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Drought characterization: A systematic literature review

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ABSTRACT

This study examined the worsening severity of global droughts caused by climate change. However, the multiple definitions and varied range of drought indices pose challenges in effectively monitoring and assessing the prevalence and severity of droughts. This study aims to give a comprehensive overview of the various drought definitions found in the literature and how they have evolved based on their applications. Specifically, the focus was to shed light on the dynamic nature of drought characterization and offer insights into the factors that shaped its conceptualization over time. Within this context, this study explored three primary categories of drought indices: climatic, remote sensing, and composite. Each category was discussed in relation to its utility in specific fields, such as meteorological, agricultural, and hydrological drought assessments, along with an analysis of their strengths and limitations. Furthermore, this study presents modified meteorological drought indices that have been adapted to better monitor agricultural droughts. Additionally, the authors used geographic information systems to create a map showing the distribution of drought-related publications globally over the past decade. The findings showed that countries with arid and semi-arid climates are more actively involved in drought research, highlighting their particular interest and concern regarding the subject matter. The implications of this study emphasize the urgent need for immediate and coordinated efforts to address the escalating issue of droughts caused by climate change. By improving monitoring and assessment methods and focusing on tailored strategies in vulnerable regions, it is possible to mitigate the far-reaching consequences of drought and to build more resilient communities and ecosystems.

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1. INTRODUCTION

Drought is a natural phenomenon that has been an enduring companion of humanity throughout history. This is one of the main risks that science cannot precisely assess and fix. Although the planet's agricultural, hydrological, meteorological, social, and economic systems are interconnected and interdependent, defining drought remains very difficult. However, climate change is expected to continue to reshape global systems and generate extreme systems (Faiz et al., 2022; Ogunrinde et al., 2023). In this context, state-of-the-art definitions and characterizations of droughts are necessary to address this risk better.

Drought assessment is usually performed using drought indices, which can allow the transformation of large amounts of data into quantitative information required for several applications, such as precise forecasting of drought, reporting drought levels, and planning contingency (Janapriya et al., 2016). Over 150 drought indices have been introduced by various researchers worldwide (Alahacoon & Edirisinghe, 2022). These indices are categorized into two main types: climatic drought and remote sensing indices. Researchers have recently attempted to optimize drought monitoring efforts by leveraging data from many variables and developing more robust methods (Abdourahamane et al., 2022; Hao et al., 2015). These are composite drought indices that integrate several simple indices using various methods.

Using only one input variable for drought indices can skew drought assessments (Garba et al., 2023). Consequently, because of drought complexity and its countless impacts, characterizing drought conditions typically involve incorporating various drought-related variables or indices. Many studies have suggested that composite drought indices allow for the characterization of combined drought effects (Abdourahamane et al., 2022; Al Adaileh et al., 2019). In addition, in previous decades, Earth observation data has emerged as an alternative to in situ measurements of hydroclimatic and land data to compute drought indices (Abdourahamane et al., 2022). Generally, studies have demonstrated that composite and remote sensing indices are suitable alternatives to climatic indices (Mustafa Alee et al., 2023).

Among many natural hazards, drought is one of the most financially burdensome and costly, and its effects on agriculture, the environment, the economy, and humans have gained attention among researchers (Ashraf et al., 2022). According to statistics, more than 35% of land and 1% of the global population are threatened by drought and desertification (Zhou et al., 2022), and drought losses are the highest among all types of natural disasters (Zhou et al., 2022). Researchers worldwide are interested in this topic. However, the number of publications differs from one region to another. Sometimes, studies and efforts are directed towards areas not directly affected by drought, while there are more vulnerable areas that require further research on this phenomenon. This review focuses on papers published between 2012 and 2022 to examine the geographic distribution of drought research. The findings of this part of the study will serve as a guide for future research in this area and help researchers focus directly on areas facing drought.

The purpose of this article is to present a comprehensive review of drought definitions over time and analyze commonly utilized drought indices for characterization. This involves a critical examination of previous research on drought characterization published in various electronic bibliographic databases. The systematic literature review is organized as follows: Abstract and introduction, materials and methods presenting research objectives, research questions, and methodology. Sections related to the results and discussion are integrated into a single section. In this section, we first present several definitions of drought over time, followed by the drought categories. Second, we present the drought indices by category. Third, we present the equation used to calculate each index, and the advantages and weaknesses of each index. We then present a map of the geographic distribution of research papers indexed by Scopus in the past decade. Finally, the review ends with concise conclusions.

2. MATERIAL AND METHODS

2.1. Research objectives and research questions

Several studies have addressed reviews of drought; however, none have studied the process in the form of a systematic literature review (SLR). The purpose of this SLR is to analyze the state of the art in drought by investigating published literature worldwide. To this end, three important research questions were formulated (Table 1): What are the most important definitions of drought in the literature? How can drought be characterized and monitored? Which regions are the focus of the drought research?

Table 1. Research questions of the present study

Research question	Purpose
What are the most important definitions of drought in the literature?	- Present all the definitions of drought in chronological order and the drought categories to demonstrate that there is no universal definition of this phenomenon.
How to characterize and monitor drought?	- Identify the methods used to monitor drought, especially drought indices. - Highlight the most effective drought indices for drought characterization.
Which regions are concerned with drought research?	- Show that drought research is important in drought-stricken regions. - Guide researchers to look for publications by country/climate type via the map of the spatial distribution of drought.

