A comprehensive assessment of remote sensing and traditional based drought monitoring indices at global and regional scale

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\textbf{ABSTRACT}

This study reports a comprehensive review on drought indices used in monitoring meteorological, agricultural, hydrological, and socio-economic drought. Drought indices have been introduced as an important approach to quantitative and qualitative calculations of drought’s severity and impact. There were 111 drought indices reviewed in this study, which fall into two categories: traditional (location-specific/model) and remote sensing (RS). Out of 111 indices, 44 belong to the traditional indices and 67 belong to the RS section. This study shows that meteorological drought monitoring has the highest number (22) of traditional indices, about 20% overall, while the lowest (7) agricultural drought monitoring is 6.3%. The specialty is that when considering remote sensing-based drought indices, 90% are used for agricultural drought monitoring and 10% for hydrological and meteorological drought monitoring. However, the study found that advances in satellite technology have accelerated the design of new drought indices and that replacing traditional location-specific data with satellite observation makes it easier to calculate more spatial distribution and resolution.

\textbf{1. Introduction}

Drought is a natural disaster that increases in intensity and duration over a long period of time and has far-reaching consequences (Wilhite and Glantz 1985; Mishra and Singh 2010). Drought, in particular, can have a devastating effect on agriculture, water supply, energy, and the natural environment, making it one of the most expensive natural disasters (Mishra and Singh 2010). Researchers and scientists have come up with various definitions of drought, but the common denominators for all of these definitions are dryness and water scarcity (Wilhite 2000). Initially, the United States National Drought Mitigation Center classified drought into three types:
meteorological, agricultural, and hydrological (Wilhite and Glantz 1985). Later, the US Geological Survey introduced the socio-economic drought category, which is actually how society feels about the effects of the droughts described above (Miyan 2015). Decreased crop yields indicate that an agricultural drought has occurred, and severe hydrological imbalances confirm the presence of a hydrological drought (Huschke 1959; Vujica et al. 1977; Rosenberg 1979). However, hydrological droughts indicate a shortage of surface and groundwater. A single torrential downpour can end a prolonged severe drought, however, it is difficult to pinpoint the beginning or end of drought (Parry et al. 2016). This implies that the quantitative and qualitative analysis of drought is a challenging phenomenon. However, among other natural disasters, researchers are paying close attention to the drought, which is affecting a significant number of people and causing severe damage to their livelihoods (Woods and Woods 2007).

The detailed study of the world’s droughts from history to the present shows that the drought that occurred in China from 1876 to 1878 was the worst, and about 83 million people were severely affected (Miyan 2015). African Sahel-drought (1968 to 1988) is considered as one of the longest and worst droughts in history, leaving more than 150 million people hungry. The worst affected countries of Sahel-drought are Senegal, Mauritania, Mali, Burkina Faso, Nigeria, Sudan, and Ethiopia (Miyan 2015). The droughts of 2002-2003 in Australia and 2004-2006 in Nigeria are of particular attention because they are the worst droughts in recent history and there were 19 million and 3.6 million people severely affected, respectively (Woods and Woods 2007).

Furthermore, a special report of the Intergovernmental Panel on Climate Change (IPCC) released in 2012 pointed out that since 1950 most parts of the world, including the Americas, Asia, Africa, Europe, and Australia, have experienced severe droughts (IPCC Special Report 2012). Droughts have been on the rise in South Asia since 2000 and have been occurring every three years in India, Pakistan, Afghanistan, and Sri Lanka over the past five decades (Miyan 2015). Furthermore, recent studies have shown that increased exposure of natural and human systems to drought increases the drought risk (Van Loon 2015). Therefore, it is important to monitor them based on the drought characteristics such a time of onset, duration, intensity, and spatial extent to minimize the damage caused by drought (Lin et al. 2020). Drought characteristics study provides space for effectively conducting the drought risk analysis and forecasting (Lin et al. 2020).

Therefore, a systematic analysis of drought occurrence, severity, and impact is a scientific approach that is very important in every part of the world. Drought indices have been introduced by various researchers using different drought indicators (Yihdego et al. 2019). The terms drought “indicator” and “index” are often used interchangeably in drought monitoring research communities (Hayes et al. 2012). Drought indicators are physical factors such as precipitation, temperature, flow, groundwater level, reservoir levels, soil moisture levels, and snowfall that represent the effects of drought with changes relative to the normal condition. Drought index is commonly referred to as numerical representations that can be used to calculate the magnitude and severity of drought using a single or combination of physical indices (Hayes et al. 2012).
Although more than 150 drought indices have been developed by various studies globally, disaster managers and decision-makers still need to work hard to select suitable drought indices for drought monitoring of a respective country/region considering climatic and geographical setting, etc. Those challenges are exacerbated in developing countries by the lack of data and their persistence. Therefore, this study focuses on a detailed review of the availability of traditional (location-specific), remote sensing (RS) based, and integrated indices of meteorological, agricultural, hydrological, and socio-economic drought. Based on whether location-specific or satellite data have been used to calculate drought indices, a separate list for meteorological, agricultural, hydrological, and socio-economic drought has been compiled so that it is easier and faster to obtain information needed for future studies.

With the advancement of satellite imaging technology, the rate of development of new drought indices has increased significantly (AghaKouchak et al. 2015; Kim and Jehanzaib 2020). Therefore, the introduction and classification of drought indices, as well as the listing of indices based on the approach of drought indicator measurement and drought types, were carried out in this study. In addition, separate lists of drought indices created by combining different basic indices were introduced. All the list of droughts described above includes the index name, equation, index measuring parameter, the approach used to calculate it as well as the reference so that any
researcher and users can easily study the different drought indices. The speciality of this study is that it not only provides a list of drought indices but also goes beyond it and presents in detail the advantages and disadvantages of using the drought indices.

2. Methodology

2.1. Methodology for drought indices assessment

Since a large number of drought indices have been introduced by various researchers to monitor drought in different parts of the world, it is necessary to find those indices through a specific approach to review them. Published articals available in Science Direct, Scopus, and Google Scholar databases have been used to extract those drought indices. Those indices found through the above database were classified according to the type of drought (i.e., meteorological, agricultural, hydrological and socio-economic) and sub-divided into traditional/location-specific and remote sensing considering the nature of data usage. Moreover, drought indices based on type remote sensing were further subdivided into simple indices such as optical, thermal, and microwave. The design of composite indices is carried out in different ways such as "combining individual simple indices in the same category through a mathematical equation (ex Vegetation Condition Index (VCI))", "combining individual simple indices in different categories through a mathematical equation (ex Vegetation Health Index (VHI)), and "in different categories" Integrated through a single simple index chart system (ex Vegetation Drought Response Index (VegDRI)). Figure 1 shows the complete methodology used to identify, classify and assess drought indices.
2.2. Drought process and types

Three types of physical droughts i.e., meteorological, agricultural, and hydrological, and one type of socio-economic drought, have been introduced through various studies on drought (Wilhite 2000). This classification is based on the drought-prone sectors and physical environments (Wilhite et al. 2007; Alam et al. 2014; Mekonen et al. 2020; Spinoni et al. 2020). Figure 2 shows the progression in meteorological, agricultural, hydrological socio-economic droughts over time and the changes in different physical properties and parameters when different droughts occurred in a particular area.

Meteorological drought is caused by a decrease in rainfall or a delay in the onset of the monsoon season, which directly affects soil moisture, resulting in poor crop health and agricultural drought (Miyan 2015). Then, declining water discharge and levels in major surface water-bearing formations such as streams, tanks, reservoirs, and large lakes are the indication of the occurrence of hydrological droughts. The end result of the overall drought process is the occurrence of socio-economic drought, which reflects the impact of drought on the socio-economic system.

Meteorological drought can occur over a specific area (district, province, or country) and over a period of time (weeks, months, or years) when actual rainfall is deficient than normal (Abubakar et al. 2020). Meteorological drought is caused entirely by a short- or long-term decrease in rainfall, but generally, agricultural drought is caused by both rainfall decreases and temperature increases. Although rainwater is directly involved in reducing soil moisture levels, it does so by catalyzing water evaporation due to temperature. Meteorological droughts are generally more frequent than other droughts as a result of current climate variability, followed by agricultural, hydrological, and socioeconomic droughts. Scientific drought monitoring with a high spatial-temporal resolution is an important strategy in a timely manner because it is of great help in drought early warning, risk management, and mitigation.

The occurrence of agricultural drought is indicated by declining yields due to crop growth stress, decrease in rainfall, the soil moisture required for plant growth gradually decreases beyond the optimum level (Korres et al. 2016). The impact on the agricultural sector depends on the duration, spatial distribution, and severity of the drought event. Although long-term droughts are not common, short-term droughts are more likely to occur, but the effect of short-term drought is less because the crop may mature before the peak of the drought. However, the effect of short-term drought varies based on the stages of cultivation (Ghosh 2019). For example, during the growing season of the crop and when it is ready for flowering or grain-filling, the maximum amount of water is required, so if the drought occurs during that time, it can have a severe effect on the crop yield. Therefore, gaining a comprehensive understanding of agricultural droughts and their occurrences is of paramount importance for crop planning, water management, and crop diversification, which are aspects of sustainable food production.

