# A new hybrid drought-monitoring framework based on nonparametric standardized indicators

Hamid R. Safavi, Vahid Raghibi, Omid Mazdiyasni and Mohammad Mortazavi-Naeini

## ABSTRACT

A drought is a multi-dimensional event characterized by changes in the atmospheric and land conditions. Hence, monitoring a single drought indicator may be insufficient for water management. The hybrid drought index (HDI) is presented as a nonparametric composite indicator for monitoring multiple components of the hydrologic cycle. The properties of the HDI can be summarized as follows: (1) HDI describes drought indicated from either climatic anomalies or available water (AW); (2) HDI describes the drought onset as early as a decrease appears in climatic variables, while it shows drought persistence until there is no longer a terrestrial deficit; and (3) HDI shows a more severe drought condition when both the climatic water balance and AW exhibit a deficit. HDI is based on the states of potential meteorological water budget and AW. The proposed integrated drought-monitoring is applied to the Zayandehrud River Basin of Iran to show the status of components and depict drought propagation through each one from climate to groundwater. Finally, HDI announces the general status of the hydrologic cycle. A monitoring system established based on HDI would also allow the managers, local businesses, and farmers to identify the status of water supply capacity and water availability.

**Key words** | drought indices, hybrid drought index (HDI), hydrological drought, meteorological drought, nonparametric method, standardized index

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## INTRODUCTION

Droughts are an exceptional lack of water compared with normal conditions (Van Loon *et al.* 2016a, 2016b). They differ from other climatic events in that they have a slow onset, evolve over months or even years, affect a large spatial region, and cause little structural damage (Wilhite *et al.* 2000). By an increased risk of hydrometeorological disasters (Li *et al.* 2017a; Ling *et al.* 2017), more than half of the 22 million deaths associated with natural hazards across the globe from 1900 to 2004 were due to drought (Below *et al.* 2007). Up to 60 million people in central and southwest Asia were affected by a persistent multi-year drought during 1999–2001, one of the largest from a global perspective (IRI 2001). Iran, Afghanistan, western Pakistan, Tajikistan, Uzbekistan, and Turkmenistan experienced the most severe impacts. Hence, continuous drought monitoring and understanding the effects of droughts on water resource systems are essential to hazard preparedness, appropriate mitigation, and sustainable development.

Drought planning for preparedness and mitigation actions should have three primary components: monitoring, risk and impact assessment, and mitigation and response (Wilhite *et al.* 2000). Drought indices are indispensable tools in a plan for detecting, monitoring, and evaluating drought impacts so that knowledge on drought conditions

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is expressed through them (Bachmair et al. 2015). Developing an integrated index for quantifying drought severity is a challenge for decision-makers in water resources and operation management policies, because a single indicator often proves inadequate for the decision-making process (Wilhite 2005). However, combining multiple variables raises challenges ranging from model development to interpretation of the results. The inter-dependence among different drought indicators (e.g., Standardized Precipitation Index (SPI; McKee et al. 1993), Palmer drought severity index (PDSI; Palmer 1965), surface water supply index (SWSI; Shafer & Dezman 1982) varies depending on location, scale, and time. Often, inconsistencies in different indicators and lack of physical explanations for such differences cause confusion and hamper effective drought assessment and decision-making (Steinemann et al. 2005).

Among the available indicators, PDSI is one of the earliest indices widely used to assess water availability in a region (Dai 2011; Rahmat et al. 2015). This indicator is useful in homogeneous regions (Ntale & Gan 2003) and is based on temperature, precipitation, and soil characteristics (Winstanley et al. 2006). Other forms of PDSI have been proposed in the literature including the Palmer modified drought index for operational real-time application (Heddinghaus & Sabol 1991), the Palmer hydrological drought index for hydrological impact considerations (Karl 1986), and the moisture anomaly or Z-index (Palmer 1968). The reader is referred to Heim (2002) for a comprehensive review of all formats of PDSI. Other improvements of the PDSI include the self-calibrated PDSI (Wells et al. 2004), or a PDSI with modified PET derivation (Burke et al. 2006; Mavromatis 2007). However, PDSI has a few limitations, including low response in detecting the onset of drought events, unclear temporal scale (Rajsekhar et al. 2015), high sensitivity to temperature, and an autoregressive characteristic (Mishra & Singh 2010).

The surface water supply index (SWSI) is an integrated drought measure which accounts for reservoir storage, streamflow, snow pack, and precipitation (Wilhite & Glantz 1985) and is formulated as a rescaled weighted sum of nonexceedance probabilities of four hydrologic components. It is an indicator of available water (AW) in mountain-water-dependent basins (Shafer & Dezman 1982). The SWSI is an appropriate measure/metric of hydrological drought for regions where snow contributes significantly to the annual streamflow (Keyantash & Dracup 2002). However, it has some shortcomings: (1) lack of a general agreement over the definition of surface water supply components; (2) variation of weights by district and month result in different statistical properties across space and time; and (3) the hydroclimatic differences that characterize river basins prevent SWSIs from having the same meaning and significance in different areas and times (Doesken et al. 1991; Heim 2002).

In recent years, many studies have proceeded to develop integrated drought indicators based on a combination of different variables or indices (Hao & Singh 2015; Mazdiyasni & AghaKouchak 2015). Some examples of such studies include the integrated index for assessment of vulnerability to drought (Safavi et al. 2014), the Joint Deficit Index (JDI; Kao & Govindaraju 2010), the Combined Drought Indicator (CDI; Sepulcre-Canto et al. 2012), the hybrid drought index (HDI; Karamouz et al. 2009), the multivariate standardized drought index (MSDI; Hao & AghaKouchak 2013), the nonparametric multivariate drought index (NMSDI; Zhu et al. 2016), and the multivariate standardized reliability and resilience index (MSRRI; Mehran et al. 2015). The MSDI utilizes a multivariate, multi-index approach that integrates drought information based on the joint probability of precipitation and soil moisture. MSRRI offers a framework for describing socio-economic drought based on inflow to reservoirs, reservoir storage, and water demand. Farahmand & AghaKouchak (2015) introduced the standardized drought analysis toolbox (SDAT) that offers a nonparametric framework for deriving univariate and multivariate standardized indices and evaluating a modified version of the MSDI for drought monitoring.

Many indices can be considered as members of the standardized drought indices (SDI) family. SPI is one such index that has been used widely in many countries (Portela et al. 2015; Li et al. 2017b). The concept of SPI has been extended to formulate new drought indices. For instance, the standardized precipitation evapotranspiration (ET) index (SPEI; Vicente-Serrano et al. 2010) was developed based on precipitation and PET data. Both SPI and SPEI rely on selection of an appropriate probability distribution to normalize the index to facilitate comparisons across climates (Núñez et al. 2014; Vicente-Serrano & Beguería 2015). SPI values are especially sensitive to the choice of parametric distribution function in the tail of the distribution (Quiring 2009). Even by using the best-fitted distribution, the distribution tails of SPI values change across space (AghaKouchak *et al.* 2010). Choice of an improper probability distribution to calculate SDI may lead to spatially or temporally inconsistent drought severity statistics (Farahmand & AghaKouchak 2015).

Previous studies have argued no single index can describe all aspects of droughts, and that a multi-index approach is needed for operational drought monitoring and prediction (Hao & AghaKouchak 2013; AghaKouchak 2015). For a comprehensive representation of drought, it is ideal to consider multiple climatic and hydrologic variables to determine their interdependent relationships in a consistent and comparable manner. The lack of a precise and objective system/model for an integrator of drought-related information from multiple sources hinders reliable and timely detection of droughts and their persistence. Therefore, the objective of this study is to propose an integrated approach for drought index based on the SDAT model that accounts for multivariate drought from the two variables representing various aspects of drought. The concepts are: (1) potential meteorological water budget: precipitation (P) and PET; and (2) AW: runoff/streamflow (R/S), surface storage (SS), and groundwater storage (GS); thus accounting for all the major elements in the water balance. To derive the composite HDI, a standardized nonparametric approach is used, which does not require parameter estimation or any a priori assumption on the underlying distribution function of the original data. The model offers the overall water supply status to be assessed, including the anthropogenic effects leading to a decrease in water availability.

With this introduction complete, the methodology is described. This section is followed by the data and study area details before applications and results are explored. A discussion section addresses the implications. The findings are summarized in the last section and remarks concluded.

