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DROUGHT FORECASTING: A REVIEW OF MODELLING APPROACHES 1990-2022

KEY WORDS: Drought forecasting, time series models, regression models, machine learning models

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ABSTRACT

Drought is a deficiency of precipitation that extends across a season or an extended period of time, resulting in an insufficient water supply to fulfil the needs of social actions and the environment. Drought forecasting plays an essential aspect of water resource management, as it enables us to predict the likelihood of droughts and take appropriate measures to mitigate their impacts. In the past 3 decades (1990-2022), various models have been developed and used to forecast droughts. The models are characterized according to their respective mechanisms: time-series models, regression analysis, stochastic, Artificial Neural Network (ANN) models, hybrid models, and dynamic models. In this review, we will explore some of the model approaches that have been used for drought forecasting during this time period.

1. INTRODUCTION

In numerous regions across the globe, water scarcity has become a frequent occurrence, primarily driven by a manifold rise in water demand attributed to population growth, as well as the development of agricultural, energy, and industrial domains. Additionally, aspects like contamination of water and climate change worsen this problem (Bates *et al.,* 2008). Droughts exacerbate the shortage of water resources, impacting both surface water and underground aquifers. They can lead to a decline in water quality, decreased water supply, harm to riparian habitats, and crop failures (Riebsame *et al.,* 1991). Therefore, understanding drought and forecasting has drawn the attention of ecologists, hydrologists, meteorologists, and agricultural scientists (Ashok K Mishra and Vijay P. Singh, 2011).

Droughts play a significant role in the planning and management of water resources (Mishra & Singh, 2010). Droughts can be classified into four distinct categories based on their characteristics: meteorological, agricultural, hydrological, and socioeconomic droughts. In conceptual terms, a meteorological drought is defined as a deficiency in precipitation over a specific region for a certain duration (Mishra and Singh, 2010). Droughts are inherently region-specific due to the variability of weather conditions, including low precipitation, dry winds, and high temperatures, which differ from one area to another. When atmospheric moisture reaches a point where it impacts soil moisture, the onset of an agricultural drought becomes imminent (Zargar *et al.,*2011). A hydrological drought is characterized by prolonged dry periods of such duration that they cause river streamflows and the water levels in aquifers, lakes, or reservoirs to drop below the long-term average levels (Dai 2011). Socioeconomic droughts have a slower development compared to the previous two categories because they encompass not only the depletion phase but also the replenishing phase of water resources. These droughts occur when water resource systems are unable to meet the water demand necessary for economic activities, as explained (Mishra & Singh, 2011). Considering that drought events can result in crop failures, disrupted food chains, and decreased water supply, the prediction of drought occurrences is unquestionably a crucial aspect of water resources planning and management, as emphasized (K.F. Fung *et al.*, 2020).

Types of Drought and Indices

Drought can be categorized into four distinct types, taking into account both physical and socioeconomic factors: meteorological, agricultural, hydrological, and socioeconomic drought. Predicting drought involves considering numerous variables. The Standardized Precipitation Index (SPI) is a suitable index for assessing drought conditions. Drought indicators are employed to grade the severity of drought, ranging from abnormally dry to moderately dry, severe drought, extreme drought, and exceptional drought (the most severe category). Meteorological drought occurs as a result of prolonged periods of insufficient precipitation.