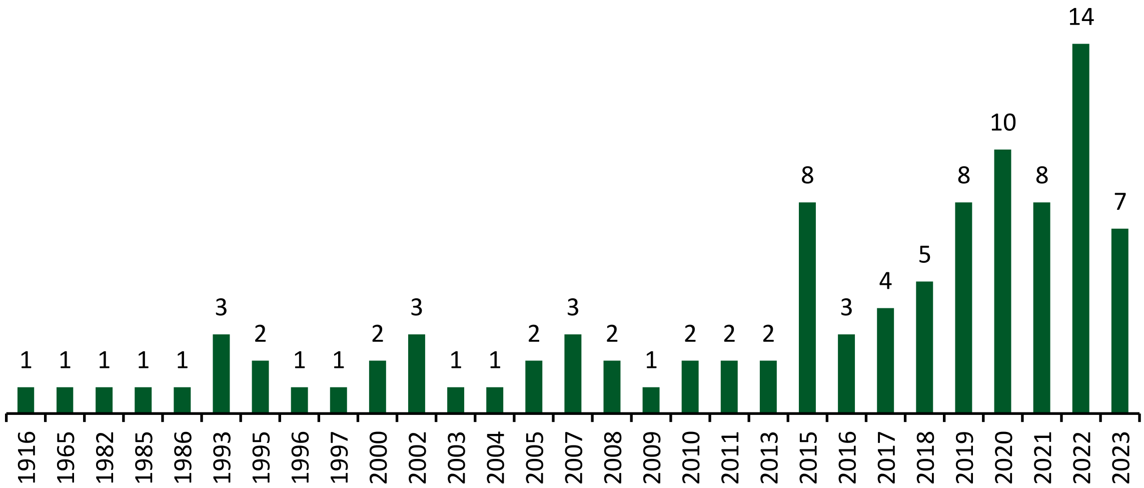

Figure 1. Distribution by the publication year of papers included in the final review

2.2. Research methodology

To conduct this systematic literature research, these electronic bibliographic databases have been used: ACM digital library, Scopus, Science direct, Dblp, Open Alex, and Google Scholar. Notably, 70% of the selected articles were either from Scopus or ScienceDirect. Keep in mind that the search was limited to specific reference dates, because we were interested in both old and recent publications (Figure 1). Additionally, only studies published in French or English were included.

The search process started by using the word "drought" as a principal keyword to select the articles. The first step was to identify articles that addressed drought. Articles were categorized into six principal themes based on titles and abstracts: characterization/monitoring of drought, drought indices, drought definitions, drought stress in agriculture, assessment of drought impact, and vulnerability assessment of drought. Only the first three themes of interest were selected based on the predefined objectives of this study. These include drought characterization/monitoring, drought indices, and definitions. The second step was to use these themes as keywords. Thus, 481 articles were selected from different electronic bibliographic databases, and based on the inclusion or exclusion criteria, only 221 papers were screened. After reading all of these articles, only 86 papers were selected and included in the final review.

Figure 2 and Table 2 illustrate the research process and criteria selection (inclusion/exclusion criteria). The inclusion criteria were: papers responding to the research questions of the SLR, papers responding to the study objectives, papers from journals or books, and the language of the articles. The exclusion criteria were as follows: papers that did not deal with the theme of drought, doctoral theses, and duplicates.

In addition to the literature review on drought, we studied the geographic distribution of published research on Scopus in the last decade. For this purpose, Scopus publications from 2012 to 2022 were used to create a map of drought publications based on their spatial distribution. The number of publications by country was retrieved using Harzing's Publish or Perish software. The search was conducted by country to develop an Excel database containing the number of studies by country. Data were processed using a geographic information system (ArcGIS 10.8) by creating homogenous areas based on the number of publication classes (Figure 2).

