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Article *in* Current Climate Change Reports · June 2018

DOI: 10.1007/s40641-018-0098-x

Current Climate Change Reports
https://doi.org/10.1007/s40641-018-0098-x

Climate Change and Drought: a Perspective on Drought Indices

Sourav Mukherjee [1] · Ashok Mishra [1] · Kevin E. Trenberth [2]

Abstract
Droughts occur naturally, but climate change has generally accelerated the hydrological processes to make them set in quicker and become more intense, with many consequences, not the least of which is increased wildfire risk. There are different types of drought being studied, such as meteorological, agricultural, hydrological, and socioeconomic droughts; however, a lack of unanimous definition complicates drought study. Drought indices are used as proxies to track and quantify droughts; therefore, accurate formulation of robust drought indices is important to investigate drought characteristics under the warming climate. Because different drought indices show different degrees of sensitivity to the same level of continental warming, robustness of drought indices against change in temperature and other variables should be prioritized. A formulation of drought indices without considering the factors that govern the background state may lead to drought artifacts under a warming climate. Consideration of downscaling techniques, availability of climate data, estimation of potential evapotranspiration (PET), baseline period, non-stationary climate information, and anthropogenic forcing can be additional challenges for a reliable drought assessment under climate change. As one formulation of PET based on temperatures can lead to overestimation of future drying, estimation of PET based on the energy budget framework can be a better approach compared to only temperature-based equations. Although the performance of drought indicators can be improved by incorporating reliable soil moisture estimates, a challenge arises due to limited reliable observed data for verification. Moreover, the uncertainties associated with meteorological forcings in hydrological models can lead to unreliable soil moisture estimates under climate change scenarios.

Keywords Drought indices · Climate change · Drought assessment · Global warming

Overview of Drought Indices

Drought is an extreme climatic event that is insidious in nature because it develops slowly and often sneaks up on one [1]. As it gradually increases in intensity and duration, it can have major consequences, making it one of the costliest natural hazards [1]. Moreover, drought has multiple eco-hydrological and socioeconomic impacts [2] including *increased risk of wildfire* [3], *water scarcity* [4], *loss of crops* [5] and *livestock* [6], *increased food prices* [7], *migration* [8], and *indirect health effects* [9]. The physical processes involved in drought are highly non-linear and involve feedbacks, and its impact propagates through multiple levels unequally that often cannot be quantified objectively [10]. Consequently, it is difficult to have a universal definition for drought [10].

However, drought definitions can be broadly categorized as either conceptual or operational [11]. *Conceptual* definition outlines the basic drought concepts with a general description of the physical processes involved, such as shortage of precipitation (meteorological drought), shortage of soil moisture (agricultural drought), shortage of water in lakes and streams (hydrological drought), and shortage of water for use by society related to water management [1, 12]. None of these are necessarily correct or wrong, and thus, all need to be recognized. On the other hand, *operational* definition focuses at identifying the onset, duration, and termination of drought episodes including their severity [1, 12]. Operational definitions aim at providing precise drought-related information to support an effective early warning system [12]. Apart from the

This article is part of the Topical Collection on *Climate Change and Drought*

✉ Ashok Mishra
ashokm@g.clemson.edu

[1] Glenn Department of Civil Engineering, Clemson University, Clemson, SC, USA

[2] National Center for Atmospheric Research, Boulder, CO, USA

Published online: 23 April 2018

above definitions, a legal definition of drought is also available [13]. In addition to the effect of drought being context-dependent, drought definitions such as that of *operational drought* [4] and *socioeconomic drought* [1, 11] are also in existence. Generalized definition of drought can be developed only through the aggregation of process-specific instantaneous droughts [10]. But, this definition is based on the assumption that these processes are in equilibrium with the long-term climate, thereby overlooking the distinction between drought and water scarcity [10, 14]. Thus, numerous and diverse disciplines adopt different drought definitions depending on the stakeholder's need as well as hydroclimatic variables included [1, 12].

Consistency among these drought definitions is a key to remove any ambiguity in framing drought policies and making decisions. The corresponding decision support tools rely on indicators and indices that are widely used to quantify the physical characteristics of drought (intensity, duration, and severity) [15]. Drought indicators and drought indices are formulated to track the hydrological cycles and are used interchangeably in drought-monitoring community [16]. *Drought indicators* are used in a broader sense that aggregate parameters such as precipitation, temperature, streamflow, groundwater levels, reservoir levels, snowpacks, soil moisture levels, and drought indices [16]. On the other hand, *drought indices* are single numeric values estimated from various hydroclimatic variables that influence drought and, therefore, it has a significant advantage over mere raw data in quantifying drought characteristics [16].

Drought assessment studies have made considerable progress so far in developing several drought indices applicable to various types of drought [1], such as Standardized Precipitation Index (SPI) for *meteorological drought* [17], Standardized Runoff Index (SRI) for *hydrological drought* [11, 18], and soil moisture percentiles for *agricultural drought* [1, 19] However, the development and choice of drought indices should be specific to the primitive as well as newly emerging real-world problems and, therefore, it depends on several factors [1]. The following section provides an overview of some of the critical factors associated with formulation of drought indices:

1. *Types of drought*: The interconnection between various types of drought that occur simultaneously or sequentially makes it difficult to distinguish between one drought type from the other [20]. For example, the propagation of meteorological drought (which is caused mainly by precipitation deficit) to agricultural (caused by soil moisture deficit) and hydrological (deficit in water storage or streamflow) drought is non-linear in nature [21, 22]. In addition, the impact of meteorological drought shifts prominently towards soil moisture (agricultural drought) that further propagates to cause water storage deficits (hydrological drought) for even longer durations (Fig. 1) [23]. This complicates the formulation of drought indices with a view of quantifying a specific type of drought independent of the others.
2. *Drought characteristic*: Drought events have multiple and interrelated characteristics such as severity, duration, peak intensity, and recurrence interval [24, 25]. Each of these characteristics may have a considerable influence on the impacts of drought. Consequently, monitoring natural and socioeconomic drought needs a joint assessment of individual drought characteristics as well as identifying the most dominant drought event specific to the impact being studied [21]. Moreover, in arid regions that naturally receive scanty or no rainfall, thereby always at the verge for water shortage, drought characteristics estimated in relative terms and absolute terms will be significantly different. In other words, the climatology of a specific region can influence drought characteristics significantly, especially if drought is measured in terms of anomalies.
3. *Climate change*: Impact of drought under a global warming scenario is more likely to aggravate in the future [26, 27]. Of course droughts have always occurred, and the variability in sea surface temperature anomalies can cause global droughts [28, 29]. In addition, a change in regional climate such as slow-moving anticyclones that alters the climatology of a region by hindering the progress of synoptic weather systems can be responsible for enhancing the land-atmosphere feedback processes [30, 31]. Due to the lack of available moisture in these regimes, the land-atmosphere feedback processes exacerbate the situation by increasing atmospheric temperatures and thus increasing the atmospheric demand for moisture, thereby leading to increased drying and heating of land surface at the same time, the impact of which is often alarming (such as wildfire risk) [3]. Figure 1 shows the connection between those processes that affects the propagation of drought under climate change.

