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Review

A Review of Methods used to Monitor and Predict Droughts

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Abstract: Drought is considered one of the severest natural disasters and it is difficult to predict it. This review article aimed to display the state of the art of methods used to predict and monitor types of droughts. We examine more than 30 indices and models to identify the strengths and weaknesses of methods and identify gaps remaining in this field. Examples of examined indies are Palmer Drought Severity Index (PDSI), Standardized Precipitation Index (SPI), and Standardized Precipitation Evapotranspiration Index (SPEI). The research found improvement in drought modeling, however, more focus and improvement are required to monitor and predict drought types. It also found that some methods outperform others such as PDSI, SPI, SPEI, EVI, NDVI, NDWI, VCI and TCI.

Keywords: drought monitoring; drought predictions; drought indices; drought models

1. Introduction

Drought is an unclear onset natural condition that is not recognizable. It is the most devastating natural event in the world that can have worldwide effects, not only in countries with low average rainfall (Hao, Singh et al. 2018, Pontes Filho, Portela et al. 2019 & Lweendo, Lu et al. 2017). In other words, drought is an unavoidable recurrent occurrence, affecting over half of the world every year. Unlike other natural disasters, their beginnings and development are unnotable and gradual, though they have cumulative and catastrophic effects. Which includes water shortages, environmental destruction, crop production reductions, health consequences and the food crisis. Therefore, it is necessary to control drought early to mitigate economic, environmental and human risk (Du, Bui et al. 2018). Drought is generally regarded because of precipitation deficiencies and hydrological propagations. Furthermore, based on the hydrological component considered, different forms of physical drought may be described such as meteorological drought, agricultural drought and hydrological drought (Liu, Zhou et al. 2016).

The later decades of the 20th century and the early 21th century have seen numerous extreme weather events, particularly in many areas around the world, including heat waves and extreme precipitation. Detecting and quantifying droughts is more difficult than other natural catastrophes such as floods, hurricanes and storms because droughts have a sluggish onset, with long-term consequences appearing months or even years after the peak (Spinoni, Barbosa et al. 2020), therefore, droughts are difficult to predict when they will start, how long they will last, and when they will end due to their spatial and temporal variability (Rahman, Rahman et al. 2021). Droughts are natural disasters that strike various parts of the globe, including (semi-) arid regions (Mtilatila, Bronstert et al. 2020), it is a recurrent natural phenomenon, which nearly 642 drought events occurs worldwide between 1900 to 2013 according to the Emergency Events Database (Nasir, Assefa et al. 2021). More than half of the world is drought-prone every year (Senay, Velpuri et al. 2015). Hence, it can be classified as one of society's most destructive natural hazards (Schubert, Stewart et al. 2016). However, it is related to climate anomalies directly associated with extended and abnormal precipitation deficiencies, which cause water insufficiency in activities dependent on water (Rahman, Rahman et al. 2021).

Droughts start with a meteorological drought, which then leads to a hydrological drought, which might result in an agricultural drought, and in severe circumstances, a socio-economic drought. The latter stage of a socioeconomic drought can have negative consequences such as agricultural and animal loss, reduced hydroelectric generation, migration, landscape deterioration, and social disputes, among other things (Campozano, Ballari et al. 2020). It usually occurs as a result of a lack of available water, which can be caused by a combination of factors such as meteorological, hydrological, or water management circumstances. Due to the variety of possible causes, complicated connections and feedbacks between them, and many repercussions on nature, people, and the economy, a comprehensive description of droughts is difficult to develop. It distinguishes four drought categories as a result of this diversity, spanning from meteorological and hydrological droughts to agricultural and socio-economic droughts. Meteorological drought indicates a lack of precipitation in comparison to long-term averages, whereas hydrological drought relates to water availability deficiency that results in shortages of usable water supplies. Agricultural drought is referred to as a plant soil moisture deficit while the socio-economic drought pertains to water scarcity impacts which restrict access to water or the provision of products and services on water availability (Mtilatila, Bronstert et al. 2020).

Drought impacts are expected to become more severe (Zhong, Cheng et al. 2020). Droughts, their extent, and severity have been increasing dramatically as a consequence of rising in climatic changes and global weather instability (Rahman, Rahman et al. 2021). It causes widespread devastation, depending on the severity of the drought and its temporal and spatial extent (Rahman, Rahman et al. 2021). Moreover, droughts have become more frequent and severe in many parts of the world in recent decades as a result of increased climate variability, which is likely to worsen global warming (Shiru, Shahid et al. 2020). In addition, it has the potential to harm both the natural environment and human activity, resulting in crop losses, desertification, urban water shortages, forest fires, and other issues. In the future decades, many densely populated countries will confront a growing threat of severe and extended drought. As a result, it is critical to adequately monitor drought and forecast its occurrence (Zhao, Lyu et al. 2014).

Since drought is a recurrent phenomenon common to all climate zones, it is hard for traditional approaches over wide areas to forecast and monitor drought (Senay, Velpuri et al. 2015). Traditional approaches for the evaluation and monitoring of drought are based on precipitation statistics, which are restricted in the region, sometimes unreliable and hardly available in near-real time. In comparison, data from the satellite sensor is reliable and can be used for the detection of drought, length and severity of drought. Vegetative conditions throughout the world are occasionally recorded using Advanced Very high-resolution Radiometer (AVHRR) data by the NOAA's National Environmental Satellite Data & Information System (NESDIS) (Thenkabail and Gamage 2004).

The effectiveness of the preparedness for droughts and mitigation would rely largely on timely information on the occurrence, progress and duration of drought. However, there is limited institutional and technological potential for monitoring and mitigating drought in many countries (mainly developing nations). Recent technical developments in satellite remote sensing have enhanced our ability to deal with early warning complexities and effective drought monitoring. Satellite remote sensing enables continuous monitoring of drought over various space and time scales, helping to generate prompt knowledge on the occurrence, progress and duration of drought (Senay, Velpuri et al. 2015). However, Due to the limited availability and inconsistencies of drought-related insitu data, remote sensing data and methods are crucial instruments to research spatiotemporal trends and the underlying drivers of droughts. Earth observations can make this difference possible by providing the opportunity of obtaining constant, coherent, temporal information over vast areas and long periods on the meteorological, hydrological and biophysical parameters (Winkler, Gessner et al. 2017). The aim of this research is to review the state of knowledge of both indices and models in current study, which are used to monitor and predict drought types.

