the Water Stress Index (WSI) will be computed across these 360 intervals. Matrix X, described in Equation 1, contains 360 rows and 2 columns, which also applies to Matrix R (Equation 2). Elements in Matrix R are derived by normalizing those in Matrix X. Using Equation 8, along with the entropy-adjusted weight coefficients previously discussed, we produce the WSI matrix, structured as one column with 360 rows. Each row in this matrix corresponds to a calculated WSI, representing the drought bivariate index.

Values within Matrix R range from zero to one, so applying the entropy-adjusted weights results in WSI values also ranging between zero and one. This study uses Equation 4 to derive the R matrix, where higher values in each R matrix basin signify greater precipitation and available surface water within the basin. Consequently, a higher drought index value implies better conditions regarding drought. In other words, as the index value approaches zero, drought conditions worsen, while values closer to one indicate reduced drought impact in the analyzed basin.

In this study, to enhance the comparison of the bivariate drought index, a separate index called the precipitation index was introduced. This precipitation index corresponds to the first column in the R matrix, representing precipitation data. Figures 4 and 5 present a 12-month continuous time series of both the bivariate drought index and the precipitation index for the Chelgerd and Esfahan-Borkhar sub-basins, representing natural and engineered basins, respectively.

It is important to note that in these analyses, lower index values indicate drought conditions, while higher values suggest water abundance in the basin under study. In Figures 4 and 5, the horizontal axis represents the examined time span (30 wet years, equating to 360 consecutive months), and the vertical axis displays the drought index values, which range between zero and one.

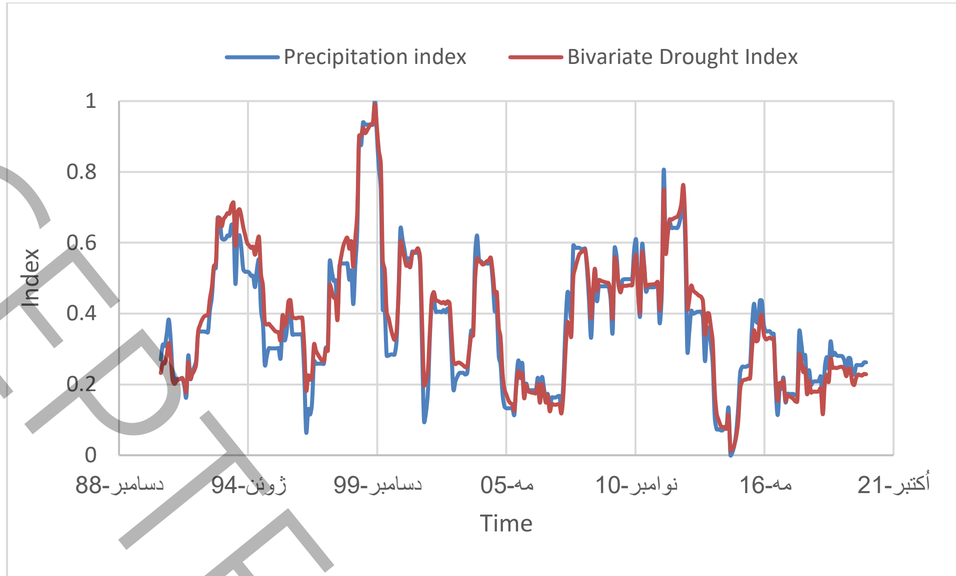


Figure 4: Time series of Precipitation index and bivariate index in Chelgerd sub-basin.