Thus, underpinning the mechanisms behind such processes is relevant to formulate reliable drought indices that should incorporate all such participating processes, including the various human contributions that influence the drought characteristics and socioeconomic conditions [21]. In addition, the non-stationarity [32] in future climate may lead to large uncertainties in quantifying droughts [33]. Therefore, drought indices need to be robust and revised by including the non-stationary climate information.

4. *The distinction between water scarcity and drought*: Water scarcity and drought have separate implications [14]. Unsustainable use of water resources can lead to water scarcity and, therefore, can be controlled, while

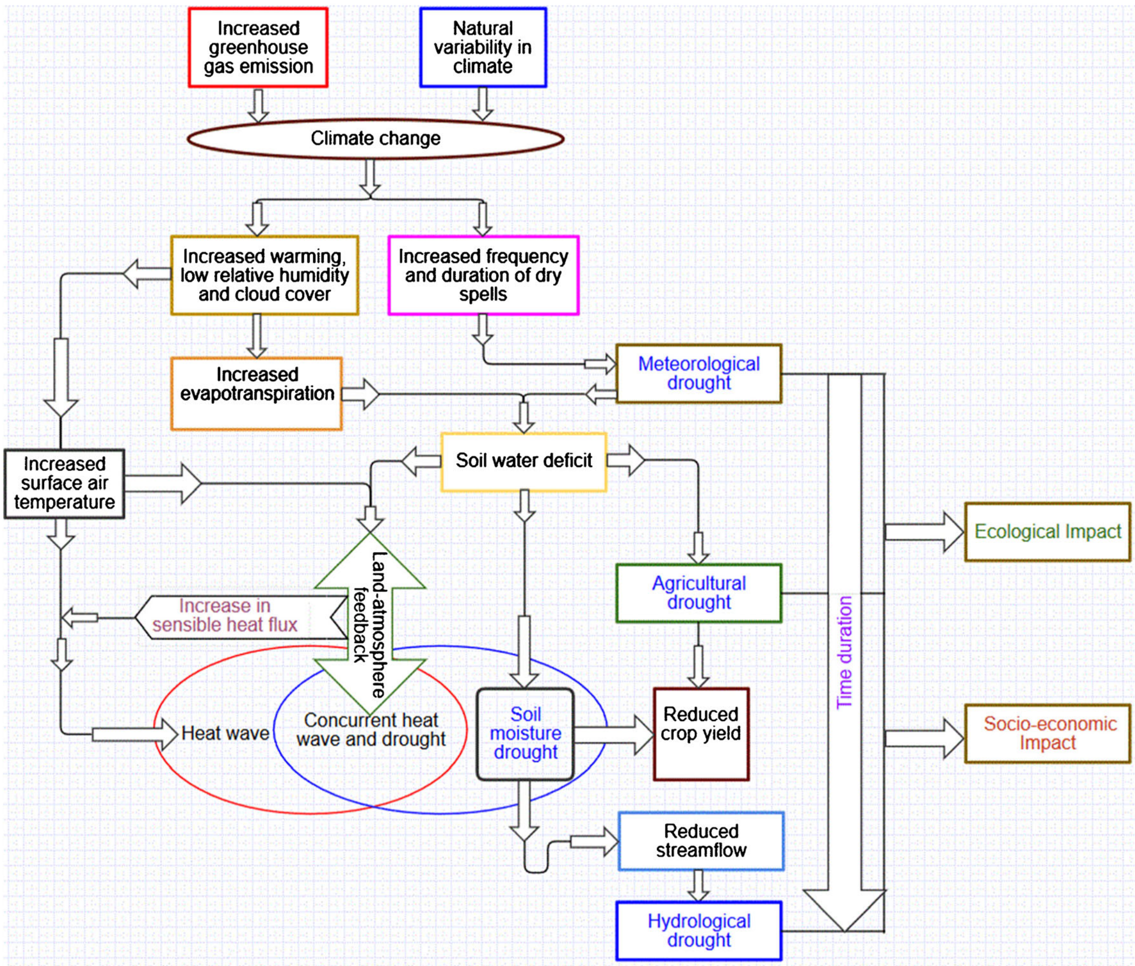

Fig. 1 Schematic diagram showing the drought propagation under climate change. (Note: this figure was revised with respect to original drought propagation concept proposed by Wilhite [12])

drought is a natural hazard and its impacts can only be mitigated by adapting to the climate variability with prior measures [14]. In arid or semi-arid regions, dry conditions quickly lead to water scarcity, and this example emphasizes that the background climatology is also a factor. Hence, in water-scarce or arid regions, where drought and water scarcity usually occur simultaneously, drought situations are more severe and further aggravate water scarcity [12, 14]. Consequently, in such regions, the choice of a suitable indicator that makes a clear distinction between drought and water scarcity is necessary in making effective water management decisions [14].

5. *Multivariate aspects of drought*: Drought is influenced by multiple hydroclimatic variables such as precipitation, runoff, potential evapotranspiration (PET), and soil moisture [1]. Thus, a single drought indicator may be insufficient to quantify drought and, therefore, such assessment requires drought indicators that blend more than one drought index or drought-affecting variables [2].

The overall objective of this article is to provide a perspective on drought indices under climate change scenarios. The section "Relevance of Drought Indices in Climate Change" presents the relevance of drought indices in climate change assessment, followed by a discussion on application and limitations of existing drought indices in the section "Application and Limitations of Existing Drought Indices." The section "Challenges Associated With Drought Indices in Climate Change Studies" provides an overview of challenges associated with drought indices for climate change studies, and summary and conclusion are provided in the section "Summary and Conclusions."

Relevance of Drought Indices in Climate Change

A number of drought indices have been developed to quantify a drought [1]. Most of the drought indices use either only precipitation or in combination with other meteorological variables. Also, numerous studies have investigated the effect of climate change on drying of global terrestrial surfaces. However, most of the studies on dryness fail to consider the background aridity [34–36] and thereby fail to incorporate the changes in available energy, air humidity, and wind speed [34]. Failure to account for such variables in formulating drought indices may lead to a spurious increase in drought under warming climate [34]. Therefore, instead of only considering contemporaneous anomalies to derive drought indices, it is important to also consider the factors that govern the background state [34]. On the other hand, it is evident that climate change-induced warming has accelerated hydrological processes, firstly, by increasing the energy available for evapotranspiration (ET) and, secondly, by increasing temperatures and thus the water holding capacity of the atmosphere [37]. Consequently, it results in more intense, widespread, and persistent extreme climatic events like droughts. Therefore, temperature is likely to be an important variable for deriving appropriate drought indices under global warming. The following section provides an overview on the importance of temperature and anthropogenic forcings for drought assessment, followed by an example highlighting the role of drought under global warming.

Reconstructions [38] and instrumental observations [39] demonstrate that the Earth's surface temperature has increased substantially over the past century, and by the end of the twenty-first century (2081–2100), it is expected to exceed the desirable limits of 1.5 and 2 °C above the pre-industrial level (1850–1900) [40]. Consequently, the intensity of precipitation has increased substantially, because as regulated by the Clausius-Clapeyron (C-C) relationship, there is an increase in atmospheric moisture holding capacity of approximately 7% per °C rise in temperature [41]. However, the surface energy available increases at a much slower rate and this governs the total precipitation amount through the availability of moisture [42]. Hence, there is also a considerable increase in longer dry periods [43]. Except for tropical hurricanes (characterized with large water vapor content), the troposphere is able to radiate away the energy released by condensed precipitation, and the distribution of relative humidity mostly remains relatively constant in both lower and higher latitudes under climate change [42]. Under such conditions, changes in mean precipitation depend on the water availability over both ocean and land surfaces [43]. However, land areas away from the oceans lack the adequate moisture supply to meet the evaporative demand of the atmosphere, leading to continental drying, high temperatures, and lower relative humidity, as found in the model projections [35, 44]. Moreover, as the ocean surface tends to warm at a slower rate than the land and the atmosphere [35, 44], there is a considerable delay in the recharge process of the atmospheric moisture to finally reach the saturation level (necessary for precipitation), thereby resulting in longer dry periods over land [45]. Longer dry spells have direct influence in initiating long-term and severe droughts [46].