Hydrological drought is indicated by the significant drop in the surface water feature such as lakes or reservoirs and groundwater level, it usually comes after meteorological and agricultural drought because surface and groundwater storage can be used for a considerable period but does not recharge due to reduced rainfall (Alsumaiei
Among other droughts, hydrological drought is taking much attention as most human activities depend on the supply/availability of water, which is primarily used for industrial, agricultural, and hydropower generation. Hydrological droughts in any area are characterized by a prolonged gradual decrease in rainfall, declining river water levels, continuous reduction of groundwater levels, decreased soil moisture, and increased evaporation (Leblanc et al. 2012). Many researchers have introduced drought indices that can be used to calculate the onset and severity of a hydrological drought through the study of the temporal variability of these parameters. Long-term data are needed to calculate these indices because of the complexity of the water cycle and the impact of climate variability on it (Mukherjee et al. 2018).

Socio-economic droughts in many parts of the world are drawing attention as the increasing water demand of the population and industry increases in proportion to the gradual decrease in rainfall and water resources. In the event of a socio-economic drought, the demand for water for various activities will exceed its supply limit, which will have a direct impact on the socio-economic process (Arab et al. 2010; Wada et al. 2011; Madani 2014; Loucks 2015; Wheater and Gober 2015). Although the socio-economic drought study is so important, it has received less attention from researchers than other droughts due to its complexity. Also, since this is difficult to calculate based on a simple mathematical equation, the most commonly used for socio-economic drought analysis is the qualitative approach rather than the quantitative approach. However, there are only a few indices designed for socio-economic drought monitoring, each of which is a complex index.

2.3. Drought indices

In the early days, absolute rainfall or rainfall deficiency was used for drought monitoring and monitoring, and it was represented as the percentage of rainfall departure (Heim 2002). However, with an increasing focus on assessing the severity of droughts and the complexity of drought studies in different climatic and ecological regions, researchers have become increasingly inclined to develop new drought indices (Steinmann et al. 2005).

Drought indices are used to monitor the variability of the drought and to calculate the magnitude. Usually, the drought index is represented by numerical values calculated using one or more variables that cause drought, and the quantitative value of that index determines the severity and intensity of the drought (Zargar et al. 2011). Drought indices can be used to monitor the drought better than the raw data of the variables that lead to drought (Stagge et al. 2015). Drought indices are generally based on drought indicators such as rainfall, temperature, soil moisture, as well as changes in crop health and declining water levels in reservoirs and rivers as a result of drought (Xing et al. 2020). Drought and drought indices are also classified in different classes based on the drought process, data, method, and technology used. Many different indices currently used for drought monitoring are divided into major two sections, in-situ, and remote sensing which are discussed separately in the scope of this study, covering meteorological, agricultural, hydrological, and socio-economic drought.
The primary purpose of creating drought indices is to identify the effects of drought based on the characteristics and nature, and there are currently more than 150 indices for drought monitoring worldwide (Zargar et al. 2011). Due to the diversity in the characteristics of droughts, new indices are being introduced by various researchers, and the current trend is to create new indices by combining the already introduced basic drought indices using different techniques (Zargar et al. 2011). Drought indices design has accelerated further due to the extraordinary and continuous development of technology that has simplified complex methods such as data storage, spatial and non-spatial data integration, analysis, and aggregation (Pei et al. 2020). Examples include cloud computing, Artificial Intelligence (AI), and big-data concepts (Jung et al. 2021).

2.4. Drought impact and importance of drought monitoring indices

The drought has a direct impact on all three major sectors: economic, environmental, and social (Wilhite and Glantz 1985; Meyer et al. 1993). Drought-induced water shortages affect production, sales, and business operations in a variety of industries. This is known as the direct effects of the drought, and the indirect economic effects of the drought stem from a reduction in interactions and transactions between industry and other related sectors. The impact on the agricultural sector is even more impressive when compared to other sectors. The reduction in crop production due to drought has a negative impact on the supply chain and the resulting economic impact and loss distribution depend on the interaction between product demand and supply (Ding et al. 2010).

In agriculture, systematic and continuous water supply throughout the cropping season is essential for the proper growth of crops (Jayawardhana and Chathurange 2020). Although the water for crop cultivation can be obtained through irrigation in some areas, it is not valid everywhere. Since rain-fed crops are grown especially in dry, semi-arid, and arid regions, the total crop production in those areas depends only on the spatial and temporal variability of rainfall (Mirza et al. 2013). In particular, systematic and accurate agricultural drought monitoring in the crop season for such areas will facilitate effective and timely action to minimize agricultural losses due to drought. In addition to drought preparedness and drought response, drought monitoring plays an important role in drought risk management, and drought monitoring involves the continuous observation of rainfall and its changes, temperature, and soil moisture throughout the crop growing season.

2.5. Evolution of drought indices

As Steinemann et al. (2005), explained the development and implementation of drought indices are highly dependent on data availability. In the early days of drought indices development, rainfall data were primarily used in synoptic meteorological stations (Van-Rooy 1965; Bhalme and Mooley 1980; Bryant et al. 1992; Byun and Wilhite 1999). According to the literature study, the first recorded study of the drought was made around 1861, which was carried out based on changes in rainfall
However, drought studies or drought indices were slow to develop until the 1960s and 1970s. Nevertheless, the rapidly growing drought related publications since the 1970s indicate that researchers are also increasingly interested in creating drought indices (Chandrasekara et al. 2021). Due to the complexity of the droughts, the researchers found that using rainfall alone was not sufficient to study the effects of the drought, so drought indices were calculated using additional variables such as temperature and evapotranspiration (Keetch and Byram 1968; Manatsa et al. 2017; Parsons et al. 2019). Further expanding the design of drought indices, in addition to temperature and evapotranspiration, the indices were designed to provide a more successful picture of drought, including water flow and soil moisture (Palmer 1965).

Traditionally, meteorological-drought monitoring was carried out locally, regionally, or globally using meteorological-drought indices calculated based on location-specific rainfall or interpolated grid data (Spinoni et al. 2019). Although the Standardized Precipitation Index (SPI) is recommended by the World Meteorological Organization (WMO) for monitoring Meteorological droughts in any part of the world, the Palmer Drought Severity Index (PDSI) (Palmer 1965), the Standardized Precipitation Evapotranspiration Index (SPEI) Drought indices are also widely used (Vicente-Serrano et al. 2010a, 2010b).

Current drought indices are developed based on specific climatic or environmental characteristics, so due to the inherent complexity of selected regions, those drought indices may have some limitations in their use in other areas. However, since the accuracy of these indices depends on the distribution of the meteorological gauge network, the spatial resolution of the drought indices derived from these data usually shows relatively courser spatial resolution (Wang et al. 2009). On the other hand, it is not advisable to rely solely on station-based data for real-time or near-term drought monitoring, as data production may be delayed from weeks to months due to the traditional method of data collection. Depending on the complexity of the droughts,
it may not be more practical to use a single drought index to capture their various effects, but combined drought indices are more appropriate (Sophie et al. 2016).

However, the growing interest in drought studies by researchers as well as observers may have been due to the unprecedented development of satellite imaging technology since the 1970s (Figure 3). The data from the study (Chandrasekara et al. 2021) can be used to argue that the results of the use of the word "drought" in the Scopus study search engine show a significant increase in drought research from the 1970s worldwide. This is because high-resolution satellite imagery (Landsat) has existed from the 1970s to date. Another interesting finding that emerges from the same data is that there has been an exponential increase in the number of drought studies since 2000. One of the main reasons for this could be the generation of daily satellite data with a medium resolution by Moderate Resolution Imaging Spectroradiometer (MODIS) covering the world since March 2000. On the other hand, MODIS satellite data is used to generate various drought indicator parameters such as temperature, soil moisture, vegetation health, surface water dynamics, etc.

2.6. Drought monitoring indices categorizations

Drought indicators and indices are usually used by a large number of researchers to study in detail of spatial distribution, duration, and severity of a drought (Steinemann et al. 2005). In the early days of drought monitoring, absolute rainfall or rainfall deficit was used, which was expressed as a percentage of rainfall outflow (Heim 2002). However, with a greater focus on assessing the severity of drought and the complexity of drought studies in different climatic as well as environmental regions, researchers are increasingly inclined to develop new drought indices (Steinmann et al. 2005). The Palmer Drought Intensity Index (PDSI) has been cited by various researchers as one of the earliest drought index developed to assess the severity of relative drought nationwide (Plamer 1965; Hayes et al. 2012). Due to various limitations in the use of the PDSI, other indices such as the Surface Water Supply Index (SWSI; Schaefer and Desmond 1982) and the Standardized Precipitation Index (SPI; McKee et al. 1993), Rainfall Anomaly Index (RAI; Van Rooy 1965) was developed.

In many drought-prone countries over the past decade, various frameworks for drought monitoring have been established to minimize the impact of drought on society, the environment, and the economy. However, most of such drought frameworks are based on single data sources only, so spatial and temporal resolution of drought information is also limited. Data from a variety of drought-related sources can be combined to produce high-quality spatial and temporal information through integrated drought indices (Zhong et al. 2020).

Today, technological advancement in satellite imagery provides a better platform for the development of comprehensive indices for drought monitoring through vegetation, rainfall data, soil moisture measurement, and evapotranspiration. In terms of satellite imagery, they had a large spatial coverage (locally and globally) as well as a continuous data supply, but monitoring drought impact at the continental level as well as agricultural field level was rather challenging in the past. However, modern advances in satellite image capture technology and image processing have led to an
increase in the spatial and temporal resolution of satellite imagery and the fusion of multiple satellite data to enable crop field level and continental level drought monitoring.

