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Scientometric Analysis-based Review of Drought Indices for Assessment and Monitoring of Drought

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Abstract

The major cause of a drought is due to the variations in the climatic conditions and the anthropogenic effects. Due to climate change and inadequate rainfall, the moisture in soil gets affected which reduces the supply of water to the vegetation and also to the groundwater resources. The onset of drought is difficult to predict but it can be monitored with the help of various influential parameters. Suitable drought resilience techniques should be adopted to recover the loss and mitigate the effect of drought in a region. Proper monitoring and management of drought mitigation strategies should be followed to prevent the occurrence of such a kind of disaster. In this study, the authors provided a scientometric analysis and a wide-ranging review on drought indices. The scientometric analysis using VOSviewer showcases the current trend in the research using the most frequently used keywords, most cited articles and authors, and the countries that contributed to the field of drought. A total of 175 articles were identified from various databases and initial screening was done to select the full text articles. The eligible full text articles were selected after excluding the least prominent articles. Finally, 45 articles were included for the final exclusive review process. The review article provides an insight on drought categorization and drought indices derived to determine the severity of drought. The best suited index for drought severity assessment is very hard to identify since it requires more time. The drought indices should be selected in such a manner, that it effectively measures and monitors the severity of drought. A widespread, informative examination of drought indices would benefit the researchers worldwide to reduce their time spent on each article. The aim of this review article is to review the scientific articles regarding drought indices and provide the best solution to derive the drought severity conditions.

Keywords: Scientometric Analysis; VOSviewer; Drought assessment; Drought monitoring; Drought indices

Introduction

Various studies illustrate the significance of drought assessment utilizing remote sensing and GIS methodologies. Vulnerability assessment is critical for developing mitigation actions to prevent ecological loss. Monitoring of drought aids in the management of drought conditions and the prevention of loss. They frequently include drought-related metrics. Drought indices forecast the likelihood and severity of a drought event. The drought factors are frequently linked to the chance of experiencing drought effects. In India, relatively little work has been done at the district level to analyze and monitor droughts. Water bodies, vegetation, forest cover, and built-up areas characterize the study area. Natural disasters and

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environmental destruction in the study area are likely due to the changes in the climatic pattern and several other parameters. However, only few research works in this area will be groundbreaking and will encourage future scientists to make required preparations. The occurrence of drought does not have a discernible beginning or end and it puts numerous human activities in risk in nearly all climatic regions (Bachmair et al., 2016; Loon et al., 2016).

Drought and aridity should be differentiated to acquire a clear decision on drought condition. Aridity is a naturally occurring imbalance in the water supply due to inadequate rainfall, variation in temperature, and low moisture in the ecosystem. Extreme temperature variations occur in an arid environment are characterized by flash floods, and periods of extremely low or no flow. While aridity is a constant aspect of the climate, drought is a transient anomaly. Drought must be viewed as a state that is relative, not absolute. Nearly all climate regimes and locations with high and low rainfall are affected by it. The effects of drought can be severe at times, having an adverse effect on the economy, the environment, and even people's personal lives.

Drought, unlike other hazards, is different in nature due to its effects, tends to endure for several years (Kim et al., 2019). As a result, the effects of recurrent drought can compound, creating issues to both environments and people (Bachmair et al., 2016). Drought can be defined in a number of ways. Drought concepts can be either theoretical or pragmatic in nature. The descriptions of drought emphasize environmental catastrophes such precipitation that is less than anticipated and are descriptive in character (Kchouk et al., 2021). When drought detection and DEWS activities expand globally, there will be a greater need for reliable, high-quality data sets and assessments to support applications at various regional and global scales. The special characteristics of satellite remote sensing data support in filling this information gap by refining the ability to monitor drought, predominantly on a global scale (Hayes et al., 2012).

Several research works establish the significance of drought condition assessment by integrating the techniques of remote sensing and GIS. Together with environmental factors, socioeconomic factors influence a community's susceptibility to drought. The changes in the climate can be assessed by the indices which are determined through drought monitoring for a region. These indices are attributed to several drought conditions. The occurrence and severity of drought can be predicted by the drought indices. The drought factors are linearly connected to drought impacts. Very few research has been carried out in India related to drought assessment and monitoring at district level.

The purpose of this study is to carry out a detailed evaluation of drought indices for assessment and monitoring of drought. An attempt was made to review the literatures related to drought indices using scientometric analysis. The scientometric review can address an important drawback of traditional review articles which lacks in terms of precision. The scientometric analysis was used in this study to objectively illustrate the research power structure, such as identifying influential authors, journals, and countries, tracking the keywords, and discovering the knowledge base of drought research. The scientometric analysis was made with co-authorship analysis containing authors, organizations and countries and also with co-occurrence analysis with author keywords. A total of 175 manuscripts published by the Scopus and PubMed database were analyzed. The critical review suggested several research themes and the accompanying issues to support future investigations based on the results of the cluster analysis. The combination of scientometric analysis and critical review can help to prevent subjectivity in the literature review and generate a thorough comprehension of the findings. The findings of this study are intended to provide researchers and practitioners with a thorough understanding of the status and research trends of drought research, as well as to encourage additional research in this domain.

Methods

Data retrieval and processing was done starting with the keyword identification and the data was obtained using the keyword search. Manual review was made to include highly cited papers according to selected keywords and also to reject least important and irrelevant papers. The VOSviewer is a tool for creating and displaying bibliometric networks. These networks can be built via citation, keywords, co-citation, co-occurrences, organizations, countries, authorship and co-authorship, and comprises of journals, individual articles and researcher details. VOSviewer also has text mining tools for creating and visualizing co-occurrence networks of keywords collected from research articles. VOSviewer was used to perform the Scientometric analysis of related literatures. The details from Scopus and PubMed were saved as 'csv' files and given as input to the software.

