A Review of Some Indices Used for Drought Monitoring

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Abstract

Drought is a natural hazard that results from a deficiency of precipitation and water availability from expected or normal amounts, usually extended over a season or longer period. Drought can be hydrological, meteorological, agricultural and socio-economical. It affects the ecology, biodiversity, hydrology and climate and economy and the wellbeing of the societies at local, regional and global levels. Drought causes for significant environmental and economic problems, which in turn affect the balance of food supply and demand leads to poverty. Therefore, drought monitoring and prediction and warning system is a very essential component to minimize vulnerabilities and risks. In this regard, drought indices play a great role. The objective of this review is to show different available drought indices used for monitoring drought events. For investigating drought using a single index is not providing better results, therefore, integrating different indices is recommended because the environmental variable is spatially different and the indices do not use the same model and there are gaps in the model. Thus, by integrating different indices it is possible to achieve better drought results.

1. Introduction

Drought is a period of abnormally dry weather results in a change in vegetation cover (Heim Jr, 2002; Tucker and Choudhury, 1987). In addition to this, drought is a period of abnormally dry weather sufficiently prolonged because of a lack of precipitation that causes a serious hydrological imbalance and has connotations of a moisture deficiency with respect to water use requirements (McMahon and Arenas, 1982). Drought is a recurrent climate process that occurs over a wide area for a longer period of time. It is a natural hazard that results from a deficiency of precipitation and water availability from expected or normal amounts, usually extended over a season or longer period of time (Mishra and Singh, 2010). Drought is one of the main natural hazards that damage crop system and environment, and economy (Burton et al., 1978; Wilhite, 1993; Wilhite and Glantz, 1985). Drought affects agricultural productivity, hydrological cycles, vegetation, and ecosystem interaction. It also affects the livelihood conditions of the people and results in poverty and famine. Therefore, monitoring of drought is very crucial to minimize the effects of drought and its related problems. To provide better information for planners and decision-makers different advanced monitoring techniques should be applied to monitor drought events (WGA, 2004). However, drought monitoring is challenging because of the complex nature of drought and massive spatio-temporal variability drought event and its comprehensive nature of impacts exhibited (Brown et al., 2008).

There are many drought monitoring systems (Funk and Verdin, 2010; Hao et al., 2014; Nijssen et al., 2014; Pozzi et al., 2013; Sheffield et al., 2008; Verdin et al., 2005) and has been applied at different scales. The drought monitoring systems can be hydrological, climate, meteorological and satellite-based indices. Climate-based drought indices are mostly used to support drought planning decisions and to prompt mitigating actions (Hayes, 2003; Keyantash and Dracup, 2002) and give information about climate change and its impact on the environments and societies. Whereas meteorological-based indices are providing basic information about drought events (Di et al., 1994; Ji and Peters, 2003; McVicar and Bierwirth, 2001; Rundquist and Harrington, 2000; Yang et al., 1998) through analyzing elements of weather and climate. Satellite-based vegetation indices are also very significant in drought monitoring and analysis (Di et al., 1994; Goetz and Prince, 1996; Goward et al., 1985; Jakubauskas et al., 2002; Malingreau, 1986; Reed et al., 1996) through investigating the response of vegetation to climate. The vegetation indices have been used to monitor drought events by analyzing the characteristics of vegetation (Rouse et al., 1974; Tucker, 1979).

Therefore, to monitor and predict drought and to extract reliable drought event information, different indices have been developed and applied at local, regional and global levels. However, due to the complex nature of drought events and its spatio-temporal variations and its wide nature of possible impacts, drought monitoring requires integrated drought indicators. It is possible to integrate satellite-based indices with climate-meteorological indices as well as hydrological and soil moisture indices. Drought can be described using different drought indicator variables like precipitation and soil moisture (Dracup et al., 1980) and vegetation responses to climate parameters.

Several studies, therefore, agreed that a single drought index is not sufficient to monitoring drought onset,

end period and persistence (AghaKouchak, 2014; Dracup et al., 1980; Hao and AghaKouchak, 2013; Kao and Govindaraju, 2010) and possible return periods. This is because, on one hand, the nature of drought and on the other hand drought indicators and climate processes varies in space and time. For instance, the study conducted by (Hao and AghaKouchak, 2013) confirmed that precipitation used to detects the drought started earlier than other indices. However, (Entekhabi et al., 1996; Heim Jr, 2002) agreed that soil moisture conditions are better in describing the drought persistence. But, satellite-based indices are better in analyzing vegetation conditions (Di et al., 1994; Goetz and Prince, 1996; Goward et al., 1985; Jakubauskas et al., 2002; Reed et al., 1996; Rouse et al., 1974; Tucker, 1979). Hence, using different drought indicators is very significant not only for drought monitoring and prediction but also to find out the causes and assess the possible consequences of drought and to set alternative mitigation strategies.

For effective drought monitoring, researchers and scientist for example (AghaKouchak, 2014; Dracup et al., 1980; Funk and Verdin, 2010; Hao et al., 2014; Hao and AghaKouchak, 2013; Kao and Govindaraju, 2010; Nijssen et al., 2014; Pozzi et al., 2013; Sepulcre-Cantó et al., 2012; Sheffield et al., 2008; Verdin et al., 2005) recommend to use integrated drought indicators. Because drought indicators have their successes and limitations in drought detection and identification. For instance, meteorological drought indicators assimilate information from global rainfall, stored soil moisture or water supply but they do not express much local spatial detail. On the other hand, the derived drought indicators calculated from satellite images are effective in providing information about spatial and temporal drought at global, regional and local scales. Remote sensing-based indices derived satellite surface parameters are one of the main drought monitoring techniques and have been widely used to study droughts (Di et al., 1994; Goetz and Prince, 1996; Jakubauskas et al., 2002; Reed et al., 1996). This is because it is capable of showing spatio-temporal variations of drought and its intensity.