The Palmer Drought Severity Index (PDSI), Percent of Normal Precipitation (PNP), and SPI are among the most commonly employed indicators for meteorological drought assessment. Meteorological drought arises from the interplay of numerous factors, with its primary association being linked to precipitation patterns. Predicting meteorological drought typically on climate forecasts (Yoon *et al.*, 2012). Meteorological forecasting plays a pivotal role in anticipating various forms of drought. Agricultural drought, in particular, is closely tied to insufficient soil moisture, which has a direct impact on crop yields. Essentially, the prediction of agricultural drought hinges on the availability of soil moisture data. Soil Moisture Deficit Index (SMDI), Crop Moisture Index (CMI), Normalized Soil Moisture (NSM), and Soil Moisture Percentile (SMP) are the most commonly used indices for agricultural drought prediction. These indices are derived mainly from soil moisture (Dutta *et al.*, 2013). Whenever there is a lack of stream flow, runoff, reservoir, groundwater level, river, etc., there will be a hydrological drought. The commonly used hydrological drought indices are the Standardized Runoff Index (SRI), Streamflow Percentile (SP), Palmer Hydrologic Drought Index (PHDI), etc. Most of the time meteorological drought leads to hydrological drought. The main factors that cause hydrological drought are low temperature, low water storage, precipitation deficit or snow accumulation, etc. Hydrological drought is chiefly shaped by climate patterns, whereas socioeconomic drought arises when demand exceeds supply. Socioeconomic drought illustrates the interaction between drought conditions and human actions, predominantly impacting societal, economic, environmental, agricultural, or economic systems.

2. Drought forecasting

Drought forecasting is an essential aspect of water resource management as it helps decision-makers to anticipate water shortages, risk management, drought preparedness, and mitigation. Over the years, numerous models have been devised for predicting drought, each possessing its own set of advantages and limitations. Drought forecasting necessitates the examination of diverse factors, including temperature, soil moisture, precipitation, and vegetation cover. These features are used to develop mathematical models that can simulate the hydrological cycle and other relevant processes. Accurate drought forecasting can help governments, communities, and individuals to take appropriate measures to mitigate the impacts of drought.

2.1 Time series models:

Time series models find common use across a wide spectrum of scientific fields, such as hydrology. Nevertheless, their application in drought forecasting has been somewhat restricted. Notably, time series models offer significant advantages, notably their systematic ability to search for identification, estimation, and diagnostic checks during model development (Mishra and Desai, 2005a). Drought forecasting relies on various well-known time series models, including the Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), and Markov chain models. These models assists in predicting forthcoming drought conditions by leveraging historical data patterns. Neural networks come into play for forecasting decomposed sub-signals at different resolution levels and then reconstructing these forecasted sub-signals. The results clearly demonstrate that the combined model substantially enhances the predictive capabilities of nueral networks for regional drought indexing. The forecasting of hydrologic drought holds a crucial role in mitigating the adverse effects of drought on water resource systems (Tae-Woong Kim and Juan B. Valdes, 2003). Here, time series models have been used for hydrological drought forecasting. Simple/multiple regression models, ARMA, and ARIMA models are commonly used time series models for forecasting. ARIMA models are used in the Vegetation Temperature Condition Index (VTCI) series and forecast its changes in the future. A novel approach to modelling spatiotemporal series is employed in the VTCI series, as introduced by (Ping Hana *et al*., 2010). By taking into account the factors influencing agricultural drought and amalgamating the forecasting outcomes for drought disaster in a given year, the Standardized Precipitation Index (SPI) series, the VTCI series, and incorporating medium to long-range weather forecast products, a forecasting system for Gaunzhong Plain can be developed. This system is expected to possess strong forecasting capabilities (Ping Han *et al*., 2010).