This study aims to provide a comprehensive and broad review of the methods used for monitoring and predicting drought. The specific objectives of this review are to: (1) explore the characteristics of drought methods in terms of which indices are ideal to detect drought, (2) review the techniques and methods employed to predict the drought. Our review will provide important insights on understanding the prediction and monitoring of the drought phenomenon.

2. Drought types and characteristics

Drought debates have become more tangible as droughts have become more common around the world, and there is no globally accepted standard definition for drought. Even among drought experts, a consensus on a single definition of drought is difficult to come by. Drought is defined as a difference in precipitation from the expected mean over a period of time. As a result, it's important to understand the context in which the drought and its effects are expressed. Drought can be classified into four major types based on the literature: (i) meteorological, which is defined as a decrease in precipitation; (ii) agricultural, which is defined as a lack of moisture in soil; (iii) hydrological, which is defined as a decrease in stream-flows and runoffs; and finally (iv) socioeconomic droughts, which are defined as a decrease in human water use while there is a decrease in water availability (Yihdego, Vaheddoost et al. 2019).

Characteristics and climate variabilities for recognizing each phase of droughts are different as shown in (Figure. 1). Although meteorological drought commences with low precipitation in an area, but it also must have high temperature, high winds, low relative humidity, fewer clouds and exposure to sunshine. These factors play a key role in occurring meteorological drought. Otherwise, only low precipitation not always reflects to drought because it might not affect by those factors as forementioned, for instance, an area might not have inadequate precipitation even though it has low precipitation because of moderate or low temperature, low humidity, fewer winds and less exposure to sunshine which they help to decrease evaporation and transpiration. Also, intensity, time and amounts of precipitation lead to drought if it reduces infiltration, runoff, deep percolation and groundwater recharge. When heavy rain falls only once a year, with little or no rain during the rest of the year, it is especially destructive to crops, as contrasted to having light rain regularly. Dry spells are conditions that are less severe than droughts but are characterized by a longer duration of dry days. Prolonged dry seasons, in particular, have a significant influence on agricultural output (Anshuka, van Ogtrop et al. 2019). Agricultural drought occurs just after moisture decreases in soil because plants and biomass rely on the soil moisture contents. If low precipitation takes for longer time it leads to hydrological drought which is water availability as a surface and groundwater reduce dramatically and impacts the streamflow, lakes, reservoirs, ponds and wetlands. Its impact on socioeconomic and environments is further, which water shortage affects wildlife habitat and people.

2.1. Metrological drought

Meteorological droughts exacerbate all other types of droughts, thus understanding them is essential for developing mitigation strategies. It happens when precipitation or the atmospheric water balance falls below the long-term average. As a result of natural climate fluctuation, it can occur in any climate regime (Shiru, Shahid et al. 2020). Since regional climatic pattern is not similar from one place to another, meteorological droughts are affected by several factors such as changes in climatological, geographical and hydrometeorological conditions, which these factors are crucial when it comes to defining meteorological drought. Simply, meteorological drought develops expeditiously and rapidly, besides it finished up quickly if it delivers efficient precipitation (Yihdego, Vaheddoost et al. 2019). Furthermore, the meteorological drought is caused by a mix of factors rather than a single cause. Other variables, such as land surface interactions or feedbacks (for example, decreased soil moisture and higher temperature), may also

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influence to the atmospheric anomaly or incidence of meteorological drought. Therefore, meteorological drought (or precipitation deficiency) is often driven by long-term abnormalities in large-scale atmospheric circulation patterns induced by anomalous sea surface temperatures (SSTs) or other distant phenomena (Hao, Singh et al. 2018).

The Microwave Integrated Drought Index (MIDI) is a new multi-sensor microwave remote sensing drought index for monitoring short-term drought, particularly meteorological drought over semi-arid regions, that integrates three variables: Tropical Rainfall Measuring Mission (TRMM) derived precipitation, Advanced Microwave Scanning Radiometer for EOS (AMSR-E) derived soil moisture, and AMSR-E derived land surface temperature (Zhang and Jia 2013).

2.2. Agricultural drought:

Agricultural drought is characterized as the deficiency of soil moisture required to meet the needs of vegetation caused by a persistent lack of precipitation, already recognized as meteorological drought, and usually results in crop failure (Almamalachy 2017). To study drought evolution, many researchers use soil moisture as a proxy. The Soil Moisture Deficit Index (SMDI) was created to measure the severity of drought. They calculated SMDI using weekly soil moisture data from the Soil and Water Assessment Tool (SWAT) hydrological model, which was found to be well correlated with SPI and PDSI (Wu 2014). It has the potential to postpone and extend the impacts of meteorological drought. Agricultural drought prediction is often conducted using indices obtained directly from soil moisture or other soil moisture-related indices (Hao, Singh et al. 2018).

Approaches to agricultural drought monitoring were split into two groups. To create drought indicators, which estimate soil moisture deficit, the first group relies on data gathered from meteorological stations that monitor precipitation and other physical characteristics. The Crop Moisture Index (CMI), Palmer Drought Severity Index (PDSI), and the Surface Water Supply Index (SWSI) are among these measurements. Second group of monitoring agricultural drought, using a collection of indices known as optical remote sensing indices. These indices provide a more straightforward way to monitor drought by direct monitoring of vegetation health by integrating the various bands of the satellite sensor. Different indicators have been created, e.g., through use of the Normalized Vegetation Differences Index (NDVI), which depends exclusively on vegetation, to monitor agricultural drought and use the Vegetation Condition Index (VCI). In addition to their change spatially and temporally, VCI-based analysis can reliably detect the start of agricultural drought episodes and also utilizing of Vegetation Health Index (VHI) has been shown to be an excellent early warning method for agricultural droughts (Almamalachy 2017).