The co-authorship analysis and co-occurrence analysis were made to visualize the map of various factors such as authors, countries, organization and keywords and the research trend was visualized (Figure 1). Manuscripts were searched in various journal search data-

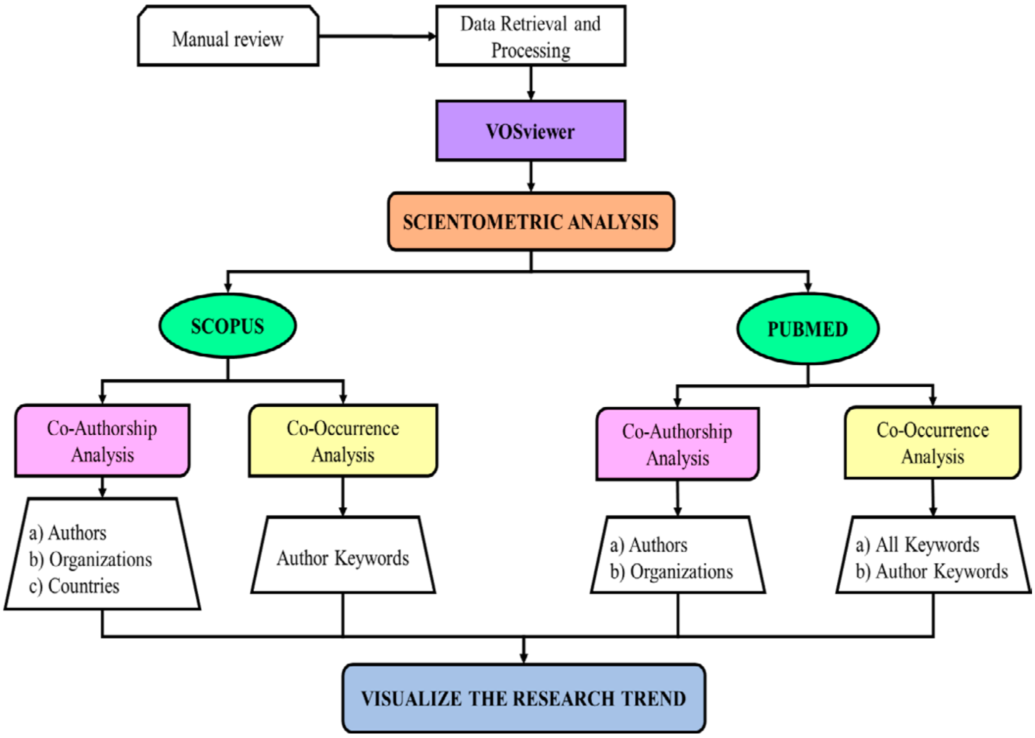

Figure 1. Outline of research

bases, including Springer, Science Direct, MDPI, Taylor & Francis and other journals. A total of 175 manuscripts pertinent to the topic were retrieved. 141 full-text papers were included in the study after an initial screening process, and 34 publications were eliminated due to a lack of relevance to the study's objective. Among 141 full-text papers, 89 were eligible for analysis, and among these 89 articles, 52 were eliminated. The study focused on the assessment and monitoring of drought using multiple indicators which are derived from both spatial information and non-spatial information. Hence, 52 articles with single indicator did not meet the requirement and were excluded from the study. An effective review was conducted using the remaining 45 full-text papers that best suited the study's significance with high citation count were included in the manuscript after rejecting 44 articles which did not meet the citation count criteria (Figure 2).

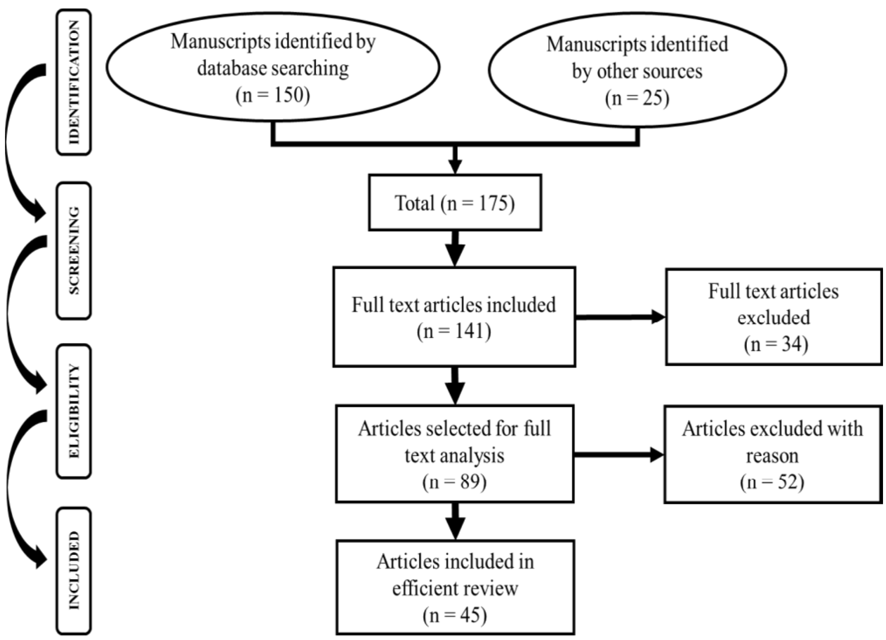

Figure 2. Flowchart showing the identification, screening, eligibility and inclusion of manuscripts for the study

Data collection and processing

The reviewed papers were mostly taken from the Scopus and PubMed databases, which comprises of influential and diverse articles. Because journal papers typically give more complete and high-quality information than other forms of publications, the article type was restricted to journal, journal in press, book chapters, and conference papers. The following keywords were used in the online search databases: ((“drought”) OR (“drought assessment”) OR (“drought monitoring”) OR (“drought indicators”)). The keyword search was made within the article title, abstract and keywords. The relevant paper appears when the selected keywords are present in the title or abstract or keywords of various manuscripts. The document language was limited to English. The time span of the articles was 1984 to 2021.

After data collection, these articles were downloaded and indexed into Mendeley reference manager. A manual review on search results was adopted to remove the unrelated papers and add some influential papers from other databases in the Mendeley. After manual review, 175 articles were identified for analysis. The search results contained 34 articles which were of least importance for the current research and thus were excluded. In the remaining 141 full text articles, 52 articles were rejected which had only a single indicator to derive drought severity. 89 articles were filtered with multiple indicators of drought. After removing 44 articles with less citation count, only 45 full text articles with high citation count was included which represents the status of drought assessment and monitoring in several regions.

The sources of publication for each research article are represented in Table 1 which shows the retrieval of data from indexed journals database. During the critical review process, the scientometric analysis gave vital information on scientific words. Based on the study results, this analysis indicates several research themes as well as the problems in the research area. Using scientometric analysis, the influential authors, countries interested in the specific study theme, organizations doing the research, and keywords were determined. Figure 3 shows the Network visualization map of Scopus author search. The threshold was fixed with the minimum number of documents and citations per author as 2. The size and color of each circle shows the frequency of occurrence and 170 authors met the threshold among 1272 authors.