## STUDY AREA AND DATA

The Zayandehrud River Basin (ZRB), which covers an area of 26,972 km$^2$ located in the center of Iran (Figure 1) with a semiarid climate (Safavi *et al.* 2013) was selected as the study area. Zayandehrud is a closed watershed, and the river provides water for domestic irrigation, industrial supply, and wastewater dilution (Safavi & Alijanian 2010). However, water resource management in the complex ZRB water system (Madani & Mariño 2009) has become a looming crisis (Madani 2014) between different parties, especially after severe droughts in recent years.

Esfahan Regional Water Board Company (ESRW), which is the authority for water allocation in the basin, divided the ZRB into 16 sub-basins (Table A1, available with the online version of this paper) based on recent studies (Safavi *et al.* 2015). Annual precipitation varies from the mountainous west to the arid east of the basin in the range of 1,500 to 50 mm, with an annual average of 140 mm (Safavi *et al.* 2016). The three main rivers in the ZRB are the Zayandehrud River, Pelasjan River, and Samandegan River (see Figure 1). The average annual R/S of these rivers is approximately 990 million cubic meters (MCM), and is controlled by the Zayandehrud Dam with a volume of 1,470 MCM (Safavi *et al.* 2015). In addition, about 633 MCM is transferred from the adjacent river basins annually. Streams downstream of the dam often do not reach the Zayandehrud River (Molle *et al.* 2009). Despite this, recharge to the aquifers from effective rainfall and the Zayandehrud River is important in this area, since groundwater is the second most reliable water resource in the basin, stored in 13 sub-basins with active aquifers (Table A2 (available with the online version of this paper), based on Paydar Consulting Engineering Co. (2010), Zayandab Consulting Engineering (2008), and Yekom Consulting Engineering Co. (2013)).

The hydroclimatic variables considered for deriving HDI include P, minimum ($T_{min}$) and maximum ($T_{max}$) temperature, R/S, SS, and groundwater level for a period of 32 years (1983–2014) on a monthly time scale. Figure 1 shows the distribution of studied stations in the ZRB with available data. The average groundwater levels and volume of the aquifers are estimated in this study using the bedrock map of the Zayandehrud aquifers prepared by Water and Wastewater Research Institute (WWRI 2012) and digital elevation model provided by ESRW. Comprehensive details of the ZRB can be found in Safavi *et al.* (2015).

## METHODS

The atmospheric processes are the starting point of drought propagation. A prolonged lack of precipitation (P) possibly

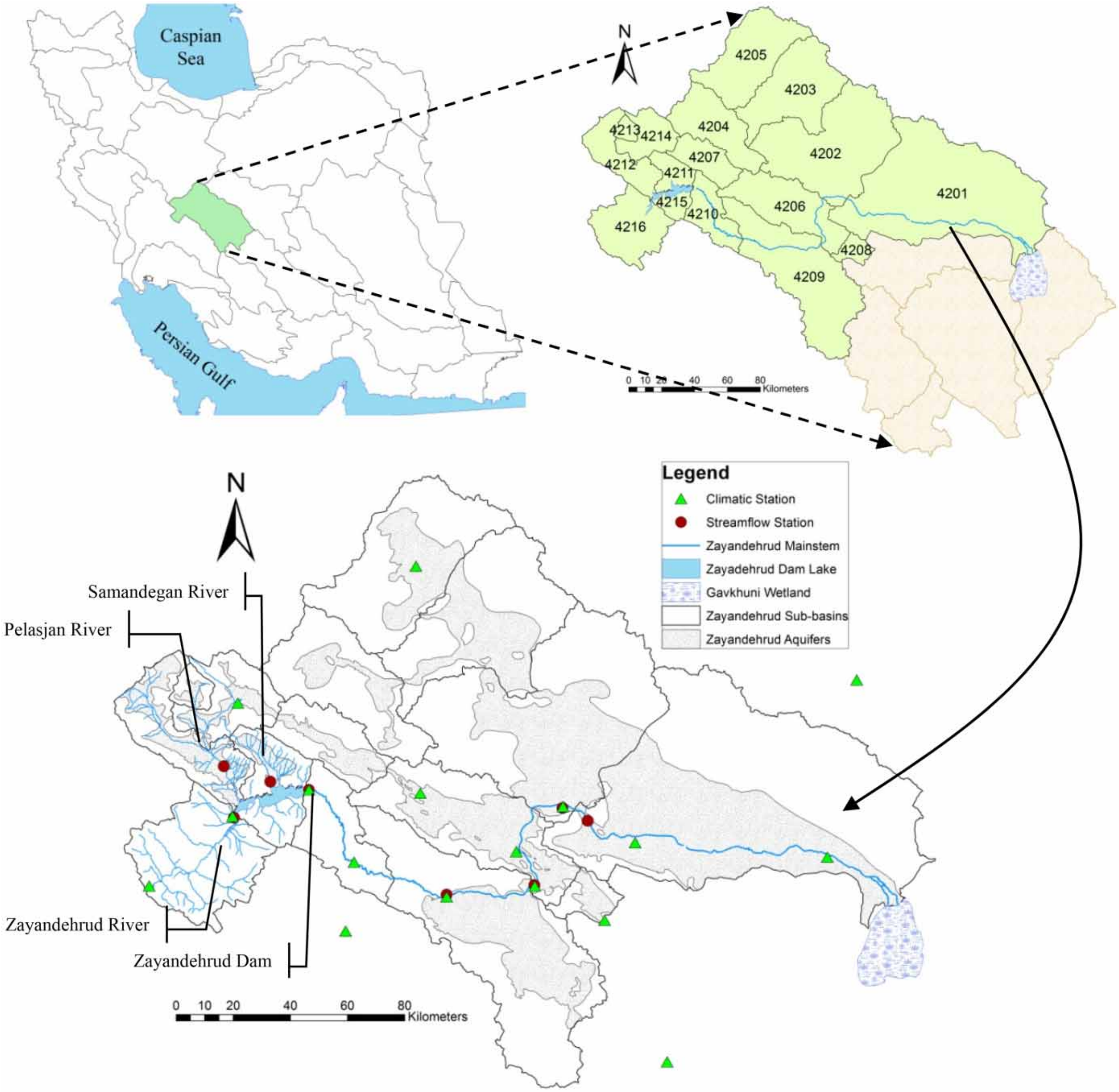


**Figure 1** | Physical layout of ZRB and location of stations. Sub-basins are presented in bold numbers.

coexisting with high PET leads to a meteorological drought. It is necessary not only to account for atmospheric conditions such as P, but also to account for any potential atmospheric conditions that may affect drought severity, such as temperature (Stagge *et al.* 2014). PET may increase due to high radiation, wind speed, or vapor pressure deficit caused by high temperature. The difference between P and PET represents a simple climatic water balance (Thornthwaite 1948) that calculates the potential meteorological water budget. This provides a more reliable measure of drought severity compared to when only P is considered (Beguería *et al.* 2014).

When a meteorological drought induces a deficit in soil moisture, an agricultural drought develops (Nam *et al.* 2012). Depletion of soil moisture storage depends on factors such as prior moisture status, precipitation, drainage to groundwater, and ET rate (Van Loon 2015). During a dry spell, continuous P deficit may lead to a hydrologic drought that is defined by below-normal water availability (Sung & Chung 2014). Soil moisture drought results in groundwater inputs reduction, which in turn, causes declining groundwater levels and decreasing groundwater discharge to the surface water system. This can be defined as groundwater drought. P decline naturally results in runoff reduction and consequently less surface water and GSs. These processes indicate the propagation of the drought signal as it moves through the terrestrial part of the hydrologic cycle (Van Loon 2015).

Hydrological drought is defined as the magnitude of the above-mentioned hydrological variables falling below a certain threshold, such as long-term mean streamflow or groundwater levels (deficiency in bulk water availability). Note that the hydrological responses normally appear with delay to P deficiencies in a basin (Kalamaras *et al.* 2010). Therefore, not all meteorological droughts will trigger a hydrological drought, because reservoirs can supply water for short periods. To capture hydrological drought, R/S, SS, and GS can collectively characterize all related sub-systems for drought assessment, and they can be a quantity of water that is available for direct use, possibly after regulation. This defines what is referred to as 'available water' in this research.