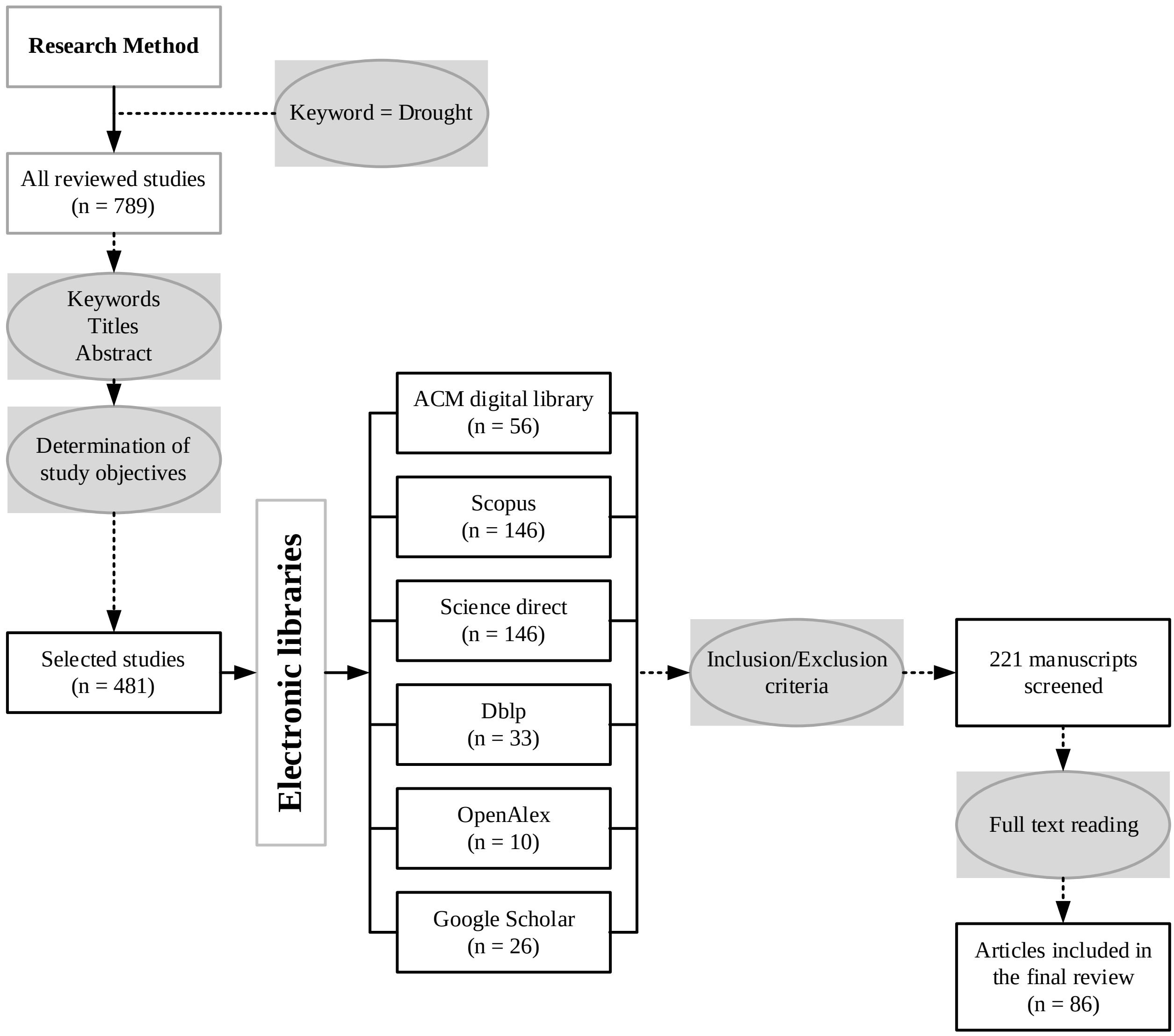

Figure 2. SLR Research process

Table 2. Inclusion and exclusion criteria used in this SLR

Inclusion criteria	Papers responding to research questions of the SLR Papers responding to the study objectives Papers from journals or books The language of the article is either French or English
Exclusion criteria	Papers that don't deal with the theme of drought Doctoral thesis Duplicates

3. RESULTS AND DISCUSSION

This paper summarizes the literature review based on three principal themes: definitions of drought, drought characterization, and indices for drought monitoring.

3.1. Drought definitions

Given its complexity, drought has several definitions. Indeed, drought is difficult to understand and define (Wilhite, 1993) even though it is a pervasive and harmful natural disaster (Wilhite & Glantz, 1985). Originally, drought as a term came from the Old English term "drugað" and the German root dreug, which means "dry." Currently, this term is generally used to characterize a period in a specific location where there is insufficient water (Funk & Shukla, 2020).

Drought has been described in several ways. The founding definitions of drought (Wilhite, 1993; Wilhite & Glantz, 1985) highlight four key aspects: slow drought emergence, the multifaceted and multisectoral nature of droughts, the multidimensional aspects of droughts (duration, extent and intensity), and the complexity of drought results. Wilhite and Glantz (1985) linked drought to long-term average conditions of equilibrium between evapotranspiration and precipitation in a specific area, a condition often judged as "normal". (Alexander, 1993) defined drought as a state of abnormally dry weather related to a severe hydrological mismatch with negative impacts such as crop failures and water shortages for humans and livestock. According to water resource-based definitions that consider water needs related to the social, economic, and biological characteristics of a specific area, drought is linked to the random condition of a drastic reduction in water availability (compared with the normal value), extending over a significant period over a large region (Rossi, 2000).

Tate and Gustard (2000) defined drought as a phenomenon characterized by slowness, deception, hazard, and complexity, resulting from a lack of precipitation compared to what is normal, which directly affects both environmental and human demands. According to (Pereira et al., 2009), drought is a temporary imbalance in water availability consisting of persistent below-average precipitation that results in a decrease in the availability of water resources. This definition indicates that drought is caused by the rupture of the rainfall regime. Another study described this phenomenon as a period of dry weather (Nagarajan, 2003). Sultana et al. (2021) integrated the notion of soil moisture into their definition. They defined drought as a climatic issue characterized by an insufficient supply of soil moisture caused by below-normal rainfall, an irregular distribution of precipitation, higher crop water requirements, or a combination of these three factors.

3.2. Drought categories

According to the American Meteorological Society and Wilhite and Glantz (1985), four categories of droughts have been determined: meteorological, agricultural, hydrological, and socioeconomic. Other studies have divided drought into the aforementioned categories, in addition to ecological drought (Crausbay et al., 2017; Wilhite & Glantz, 1985). In the next section, we highlight the definition of each category.

3.2.1. Meteorological drought

Meteorological drought is described as an overall deficit in annual precipitation compared to the average of several years over a specified period. It is also characterized by a reduction or bad distribution, even in the absence of rain in a given region for some time (Faye, 2023). It occurs following a rise in atmospheric temperature, leading to a significant fall in average rainfall for an extended duration over a region (Kumar et al., 2019).

Most meteorological droughts tend to have shorter durations, ranging from days to weeks but are also expected to span months or seasons (Yu et al., 2020). Meteorological droughts directly affect the environment, and if prolonged, trigger agricultural and hydrological droughts (Yu et al., 2020). Meteorological droughts are considered to be early warning indicators of significant drought events.

Typically, meteorological drought is closely related to physical factors such as variations in precipitation and temperature, resulting in an inevitable episode of drought (Gholizadeh et al., 2022).

3.2.2. Agricultural drought

Droughts are usually triggered by a period of rainfall scarcity, with the quantity of rainfall below the long-term average (Abdourahamane et al., 2022), known as meteorological drought. This can result in a decrease in the soil moisture, which affects agricultural productivity (Abdourahamane et al., 2022). As a consequence, agricultural drought is a result of meteorological drought. Agricultural drought is characterized by an extremely dry period that decreases soil moisture levels and hinders crop development. This type of drought occurs when the quantity of water required for crops and evapotranspiration exceeds available soil moisture. The severity of a drought depends closely on seasonal variations in rainfall, varying from mild to extreme conditions. Agricultural drought begins when plant roots cannot acquire soil moisture quickly enough to maintain the internal water balance of the crops (Mladenova et al., 2020). Agricultural drought also results from low and irregular rainfall and/or increased crop water demand (evapotranspiration) (Hadri et al., 2021).