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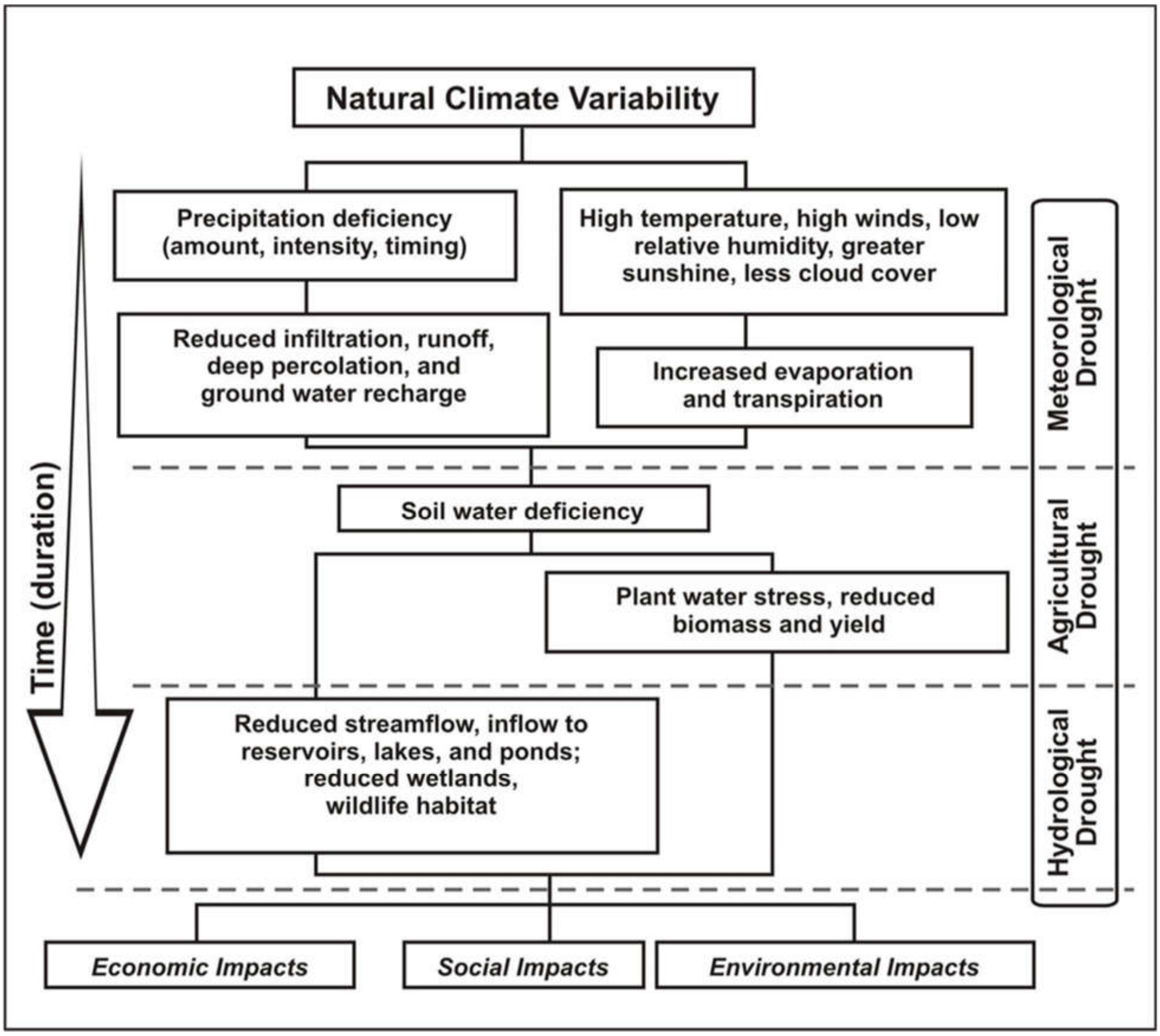

Figure 1. Drought types and durations with their indicators((NDMC) 2021).

2.3. Hydrological drought

The average global surface temperature in the previous century has risen by around 0.85 °C, according to the IPCC Fifth Assessment Report (Pachauri, Allen et al. 2014). Global warming can influence the hydrological cycle through change in evapotranspiration, precipitation, runoff, flooding, etc. Drought occurrences in certain places are thus going to worsen. Semiarid area, since the late 1990s, has seen severe and extended dry spells (Wang, Gu et al. 2019). Droughts have become more common in recent years, and their effects are being exacerbated by rising water demand and climate-related variability in hydro-meteorological variables. As a result, hydrological drought has gotten a lot of publicity (Mishra and Singh 2011). Hydrological droughts are more connected to water needs, and they occur when there is a significant drop in natural streamflow or groundwater levels, as well as the decline of storing water in reservoirs and lakes for water supply. As a result, hydrological droughts are extremely essential and crucial for both urban and industrialized areas, as well as agricultural activities. Hydrological droughts have the greatest influence on water resource management. As a result, contamination of water resources aggravates the hydrological drought condition. Hydrological drought is not only linked to the fall in precipitation, but decreases in surface flow and decreases in groundwater levels also have joint consequences. It is in force in dry seasons where due to continuous dry weather condition water demand cannot be properly fulfilled. In all

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drought-stricken areas, the length, intensity and frequency of drought are all linked. (Şen 2015).

Although droughts are caused by a lack of precipitation, the transition from meteorological to hydrological (and agricultural) drought is not rapid and is driven by complex physical factors. As a result, not all meteorological droughts will result in hydrological droughts. While this causal mechanism is mostly connected to antecedent precipitation shortfall, additional variables such as low water storage, low temperatures, and snow accumulation may influence the incidence of hydrological drought (Hao, Singh et al. 2018).

3. Drought modelling and predictions

Drought duration models are well-established and developed, whereas drought severity modelling studies are less well-developed in the literature. In terms of frequency characterization and forecasting, the duration component is undeniably significant, but the severity aspect is as crucial. For example, when it comes to sizing storage reservoirs to manage droughts, severity is a critical factor (Şen 2015). However, for mitigation plans and preparation in disaster areas worldwide, quality and trustworthy drought predictions are crucial. Drought forecasting relies heavily on prediction models, such as empirical or data-driven models. Recently, several modelling approaches have been made viable to gain insight into precipitation abnormalities and ultimately enhance drought monitoring capacity (Anshuka, van Ogtrop et al. 2019). In reality, the majority of drought models rely on historical precipitation (meteorological drought) and streamflow (hydrologic drought) data. Because early models are based on a single location, preliminary drought prediction approaches only take into account temporal fluctuations. However, a simple and local examination of their validity in a small area around the primary site is also examined. Early models are mostly focused on frequency analysis procedures and are based on probabilistic, statistical, and stochastic modelling approaches (Şen 2015).