In a different study conducted in a hyper-arid climate region, linear stochastic models such as ARIMA are employed to predict drought conditions using the Standardized Precipitation Evaporative Index(SPEI) as described by(Amr Mossad and Abdulrahman Ali Alazba, 2015). There-fore ARIMA models worked better whenever there is different timescales to forecast drought. ARIMA models gave more precise results, which helped locals, resource management committee and government to take necessary mitigation measures for severity of drought well in advance. Therefore, this study suggests that ARIMA models can serve as valuable tools for drought forecasting, offering the ability for water resource managers and planners to proactively implement measures based on the anticipated drought severity. Among the various models (AR, MA, ARMA, and ARIMA) applied to the computed three-month RDI time series using observed data from 1980 to 2010 at all stations, the model with the lowest AICC value was selected as the optimal choice. The application of the linear stochastic model (ARIMA) proved successful in forecasting droughts for the Bundelkhand region in Central India. The temporal patterns of droughts revealed that the area consistently faced frequent moderate and severe droughts(i.e., SPI<-1) throughout most months of the year. Linear stochastic models can be employed to forecast SPI time series at various time scales, enabling the detection of drought severity. This information can be highly valuable for local authorities and water resource planners, allowing them to proactively implement precautionary measures in response to the anticipated drought severity (N M Alam *et al*., 2013). There are many other types of regression models using which we can study the pattern. Seasonal Autoregressive Integrated Moving Average Models (SARIMA) can be instrumental in analyzing and understanding seasonal patterns, as well as elucidating the characteristics of drought patterns. The seasonal Decomposition of Time Series (SDT) method decomposes the chronological data into seasonal, cyclical, erratic, and secular trends. Also, it helps in forecasting drought. In the field of Time Series analysis, Long Short Term Memory (LSTM) and Recurrent Neural Network (RNN) models are employed for conducting in-depth statistical analysis.

2.2 Regression analysis:

Regression analysis stands as an early contender and a frequently employed method for forecasting in time series predictions. Regression analysis is a statistical method to examine the relationships between variables (Sykes, 1993). The act of this method is generally based on the number of independent variables, type of dependent variables, and shape of the regression line. For example, a multiple regression predicts one variable from two or more independent variables. The equation is of the type, $Y=a+bX_1+cX_2+dX_3+....+\mathcal{E}t$. Here the dependent variable is a drought forecasting parameter, whereas the independent variables are explanatory variables such as precipitation, soil moisture, streamflow, temperature etc. for drought forecasting. In essence, the wide range of regression analysis used for time series forecasting includes logistic regression and log-linear regression (K. F. Fung *et al.,* 2020). A regression model which is developed considering the grain yield of a main crop as an agricultural drought quantifying parameter and variables affecting the grain yield in the region as explanatory variables for agricultural drought forecasting (Kumar and Panu, 1997). This regression model was able to predict the grain yield of the main crop several months ahead of crop harvesting operations and was, in turn, able to assess the agricultural drought severity as mild, moderate, or severe. A similar study was done by Leilah and Al-Khateeb (2005) in which the association between wheat grain yield and its components under drought conditions of Saudi Arabia.

2.3 Stochastic models:

Stochastic models have found extensive use in scientific applications, including analysis and modelling of the hydrologic time series. The advantages of stochastic models include better consideration of the serial linear correlation characteristic of time series; capability to search systematically for identification; estimation and diagnostic check for model development; and SARIMA requires only a few parameters to describe non-stationary time series for both within and across seasons. The various types of stochastic models are Markov chain models, ARIMA models, Generalized Additive Models for location, Copulas models, etc. Two important and popular classes of stochastic models are the ARIMA and the SARIMA (Mishra *et al*. (2007)). Markov chain model are based on the current state to predict the future state about drought. Here drought can be classified as mild, moderate and severe. There is a hidden Markov models which is used for drought forecasting using various drought indices such as Standardized Precipitation Index, Palmer Drought Severity Index etc., The Generalized Additive Models are useful for modelling observations with different sources. In case of drought prediction, it shows a non-linear relationships between weather parameters, climatic variables and various drought indices. Copulas are also useful models in understanding the dependency structure climatic variables, soil parameters, or temperature and rainfall, which contribute major part of drought forecasting. As a conclusion, each stochastic model has its own efficiency, strengths and drawbacks. Depending on available data, nature of the available data, the level of complexity required etc., drought prediction can be made. In another study, Hyper-Arid climate place is chosen for drought forecasting using Stochastic models. Many Auto Regressive Integrated Moving Average models are used for drought forecasting. The Standardized Precipitation Evapotranspiration Index has been used to check the severity of drought. The development of Autoregressive model involves of few steps. They are parameter estimation, model identification, and diagnostic checking. Finally, results show that SPEI is considered to be the most powerful drought index to examine drought in Hail regions (Amr Mossad and Abdulrahman Ali Alazba, 2015). In another study, drought forecasting has been done in Bundelkhand region in Central India. Here SPI series has been considered for different time scales. Also suitable linear stochastic model is developed through seasonal and non-seasonal ARIMA model. To select the best model Akaike Information Criterion (AIC), Coefficient of determination (R^2), and Schwarz Bayesian Criterion (SBC) was used. Results say that to detect drought severity in the Bundelkhand region, linear stochastic model can be used (Alam *et al.* 2014). ARIMA model was used to forecast drought in another study which was held in Southern Taiwan. Forty year data is used to train the model , AIC, SBC, and R^2 are used for model efficiency. The results show that ARIMA model based on SPI, works best for drought forecasting (Hsin-Fu Yeh and Hsin-Li Hsu, 2019).