In classifying drought indices, the physical parameters used to create the index and the type of drought information that the index provides are considered (Steinemann et al. 2005; Niemeyer 2008). According to the four major drought categories, the four indices class such as meteorological, agricultural, hydrological, and sociological drought can be defined. But no matter how advanced the technology, there is a lack

Figure 4. Relationship of location-specific/Model-based drought indicators and indices.
| Index                      | Equation                                                                 | Indicators | Key Reference                           | Citations |
|----------------------------|--------------------------------------------------------------------------|------------|-----------------------------------------|-----------|
| Percent of Normal Index (PNI) | \( PNP = \frac{P}{P_n} \times 100 \)                                    | P          | Willeke et al. 1994                    | 174       |
| Deciles Index (DI)         | grading of rainfall values using a specific time interval                | p          | Gibbs and Maher 1967                   | 1038      |
| Standardized Precipitation Index (SPI) | \( g(x) = \frac{x - \mu}{\sigma} \), for \( x > 0 \) | P          | McKee et al. 1993                     | 9230      |
| Cumulative Precipitation Anomaly (CPA) | \( CPA = \sum_{i=1}^{n} P_i - P_a \)                                    | P          | Foley 1957                             | 259       |
| Effective Drought Index (EDI) | \( EDI = \frac{\sum_{i=1}^{n} P_i}{n} - \frac{\sum_{i=1}^{n} P_m}{n} \) | p          | Byun and Wilhite 1999                  | 672       |
| Selyaninov’s hydrothermal coefficient (HTC) | \( HTC = \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} P_0} \)               | P, T       | Selyaninov 1983                        | 83        |
| China Z Index (CZI)        | \( Z_i = \frac{S_i + 1}{\sqrt{3}} \)                                    | p          | Ju et al. 1997                         | 82        |
| Z-Score drought Index (ZI) | \( Z = \frac{P - \mu}{\sigma} \)                                      | p          | Akhtari et al. 2009                    | 105       |
| Standardized Precipitation Evapotranspiration Index (SPEI) | \( SPEI = W - \frac{C_W + C_W}{3 W} \)                                   | P, PET     | Vicente-Serrano et al. 2010a           | 4709      |
| Palmer drought severity index (PDSI) | \( PDSI = PDIS_{i-1} + 0.13PDIS_{i-1} \)                                | P, T, SM   | Palmer 1965                           | 6510      |
| Palmer Z Index             | \( Z = \frac{P - \mu}{\sigma} \)                                      | P, T, SM, ET, SF | Palmer 1965                           | 6510      |
| Reconnaissance Drought Index (RDI) | \( \alpha_k(i) = \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} P_{et}^k} \)  | P, PET     | Tsakiris 2004                         | 6         |
| effective Reconnaissance Drought Index (eRDI) | \( \alpha_k(i) = \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} P_{et}^k} \)  | P          | Zarei et al. 2019                    | 10        |
| Rainfall Anomaly Index (RAI) | \( RA = \frac{P - \mu}{\sigma} \)                                      | P          | Van Rooy 1965                         | 692       |
| Keetch-Byram Drought Index (KBDI) | It is a modeled based approach and P and SM analyzed using water balance model | P, SM      | Keetch and Bayam 1968                  | 709       |
| Bhalme and Mooley Drought Index | \( \text{Precipitation departure monthly or annual from long-term mean.} \) | P          | Bhalme and Mooley 1980                | 698       |
| Self-Calibrated Palmer Drought Severity Index (sc-PDSI) | \( Z = \sum_{i=1}^{12} d_i | K_i \)                                  | P, T, SM   | Wells et al. 2004                    | 1108      |
| Modified Palmer Drought Severity Index (MPDSI) | Set of complex equations applicable for the calculation, include additional parameter stream flow. | P, T, SF, SM, ET | Palmer 1965,                     | 6510      |
| Aridity Index (AI)         | \( AI = \left( \frac{P - \mu}{\sigma} \right) \times 100 \)            | P, AET and PET | Thomthwaite 1931                     | 859       |
| Humidity Index (HI)        | \( HI = \left( \frac{P - \mu}{\sigma} \right) \times 100 \)            | P, AET and PET | Thomthwaite (1931, 1948)              | 859       |
| Aridity Anomaly Index (AAI) | \( AAI = \frac{\mu - \mu_{P}}{\sigma} \)                                | AET        | Gommes 2012                           | 6         |
| Weighted Anomaly Standardized Precipitation(WASP) | \( Sn = \sum_{i=1}^{n} \left( \frac{P_i - \mu}{\sigma} \right) + \frac{P_i}{\mu} \) , \( WASP = \frac{S_i}{\sigma} \) | P          | Lyon and Barnston 2005                | 156       |

(P: Precipitation, Pi: Normal precipitation, T: Temperature, PET: Potential evapotranspiration, SF: Stream flow, ET: Evapotranspiration, N: Number, \( \mu \): average (mean), \( \sigma \): Standard deviation, Cst: coefficient of skewness, \( \Psi si \): Z score, \( d \): water deficiency (w), \( P_e \): water need). Total number of citations are provided only up to 10 November 2021.
of indices designed to monitor socio-economic drought mainly due to the lack of socioeconomic data availability even in the developed countries.

3. Results and discussion
3.1. Relationship location-specific/model-based drought monitoring indicators and indices

The highest number of drought indicators and indices are available for meteorological drought monitoring and followed by hydrological drought monitoring. Figure 4 shows that there is no a single index used for agricultural drought monitoring alone in terms of traditional drought indices. However, there are a small number of agricultural drought indices, all of which have been created using meteorological drought indicators such as rainfall, temperature, soil moisture, evapotranspiration. Even though socio-economic drought monitoring has become more important, the speciality is that a minimum number of such indices have been developed.

3.1.1. Location-specific/model-based meteorological drought indices

Meteorological drought monitoring indices are the most historic of all drought indices and are largely based on calculations of variations in precipitation and soil water content based on location readings. Therefore, the quantitative and qualitative information obtained from this is shown to be more accurate. But with the advancement of modern data science and satellite technology, spatial data with higher spatial resolution than traditional location-based data have been increasingly used in recent times to calculate these meteorological drought indices as well. Although the indices listed in Table 1 are fundamental to meteorological drought monitoring, some indices have been shown by researchers in various studies to be more effective in agricultural drought monitoring (Meisam et al. 2014; Xianfeng et al. 2016; Myronidis et al. 2018). The main reason for this is that the first effect of drought is observed by materialization through crops. Table 1 shows a detailed description of the location-specific meteorological drought indices, including name, equations (if applicable), application, and the parameters.

Initially, meteorological drought indices were created using only location-specific precipitation data, but later the indices were advanced by combining temperature, soil moisture, and evapotranspiration data with rainfall. Among all other measured drought indices, SPI, RAI, and PDSI are widely used around the world because of their potential for use in drought forecasting, monitoring, and planning operations (Yang et al. 2019; Hoffmann et al. 2020).

Percent Normal Index (PNI) is calculated as an average percentage of rainfall that can be calculated for different time periods and can also be used more effectively for drought monitoring in a given area or season (Hayes 2006). Decile Index (DI) is defined as the ranking of rainfall values using a specific time interval over a historical period. The use of long-term rainfall data is essential for a more accurate estimate of DI (Gibbs and Maher 1967). This index can also be used to perform calculations for any period of time, such as SPI, PNI, and RAI. Reconnaissance Drought Index (RDI) is calculated based on the rate of precipitation and potential evapotranspiration while
the effective Reconnaissance Drought Index (eRDA) is calculated by replacing the rainfall with effective rainfall.

At the inter-regional workshop on Drought indices and Early Warning Systems organized by the World Meteorological Organization (WMO) in 2019 December, 22 countries agreed to use SPI as the best index for meteorological drought monitoring (Michael et al. 2011). The advantage of calculating the SPI is that the non-standard distribution of rainfall is converted into a standardized distribution at different time frames. Here, precipitation data is first transformed to the gamma distribution and then converted to a normal distribution using the normal probability transformation (McKee et al. 1993). Then, the mean of the data sets to zero and the values above zero representing wetness, and values below zero indicate dryness. This methodology provides a good solution to the anomalies caused by the use of non-standardized distribution for drought monitoring. SPI can be calculated using any time period so that short-term as well as long-term drought monitoring, but the most commonly used are for periods 1, 3, 6, 12, 24, and 48 months. For SPI calculations, 50 years of data usage is recommended even if 30 years of continuous data is sufficient (Guttman 1999).

Effective Drought Index (EDI) is calculated using daily data and its values are standardized in a manner similar to SPI values. When the EDI values range from -1.0 to 1.0, it is normal and when the EDI is less than or equal to -2.0, it is called a severe drought (Byun and Wilhite 1999). The EDI also provides an overview of drought duration. The Selyaninov’s hydrothermal coefficient (HTC) Index is commonly used to stabilize water-deficient areas, as it uses both precipitation and temperature parameters to accurately predict changes in crop moisture content. In terms of HTC values, very dry conditions represented by HTC <= 0.7, and dry conditions were assumed for < 0.7 and 1.0 of HTC (Selyaninov 1958). However, the Chinese -Z- Index (CZI) is easier to calculate compared to other drought indices and it can also be used as an alternative to the SPI, and statistical Z-scores or standard scores can be used as another drought indicator to monitor drought, but the Z-score is actually part of the CZI (Ju et al. 1997). Occasionally there is confusion with CZI and SPI. However, since gamma distribution or Pearson III type distribution is not used, it is much easy to calculate. Also, it is not advisable to use it in small time frames as no distribution function is used.