The extra heat due to global warming has accelerated the drying process in the recent past [27, 47], which is likely to cause more severe, persistent, and widespread droughts in the future with respect to the current climate [48, 49]. Furthermore, increases in severity of drought in future climates could be largely caused by the mean state change in the warming world. Previous studies have investigated the mean state aridity change due to global warming in terms of an aridity index defined by the ratio of annual precipitation to annual PET [34, 36, 50], and it is also shown that terrestrial climate would become drier as the Earth warms [34, 35], which leads to the expansion of the world drylands [36]. Furthermore, the anticyclonic regimes commonly present in setting up a drought are characterized by weather patterns that steer precipitating weather systems elsewhere and create a stable atmosphere that shuts down local convection. Hence, once the weather conditions are favorable for drought, climate change exacerbates the problem by adding small amounts of heat that accumulate over time, increasing temperatures and ET (drying) [26, 30]. Furthermore, due to limited moisture availability over land, such climate regimes experience a considerable rise in sensible heat fluxes (due to the absence of cooling by evaporation) during limited supply of latent energy fluxes (due to soil moisture depletion), thereby further raising the land surface temperature [37, 51]. This coupling effect between soil moisture and temperature is commonly referred as soil-temperature coupling [31, 37] and can be a potential stressor for wildfire risk [52]. Observational studies confirm relationships between surface moisture deficit (leading to preceding drought conditions) and hot extremes in regional [53] as well as global [54] scales. Moreover, it is observed that higher correlation between warmer and dry conditions can increase the likelihood of concurrent heat and drought events [55]. Therefore, owing to the increasing exposure of heat events [56, 57], the compound effect of heat wave and drought will more likely have severe impacts in the future. Thus, temperature that directly controls evaporation and ET should be considered as an important contributor to drought events under the global warming scenarios [58]. Existing and popular indices used in drought studies under climate change incorporate the atmospheric demand (Standardized Precipitation Evapotranspiration Index (SPEI)) [59] and temperature effect with a crude approximation of potential evapotranspiration (Palmer Drought Severity Index (PDSI)) [60].

Interestingly, drought events during the last few decades, as well as projected in the future, are less likely to be comparable to the medieval droughts due to induced warming from greenhouse gas emissions, land cover, and land use changes from anthropogenic contributions [27, 49, 61, 62]. One such evidence of anthropogenic influence is the warming of the Indian Ocean that, coupled with the increase in sea surface temperature anomalies, caused the unprecedented Sahelian drought during the late twentieth century [63, 64]. Also, observed records indicate increased severity and frequency of droughts over California during the past two decades related to anthropogenic warming [65, 66]. It is reported that early runoff due to early melting of snowpack in the region has affected the moisture content from the top soil layer, thereby exacerbating hydrological drought during the summer [65]. Furthermore, anthropogenic contribution to recent and projected increase in drying trends in Syria has been reported by Kelley et al. [67]. The increasing and long-term drying trend has been attributed to the changes in precipitation driven by the increase in mean sea level pressure together with the long-term increase in warming over the Eastern Mediterranean Region for which no natural cause is apparent [67]. This is well supported by the positive response of the long-term drying to the increase in greenhouse gas emission based on the model simulations that correlates well with the twentieth-century-observed precipitation trends in the Mediterranean Region [67, 68]. The combined effect of climate change on increased drying and land use changes has aggravated the drought impact in the region [69], causing migration of as many as 1.5 million people from rural to urban areas that contributed to the onset of Syrian civil war [67, 70].

Thus, drought quantification cannot be fully understood only based on the natural variability of climate as anthropogenic influence also plays a significant role in triggering as well as propagating drought events [1, 71]. Consequently, efforts have been made based on the existing climate models to detect anthropogenic contributions and attribute its influence on various climate extremes, including drought [71, 72]. In addition, the increase in population density further aggravates the human component influencing drought [1]. For example, due to increased land use in overpopulated regions, runoff has increased substantially, thereby leaving little water to percolate into the soil [73]. Together with an increase in water demand for domestic [74], agricultural, and energy [75] sectors in highly populated regions, drought can pose a significant potential threat in the future. Therefore, a realistic assessment of drought also needs to incorporate such effects arising from the increase in anthropogenic influences.

From the above discussion, it can be observed that variables associated with temperature (e.g., PET) play an important role in triggering droughts (dry spells); therefore, it must be considered in deriving drought indices for climate change assessment. In addition, the uncertainty associated with projected temperature is comparatively less with respect to precipitation based on the global climate model (GCM) outputs. In addition to temperature, other variables, such as precipitation, infiltration loss, and runoff, also significantly contribute to the occurrence of drought [26]. Drought indices and indicators should assimilate all these factors to quantify drought characteristics in the context of non-stationary climate [26].

Example of the Association Between Drought Indices and Land Surface Warming

In this section, we investigate the association between global warming and droughts. The self-calibrated PDSI (PDSI_sc) [60, 76] was selected for our analysis, as it is based on the physical water balance and it incorporates the effects of precipitation, temperature, PET, and runoff. The PET is best estimated based on the Penman-Monteith (PM) method [77, 78] instead of the simple Thornthwaite (TH) method [79] that leads to overestimation of drying in energy-limited areas [26]. The PDSI_sc can successfully capture long-term changes in drought with response to global warming, and it has been used in previous studies related to large-scale drying trends [26, 48, 80].

Therefore, we analyze the long-term temporal changes in drought using PDSI_sc as a measure of dryness to investigate whether overland droughts (drying) go hand-in-hand with rise in land surface air temperature (LSAT) by using the historical period (Fig. 2). Because a steady and sharp rise in global tropospheric temperature has been experienced since the mid-1970s [63, 81], this analysis is focused from 1975 onwards. Our analysis is based on continental averages; however, it is important to note that land-atmosphere feedback processes, which have major influence on drought, can be more accurately explained at finer scales.

We obtained a global gridded monthly observed PDSI_sc dataset [76, 82] (1850–2014) available at 2.5° resolution. Observed monthly LSAT was obtained from the updated CRUTEM4 dataset (1850–2017) at 0.5° resolution, as developed by the UK Meteorological Office Hadley Centre and the Climatic Research Unit at the University of East Anglia [83]. The gridded LSAT and PDSI_sc data are spatially averaged over the six continents. Finally, anomalies in continental mean annual LSAT are estimated for the period 1975–2014 with respect to the reference period 1961–1990.