Consecutive droughts cause losses of land, crop yield, and quality (Li et al., 2015). In addition, assessing and monitoring droughts impact on crops is crucial for better management of agriculture and implementation of adaptation strategies to reduce damaging effects of agricultural drought (Nam et al., 2022; Van Huong et al., 2022).

3.2.3. Hydrological drought

This drought category is simply described as the difference between the time series of water supply and demand. The supply time series is characterized by a river flow versus the demand time series, which characterizes the demand of a particular user, or simply by the total demand of all users. When demand is higher than supply, water shortages occur; in this direction, the beginning of storage is a barometer of water shortages (Tareke & Awoke, 2022). Achite et al. (2023) defined this kind of drought as a lack of groundwater supplies or streamflow shortages. Other researchers have defined hydrological drought as a significant reduction in available water (surface and underground water). Hydrological droughts depend on the time of onset, duration, and frequency of occurrence (Sultana et al., 2021).

3.2.4. Socio-economic drought

If one of the three drought categories previously quoted (meteorological, agricultural, and hydrological) negatively impacts society by causing water shortages, food crises, migrations, and conflicts and impacts the economy by significantly increasing the prices of water, food, and other related products, a socioeconomic drought automatically occurs (Abdourahamane et al., 2022; Mogano & Mokoele, 2019). Crausbay et al. (2017) demonstrated that socioeconomic drought occurs when the demand for water does not meet the domestic supply.

In 2015, the United Nations defined Sustainable Development Goals (SDGs), including clear goals aimed at improving people's conditions around the world. Indeed, drought directly compound water stress, menaces human food security, lead to environmental and ecological crises, increases poverty, and hinders sustainable development (Zhang & Yuan, 2020). In summary, drought is a costliest natural hazard worldwide and negatively affects society and the environment. Droughts have led to annual losses estimated at US$6-8 billion, which is higher than that of other weather-related disasters (Sun et al., 2022).

3.3. Indices for drought monitoring

Many drought indices have been introduced and used in various ways in the literature. Drought indices can be classified based on their nature, such as meteorological, agricultural, or hydrological indices. They can also be classified using the nature of the drought index as climate, remote sensing, or composite. We present indices that are generally adopted to assess drought over time.

3.3.1. Simple indices

3.3.1.1. Climatic indices

Drought indices that use climatic parameters allow quantitative and qualitative assessments of drought by monitoring drought characteristics such as amplitude, duration and spatial extent (Sahoo et al., 2015). Most studies aimed at characterizing drought have used simple univariate or multivariate indices. Drought monitoring and identification efforts typically involve creating an index that can include a single relevant variable or a combination of variables. For example, the Standardized Precipitation Index (SPI) uses only precipitation and is sufficient to characterize meteorological drought. However, when considering longer-term conditions such as agricultural drought, precipitation alone may not be significant in characterizing other ground conditions such as soil moisture and atmospheric demand from the land surface. In addition, univariate indices cannot be enough for a good drought monitoring; as a result, they can hinder the correct decision (Wei, Zhang, Zhou, Xie, et al., 2021; Won et al., 2020).

For fire risk assessment in the Pacific Northwest, Munger (1916) adopted a drought index calculated using the number of consecutive days for which the rainfall recorded during 24-hour was below 1.27 mm. Subsequently, he devised a graphical method to illustrate drought intensity exploiting the area of a right-angled triangle, whose height and base are proportional to the drought duration. Half of the square of the drought duration in days yields the Munger index equation.

In 1965, Palmer developed a meteorological index called the Palmer Drought Severity Index (PDSI), which was used to obtain a specific definition of drought and to compare drought episodes using a specific technique. He noted that there are several definitions of drought and that it is difficult to precisely define their meaning. However, He ended up affirming that all drought indices deal with the variations in water scarcity and simply defined drought as a prolonged and abnormal lack of moisture". Generalizing the definition of drought helped Palmer derive an index that may be adopted with all definitions of drought (PDSI) (Moorhead et al., 2015). This index identifies and assesses the severity of drought events and determines the onset, end, and severity of the drought (Yan et al., 2013). This index is a crucial first step in developing drought indices, as it has often been used to evaluate drought and wet conditions, without considering temporal scales (Wang et al., 2015). Although referred to as a meteorological drought index, the PDSI focuses on evapotranspiration, precipitation and soil moisture conditions (Yan et al., 2013). It uses a water balance model to determine moisture availability in the study region (Palmer, 1963).

Using meteorological approach for monitoring agricultural drought is inappropriate, the Crop Moisture Index (CMI) was developed by Palmer in 1968 as a tool for monitoring drought in agricultural regions. This index estimates the short-term changes in soil moisture that impact crop growth. Except for responding faster to change conditions than the PSDSI, the CMI is similar to the PDSI in terms of its limitations and complexity, as noted by Moorhead et al. (2015). The CMI is based on a water balance model to analyze the precipitation and temperature data.

The Surface Water Supply Index (SWSI) was introduced by Shafer (1982) to ameliorate the PDSI limits. Indeed, SWSI is specifically adopted to quantify hydrological drought and is based on the non-exceedance probabilities of precipitation, reservoir storage, snow accumulation, and stream flow. The fact that SWSI is oriented to monitor surface water supplies explains its limits in monitoring agricultural drought

(Moorhead et al., 2015). To calculate this index, four hydrometeorological components are used: precipitation, snowpack, streamflow, and reservoir storage, based on the probability distributions of the monthly time series of the individual component indices. Also, this is an adequate drought indicator for snow-dominated regions. SWSI was calculated using the mathematical Formula 1 mentioned in Table 3. Also, the drought classification using SWSI is presented in Table 4.

In 1986, Karl developed the Palmer Hydrological Drought Index (PHDI). It is a drought index derived from the PDSI and used to assess hydrological drought. This index is easy to calculate using a simple water-balance model based on temperature and precipitation (Shin et al., 2020). In summary, the PHDI and PDSI were calculated using the ratio Pe (0-100%) of the moisture received to the moisture required, with a small difference. Indeed, the drought ended when Pe was greater than 0% for the PDSI, while it ended when Pe reached 100% for the PHDI (Karl, 1986). The drought classification using the PHDI is presented in Table 5.