Table 1. Source of 175 articles retrieved from various indexed journals, 1984–2021

№	Name of Journal	Number of Articles
	Science Direct – (53 nos.)	
1	Agricultural and Forest Meteorology	4
2	Journal of Hydrology	5
3	Remote Sensing of Environment	7
4	Science of the Total Environment	5
5	Ecological Indicators	3
6	Agricultural Water Management	1
7	Alexandria Engineering Journal	1
8	Computers and Electronics in Agriculture	1
9	Ecological Engineering	1
10	Geoderma	1
11	ISPRS Journal of Photogrammetry and Remote Sensing	1
12	Applied Geography	1
13	Environmental Modelling & Software	1
14	Atmospheric Research	2
15	Physics and Chemistry of the Earth, Parts A/B/C	1
16	Journal of Arid Environments	1
17	Journal of Environmental Management	1
18	Ecological Informatics	1
19	Modern Cartography Series	1
20	Energy Procedia	1
21	International Journal of Applied Earth Observation and Geoinformation	1
22	Perspectives in Science	1
23	Climate Risk Management	4
24	Weather and Climate Extremes	2
25	ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences	2
26	Global and Planetary Change	1
27	Environmental Research	2
	MDPI – (33 nos.)	
1	Remote Sensing	16
2	Water	9
3	Sensors	3
4	Sustainability	1
5	Forests	1
6	International Journal of Geo-Information	1
7	Atmosphere	2
	Springer – (38 nos.)	
1	SN Applied Sciences	11
2	Arabian Journal for Science and Engineering	3

№	Name of Journal	Number of Articles
3	Science China Technological Sciences	5
4	Journal of Central South University	1
5	Iranian Journal of Science and Technology	1
6	KSCE Journal of Civil Engineering	13
7	Smart Water	1
8	Journal of Earth System Science	1
9	Palgrave Communications	1
10	Nature Geoscience	1
	Taylor & Francis – (16 nos.)	
1	Journal of Integrative Environmental Sciences	2
2	Geocarto International	4
3	Remote Sensing of Drought: Innovative Monitoring Approaches	10
	Others - (35 nos.)	
1	Journal of Sensors	6
2	Wiley Interdisciplinary Reviews	1
3	Asian Journal of Environment and Disaster Management	1
4	AIMS Environmental Science	1
5	International Journal of Environment and Geoinformatics	1
6	Natural Hazards and Earth System Sciences Discussions	2
7	IEEE Access	1
8	Handbook of Drought Indicators and Indices, Integrated Drought Management Program	1
9	IOP Conference Series: Earth and Environmental Science	3
10	Meteorological Applications	5
11	International Journal of Atmospheric Sciences	1
12	The Scientific World Journal	1
13	Atmospheric Science Letters	1
14	American Journal of Climate Change	1
15	Journal of Geography and Geology	4
16	International Journal of Agriculture Sciences	1
17	Journal of Climate and Applied Meteorology	1
18	International Conference on Geoinformatics	1
19	Environmental Reviews	2

Figure 4 shows the Network visualization map of Scopus countries search with the minimum number of documents and citations of a country as 2, and 54 countries met the threshold among 75 countries. Most of the research interests emerged in countries such as United States of America, China, Germany, Spain, Pakistan, Australia etc.

Figure 5 shows the Network visualization map of Scopus author keywords search with the minimum number of occurrences of a keyword as 2, and 130 author keywords met the threshold among 896 author keywords. Most of the author keywords retrieved from Scopus database were Drought, Remote sensing, Drought monitoring, Standardized Precipitation Index, Evaporation, Climate variability, Rainfall etc.

Figure 6 shows the Network visualization map of PubMed author search with a minimum number of documents of an author as 1, and all the 1255 authors met the threshold.

Figure 7 shows the Network visualization map of PubMed author keywords with the minimum number of occurrences of a keyword as 2, and 67 author keywords met the threshold among 800 author keywords. Most of the keywords used by various authors worldwide, retrieved from the PubMed database were Drought, Remote sensing, Climate change, Drought indices etc.

Figure 8 shows the Network visualization map of PubMed all keywords with the minimum number of occurrences of a keyword as 2, and 255 keywords met the threshold among 1243 keywords. While including all keyword searches in PubMed database, most of the common keywords used worldwide were Environmental monitoring, Drought, Temperature, Ecosystem, Water pollutants, Drought monitoring etc.

The list of organizations containing highly cited documents were identified using Scopus database search was represented in Table 2. A total of 8 organizations were identified with citation count varying from 6 to 100. Centre for Ecology and Hydrology, UK, contributed 3 papers with the highest citation count of 100. State Key Laboratory of Hydrology-Water Resources and Hydraulic Engineering, China, contributed 5 papers with next highest citation count of 68. South African Weather Service, South Africa, contributed 3 papers with next highest citation count of 54. The frequency and trend of literature data for different years were retrieved from the database and plotted to analyze the trend in literatures related to the study (Figure 9).

The following section explains the articles included for the final review process that are the same as obtained through Scopus or PubMed databases. These articles include the review of several types of drought indices and discussion on the most appropriate drought index for drought assessment and monitoring.