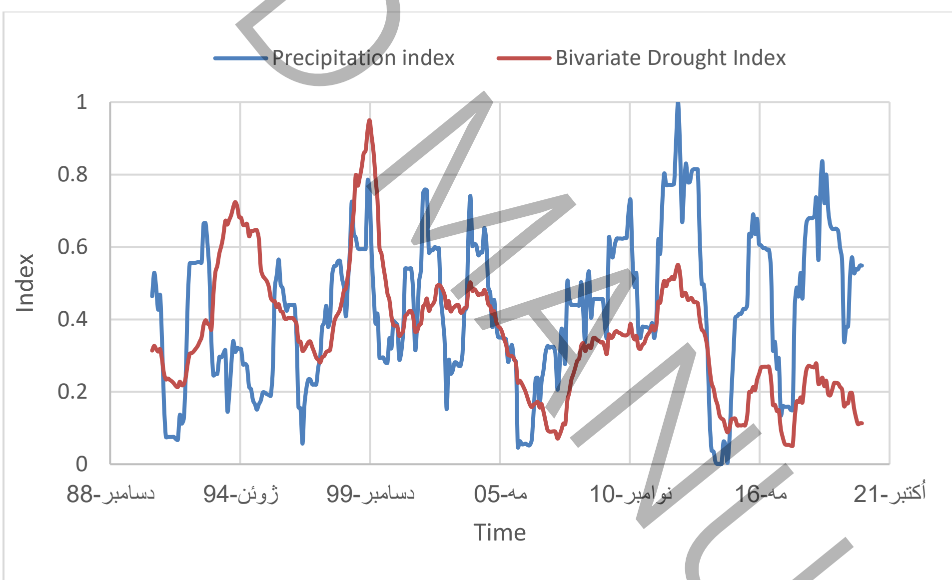


Figure 5: Time series of Precipitation index and bivariate index in Esfahan-Borkhar sub-basin.

As shown in Figure 4, the difference between the rainfall index and the combined index in the Chelgerd basin is minimal, measuring less than 5 percent. This suggests a strong correlation between rainfall patterns and the overall drought assessment in the region, indicating that precipitation plays a dominant role in shaping the combined index values. This is because, in natural basins, precipitation is converted to surface runoff through natural processes. Essentially, the volume of surface water is determined by the amount of natural runoff within the basin, with runoff in these basins being a proportion of the total precipitation.

Figure 5 depicts the precipitation index and the bivariate index in the engineered sub-basin of Esfahan Borkhar, showing a 45% difference between them. This variation occurs because, in engineered basins, surface water volume is regulated by dams. For example, in the Esfahan Borkhar sub-basin, surface water availability depends on the outflow from the Zayandehrood Dam. Consequently, the second component of the bivariate drought index does not align with the first component, which represents the basin's precipitation.

The final stage in determining the bivariate drought index involves validating the index. For this, the Normalized Difference Vegetation Index (NDVI) was utilized as a vegetation measurement index to validate the bivariate drought index. NDVI, often referred to as an agricultural drought or remote sensing index, has a numerical range from -1 to +1. Various satellite systems measure NDVI components, but the MODIS satellite, operated by NASA, is especially reliable and precise. MODIS provides NDVI values based on latitude and longitude every 16 days or monthly. The process of creating an NDVI time series aligns with the bivariate drought index, producing a continuous 12-month time series estimate. Monthly NDVI values were first extracted from MODIS for the geographic area of the Zayandehrood watershed. Using GIS software, the monthly average NDVI was then calculated for both the natural (Chelgerd) and engineered (Esfahan Borkhar) sub-basins of the Zayandehrood watershed. Finally, to develop a continuous 12-month NDVI series, the annual average NDVI for each basin was calculated continuously.

To validate the bivariate drought index, the NDVI index was used as an indicator of agricultural conditions in the study area. A linear relationship was established between the target index and the NDVI, and the correlation coefficient for this relationship was calculated. As shown in Table 2, the precipitation index (representing normalized precipitation levels) was also used to compare results with the second variable drought index. In the upstream sub-basin, the correlation coefficient ($R^2$) between the precipitation index and the NDVI is 0.74, while the correlation between the bivariate drought index and the NDVI is 0.81. In the downstream sub-basin, the $R^2$ between the precipitation index and the NDVI is 0.52, whereas the correlation between the second variable drought index and the NDVI is notably higher at 0.87.

Table 2- Correlation coefficient ($R^2$) between the precipitation index or the bivariate drought index and the NDVI in Chalgerd and Esfahan-Borkhar sub-basins.

| Correlation ($R^2$) | Precipitation | Available Surface Water |
|---|---|---|
| NDVI Upstream | 0.74 | 0.81 |
| NDVI Downstream | 0.52 | 0.87 |

The results indicate that, in the natural sub-basin (Chelgerd), there is little difference between the correlation of the bivariate drought index with the NDVI and that of the precipitation index with the NDVI. This is because, in natural basins, surface water volume is directly influenced by precipitation levels without human intervention; thus, the available surface water volume is largely a factor of the natural precipitation received. Consequently, precipitation indices or meteorological drought indices like the SPI can be used to assess drought conditions in natural basins.