The Standardized Precipitation Index (SPI) was developed by McKee et al. (1993) to overcome the shortcomings of the PDSI. SPI was developed based on standardized precipitation to create an index for defining drought. It is characterized by its simplicity in calculating and its ability to use multiple timescales and parameters (Abu Hajar et al., 2019; Moghbeli et al., 2020; Zhim et al., 2019).

One weakness of this index is that the use of a single input (precipitation) does not highlight the totality of factors that can influence drought. To achieve reliable results, it is crucial to rely on long-term rainfall series (Dutta et al., 2015); the optimal period is approximately 50–60 years (Cammalleri et al., 2022; Svoboda et al., 2015). According to McKee et al. (1993), the analysis of different series of SPIs allows the differentiation of two types of droughts: the first one represents short-term droughts that are related to the time scales of 1, 3, and 6 months, whereas the ones related to the time scales of 12, 24, and 48 months represent long-term droughts. It should be emphasized that short-term timescales are very sensitive to moisture conditions and are particularly adopted for meteorological and agricultural drought studies, as opposed to long-term timescales that are adopted for hydrological drought studies. SPI was calculated using Formula 2 as mentioned in Table 3. The degree of drought was classified into five levels according to the SPI values: no drought, mild drought, moderate drought, severe drought, and extreme drought (Table 6).

Narasimhan and Srinivasan (2005) developed two agricultural drought indices to overcome the shortcomings of the PDSI and SPI. These are the Evapotranspiration Deficit Index (ETDI) and the Soil Moisture Deficit Index (SMDI). Owing to the variability in precipitation and soil characteristics, a finer resolution that uses these factors is preferred for drought indices. To calculate the ETDI, we first calculated the weekly water stress ratio (WS) according to Formula 3 cited in Table 3. The calculation and interpretation methods are described in detail in Narasimhan and Srinivasan (2005) and Moorhead et al. (2015).

Table 3. The formulas used to calculate drought indices

Drought index	Formula	Formula details
Surface Water Supply Index	$$SWSI_t = \frac{W_1 P_t^{snow} + W_2 P_t^{prec} + W_3 P_t^{strm} + W_4 P_t^{resv} - 50}{12} \quad (1)$$	w_1, w_2, w_3, and w_4: weights for each hydrometeorological component, $w_1 + w_2 + w_3 + w_4 = 1$ t: monthly time step P_t: non-exceedance probability (in %) for component i snow: snowpack at time t prec: precipitation at time t strm: streamflow at time t resv: reservoir storage at time t
Standardized Precipitation Index	$$\mathrm{SPI} = \frac{(X_i - X_m)}{S_i} \quad (2)$$	X_i: cumulative rainfall for a year X_m: average annual rainfall observed for a given series S_i: standard deviation of annual rainfall observed for a given series
weekly water stress ratio	$$\mathrm{WS} = \frac{PET - AET}{PET} \quad (3)$$	AET: actual evapotranspiration PET: potential evapotranspiration
Vegetation Condition Index	$$\mathrm{VCI} = \frac{\mathrm{NDVIi,j} - \mathrm{NDVIi,min}}{NDVIi,\mathrm{max} - \mathrm{NDVIi,min}} \quad (4)$$	$NDVI_{i,j}$: NDVI for pixel i at time j $NDVI_{i,\ min}$: long time-series minimum NDVI for pixel i $NDVI_{i,max}$: long time-series maximum NDVI for pixel i
Temperature Condition Index	$$\mathrm{TCI} = \frac{\mathrm{LSTi,max} - \mathrm{LSTi,j}}{\mathrm{LSTi,max} - \mathrm{LSTi,min}} \quad (5)$$	$LST_{i,j}$: LST for pixel i at time j $LST_{i,min}$: long time series minimum LST for pixel i $LST_{i,max}$:long time-series maximum LST for pixel i
Vegetation Health Index	$$\mathrm{VHI} = \mathrm{a} \times \mathrm{VCI} + (1 - \mathrm{a}) \times \mathrm{TCI} \quad (6)$$	a and (1-a) specify the relative contributions of the VCI and TCI to the value of the VHI

Table 4. Drought classification using SWSI

Drought categories	SWSI range
Extremely wet	3.1 - 4.2
Moderately wet	2.1 - 3.0
Slightly wet	1.1 - 2.0
Near-average	(-0.9) - 1.0
Slightly dry	(-1.9) - (-1.0)
Moderately dry	(-2.9) - (-2.0)
Extremely dry	(-4.2) - (-3.0)

Table 5. Drought classification according to PHDI

Drought categories	PHDI
Extremely dry	≤ (-4.0)
Severely dry	(-3.99) - (-3.00)
Moderately dry	(-2.99) - (-2.00)
Near normal	(-1.99) - 1.99
Moderately wet	2.00 - 2.99
Severely wet	3.00 - 3.99
Extremely wet	≥ 4.0

Table 6. Drought intensity classification according to SPI and SPEI indices

Drought intensity	Range of SPI	Range of SPEI
Extremely dry	2.0 ≤ SPI	1.83 ≤ SPEI
Severely dry	2 < SPI < 1.5	1.82 < SPEI < 1.43
Moderately dry	1.49 < SPI < 1.0	1.42 < SPEI < 1.0
Near normal	(-1.0) ≤ SPI ≤ 1.0	(-1.0) ≤ SPEI ≤ 1.0
Moderate drought	(-1.49) < SPI < (-1.0)	(-1.42) < SPEI < (-1.0)
Severe drought	(-2.0) < SPI < (-1.5)	(-1.82) < SPEI < (-1.43)
Extreme drought	SPI ≤ (-2.0)	SPEI ≤ (-1.83)

The Recognition Drought Index (RDI) was first introduced by Tsakiris and Vangelis (2005). This index is more reliable for characterizing meteorological droughts in arid and semiarid zones. It uses natural factors affecting drought, like evapotranspiration, precipitation, and soil and vegetation cover characteristics. Additionally, this index is powerful for both meteorological and agricultural drought (Mohammed, 2021). Similar to SPI, the RDI can be computed for any time scale. The estimation method for this index is detailed by Moorhead et al. (2015) and Achite et al. (2023).