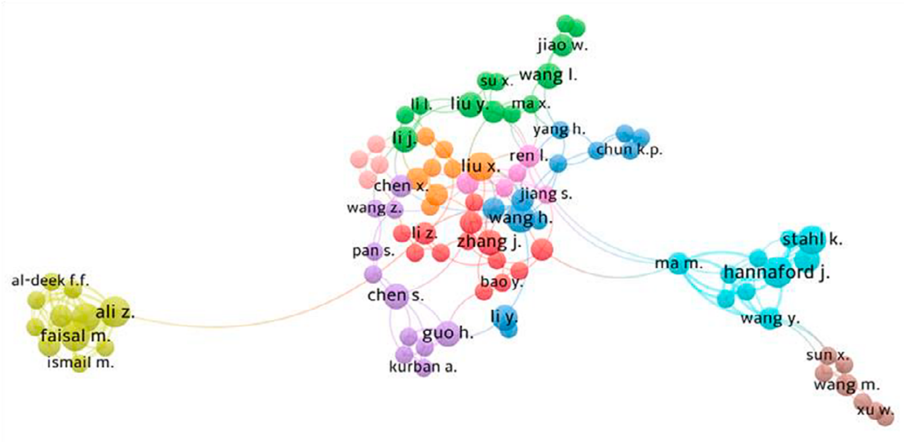

Figure 3. Network visualization – Scopus Author search

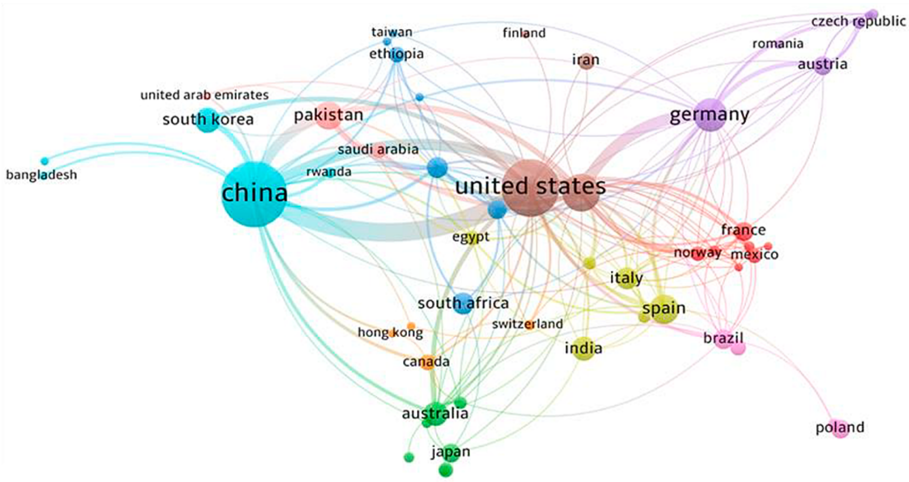

Figure 4. Network visualization – Scopus Country search

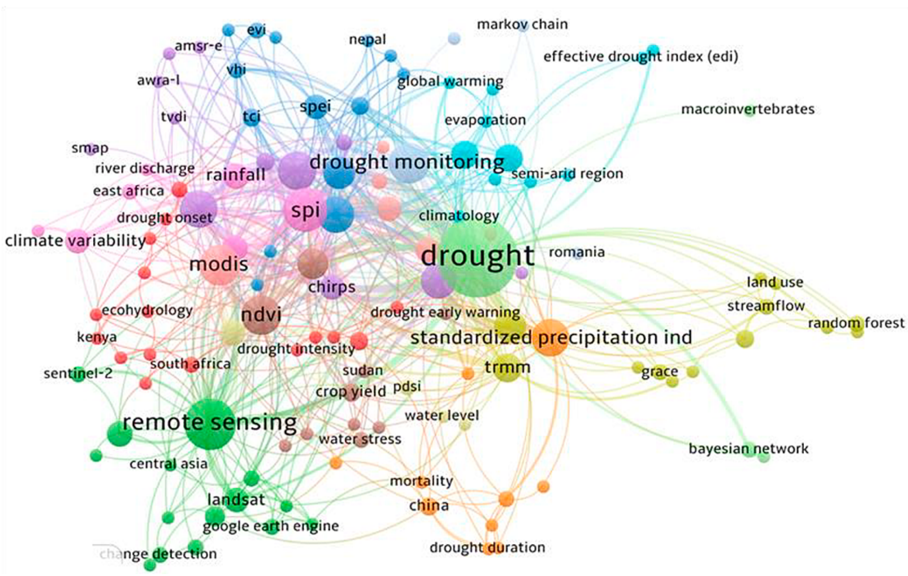

Figure 5. Network visualization – Scopus Author Keyword search

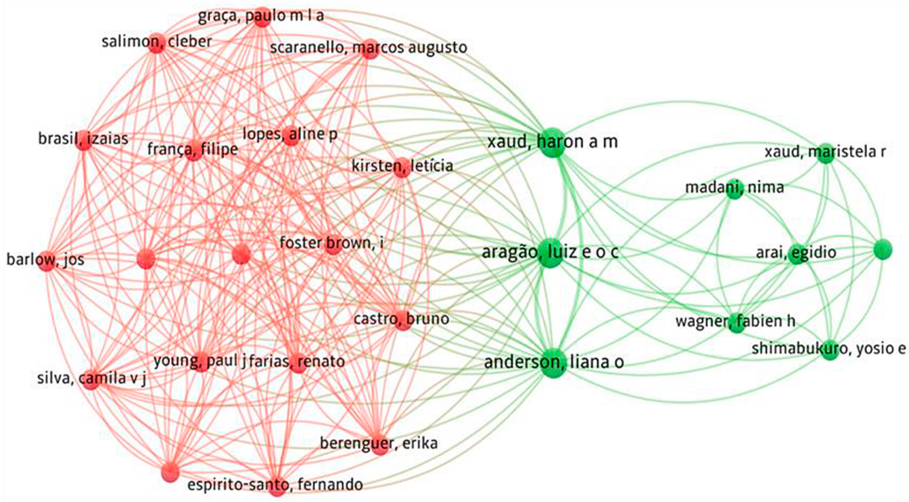

Figure 6. Network visualization – PubMed Author search

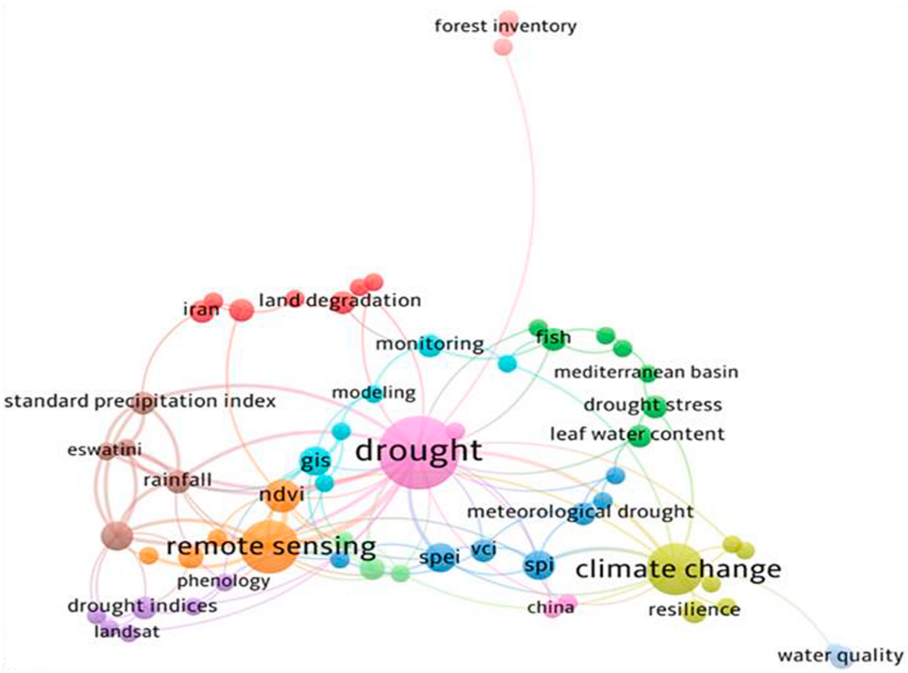

Figure 7. Network visualization – PubMed Author Keyword search

Table 2. Scopus database – Organization details

№	Organizations	Documents	Citations
1.	College of Hydrology and Water Resources, Hohai University, Nanjing, 210098, China	3	37
2.	State Key Laboratory of Hydrology-Water Resources and Hydraulic Engineering, Hohai University, Nanjing, 210098, China	5	68
3.	Centre for Ecology and Hydrology, Wallingford, United Kingdom	3	100
4.	Department of Statistics, Quaid-I-Azam University, Islamabad, Pakistan	6	17
5.	School of Geodesy and Geomatics, Wuhan University, Wuhan, 430079, China	4	31
6.	South African Weather Service, Private Bag X097, Pretoria, 0001, South Africa	3	54
7.	State Key Laboratory of Water Resources and Hydropower Engineering Science, Wuhan University, Wuhan, 430072, China	3	6
8.	University of Chinese Academy of Sciences, Beijing, 100049, China	3	36

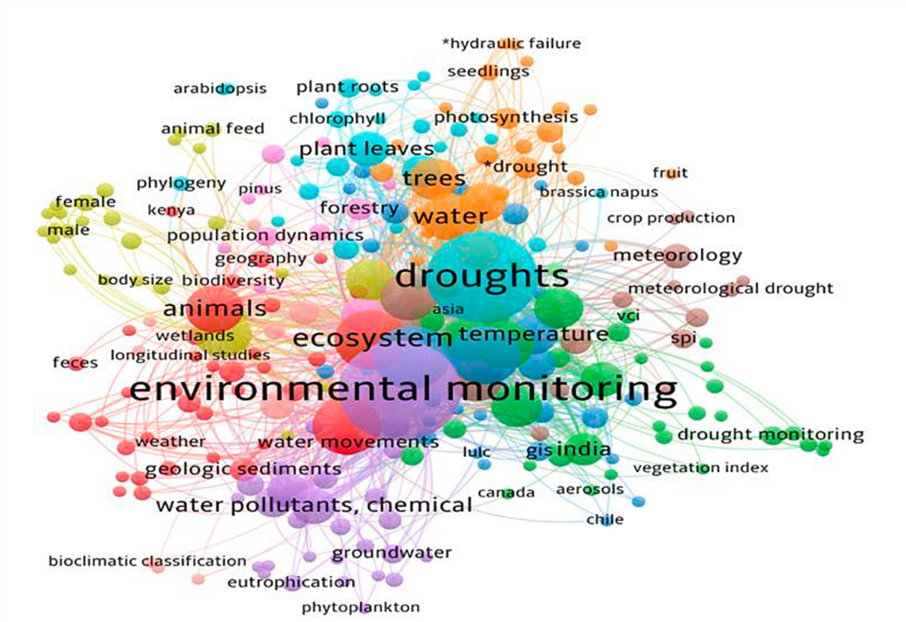

Figure 8. Network visualization – PubMed all keyword search

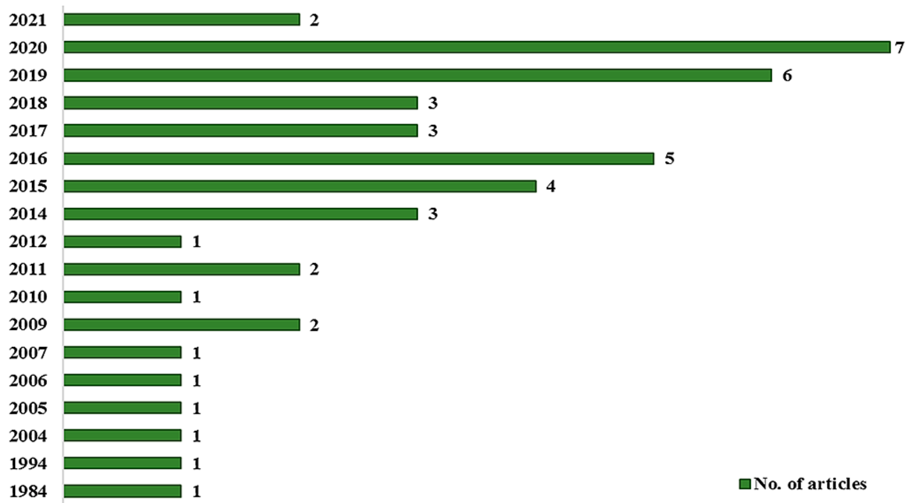

Figure 9. Frequency and trend of literatures

Types of drought indices

Several factors are involved in the characterization of drought which are based on the meteorological, hydrological, and agricultural parameters. The review was carried out for the several drought indices which include meteorological indices, hydrological indices, agricultural indices and composite drought indices. The result of varying rainfall is region specific relating to the atmospheric circumstances of that region, defines the Meteorological drought. The progressive occurrence of precipitation