Especially, standardized precipitation evapotranspiration index (SPEI) has been developed to detect the effects of droughts due to global warming. Like PDSI, this index also considers the effect of evapotranspiration on drought severity but it is easy to calculate than the PDSI (Palmer 1965). The calculations of PDSI are more complicated than other meteorological drought indices because they are based not only on the precipitation at a specific location but also on the concept of supply and demand in the water balance equation. Like many other indices, PDSI responds to wet and dry conditions with values ranging from -4 to +4, the negative values indicating non-drought and drought, respectively (Palmer 1965). Humidity Index (HI) has to be defined in contrast to Aridity Index (AI) as a ratio of the monthly differences between precipitation and potential evapotranspiration when the precipitation is greater than the potential evapotranspiration and sum of the monthly values of the potential
Table 2. List of hydrological drought indices.

| Index                                      | Equation                                      | Data      | Key Reference          | Citations |
|--------------------------------------------|-----------------------------------------------|-----------|------------------------|-----------|
| Streamflow drought index (SDI)             | $g(x) = \frac{x^{\lambda} e^{\frac{x^2}{\beta^2}}}{\beta \Gamma\left(\frac{\lambda}{2}\right)}$ for $x > 0$ | Discharge | Nalbantis and Tsakiris 2009 | 654       |
| Regional streamflow deficiency index (RDI) | $RDIC(t) = \frac{1}{n} \sum_{i=1}^{n} DC_i(t)$ | Discharge | Stahl 2001             | 185       |
| Surface Water Supply Index (SWSI)          | $WSI = \frac{SNOW + PR + PRAM - DRW - 50}{12}$ | Snow, R, Discharge, reservoir water storage | Shafer and Dezman 1982 | 823       |
| Groundwater Resource Index (GRI)           | $GRI = \frac{GI}{GW}$                          | Groundwater level | Mendicino et al. 2008 | 222       |
| Plamer Hydrological Drought Index PHDI     | This index is based on the original PDSI calculation, but changed taking into account water storage, surface water flow and groundwater parameters. | P, T, Available Water Amount | Palmer 1965 | 6510      |
| Water Balance Derived Drought Index        | Use the water balance model outputs to estimate the drought | Water balance system | Vasiliades et al. 2011 | 151       |
| Standardize water level index (SWLI)       | $g(x) = \frac{x^{\lambda} e^{\frac{x^2}{\beta^2}}}{\beta \Gamma\left(\frac{\lambda}{2}\right)}$ for $x > 0$ | Water level | Bhuiyan 2004          | 156       |
| Standardized Reservoir Supply Index (SRSI) | $g(x) = \frac{x^{\lambda} e^{\frac{x^2}{\beta^2}}}{\beta \Gamma\left(\frac{\lambda}{2}\right)}$ for $x > 0$ | Inflow    | Gusyev et al. 2015    | 13        |
| Standardized Streamflow Index (SSFI)/SSI   | $g(x) = \frac{x^{\lambda} e^{\frac{x^2}{\beta^2}}}{\beta \Gamma\left(\frac{\lambda}{2}\right)}$ for $x > 0$ | Discharge | Liu et al. 2016       | 8         |
| Aggregate Drought Index (ADI)              | $ADI_{i,k} = \frac{DU_{i}}{DU}$               | Keyantash & Dracup 2004 | 304       |
| Standardized Snowmelt and Rain Index (SMRI)| $g(x) = \frac{x^{\lambda} e^{\frac{x^2}{\beta^2}}}{\beta \Gamma\left(\frac{\lambda}{2}\right)}$ for $x > 0$ | P, Snow   | Staudinger et al. 2015 | 73        |
| Reclamation drought Index (RDI)            | $RDA = \frac{Supply + demand}{GI}$            | Water supply and demand | Weghorst 1996 | 105       |

($X_{\mu}$: Long term mean, $X_{\sigma}$: Long term standard deviation, DI – Discharge, GI: Groundwater level, Wi: Reservoir water level, a, d, c, d are constants). Total number of citations are provided only up to 10 November 2021.
evapotranspiration for the number of months which are having excess rainfall at a specific location or area (Thornthwaite 1931, 1948). The sc-PDSI is calculated by automatically calibrating the empirical constants so that it can be used anywhere and calculating the PDSI. scPDSI shows a better spatial distribution in drought than PDSI, and analyses show that it also captures extreme wet and dry conditions well. The Palmer-Z index can also be introduced as a derivative of PDSI (Palmer 1965). The main difference in the Modified Palmer Drought Severity Index (MPDSI) is the start and end time in drought calculation, but it responds better than PDSI, and it is more suitable for real-time monitoring. The Weighted Anomaly Standardized Precipitation (WASP) Index is used to summarize the weighted standardized monthly rainfall, and the main advantage of the WASP - Index is the use of the weighting factor, which also captures the variability of small rainfall at the beginning or end of the dry season (Lyon and Barnston 2005).

### 3.1.2. Location-specific hydrological drought indices

Hydrological droughts begin when there is an imbalance between water demand and supply due to abnormal depletion of water resources in rivers, groundwater, reservoirs, and lakes (Van Loon 2015). Compared to meteorological droughts and agricultural droughts, hydrological droughts can last from months to years, covering a wide area (Kim and Jehanzaib 2020). Recent research has scientifically confirmed the mechanism of a drought, as well as changes in time and spatial, and a number of articles have shown that drought is not simply a decrease in rainfall, but that is become more complex due to different hydrological processes (Kim and Jehanzaib 2020). Various researchers have further pointed out that more attention should be paid to the hydrological drought as its impact is greater than other droughts (Mishra and Singh 2010). Table 2 represents most of the traditional drought indices used in hydrological drought monitoring studies worldwide.

Hydrological drought indices are primarily developed based on hydrodynamic parameters such as river flow, runoff, reservoir water level, and groundwater level (Thakur et al. 2017). Furthermore, when critically assessing the hydrological drought

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**Table 3. List of agricultural drought monitoring indices (AET – Actual Evapotranspiration, PET – Potential Evapotranspiration, P – Precipitation, T – Temperature, SM – Soil Moisture).**

| Index                                      | Equation                                                                 | Data | Key Reference                      | Citations |
|--------------------------------------------|--------------------------------------------------------------------------|------|-----------------------------------|-----------|
| Crop Moisture Index (CMI)                  | Use a water balance model to analyze the precipitation and temperature data | SM   | Palmer 1968                       | 952       |
| Crop Water Stress Index (CWSI)             | CWSI = 1 − \(\frac{AET}{PET}\)                                        | AET, PET | Idso et al. 1981                  | 1540      |
| Crop specific drought index (CSDI)         |                                                                          | P, T, ET | Meyer et al. 1993                | 53        |
| Soil Moisture Deficit Index (SMDI)         | SMDI = 0.5 × SMDI\(_{t-1}\) + \(\frac{SO}{50}\)                      |      | Narasimhan and Srinivasan 2005   | 668       |
| Modified Soil Moisture Deficit Index (MSWDI)| MSWDI = \(\frac{WD}{50}\)                                               | SM   | Yang et al. 2017                  | 26        |
| Relative Soil Moisture (RSM)               | \(R_{sm} = \frac{W}{f_c} + 100\%\)                                     | P, T, ET | Thornthwaite and Mather 1957      | 2714      |
| Agriculture Drought Index (DTx)            | Calculate the integrated transpiration deficits base on the water balance model |      | Matera et al. 2007                | 27        |

Total number of citations are provided only up to 10 November 2021.
indices, it appears that five drought indices called SDI, SWLI, SRSI, SSFI, and SMRI have been calculated using the SPI calculation approach by replacing precipitation with a hydrological parameter such as river discharge, reservoir water level, reservoir water supply respectively (Mtilatila et al. 2020). The destruction shown in the SMRI is that the sum of precipitation and snowmelt is used as a single parameter compared to other standardized indices. The Groundwater Resource Index (GRI) has been developed to quantify groundwater retention to assess drought conditions. Palmer Hydrological Drought Index (PHDI) compares meteorological and hydrological drought parameters over space and time (Heim 2002). Rainfall, evaporation, streamflow, reservoir storage, soil moisture, and snow water content are used to calculate the Aggregate Drought Index (ADI) separately, which are then used to extract the leading hydrological index from them using the correlation between the data through Principal Component Analysis (PCA). Reclamation Drought Index (RDI) calculation is done in the same way as SWSI, however, the temperature variable, as well as the duration, is also included in this index.