The Standardized Precipitation Evapotranspiration Index (SPEI) was introduced by Vicente-Serrano et al. (2010). The SPEI is a multiscale drought index that evaluates the balance between precipitation and PET. The SPEI calculation should be preceded by the estimation of the ETo. Vicente-Serrano et al. (2010) used Thornthwaite's method (1948), however, he emphasized that there are other methods that are suitable for SPEI calculation. Alike SPI, the SPEI adapts for different drought definitions because it may be computed on multiple time scales. Additionally, as the SPEI calculation is based on Eto estimation, it considers variations in temperature, wind speed, and other parameters that affect drought (Moorhead et al., 2015). The threshold values of the SPEI are listed in Table 6.

In addition to the aforementioned indices, several other climatic indices have been suggested. These include the Accumulated Drought Index (ADI) (Sivakumar et al., 2011), Relative Water Deficit (RWD) (Sivakumar et al., 2011), and the streamflow drought index (SDI) (Nalbantis & Tsakiris, 2009). In summary, each of these indices has strengths, as well as the limitations analyzed in Table 7.

3.3.1.2. Remote sensing indices

Several indices based on remote sensing data, called satellite-based indices, have been introduced in last years to effectively monitor drought. These have proven to be promising approaches to drought monitoring. They provide real time spatiotemporal monitoring of Earth's surface changes (Ma et al., 2021). The accuracy of conventional indices faces many constraints such as data gaps, inappropriate monitoring networks, and data unavailability at the required spatiotemporal scales (Bageshree et al., 2022). In addition, these traditional indices depend closely on ground-based hydrometeorological data, which are typically obtained from individual meteorological stations, and the density and distribution of ground station networks are limited and not representative (Danandeh Mehr et al., 2023). According to Huang et al. (2018), meteorological stations show their limits at the regional level, because it is difficult to cover very large areas with sufficient stations. In other words, scattered meteorological data obtained from these large areas are inevitably insufficient to detect timely drought, monitor it, and make decisions regarding it (Mustafa Alee et al., 2023). Remote sensing-based indices have several advantages such as good resolution, near real-time, and consistent data observations (AghaKouchak et al., 2015). In the next section, we present the most widely used remote-sensing drought indices.

Vegetation Condition Index (VCI) was introduced by Kogan (1995b). It uses the Normalized Difference Vegetation Index (NDVI) obtained from satellite data. The NDVI is a vegetation and remote sensing index that measures plant health and plant area of coverage in a broad sense. The NDVI values range between −1.0 and 1.0 (Mustafa Alee et al., 2023). The VCI is calculated for each pixel and month of the year, considering the range of NDVI for each location. Formula 4 (Table 3) was used to calculate this index. It directly measures vegetation health and assesses the duration, intensity, and impact of drought worldwide with good spatial resolution (Karimi et al., 2022).

Temperature Condition Index (TCI): The algorithm for TCI is Land Surface Temperature (LST) normalization for each pixel using the maximum and minimum temperatures in the given time series. It was computed using the Formula 5 cited in Table 3 (Kogan, 1997). LST as a variable is crucial for characterizing agricultural drought because it indirectly represents soil evapotranspiration (Waseem et al., 2015).

The Vegetation Health Index (VHI) was developed by Kogan (1995b, 1997). As a combination between VCI and TCI, the VHI was calculated using the Formula 6 mentioned in Table 3. Obviously, the VHI allows to characterize better drought compared to each of VCI and TCI individually.

The Standardized Vegetation Index (SVI) was introduced by Peters et al. (2002). It is based on a normalization procedure for the NDVI derived from satellite data.

Table 7. Strengths and limits of climatic drought indices

Indices	Strengths	Limitations
The Palmer Drought Severity Index (PDSI)	- Well adapted to assess agricultural drought - Appropriate for long term condition	- Responds slowly to detect short-term dry spells - Needs a complete series of data - Needs large spatial lumping of physical parameters - Does not account for the effect of land use/land cover on the water balance
Standardized Precipitation Index (SPI)	- Easy to compute for any time scale and parameter - Appropriate to characterize meteorological drought	- Univariate, Use only precipitation as an input - Sensitive to the length of the precipitation record (needs long-term rainfall series)
Crop Moisture Index (CMI)	- Appropriate for short-term agricultural drought - Responds faster to changing conditions compared to PDSI	- Assumes that parameters like land use/land cover and soil properties are unchanged for all climatic regions
The Surface Water Supply Index (SWSI)	- Good to monitor agricultural drought	- Not adapted for agricultural drought
Palmer Hydrological Drought Index (PHDI)	- Easy to calculate using a simple water-balance	- Frequencies vary by region and time of year
Evapotranspiration Deficit Index (ETDI) Soil Moisture Deficit Index (SMDI)	- Useful to assess agricultural drought	- Takes into account solely the modeled soil moisture and evapotranspiration deficits, disregarding soil properties under various climate conditions.
The Recognition Drought Index (RDI)	- Low data requirements - Powerful for both meteorological and agricultural drought - Can be calculated at any time scale	- More reliable in arid and semiarid regions
The Standardized Precipitation Evapotranspiration Index (SPEI)	- Can be calculated on multiple time scales	- Sensitivity to evapotranspiration estimation