deficiency is defined as a meteorological drought. When there is a prolongation in precipitation drought, it leads to hydrological drought resulting in reduced water level, decrease in volume of reservoir and shrinkage of rivers. An aridity index (AI) is a measure of dryness in the climate of a particular area. There are a variety of aridity indices that have been derived and these indicators are used to identify, locate the water shortage areas. AI is derived as the ratio of precipitation to the potential evapotranspiration (P/PET), which is a useful indicator of aridity based on long-term climatic water deficiencies. Meteorological indices identified the drought condition of the region, because insufficient rainfall is one of the major influential factors in drought condition assessment.

William M. Alley (1984) investigated the commonly used regional drought index called the Palmer Drought Severity Index, but unfortunately, the index quantified features using random rules. Chopra (2006) identified the limitations of PDSI and resolved it by analyzing the spatial and non-spatial data. The drought risk zones were identified using temporal images of NDVI and SPI using meteorological data. SPI, Rainfall, NDVI and food grain anomaly were used for correlation and regression analysis. From the analysis, it was identified that, the temporal changes in NDVI and precipitation are closely related to each other. The temporal variation of NDVI is not sufficient to identify the deficiency in precipitation. Shukla (2007) formed a drought pattern with the spatial and temporal data using satellite-derived NDVI and SPI to overcome the problem. The classification of drought condition with respect to SPI and SVI clearly explained the drought classes in terms of data descriptors. The future drought pattern identification model called the 3-D Markov random field model was created. Since the region related data was lacking on the basis of NDVI for drought modeling, the understanding on regional drought was incomplete.