2.4 Artificial Intelligence Model:

Artificial Intelligence model uses both quality and quantity of data available to forecast drought. There are many AI models to study drought patterns. Some of them are machine learning models, deep learning models, climate models and downscaling, Reinforcement learning, hybrid models, etc., Machine learning algorithms are commonly used AI techniques to forecast drought. In this model, Support Vector Machines (SVM), regression, random forest techniques, and decision trees are used to study historical data and weather parameters to predict drought. Also, data obtained from satellites and remote sensing helps to study environmental changes due to lack of water. This type of data is useful in collecting soil moisture, and vegetation conditions that contribute to drought forecasting. In one of the studies, the author used AI-based techniques for fluvial flood forecasting and meteorological drought forecasting. The author has used indices to study the precipitation level such as Standardized Precipitation Index (SPI) and various methods such as Convolution Neural Networks, Wavelet Adaptive Neuro-Fuzzy Inference Systems (WANFIS), and Long-Short Term Memory networks are used for flood and drought forecasting. The study was done in the tropical region and arid region for flood and drought respectively. Finally, the author could conclude by saying that Convolution Neural Network performs best in flood prediction and Wavelet Adaptive Neuro-Fuzzy Inference Systems performs best in drought prediction (Kasuni E. Adikari *et al.*, 2021).

2.5 Machine learning models:

Machine learning models are becoming increasingly popular for drought forecasting due to their ability to learn from historical data and make accurate predictions. Machine learning algorithms are basically Artificial Intelligence (AI) models. These algorithms are planned according to previous experiences and problems. Machine learning algorithms are divided into two parts, namely, supervised learning and unsupervised learning. These models use algorithms such as Random Forest, Support Vector Machines (SVMs), and Artificial Neural Networks to forecast droughts. To discover drought pattern from the data, Neural networks are used, which is a class of nonlinear models. From the past experience, theoretically it has been proved that Neural networks are used to estimate any complex pattern or functional relationship with greater accuracy (A.K. Mishra, V.P. Singh, 2011). An Artificial Neural Network is a system that is similar to an information processing system and the structure resembles brain (Mairer *et al.*,2010). In 1940's an ANN modelling method was developed (McCulloch and Pitts, 1943) and gradually progressed with advances in calibration methodologies (Rahul Patil et al. 2020). An ANN model was fitted to the SPI time series at different timescales. Typically, a forecasting application involves the application of a three-tier feed-forward architecture, comprising an input layer, a concealed layer, and an output layer. The input nodes can be: (i) suitable previously lagged observations of drought quantifying time series, (ii) explanatory variables for quantifying drought, or (iii) a combination of both (i) and (ii). The input information is processed by utilizing hidden nodes that incorporate suitable nonlinear transfer functions, while the output layer is used for forecasting for different lead times (A.K. Mishra, V.P. Singh, 2011). In another study of forecasting Indian monsoon rainfall which is included within the year, the author says that ANN models are good in handling multifaceted unstructured data. In this study hundred year data has been used to study the structure of the rainfall pattern. Here a model is developed for four sets of data. The developed model is accomplished by updating as the length of the sample increases (Kokila Ramesh and R.N. Iyengar, 2017).