Drought prediction is essential for early notification and drought response. Drought prediction can be achieved based on statistical, dynamic and hybrid methods. Statistical drought forecasting is obtained by modelling the connection between drought indices of concern and a set of possible predictors, which includes large scale climatic indices, regional climate variables, and land starting conditions. Dynamical meteorological drought forecasting is based on seasonal climate forecasts from General Circulation Models (GCMs), which can be used to drive hydrological models for agricultural and hydrological drought prediction, with predictability decided by both climate forcing and initial conditions (Mishra and Singh 2011).

The key to statistical prediction is to develop models that define temporal or spatial dependencies between predictands and predictors. These models offer several approaches to investigate the complicated connections between the drought indicator to be predicted and a set of predictors from past times. Time series model, regression model, artificial intelligence model, Markov chain model, and conditional probability model are the most widely used in statistical approaches (or data-driven methods). However, a vast variety of predictors, such as SST, Geo-potential High, the Southern Oscillation Index (SOI), Pacific Decadal Oscillation (PDO) index or Multivariate ENSO Index (MEI) can also be involved in statistical precipitation (or meteorological dryness) in a given location. Multiple predictor units for statistical drought forecasting can be merged to minimize dimensionality. One of the most widely used approaches for dimension reductions is the Principal Component Analysis (PCA) and the Canonical Correlation Analysis (CCA). For example, if several predictors are available (for example in SST fields), the PCA is often applied to decrease the dimension (or compressed data) to prevent overfit and multi-linearity that may be coupled with a multi-linear climate forecast regression model. The CCA technique is utilized to discover correlation patterns between predictor and predictand field for climate prediction whenever the logistic regression is a vector (or multivariate regression variables) with numerous predictors (Hao, Singh et al. 2018).

Kumar and Panu (1997) successfully developed a regression model for agricultural drought forecasting that used grain yield of a primary crop as the agricultural drought quantified parameter and variables influencing grain yield in the region as independent variables. This regression model predicted the grain production of the primary crop multiple months ahead of crop harvest season, and as a result, was able to identify the agricultural drought intensity as mild, moderate, or severe (Mishra and Singh 2011). Regression analysis is generally utilized for two separate conceptual purposes. First, regression analysis is frequently applied for prediction and forecasting, and its application overlaps significantly with the area of machine learning. Second, regression analysis may be used to identify causal connections between independent and dependent variables in particular cases. Essentially, regressions show only connections between a dependent variable and a set of independent variables in a defined dataset. The most popular kind of regression analysis is linear regression, where one identifies the line(s) that closely matches data according to a specified mathematical criterion(Javier Fernandez 2020).

Linear regression is a traditional model of hydrological and climatological statistical prediction (Hao, Singh et al. 2018). For hydrological forecast extreme models have proved beneficial, in combination with meteorological variables like air pressure, air surface and SST temperatures, wind speed and precipitation data. For example, regression models are employed to evaluate the association of the standardized differential vegetation index with the SPI. Moreover, multiple linear regression models (MLR) have also been used properly to predict drought. In Greece, SPI and MLR were employed to conduct spatio-temporal drought analyses and characterize the various return times. Despite regression analysis being a widely used approach, it has significant drawbacks. One of the constraints is the assumption of linearity between predictor and predictand, which limits its capability for long-term forecasting. Another conceptual barrier is the complexity in comprehending underlying causal mechanisms and multicollinearity (Anshuka, van Ogtrop et al. 2019).

Time series models are extensively utilized in a wide range of scientific disciplines, particularly hydrology; nevertheless, applications for drought forecasting are restricted. One of the most significant strengths of time series models is their systematic exploration capacity for recognition, estimation, and model progress diagnostic checks (Mishra and Singh 2011). The use of stochastic methods is a popular strategy for forecasting time series. Time series models include seasonal autoregressive integrated moving average (SARIMA), as well as autoregressive integrated moving average (ARIMA), moving average models (MA) and autoregressive (AR) (Hao, Singh et al. 2018 & Anshuka, van Ogtrop et al. 2019). ARIMA and SARIMA are the most often utilized of these models. SPI forecasting, drought threshold setting, and hydrological drought forecasting have all been conducted using ARIMA/SARIMA models (Anshuka, van Ogtrop et al. 2019). SARIMA models can sufficiently characterize time series that demonstrate nonstationary both within and across seasons, whilst time series models like ARIMA successfully recognize serial linear association among observations (Mishra and Singh 2011). In contrast, Zhang, Li et al. (2017) found that the ARIMA model had the weakest SPI predicting performance when compared to ANN and wavelet-transformed ANN (WANN). The ARIMA method's inability to manage nonlinearity and non-stationarity in data is a well-known drawback. To solve this problem, researchers created a hybrid model that combined the features of ARIMA and ANN, yielding results that were superior to those obtained using the ANN and ARIMA models alone (Anshuka, van Ogtrop et al. 2019). Furthermore, for drought prediction, the ARIMA model is applicable based on these drought indices on various time scales (e.g., 3- and 6-month SPI) and other drought indicators, including the Palmer Drought Index and the standard streamflow index. The primary constraint of this model would be that the predictor has a linear relation with the predictor, and hence the nonlinear features are not obtained in general (e.g., the response of soil moisture to precipitation deficit). Furthermore, the model for time series does not take other variables impacting drought events into account, because they are solely dependent on the presence of a certain indicator (Hao, Singh et al. 2018).

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Due to their complexity, probability models are effective for drought prediction as well as quantifying uncertainty associated with hydro-meteorological factors that cause droughts (Mishra and Singh 2011). Another sort of model used in stochastic processes is Markov chains. The Markov model has been utilized frequently in applications such as the forecast of metrological droughts, probabilistic drought classification and identification of the probability of drought transition (Anshuka, van Ogtrop et al. 2019). The challenge of drought prediction in this situation may be defined as the transition from the wet or normal condition to the dry state (or the other way around), and hence the transition probability must be predicted. This may be addressed using the Markov chain (MC) model, which is based on a stochastic process with a countable state space and assumes that future states are solely dependent on the current state (Hao, Singh et al. 2018). The MC models are widely utilized for drought prediction depending on the drought statuses of several indicators, such as the Palmer Drought Index, the SPI, and the Standardized Hydrological Index (SHI) (Hao, Singh et al. 2018).