Praveen and Ramachandran (2015) simulated the future climate by percent deviation analysis. The result of simulation showed a moderate to mild drought condition in the selected region. 12 months SPI analyzed the severity and frequency of previous drought events. Even though the future climate prediction was done for a coastal stretch, the precipitation deviation was difficult to predict. Proper warning and preparedness programs should be made to deal with the disaster. Oloruntade et al. (2017) studied the drought by analyzing meteorological and standardized runoff index. The result from this study identified that the temperature condition exaggerated the hydrological droughts than that caused by the rainfall. This condition was due to the higher correlation among the reservoir and evapotranspiration index in the basin. The study results provide effective water resource planning and management for the basin. Panda and Sahu (2019) investigated the long-term variations and oscillations in weather across the Odisha districts of Kalahandi, Bolangir, and Koraput. This research looked at weather data from 1980 to 2017. Statistical trend analysis tools were used to discuss and examine the concerns. Rainfall trends were found to be statistically significant, and the findings were shown to be statistically significant from 1980 to 2017. The maximum temperature trend analysis is statistically significant; however, the minimum temperature trend analysis is not statistically significant.

Soundariya and Karunakaran (2019) identified the actual and average rainfall trends using the data for 45 years of district-level monthly rainfall. The findings were used to account for and evaluate the occurrence of extreme weather events. According to the findings, the current climate variability process will raise the occurrence of catastrophic conditions in high-risk zones by 53%. The North East and Southwest monsoons, which provide critical rainfall to Tamil Nadu, vary as much as other seasons. These modifications will have an effect on agricultural planting and harvesting. This report recommends proper technology and strategies to lessen and overcome the consequences of climate extremes. Asfaw et al. (2018) used gridded monthly precipitation and temperature data to examine the change in rainfall and temperature in north-central Ethiopia from 1901 to 2014. The data was examined using the coefficient of determination, PDSI, and anomaly index by the researchers. Furthermore, the trend test identified a time series trend.

Tian, Yuan and Quiring (2018) determined the best approach for drought monitoring, six meteorological indices were estimated: Palmer's Drought Severity Index, Palmer's Z-index, Standardized Precipitation Index, Standardized Precipitation Evapotranspiration Index, Precipitation percentiles, and Percent of Normal indicator. Drought indices were analyzed using agricultural yield and soil moisture data. SPEI was found to be typical for identifying soil moisture. In terms of agricultural yield, the Z-index and SPEI had a stronger association. They demonstrated that there is no sole drought index that can accurately predict drought conditions. Costa and Rodrigues (2017) calculated the Rainfall Anomaly Index (RAI) to analyze the spatiotemporal variation of rainfall in Ceara's Salgado Basin. Seven met stations' daily rainfall data from 1974 to 2015 were used. Using the data provided, the RAI was represented in spatial distribution maps. The historical series represented dry years rather than rainy ones. The RAI varied, with the part near Chapada do Araripe being drier. Extreme anomaly years were linked to events involving sea surface temperature anomalies, which favored their occurrence.

Oloruntade et al. (2017) examined two meteorological drought indicators, namely SPI, SPEI, and hydrologic drought index, the standardized runoff index to determine the drought. Because of the stronger association between the SRI and SPEI in the basin, the results demonstrated that hydrological drought are more exaggerated by temperature than rainfall. A closer look at the rate of the various situations reveals that it has been extra for a normal situation, with excessively dry and wet conditions being extremely unusual. However, given the predicted universal warming conditions, a setback of the existing normalcy may occur soon; the study's findings serve as a foundation for successful water utilization and managing the watershed. Avdan and Jovanovska (2016) suggested the use of Landsat 8 data and the automatic mapping technique, for measuring land surface temperature. In this technique, the authors employed Landsat 8 band 10 data from a thermal infrared sensor band. This method was found to be a successful technique for LST recovery. The air temperature and the satellite-derived land surface temperature were assessed as a part of the field verification, with a standard deviation of 2.4°C for the first trial and 2.7°C for the second trial.

Praveen and Ramachandran (2015) modelled the future climate of the Thiruvallur coast in South India. Temperatures rose as precipitation fell, according to the data. The drought is moderate to light, according to the percent deviation analysis. SPI – 12 looked into the frequency and severity of previous droughts. The years 1982, 1980, and 1999 were all unusually dry. It is necessary to build drought warning and preparedness systems in order to deal with drought. Nyatuame, Owusu-Gyimah and Ampiaw (2014) analyzed the rainfall records from 1981 to 2011, and detected the precipitation trends in the Volta Region and demonstrated climate change. For the study, they acquired monthly and yearly rainfall records from the Ghana Meteorological Department's headquarters in Accra. Statistical analysis was used to evaluate whether there was a statistically significant difference between the months and years analyzed. The northern zone received the greatest rain, followed by the center zone and the coastal zone. Rainfall patterns, on the other hand, were erratic. The yearly mean rainfall was 202.6 mm (highest) and 29.9 mm (lowest).

The limitations of various methods adopted by several researchers showcased that, the use of single indicator such as rainfall will not determine the effect of drought. Also, the meteorological drought indices use only rainfall, temperature and evapotranspiration data and hence it is not sufficient to analyze the drought. Therefore, the use of hydrological drought indices is studied to link the effects of meteorological and hydrological condition, which determines the drought. Hydrological droughts occur in an organized manner along with or after the incidence of meteorological and agricultural droughts. The deficiency in rainfall reflects slowly in the hydrological structure mechanisms like stream flow, soil moisture, reservoir and groundwater. The lack of moisture in the soil, low stream flow, lowering of groundwater leads to hydrological drought condition. Examining the hydrological parameters helps in determining the drought condition of a region.

Narasimhan (2004) calculated the moisture in soil and evapotranspiration using the climate data. The evapotranspiration index was assessed and soil moisture modeling was done using NEXRAD rainfall data. There was a strong correlation identified between the derived indices and wheat and sorghum. This correlation analysis implies that these factors are noble predictors of agricultural drought. The soil moisture modeling using rainfall data improved the drought monitoring. The agricultural drought declaration is made by the past research on meteorological and hydrological drought indices which are the major causes of stress in vegetation. The information identified by the satellite data determines the precise drought condition which provides a near-real time data.