Furthermore, studies (Bayarjargal et al., 2006; Ji and Peters, 2003; McVicar and Bierwirth, 2001; Rundquist and Harrington, 2000) showed that using of meteorological-based indices and satellite-based indices are very significant for drought study because they have good agreement between them and better in estimation of drought affected areas. For instance, drought monitoring results obtained from satellite-based indices such as Normalized Difference Vegetation Index (NDVI) and/or NDVI-derived like Normalized Difference Vegetation Index Anomaly (NDVIA), Standardized Vegetation Index (SVI), Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) and hybrid indices like Vegetation Health Index (VHI), and Drought Severity Index (DSI) were agreed with the results of meteorological-based indices like Palmer Drought Severity Index (PDSI), Standardized Precipitation Index (SPI), and Standardized Soil Moisture Index (SSI). Furthermore, integration of meteorological-based indices, satellite-derived indices, and hydrological model indices enable to achieve better results in the study of drought monitoring and prediction. Currently, drought monitoring studies conducted range from purely precipitation-based indices (Clark et al., 2003; Kurnik et al., 2011; Naumann et al., 2014), a combination of precipitation-based and climate models indices (Dutra et al., 2013; Yang et al., 2014), to a combination of precipitation-based indices, soil moisture condition indices and satellite-based indices such as NDVI (Anderson et al., 2012; Nicholson, 2014). The objective of this review is to evaluate different drought indices used for drought monitoring.

2. Types of Drought

Drought is a natural phenomenon largely driven by a deficit of precipitation and it happened for a longer period of time. It is a complex phenomenon and it is difficult to define and monitor. Mostly it related to the absence of water. It happened at different time scales and it has diversified impact on economy, environment, hydrology, ecology, and societies. Drought can be classified into four types: (1) agricultural drought, (2) hydrological drought, (3) meteorological drought, and (4) socioeconomic drought (https://www.ncdc.noaa.gov/monitoring-references/dyk/drought-definition). Depends on the causes of drought and its possible impacts, it can be classified into three namely: (a) agricultural drought, based on its impacts on soil moisture condition and yields; (b) meteorological drought, based on precipitation abnormalities compared with long-term climatology, and (c) hydrological drought, based on streamflow deficits, depletion of groundwater and reservoirs water level reduction (Cammalleri et al., 2016). However, (Wilhite and Glantz, 1985) categorized drought into four basic approaches to measure drought events, namely: *agricultural, meteorological*, *hydrological* and *socioeconomic*.

2.1 Agricultural Drought

Agricultural drought happened when crop affected and yield declined. It mainly resulted from soil moisture deficits and its effect on the crop cultivation in the season. Satellite-derived indices are widely used for monitoring and predicting crops and agricultural drought. Therefore, agricultural drought indices derived from satellite remote sensing have been widely used for drought study because of high spatial resolution, large spatio-temporal coverages, and their ability to detect drought events timely and accurately (Kogan, 1995). For instance, remotely sensed vegetation condition indices, such as NDVI and VCI and satellite-derived temperature indices like TCI and combination of vegetation condition and temperature indices VHI have been widely applied for agricultural

drought monitoring (Brown et al., 2008). Moreover, numerous drought indices which used drought-related parameters, for example, vegetation greenness, temperature, evapotranspiration, rainfall, soil moisture, and vegetation moistures, have been developed and commonly applied for agricultural drought monitoring and analysis (Anderson et al., 2010; Wang and Qu, 2007; Xu et al., 2011). Studies for instance (Agutu et al., 2017; Anderson et al., 2012; Mwangi et al., 2014; Rojas et al., 2011; Shukla et al., 2014) have studied agricultural drought using integrated indices of SPI, NDVI and soil moisture. Information about agricultural drought is very essential for assessment of onset season crop management, termination of season crop production management and crop loss and yield reduction (Murthy et al., 2007).

2.2 Meteorological Drought

Meteorological drought occurs when dry weather conditions and patterns dominate the area. This means precipitation is less than its normal and there are weather patterns changes. Therefore, such kind of drought is referred to as dryness resulted from rainfall deficit (Beersma and Buishnd, 2007). Meteorological drought also involves when precipitation falls below the standard required by plants and animals or change in the intensity of rain that results in a decline in relative humidity and cloudiness and increases in temperature and evapotranspiration (Estrela et al., 2000; Hong et al., 2004). Therefore, monitoring of precipitation and temperature and relative humidity is very essential. This can be done using meteorological drought indices such as Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Aridity Index (AI), Percent of Normal Precipitation, Crop Moisture Index (CMI), Palmer Drought Severity Index (PDSI), Rainfall Anomaly Index (RAI), Evapotranspiration Deficit Index (ETDI), Soil Moisture Anomaly (SMA), and Soil Moisture Deficit Index (SMDI).

2.3 Hydrological Drought

Hydrological drought occurs when the level of surface water and the groundwater table is less than the long-term average. In this type of drought, indicators such as streams, lakes and groundwater levels are very low (Clausen and Pearson, 1995). Furthermore, hydrological drought occurs when low water supply becomes evident, especially in streams, reservoirs, and groundwater levels, usually after many months of meteorological drought. It is most common when water resources used for human, animal and industry consumption and to support agricultural activities reached low levels. It resulted from climate fluctuations. Besides these, LULC change and its impact on land degradation, and dam construction has impacts on hydrology and bring severe hydrological drought. Hydrological drought takes much longer to develop and then recover while meteorological drought can begin and end rapidly. Hydrological drought can be monitored and predicted using indices such as Palmer Hydrological Drought Severity Index (PHDI), Standardized Reservoir Supply Index (SRSI), Standardized Water-level Index (SWI).

2.4 Socio-economic Drought

Socioeconomic drought refers to conditions whereby the water demand outstrips the supply, leading to societal, economic, and environmental impacts (Dinar and Mendelsohn, 2011; Hayes et al., 2011; Zseleczky and Yosef, 2014). Socioeconomic drought, defined as conditions whereby the water supply is not sufficient to satisfy the local demand, is the least investigated type of drought (Mehran et al., 2015). It happens when water resources needed for industrial, agricultural and household consumption is less than what is needed and so this situation results in socio-economic anomalies. The socioeconomic drought happens due to anomalies resulted from water shortage (Karl and Knight, 1985). Mostly, socio-economic drought relates the supply and demand of numerous commodities to drought events. This drought affects the environment and economic activities of societies and brings poverty, unemployment, and disease. It depends on spatio-temporal processes in supply and demand and variations of elements of agricultural, meteorological and hydrological drought.