Hybrid models are essential to obtain the strengths of individual models in order to predict droughts for better precision and higher lead times in comparison to individual models. A hybrid model was formed by merging a linear stochastic model and a nonlinear artificial neural network to predict droughts by applying a Standardized Precipitation Index series, taking advantage of the benefits of both stochastic and ANN models. The hybrid model is revealed to be more accurate in forecasting droughts (Mishra and Singh 2011).

Combining the learning techniques of ANN with the neuro-fuzzy methodology for adaptive networks resulted in a hybrid model known as adaptive network-based fuzzy inference systems (ANFIS). It has been observed that using fuzzy logic alone has reduced predictability; however, using a mixed method, such as ANFIS, yielded superior results in predicting SPI. The ANFIS model also predicted different drought classes of the effective drought index with approximately 90% accuracy rate. Wavelet-transformed fuzzy logic over wavelet-transformed neural network was used to forecast the Palmer Modified Drought Index (PMDI) for the long term (6–12 months) (Anshuka, van Ogtrop et al. 2019).

There were restrictions to a single model. A single linear or nonlinear model is not appropriate for usage since the research object's time series has both linear and nonlinear components. Therefore, a hybrid model was created by combining the advantages of the ARIMA and LSTM models, as well as the hybrid ARIMA-SVR mode. ARIMA is a linear model commonly applied in drought prediction, and LSTM is a deep learning method that has achieved significant development in time series prediction. The hybrid ARIMA-LSTM model seems to be more predictive than that of other models, showing the hybrid model can help strengthen short-term predictive accuracy and is also better suited to long-term drought. However, using LSTM architecture to predict short-term time series or meteorological drought indices is difficult. The multi-time scale SPI and SPEI are predicted using LSTM, and it was discovered that the model could better process real-time nonlinear data and produce a good long-term prediction. Furthermore, three hybrid models have a higher predictive precision than three single models (ARIMA, SVR, LSTM). Hence, a number of hybrid models are employed for the prediction of the drought index since the exact prediction is not high or cannot the short-term prediction accuracy be improved (Xu, Zhang et al. 2021).

Machine learning is a useful method for analyzing complicated and data-rich occurrences such as droughts (Felsche, Ludwig et al. 2021). In many situations, linear models are unable to capture the complex interaction in the hydroclimatic system. In order to model complex interactions between hydroclimatic variables for a variety of applications, the Artificial Intelligence (AI) (or machine learning, soft computing) models, including the Artificial Neural Network (ANN), the Fuzzy Logic (FL), Support Vector Machine (SVM) or Support Vector Regression (SVR)), Genetic Algorithm (GA) or genetic Programming models and Wavelet Transformation can be used. Various AI models, such as ANN, SVM, and wavelet transformation, have been utilized to describe complicated and

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nonlinear relationships between drought indices and affecting variables for drought prediction (Hao, Singh et al. 2018).

ANNs are a Machine Learning method that can learn discrete, real, and vector valued functions while being extremely resistant to errors in training data (Adede, Oboko et al. 2019). Pitts and McCulloch initially proposed artificial neural networks in 1943. Mc Clelland and Rumelhart created backpropagation algorithms in the mid-1980s, which could be used to train complicated networks. These models have been effectively employed in hydrology since the early 1990s (Nabipour, Dehghani et al. 2020). The idea of neurons, which is based on the functional system in the human body, gave rise to ANN. An ANN makes reliable forecasts despite having a poor grasp of the physical correlation between the input and output variables, which is a major benefit when there is a lack of understanding between two variables. An ANN is particularly valuable since it can simulate nonlinear data interactions, which is common in hydrological investigations. Precipitation prediction from remotely sensed information using Artificial Neural Networks–Climate Data Record, for example, employed ANNs to build the satellite-derived precipitation product (Anshuka, van Ogtrop et al. 2019). An advantage of the ANN technique is that the modeler does not require to completely define the intermediate interactions between inputs and outputs (physical processes). This property makes ANNs particularly suited for analyzing complicated processes such as drought prediction, in which the interactions with the output of several input variables have to be investigated (Morid, Smakhtin et al. 2007).

SPI is used in machine learning models for forecasting with artificial neural networks (ANN) and support vector regression models (SVR). Because they are excellent in dealing with the non-linear properties of hydrologic data, these machine learning or data-driven models have grown in popularity in hydrologic forecasting. However, the capacity of both ANN and SVR models to deal with non-stationary data is a significant drawback. To address this constraint, researchers have increasingly attempted to use wavelet analysis to pre-process hydrologic data inputs (Belayneh, Adamowski et al. 2013). Moreover, another study demonstrated that the support vector machine (SVM), which was firstly investigated by Cortes and Vapnik, (1995), is a popular machine learning model. SVMs are simple to train, have a high efficiency, and can cope well with noisy data. SPI was forecasted using the least squares support vector machine (LSSVM), which yielded encouraging results (error value of approximately 0.1 and correlation of 0.9). Comparison has been done between these machine learning models, ANN, ANFIS, and SVM, and found that SVM outperformed neural networks and ANFIS in predicting SPI (Anshuka, van Ogtrop et al. 2019).

4. Drought Indices and Indicators

There are several drought indices, each with its own set of data input criteria and offering a somewhat different assessment of drought.

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Table 1. Summary of indices and indicators used around the world for drought detection.