The use of satellite derived vegetation indices and moisture indices compared the depth to groundwater (Seeyan et al., 2014). It was identified that, the values of NDVI at various depth to water level showcased the locations of low groundwater levels which increased the vegetation cover and crop variety. The temperature parameter will be considered for identifying the soil moisture of a location. The limitation of this study was overcome by examining the variation in LST of multi-temporal data (Orhan et al., 2014). The comparison of few satellite-derived drought indices with field observations did not offer much evidence on the hydrological drought. The limitation of previous studies was overcome by various researchers. The identification of spatio-temporal differences of groundwater drought and spotting of drought prone areas were done by deriving a standardized water level index (Ganapuram et al., 2015). The index found the temporal variations of drought characteristics in groundwater. The spatial pattern of drought occurred in the groundwater was interpolated using various techniques in GIS.

Since, deriving one index for hydrological drought identification will not provide much clear information on the drought severity, LST was derived using the Landsat data for drought monitoring (Nugraha et al., 2019). The minimum and maximum LST was used to identify the temperature condition index (TCI) and crop water stress index (CWSI). The results showed a zero TCI signifying the dry condition, and a positive CWSI signifying a wet condition. There was a contradicting result on both the indices values. So, the introduction on Artificial Neural Networks and hybrid optimization techniques were made to predict the short-term hydrological drought (Nabipour et al., 2020). According to the results found, it was identified that, the hybrid model exceeded the traditional ANN technique. The limitation of the study was the data availability to performing ANN technique, involving high training samples for the investigation. To overcome this, the integrated approach was followed to identify the groundwater potential zones which provides necessary details on hydrological drought. The

ArcGIS software was used to create layers such as groundwater level and movement regulating features. The integration of Remote sensing and GIS with Analytical Hierarchy Process (AHP) created different groundwater potential zones, aiding in sustainable use of groundwater. The decision-making process offers finest results using the datasets which were utilized for the analysis (Allafta et al., 2021).

The combined effect of meteorological and hydrological drought showcases the adverse effects of drought. They also possess severe effects on the vegetation and crop growth. Therefore, a proper analysis of agricultural condition should be made to identify the agricultural drought condition of a region. Several agricultural parameters such as crop type, cropping pattern, seasonal crop information should be studied to determine the effect of drought. Agricultural drought links numerous drought characteristics to agricultural impacts both in meteorological and hydrological aspects. Agricultural drought chiefly emphases on shortage in rainfall, differences in soil moisture levels, evapotranspiration, and lowered levels of groundwater. Demand in crop water is recognized by the biological features of the crops, the developmental stages, soil properties and weather condition. Multiple criteria analysis should be made to examine the crop stress which showcases the factors responsible for it. Meteorological and hydrological parameters are considered for deciding the occurrence and extent of agricultural drought.

Multi-criteria decision-making analysis in GIS system was made to determine the drought vulnerable areas in Tamil Nadu, India (Chandrasekar et al., 2009). The significant aspects of climate, biotic, edaphic, and social factors were considered for the analysis. The blocks selected by the Drought Prone Area Programme (DPAP) by the Federal Government of India was coinciding with the drought sensitive areas identified from the study. The multi-criteria analysis differentiated the classes of drought and major portion of land was covered by forest. The study was carried for the entire state and this will not provide precise information on the variations in the agriculture. The results were generic for the entire state with least real time information on variations in crop cultivation. Naresh Kumar et al. (2009) used the monthly data of precipitation to calculate precipitation index standardized with the minimum and maximum values. When there is extremely high or extremely low precipitation, the index values under estimated the degree of wetness and dryness with respect to the actual precipitation and deviated precipitation. When the data used is for a longer period, the index values represented a longer range with no improvement in sensitivity of drought years. Haas (2010) assessed and related the soil moisture in the Stockholm region using hydrological inputs with a remote sensing perspective. Soil moisture modelling uses the elevation data derive the Topographic Wetness Index. Soil moisture measurements in-situ are directly related to the calculated soil moisture indices. After classifying the index values to low, medium and high, it was observed that there was no higher correlation between the value groups. So, it was identified that, thorough analysis of the model should be made to judge the capability of the model. To utilize the model for various forecasts, huge amount of field observations and methods are necessary to make the model efficient for estimating soil moisture over large areas.

Hazaymeh and K. Hassan (2016) identified the significance of drought in agriculture and the procedures to monitor the condition of drought. They found that field data indices provided accurate results than other methods, but the method was not capable of providing spatial dynamics over a large area. To overcome this issue, an examination was made to identify the variation of drought in agriculture over several years (Vaani & Porchelvan, 2018). They used the normalized difference vegetation index to identify the condition and strength of vegetation. The frequently prone and severely prone drought conditions were found at the time of analysis and were used to identify various methods to increase the crop productivity. The frequent drought necessitates the officials to prepare action plans to identify the drought risk areas based on the severity condition. The drought severity maps were created for the entire state, so the results were generic and does not specify the location specific information of drought.

Adi Nugraha, Gunawan and Kamal (2019) initiated the capability of temporal data using surface temperature retrieval methods to monitor the drought. The correlation was performed between PCA, crop water stress and condition of temperature index and a positive relation was identified. The limitation of temporal data in drought assessment is the cloud cover due to which poor results will be obtained. Kalubarme, Acharya and Shukla (2019) used the Remote sensing and GIS techniques to identify the effect of climate change on crop cultivation. Different satellite data products were used for LULC change detection in the regions of crop cultivation. The normalized vegetation index showed the quantity of greenness in vegetation but the results were not sufficient to determine the drought severity in that region. The water stress in vegetation due to temperature variation was tested using Landsat data for determining the drought severity (Lottering et al., 2020).

The T-VWSI was capable of identifying and mapping the drought over large geographical areas. Further, Mun et al. (2020) used a framework for climate change to assess the drought vulnerability of reservoirs providing water to crops and developed the vulnerability maps. The results of the study revealed the agricultural drought condition in the selected region. The regional drought vulnerability was also identified to provide mitigation plans and support the drought affected areas. Several algorithms were created to identify the condition of drought (Amina & Rhinane, 2020). Spectral vegetation indices and surface temperature characteristics were evaluated to determine the temperature and moisture indices. Landsat 8 data was used to perform the split-window algorithm to determine the soil moisture information of the study area.