The relationship between drying and rise in LSAT is well accounted by the negative correlation magnitude observed for all the six continents, with relatively stronger correlation for South America (−0.68), Africa (−0.48), and Australia (−0.48) (Fig. 2). Furthermore, the results from Fig. 2 clearly indicate that drought indices, such as PDSI_sc, possess the required skill to capture the severe drying patterns due to increased loss of soil moisture by overland evaporation. However, there are limitations to the assessment of drought characteristics based on drought indices, as discussed in the following section.

Application and Limitations of Existing Drought Indices

Drought indices have evolved considerably through recent decades, keeping up with the evolution of drought itself under

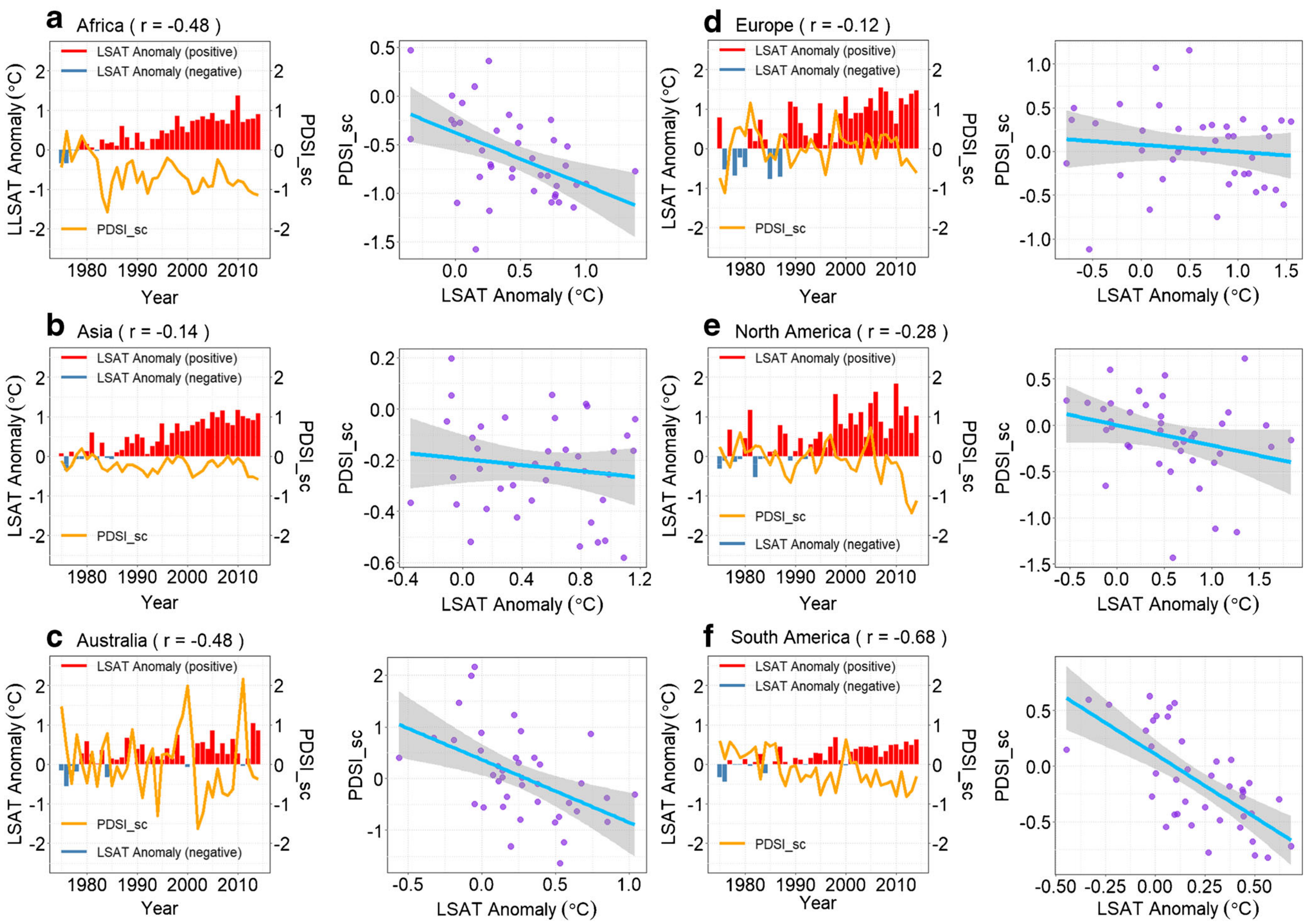

Fig. 2 (Left) anomaly in spatially averaged yearly observed LSAT for the period 1975–2014 with respect to the period 1961–1990 (bar plot with positive (red) and negative (steel blue) anomaly) and in spatially averaged annual PDSI_sc (line; orange) for the period 1975–2014. (Right) scatterplot (violet) and regression line (blue) of annually averaged PDSI_sc and LSAT anomaly for **a** Africa, **b** Asia, **c** Australia, **d** Europe, **e** North America, and **f** South America. It is to be noted here that monthly PDSI_sc values are annually averaged and then correlation coefficients are estimated against anomaly based on yearly observed LSAT

the changing climate. This section provides an overview of commonly used drought indices along with their limitations and skill to adapt to the climate change.

1. *Palmer Drought Severity Index*: PDSI was originally developed by Palmer [60] and is based on the primitive soil water balance that considers precipitation, runoff, and evaporative demand for a specific region. Nevertheless, the calibration period has a strong influence on the PDSI value and it can be a limitation for its use in areas other than used for the calibration [84]. Guttman [84] showed that PDSI, being an autoregressive process, inherits a long-term memory owing to the temporal effect of the soil and atmospheric moisture conditions. Further scope of improvement in PDSI remains in the context of other shortcomings such as (i) fixed temporal scale and inherent autoregressive characteristic of PDSI over water-stressed regions [85], (ii) an inherent timescale that makes PDSI unsuitable for hydrological droughts [1], (iii) assumptions that any form of precipitation as rain leads to ambiguity in the application of PDSI in winter months and at high elevations [1]. For example, Sheffield et al. [86] found a marked difference in drought characteristics based on model-simulated and PDSI datasets over the snow-dominated regions, which is attributed to the inadequate representation of winter processes in the calculation of PDSI; (iv) PDSI also inherits a negative bias in runoff estimations by assuming that runoff occurs only after all the soil layers are saturated [1], and (v) PDSI suffers from a considerable time lag in identifying developing and diminishing droughts [87].

Moreover, Palmer [60] used an empirical approach and averaged the climatic characteristics and duration factors in the estimation of PDSI over very few regions, which limits the comparison of PDSI values among diverse climatological regions [88]. Overall, it can be said that PDSI is a relative measure of drought and the methods adopted to calibrate it are based on the previous climate scenario which is no longer valid in the context of the continuously changing climate [26, 48]. To overcome this spatial inconsistency in PDSI, Wells et al. [76] proposed PDSI_sc that self-calibrates (sc) the index at any location automatically by replacing the empirical climate characteristics and duration factors with dynamically derived values based on the historical climate data of that region.