In contrast, a significant difference exists in the engineered Esfahan Borkhar sub-basin between the correlation coefficients of the precipitation index with the NDVI and the bivariate drought index with the NDVI. This disparity arises because, in engineered basins, stored water resources are managed to meet various needs—domestic, agricultural, industrial, or environmental—based on water resource management decisions. Therefore, for engineered basins, the bivariate drought index is recommended for assessing drought and water resource status, while in natural basins, changes in precipitation alone can be sufficient for determining drought conditions.

To categorize drought, specific drought triggers must be defined. These triggers, or thresholds, are boundary values that help identify the type of drought occurring in a particular area. Essentially, drought thresholds allow for the translation of quantitative values from drought indicators into descriptive terms representing drought severity. As noted in the index input matrix (R matrix) in Chapter 3, the inputs for the second drought index variable display a uniform distribution.

Consequently, based on calculations involving the bivariate drought index using a modified entropy weighting approach, the output of this index also follows a uniform distribution. Since the second drought index variable's output is uniformly distributed and ranges between zero and one, this interval can be divided into five categories to establish the drought index thresholds. Table (3) presents the drought thresholds based on the bivariate index. In Table (3), Rank 1 indicates severe drought (range from 0 to 0.2), Rank 2 indicates moderate drought (range from 0.2 to 0.4), Rank 3 represents normal conditions (range from 0.4 to 0.6), Rank 4 corresponds to moderate wet conditions (range from 0.6 to 0.8), and Rank 5 to extremely wet conditions (range from 0.8 to 1). As seen, a decrease in the second variable index signals increasing drought severity, while an increase indicates less severe drought conditions.

Table 3- Drought index thresholds.

| Type | Range |
|---|---|
| Extreme Drought | $0<DI<0.2$ |
| Moderate Drought | $0.2<DI<0.4$ |
| Normal | $0.4<DI<0.6$ |
| Moderate Wet | $0.6<DI<0.8$ |
| Extreme Wet | $0.8<DI<1$ |

According to the thresholds outlined in Table (3), Figures (6) and (7) display the drought or wet conditions for two sub-basins, Chelgerd and Esfahan Borkhar, across the water years from 1991 to 2020, covering the years analyzed in this study.

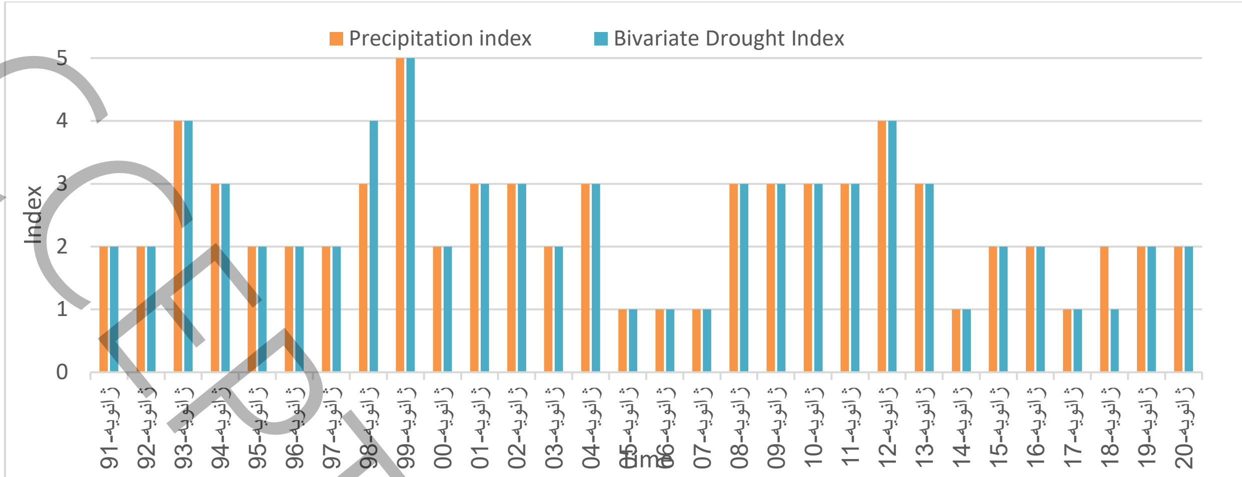


Figure 6: Drought or wet condition based on precipitation and bivariate index in Chelgerd sub-basin.