The P and PET variables are generally the summation or weighted summation of data from several sites in or near the sub/basin of interest. The difference between P and PET for the month $i$, $D_i = P_i - PET_i$, provides a simple measure of climatic water balance for the analyzed month (as in SPEI). The performance of Modified Hargreaves (MH) for monthly PET calculation is remarkable in comparison to Penman–Monteith, and the very low data demand of MH makes it attractive when inaccuracy in weather measurements is common (Droogers & Allen 2002). MH was selected in this study due to lack of data and possible inaccuracies; however, any other method is also applicable in the case of data availability. R/S is accumulated from observed volumes at a specific time scale at stations with readily available data where each sub/basin's streamflow is represented by a station chosen by experts. GS volume can be estimated by the difference of groundwater and bedrock level to have saturated volume and multiplying by specific storage. SS and GS are used for the first of the month plus for each one inflow volume for one or more previous months with regard to desired time scale, while $D$ and R/S data are cumulative amounts for a particular period, such as one or more previous months. The total volume of reservoirs and R/S accounts for the 'available water' for the month $i$, i.e., $AW_i = SS_i + GS_i + R_i/S_i$. The climatic water balance and the AW series are indexed by bivariate HDI to make a probabilistic assessment of droughts.

Previous months are considered for current hydrologic conditions of the area, and it is possible to consider subsequent months as a forecast of water availability in the future (Garen 1993). It is possible to use the forecasts as input to the HDI rather than using the basic input data directly.

The attractive features of a standardized index (SI) introduced by McKee *et al.* (1993) are that (Kao & Govindaraju 2010): (1) it can be applied to precipitation (SPI), streamflow (SSI; Vicente-Serrano *et al.* 2012), etc., (2) it does not incur model assumptions, and (3) it is a probability measure by definition, so that drought severity is comparable with various locations and among variables. However, a generalized framework for drought monitoring requires an investigation of multiple indicators (P, ET, R/S, groundwater, etc.) which often have different distribution functions (Farahmand & AghaKouchak 2015).

To cope with the above-mentioned challenge, this paper applies a nonparametric methodology to handle different meteorological and hydrological variables without the necessity of having representative parametric distributions. This can be very useful, especially in the case of multiple drought indicators (e.g., Nijssen *et al.* 2014). As a natural extension of the SI, an empirical probability can be used to derive a nonparametric SI instead of any parametric distribution function. In the original SPI, the cumulative probability distribution of precipitation is described using a two-parameter gamma probability function and parameter estimation, which is then transformed using the inverse of the standard normal distribution (McKee *et al.* 1993). Instead of the gamma (or any other parametric) distribution function, the empirical Gringorten plotting position, suggested by Hao & AghaKouchak (2014), is used to derive the univariate probability as follows (Gringorten 1963):

$$p(x_i) = \frac{i - 0.44}{n + 0.12} \tag{1}$$

where $i$ is the rank of the observed values in descending order, $n$ is the number of observations, and $p(x_i)$ is the corresponding empirical probability of variable X which denotes each one of P, D, SS, etc., at a specific time scale (e.g., 1 month or 6 months). The outputs can be transformed into SI as:

$$SI = \Phi^{-1}(p) \quad (2)$$

where $\phi$ is the standard normal distribution function. To ease the calculations, it is also possible to standardize the percentiles using the commonly used approximation of $SI$ (Abramowitz & Stegun 1964; Naresh Kumar *et al.* 2009; Farahmand & AghaKouchak 2015). A sequence of positive SI signifies a wet period, and a sequence of negative values represents a dry period.

This paper extends the suggested nonparametric approach to higher dimensions to obtain a multivariate drought index for arbitrary (sets of) drought relevant variables. For two drought variables (e.g., X = D and Y = AW), the bivariate distribution is defined as $p_r = P(X \leq x,\ Y \leq y)$, where $p_r$ is the joint probability of X and Y (e.g., climatic water balance and AW). The empirical joint probability can be estimated using the multivariate model of the Gringorten plotting position (Yue *et al.* 1999) by having the joint probability of two (or more) variables:

$$p_r(x_k,\ y_k) = \frac{m_k - 0.44}{n + 0.12} \quad (3)$$

where $m_k$ is the number of occurrences of the pair $(x_i, y_i)$ for $x_i \leq x_k$ and $y_i \leq y_k$, and $n$ is the sample size. Similar to univariate indices, one may standardize the joint empirical probability to derive the HDI ($HDI = \phi^{-1}(p_r)$). Similar to standardized indices, HDI can be used to provide drought information over different time scales, i.e., 1, 3, 6, and 12 months. It should be mentioned that there are other uni- and multivariate nonparametric methods that can be used to have nonparametric indicators (e.g., Weibull). Different empirical methods typically lead to similar results for long-term data sets which are needed for drought assessment (Turnbull 1976). Other methods for deriving joint empirical probabilities, such as the Kendall (Ghoudi & Rémillard 2004), can be used for deriving nonparametric multivariate indicators. To eliminate seasonality, the empirical probability is considered separately for each of the 12 monthly time series. The concept of HDI has been tested and validated for P and soil moisture for monitoring droughts (Hao & AghaKouchak 2014). The properties of bivariate probability distribution, as HDI, and its differences from its marginal univariate distributions have been demonstrated by Hao & AghaKouchak (2013) and the joint index interpretation brought through a numerical example.

First, Kao & Govindaraju (2010) described the concept of using the joint cumulative probability as the overall drought indicator to propose the joint index. Hao & AghaKouchak (2013) used the joint cumulative probability of precipitation and soil moisture to construct the MSDI as an extension to the original SPI. In this study, the climatic water balance (potential meteorological water budget) and AW (total volumetric water in hydrological system) are used to derive the HDI to describe properties of the hydrologic cycle. The bivariate drought model links individual indicators into a composite model as an overall assessment of drought.

## RESULTS

The generalized framework for generating consistent drought indicators presents an opportunity to create indices of each hydrologic cycle component based on the difference between P and PET (SPEI), streamflow (SSI), surface reservoir (SSRI), groundwater reservoir (SGRI), available water (AWI), etc. These series show the status of each component and depict drought propagation through each component from climate (SPEI) to groundwater (SGRI). Finally, HDI announces the general status of the hydrologic cycle. Similar to the SPI, the SIs come from the (joint) probability of the variables of interest that can be used to provide drought information over different time scales (e.g., 1, 3, 6, and 12 months). On shorter time scales (3 or 6 months), changes in drought occurrence demonstrate that the dry and wet periods are short and have a high frequency, and at a 12-month time scale, droughts exhibit less variability (Vicente-Serrano *et al.* 2012). The use of the different time scales for drought analysis allows short-term and long-term anomalies in the basin (e.g., Vidal *et al.* 2010), and to better identify drought impacts (Vicente-Serrano *et al.*