Further improvement in PDSI has been made by replacing the TH [79] method with the PM [77, 78] method in the calculation of PET. PET based on the TH method [79] neglects climate variables such as solar and longwave radiations, humidity, and wind speed which affect the rate of moisture loss from the upper soil layers [26]. This leads to overestimation of drying in energy-limited areas [26]. The PM method [77, 78] can overcome these limitations for the estimation of PET. As a result, the self-calibrated PDSI based on the PM method (scPDSIpm) can be more appropriate to estimate large-scale changes in droughts (mainly agricultural droughts) in the context of global warming [27]. More recently, few other challenges have emerged, associated with the estimation of PET, as discussed in the section "Sparse Availability of Precipitation Data." However, it is also important to note that PDSI actually tries to incorporate ET along with runoff, soil recharge, and moisture using precipitation, temperature, and available soil water data [60]. Despite several criticisms, PDSI gives a complete picture of the water cycle and remains as one of the most comprehensive drought indices [89]. Overall, PDSI_sc is a readily available standardized drought index and it can successfully capture long-term relative drying patterns in response to global warming [27, 48, 80, 82, 90].

2. *Standardized Precipitation Index*: The SPI [17] is one of the most popular indices used mainly to quantify meteorological drought. The SPI is based on a probabilistic approach, its estimation only requires precipitation data, and it is relatively easy to calculate. Nevertheless, exclusion of temperature, PET, wind speed, and soil moisture data as an input variable is a major limitation for generating reliable drought information under the warming climate [1, 59, 91].
3. *Reconnaissance Drought Index* (*RDI*) and *Standardized Precipitation Evapotranspiration Index*: (i) The RDI [92] is an improvement over the SPI, and it includes PET as one of the key variables. However, PET assesses the atmospheric demand for water but does not necessarily relate to ET because it needs to also assess the water availability. The RDI was used for drought monitoring and climate change impact assessment on water resources [93]. The RDI for a given time period is estimated as a ratio between accumulated precipitation and PET [92]. However, the RDI lacks the ability to capture the variability of drought effectively with respect to change in temperature [59]. Application of RDI may not be suitable when PET is equal to zero [59]. (ii) The SPEI [59] provides a relatively flexible approach that captures the combined effect of precipitation and PET [59]. Moreover, the SPEI performs adequately by considering equal sensitivity to precipitation and ET_{ref} [94]. However, the SPEI may have few limitations in the case of comparing drought events between different climatic regions. For example, in semi-arid regions, the SPEI may be more sensitive towards the ET_{ref}, while in humid regions, it shows more sensitivity to precipitation [94]. Moreover, unlike the PDSI, the SPEI is not based on the water budget framework and fails to incorporate the soil moisture component for identifying agricultural droughts [59].
4. *Multivariate Drought Index* (*MDI*): MDIs are combinations of multiple hydroclimatic variables or drought indicators [95] that provide an alternative way to capture multiple aspects of drought conditions for efficient drought monitoring and early warning [96, 97]. Some of them can be listed as follows:

   (a) *Objective Blend of Drought Indicators* (OBDI): Svoboda et al. [98] proposed OBDI based on the linear-weighted average of multiple drought indices
   (b) *Aggregated Drought Index* (ADI): The ADI [99] is constructed separately for each month using drought-affecting variables such as precipitation, streamflow, PET, reservoir storage, soil moisture, and snow water content. Principal component analysis is used to find the dominant hydrological signals corresponding to each drought type (*meteorological*, *hydrological*, and *agricultural*) [99]. However, PCA has limitations such as assumption of linearity in data transformation and dimensional reduction in the direction based on maximum variance
   (c) *Joint Drought Index* (JDI): The JDI [100] considers joint probabilities of precipitation and streamflow using multivariate probability distribution (e.g., copula)
   (d) *Multivariate Standardized Drought Index* (MSDI): The MSDI [101] is introduced as a joint distribution of precipitation and soil moisture using a copula. Nevertheless, a copula has limitations such as lack of its ability to model high-dimensional dependence structure
   (e) Rajsekhar et al. [2] proposed the Multivariate Drought Index that uses kernel entropy component analysis (KECA) and incorporates variables such as precipitation, runoff, PET, and soil moisture. This index allows the user to extract higher information related to drought characteristics based on higher magnitude of entropy value [2]. However, soil moisture data are subjected to

large uncertainties and this reduces the confidence in the application of these indices.

5. *Relative Drought Indices*: Drought indices such as relative SPI (rSPI) and relative PDSI (rPDSI) are developed with an aim to provide an improvement in drought assessment under the non-stationary climate by providing an alternative way to compare drought between two or more time periods as well as between two or more stations. The former is achieved when drought indices are calibrated using aggregated observational data from all the stations based on a given reference period and then applied to future climate. This method can be applied to estimate the spatial shift of drought due to climate change [102]. On the other hand, the latter method is based on observational data from a given station, thereby allowing the user to capture the temporal changes of drought in the future with respect to the present climate [102]. However, the indices derived using the second methodology may have shortcomings such as lack of comparability between different climate regions [102].

Challenges Associated With Drought Indices in Climate Change Studies

Although drought indices are useful to study climate change impact assessment, the following section discusses major challenges and limitations for such studies.

Disagreement Among Drought Indices

The global mean temperature indirectly reflects the evaporative demand of the atmosphere in the absence of adequate moisture. Therefore, we estimated and compared the sensitivity of the abovementioned drought indices (SPI, SPEI, and PDSI_sc) with respect to rise in global mean temperature. The drought indices based on a shorter temporal window of 1 month were selected and derived for the entire globe: (i) SPI-1 was generated using precipitation dataset provided by the Global Precipitation Climatology Centre (GPCC) [103] (http://gpcc.dwd.de/) at 0.5° resolution, (ii) SPEI-1 data is downloaded at 0.5° resolution from Global SPEI dataset (available at http://spei.csic.es/database.html). This SPEI dataset is based on monthly precipitation and PET data available at the Climate Research Unit of the University of East Anglia that uses CRU TS version 3.23 dataset [104] (https://www.esrl.noaa.gov/psd/data/gridded/data.gpcc.html). The PET is estimated using the Penman-Monteith method [77, 78], and (iii) we use the same monthly dataset for PDSI_sc [76, 82] as in the previous analysis for Fig. 2.

The global gridded datasets of SPI-1, SPEI-1, and PDSI_sc are spatially averaged to generate time series at monthly scale. We analyze the sensitivity of mean annual drought indices at continental scale with respect to the change in the corresponding observed annual mean LSAT for the period 1901–2013 (Fig. 3). The LSAT is averaged at annual scale for estimating the anomalies so that any seasonal influence in the analysis is avoided. To perform the sensitivity analysis, we organized the magnitude of drought indices in temperature increments corresponding to temperature anomalies nearest to every 0.25 °C change in global mean temperature ranging from − 0.5 to 0.75 °C.

Figure 3 shows the box plots corresponding to an incremental change in temperature. We selected a shorter temporal scale that allows the drought indices to capture the influence of the warming on the loss of soil moisture leading to drying more effectively [1]. It can be noted that as compared to PDSI_sc, SPI-1 and SPEI-1 show a little change with rise in overland warming (Fig. 3). This may not be surprising as the SPI does not incorporate temperature or related variables as an input. On the other hand, the SPEI lacks the ability to produce comparable results between different climate regimes subjected to long-term drying [94]. Furthermore, the SPEI does not include the soil moisture information and, therefore, does not respond to the soil moisture drought adequately during the historic period [59].