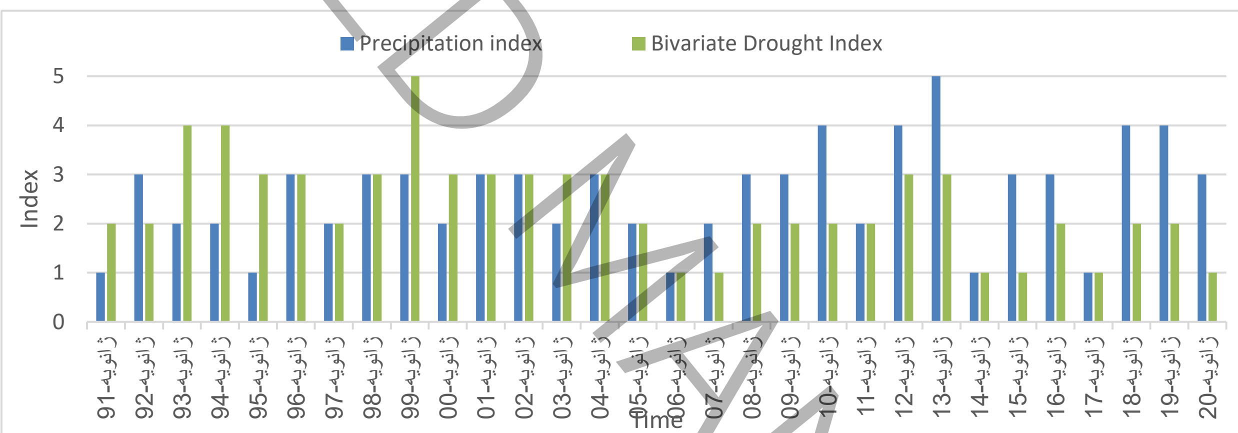


Figure 7: Drought or wet condition based on precipitation and bivariate index in Esfahan sub-basin.

## 5. Conclusion

The primary aim of this study was to create a comprehensive multivariate drought index, referred to as the integrated drought index, which encompasses meteorological, hydrological, and agricultural components. Rainfall was identified as the key factor in assessing the meteorological dimension of drought. Additionally, the volumes of surface and groundwater resources were utilized to represent hydrological aspects of drought.

The initial step in developing the integrated drought index involved determining the method for combining these indicators. After reviewing various approaches in existing studies, the entropy weighting method was chosen. The process for calculating input weights for the integrated index is detailed in the methodology section, including an explanation of a modified entropy weight designed to address limitations identified in prior studies. Using rainfall, surface water volume, and groundwater volume as inputs, the integrated drought index was subsequently calculated. This index can function as a bivariate model (pairing rainfall with either surface or groundwater volume) or as a multivariate model (incorporating rainfall, surface water, and groundwater volumes).

For validation purposes, the Normalized Difference Vegetation Index (NDVI), a remote sensing tool, was used. NDVI data, acquired from MODIS satellite imagery, were correlated with the integrated drought index to verify its accuracy. NDVI, as an agricultural drought indicator, allowed the combined use of rainfall, surface water, groundwater, and NDVI parameters to provide a detailed and comprehensive drought assessment across meteorological, hydrological, and agricultural dimensions. Finally, the integrated drought index was recalculated based on the weighted and normalized input parameters, with the NDVI index supporting its validity.

## 6. References


1. R. Stupazzini. "European Union Regulation of Water Stress Risks. " Published online by Cambridge University Press: 16 November 2023.
2. https://www.climate.nasa.gov.
3. https://www.nationalgeographic.org.
4. M. Khoshoei, H. R. Safavi and A. Sharma. "Relationship of drought and engineered water supply: Multivariate index for quantifying sustained water stress in anthropogenically affected subbasins. " Journal of Hydrologic Engineering. 2019, 24 (5): 1-9.
5. M. Khoshoei, H. R. Safavi and A. Sharma. "Water Supply Sustainability Revisited: Assessment Methodology for Multiple Water Resources. " Journal of Water Resources Planning and Management. 2023, 149 (12): 1-11.
6. M. Khoshoei, and H. R. Safavi. "Developing the Drought Index in Natural and Engineering Sub-basins (Case Study: Zayandehrood Basin). " Iran-Water Resources Research. 2023, 19: (4), 48-61.