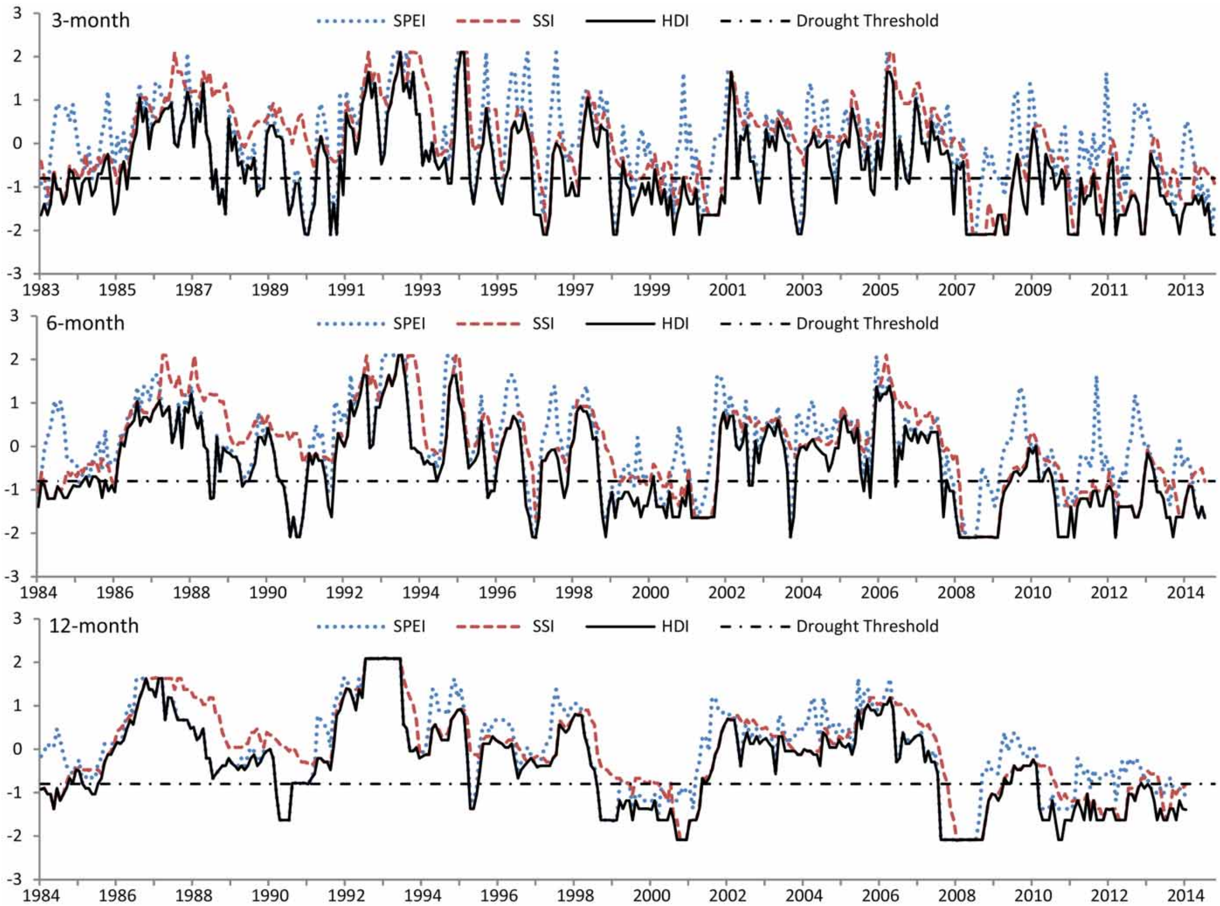


**Figure 2** | Time series of SIs for time scales 3, 6, and 12 months for sub-basin 4216. SPEI, standardized precipitation-ET Index; SSI, standardized streamflow index; HDI, hybrid drought index.

2011). As in the original SI, a negative HDI indicates that the condition of hydrologic cycle is dry (drought), while a positive HDI represents a wet condition of hydrologic cycle. HDI near zero refers to normal conditions.

The moderate drought threshold (severity $<-0.8$) represents ~20th percentile of the variable of interest. In the following, the performance of HDI, which incorporates multiple drought types, is examined to determine how reliably it presents the onset, termination, and magnitude of drought events. The performances of the SIs in drought monitoring are assessed for the historic droughts with respect to observations. The SI series of each sub-basin in the ZRB were computed. Results for selective sub-basins within each climate region were used for visualization of each index performance, whether the integrated framework is practical or not. The chosen sub-basin codes are 4216 in mountainous region, 4206 in foothills, and 4205 in semi-arid region.

Figure 2 shows the different time series (3, 6, and 12 months) of SIs for sub-basin 4216 (see Appendix, available with the online version of this paper). Streamflow is the only source of AW in this sub-basin. Consequently, the HDI is controlled by climatic water balance and streamflow as the only components of AW represented by SPEI and SSI (or AWI), respectively. This demonstrates that the HDI determines drought onset like the SPEI, and depicts drought termination like the SSI. Since HDI was derived from the combination of climatic water balance and AW (here, streamflow) data, it captured the onset, persistence, and termination of droughts better than SPEI or SSI, and thus its identification results are more reliable in regard to its integral definition.

In the ZRB, the periods of 1999–2002 (IRI 2001) and 2008–14 include two major drought periods through the basin with different characteristics depending on local conditions, and the water abundant period of 1992–95 (Safavi

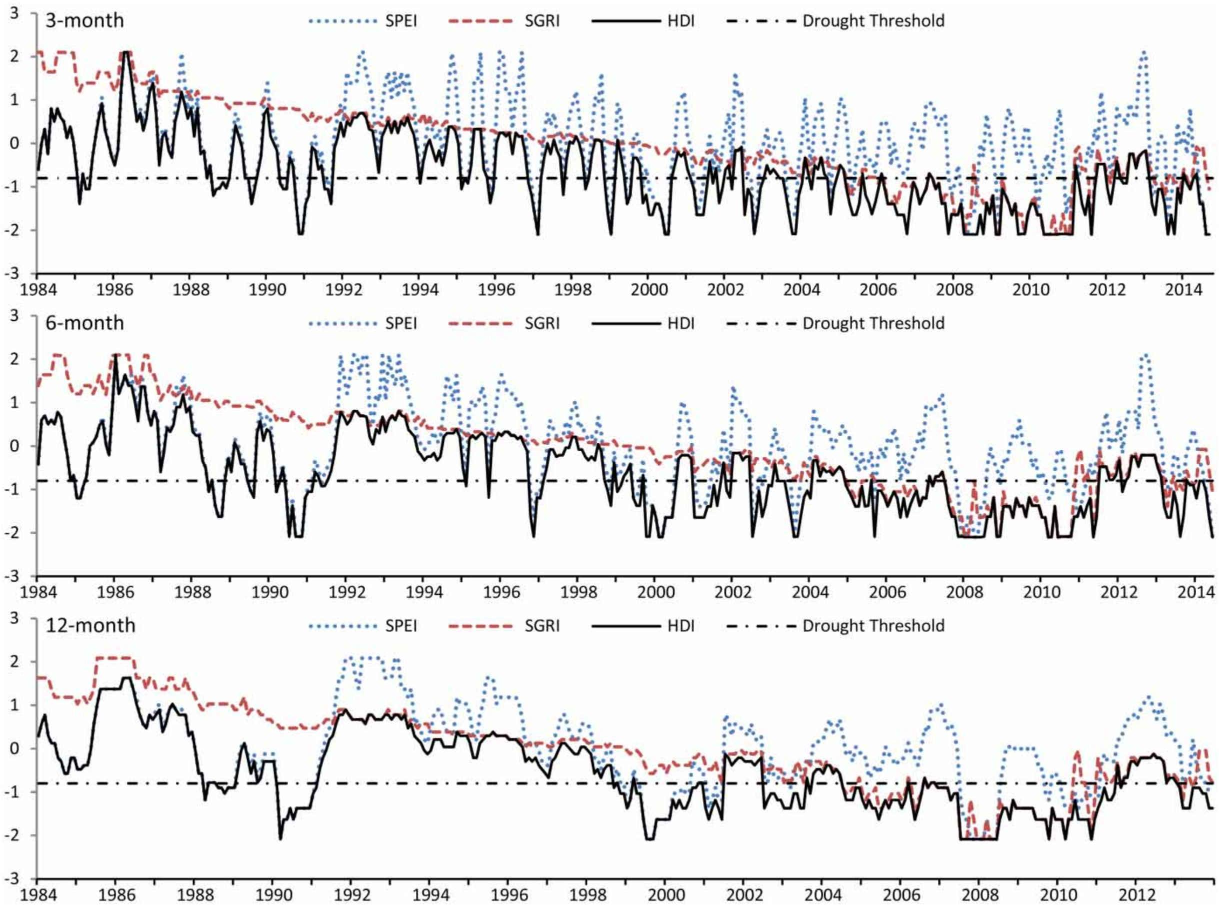


**Figure 3** | Time series of SIs for time scales 3, 6, and 12 months for sub-basin 4205. SPEI, standardized precipitation-ET index; SGRI, standardized groundwater reservoir index; HDI, hybrid drought index.

*et al.* 2015). During 1999–2002, if SPEI quantifies drought, it showed drought conditions with a few fluctuations until October 2001 with an early severity $<-2$ (~2nd percentile) (6-month) which declined gradually (Figure 2). In the case of SSI, a drought condition was signified mainly during 2000–02 with a late severity $<-1.5$ (~6th percentile) (6-month). Thus, none of these drought indices predicts fluctuations in drought in the same way. Nevertheless, HDI showed the presence of drought throughout April 1999 until March 2002 which had an average severity of $-1.5$ (6-month). Persistent drought condition after 2008 is indicated by HDI, while SPEI and SSI show continuous oscillations in these years. Hence, one might conclude that a no-drought condition had occurred, instead of the actual drought condition, if only one of the indices were trusted.