3.1.3. Location-specific/model-based agriculture drought monitoring indices

Crop Moisture Index (CMI) represents a short-term agricultural drought where rapid changes in soil moisture can be detected. CMI responds to normal conditions but does not represent local changes caused by isolated rainfall and analyzes precipitation and temperature in a water equilibrium model. Crop Water Stress Index (CWSI) is
| Index                                      | Equation                                                                 | Drought Type | Key Reference          | Citations |
|--------------------------------------------|--------------------------------------------------------------------------|--------------|------------------------|-----------|
| Moisture Stress Index (MSI)                | MSI = \( \frac{R_{swir}}{R_{nir}} \)                                    | H            | Hunt and Rock 1989     | 1166      |
| Vegetation Index Number (VIN)              | VIN = \( \frac{R_{nir}}{R_{red}} \)                                     | A            | Pearson and Miller 1972| 755       |
| Ratio Vegetation Index (RVI)               | RVI = \( \frac{R_{nir}}{R_{swir}} \)                                   | A            | Pearson and Miller 1972| 755       |
| Shortwave Infrared Water Stress Index (SIWSI) | SIWSI = \( \frac{R_{swir} - R_{nir}}{R_{swir} + R_{nir}} \)            | H            | Fensholt and Sandholt 2003 | 450      |
| Normalized Difference Snow Index (NDSI)    | NDSI = \( \frac{R_{green} - R_{swir}}{R_{green} + R_{swir}} \)         | H            | Valovcin 1978           | 25        |
| Simple Ratio Water Index (SRWI)            | SRWI = \( \frac{R_{nir}}{R_{swir}} \)                                  | A            | Zarco-Tejada et al. 2003| 606       |
| Difference Vegetation Index (DVI)          | DVI = \( R_{nir} - R_{red} \)                                           | A            | Lillesand and Kiefer (1987) | 451      |
| Perpendicular Drought Index (PDI)          | PDI = \( \frac{1}{\sqrt{M_2 + 1}} \left( \frac{R_{red} + M + R_{swir}}{1 - f} \right) \) | A            | Ghulam et al. 2008     | 279       |
| Modified Perpendicular Drought Index (MPDI) | MPDI = \( \frac{R_{red} + M + R_{swir}}{R_{red} + M - \sqrt{M_2 + 1}} \) | A            | Ghulam et al. 2007     | 279       |
| Simple Ratio Water Index (SRWI)            | RVI = \( \frac{R_{red}}{R_{nir}} \)                                    | A            | Zarco-Tejada and Ustin 2001 | 88        |
| Normalize Difference Water Index (NDWI)     | NDWI = \( \frac{R_{nir} - R_{swir}}{R_{nir} + R_{swir}} \)              | A            | Gao 1996               | 4761      |
| Land surface water Index (LSWI) NDII       | LSWI = \( \frac{R_{nir} - R_{swir}}{R_{nir} + R_{swir}} \)              | H/A          | Gao, 1996              | 4761      |
| Surface water Capacity Index (SWCI)         | SWCI = \( \frac{R_{swir} - R_{nir}}{R_{swir} + R_{nir}} \)              | H            | Zhang et al. 2013      | 19        |
| Leaf Water Content Index (LWCI)             | Classify RS observed leaf water content to define the plant health      | A            | Hunt et al. 1987       | 375       |
| Infrared Percentage Vegetation Index (IPVI) | IPVI = \( \frac{R_{nir}}{R_{swir}} \)                                  | A            | Crippen 1990           | 578       |
| Tasseled Cap Wetness (TCW)                 | TWC = \( 0.1509 (band 1) + 0.1973 (band 2) + 0.3279 (band 3) + 0.4572 (band 4) \) | A            | Crist and Cicone 1984  | 1483      |
| Normalize difference vegetation Index (NDVI)| NDVI = \( \frac{R_{nir} - R_{swir}}{R_{nir} + R_{swir}} \)             | A            | Tucker, 1979           | 9443      |
| Cubed Ratio Vegetation Index (CVI)          | CVI = \( \left( \frac{R_{nir}}{R_{swir}} \right)^3 \)                  | A            | Thenkabail et al. 1994 | 119       |
| Global Vegetation Moisture Index (GVMI)     | GVMI = \( \frac{(R_{nir} - 0.1) - (R_{swir} + 0.2)}{(R_{nir} - 0.1) + (R_{swir} + 0.2)} \) | A            | Cecatto et al. 2002    | 652       |
| Enhanced Vegetation Index (EVI)            | EVI = \( G \cdot \frac{R_{nir} - R_{red}}{R_{nir} + R_{red}} \)         | A            | Liu and Huete 1995     | 968       |
| Normalized Multiband Drought Index (NMDI)   | NMDI = \( \frac{R_{red} - (R_{red} + R_{swir})}{R_{red} + (R_{red} + R_{swir})} \) | A            | Wang and Qu 2007       | 325       |
| Visible and Shortwave Drought Index (VSDI)  | VSDI = \( 1 - \frac{R_{nir}}{R_{red} + R_{swir}} \)                     | A            | Zhang et al. 2013      | 54        |
| Shortwave Infrared Water Stress Index (SIWSI) | SIWSI = \( \frac{R_{swir} - R_{nir}}{R_{swir} + R_{nir}} \)             | A            | Fensholt and Sandholt 2003 | 450      |
| Soil Adjusted Vegetation Index (SAVI)       | SAVI = \( \frac{R_{swir} - R_{nir}}{R_{swir} + R_{nir}} \)              | A            | Huete 1988             | 6973      |

(continued)
| Index                                          | Equation                                                                 | Drought Type | Key Reference | Citations |
|-----------------------------------------------|--------------------------------------------------------------------------|--------------|---------------|-----------|
| Modified Soil Adjusted Vegetation Index (MSAVI) | $\text{MSAVI} = \left(\frac{R_{\text{nir}} - R_{\text{red}}}{R_{\text{nir}} + R_{\text{red}} + L}\right) \times (1 + L)$ | A            | Qi et al. 1994 | 2645      |
| Optimized Soil-Adjusted Vegetation Index (OSAVI) | $\text{OSAVI} = \frac{1 + 0.16\times\frac{R_{\text{nir}} - R_{\text{red}}}{R_{\text{nir}} + R_{\text{red}} + 0.16}}{\frac{R_{\text{nir}} - R_{\text{red}}}{R_{\text{nir}} + R_{\text{red}} + 0.16}}$ | A            | Rondeaux et al. 1996 | 2032      |
| Transformed Soil-Adjusted Vegetation Index (TSAVI) | $\text{TSAVI} = \frac{a (R_{\text{nir}} - a + R_{\text{red}} - b)}{\Delta R_{\text{nir}} + R_{\text{red}} + a + b}$ | A            | Baret and Guyot 1991 | 2438      |
| Adjusted Transformed Soil-Adjusted Vegetation Index (ATSAVI) | $\text{ATSAVI} = \frac{a (R_{\text{nir}} - a + R_{\text{red}} - b)}{\Delta R_{\text{nir}} + R_{\text{red}} + a + b + 0.08(1 + a^2)}$ | A            | Baret and Guyot 1991 | 2438      |

($R_{\text{swir}}$: Shortwave infrared image band, $R_{\text{nir}}$: Near-Infrared image band, $R_{\text{red}}$: Red image band, $R_{\text{blue}}$: blue image band, $R_{\text{green}}$: Green image band, $R_{\text{swir1}}$: Shortwave infrared image band1, $R_{\text{swir2}}$: Shortwave infrared image band2, G, c1, c2, L, a, b – constants, fv: Vegetation factor, M: Slope, A: Agricultural Drought, H: Hydrological Drought). Total number of citations are provided only up to 10 November 2021.
calculated using Actual Evapotranspiration (AET) and Potential Evapotranspiration (PET), which are calculated using canopy temperature, air temperature, and net radiation estimates, and the energy balance equation is also used (Jackson et al. 1981). When calculating the Crop Specific Drought Index (CSDI) in addition to climatic data such as temperature and rainfall, soil and crop phenomenon information is also required intensively. Corn Drought Index (Meyer et al. 1993) and Soybean Drought Index (Meyer et al. 1993) are some of the examples for CSDI. Table 3 represents the list of traditionally used agriculture drought monitoring indices.

3.2. Remote sensing-based drought indices

As noted by many reviews, meteorological and hydrological drought monitoring has been at the forefront of traditional drought indices design, while agricultural drought monitoring has only a handful of indices (Table 3). But many reviews show that the development of agricultural drought indices has greatly increased since the advent of satellite Remote Sensing (AghaKouchak et al. 2015; Yoon et al. 2020). RS-based drought indices are derived from optical, infrared, thermal imaging reflective signatures, as well as microwave backscatter imaging. The variability of the physical parameters that arise in the soil and canopy surface during droughts is determined using red, infrared, shortwave, and thermal spectral bands in particular. The physical parameters used for drought monitoring based on satellite data are soil moisture, vegetation biomass, chlorophyll, organic matter, canopy or soil temperature, and surface water storage (Chanyang et al. 2020). The study of drought indices using remote sensing data can be divided into four main categories as optical, thermal, microwave, and integrated indices, and they can be further analyzed separately in detail according to meteorological, agricultural and hydrological drought.

Drought indices that identify and are used to develop drought indices are different from each other in terms of optical, thermal, and microwave remote sensing (Figure 5). Most drought indices that are simply calculated using surface reflection or backscatter image bands can be called basic indices. The other category is the intermediate index, which is calculated using the numerical parameters of the minimum, maximum, average, or standard deviation of the long-term variables of these basic indices. The final category is the composite index generated by combining the various basic or intermediate indices with the optical, thermal, and microwave remote sensing drought indices. For example, the Integrated Drought Severity Index (IDSI) has been developed by integrating optical (VCI), thermal (TCI), and microwave (PCI) RS indices through principal component analysis (Amarnath et al. 2017). Figure 5 provides a detailed representation of the indices which were used to generate various RS drought indices and the relationship between each drought indices.