Table 8. Principal remote sensing drought indices

Drought index	Variables	References
Vegetation Condition Index (VCI)	NDVI	Kogan (1995a, 1995b)
Temperature Condition Index (TCI)	NDVI	Kogan (1995a, 1997)
Vegetation Health Index (VHI)	NDVI, LST	Kogan (1995a, 1995b, 1997)
Normalized Difference Water Quantity Index (NDWI)	Green, NIR	McFeeters (1996)
Temperature Vegetation Dryness Index (TVDI)	NDVI, LST	Sandholt et al. (2002)
Vegetation Drought Response Index (VegDRI)	Precipitation, Temperature, Available water content, Land cover, Ecoregion	Brown et al. (2008); Tadesse et al. (2017)
Vegetation Temperature Condition Index (VTCI)	NDVI, LST	Sun et al. (2008)
Perpendicular Drought Index (PDI)	NIR, Red	Ghulam, Qin and Zhan (2007)
Modified Perpendicular Drought Index (MPDI)	NIR, Red	Ghulam, Qin, Teyip, et al. (2007)
Stress index based on evaporation (ESI)	ET, PET	Anderson et al. (2011); Anderson et al. (2007)
Drought Severity Index (DSI)	NDVI, ET, PET	Mu et al. (2013)

The similarity between The SVI and VCI, especially in that both showed the same limitations for agricultural drought monitoring.

Huang et al. (2018) showed that DSI is suitable to monitor agricultural drought by evaluating the performance of three typical drought indices based on remote sensing: Drought Severity Index (DSI), Vegetation Drought (TVDI), and Vegetation Health Index (VHI). Accepting that remotely sensed drought indices for agricultural drought monitoring have many advantages, it is to mention their limitations. For example, NDVI exhibits a delayed response to drought (Liu et al., 2018). Thus, VHI and LST, which were calculated using NDVI, had the same response. The estimation of the latter is affected by the morphological characteristics of different crops at different growth stages on the surface emissivity (Wang & Wang, 2022). In addition, TVDI is closely impacted by the uncertainty of the NDVI and LST (Huang et al., 2018). Table 8 summarizes informations related to the principal remote sensing drought indices found in the literature.

3.3.2. Composite indices

Drought is among the most dangerous and risky natural hazards worldwide, affecting many people in several ways. Therefore, it is important to continuously improve comprehensive and monitoring assessments, as multivariate or univariate drought indices can monitor one type of drought, but cannot provide complete information about drought from meteorological to agricultural aspects. Thus, there is no single drought index for any type of drought in a specific region (Tian et al., 2018). In addition, the physical categories of drought are linked; therefore, a single index is not sufficient to quantify the combined effects of these three types of droughts (Abdourahamane et al., 2022). In addition, all available drought indices have limitations (Tareke & Awoke, 2022). To overcome these problems, a new type of index was introduced. These are composite drought indices that combine different drought indicators into individual indices.

Recently, many researchers (Abdourahamane et al., 2022; Bageshree et al., 2022; Hao et al., 2015; Karimi et al., 2022) have focused on integrating composite drought indices to optimize drought monitoring. Bageshree et al. (2022) proposed a multivariate joint drought index (JDI) for the assessment of agricultural drought in semiarid regions. This index combines the Standardized Precipitation Index (SPI), Soil Moisture (SSI), Standardized Groundwater index (SGI), and Standardized Runoff Index (SRI). In addition, this study proves that JDI is efficient in characterizing the combined effects of drought. For the same purpose, Karimi et al. (2022) integrated four satellite-based drought indices to develop a composite drought index as a meteorological and agricultural drought index. These indices include the Precipitation Condition Index (PCI), Soil Water Index (SWI), Temperature Condition Index (TCI), and Vegetation Condition Index (VCI). For appropriate agricultural drought monitoring, Lee et al. (2021) developed an Integrated Crop Drought Index (ICDI) that integrated meteorological, hydrological, and vegetation factors. For example, the Vegetation Drought Response Index (VegDRI) incorporates SPI, PDSI, NDVI, and biophysical data (Brown et al., 2008). The scaled Drought Condition Index (SDCI) integrates the VCI, TCI, and precipitation condition indices (Wei, Zhang, Zhou, Zhou, et al., 2021). Zhang et al. (2017) conducted a work that evaluates the performance of 13 remotely sensed drought indices across the continental United States to study drought phenomena. They concluded that there was variation in the usefulness of drought indices among the climatic zones. Therefore, the authors proposed the use of combined or composite indices.

Several methods have been used to create composite drought indices using multiple indicators, such as Copula Functions (Liu et al., 2019), multivariable linear regression (Liu et al., 2020), Principal Component Analysis (PCA) (Abdourahamane et al., 2022; Bageshree et al., 2022), and Ordered Weighted Averaging (OWA) (Zhu et al., 2018). Principal Component Analysis was used to reduce the dimensionality of a dataset containing a large number of correlated variables by reconstructing a smaller collection while retaining the majority of the information from the original data. The use of this method was first discussed by Keyantash and Dracup (2004), who introduced the Aggregate Drought Index (ADI).

3.4. Introducing the modified drought indices

Several studies have proposed modified drought indices based on existing indices. The next section presents and discusses some of these adaptations.

3.4.1. Modified Reconnaissance Drought Index

The Reconnaissance Drought Index (RDI) is a universal meteorological drought index. It is used as an effective index for agricultural drought assessment, but its use of total precipitation does not allow for precise characterization of agricultural drought. To improve the performance of agricultural drought analysis, Tigkas et al. (2016) suggested a new version of this index, the Modified Reconnaissance Drought Index (RDIe). The RDIe uses the effective precipitation and total precipitation. Effective precipitation, a contributing factor to agricultural production, is the quantity of water that the root systems of plants can use effectively (Tigkas et al., 2016).

The calculation method for RDIe remains the same and replaces total precipitation by effective precipitation (Tigkas et al., 2016).