Drought Indices and indicators	Purposes	Advantages	disadvantages	Origins	Research examples
Palmer Drought Severity Index (PDSI)	Used for measuring long-term meteorological drought, is perhaps the most well-known. Despite criticisms regarding the PDSI as a drought severity indicator and its use to assess effect, it is extensively used by a wide range of users.	It was mainly proposed as a means of recognizing droughts affecting agriculture. Furthermore, PDSI strengths are it is used worldwide and output are widespread. PDSI in the scientific literature extremely robust for diagnosing drought since it uses soil data and a comprehensive water balance technique.	The requirement for serially full data might cause issues. PDSI does indeed have a timescale of roughly nine months, resulting in a lag in recognizing drought situations due to the simplicity of the soil moisture component within the computations. As well as PDSI does not manage frozen precipitation or frozen soils effectively	Created by W.C. Palmer (1965) as a climatological instrument	(Heddinghaus and Sabol 1991) & (Svoboda and Fuchs 2016)
Standardized Precipitation Index (SPI)	The SPI is a statistical probability-based indicator of drought that was designed to be spatially invariant. It is created by standardizing the probability of measured precipitation for any duration; shorter duration of weeks or months can be exploited to adapt this index to agricultural interests, while greater durations of years can be employed to employ this index to water supply and water management interests.	It just requires precipitation data; It is a spatially consistent indicator of drought severity and intensity that can be compared across space and time; (3) It can be developed for various time scales (i.e., 1, 3, 6, 9, 12, and 24 months). (4) World Meteorological Organization (WMO) recommends SPI for monitoring droughts, especially, meteorological droughts	SPI cannot characterize elements of agricultural or hydrological drought like multi-variable indices because it only considers precipitation.	McKee et al. (1993, 1995) developed the SPI to provide proper a moisture supply index	(Meng, Ford et al. 2017) & (Anshuka, van Ogtrop et al. 2019) & (Svoboda and Fuchs 2016)
Standardized Precipitation Evapotranspiration Index (SPEI)	The SPEI makes it possible to compare the severity of drought with time and place. Its multi-scalar character which allows for the detection, monitoring and analysis of droughts by various scientific disciplines.	SPEI can account for the influence of temperature on a drought condition because temperature data is included alongside precipitation data. The result is relevant to all climate zones, and the findings are comparable since they are standard. SPEI is an ideal index for examining the impact of climate change by Using temperature data,	Because inadequate data is available, the necessity for a serially full dataset for both temperature and precipitation may limit its applicability.	Developed by Vicente-Serrano et al. at the Instituto Pirenaico de Ecologia in Zaragoza, Spain.	(Vicente-Serrano, Beguería et al. 2010) & (Svoboda and Fuchs 2016)
The NOAA Drought Index (NDI)	Estimate agricultural production using meteorological and climate data from across the world, which provides an early warning system to detect agricultural drought in developing countries.	It needs only precipitation, in a monthly time	At least 30 years of data are necessary. It requires converting monthly precipitation to weekly precipitation values as input data	(NDI) was introduced by (Strommen and Motha) in the early 1980s	(Quiring, Papakryiakou et al. 2003) & (Svoboda and Fuchs 2016)

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Aridity Anomaly Index (AAI)	It is calculated for periods of one week or two weeks. The real aridity is evaluated to the normal aridity for that era for each period. Negative numbers show an excess of moisture, and positive values show a stress of humidity.	This approach may be used to evaluate both winter and summer cultivation seasons. Furthermore, it has specific benefits for agriculture which computations are straightforward, and drought descriptions (mild, moderate, or severe) are dependent on deviations from normal.	It also has a weakness that makes it unsuitable for long-term or multi-seasonal events	(AI) is developed by the India Meteorological Department	(Rathore, Sud et al. 2014) & (Svoboda and Fuchs 2016)
Effective Drought Index (EDI) **(Meteorological parameters)**	EDI was presented as a method for detecting droughts, including the precise beginning and ending of the drought period, as well as the length and intensity of droughts by employing a novel method of effective precipitation (EP).	EDI may be calculated for any place where precipitation is collected with a single input that is necessary for computations. EDI is standardized in order to compare the performance of all climatic regimes. It can determine the start, end and length of drought episodes well.	The influence of temperature on drought circumstances is not directly incorporated when precipitation is only taken into consideration. Daily data may make using EDI in an operational setting challenging since daily changes to input data may not be possible.	Developed by Byun and Wilhite in (1999), along with staff at NDMC	(Kamruzzaman, Cho et al. 2019) & (Svoboda and Fuchs 2016)
Rainfall Anomaly Index (RAI) (Meteorological parameters)	Use normalized precipitation data based on the history of the station in a certain location. RAI is versatile in that it can be analyzed at multiple timescales, so it can address droughts that impact agriculture, water resources, and other fields.	Simple to compute, having only one input (precipitation) that may be analyzed on a monthly, seasonal, or yearly timeline.	It is necessary to have a serially full dataset with missing value estimations. Within-year fluctuations must be minor in comparison to temporal variations.	Van Rooy started his project in the early 1960s.	(Svoboda and Fuchs 2016)
Drought Area Index (DAI) (Meteorological parameters)	It was designed as a way to better understand monsoon rainfall by predicting both flood and drought events based on monthly precipitation.	Mostly concentrated in tropical monsoon seasons.	Failure to apply to different regions or climatic regimes.	Bhalme and Mooley of the Indian Institute of Tropical Meteorology developed it in the late 1970s.	(Svoboda and Fuchs 2016)
Keetch–Byram Drought Index (KBDI) (Meteorological parameters)	(KBDI) is utilized for drought assessment for fire control planning requirements. The effects of drought on highly flammable are well recognized. In times of drought, plants are water-stressed.	It exhibits an area's moisture deficiency and would be scaled to illustrate the peculiarities of each place. The calculations are straightforward and the approach is easy to apply.	The limitation of availability of moisture and the specific climatic conditions lead to developing drought, which these factors may or may not be true for every location	The work of Keetch and Byram in the late 1960s was done in the United States. It is mostly an indicator of fire.	(Xanthopoulos, Maheras et al. 2006) & (Svoboda and Fuchs 2016)
Reclamation Drought Index (RDI) (Meteorological parameters)	It is mostly applied to monitor river basin water supplies.	Every basin is really special. It represents temperature impacts on climate, as opposed to SWSI. The wet and dry scales permit wet and dry conditions to be monitored.	Calculations are done for each basin; thus, it is difficult to make comparisons. All inputs can cause delays in data	This drought index was created by the United States Bureau of Reclamation in the mid-1990s.	(Svoboda and Fuchs 2016)