3.2.1. Optical remote sensing drought indices

The traditional approach is more prominent for met and hydro drought monitoring, but the RS method dominates e agriculture drought monitoring. The approach to characterizing drought is mainly based on monitoring the soil water balance, its deficiency and crop health, water stress, snowpack, and canopy temperature (Paredes-
A large number of indices have been developed to study the variability of the above parameters during the dry weather for drought monitoring in different ways. Furthermore, complex indices have also been developed by integrating several parameters that represent crop stress (Khan et al. 2016). Table 4 describes the various simple optical RS-based drought indices in detail.

The moisture stress index (MSI) is calculated using simple ratios of SWIR and NIR reflectance bands of optical satellite data and while lower SMI values represent drought and higher values represent wetness. Normalized Difference Snow Index (NDSI) calculates the amount of snow cover in the area. Pixels with an NDSI value of > 0 are considered to have some amount of snow, and the magnitude of this value can be used to determine whether or not a hydrological drought occurs during snow season. This index is much more used full in temperature countries to monitor the drought. Perpendicular Drought Index (PDI) is a simple and effective index to use for drought monitoring but the weakness here is the lack of accuracy for vegetation-rich and barren lands. The Modified Perpendicular Drought Index (MPDI) was introduced to overcome the weaknesses in PDI and introduced the updated index by replacing a fraction of the vegetation to differentiate the effect of vegetation.

The Normalized Difference Water Index (NDWI) can be used to estimate the water content of vegetation canopies or submerged areas of the ground (Gao 1996). However, NDWI is sensitive to changes in the liquid water content of vegetation canopies and open water areas. The index calculates similar to NDWI but by using the second band of SWIR (2100 nm) called LSWI. If the value of both NDWI and LSWI is less than 0.1 basically represents the drought. The surface water capacity index (SWCI) defines as a surface moisture index constructed using the normalized difference between two SWIR bands of a given satellite system. SWCI has the ability to represent dry surface conditions and the value of the index ranges from −1 to 1. When the value of SWCI is less than 0.2, the particular area is under drought.

### Table 5. List of optical satellite-based composite drought indices (VI: Vegetation index, NDSI: Normalize Difference Snow Index, NDVI: Normalized Difference Vegetation Index (NDVI), Normalized Different Snow Index (NDSI), min: minimum value, max: maximum value, VIs: Long term mean, VIs: Long term standard deviation, A: Agricultural Drought, H: Hydrological Drought).

| Index | Equation | Drought Type | Key Reference | Citations |
|-------|----------|--------------|---------------|-----------|
| Anomaly Vegetation Index (AVI) | \( AVI = \frac{VI - Vi_{l}}{Vi_{r}} \) | A | Chen et al. 1994 | 89 |
| Snow Condition Index (SCI) | \( SCI = \frac{NDSI_{max} - NDSI_{min}}{NDSI_{max} - NDSI_{min}} \) | H | Kogan 1995 | 1095 |
| Vegetation Condition Index (VCI) | \( VCI = \frac{NDVI_{max} - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \) | A | Kogan 1995 | 1095 |
| Normalize Difference Drought Index (NDDI) | \( NDDI = \frac{NDVI - NDWI}{NDVI - NDWI} \) | A | Gu et al. 2007 | 543 |
| Normalized Moisture Index (NMI) | \( NMI = NDVI - NDWI \) | A | Jang et al. 2006 | 33 |
| Weighted Difference Vegetation Index (WDVI) | \( WDVI = NIR - NDWI \) | | Richardson and Wiegand 1977 | 1902 |
| Standardize Vegetation Index (SVI) | \( SVI = \frac{VI - Vi_{l}}{Vi_{r}} \) | A | Peters et al. 2002 | 530 |

Total number of citations are provided only up to 10 November 2021.
Tasseled Cap Wetness (TCW) index is also suitable for agricultural drought monitoring because it highlights the direct relationship between soil and vegetation, which are important physical parameters of the land surface through spectral characteristics through Tasseled Cap (TC) transformation (Crist and Cicone 1984; Dzakiyah and Saraswati 2020).

As defined by (Fensholt and Sandholt 2003), Normalized Difference Infrared Indexes (NDII) calculated using NIR, and SWIR images of optical satellite images show that lower values are closer to drought and higher values indicate no drought. Normalized Difference Vegetation Index (NDVI) is a remote sensing-based index for quantitative calculation of the greenness (health) of vegetation (Rouse et al. 1974). NDVI values range from 1 to 0, while healthy NDVI values are greater than 0.3, and lower NDVI values represent barren or drought-tolerant plants. It is best to study the time-series profile of NDVI to gain a better understanding of the agricultural drought (Kogan 1990). In addition to the NIR and Red bands the blue image band is used to calculate Enhanced Vegetation Index (EVI). Canopy variations in EVI are better suited for drought monitoring as they respond better to canopy type, variation, architecture, and plant physiognomy compared to NDVI (Huete et al. 2002). The Normalized Multiband Drought Index (NMDI) has been designed to capture the signatures of the soil and vegetation spectrum using the NIR, SWIR1, and SWIR2 image bands. NMDI is very sensitive to soil wetness and dryness as well as weak and thick vegetation, while dry bear soil and dry vegetation show a higher NMDI value and a lower nominal value for wet and heavy vegetation (Wang and Qu 2007). The optical and Shortwave Infrared Drought Index (VSDI) is calculated using optical spectral bands (SWIR, Red, and Blue), and it can be used effectively to monitor soil and vegetation moisture availability.

3.2.2. Optical satellite-based composite drought indices

Annual to weekly vegetation indices are used to study surface soil and vegetation dynamics over anomaly calculation (Marj and Meijerink 2011). This Snow Condition Index (SCI) index is obtained by calculating the change of Normalized Difference Snow Index (NDSI) over time relative to the long-term minimum and maximum values. This makes it more appropriate to use than the NDSI value alone for hydrological drought monitoring. The Vegetation Condition Index (VCI) is a simple index...
that defines the current vegetation status deviation relative to the long-term calculated minimum and maximum (Kogan 2001). The VCI index can be calculated using both NDVI and EVI; while the VCI values are closer to 0 it indicates the occurrence of agriculture drought. Both the NDVI and NDWI indices were used to compute the Normalize Difference Drought Index (NDDI) and Normalized Moisture Index (NMI) indices, and the distinctive feature of Weighted Difference Vegetation Index (WDVI) is the combination of the NIR image data with the NDWI index. Table 5 describes the various optical satellite-based composite drought indices in detail.

3.2.3. Thermal remote sensing drought indices

Although various studies have shown that surface temperature obtained from remote sensing systems is suitable for measuring agricultural drought, it is more suitable for sparse canopies or empty lands than for vegetative lands. The accuracy of drought detection is proportional to the accuracy of the surface temperature measurement accuracy by remote sensor data, and the uncertainty of drought detection by temperature is further increased by the heterogeneity of the Earth’s surface. Apparent thermal inertia (ATI) can be easily generated using remote sensor data; however, the uniqueness of ATI is that it is a relative measure of the solar albedo that reflects the temperature differences. The Temperature Condition Index (TCI) proposed by Kogan (1995) and Kogan (1997) is a simple drought index that can determine the temperature of vegetation and is more suitable for homogeneous terrain to detect the drought. Although the Normalized Difference Temperature Index (NDTI) is more suitable for drought monitoring than AAT and TCI as it eliminates seasonal variations, the calculation of NDTI is more complicated than the others. Table 6 shows the indices used for drought monitoring based on thermal remote sensors.

3.2.4. The optical and thermal composite index

Table 7 shows some of the indices that have created drought monitoring, combining basic optical and thermal drought indices calculated using satellite imagery by various researchers. The Vegetation Health Index (VHI) is a combination of VCI and TCI data that provides extensive drought monitoring capabilities compared to VCI and TCI individually to monitor drought (Kogan 2002; Bhuiyan et al. 2006; Alahacoon et al. 2021). The Water Supply Vegetation Index (WSVI), also called as Vegetation Water Supply Index (VWSI), is calculated by the simple ratio between NDVI and
temperature, while Modified Water Supply Vegetation Index (MWSVI) is calculated by the relative ratio of NDVI and T. However, various researchers have shown that composite indices are more suitable for drought monitoring than a single index.

3.2.5. Microwave RS drought indices

Microwave remote sensing is used to detect the dielectric constant between water, soil, and vegetation and to provide information about the water content. This method neutralizes the effects of clouds, thus providing better results for drought studies (Wang and Qu 2009). Drought indices calculated by microwave remote sensing are shown in Table 8, with Precipitation Condition Index (PCI), Soil Moisture Condition Index (SMCI), and Soil Water Index (SWI) indices being the most commonly used indices.

The PCI calculation examines the variability in current rainfall relative to the long-term minimum and maximum rainfall. PCI values are in the range of 0-1, values close to 0 indicate marginal stress, and values close to 1 indicate a healthy state (Faridatul and Ahmed 2020). The Microwave Polarization Difference Index (MPDI) is designed to determine the soil moisture and visible depth of vegetation using polarized brightness temperature observed through V and H polarization satellite images. The Normalized Backscatter Moisture Index (NBMI) provides the ability to map soil moisture conditions over a large area using C-band SAR data. It can provide high spatial and temporal resolution, and the disadvantage of that indices is the inability to penetrate vegetation canopies.