The different time series of sub-basin 4205 are displayed in Figure 3 (SIs of 3, 6, and 12 months). Groundwater is the only source of AW in this sub-basin. Therefore, the SPEI presents the climatic water balance, and the SGRI (or AWI) describes GS status as the sole component of AW. SPEI starts and ends rapidly, and SGRI is the representative of groundwater drought that propagates slowly and lasts for a longer time. The imbalance between water availability/supply and demand in 4205 caused water scarcity, due to the overexploitation of water resource when demand for water was higher than water availability. Thus, the effect of human activity on the hydrological system made water shortage more severe or raised water stress. In the early years of the study period, GS mitigated drought effects, but groundwater withdrawal worsened drought condition during the final years in spite of HDI heralding conditions getting worse causing more severe drought.

The drought periods of 1999–2002 and 2008–14 and the wet period of 1992–95 are well represented in 4206 by HDI.

Figure 3 shows that if only SGRI was accepted as a drought indicator, it would have determined a no-drought condition during 1999–2002. Meanwhile, the SPEI terminated drought conditions in March 2001 with a severity $<-2$ (6-month) at mid-period. For the time window of 2008–14, the SPEI shows drought severity of $-2$ (6-month) with starting maximum in 2008 and normal condition thereafter, with a few fluctuations. The SGRI shows drought until March 2011 when persistent drought with a severity of $-1.5$ to $-2$ (6-month) happened in the past months. After August 2012, the drought condition improves until it begins to show the start of another drought event on July 2013 that soon reaches severity of $-2$ (6-month). The HDI generally reflects the severity of the SPEI or SGRI, whichever is lower or worst than both with respect to drought severity. In 2008, SPEI and SGRI show drought condition with different severities (6-month) versus time but their joint probability, HDI, has a severity of $-2$ (6-month) during the same period, which indicates worst condition in regard to the two variables.

The last case of the SI time series is sub-basin 4206 in Figure 4 (SIs of 6 and 12 months). 4206 is one of the very important sub-basins of ZRB with regard to its interaction with the river. 4206 is a complex sub-system of ZRB, because of the conjunctive use of the surface and groundwater, and the interaction between river and groundwater resources, as well as the development of agriculture, industries, and urban demand growth (Safavi *et al.* 2015). Sources of AW in 4206 are its surface water reservoir, streamflow, and groundwater reservoir. Hence, the SIs representing 4206's status are SPEI for the climatic water balance, SSRI for surface water reservoir, SSI for streamflow, SGRI for GS, and AWI for AW, which is the total amount of water from surface and groundwater reservoirs and streamflow.

The occurrence and magnitude of hydrologic droughts are heralded by AWI, and the contributions of SPEI and AWI for revealing that hydroclimatic drought patterns can be manifested in HDI.

The SI series scheme presents the status of water resources during the 1999–2002 drought period (Figure 4), and it is possible to see how well the indices captured the beginning and end of a drought event. The SPEI detects a drought condition in May 1999 until March 2001 with a severity $<-2$ (6-month) in 1 month. However, drought effects appear in SSI and SSRI with a long delay with a severity $<-2$ (6-month), respectively. This occurs while SGRI predicts a no-drought condition, but water stress is clear on the groundwater resource. On the other hand, AWI heralds a hydrologic drought 1 year later. The HDI incorporated multiple drought forms throughout the hydrologic cycle to identify effectively the onset of the drought event in May 1999, its persistence, and its termination in May 2002. When one of the variables brings in drought condition, the severity of HDI looks likes that one, and whenever both variables show deficit, HDI's severity become worse than both univariate distributions as a bivariate probability (Hao & AghaKouchak 2013). This happened in 2000, 2011, and 2013 when the severity of HDI reached $-2$ while SPEI and AWI suffered lower severities of drought. Before the hydrologic system recovers from a multi-year drought condition completely during the subsequent years, another drought period begins in March 2008. It is clear that drought signals propagate through the hydrologic system more quickly due to the lack of replenishment of storage in surface and underground reservoirs. Drought influence appears with a delay of less than 6 months in all parts of the hydrologic cycle in which SGRI figures the groundwater drought condition in August 2008. Despite some fluctuations in SSI and SSRI after preliminary drought shock and with AWI on the road to improvement, HDI distinguishes multi-year drought persistence in the hydrologic cycle.

Groundwater usage for irrigation in ZRB had reached 3,271 MCM/year (52% of total demands) in 2006 (Safavi *et al.* 2015). It is highly likely that the significant amount of water withdrawn for irrigation and resulting groundwater depletion in ZRB considerably worsens the drought conditions (SGRI in 4205 and 4206 during 2008–14). The community has a groundwater supply and drawdowns have increased to provide the same amount of water. Thus, the groundwater levels withdrew to react to pumping stress in dry periods. The suggested integrated drought-monitoring framework was to provide some examples of the impact of historical and possible future climate variations and change on surface and groundwater resources.

GS in aquifers (northern areas like 4205) permits pumping for short periods of time at rates greater than recharge.

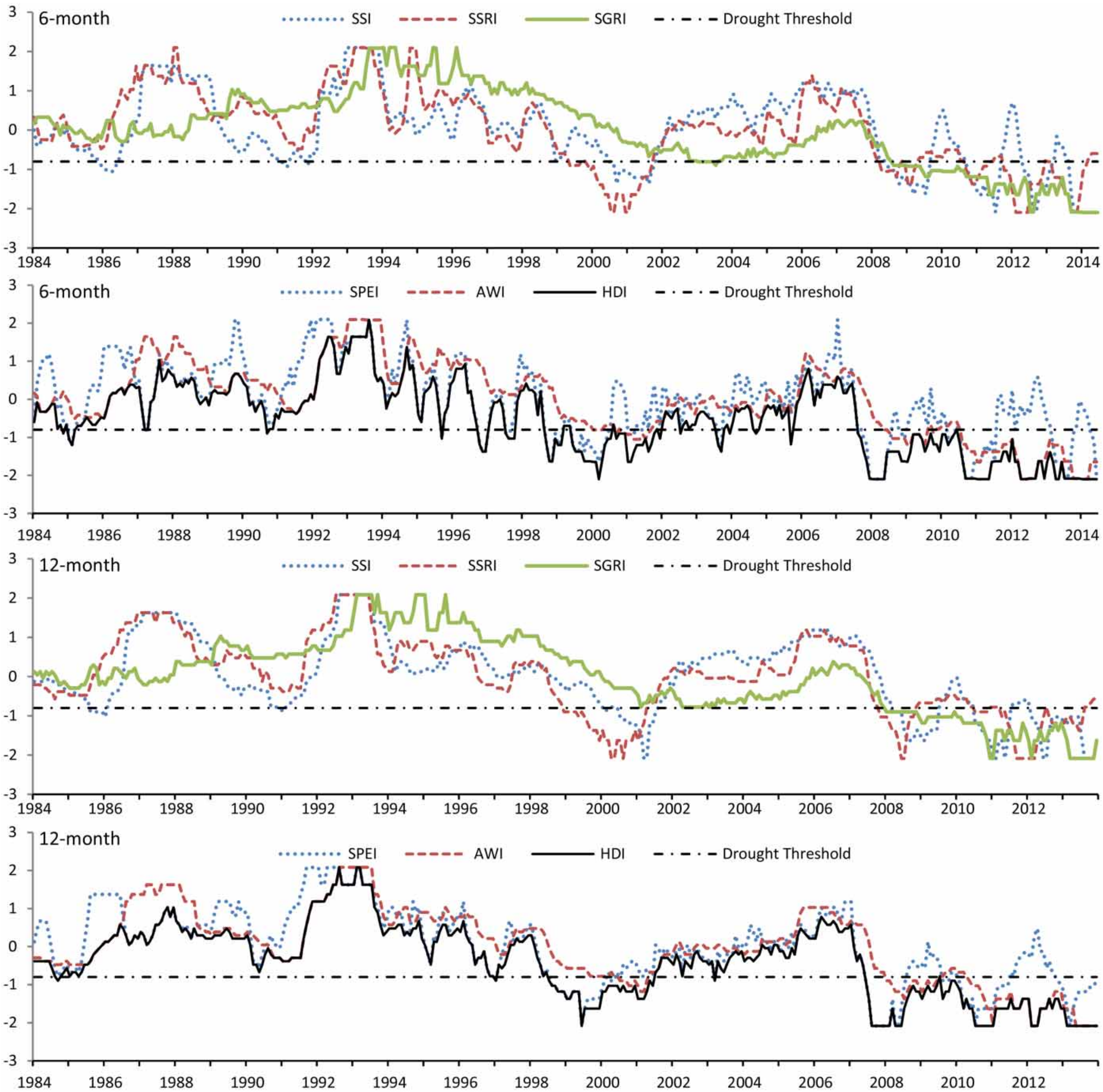


**Figure 4** | Time series of SIs for time scales of 6 and 12 months for sub-basin 4206. The first scheme of each time scale shows the series of hydrologic elements and the second shows the series of hydrologic cycle.