However, PDSI_sc captures a consistent increase in drying with the rise in temperature (Fig. 3). This may be due to its ability to capture long-term droughts by incorporating soil moisture deficit or surplus from the previous months [105]. Thus, while one drought index responds to the long-term drying with rise in temperature effectively, the other two indices seem to behave differently. This can be a major limitation among drought indices to adequately detect climate change impacts on drought characteristics under various climate regimes and temporal scale. Thus, apart from the disparity in defining drought objectively [10], drought indices can arrive at different results that leads to ambiguity in the decision or policy-making process related to impact assessment under climate change.

Sparse Availability of Precipitation Data

It has been shown that sparse and poor quality of precipitation data [106] generate large uncertainties in quantifying spatio-temporal drought assessment under climate change [26, 27, 80, 107]. For example, Sheffield et al. [80] underestimated long-term drying based on PDSI_sc using NCEP/NCAR reanalysis data from four different precipitation datasets (CRUTS 3.10, DaiP, GPCC V4, and WilP). Out of these four products, CRUTS 3.10 has a poor spatial coverage since 1990 [107]. In other words, datasets based on poor gauge coverage can produce substantial uncertainty when gaps are filled with data from different sources (e.g., neighboring grid points) based on some climatology statistics [107]. Therefore, the compound effect of uncertainties in estimating topographical

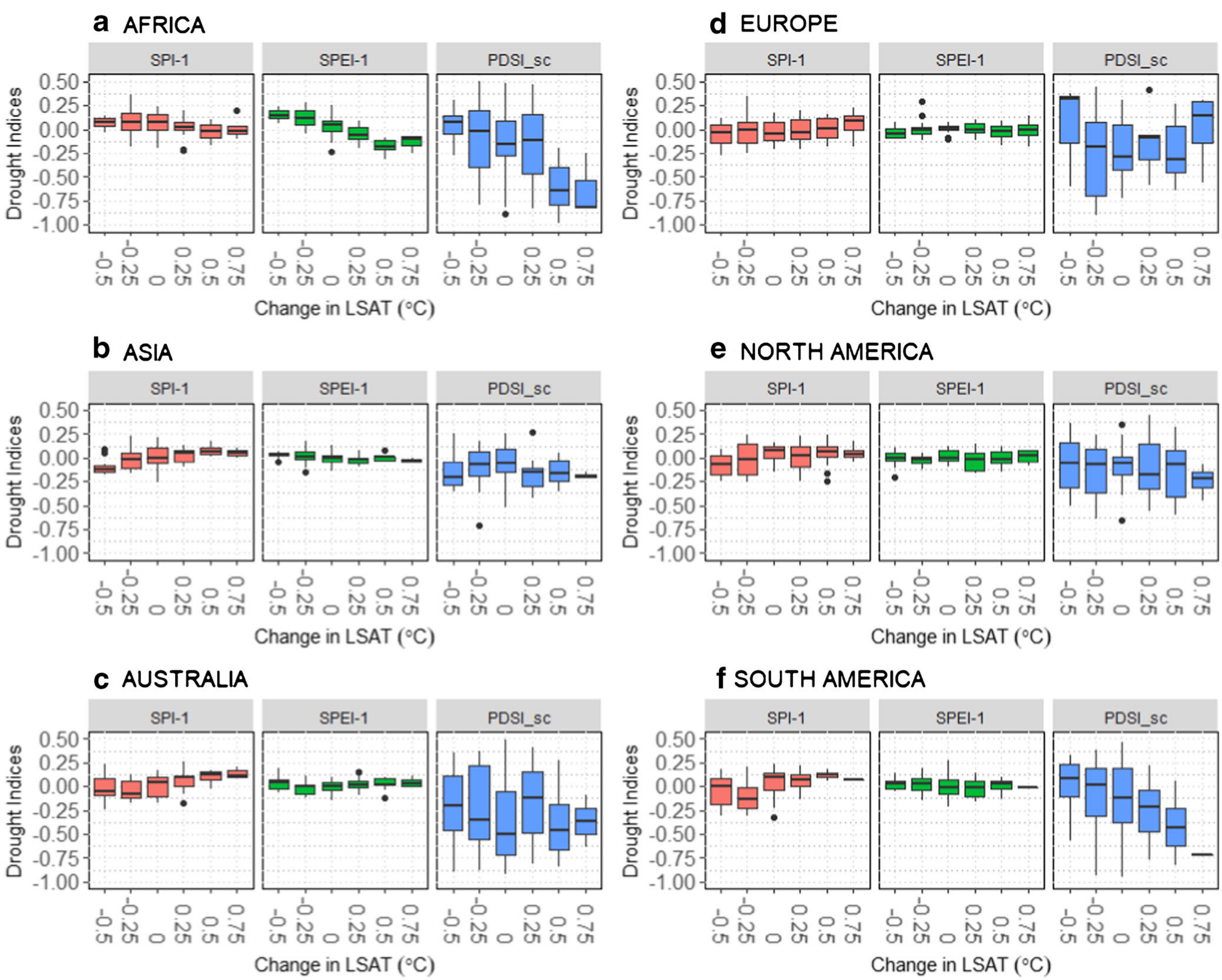

Fig. 3 Sensitivity of drought indices with change in LSAT for the six continents. **a** Africa. **b** Asia. **c** Australia. **d** Europe. **e** North America. **f** South America. Box plot showing median, interquartile range (IQR), outliers, and overall range excluding the outliers for the annual mean of continental averaged drought indices, SPI-1 (red); SPEI-1(green); and monthly PDSI_sc (blue) for every 0.25 °C change in LSAT during the period 1901–2013. To estimate the statistics related to box plot, values of drought indices are accumulated in bins corresponding to temperature anomalies nearest to every 0.25 °C change in global mean temperature ranging from − 0.5 to 0.75 °C

variables [108], coarse resolution of climate model outputs [109], and poor quality of precipitation dataset can generate large uncertainties in the calculation of drought indices.

Moreover, hydrological drought prediction requires high-quality data to improve initial hydrological conditions based on which future droughts are estimated. Data assimilation (DA) that merges observation (in situ or remotely sensed) with model output overcomes such limitation on data availability, and it improves the accuracy of drought prediction by providing accurate initial conditions [110]. Various Land Data Assimilation Systems (LDASs) have been developed so far, some of them are discussed as applicable to drought-related studies: the North America Land Data Assimilation System (NLDAS) [111], Global Land Data Assimilation System (GLDAS) [112], and Coupled Land and Vegetation Data Assimilation System (CLVDAS) [113] that can improve drought assessment under climate change. The land surface models (LSMs) provide improved parameterizations for seasonal and diurnal simulations of water fluxes, energy fluxes, and state variables that are essential for monitoring agricultural and hydrological droughts at hourly and daily timescales [114]. In addition, LSMs such as NLDAS-2 provide soil moisture for various depths and surface and sub-surface runoff data that enhance the accuracy to estimate agricultural and hydrological drought over North America, respectively. For example, top 2-m soil moisture anomaly can be indicative of agricultural drought, whereas the total runoff can indicate hydrological drought [114]. However, land surface models are still undergoing improvement in the applied physics to the horizontal and vertical distribution of soil hydraulic properties, incorporation of sink holes, and representation of the spatio-temporal distribution of precipitation [115].