3. Drought Indices

Drought indices are important elements of drought monitoring and assessment since they simplify complex interrelationships between many climates and climate-related parameters. According to (Wilhite et al., 2000) indices make it easier to communicate information about climate anomalies and enables to assess quantitatively climate anomalies in terms of frequency, intensity, duration, and spatial extent. Drought indices are useful for mapping spatial and temporal water deficit and supply. This information is very critical in assessing agricultural drought risk and analyzing and monitoring soil water content available for crop and crop yield. Besides, drought indices are used to define natural disaster conditions and the response of government to hazard mitigation and copying strategies. Indices are also essential for modeling climate data such as precipitation and temperature obtained from both meteorology and remotely sensed datasets. Besides, drought indices are significant in hydrological drought monitoring through assessing water storage in reservoirs, soil water levels, and other related parameters. A variety of drought indices have been developed to quantify whether or not a region is experiencing

drought and to categorize the seriousness of the drought. Some of the indices are discussed in the following section.

3.1   Normalized Difference Vegetation Index

The NDVI is the most commonly used satellite-based indices used for short real-time drought monitoring (Bayarjargal et al., 2006). However, it does not use for long real-time drought monitoring. The NDVI is a measure of the greenness, or vigor of vegetation. It is a good indicator of green biomass, Leaf Area Index (LAI), and patterns of production. This index is derived based on the known radiometric properties of plants, using visible (red) and near-infrared (NIR) radiation (Chen et al., 2014; Dorigo et al., 2012; Guan et al., 2012; Rojas et al., 2011).

The NDVI can be computed using the following formula.

$$\text{NDVI} = (NIR - RED) / (NIR + RED) \tag{1}$$

Where: NIR and RED are the reflectance in the near infrared and red bands.

The NDVI values range from −1 to +1, with values near zero indicating the absence of green vegetation and values near +1 indicating the highest possible density of vegetation whereas values below zero indicating waterbodies. Huete and Tucker (1991) found that NDVI can be used for studying vegetation cover and functions of ecosystems. Studies (Nicholson and Farrar, 1994; Richard and Poccard, 1998; Schmidt and Karnieli, 2000) also showed that NDVI has strong relationships between green LAI, green biomass production, rainfall and soil moisture. The results of the study done by Ji and Peters (2003) confirmed that the NDVI is an effective indicator of vegetation response to drought conditions.

The NDVI has been used for drought monitoring and characterization (Anderson et al., 2012; Anyamba and Tucker, 2005; Nicholson, 2014). Moreover, NDVI and NDVI derived indices have been used to monitor different droughts and assess its impacts on vegetation health (Bayarjargal et al., 2006; Kogan, 1995; Rhee et al., 2010). Many studies used NDVI for analyzing drought conditions through integrating with VCI and LST (Bayarjargal et al., 2000; Karnieli, 2000; Karnieli and Dall'Olmo, 2003; Kogan, 1997; Kogan et al., 2004; McVicar and Bierwirth, 2001). Besides, NDVI and NDVI derived indices have been used to monitor drought affected areas both at regional and local scales (Gonzalez-Alonso et al., 2000; Ji and Peters, 2003; Liu and Negron-Juarez, 2001; Salinas-Zavala et al., 2002; Tucker and Choudhury, 1987). The NDVI has been also used extensively drought and other related studies at local, regional and global scales (Chen et al., 2014; Dorigo et al., 2012; Guan et al., 2012; Rojas et al., 2011; Verdin et al., 2005). According to Bayarjargal et al. (2006) NDVI has good relations with NDVIA and VCI. This indicates that drought information obtained from these indices are alike. He also confirmed that TCI, VHI and DSI have better relations and the result obtained from them are similar. However, the NDVI has a negative relationship with TCI. It is possible to obtain similar drought affected areas through integrating NDVI with TCI, VCI, NDVI anomaly, and VHI and meteorological indices like PDSI. The NDVI also used to monitor agricultural drought though it requires ground truth data such as crop pattern, rainfall, soil type, irrigation, crop season (Murthy et al., 2007).

3.2   Normalized Difference Vegetation Index Anomaly

The NDVIA is a standardized NDVI anomaly used to indicate drought conditions as compared to the average on a range of time scales (Anyamba et al., 2001). The index derived from NDVI and can be used to assess seasonal crop conditions (Legesse and Suryabhagavan, 2014; Murali et al., 2008). The index can be computed as follows.

$$\text{NDVI anomaly} = 100 * \frac{\text{NDVI}_{max\ i} - \text{Mean NDVI}_{max}}{\text{Mean NDVI}_{max}} \tag{2}$$

Where: $\text{NDVI}_{max\ i}$= Maximum NDVI in the growing season in ith year; Mean NDVI_{max} = long term mean maximum NDVI in the growing season.

By integrating both the NDVIA and SVI it is effective to monitor drought conditions mainly over Africa and America (Anyamba et al., 2001; Bayarjargal et al., 2006; Peters et al., 2002). Higher NDVIA indicates lower drought conditions and the vegetation is not vulnerable for drought.

3.3   Vegetation Condition Index

The VCI is a pixel-wise normalization of minimum and maximum NDVI developed by (Kogan, 1990). This index is useful for making relative assessments of changes in the NDVI signal by filtering out the contribution of local geographic resources to the spatial variability of NDVI (Quiring and Ganesh, 2010). Jain et al. (2010) stated that VCI is an indicator of the status of vegetation cover as a function of minimum and maximum NDVI encountered for a given ecosystem over many years. The VCI normalizes NDVI and used for comparison of different ecosystems at different scales. It is an attempt to separate the short-term climate signal from the long-term ecological signal, and it is a better indicator of water stress conditions than NDVI. The significance of VCI is strongly related to the relation between the vegetation index and the vitality of the vegetation cover under investigation (Bayarjargal et al., 2006). The VCI is advantageous as it can isolate weather-related vegetation stress (Kogan, 1995; Quiring and Ganesh, 2010; Rojas et al., 2011) and correspond to water availability. According to

Kogan (1990) VCI is related to the long-term minimum and maximum NDVI and is defined as

$$VCI = 100 * \frac{NDVI_i - NDVI_{min}}{NDVI_{max} + NDVI_{min}} \qquad (3)$$

Where: $NDVI_i$ is the monthly NDVI, while $NDVI_{max}$ and $NDVI_{min}$ are multiyear maximum and minimum NDVI, respectively.

The VCI separates the short-term weather-related NDVI fluctuations from the long-term ecosystem changes (Kogan, 1995, 1990). It varies in the range 0 and 100 to reflect relative changes in the vegetation condition from extremely bad to optimal (Kogan, 1995; Kogan et al., 2003). The higher the VCI, the lower the vegetation stress to drought and vice versa. The VCI characterize by varying moisture conditions of vegetation, and higher VCI values correspond to favorable moisture conditions and represent unstressed vegetation. The index has been used for spatial and temporal drought monitoring at global, regional and local scales.