3.2.6. Integrated drought indices

Due to the different trends in drought detection in different remote sensing indices, researchers have created a composite index by combining basic drought indices using different methods as in Table 9 (Wang et al. 2008; Hao and AghaKouchak 2013).

Vegetation Drought Response Index (VegDRI) is a hybrid drought index produced by combining satellite data-based calculations on climatic, biophysical features, and vegetation conditions. The concept of VegDRI was introduced by Rouse et al. (1974)
Table 9. List of integrated drought indices (Ts: Surface Temperature, Tmin Tmax: minimum and maximum of surface temperature at dry edge, Vi: Vegetation index, TVwet/der: Temperature Vegetation at wet and dry edge, Tc: Temperature condition, ETa: Actual evapotranspiration, ETref: reference evapotranspiration, TsNDVImax, TsNDVImin: maximum and minimum land surface temperatures of pixels which have same NDVI value in a study area, respectively, TSD: Total storage, Ta: Air temperature, APET: Actual PET, PPET: Potential ET, VCI: Vegetation Condition Index, TCI: Temperature Condition Index, PCI: Precipitation Condition Index, MTCI: Modified Temperature Condition Index, C: constant, N: Number).

| Index | Equation if applicable or simple | Parameter | Key Reference | Citations |
|-------|----------------------------------|-----------|---------------|-----------|
| Vegetation Drought Response Index (VegDRI) | Complex calculation | Composite Index | Brown et al. 2008 | 461 |
| Temperature Vegetation Dryness Index (TVDI) | TVDI = \( \frac{Ts_{max}}{Ts_{min} + Ts_{max}} \) | LST-NDVI 2D-space | Sandholt et al. 2002 | 1816 |
| Temperature Vegetation Wetness Index (TVWI) | TVWI = \( \frac{TV_{wet} + TV_{dry}}{TV_{dry}} \) | LST-NDVI 2D-space | Hassan et al. 2007 | 68 |
| Vegetation Supply Water Index VSWI | VSWI = \( \frac{Vi}{Tc} \) | Vi-Vegetation Index | Carlson et al. 1994 | 952 |
| Total Storage deficit index (TSDI) | TSDI = \( p \times TSDI_{k} + q \times TSD_{k} \) | TSD | Yirdaw et al. 2008 | 160 |
| Evaporative Stress Index (ESI) | ESI = \( \frac{ETa}{ET_{ref}} \) | | Anderson et al. 2011 | 391 |
| Vegetation Temperature Condition Index (VTCI) | VTCI = \( \frac{Ts_{max} - Ts_{min}}{Ts_{max} + TV_{dry}} \) | T, NDVI | Wang et al. 2001 | 193 |
| Temperature-Vegetation Dryness Index (TVDI) | TVDI = \( \frac{Ts_{min} + TV_{dry}}{TV_{dry}} \) | T, VI | Sandholt et al. 2002 | 1816 |
| Water Deficit Index (WDI) | WDI = \( \frac{(Ts_{max} - Ta_{max}) - (Ts_{min} - Ta_{min})}{(Ts_{max} - Ta_{max}) + (Ts_{min} - Ta_{min})} \) | PET | Verdin and Klaver 2002 | 152 |
| Water Requirement Satisfactory Index (WRSI) | WRSI = \( \frac{(APET)}{PPET} \times 100 \) | PET | Verdin and Klaver 2002 | 152 |
| Geo-WRIS | Statistical Model | ET, PET, NDVI | Bryant et al. 1992 | 76 |
| Drought Severity Index (DSI) | DSI = \( \frac{Z - Z_{l}}{Z_{r}} \) | ET, PET, NDVI | Rhee et al. 2010 | 501 |
| Scaled Drought Severity Index (SDCI) | SDCI = \( c_{v} \times VCI + c_{p} \times PCI + c_{T} \times TCI \) | P,T,NDVI | Rhee et al. 2010 | 501 |
| Integrated Drought Severity Index (IDSI) | IDS = \( SMCI + MTCI + VCI \) | P, T, NDVI | Amarnath et al. 2017 | 1 |
| Soil Moisture Agriculture Drought Index (SMADI) | SMADI = SMCI \( \times MTCI \) | SM, MTCI, VCI | Sánchez et al. 2016 | 81 |
| Vegetation Soil-Water Deficit (VSWD) | VSWD = \( \sum_{i=1}^{N} VSWD_{i} \) | P, S – soil water content, PET | Cao et al. 2019 | 13 |

Total number of citations are provided only up to 10 November 2021.
based only on NDVI and has proven to provide valuable information on plant health. This indicator represents the vegetation stress associated with the drought and can perform calculations for regional scales at medium to high resolution. However, it is also possible that the stress on vegetation cannot be identified based on the variability of the NDV alone (Heim 2002). The VTCI, TVDI, TWI, and TVI indices are designed using the scatter plot approach (Triangular or trapezoidal) of temperature and vegetation indices, as shown in Figure 6. This approach mostly works on the regional scale, and it is not working on the small scale. The VTCI, TVDI, TWI, and TVI indices combine NDVI (vegetation) and LST (thermal) characteristics, and they can be used to effectively monitor drought based on temperature and vegetation conditions (Patel et al. 2012).

The Scaled Drought Severity Index (SDSI) was developed by Rhee et al. (2010) and is used as a multi-sensor index to monitor agricultural drought in arid, semi-arid, and humid areas. Here the three derivatives of vegetation, precipitation, and Temperatures such as VCI, PCI, and TCI are combined on a scale from 0 to 1. The Vegetation Soil-Water Deficit (VSWD) method differs from other drought indices methods in that it combines the parameters of precipitation, soil moisture, and Potential EvapoTranspiration (PET) to generate the composite drought index. Therefore, using the VSWD index can identify the drought with greater accuracy. The average surface/terrestrial water storage is calculated based on gravity measurements based on the Gravity Recovery And Climate Experiment (GRACE) satellite data to generate the Total Storage Deficit Index (TSDI). The Water Requirement Satisfactory Index (WRSI) is used to monitor crop performance during the growing season using the actual and potential evapotranspiration ratio, which indicates the amount of water in the crop. This WRSI is crop-specific and responds directly to drought stress.

3.3. Socio-economic drought indices

Adequate drought indices for socio-economic drought monitoring and analysis were not created until recently. Over the past few years, however, researchers have been

Figure 6. Triangular and trapezoidal representation of Temperature (T) and Vegetation indices (Sandholt et al. 2002).
able to develop several socio-economic indices such as Multivariate Standardized Reliability and Resilience Index (MSRRI), Water Resources System Resilience Index (WRSRI), and Socioeconomic drought index (SEDI).

3.3.1. Multivariate Standardized Reliability and Resilience Index (MSRRI)

Two new indices called Water Storage Resilience (WSR) index and the Inflow-Demand Reliability (IDR) index have been developed to calculate MSRRI (Zhao et al. 2019). The IDR index is derived by calculating the difference in the percentage of water flow to the water source that is considered relative to the water demand over a given period of time. The WSR index calculates whether the considered water storage can meet the water demand for the selected period of the reservoir. The key factors that depend on the value of the year are the monthly inflow, the monthly water demand, the monthly storage, and the total water demand. The statistical calculations marginal probabilities, empirical probability transformation, multivariate model of the Gringorten plotting position were used to calculate MSRRI.

3.3.2. Water Resources System Resilience Index (WRSRI)

Water Resources System Resilience Index (WRSRI) represents the percentage of pre-water shortages for a socio-economic drought that can be recovered from excess water during the periods considered by analyzing historical drought occurrences (Liu et al. 2020). This approach is much more similar to MSRRI approach.

3.3.3. Socioeconomic Drought Index (SEDI)

The Socio-Economic Drought Index (SEDI) is designed to identify and evaluate socioeconomic drought events of varying severity, i.e., moderate, severe, and extreme (Shi et al. 2018). First, the minimum water requirement (MWR) of the river basin required to carry out the various functions of the river basin without interruption is calculated. Secondly, the occurrence and duration of hydrological drought are determined using data discharge data recorded at either hydrological station or simulated through the hydrological model. Finally, the SEDI value can be calculated by combining the effects of water scarcity and drought periods calculated above and then categorized into four different severity classes as shown in Table 10 (Shi et al. 2018).