Estimation of PET

PET refers to the atmospheric evaporative demand and is extensively used in drought studies as a direct measure of relative dryness [48, 107] or as an input variable in the estimation of PDSI [60], RDI [92], and SPEI [59]. However, the selection of model used to estimate PET is crucial in the reliable assessment of drying under the changing climate. For instance, the temperature-based model derived based on historical records to estimate PET is unlikely to reproduce reliable PET during the late twenty-first century. In other words, under the warming climate scenario, purely temperature-based models (TH method [79]) are likely to overestimate drying in the future climate [116]. Thus, climate variables such as radiation, wind speed, vapor pressure deficit, and humidity need to be considered. Consequently, the PM method that takes into account all of these climate variables is found to be more robust in the estimation of PET compared to other existing methods and has been extensively used in the context of studying the temporal and spatial variability of drought in the twenty-first century [48, 117]. However, large uncertainties can be seen due to the lack of reliable forcing data to calculate scPDSIpm [27, 107]. For example, changing cloud cover that controls the incoming solar radiation and wind speed variations that effect the rate of ET are more region specific [107, 118]. Along with spatiotemporal inhomogeneity of forcing data, these variables can trigger uncertainties in the global-scale assessment of drought under climate change [26, 27]. There are conflicting views if estimated drying under climate change will be significantly different, depending on whether precipitation or PET is used as the drought variable [119]. In addition to that, under high CO_2 conditions, plants actually become more *efficient* and the resulting water savings that plants experience keeps higher amounts of water on land on average—i.e., the conventional drought indices might not account for this, leading to an overestimation of drought severity [120]. Furthermore, Milly and Dunne [121] reported discrepancies in the estimation of the change in PET that leads to bias in continental drying trends. It is primarily attributed to the fact that stomatal conductance is not included as an input while estimating PET, and also due to the parameterization of sensible heat flux in terms of the gradient of potential temperature rather than temperature [121]. To avoid such discrepancies, an alternative method to estimate PET using the energy-based approach is proposed [121]. The proposed method assumes that long-term latent heat flux of PET is equal to the net radiation absorbed at the land surface [121]. However, the robustness of this approach requires more investigation and validation.

Downscaling of Meteorological Variables

Temperature and precipitation are the primary meteorological variables of the hydrological processes [1] with higher uncertainty associated with precipitation in terms of its spatiotemporal distribution. Therefore, there is a need to develop robust downscaling methods to generate rainfall information at finer resolution to minimize the associated uncertainties [109, 122]. Consequently, drought indices derived from precipitation require effective downscaling techniques that can resolve discrepancies arising from scale issues [123], thereby helping the stakeholders to improve decision making [1]. However, drought assessments using GCM outputs are limited owing to considerable high bias associated with the precipitation estimates [124, 125], in addition to substantial intrinsic uncertainties originating from the inter-model variability [126–128]. This can be partly overcome by adopting simultaneous bias correction and spatial downscaling approaches [129]. In addition, GCMs do not exhibit a high degree of predictability especially over the extra-tropics owing to the limited physical understanding of the ocean-atmosphere interactions in those regions [130]. This sets a major limitation to specify initial conditions for meteorological drought prediction [131].

Moreover, downscaling techniques face multiple challenges [132]. For example, (i) when a *change factor method* [122, 133] is applied to the coarser GCM outputs, it fails to include the local climate features, while transferring the relative change in signals directly to the scaled historical dataset. This limits the capability of this method to represent the change in climate, including time of occurrence and periodicity of events (such as drought) [132]. (ii) Although *statistical downscaling methods* are simpler than *dynamical downscaling methods* in terms of methodology and computational resources, it has considerable limitations. For example, statistical downscaling is done for each variable at individual grid points, thereby incorporating bias when applied to several variables or to several locations within one region [134]. In addition, the assumption of stationarity in the present climate will also be valid under the future climate scenarios, which implies overconfidence on the GCM's ability to simulate the future climate variables (especially rainfall) [132]. Whereas, (iii) a *dynamical downscaling method* clearly ignores the upscaled information from the local scale (sub-grid cells of GCMs) to the coarser grid cells and considers only one-way mode of transferring information (i.e., from the GCM to the nested RCM). Thus, the large-scale climate characteristics influenced by the local climate patterns may not be captured in the downscaled product [135].

Another challenge in downscaling methods arises from the lack of adequate hydrometric data in different parts of the world, specially developing countries [136]. However, with the advancement in DA techniques and land surface models, it is now possible to generate hydrological fluxes at finer resolutions [137]. For example, LDAS (https://ldas.gsfc.nasa.gov/) incorporates the high-resolution vegetation and soil coverages and provides merged data products at 0.25° resolution and 0.125° resolution for global and regional (across central North America) analyses, respectively. Within this framework, the GLDAS [112] provides high-quality global land surface fields (implementing snow cover, water equivalent, soil moisture, surface temperature, and leaf area index) at 1° and 0.25° resolution from 1979 onwards that support several present and future climate predictions for various types of water resources applications.

Choice of Baseline Period

The choice of baseline period plays an important role when comparing future drought under climate change with respect to historical drought as the reference period [27, 80, 90, 107, 138]. It is well known that by considering a longer (entire) period as the base period, the drought indices can be better calibrated and the future drought events can be compared with appropriate historical droughts [60, 90, 107]. However, the improper choice of base period with respect to which drought events are evaluated can produce considerable bias in the drought assessment under climate change. For example, Sheffield et al. [80] and Dai [48] used two different baseline (historical) periods (1950–2008 and 1950–1979, respectively) to quantify changes in drought under global warming. The average drought characteristics (e.g., duration, severity) were different based on two different baseline periods, which further led to difference in interpretation when future droughts (under climate change) were compared to historical drought characteristics. In ideal scenarios, it is important to choose a baseline climatology that captures historical major drought events, for example, in this case, the inclusion of the Dust Bowl: the dry 1930s (1930–1931, 1934, 1936, and 1939–1940) [29] in the baseline period is likely to yield a different set of results [26]. In addition, the selection of 1950–2008 as the baseline period may include the effects of recent anthropogenic climate change that may be responsible to mask the climate change signals in the results of the analysis [26].

Similarly, the choice of different baseline periods can generate discrepancies in summarizing the results related to the same drought episode. For example, William et al. [71] and Luo et al. [138] investigated the causes behind the recent multiyear California drought (2012–2014). William et al. [71] reported that the anthropogenic warming trends account for 8–27% of the anomaly in 2012–2014 drought. On the other hand, Luo et al. [138] suggest that this multiyear drought most likely resulted from natural variability of climate and dominated by precipitation rather than temperature. The difference in results may be due to the usage of different drought indices, as well as the selection of different baseline periods: 1931–1990 [71] and 1979–2015 [138]. Thus, the baseline period should be appropriately chosen with caution by considering the drought aspect being studied.

Non-stationary Climate and Choice of Probability Distribution

The appropriate selection of probability distribution plays an important role in deriving robust drought indices under climate change, especially considering stationary (historical) vs. non-stationary (future scenarios) patterns of climate variables. For example, calculation of SPI [17] is based on either a gamma distribution [17] or Pearson type III distribution [139], whereas calculation of SPEI is based on a log-log distribution [59]. These distributions perform considerably well in fitting the time series of the hydroclimatic variables over a wide range of climatic region [140]. However, the selection of a single suitable probability distribution is challenging [141]. Vicente-Serrano et al. [141], while investigating best probability distributions to calculate the Standardized Streamflow Index (SSI), reported that most commonly used probability distributions (log-normal, Pearson type III, log-logistic, general extreme value, generalized Pareto, and Webull) for flow frequency analysis provided good fits to streamflow data. However, none of the six probability distributions were able to adequately fit the streamflow series based on L-moment diagram. Therefore, the selection of distribution in developing a drought index is crucial and, if not done with caution, can generate large uncertainties.