3.4 Temperature Condition Index (TCI)

The TCI is developed by Kogan (1995) to determine temperature-related vegetation stress and also stress caused by excessive wetness. Surface temperature is very sensitive to water stress and has been identified as a good indicator of water stress. This index is based on brightness temperature (BT) and represents the deviation of the current month's temperature from the recorded maximum. The TCI is calculated from thermal bands converted to BT (Kogan, 1997; Singh et al., 2003). The TCI can be calculated as

$$TCI = 100 * \frac{BT_{max} - BT}{BT_{max} + BT_{min}} \qquad (4)$$

Where: BT, BT_{min}, and BT_{max} are the seasonal average of weekly brightness temperature, its multi-year absolute minimum, and maximum, respectively.

Subtle changes in vegetation health due to thermal stress in specific could be monitored through analysis of TCI data (Kogan, 2002, 2001, 1995). The TCI characterize by varying thermal conditions of vegetation. The TCI are estimated relative to the minimum and maximum temperature envelopes. The TCI reflects different responses of vegetation to temperature. High temperatures in the middle of the growing season indicate unfavorable conditions for drought, while low temperatures indicate mostly favorable conditions (Bayarjargal et al., 2006; Owrangi et al., 2011). Furthermore, using meteorological observations, as well as the relationship between ground surface temperature and moisture regimes, drought-affected areas can often be detected before biomass degradation occurs. Hence, TCI plays a key role in drought monitoring.

3.5 Vegetation Health Index

The VHI is an additive combination of VCI and TCI developed by Kogan (1995, 1997). This index is used to monitor vegetation health, moisture, and thermal conditions as well as to determine drought affected areas. The VHI represents overall vegetation health (Kogan, 2001) and it used for drought mapping. Vegetation health index can be computed as:

$$VHI = 0.5(VCI) + 0.5(TCI) \qquad (5)$$

The NDVI, VCI, TCI and VHI have been employed to assess vegetative drought. The VCI based drought severity can be in the range below 10 for extreme drought and above 40 in the absence of drought (Kogan, 2002). The VHI is found to be more effective for monitoring vegetative drought compared to other indices (Kogan, 2001, 1990; Singh et al., 2003). Integrating VHI with VCI and TCI have been widely used for drought detection and vegetation stress mostly for monitoring agricultural drought in different parts of the world (Bayarjargal et al., 2006; Kogan, 1997; Kogan et al., 2004; Seiler et al., 1998). The NDVI, VCI and TCI are the main indices that frequently used for drought monitoring and identification and weather impact assessment on vegetation (Kogan et al., 2003; Unganai and Kogan, 1998). Besides, the integrated vegetation indices of NDVI, VCI, TCI and VHI have been widely applied for agricultural drought monitoring (Brown et al., 2008; Yagci et al., 2011).

3.6 Vegetation temperature condition index

The VTCI has been used for agricultural drought monitoring through monitoring the spatial pattern of vegetation. The VTCI is an integrated satellite-based land surface reflectance and it shows the change in land surface temperature and NDVI (Wan et al., 2004). The VTCI is based on the relationship of surface temperature (Ts)-NDVI. This index can be computed as expressed in equation 6.

$$VTCI = \frac{LST_{NDVIimax} - LST_{NDVIi}}{LST_{NDVIimax} - LST_{NDVIimin}} \qquad (6a)$$

$$Where \ LST_{NDVIimax} = a + b \ NDVIi \qquad (6b)$$

$$LST_{NDVIimin} = a' + b'NDVIi \qquad (6c)$$

The $LST_{NDVIimax}$ and $LST_{NDVIimin}$ are maximum and minimum LSTs of pixels, which have the same $NDVI$ value, respectively. LST_{NDVIi} denotes actual LST of one pixel whose $NDVI$ value is $NDVIi$. Co-efficients a, b, a' and b' can be estimated from an area large enough (where soil moisture extends from wilting point to field capacity at

pixel level).

The VTCI allows for detecting and monitoring the spatial extent of drought-affected agricultural areas. Furthermore, the interpretation of drought duration from time series of VTCI can depict the severity of drought stress effects on crop performance. The VTCI is very crucial in providing information about drought stress condition solely by satellite measurements. Several researchers have been used this index (Patel et al., 2012; Wan et al., 2004) for drought monitoring. The VTCI had a significantly positive relation with crop moisture index. The VTCI also used to monitor agricultural drought. The index indicates the severity of drought stress on the performance of the crop. The VTCI drought information is related to crop yield anomalies (Patel et al., 2012).

3.7 Standardized Vegetation Index (SVI)

The SVI has been used to monitor areas affected by drought and vegetation conditions in terms of relative greenness at pixel level overtime periods (Peters et al., 2002). The NDVIA and SVI have been successfully used to monitor drought conditions over Africa and America (Anyamba et al., 2001; Bayarjargal et al., 2006; Peters et al., 2002). Drought information obtained from SVI is similar to NDVI (Bayarjargal et al., 2006).

$$\text{SVI} = \frac{\text{NDVI}_{ijk} - \overline{\text{NDVI}_{ij}}}{\sigma \text{NDVI}_{ij}} \qquad (7)$$

Where: NDVI_{ijk} is monthly NDVI for pixel i in month j for year k; $\overline{\text{NDVI}_{ij}}$ = multiyear average NDVI for pixel i in month j; σNDVI_{ij} represent standard deviation of NDVI for a pixel i in the month j.

3.8 Vegetation Drought Response Index (VegDRI)

The VegDRI method of drought monitoring has the approaches of integrated climate-based drought index, satellite-based NDVI values of vegetation conditions and biophysical parameters. The VegDRI is one of the drought monitoring techniques used to investigate spatial and time-series of drought across local to global scales. The VegDRI has good relations with SPI, PDSI and RAI (Brown et al., 2008). Vegetation response index has been also used for monitoring and predicting drought (Tadesse et al., 2005).