2.6 Hybrid models:

Hybrid models amalgamate various modelling approaches to enhance the precision of drought forecasting. Hybrid models prove to be valuable in harnessing the strengths of individual models, enabling more accurate predictions of drought and extending the lead time beyond what can be achieved by individual models alone. For example, wavelet transform methods can capture useful information at various resolution levels, whereas a neural network model can forecast the decomposed sub-signals at various resolution levels obtained from wavelets and reconstruct forecasted sub-signals to the original series. The Applicability of this hybrid model was showcased by a study conducted by (Kim and Valdes, 2003), wherein they used the Palmer Drought Severity Index(PDSI) as a drought indicator. The results illustrated an enhancement in the predictive capabilities of neural networks when forecasting regional droughts. A hybrid model, combining a linear stochastic approach and a nonlinear ANN, is employed to predict droughts using the Standardized Precipitation Index series. This approach connects the strengths of both stochastic and ANN models (Mishra *et al.* 2007). A combination of wavelet and fuzzy logic (WFL) models for long lead-time drought forecasting using the Palmer drought series is developed for forecasting (Ozger *et al.* 2012). The hybrid model was found to forecast droughts with greater precision. There are various types of approaches are used to develop hybrid models. For example, the ARIMA model and various indices such as Standardized Precipitation Index (SPI), can be used to study long-term drought patterns. Also, Artificial Intelligence and machine learning algorithms such as random forest, support vector mean, artificial neural network, etc., can be used to study complex patterns of drought conditions.

The main advantage of this type of hybrid model is, it can handle vast data sets. The hybrid model can be a combination of data collected from various sources such as remote sensing data, weather station data, and satellite imagery data. This approach helps us to make predictions about drought. Also helps us to know the relationships between environmental factors and drought. Hybrid models can give more precise and accurate data for drought forecasting and help people to take mitigation measures against it.

2.7 Conditional Probability model:

The joint probability distribution has been frequently been employed to classify the combined nature of multiple drought variables, from which the conditional distribution can be constructed. Many studies have been conducted for the prediction of hydroclimatic variables. Conditional probability can be calculated by using the formula: Probability (Drought occurrence | Definite Conditions) = Probability (Drought and Definite conditions)/ Probability (Definite Conditions). In the given formula the first step is to identify the event, here it can be drought or climatical conditions or weather conditions. Then in the next step, we have to gather data based on past drought conditions and their impact. Conditional probabilities are helpful in estimation of drought when the climatic and weather conditions are observed.

Research Methodology:

From the literature survey, the following methodology is used in the drought forecasting. Firstly, the data related to soil types, soil nutrients, weather parameters, meteorological parameters etc has to be collected from various sources. Then data has to be classified according to village, taluk, district-wise, and state-wise. Then based on the risk factors and drought database the model has to be fitted. Finally, the model validation is made using the coefficient of determination, AIC or BIC. The following figure shows the research process of drought forecasting.

3. CONCLUSION:

The review of drought forecasting models from 1990 to 2022 has shown that different approaches have been used, including time-series modelling, stochastic modelling, Artificial Neural Network modelling, regression modelling, hybrid modelling, and machine learning. Every approach possesses its own set of advantages and disadvantages, and the selection of a modelling approach hinges on factors such as the desired level of accuracy, data availability, and resource constraints. Additionally, numerous criteria exert influence on the performance and precision of forecasting models, as evidenced in the literature, which also suggests that the implementation of preprocessing techniques can augment model accuracy.

The examination of modelling techniques in the context of drought prediction is of paramount importance in the fields of hydrology, meteorology, and in addressing agricultural crises. In summary, various methods exists for forecasting drought, with the selection of appropriate input variables based on relevant time scales and lead time duration representing crucial factors for achieving precision in prediction.

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