3.4. Drought monitoring platforms and indices

Researchers around the world have introduced a variety of drought indices that have been used more effectively to build different levels of drought monitoring platforms. Considering the world’s drought monitoring platforms, they can be identified as

| Value | Definition | Water storage level (WSL) | Drought Duration level (DDL) |
|-------|------------|---------------------------|-----------------------------|
| 1     | Slight     |                           | Quarterly (i.e., 1-3 month) |
| 2     | Moderate   | RSP < 40%                 | Semi-annual (i.e., 4-6 month)|
| 3     | Severe     | 40% < RSP < 60%           | Annual (i.e., 7-12 month)   |
| 4     | Extreme    | RSP < 80%                 | More than 12 month          |

| Value | Definition | Water storage level (WSL) | Drought Duration level (DDL) |
|-------|------------|---------------------------|-----------------------------|
| 1     | Slight     | RSP < 40%                 | Quarterly (i.e., 1-3 month) |
| 2     | Moderate   | 40% < RSP < 60%           | Semi-annual (i.e., 4-6 month)|
| 3     | Severe     | 60% < RSP < 80%           | Annual (i.e., 7-12 month)   |
| 4     | Extreme    | RSP < 80%                 | More than 12 month          |
Table 11. List of global drought monitoring platforms.

| Drought Monitoring Platform                                      | Drought monitoring Indices                                      | Link                                                                 |
|------------------------------------------------------------------|------------------------------------------------------------------|----------------------------------------------------------------------|
| ClimatView - a tool for viewing monthly climate data             | Standardized Precipitation Index (SPI)                           | http://ds.data.jma.go.jp/tcc/tcc/products/climate/climatview/frame.php?&s=1&r=0&d=0&y=2019&m=2&e=8&t=0&l=0&s=1   |
| Flood and drought portal                                         | Standardized Precipitation Index (SPI), Effective Drought Index (EDI), Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Swatsoil water index (SWI), Vegetation health index (VHI), Agricultural Stress Index (ASI), Combined Drought Index (CDI) | https://www.flooddroughtmonitor.com/home                                |
| Global drought Information System                                | Standardized Precipitation Index (SPI), Vegetation Health Index (VHI) | https://gdis-noaa.hub.arcgis.com/pages/drought-monitoring            |
| IRI Global drought analysis tool                                 | Standardized Precipitation Index (SPI),                          | https://iridl.ldeo.columbia.edu/maproom/Global/Drought/Global/CPC_GOB/Analysis.html |
| Global integrated drought monitoring and prediction system (GiDMaPS) | SPI - Standardized Precipitation Index                           | http://drought.eng.uc.edu/                                            |
|                                                                  | SSI - Standardized Soil Moisture Index (Hao and AghaKouchak 2013a) |                                                                      |
|                                                                  | MSDI - Multivariate Standardized Drought Index (Hao and AghaKouchak 2013b) |                                                                      |
| SPEI Global Drought Monitor                                      | SPEI                                                             | https://spei.csic.es/map/maps.html?months=1#month=2#year=2021         |
| African Flood and Drought Monitoring System                      | Standardized Precipitation Index (SPI), Normalized Difference Vegetation Index (NDVI), |                                                                      |
| CIIFEN Drought Monitor                                           | Standardized Precipitation Index (SPI),                           | https://ciifen.org?option=com_content&view=article&id=2172&Itemid=469&lang=es |
| North America Drought Monitoring System                          | Standardized Precipitation Index (SPI), Percent of Average Precipitation, Palmer Drought Index | https://www.ncdc.noaa.gov/temp-and-precip/drought/nadm/maps            |
| European Drought Observatory                                     | Combined Drought Indicator (CDI), Standardized Precipitation Index (SPI), Soil Moisture Anomaly (SMA), Vegetation Productivity Anomaly (fAPAR Anomaly) | https://edo.jrc.ec.europa.eu/edov2/php/index.php?id=1000               |
| South Asia Drought Monitoring System (SADMS)                     | Integrated Drought Severity Index (IDSi), Standardized Precipitation Index (SPI), Soil Moisture Index, Vegetation Condition Index (VCI), Temperature Condition Index (TCI), Precipitation Condition Index (PCI) | http://dms.iwmi.org/                                                    |
global, continental, and country-level systems. What is more special about these platforms is that they can detect the spread of drought all over the world at once. Table 11 shows the information on several of the platforms analyzed, indicating that more than 90% of the SPI index has been used and that only the Agricultural and Meteorological Drought Index has been used.

4. Conclusions

As a result of decades of hard work by various researchers and scientists, systematically developed drought indices have opened up more scope for a more analytical study of the world’s historical, current, and future droughts. In the early days of drought index development, they were almost all based on changes in the drought indicator at a given location. Over time, however, more complex and productive drought indices were developed by combining different drought indices. On the other hand, a study of drought characteristics is an essential factor in drought management operations, and drought indices provide the qualitative and quantitative information required for it. Furthermore, drought indices can be used specifically for historical drought monitoring, drought forecasting, drought level or intensity calculations, contingency planning, impact assessment, and drought forecasting, as well as drought hazard, vulnerability, and risk assessment.

There were 111 drought indices reviewed in this study, which fall into two categories: traditional (location-specific/model) and remote sensing. Out of 111 indices, 44 belong to the traditional indices and 67 belong to the remote sensing section. This review has found that researchers have created the highest number of indices to monitor meteorological drought based on conventional (location-specific) data and that number is 22. Although 14 indices can be identified for hydrological drought monitoring, it is striking that there are only 7 indices for agricultural drought monitoring. One of the reasons for having fewer indices based on location-specific data for agricultural drought monitoring is the practical difficulties in measuring agriculture drought indices. However, physically measured parameters are used to calculate location-specific drought indices, and the popularity of these indices seems to be steadily declining due to high data cost, unavailability of long-term data, and significant data gaps. The main factor influencing the decline in interest in those drought indices is the availability of satellite data, which is freely available and provides other advantages such as easy calculation and data handling, large spatial coverage, data availability at high spatial, temporal resolution, etc.

The review found that the PDSI, SPI, and NDVI indices were the most popular in drought monitoring and were used equally for all parts of the world. This is best illustrated by the number of citations available for these indexes, for example, SPI has the highest number of citations when considering location-based indexes at 9230, followed by PDSI with 6510 citations. However, it also appeared that there was a fundamental lack of a universal definition of some drought indices. Furthermore, the NDVI index is widely used in comparison to other basic indices to create various compact drought indices, and the NDVI index shows a high number of citations of 9433, among other RS based drought indices. In some drought indices, the originally proposed index (e.g., VHI, TCI, VCI, SWI) may be modified or re-presented in another journal (Kogan 1990, 1995, 1997, 2001, 2002; Bhuiyan 2004; Bhuiyan et al.
In such cases, the total number of citations for a particular index can be calculated using all citations in different articles. But in this study, the focus is only on parent article of the particular index.

Currently, there are only a handful of drought indices that indicate the effects of drought, but about 90% to 95% of indices are depending on the drought types and applications. Therefore, it is more appropriate for researchers to pay more attention to the design of the drought indices and applications coverage relative to the impact of the drought, as ability or drought recovery is depends on the impact of drought. With the advent of satellite remote sensing data, a rapid increase in new drought indices designs and drought studies was detected. The study of satellite data-based drought indices showed that most of the historically calculated location-based (more than 95%) drought indices could be easily calculated using RS data with greater spatial resolution. Therefore, RS-based drought indices are also used by many researchers around the world as an important substitute for location-based or traditional drought indices.

The inconsistency identified in this study is that the same drought index has been used by different researchers to analyze different types of drought. As an example, the SPI index has been used for meteorological, hydrological, and agricultural drought monitoring. Someone can argue how successful this is. However, this detailed review confirms that the number of the drought indices created for socio-economic drought monitoring is less than the number of fingers on the hand, and those indices have been developed over the past five years. Thus, socio-economic drought monitoring seems to have received less attention from researchers, and in fact, this requires more data as well as more complex analytical techniques to calculate.

Considering the satellite-based drought monitoring indices, it is clear that more than 90% of the total indices are designed for agricultural monitoring. However, it can be identified an increasing tendency to generate meteorological and hydrological drought indices using satellite-derived data such as precipitation, snow, currents, surface water area, etc. Long-term (1960–2020) analysis of drought studies around the world has identified an increase in the number of drought studies due to satellite data (Landsat) since the 1970s, and the number of studies has increased exponentially since 2000 due to the availability of MODIS data. Despite the increase in the number of studies at that time, there were no sophisticated methods for data processing and data handling as they exist today. However, with today’s existing data visualization and processing platforms such as Google Earth Engine (GEE), Copernicus cloud platform, and data analysis techniques (Artificial Intelligence – AI, Neural Networks – NN and Big data, cloud computing) it is possible to predict that more effective and accurate drought indices will be generated.

However, the study emphasizes that a large number of global and regional drought monitoring platforms are being created as a result of the efforts of researchers who have been creating drought indices over the years. These platforms play an invaluable role in drought risk management. A review of the most popular drought monitoring platforms used for the study also found that 90% of those platforms provide weekly or monthly drought information using SPI indices and about 60% use NDVI or its derivatives. This is also a good example of the popularity of SPI and NDVI drought monitoring indices.

Despite the popularity of RS drought indices in drought monitoring around the world, there are a number of challenges still to be addressed. When considering
satellite data major challenges are the inefficiency of the use of optical satellite imagery in tropical countries for short-term drought monitoring due to intensive clouds and less possibility for fine-scale drought monitoring. Furthermore, creating a more consistent historical database, integrating future and historical-remote remote sensing data into a common platform for improving the system for drought forecasting, and developing a methodology for the existence and filling of historical data gaps are more challenging. However, it would be more appropriate to develop a protocol to verify the validity of both remote sensor-based and location-based drought indices, which would be of great help for further improvement of drought studies.

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Conflicts of interest

The authors declare no conflict of interest.

Data availability

All data, models, and code generated or used during the study appear in the submitted article and the data extracted from Scopus (https://www.scopus.com/home.uri), Google Scholar (https://scholar.google.com/) and Science Direct (https://www.sciencedirect.com/).

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