However, many aquifers are greatly limited in areal extent and thickness, and pumping at rates much above recharge rates for extended periods results in depletion of aquifers (SGRI in 4205).

After severe droughts and withdrawing of GS, groundwater availability in 4201, 4206, and 4209 is heavily weighted toward the basin's river. Alluvial aquifers are in hydraulic communication with the river streaming across the sub-basins in which the aquifer is situated. Specifically, the north-eastern (4201) and central (e.g., 4206) areas are particularly important from a socio-economic point of view, as the most important agricultural areas of the region. This is while AWI and HDI indicate serious reduction in AW in these areas and raised social tensions in past years approve this.

## DISCUSSION

The proposed HDI incorporates the overall drought conditions reflected from climatic water balance and AW. Its notion of multivariate drought assessment using SDAT has been quantitatively validated against other drought indicators and reference data (Hao & AghaKouchak 2014). The time series of sub-basins were primarily consistent, meaning the nonparametric approach to characterize wet and dry conditions is reliably effective. This is in agreement with the Farahmand & AghaKouchak (2015) study, which argued that the suggested nonparametric approach is a statistically consistent drought index based on different drought-related variables.

SPEI represented the meteorological drought that it may start and end rapidly. AWI represented hydrological drought, which develops and recovers slowly and may last for a longer time. For both droughts and all time scales, SPEI and HDI initially detect the onset, while AWI and HDI describe the drought persistence and termination. It should be noted that HDI might not determine the same severity magnitude as a univariate index like SPEI. The reason is that the probability corresponding to any given quantile of a bivariate distribution is not the same as the univariate distribution of each variable. Hence, a single variable-based drought index has a fundamentally different distribution than multivariate ones and univariate component functions are not bounds for their multivariate function. Therefore, generally, HDI resembles the highest severity of the SPEI and AWI.

One property of the HDI is that, if the two variables (here, climatic water balance and AW) indicate drought (show a deficit), the HDI would lead to a more severe drought condition than either SPEI or AWI. For this reason, one can see that the severity of drought increases in the 3- and 6-month HDI more quickly than in the 3- and 6-month SPEI and AWI and may lead to more severe drought conditions than either SPEI or AWI, especially when both show a deficit. At the same time, this property of the HDI can lead to detecting upcoming severe droughts earlier, if both input variables (climatic water balance and AW) exhibit a departure from the climatology (Hao & AghaKouchak 2013).

From a general perspective, water users rely on all kinds of water resources. In ZRB, surface and groundwater resources are used for agriculture, domestic, and industry purposes (Safavi *et al.* 2015). To match the long-term sustainability of drought, they need to integrate the resources with their strategies. In times of low surface flow, water users throughout the basin tend to turn to groundwater as a backup supply (as shown by SGRI in 4206 during 1999–2002 and after 2008). The generally unregulated use of groundwater frequently causes negative impacts on water users. Groundwater management issues are increasingly affecting the ZRB.

SIs provide drought information from a hydrometeorological point of view, which are more applicable to water resources managers and local farming. Matching the imminent hazard with the vulnerability of farming systems and rural communities enables decision-makers to adopt response strategies for the greatest impact (Ayalew 1997).

By recent years, the drought situation was being described as the 'worst on record' (as shown by HDI during 2008–14) and a public appeal was launched to raise funds for drought-affected farmers. A drought relief payment is announced annually to help farmers. It is restricted to farmers in areas declared to be experiencing drought circumstances. First, the continuing lack of an agreed-upon definition of drought circumstances hinders the establishment of a stable, predictable environment within which policy-makers and farmers must operate. While the trigger point at which support and its nature becomes available remains fluid, farmers' risk management strategies will be hampered. Even with the development of the SPI, one of the major limitations to drought monitoring is to use a single indicator or index to represent the diversity and complexity of drought conditions and impacts (Wilhite 2005). The SIs, especially HDI, are designed in this research to address many of the weaknesses like this and are intended to provide a direct answer to the questions most commonly posed by water managers.

Agricultural drought is most sensitive to precipitation deficits, while groundwater may respond to a 6-month or longer precipitation deficit. Groundwater levels often are slower (e.g., SGRI In 4206 during 1998–2002) than streamflow (SSI) to respond to precipitation deficits, only after soil moisture and streamflows are down. Groundwater levels also recover more slowly (e.g., SGRI In 4206 during 2002–08) from drought and do so only after precipitation exceeds ET and soil moisture demands.

Environment has a key role in determining the supply of clean water. For example, large quantities of water in the deep 4201 aquifer underlay much of the sub-basin, but much of this groundwater is of poor quality. Large quantities of water could be pumped from this deep aquifer, but would not be proper for long-term irrigation due to soil deterioration. Hence, surface water is essential for irrigation after one or two seasons.

## CONCLUSIONS

Drought mitigation and water resources management need reliable drought monitoring systems. The efficiency of these systems in analyzing extremes is highly controlled by the indices which must take into consideration and integrate different information aspects. Within the study, the information of variables is combined by using the nonparametric standardized framework, which is distribution-free and can overcome the limitations of existing parametric approaches. The paper presented different types of drought in the hydrologic cycle. Several components related to drought were defined for management decisions. A multi-scalar, multi-index framework described drought on the states of hydroclimatic variables of two newly defined concepts, climatic water balance and AW. Climatic water balance describes a simple balance of P and PET. AW considers hydrologic variables of R/S, and surface and ground water reservoirs. The general status of the hydrologic cycle is outlined by a multivariate, multi-scalar integrated drought monitoring framework, namely, the HDI, for declaring droughts based on the states of multiple variables, climatic water balance, and AW. A nonparametric approach is used to describe the univariate and joint distribution of newly defined concepts to derive HDI for drought monitoring on a consistent and comparable scale. It is unique in the sense that SIs account for all the physical forms of drought, thus bringing in a broader perspective for drought quantification. The HDI and other SIs (i.e., SPEI, SSI, SSRI, SGRI, and AWI) are used to describe two major recent droughts in the ZRB.

Drought events of the ZRB have been studied between the years of 1983 and 2014 and this data record is used to construct the SIs and HDI. From the two scenarios, SPEI is good at predicting the onset of drought, whereas AWI is better at detecting drought termination. SSI, SSRI, and SGRI show drought development throughout hydrologic elements. HDI captures the drought onset similar to the SPEI, drought termination similar to the AWI, and drought duration as well as its transition periods. Thus, it is superior to univariate drought indices in describing the drought onset and persistence that combine the bivariate properties. In fact, the HDI can create better drought monitoring potentially if each of the selected drought-related variables can capture certain aspects of droughts.

The method can furnish water resources planners and policy-makers with valuable information in developing appropriate management to cope with drought consequences. It is indicated that drought monitoring and prediction should be based on multiple sources of information. The HDI is not intended to replace expert knowledge or any other drought index. The HDI is an additional source of information to provide more insights into drought monitoring.

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## REFERENCES

Abramowitz, M. & Stegun, I. A. 1964 *Handbook of Mathematical Functions: With Formulas, Graphs, and Mathematical Tables*, Vol. 55. Courier Corporation, Chelmsford, MA, USA.

AghaKouchak, A. 2015 A multivariate approach for persistence-based drought prediction: application to the 2010–2011 East Africa drought. *Journal of Hydrology* **526**, 127–135.