3.4.2. Agricultural Standardized Precipitation Index

Tigkas et al. (2019) suggested modifying the SPI meteorological index to adapt to agricultural drought. They introduced a new index called the Agricultural Standardized Precipitation Index (aSPI)". SPI and aSPI are similar because they use only meteorological input data, except that effective precipitation is used instead of the total precipitation in the aSPI.

3.5. Geographic distribution of Scopus published research in the last decade

To emphasize that drought research attracts only countries or regions characterized by arid and semi-arid climates, a map of the spatial distribution of drought publications was created (Figure 3). As illustrated on the map, China has the highest number of publications, followed by India. China contributed to 8% of the publications in Scopus. The Mediterranean region, which stands out for the number of extreme climatic conditions, namely drought and flooding, Spain distinguishes itself as being in 6th place, with several publications that exceed 1400/10 years.

By analyzing the data, it was observed that countries that have been suffering from drought are the most studied. For example, China, one of the major ‘‘hot spots’’ for high-intensity droughts, has faced extreme droughts that have had a negative socioeconomic impact in the last decades (Herrera-Estrada et al., 2017; Yao et al., 2020) and will continue to face more extreme droughts in the future (Yao et al., 2020). India has also experienced many severe drought periods and has recorded a large history of droughts that have negatively impacted the environment and economy (Shah & Mishra, 2020). In addition, the number of publications in Australia is high because of its sensitivity to droughts.

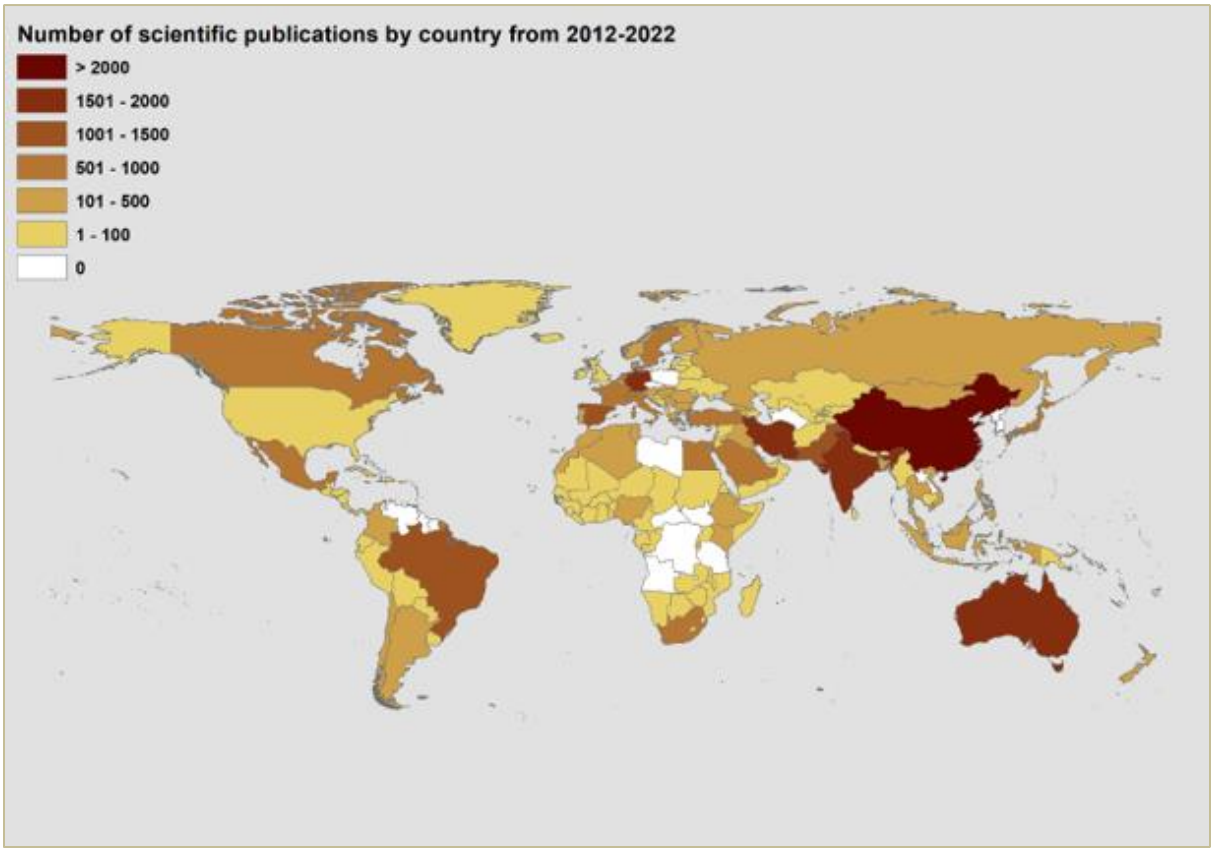

Figure 3. Number of SCOPUS publications by Country during 2012-2022

In addition, it is obvious that countries located in tropical regions are characterized by low publication numbers, which is proven by the absence of drought problems in these areas, such as Angola, the Central African Republic, the Democratic Republic of the Congo, Tanzania, and Venezuela.

During the last few years, 195 countries have published fewer than 10 publications per year in Scopus, with 77 countries with no publications. Concerning Morocco, the figures show that the number of publications (144 publications/10 years or 14 publications/year) remains very low given the present nationwide water shortage and the number of drought periods experienced.

CONCLUSION

Drought is a long-lasting natural phenomenon with complex connections to agriculture, hydrology, meteorology, society, and the economy, making it challenging to precisely define. Drought indices fall into climatic and remote sensing categories, with composite indices enhancing the monitoring. As climate change intensifies droughts, immediate, coordinated action is needed to improve monitoring, utilize Earth observation data, and develop customized strategies for at-risk regions. This study highlights the urgent need to address the increasing challenges posed by droughts in the context of climate change.

Declaration of Competing Interest

The authors declare that no competing financial or personal interests that may appear and influence the work reported in this paper.

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