3.9 Drought Severity Index (DSI)

The DSI can be computed using different input datasets, for instance, satellite-based NDVI and LST, and precipitation-based method. Bayarjargal et al. (2006, 2000) suggested that the DSI is calculated as subtraction of standardized LST and NDVI for a certain month, and based on the normalization approach to bring diverse variables such as NDVI and LST into the same, comparable, and scale in terms of their ranges.

$$\text{DSI}_{ijk} = \Delta \text{LST}_{ijk} - \Delta \text{ANDVI}_{ijk} \qquad (8a)$$

$$\Delta \text{LST}_{ijk} = \frac{\overline{\text{LST}_{ij}} - \text{LST}_{ijk}}{\sigma \text{LST}_{ij}} \qquad (8b)$$

$$\Delta \text{NDVI}_{ijk} = \frac{\overline{\text{NDVI}_{ij}} - \text{NDVI}_{ijk}}{\sigma \text{NDVI}_{ij}} \qquad (8c)$$

Where: LST_{ijk} is monthly LST for pixel i in month j for year k; $\overline{\text{LST}_{ij}}$ = multiyear average LST for pixel i in month j; σLST_{ij} represent standard deviation of LST for a pixel i in the month j.

The DSI can also retrieve using ET/PET and NDVI datasets as input (Mu et al., 2013). The index is based on ET/PET and NDVI. First, Ratio can be computed from ET and PET using the following formula.

$$Ratio = \frac{ET}{PET} \qquad (9a)$$

The standard deviation of Ratio σ_{Ratio} and Ratio average ($\overline{Ratio}$) are computed on a grid cell-wise base. The standardized Ratio (Z_{Ratio}) can be computed as follows.

$$Z_{Ratio} = \frac{Ratio - \overline{Ratio}}{\sigma_{Ratio}} \qquad (9b)$$

Whereas the standardized NDVI (Z_{Ratio}) can be calculated as follows

$$Z_{NDVI} = \frac{NDVI - \overline{NDVI}}{\sigma_{NDVI}} \qquad (9c)$$

The standard Ratio and NDVI are summed together to obtain Standardized value

$$Z = Z_{Ratio} + Z_{NDVI} \qquad 9d$$

Finally, DSI can be computed the equation below

$$DSI = \frac{Z - \overline{Z}}{\sigma_Z} \qquad (10)$$

The result obtained from DSI has better relation with PSDI. The DSI has been used to monitor and analyze drought

from regional to global levels.

3.10   Evaporative drought index (EDI)

The EDI is a meteorological-based drought index developed by Yao et al. (2010). The index integrated remote sensing data and sensitivity to the vegetation drought response. The integrated data enables EDI capable of monitoring and detecting drought vulnerabilities and risks. Thought EDI is effective in drought monitoring, there are some limitations. The first drawback is the statistical models used to calculate PET and ET lack physical basis and can result in uncertain ET and PET estimates and this brings inaccurate EDI. The second limitation of EDI is it is very difficult to easily quantify the wetness or dryness of a region in a particular month or year.

3.11   Standardized Precipitation Index (SPI)

The SPI is a meteorological index developed by McKee et al. (1993). This index has been used to monitor meteorological drought principally to assess anomalous and extreme precipitation. The SPI can compute by dividing the difference between the normalized seasonal precipitation and its long-term seasonal mean precipitation by the standard deviation. The SPI drought values range between 2 and -2 (Agnew, 2000). The SPI can be computed as,

$$SPI = \frac{X_{ij} - X_{im}}{\sigma} \tag{11}$$

Where: X_{ij} is the seasonal precipitation at the ith rain gauge station and j[th] observation, X_{im} the long-term seasonal mean and σ is its standard deviation.

The SPI is the most widely used index for monitoring drought events and is based on precipitation and it shows precipitation condition relative to long-term climatological process and changes. SPI is a commonly used index that has been functional from global to local scale studies (AghaKouchak and Nakhjiri, 2012; Andreadis et al., 2005; Damberg and AghaKouchak, 2014; Shukla et al., 2011; Wang et al., 2011). This is because it allows to assess drought across different time scales, and it is simple, standardized nature and spatially invariant. Guttman (1999, 1998) and Svoboda et al. (2012) stated that SPI expresses precipitation anomalies with respect to its long-term average. However, SPI mostly used two-parameter gamma probability distribution to model precipitation data. This may not represent precipitation model and it is the main limitation of SPI (Angelidis et al., 2012). On the other hand, three-parameter distribution functions are best for precipitation data modeling (Angelidis et al., 2012; Guttman, 1999; Quiring, 2009). Quiring (2009) argued that the computed SPI values are very sensitive to the fitted parametric distributions, especially at the tail ends of the distribution.

The SPI is used to examine the severity and spatial patterns of drought distribution in a given region (Guttman, 1998; Thavorntam and Mongkolsawat, 2006). It is designed to quantify the impacts of precipitation deficit on groundwater, reservoir storage, soil moisture, and streamflow for multiple time scales. The SPI can be calculated at different time scales and hence can quantify water deficits of different duration. This index was designed to show that it is possible to simultaneously experience wet conditions on one or more-time scales and dry conditions at another time scale. Therefore, the SPI is effective in measuring both wet and dry events. Therefore, it has been used in many studies (Agnew, 2000; Farahmand and AghaKouchak, 2015; Guttman, 1999; McKee et al., 1995; Ntale and Gan, 2003; Quiring, 2009; Svoboda et al., 2012; Vicente-Serrano et al., 2006) to determine the frequency of precipitation distribution like the effect of the time scales on the drought parameters, and the spatial classification of drought patterns. Ntale and Gan (2003) compared the time scale of PDSI, Bhalme-Mooley index, and SPI, and argued that SPI could use any time scale which aid in monitoring drought in Eastern Africa. Besides, previous studies (Ji and Peters, 2003; Khan et al., 2008; Patel et al., 2007; Sims et al., 2002; Szalai et al., 2000; Vicente-Serrano, 2007; Vicente-Serrano et al., 2006; Vicente-Serrano and Lo´pez-Moreno, 2005) have showed the variations response of the SPI to vegetation activities, soil water content, crop production, discharge of river, reservoir storage at different time scales.

The SPI results of drought monitoring are consistent with SSI and MSDI (Hao and AghaKouchak, 2014, 2013). Lloyd-Hughes and Saunders (2002) and Redmond (2002) agreed that the SPI is highly correlated with the PDSI mainly at time scales of 6–12 months. The SPI also has better correlation with NDVI and drought monitoring results of these indices are related (Ji and Peters, 2003). Moreover, drought result estimated from PDSI is consistent with SPI. However, some studies have also found that the PDSI explains the variability in crop production and the activity of natural vegetation better than the SPI (Kempes et al., 2008; Mavromatis, 2007).