			generation in an operational context.		
Soil Moisture Anomaly (SMA) (Soil moisture parameters)	Extensively used to monitor drought impacts on crops and agriculture world-wide which can predict the circumstances of beginning and duration of agricultural drought.	Taking both the temperature and the precipitation impacts into consideration, it evaluates moisture at various levels of the soil and is more flexible to different locations than PDSI.	Calculation is difficult due to the data required. Assessments of potential evapotranspiration vary significantly by area.	Developed in the United States, in the mid-1980s, by Bergman et al. as a method for assessing circumstances of global drought.	(Svoboda and Fuchs 2016)
Evapotranspiration Deficit Index (ETDI) (Soil moisture parameters)	The ETDI employs both actual evapotranspiration (ET) and potential evapotranspiration (PET) data, which are valuable for predicting and monitoring short-term agricultural drought.	It is actually useful to identify wet and dry period, by analyzing both PT and PET	The calculations are based on SWAT model output. When evapotranspiration is great and precipitation is highly variable, the spatial variability of ETDI increases dramatically.	Developed in 2004 at the Texas Agricultural Experiment Station in the United States by Narasimhan and Srinivasan,	(Wambura 2021) & (Svoboda and Fuchs 2016)
Standardized Reservoir Supply Index (SRSI) (Hydrological parameters)	Monthly data are employed to construct a probability distribution function of reservoir data storage, similar to SPI, to offer insight on water availability for a location or a basin within a range of severely dry to extremely wet.	Simulates SPI computations using a conventional gamma distribution of the probability distribution function, making it simple to compute.	Changes in utilization of water resources and losses owing to evaporation are not taken into consideration.	Gusyev et al. in Japan invented this method to analyze reservoir data in drought condition.	(Svoboda and Fuchs 2016)
Standardized Water-level Index (SWI) (Hydrological parameters)	It investigates the influence of drought on groundwater recharge using data from wells, which is especially useful in places with regular seasonal low flows on major rivers and streams.	Drought's influence on groundwater is a critical factor in agricultural and municipal water supply.	Groundwater is the only factor considered, thus the interpolation between sites may not be indicative of the region or climatic regime.	Bhuiyan developed the method to estimate groundwater recharge deficiencies at the Indian Institute of Technology in India.	(Svoboda and Fuchs 2016)
Streamflow Drought Index (SDI) (Hydrological parameters)	Drought periods are monitored and identified using a specific gauge, which may or may not reflect broader basins.	The program is straightforward to implement and easily accessible. Missing data is acceptable, the results are more realistic and accurate and various timescales can be investigated.	A single input (streamflow) might distort the outcomes in the periods of no flow	Nalbantis and Tsakiris developed it on the basis of SPI's approach and calculations.	(Svoboda and Fuchs 2016)
Vegetation Drought Response Index (VegDRI) (Remote sensing with ground data)	Developed as a drought-induced vegetation stress monitor, with a mix of remote sensing, climate-based indicators and other biophysical information and land-use data. It is largely used in agricultural applications as a short-term drought indicator.	Innovative and integrated surface and remotely sensed data technology	It is definitely not valuable for the periods on little or no vegetation due to short recording period of remote sensed data.	Designed by a team of NDMC scientists	(Svoboda and Fuchs 2016)

Combined Drought Indicator (CDI) (Modelled with multiple indices)	Applied to predict droughts with agricultural consequences by combining three drought indicators: SPI, soil moisture, and data from remotely sensed vegetation	A combination of remotely sensed and surface data ensures a strong spatial coverage at a high resolution.	It's challenging to replicate, and it is generally unavailable outside of Europe.	Sepulcre-Canto et al. developed it at the European Drought Observatory.	(Svoboda and Fuchs 2016)
Global Integrated Drought Monitoring and Prediction System (GIDMaPS) (Modelled with multiple indices)	Based on several satellite- and model-based precipitation and soil moisture data sets, the system provides meteorological and agricultural drought signals. This contains a near-real-time monitoring component as well as a seasonal probabilistic forecast module.	It is ideal for locations with a scarcity of reliable surface observations over lengthy periods of time. It is quite simple to use because it is calculated without the requirement for user input.	Grid sizes may not accurately reflect all locations and climatic regimes.	Hao et al. from the University of California in Irvine, California, developed a method to monitor and predict drought throughout the world.	(Hao, AghaKouchak et al. 2014) & (Svoboda and Fuchs 2016)
Global Land Data Assimilation System (GLDAS) (Remote sensing and modelled with multiple indices)	Based on present circumstances, it is useful for estimating river and streamflow forecasts as well as runoff components; it is great for monitoring droughts with various consequences.	Useful for monitoring emerging droughts in locations with limited data.	For island nations, the grid size is insufficiently fine.	NASA and NOAA scientists from the United States	(Svoboda and Fuchs 2016)
Surface Water Supply Index (SWSI)	Used to detect drought conditions caused by hydrological fluctuations. SWSI identifies the approximate frequency of mild drought, moderate drought, and severe drought and extreme drought.	Takes Palmer's work with PDSI into consideration but adds more details (snow accumulation, snow-melting, runoff and water reservoir) comprising information about the water supply, and basin level calculation.	Since the computations might differ between basins, as a result basins and homogenous regions are difficult to compare.	Developed for directly addressing some of the restrictions identified in PDSI by Shafer and Dezman in 1982.	(Doesken and Garen 1991) & (Svoboda and Fuchs 2016)
Enhanced Vegetation Index (EVI)	It is used to identify drought stress across various terrain. Mainly linked to the development of agricultural droughts. EVI is more responsive to the canopy, canopy and architectural changes and physiognomy of plants.	High resolution and strong spatial coverage across all regions.	Other than drought, stress on plant canopies can occur, and it is difficult to distinguish them using simply EVI. The record time for satellite data is limited, making climate research challenging.	It was developed by Huete, a team of people from Brazil and the University of Arizona, USA, that developed a method for monitoring vegetation conditions depending on (MODIS).	(Huete, Didan et al. 2002) & (Svoboda and Fuchs 2016)
Normalized Difference Vegetation Index (NDVI)	Droughts affecting agriculture are identified and monitored using this method. NDVI is calculated using radiance levels obtained in both the visible and near-infrared channels. It evaluates the greenness and vigor of vegetation over a seven-day	The employment of satellite data to assess the condition of vegetation in connection to drought events is novel. High resolution and extensive spatial coverage.	Data processing is critical to NDVI, and a strong system is required for this phase. Satellite data does not have a lengthy history.	Tarpley et al. and Kogan collaborated with the National Oceanic and Atmospheric Administration (NOAA) in the United States to	(Kogan 1995) & (Svoboda and Fuchs 2016)