Furthermore, it is well known that *stationarity* that implicates physical constancy of mechanisms involved in the hydrologic processes is no longer applicable due to the substantial anthropogenic changes in the present climate [32, 142]. Thus, drought characteristics will be different between stationary and non-stationary climate. Therefore, non-stationary statistics that are deterministic functions of time should be implemented in reliable assessment of hydrologic processes in the changing climate [32]. For example, the selection of probability distributions for precipitation is often challenged by significant zero values (mostly in dry climates), highly left skewed distributions, as well as limited data lengths [1]. Also, due to the non-stationary nature of climate variables under future climate scenarios, the probability distribution parameters of precipitation will change over time. Therefore, it is important to consider non-stationarity by changing the probability distribution parameters over different timescales to improve drought assessment under climate change. Considering the strong association between precipitation and soil moisture, a similar assumption will also hold for soil moisture.

Defining the Role of Anthropogenic Influence

Apart from the natural variability of climate, human activities have a significant control on drought initiation, propagation, and societal impacts [1, 66, 67, 69, 70, 74, 143]. Consequently, drought risk management is directed towards either adaptation to the natural causes of drought or mitigation of human-induced drought [143]. Identifying the anthropogenic causes of drought is crucial to assign proper weight to improve water management policies [74, 143]. However, the coupling of human components in hydrological models is in a preliminary stage for appropriately characterizing droughts under climate change. It is necessary to identify the associated challenges in distinguishing between natural and human influences due to the interplay between climate, soil, and vegetation dynamics [144, 145].

Detection and attribution (D&A) techniques [146], developed so far, use the combination of observation and GCMs in a virtual forcing scenario. This may allow the models to calculate drought characteristics in the absence of human influences [65, 71, 138]; however, the GCMs are vulnerable to uncertainties arising from boundary conditions, variability in the Earth system, parameter estimation, and model structure [147]. Furthermore, lack of observations for verification, and dependence on the model selection and the applied methodology, makes the existing D&A techniques less reliable in risk assessment of drought under the anthropogenic influence [148]. Therefore, quantifying uncertainties by estimating confidence intervals for risk ratios [148], and multimodel averaging rather than relying on individual model results [149], is necessary to avoid overconfidence in drought risk assessment based on drought indices. Moreover, uncertainties depend on the sample size of data and the severity of drought being studied; therefore, extra caution is needed while applying D&A methods [147].

Human-made infrastructures, such as dams and reservoirs, can also greatly affect the propagation of soil moisture and hydrological drought [74, 150]. Drought indices should capture such changes in drought propagation along with other human interactions such as dynamic changes associated with land use, irrigation efficiency, and rapid increase of population. However, such dynamics of human interactions is still in a preliminary stage in existing large-scale hydrologic modeling framework, and scientific advances are needed to overcome the aforementioned challenges.

Summary and Conclusions

A comprehensive discussion on the role of drought indices for climate change assessment is provided in this article. Existing drought indices were reviewed and compared based on their skill and limitations to capture drought characteristics in a non-stationary climate. Major shortcomings related to the formulation of drought indices under the changing climate, including the lack of robust approaches to separate the human component from the natural variability of climate, choice of baseline period, use of non-stationary climate information, and lack of observed data for validation, were discussed. Significant progress is being made in drought research, and there is a scope to improve formulation of efficient drought indices with the hope of better drought preparedness by filling the gaps arising due to such shortcomings. The following conclusions can be drawn from this study:

1. The performance of drought indices, such as PDSI_sc, SPI, and SPEI, showed different degrees of sensitivity against the same level of observed warming at continental scale. Therefore, the formulation of drought indices without considering the factors that govern the background state may lead to drought artifacts under a warming climate.
2. Estimation of PET based on the energy budget framework can be a better physically based approach compared to only temperature-based equations. Also, uncertainties due to the spatial inhomogeneity in forcing data need to be considered to estimate PET for drought assessment under climate change [26, 27].
3. Major advancement in hydrologic modeling for drought assessment has been made with the development of LDAS. Land surface models have been successful in maintaining water and energy balance at macro-scale levels, thereby accurately capturing the components of hydrological fluxes in the top 1–2 m of the land surface at hourly and daily timescale, as well as at finer resolution [18]. These models have considerably improved the near-real-time assessment of drought by providing modeled soil moisture, soil water equivalent, and runoff estimates at diurnal timesteps [18]. However, shortcomings need to be addressed in the existing LSMs by reducing uncertainties in hydrological fluxes by integrating in situ measurements and remotely sensed products [114, 115].
4. The choice of appropriate methodologies to develop drought indices for climate change assessment should consider projected climate variables with less uncertainty. This can be achieved by climate models simulating the best estimates of PET [107, 118, 121], and atmospheric demand or soil moisture [119, 151]. Specially, drought projections based on soil moisture-derived indices should be treated with extra caution owing to the lack of suitable observations for verification [33, 119]. Besides, there remains great uncertainty in what the future climate will be [152]; therefore, multimodel assessment is recommended against assessment using individual models [149].
5. Apart from the natural variability of climate, increase in severe and persistent droughts due to anthropogenic influence is reported in the last few decades [48]. Separating the natural causes from the human-induced factors is most likely to make drought assessment more realistic, thereby helping policy makers to simplify the complexities related to the water management decisions [153]. This can be achieved by objectively defining the role of human activity in drought assessment using drought indices.
6. Drought indices are widely used in multiple purposes by different stakeholders [154]. However, the actual usefulness

and proper implementation of drought indicators/indices rely on how easily they can be interpreted by the stakeholders and serve the end user's needs [1]. On the other hand, climate change affects a wider range of interconnected sectors [155], thereby further increasing the inherent complexity of quantifying socioeconomic droughts [1].

7. Climate model outputs as well as observed data are often available at coarser resolution, and it may limit our understanding on the hydrologic processes at finer scale [109]. Consequently, improved downscaling approaches should be developed to transform the information from coarser resolution to finer grid cells, thereby improving the assessment of drought impacts more realistically [1, 122]. For a good overview of different downscaling approaches for climate change assessment, see Maraun et al. [109]. Along with proper bias correction techniques, downscaling can provide quality data inputs for reliable drought assessment studies [156, 157]. Furthermore, an optimized model selection approach can be useful to select models with minimum uncertainty which should be adopted while downscaling drought indices based on climate models to capture their future variability [158].
8. The non-stationarity associated with climate change is likely to alter the parameters of the probability distributions of input variables in the formulation of drought indices. Therefore, adopting appropriate methods to capture non-stationary information for characterizing drought under climate change will likely to generate reliable information for risk assessment and infrastructural management under the changing climate. Moreover, spatial drought risk can be investigated by integrating multiple drought characteristics (e.g., severity-duration-frequency (SDF)) [159, 160] that allows the user to compare historical major droughts with future scenarios under climate change [161].

Acknowledgements We wish to thank the Editor and the reviewers for their positive and constructive comments that helped us to improve the article significantly.

Funding Information This study was supported by the National Science Foundation (NSF) award no. 1653841.

Compliance with Ethical Standards

Conflict of Interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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