AghaKouchak, A., Ciach, G. & Habib, E. 2010 Estimation of tail dependence coefficient in rainfall accumulation fields. *Advances in Water Resources* **33** (9), 1142–1149.

Ayalew, M. 1997 What is food security and famine and hunger? *Internet Journal for African Studies* **1** (2). Available from: http://www.bradford.ac.uk/research-old/ijas/ijasno2/ayalew.html.

Bachmair, S., Kohn, I. & Stahl, K. 2015 Exploring the link between drought indicators and impacts. *Natural Hazards and Earth System Sciences* **15** (6), 1381–1397.

Beguería, S., Vicente-Serrano, S. M., Reig, F. & Latorre, B. 2014 Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. *International Journal of Climatology* **34** (10), 3001–3023.

Below, R., Grover-Kopec, E. & Dilley, M. 2007 Documenting drought-related disasters: a global reassessment. *The Journal of Environment & Development* **16** (3), 328–344.

Burke, E. J., Brown, S. J. & Christidis, N. 2006 Modeling the recent evolution of global drought and projections for the twenty-first century with the Hadley Centre climate model. *Journal of Hydrometeorology* **7** (5), 1113–1125.

Dai, A. 2011 Characteristics and trends in various forms of the Palmer Drought Severity Index during 1900–2008. *Journal of Geophysical Research: Atmospheres* **116**, D12115.

Doesken, N. J., McKee, T. B. & Kleist, J. 1991 *Development of a Surface Water Supply Index for the Western United States*. Climatology Report Number 91–3, Colorado State University, Fort Collins, CO, USA.

Droogers, P. & Allen, R. G. 2002 Estimating reference evapotranspiration under inaccurate data conditions. *Irrigation and Drainage Systems* **16** (1), 33–45.

Farahmand, A. & AghaKouchak, A. 2015 A generalized framework for deriving nonparametric standardized drought indicators. *Advances in Water Resources* **76**, 140–145.

Garen, D. C. 1993 Revised surface-water supply index for western United States. *Journal of Water Resources Planning and Management* **119** (4), 437–454.

Ghoudi, K. & Rémillard, B. 2004 Empirical processes based on pseudo-observations. II. The multivariate case. *Asymptotic Methods in Stochastics* **44**, 381–406.

Gringorten, I. I. 1963 A plotting rule for extreme probability paper. *Journal of Geophysical Research* **68** (3), 813–814.

Hao, Z. & AghaKouchak, A. 2013 Multivariate standardized drought index: a parametric multi-index model. *Advances in Water Resources* **57**, 12–18.

Hao, Z. & AghaKouchak, A. 2014 A nonparametric multivariate multi-index drought monitoring framework. *Journal of Hydrometeorology* **15** (1), 89–101.

Hao, Z. & Singh, V. P. 2015 Drought characterization from a multivariate perspective: a review. *Journal of Hydrology* **527**, 668–678.

Heddinghaus, T. R. & Sabol, P. 1991 A review of the Palmer Drought Severity Index and where do we go from here. In: *Proceedings of the 7th Conference on Applied Climatology, Salt Lake City, UT, USA*, pp. 242–246.

Heim, R. R. 2002 A review of twentieth-century drought indices used in the United States. *Bulletin of the American Meteorological Society* **83** (8), 1149–1165.

International Research Institute (IRI) for Climate and Society 2001 *The Drought and Humanitarian Crisis in Central and Southwest Asia: A Climate Perspective*. IRI Special Report No. 01–11, Columbia Earth Institute, New York, USA.

Kalamaras, N., Michalopoulou, H. & Byun, H. R. 2010 Detection of drought events in Greece using daily precipitation. *Hydrology Research* **41** (2), 126–133.

Kao, S. C. & Govindaraju, R. S. 2010 A copula-based joint deficit index for droughts. *Journal of Hydrology* **380** (1), 121–134.

Karamouz, M., Rasouli, K. & Nazif, S. 2009 Development of a hybrid index for drought prediction: case study. *Journal of Hydrologic Engineering* **14** (6), 617–627.

Karl, T. R. 1986 The sensitivity of the Palmer drought severity index and Palmer's Z-index to their calibration coefficients including potential evapotranspiration. *Journal of Climate and Applied Meteorology* **25** (1), 77–86.

Keyantash, J. & Dracup, J. A. 2002 The quantification of drought: an evaluation of drought indices. *Bulletin of the American Meteorological Society* **83** (8), 1167–1180.

Li, X., Zhang, Q., Zhang, D. & Ye, X. 2017a Investigation of the drought–flood abrupt alternation of streamflow in Poyang Lake catchment during the last 50 years. *Hydrology Research* **48** (5), 1402–1417. doi:10.2166/nh.2016.266.

Li, Y., Chen, C. & Sun, C. 2017b Drought severity and change in Xinjiang, China, over 1961–2013. *Hydrology Research* **48** (5), 1343–1362. doi:10.2166/nh.2016.026.

Ling, H., Deng, X., Long, A. & Gao, H. 2017 The multi-time-scale correlations for drought–flood index to runoff and North Atlantic Oscillation in the headstreams of Tarim River, Xinjiang, China. *Hydrology Research* **48** (1), 253–264. doi:10.2166/nh.2016.166.

Madani, K. 2014 Water management in Iran: what is causing the looming crisis? *Journal of Environmental Studies and Sciences* **4**(4), 315–328.

Madani, K. & Mariño, M. A. 2009 System dynamics analysis for managing Iran's Zayandeh-Rud river basin. *Water Resources Management* **23** (11), 2163–2187.

Mavromatis, T. 2007 Drought index evaluation for assessing future wheat production in Greece. *International Journal of Climatology* **27** (7), 911–924.

Mazdiyasni, O. & AghaKouchak, A. 2015 Substantial increase in concurrent droughts and heatwaves in the United States. *Proceedings of the National Academy of Sciences* **112** (37), 11484–11489.

McKee, T. B., Doesken, N. J. & Kleist, J. 1993 The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology*. American Meteorological Society, Boston, MA, USA, Vol. 17, No. 22, pp. 179–183.

Mehran, A., Mazdiyasni, O. & AghaKouchak, A. 2015 A hybrid framework for assessing socioeconomic drought: linking climate variability, local resilience, and demand. *Journal of Geophysical Research* **120** (15), 7520–7533.

Mishra, A. K. & Singh, V. P. 2010 A review of drought concepts. *Journal of Hydrology* **391** (1), 202–216.

Molle, F., Ghazi, I. & Murray-Rust, H. 2009 Buying respite: Esfahan and the ZayandehRud river basin, Iran. In: *River*

*Basin Trajectories: Societies, Environments and Development* (F. Molle & P. Wester, eds). CABI, Wallingford, UK; International Water Management Institute (IWMI), Colombo, Sri Lanka, pp. 196–214.

Nam, W. H., Choi, J. Y., Yoo, S. H. & Jang, M. W. 2012 A decision support system for agricultural drought management using risk assessment. *Paddy and Water Environment* **10** (3), 197–207.

Naresh Kumar, M., Murthy, C. S., Sesha Sai, M. V. R. & Roy, P. S. 2009 On the use of Standardized Precipitation Index (SPI) for drought intensity assessment. *Meteorological Applications* **16** (3), 381–389.

Nijssen, B., Shukla, S., Lin, C., Gao, H., Zhou, T., Sheffield, J., Wood, E. F. & Lettenmaier, D. P. 2014 A prototype global drought information system based on multiple land surface models. *Journal of Hydrometeorology* **15** (4), 1661–1676.

Ntale, H. K. & Gan, T. Y. 2003 Drought indices and their application to East Africa. *International Journal of Climatology* **23** (11), 1335–1357.

Núñez, J., Rivera, D., Oyarzún, R. & Arumí, J. L. 2014 On the use of standardized drought indices under decadal climate variability: critical assessment and drought policy implications. *Journal of Hydrology* **517**, 458–470.

Palmer, W. C. 1965 *Meteorological Drought*, Vol. 30. US Department of Commerce, Weather Bureau, Washington, DC, USA.

Palmer, W. C. 1968 Keeping track of crop moisture conditions, nationwide: the new crop moisture index. *Weatherwise* **21**, 156–161.

Paydar Consulting Engineering Co 2010 *Updating Studies of Water Resources in the Zayandehrud River Basin*. Iran Ministry of Energy, Tehran, Iran (in Persian).