3.12   Palmer Drought Severity Index (PDSI)

The Palmer drought severity index (PDSI) is a meteorological-based drought index developed by Palmer (1965). It measures the effect of accumulated monthly rainfall deficit relative to the monthly rainfall (NDMC (National Drought Mitigation Center), 2003). Dai et al. (1998) stated that PDSI has an approach of the water balance model and it takes into account precipitation, temperature, and soil moisture (water) content. The PDSI incorporates antecedent precipitation, moisture supply and demand into a hydrological accounting system. Palmer used a two-

layer bucket-type model for soil moisture computations and made certain assumptions relating to field water-holding capacity and transfer of moisture to and from the layers Theoretically, the PDSI is a standardized measure, ranging from about 210 (dry) to 110 (wet), of surface moisture conditions that allows comparisons across regions and time. The PDSI has good relations with moisture conditions (Dai et al., 2004).

Even though PDSI has some limitations, it has been widely used for drought detection (Heim Jr, 2002) and drought characterization (Dai, 2011c; Dai et al., 2004). This index has been widely used for drought monitoring (Dai, 2011a, 2011b; Dai et al., 2004; NDMC (National Drought Mitigation Center), 2003; Wells et al., 2004). Dai et al. (2004) pointed out that PDSI is very good in generalizing and analyzing critical hydrological processes and it is essential in monitoring meteorological drought. They also found that the PDSI correlates with soil moisture during warm seasons. Dai (2011a) found that the PDSI show similar long-term trends and correlations with observed monthly soil moisture, yearly streamflow, and satellite-observed water storage changes.

The index enables measurement of both wetness (positive value) and dryness (negative values), based on the supply and demand concept of the water balance equation, and thus it incorporates prior precipitation, moisture supply and demand, runoff, and evaporation at the surface level. Nevertheless, the PDSI has several deficiencies (Akinremi et al., 1996; Weber and Nkemdirim, 1998), including the strong influence of calibration period, its limited utility in areas other than that used for calibration, spatial comparability problems, and subjectivity in linking drought conditions to the index values. The PDSI lacks the multiscalar character essential for both assessing drought in relation to different hydrological systems and differentiating among different drought types.

$$\text{PDSI}_{ijk} = \text{PDSI}_{ik} \left\{ j^{-1} + \left[\frac{Z_{ijk}}{3} + 0.103 * \text{PDSI}_{ij-1k} \right] \right\} \tag{12}$$

Where: PDSI_{ijk} and PDSI_{ij-1k} are monthly PDSI for pixel i for year k in a current month j and previous month j−1; Z_{ijk} is monthly moisture status for pixel i in month j for year k.

3.13 Standardized Precipitation Evapotranspiration Index (SPEI)

The SPEI is a meteorological based drought index used to monitor drought conditions (Vicente-Serrano et al., 2010). The SPEI used three-parameters probability density function and log-logistic distribution of the variables can be expressed as

$$F(x) = \frac{\beta}{\alpha} \left(\frac{x - \gamma}{\alpha} \right)^{\beta-1} \left[1 + \left(\frac{x - \gamma}{\alpha} \right)^{\beta} \right]^{-2} \tag{13}$$

Where, α, β and γ are scale, shape and origin parameters, respectively, for D values in the range ($\gamma > d < \infty$). These three parameters can be computed using L moments procedures following (Singh et al., 1993):

$$\beta = \frac{2W_1 - W_0}{6W_1 - W_0 - 6W_2} \tag{13a}$$

$$\alpha = \frac{(W_0 - 2W_1)\beta}{\Gamma(1 + 1/\beta) \ \Gamma(1 - 1/\beta)} \tag{13b}$$

$$\gamma = W_0 - \alpha \ \Gamma\left(\frac{1 + 1}{\beta} \right) \Gamma\left(\frac{1 - 1}{\beta} \right) \tag{13c}$$

where $\Gamma\beta$ is the gamma function of β

The probability distribution function of the D series, according to the log-logistic distribution, is given by

$$F(x) = \left[1 + \left(\frac{\alpha}{x - \gamma} \right)^{\beta} \right]^{-1} \tag{13d}$$

The F(x) values for the D series at different time scales adapt very well to the empirical F(x) values at the different observatories, independently of the climate characteristics and the time scale of the analysis. With F(x) the SPEI can easily be obtained as the standardized values of F(x). It can be computed as given in equation 14 (Abramowitz and Stegun, 1965).

$$\text{SPEI} = \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \tag{14}$$

Where: $W = \sqrt{-2\ln(P)}$ For $P \le 0.5$; W is the probability of exceeding a determined D value, $P = 1 - F(x)$. If $P > 0.5$, then P is replaced by $1 - P$; The constants of the algorithm are $C_0 = 2.515517, C_1 = 0.802853, C_2 = 0.010328, d_1 = 1.432788, d_2 = 0.189269$ and $d_3 = 0.001308$

The SPEI considers the possible effects of temperature variability and temperature extremes beyond the context of global warming. Like the PDSI and SPI, the SPEI can measure drought severities including its intensity and duration, and it can identify the onset and end of drought episodes. The SPEI allows for comparison of drought severities through time and space since it can be calculated over a wide range of climates. The SPEI has a crucial advantage over other most widely used drought indices. This advantage is that SPEI considers different effects of PET on drought severity and its multiscalar characteristics which enable identification of different drought types and effects.

3.14 Aridity Index (AI)

Aridity indices have greater value for tracking the effects of climate change on local water resources (Vicente-Serrano et al., 2006; Walton, 1969) if sufficiently accurate data are available for mapping local changes in the values of the indices over time. The AI is based on the values of precipitation. A commonly used rainfall-based definition is that an arid region receives less than 10-in or 250 mm of precipitation per year. This criterion for aridity was used by the Intergovernmental Panel on Climate Change (IPCC, 2007). Semiarid regions are commonly defined by annual rainfalls between 10 and 20-in (250 and 500 mm). The (UNESCO, 1979) aridity index (AI) is based on the ratio of annual precipitation (P) and potential evapotranspiration rates.

$$\text{AI} = P/ETp \tag{15}$$

3.15 Rainfall Anomaly Index (RAI)

The RAI is a meteorology-based index used to indicate the deficiency of rainfall compared to the normal seasonal rainfall in a given region. It is used to indicate the meteorological drought for the growing seasons of regions. It is computed as:

$$\text{RAI} = 100 * \frac{\text{RF}_y - \text{RF}_a}{\text{RF}_a} \tag{16}$$

Where: RAI is rainfall anomaly for given year, RF_y is seasonal rainfall for given year and RF_a mean seasonal rainfall. The negative rainfall anomalies signified that precipitation was less than the average seasonal rainfall for a particular place (Shaheen and Baig, 2011).