The drought condition assessment will be made effective by deriving various indices of drought. The combination of meteorological, hydrological, and agricultural drought indices derivation proves to be an effective procedure to identify the severity condition of drought in a region. Composite drought indices analysis provides fullest information on the severity condition of drought in a region. The use of composite drought index will be efficient and produces effective results on drought assessment and monitoring. The impact of weather influences the source of various commercial factors like food, water, and hydroelectric power. Due to the climate irregularity, the availability of water is plentiful in some places but inadequate in other places to meet the demand. During the exceedance of demand, the supply is dependent on the deficit in water supply. This excess demand is called as the socio-economic drought which is related to the social and economic factors. The use of multiple drought indices will greatly help in speeding up the decision-making process. By combing the meteorological, hydrological and agricultural drought characteristics, the socio-economic drought condition of a region can be studied.

Chandrasekar, Sesha Sai and Behera (2011) investigated the early drought season in Andhra Pradesh and Tamil Nadu. The soil moisture identification was made during the cropping seasons. The agricultural drought was identified based on the land surface water index which uses shortwave-infrared region and soil water balance model. Soil moisture values were obtained both in temporal manner and across an area. There was a possibility of agricultural drought in the study area. Since the scope of research was confined to huge area, there was only less amount of information on drought. Dhanya and Ramachandran, (2015) conducted focus group talks and semi-structured questionnaire surveys to discover the perception of farmers on climate change and identify the need for adaptation. The salient points highlighted by farmers during the questionnaire survey which affects the crop cultivation were increased warmness, late onset, consistent dry phases, and weakening soil moisture. The perception of farmers was reliable with the Mann–Kendall test, and Sens' slope estimator test that analyses the trend in rainfall data but the results were not matching with the entire rainfall. Various adaptation requirements were identified by farmers, some of which were field-specific adaptation procedures and policies. Zhao and Hu (2015) observed the drought using vegetation indices, Cloud Parameters Method, and precipitation index. According to the results, the cloud features indicate the drought severity conditions.

Han et al. (2019) created a new combined drought monitoring index. The efficiency of the index in monitoring drought was authenticated using SPI, soil moisture, and other remote sensing drought indices. The combined drought monitoring index was associated with SPI and moisture in soil while comparing to other indices. Combined drought monitoring index utilizes the machine learning to analyze the correlations between various components to identify the drought index, but the limitation of the study was the data availability. A combined drought index was developed to predict the onset of agricultural drought and its origin using land, meteorology and remote sensing-based observations (Chattopadhyay et al., 2020). Weighted overlay analysis was performed by assigning ranks and weights for the selected parameters. With the results from overlay analysis, the severity condition was divided into five classes i.e., no drought to extreme drought condition.

A comprehensive remote sensing drought index (CRSDI) was derived using the strengths of other drought indices derived with respect to remote sensing factors (Shojaei & Rahimzadegan, 2020). CRSDI was found efficient in identifying the drought for a selected region. Further, Balaganesh et al. (2020) used agricultural and dairy indicators to derive a new composite drought vulnerability index (CDVI). The study was made at state level and it was identified with the sensitivity map, that nearly 12 districts were highly prone to drought, whereas 8 districts were moderately prone and 10 districts were least prone to drought severity. Water conservation and suitable agricultural protection plans and protection for the livelihood of dairy should be made by the government to bring down the susceptibility of drought.

The influential factors required to determine the drought severity condition are used in composite drought monitoring indices. The combination of meteorology, hydrology and agricultural drought indices proves to be an efficient and effective way to assess the drought severity assessment for a location.

Results and discussion

The articles identified using proper keywords in various search databases indicates accurate search results. Scientometric analysis provided necessary details on the scientific knowledge on the drought indices and their role in assessment and monitoring the drought condition using the collected article data. Researchers involved in drought monitoring used various approaches to detect and monitor drought conditions around the world. The majority of the research incorporated the use of drought indices to assess drought conditions based on a variety of factors influencing natural features. Rainfall, temperature, and other climatic conditions were the most important elements influencing land surface characteristics. Satellite-derived indices were also used to monitor drought conditions that was found to be more accurate and efficient. Algorithms were developed to assess the drought severity index, as well as an examination of the relationship between the components under consideration for analysis.

Various drought assessment and monitoring research have proven to be effective for assessing susceptibility in a region. The integrated use of spatiotemporal elements and satellite data for drought-related studies were also examined. Drought indices proved to be reliable in measuring the severity of the drought. PDSI forecasts drought in an area based on precipitation and temperature data. Palmer indices were deemed inadequate for drought underwater management research due to their difficult calibration, lack of transparency, ignorance of water scarcity, and changes in human water balance (Steinemann et al., 2005). Some meteorological indicators, such as SPI, deciles, percent of normal precipitation, EDI, and RAI, are simple to calculate using simply a region's precipitation data. Weaknesses in meteorological drought indices include imprecision in drought beginning, ending, and accumulated stress, failure to account for the aggravating effects of runoff and ET, and inability to monitor in real time due to being monthly based (Zargar et al., 2011). NDVI is a drought-detection metric that is calculated for the majority of places using satellite data (Svoboda & Fuchs, 2016).

Cloud cover produced by climatic circumstances, as well as the effects of the sun's surface geometry on the sensor, can be reduced using NDVI algorithms. As a result, it distinguishes vegetated zones from other types of surfaces in general (Zargar et al., 2011). TCI and VCI employ satellite data and are sometimes encountered with NDVI estimates. TCI and VCI are used by VHI to calculate the health of plants. It is one of the first attempts to use remotely sensed data to detect drought. The water supply vegetation index (WSVI) detects drought by combining vegetation information with remotely sensed temperature data (Chen et al., 1994).

Conclusion

As a result of the reviewing various research articles, it was identified that, a single factor or parameter cannot provide detailed information on drought severity. Drought assessment and monitoring was carried out by various researchers all over the world using the meteorological indices, hydrological indices, and agricultural indices. The result was to assess the particular type of drought. The combined effect of meteorology, hydrology and agriculture proves to be efficient to determine the onset and will be useful for long term monitoring. The major influential parameters including the meteorological, hydrological, agricultural and socio-economic drought should be combined to assess and monitor the drought condition. Various satellite derived as well as spatio-temporal drought indices are involved in determining the severity of drought in many places. The combined effect of these indices should be analyzed to accurately predict and monitor drought severity of a region.

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