	period to reduce cloud contamination and to detect drought-related stress in vegetation.			develop this model.	
Vegetation Condition Index (VCI)	Used in combination with NDVI and TCI to assess vegetation in drought-affected agricultural areas. It concentrates on the effect of drought on vegetation via AVHRR thermal bands and can provide information on the onset, length, and intensity of drought by detecting vegetation variations and matching them to historical values.	High resolution and strong spatial coverage across all regions.	Cloud contamination potential and a limited period of record	Developed by Kogan in collaboration with NOAA in the United States.	(Kogan 1995) & (Liu and Kogan 1996) & (Svoboda and Fuchs 2016)
Temperature Condition Index (TCI)	Used in combination with the NDVI and the VCI for Vegetation drought assessment. TCI uses AVHRR thermal bands to evaluate stress on vegetation induced by high temperatures and excessive moisture.	High resolution and strong spatial coverage across all regions.	Cloud contamination potential and a limited period of record	Developed by Kogan in collaboration with NOAA in the United States.	(Kogan 1995) & (Svoboda and Fuchs 2016)
Normalized Difference Water Index (NDWI) and Land Surface Water Index (LSWI)	It is used as a form of stress detection to assess drought in agriculture. Much like NDVI, but the near-infrared channel is used to measure water content of the vegetation canopy	High resolution of every terrain and strong spatial coverage. It is different to NDVI in terms of highly detecting water bodies and other features	Stress on plant canopies can be induced by effects other than drought and they are hard to identify using NDWI solely.	Gao's work at the (NASA) in the mid-1990s led to the development of this method.	(Chandrasekar, Sesha Sai et al. 2010) & (Svoboda and Fuchs 2016)

5. Indices of Climate Variability

The ENSO phenomena in the tropical Pacific is very essential because of its profound effect on hydro-meteorological catastrophes such as floods and droughts outside of tropical areas (Sigdel, Ikeda et al. 2010). The El Nino-Southern Oscillation (ENSO) mode of climatic variables, which is related to irregular, quasi-periodic variations in sea surface temperature (SST) and air pressure (AP) over through the tropical Pacific Ocean, is probably the most effective, manifestly paired inter-annual climate indication and the most vital phenomenon in the interaction of atmospheric and ocean dynamics. ENSO is referred to as the Walker circulation system due to a differentiation in air pressure and sea surface temperature (SST) throughout the Pacific Ocean, both west and east. During a positive Southern Oscillation (SO) stage, the tropical West Pacific is hot and rainy with a low-pressure system, while a high-pressure system over the Eastern Pacific has cold and dry weather (Norel, Kałczyński et al. 2021). The significant link between ENSO and seasonal average precipitation and temperature abnormalities that are thought to be essential determinants of drought onset. The fluctuations of droughts and wet spells are largely influenced by ENSO. The warm phase (El Niño) and cold phase (La Niña) of ENSO occur on a regular basis, which is its most notable feature (Özger, Mishra et al. 2009). In the south and centre of Southeast Asia and the Pacific area, there was a statistically significant relationship between ENSO and precipitation anomalies, but no such link was found in the north. Furthermore, several pieces of evidence point to a significant connection between climate indices and Middle East hydro-meteorological variables. Previous studies have all identified connections between climatic indices and hydro-meteorological variables in respective research areas. ENSO and Arctic Oscillation (AO) are usually key contributors to the impact of hydrological droughts among the climatic indicators. The ENSO Index has a significant influence more than AO on droughts (Huang, Huang et al. 2016).

The North Atlantic Oscillation (NAO) is a type of weather phenomenon that occurs in the North Atlantic. The term NAO is defined as cyclic variations in air pressure in the Icelandic Low and Azores High. If the NAO index has a positive (seasonal or monthly) reading, the air pressure difference between the Icelandic Low and the Azores High is great. The continents close to the North Atlantic–Europe and North America–are affected by the NAO mode of natural variability. The Atlantic storm track intensifies and pushes northward during the positive phase of the NAO index. Winters in Europe are hot and humid, but winters in Greenland and northeastern Canada are cold and dry. The storm path is lighter and therefore more eastward during a negative phase of the NAO index, leading to rainy winters in southern Europe and the Mediterranean and colder winters in northern Europe (Norel, Kałczyński et al. 2021).

Inter-decadal Pacific Oscillation (IPO) or Pacific Decadal Oscillation (PDO) is another expression of the ocean–atmosphere system's unpredictability. It is a decadal-scale temperature oscillation pattern in the Pacific Ocean's surface waters, sometimes referred to as a lengthy ENSO-like Pacific climate oscillation trend. In the extratropical North Pacific, the PDO is a dominant mode of multi-decadal oscillation in Sea Surface Temperature (SST). Another phenomenon that occurs every 60 to 90 years in the North Atlantic (SST) is Atlantic Multidecadal Oscillation (AMO) which is a consistent pattern of periodic variations that might be considered to represent internal climate variability (Norel, Kałczyński et al. 2021).

6. Conclusion

Drought is a natural phenomenon, which occurs in all climatic zones, it affects almost half of the world. There are many indices, which can be used to detect drought in early warning, but some of them outperform than others such as PDSI, SPI, SPEI, EVI, NDVI, NDWI, VCI and TCI. Since drought indices depend on input data, some of them require fewer data such as SPI, it is ideal for those areas that do not have enough data and sometimes station data is not available, for detecting drought must rely on remote sensing indices such as NDVI, NDWI, VCI and TCI.

Drought prediction is essential for early notification and drought response. The key to statistical prediction is to develop models that define temporal or spatial dependencies between predictands and predictors. Several models are developed for predicting drought. On one hand, Hybrid models are essential in order to predict droughts for better precision and higher lead times in comparison to individual models. On other hand, Machine learning is a useful method for analyzing complicated and data-rich occurrences such as droughts. In many situations, linear models are unable to capture the complex interaction in the hydroclimatic system. Furthermore, Time series models are extensively utilized in a wide range of scientific disciplines, particularly hydrology.

Climatic indices must be considered when for predict and detecting drought, especially ENSO and SST because of the fluctuations of droughts and wet spells are largely influenced by ENSO. The warm phase (El Niño) and cold phase (La Niña) of ENSO occur on a regular basis, which is its most notable feature.

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