3.16 Standardized Soil Moisture Index (SSI)

The SSI has been used for drought monitoring and seasonal drought forecasting but it may not replace SPI. The SSI is one of the drought indicators which allows for the description of soil moisture across different timescales (AghaKouchak, 2014). It is good in drought monitoring and prediction through analyzing the water available in the soil. The result of drought information obtained from SSI is similar to SPI, therefore, it has a good correlation (Hao and AghaKouchak, 2013). Because of soil moisture is the primary source of water for vegetated lands, therefore, it is one of the best indicators of moisture stress of vegetation due to deficiency of precipitation. Thus, quantifying soil moisture in the plant root zone is very significant for determining the vegetation stress (Cammalleri et al., 2016) and monitoring and analyzing drought. Soil moisture is a very suitable parameter to monitor and quantify the impact of water shortage on vegetated lands due to its effects on the terrestrial biosphere and the feedback into the atmospheric system. Evapotranspiration-derived indices are identified as key parameters for water stress assessment and quantification, as well as for spatio-temporal monitoring of drought events from continental to regional scales (Anderson et al., 2013; Sheffield and Wood, 2007; Wang et al., 2011). On the one hand plant water stress quantify the status of the soil moisture at a certain time compared with the possible range of variability for that specific site without accounting for the previous history and natural climatology of the site (Hogg et al., 2013; Sridhar et al., 2008). As a result, water deficit indices are capable to provide the degree of water stress, but they do not provide information regarding the frequency of water stress levels reached in a particular period.

Soil moisture or evapotranspiration-derived anomaly indicators are mainly focused only on the rarity of an event rather than considering the actual water deficit conditions that occurred (Anderson et al., 2013, 2007; Sepulcre-Cantó et al., 2012). Hence, these approaches are robust for monitoring environments mainly if there is strong inter-annual variability. However, the approaches may lead to overestimation of drought events if there are small inter-annual variability in the area. Similar to anomalies there is a problem of the percentile probability distribution, for instance, inadequate variability in soil moisture and small variations can lead to extreme percentiles that are indeed close to the normal status (Sheffield et al., 2004). These approaches are very significant and provide accurate information about drought events when they applied over very small areas.

According to Cammalleri et al. (2016) soil moisture, θ (m3m_3), ranges between the residual content (θr), and saturation (θs). But soil moisture is a controlling factor in a narrow range of soil water content and is usually between the plant wilting point (θwp) (he minimal point of soil moisture the plant requires not to shrivel) and a critical content (θcr); (a significant soil water content level required by plant and necessary for crop production). (Seneviratne et al., 2010) stated that soil moisture is not a limiting factor during wet regime (θcr<θ<θs) and the plant is not able to recover from wilt during dry regime (θr<θ<θwp).

The s-shaped curve method proposed by van Genuchten (1987) which used to compute water availability/deficit from soil moisture data. The proposed method allows rescaling θ into a water deficit index, d, ranging between 0 (no deficit) and 1 (full deficit):

$$d = \frac{1}{1 + \left(\frac{\theta}{\theta_{50}}\right)^n} \tag{17}$$

Where: θ_{50} is the average between θcr and θwp and n is an empirical shape factor. In agro-hydrological applications, θcr and θwp are usually derived from the soil water retention curve as a function of the water potential values corresponding to fully open and fully closed stomata, respectively. the effect of soil moisture variability is negligible when θ is greater than well-watered condition (wet regime) and, analogously, that no differences in plant water stress can be observed if θ goes below the wilting point (down to the residual soil water content).

However, double-bonded variables (as both θ and d) are generally characterized by a skewed distribution. Sheffield et al. (2004) pointed out that a better statistical representation of soil moisture data can be obtained through the beta distribution. This distribution can reproduce the statistical structure of d, given that the logistic transformation of equation (17) further increases the constraints of the two boundaries (Gupta and Nadarajah, 2004).

The probability density function (pdf, f) and cumulative density function (cdf, F) of the beta distribution can be expressed as respectively.

$$f\,(d; a, b)\ = \frac{1}{B\,(a, b)}\,d^{(a-l)}(1 - d)^{(b-1)} \qquad (18a)$$

$$F\,(d; a, b) = \frac{B(d; a, b)}{B\,(a, b)} \qquad (18b)$$

where a, b ≥ 0 are the shape parameters, B(a, b) is the beta function and B(d; a, b) is the incomplete beta function (Olver et al., 2010); and the beta distribution supports d ∈ [0, 1].

Sheffield et al. (2004) also suggested to use F(θ) to detect drought using a defined threshold (e.g. F(θ)>0.9). This method implicitly assumes that the reference 'usual' state for a given month is the median of the distribution, analogously to how the z-score uses the mean. Once the mode, m, is selected as the reference 'usual' status of water deficit, the simplest way to define how probabilistically close an event d is to the mode is to use the probability that a generic event lies between d and m, computed as |F(d)_F(d =m)| (Cammalleri et al., 2016). Focusing only on d ≥m, which are the values of interest for drought detection, it is clear how |F(d)_F(d =m)| ranges between 0 and [1_F (d =m)]; hence, to have a standardized index, it is necessary to feature-scaling this quantity through the possible range of variability, as

$$F*(d)\ = \begin{cases} \dfrac{F(d) - F(d = m)}{1 - F(d = m)} & d \geq m \\ 0 & d < m \end{cases} \qquad (19)$$

The standardized percentile [F*(d)] in equation 8 represents the probability of occurrence of an event with respect to the subsample of the values d ≥m; it varies between 0 (for the mode or lower values) and 1 [for the maximum difference 1_F(d =m)]. The feature-scaling standardization performed through equation (19) considers that the full distribution is split by m into two subsets that likely have very different tails (due to the skewness). The mode computed from the theoretical beta distribution, m= (a_1)/(a + b_2) for a, b>1, (Cammalleri et al., 2016).