7. M. Khoshoei, H. R. Safavi and A. Kazemi. "Integrated Index for Drought Assessment in Isfahan Province. " Journal of Water and Soil Science. 2023, 27(1): 113-136.
8. V. A. Smith, and D. R. Maidment. "Texas Integrated Drought Information System. A Prototype of the Trinity River Basin, University of Texas at Austin. " 2008.
9. M. Karamouz, K. Rasouli, and S. Nazif. "Development of a hybrid index for drought prediction." Journal of Hydrologic Engineering. 2009, 14, pp.617-627.
10. R. P. Pandey, A. Pandey, R. V. Galkate, R. H. Byun, and B. C. Mal. "Integrating hydro-meteorological and physiographic factors for assessment of vulnerability to drought.", Water Resources Management, 2010, 24, pp.4199-4217.
11. S. Pandey, A. C. Pandey, M. S. Nathawat, M. Kumar, and N. C. Mahanti. "Drought hazard assessment using geoinformatics over parts of Chotanagpur plateau region, Jharkhand, India.", Natural hazards, 2012, 63, pp.279–303.
12. L. Liu, Y. Hong, C. N. Bednarczyk, B. Yong, M. A. Shafer, R. Riley, and J. E. Hocker. "Hydro-Climatological Drought Analyses and Projections Using Meteorological and Hydrological Drought Indices: A Case Study in Blue River Basin, Oklahoma.", Water Resources Management, 2012, 26:2761–2779.
13. Z. Hao, and A. AghaKouchak, "Multivariate Standardized Drought Index: A parametric multi-index model.", Advances in Water Resources, 2013, 57:12–18.
14. D. Rajsekhar, V. P. Singh, and A. K. Mishra, "Multivariate drought index: An information theory based approach for integrated drought assessment.", Journal of Hydrology, 2014, 526: 164-182.
15. H. R. Safavi, M. Khoshoei Esfahani, and A. R. Zamani. " Integrated index for assessment of vulnerability to drought, case study: Zayandehrood River Basin, Iran. " Water Resources Management. 2014, 4 (28): 1671-1688.
16. S. Huang, J. Chang, G. Leng, and Q. Huang, "Integrated index for drought assessment based on variable fuzzy set theory: A case study in the Yellow River basin, China.", Journal of Hydrology, 2015, 527: 608–618.
17. M. Waseem, M. Ajmal, and T. W. Kim, "Development of a new composite drought index for multivariate drought assessment.", Journal of Hydrology, 2015, 527: 30–37.
18. M. Khoshoei Esfahani, H. R. Safavi, A. R. Zamani, "Design of Drought Monitoring System Based on Integrated Index in Zayanderood River Basin -Iran. " Journal of water and soil science, 2016, 20 (75) :27-43.
19. M. A. Faiz, Y. Zhang, X. Zhang, X. Ma, S. K. Aryal, T. T. V. Ha, F. Baig, F. Naz, "A composite drought index developed for detecting large-scale drought characteristics. " Journal of Hydrology, 2022, 605: 127308.
20. D. Shah, V. Mishra, "Integrated Drought Index (IDI) for Drought Monitoring and Assessment in India. " Water Resources Research, 2020 56:2.
21. W. Wei, J. Zhang, L. Zhou, "Comparative evaluation of drought indices for monitoring drought based on remote sensing data. " Enviromental Science Pollute Research, 2021, 28, 20408–20425.
22. Z. Li, Y. Han, T. Hao, "Assessing the Consistency of Remotely Sensed Multiple Drought Indices for Monitoring Drought Phenomena in Continental China. " IEEE Transactions on Geoscience and Remote Sensing, 2020, 58:8.
23. L. Zhou, W. Wang, C. He, "Investigation of New Integrated Drought Monitoring Model Taking into Account the Effects of Climate Anomalies. " Journal of the Indian Society of Remote Sensing, 2024, 52, 1649–1660
24. Z. Heidarizadi, M. Ownegh, C. B. Komaki, "Assessment of drought risk using multi-sensor drought indices and vulnerability factors: a case study of semi-arid region in Iran. " Arabian Journal of Geosciences, 2024, 17, 73.