Portela, M. M., dos Santos, J. F., Silva, A. T., Benitez, J. B., Frank, C. & Reichert, J. M. 2015 Drought analysis in southern Paraguay, Brazil and northern Argentina: regionalization, occurrence rate and rainfall thresholds. *Hydrology Research* **46** (5), 792–810.

Quiring, S. M. 2009 Developing objective operational definitions for monitoring drought. *Journal of Applied Meteorology and Climatology* **48** (6), 1217–1229.

Rahmat, S. N., Jayasuriya, N. & Bhuiyan, M. 2015 Assessing droughts using meteorological drought indices in Victoria, Australia. *Hydrology Research* **46** (3), 463–476.

Rajsekhar, D., Singh, V. P. & Mishra, A. K. 2015 Multivariate drought index: an information theory based approach for integrated drought assessment. *Journal of Hydrology* **526**, 164–182.

Safavi, H. R. & Alijanian, M. A. 2010 Optimal crop planning and conjunctive use of surface water and groundwater resources using fuzzy dynamic programming. *Journal of Irrigation and Drainage Engineering* **137** (6), 383–397.

Safavi, H. R., Chakraei, I., Kabiri-Samani, A. & Golmohammadi, M. H. 2013 Optimal reservoir operation based on conjunctive use of surface water and groundwater using neuro-fuzzy systems. *Water Resources Management* **27** (12), 4259–4275.

Safavi, H. R., Esfahani, M. K. & Zamani, A. R. 2014 Integrated index for assessment of vulnerability to drought, case study: Zayandehrood River Basin, Iran. *Water Resources Management* **28** (6), 1671–1688.

Safavi, H. R., Golmohammadi, M. H. & Sandoval-Solis, S. 2015 Expert knowledge based modeling for integrated water resources planning and management in the Zayandehrud River Basin. *Journal of Hydrology* **528**, 773–789.

Safavi, H. R., Sajjadi, S. M. & Raghibi, V. 2016 Assessment of climate change impacts on climate variables using probabilistic ensemble modeling and trend analysis. *Theoretical and Applied Climatology* 1–19. doi:10.1007/s00704-016-1898-3.

Sepulcre, G., Horion, S. M. A. F., Singleton, A., Carrao, H. & Vogt, J. 2012 Development of a Combined Drought Indicator to detect agricultural drought in Europe. *Natural Hazards and Earth System Sciences* **12** (11), 3519–3531.

Shafer, B. A. & Dezman, L. E. 1982. Development of a Surface Water Supply Index (SWSI) to assess the severity of drought conditions in snowpack runoff areas. In: *Proceedings of the Western Snow Conference*, Vol. 50, pp. 164–175. Colorado State University, Fort Collins, CO, USA.

Stagge, J. H., Tallaksen, L. M., Xu, C. Y. & Van Lanen, H. A. J. 2014 Standardized precipitation-evapotranspiration index (SPEI): Sensitivity to potential evapotranspiration model and parameters. In: *Proceedings of FRIEND-Water 2014, Montpellier, France*, October 2014 (IAHS Publ. 363, 2014).

Steinemann, A. C., Hayes, M. J. & Cavalcanti, L. 2005 Drought indicators and triggers. In: *Drought and Water Crises: Science, Technology, and Management Issues* (D. Wilhite, ed.). CRC Press, Bocat Raton, FL, USA, pp. 71–92.

Sung, J. H. & Chung, E. S. 2014 Development of streamflow drought severity–duration–frequency curves using the threshold level method. *Hydrology and Earth System Sciences* **18** (9), 3341–3351.

Thornthwaite, C. W. 1948 An approach toward a rational classification of climate. *Geographical Review* **38** (1), 55–94.

Turnbull, B. W. 1976 The empirical distribution function with arbitrarily grouped, censored and truncated data. *Journal of the Royal Statistical Society. Series B (Methodological)* **38** (3), 290–295.

Van Loon, A. F. 2015 Hydrological drought explained. *Wiley Interdisciplinary Reviews: Water* **2** (4), 359–392.

Van Loon, A. F., Gleeson, T., Clark, J., Van Dijk, A. I., Stahl, K., Hannaford, J., Di Baldassarre, G., Teuling, A. J., Tallaksen, L. M., Uijlenhoet, R. & Hannah, D. M. 2016a Drought in the Anthropocene. *Nature Geoscience* **9** (2), 89–91.

Van Loon, A. F., Stahl, K., Di Baldassarre, G., Clark, J., Rangecroft, S., Wanders, N., Gleeson, T., Van Dijk, A. I. J. M., Tallaksen, L. M., Hannaford, J., Uijlenhoet, R., Teuling, A. J., Hannah, D. M., Sheffield, J., Svoboda, M., Verbeiren, B., Wagener, T. & Van Lanen, H. A. J. 2016b Drought in a human-modified world: reframing drought definitions, understanding, and analysis approaches. *Hydrology and Earth System Sciences* **20** (9), 3631–3650.

Vicente-Serrano, S. M. & Beguería, S. 2015 Comment on 'Candidate distributions for climatological drought indices

(SPI and SPEI)' by James H. Stagge et al. *International Journal of Climatology* **36** (4), 2120–2131.

Vicente-Serrano, S. M., Beguería, S. & López-Moreno, J. I. 2010 A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *Journal of Climate* **23** (7), 1696–1718.

Vicente-Serrano, S. M., Beguería, S. & López-Moreno, J. I. 2011 Comment on 'Characteristics and trends in various forms of the Palmer Drought Severity Index (PDSI) during 1900–2008' by Aiguo Dai. *Journal of Geophysical Research: Atmospheres* **116** (D19). doi:10.1029/2011JD016410.

Vicente-Serrano, S. M., López-Moreno, J. I., Beguería, S., Lorenzo-Lacruz, J., Azorin-Molina, C. & Morán-Tejeda, E. 2012 Accurate computation of a streamflow drought index. *Journal of Hydrologic Engineering* **17** (2), 318–332.

Vidal, J. P., Martin, E., Franchistéguy, L., Habets, F., Soubeyroux, J. M., Blanchard, M. & Baillon, M. 2010 Multilevel and multiscale drought reanalysis over France with the Safran-Isba-Modcou hydrometeorological suite. *Hydrology and Earth System Sciences* **14** (3), 459–478.

Water and Wastewater Research Institute (WWRI) 2012 *Climate Change Effects in Precipitation and Temperature in Zayandehrud River Basin.* Isfahan University of Technology (IUT), Isfahan, Iran.

Wells, N., Goddard, S. & Hayes, M. J. 2004 A self-calibrating Palmer drought severity index. *Journal of Climate* **17** (12), 2335–2351.

Wilhite, D. A. ed. 2005 *Drought and Water Crises: Science, Technology, and Management Issues*. CRC Press, Boca Raton, FL, USA.

Wilhite, D. A. & Glantz, M. H. 1985 Understanding: the drought phenomenon: the role of definitions. *Water International* **10** (3), 111–120.

Wilhite, D. A., Hayes, M. J., Knutson, C. & Smith, K. H. 2000 Planning for drought: moving from crisis to risk management. *JAWRA Journal of the American Water Resources Association* **36**(4), 697–710.

Winstanley, D., Angel, J. R., Changnon, S. A., Knapp, H. V., Kunkel, K. E., Palecki, M. A., Scott, R. & Wehrmann, H. A. 2006 *The Water Cycle and Water Budgets in Illinois: a Framework for Drought and Water Supply Planning*. ISWS I/E, 2006–02.

Yekom Consulting Engineering Co. 2013 *Updating Integrated Water Resources Studies in Iran.* Gavkhooni Basin Report, Iran (in Persian).

Yue, S., Ouarda, T. B. M. J., Bobée, B., Legendre, P. & Bruneau, P. 1999 The gumbel mixed model for flood frequency analysis. *Journal of Hydrology* **226** (1), 88–100.

Zayandab Consulting 2008 *Determination of Resources and Consumptions of Water in the Zayandehrud River Basin.* Esfahan Regional Water Company, Esfahan, Iran (in Persian).

Zhu, Y., Chang, J., Huang, S. & Huang, Q. 2016 Characteristics of integrated droughts based on a nonparametric standardized drought index in the Yellow River Basin, China. *Hydrology Research* **47** (2), 454–467.

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