3.17 Soil moisture based DSI

The DSI can be computed from SSI formula and it is based on monthly root zone soil moisture data and accounts for both the magnitude of the associated water deficit, d factor, and the probability that the observed value is dryer than a reference 'usual' condition for the specific site and period, p factor. The DSI is based on the square root of the product of these two factors (Cammalleri et al., 2016).

The observed water deficit intensity (d) and rarity of the event in comparison with that of the history of the site (p) are the two main factors that influencing drought event. The DSI aims at combining the two indices to obtain a single measure of the severity of a specific soil water status in terms of drought (Cammalleri et al., 2016). Stated that DSI have to be the same as p and d when there is good agreement between the two indices, while DSI have to low values when p close to zero (independent from d) or if d is close to zero (independent from p). There is no medium/high DSI values if one of the conditions of deficit/rarity is not met. In all the other cases, DSI should assume a somewhat intermediate value between the two indices (Cammalleri et al., 2016). A possible solution to obtain a DSI that behaves as described is to use a simple multiplicative-based relationship, as

$$DSI\ = \sqrt{p.d} \qquad (20)$$

Where the square root allows at returning DSI = p (or d) when p = d. It is simple to verify that equation 20 respects the imposed constrains: DSI→0 if p→0, and DSI→0 if d→0. The DSI values range between 0 and 1, where 0 represent no drought and 1 indicates the most extreme drought event.

3.18 Water Requirement Satisfaction Index (WRSI)

The WRSI is a model-driven drought indicator developed by the Food and Agriculture Organization of the United Nations in the 1980s (FAO, 1986), to monitor seasonal crop performance. The basic idea was to provide an index

that can accurately show the percentage of the idealized crop water requirement that is met by rainfall during a crop growing season. The WRSI was developed, mainly, for monitoring seasonal crop performance through its growth and development, and for final yield prediction well in advance. It depends mainly on the nature and stage of growth of the crop together with the environmental conditions. The WRSI for a season is based on the water supply and demand crop experiences during a growing season. The index is a useful indicator of crop performance based on the availability of water during the crop growing season. Crop water requirement is the amount of water required to compensate for the evapotranspiration loss from the cropped field (FAO, 1998, 1977; Legesse and Suryabhagavan, 2014).

The studies conducted by Food and Agricultural Organization (FAO), (FAO, 1986, 1977) have shown that WRSI can be related to crop production, using a linear yield-reduction function specific to a crop. Recent studies (Senay and Verdin, 2001; Verdin and Klaver, 2002) demonstrated a regional implementation of WRSI in a grid cell-based modeling environment. Seasonal WRSI is currently operational as monitoring and forecasting tool for region-wide food security analyses in drought prone countries in Sub-Saharan Africa. According to the results of evaluations made by Verdin and Klaver (2002) on the performance of the model using district-level crop yield data of 1996-1999 from Ethiopia, WRSI values and crop yield data were significantly correlated ($r = 0.77$). Thus, the model was particularly found success in capturing the response of the crop during relatively dry years. According to Legesse and Suryabhagavan (2014) WRSI based agricultural drought assessment can better capture agricultural drought events.

The WRSI can be computed as the ratio of seasonal Actual Evapotranspiration (AET) to the seasonal crop Water Requirement (WR):

$$WRSI = 100 * \frac{AET}{WR} \qquad (21a)$$

Where WR is calculated from the Penmane Monteith potential ET (PET) using the crop coefficient (Kc) to adjust for the growth stage of the crop as

$$WR = PET * kc * 100 \qquad (21b)$$

3.19   Crop Moisture Index (CMI)
The crop moisture index (CMI) is a meteorological based index developed by Palmer (1968). This index measures the amount of moisture required for crop and used for monitoring short-term drought. The CMI is normally calculated with a weekly time step and is primarily based on the mean temperature, total precipitation for each week, and the CMI value from the previous week. In each crop growing seasons, CMI normally begins and ends near zero. The CMI gives the short term or current status of purely agricultural drought or moisture surplus and can change rapidly from week to week (Patel et al., 2012).

3.20   Crop Soil Water Balance Model (CSWB)
The Crop Soil Water Balance (CSWB), developed by (FAO, 1979), is a ground-based calibration model, commonly, used in Africa for drought monitoring purposes. The CSWB model utilizes ground-based agro-meteorological data to estimate crop conditions. When combined with crop production functions, the model can estimate yields. These models are based on the physical principles of energy and/or mass (water) conservation equations (Senay et al., 2013a, 2013b). Mukhala and Hoefsloot (2004) also explain CSWB as the difference between the effective amounts of rainfall received by the crop and the amounts of water lost by the crop and soil due to evaporation, transpiration and deep infiltration, by considering the amounts of moisture held by the soil and water available to the crop. More precisely speaking, the CSWB model is a book-keeping method that accounts for water gained or lost by recording the cumulative water stress of a specific crop for each time increment over the entire growing season. The ultimate aim of the water balance model is to account for the plant's water consumption during the growing season, as it is used to determine whether the rainfall was adequate for the maximum growth of crops (Reynolds et al., 2000).

4. Future Research Directions
Different researches have been conducted in the area of drought using different drought studies. Most previous drought studies have been used from one to four indices. However, the nature of drought is varying in space and time, therefore, to identify and characterized drought different drought indices should be applied and comparison study have to be conducted. Thus, integrating satellite information with ground-based meteorological data and hydrological information and socio-economic data is the basic option to obtain reliable drought information. Therefore, future drought studies should be done through integrating different indices. Drought investigation is very difficult task because it used different data types and requires timeseries analysis. Hence, scientists and researchers have to strongly work to develop new algorithms and easy interface software to process data easily. Drought is a natural hazard that cannot remove; therefore, researcher should focus on the techniques of mitigation, adaptation and resilience strategies.

5. Conclusions

Drought is a natural phenomenon that happened for a longer time. It occurred due to climate change and its related factors. It causes different socio-economic, environmental and hydrological problems and affects food security. Therefore, drought monitoring and prediction are very essential to mitigate its impacts. Recently, different indices are available to monitor and predict drought and identify vulnerable areas and risk populations. However, identifying the most suitable indices is very significant which is depends on the nature of the study area, the objective of the study and types of drought that happened in the study area. For investigating drought using a single index is not providing better results, therefore, integrating different indices is recommended because the environmental variable is spatially different and the indices do not use the same model and there are gaps in the model. Thus, by integrating different indices it is possible to achieve better drought results.

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Conflict of interest

We declare that there is no conflict interest among authors.

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