

# An Analysis of Drought Detection and Monitoring Techniques

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**Abstract**—India is very diverse country in terms of climatic conditions and also agricultural productions. The varied climatic conditions lead to different natural hazards experienced by people such as floods, droughts, storms, etc. which differs from region to region. A drought is an event of prolonged shortages in the water supply, whether atmospheric, surface water or groundwater. It is necessary to accurately study onset and duration of drought to understand this natural hazard and reduce its effects on people and livestock. Many researchers in the past have done analysis and observations on monitoring and predicting drought using remote sensing, statistical analysis, deep learning and machine learning techniques such as Deep Belief Networks, Artificial Neural Networks, Support Vector Machines and Linear Regression. This paper aims to do a comparative analysis of several research techniques used for drought prediction and monitoring techniques.

**Keywords**—Drought, prediction, SPI, deep learning, machine learning.

## I. INTRODUCTION

Droughts are prolonged period of deficient rainfall leading to shortages of water in a region. Droughts are declared when the total rainfall received in a region is less than 50% of average rainfall. Hence, it is necessary to predict such a natural hazard which affects 42% of the country's land area and affects 300 million people in India. In India, drought is categorized into three types of drought- meteorological drought, hydrological drought and agricultural drought. The effects of drought can be reduced to a certain limit if it is predicted prior to the occurrence of drought. Drought indices are the numerical depictions of the drought severity based on the inputs provided such as climatological and meteorological inputs. There are several drought indices available and no single index is applicable to all kinds of drought. The selection of index is dependent on the climatic conditions that trigger drought in a region, basin or location and if the same climatic conditions are inputs for calculation of indices as well. For the climatic conditions of Maharashtra, Standard Precipitation Index (SPI) and Normalized Difference Vegetation Index (NDVI) are mainly used for drought assessment. This paper focuses on various techniques such as Empirical Mode Decomposition [10], Deep Belief Networks [7], Recurrent Neural Network [5], Support Vector Regression [7], Artificial Neural Network [14] and long – short term memory[4][11].

## II. LITERATURE SURVEY

N. A. Agana, et. al. [7] have proposed a hybrid predictive model based on denoised empirical mode decomposition (EMD) and deep belief networks (DBN) across the Colorado river. It first decomposes the data into several intrinsic mode functions (IMFs) and reconstructs original data using only pertinent IMFs. Then, the model applies Detrended Fluctuation analysis (DFA) to individual IMFs to establish a threshold value. Then, it identified the inapplicable IMFs and repressed it. The model was used for prediction of different time scale drought indices using Standardized Streamflow Index (SSI) as drought index. The model uses DBN that has 2 stacked RBM layers, where feature activation of one layer is used as a training data for next RBM layer. EMD is the signal preprocessing algorithm used here for data decomposition. This model was compared with conventional regression models such as SVR and MLP and it provides better prediction and better accuracy as compared to them. This paper showed that the DBN along with EMD algorithm outperforms conventional models such as SVR and MLP in terms of efficiency and

accuracy. The 12 month SPI for one month time lead forecast errors of EMD-DBN of values for different stations ranges from RMSE 0.006 to 0.01, MAE 0.004 to 0.008 and NSE 0.99.

H. Moghari, et. al. [8] have developed a forecasting model using Recursive Multi-layer perceptron (RMLP) and Recursive Support Vector Regression (RSVR) optimized using Imperialist Competitive Algorithm (ICA) for Gorganrood basin in Iran. The developed model was compared with a conventional model, Autoregressive Integrated Moving Averages (ARIMA). The model uses SPI with 1-6-month lead times. The paper also suggests that the increase in lead time leads to decrease in accuracy, however, increase in SPI scales provided better accuracy. For SPI-24 timescale and one lead time forecasting; R, RMSE, and, MSE values for ARIMA model was 0.90, 0.484, and 0.322 while, for ICA-RMLP was 0.967, 0.277, and 0.188, respectively and for ICA-RSVR were 0.969, 0.278, and 0.186, respectively. This paper suggests that this model can be used for practical drought warning systems. It concluded that the efficiency and accuracy of RMLP and RSVR via ICA performs much better than ARIMA model.

J.A. Le, et. al. [5] have proposed a RNN model to explore the relation between the wetness and dryness in the region of California due to El Nino. They considered the Palmer Z Index (PZI) as drought index. The RNN layer comprises of 2 fully connected recurrent layers with 40 nodes per layer and ReLu activation function, 14 input nodes and 2 output nodes. To predict into several months in future, the output is connected to 12 element prefixes allowing it to predict several months in advance. The model uses backpropagation through time algorithm. The model provided insights that the drought in southern California will continue even after winters there during El Nino season 2015-16. The correlation coefficient for one to three month timescale ranges from 0.434 to 0.610.

F. Zambrano, et. al. [9] proposed a model for early agricultural drought warning system. This study was done to check whether variation in agricultural produce can be easily assessed by NDVI. The predictions were performed with 1-6-month lead time. The models used were optimal linear regression and Multilayer feed forward neural network. The study area is Chile because of its variation in cropping patterns and climatic conditions. Both the models OLR and DL models showed that  $zcNDVI^I$  was effective for predicting  $zcNDVI^S$ . However, for the northern region, the OLR model provided slightly accurate results and for the southern region, DL gave better results. The study proves that OLR and DL can accurately predict productivity anomalies ( $zcNDVI$ ). Prediction accuracy measure of  $RMSE_{cv}$  values are 0.21(OLR) and 0.20(DL) and  $R_{cv}^2$  0.95(OLR) and 0.96(DL).

Y. Tian, et. al. [10] proposed a SVR model based system to predict agricultural drought in the Xiangjiang River basin of China. In addition to this, they did a study that aims to provide a relation between soil moisture and drought. The study suggests SPEI with timescale 6 to know about soil moisture conditions for the selected study area and SPEI-6 with one month time lag was used to build the model. Along with drought indices, additional element called WPSH i.e. Western Specific Subtropical High and El Nino Oscillations were used to increase the accuracy of the prediction model. The study showed that the SVR model was more accurate for one month lead time prediction than three months lead time predictions. Prediction accuracy measures for one, two and three timescale are as follows MSE (training) - 0.223 to 0.303, MAPE (testing) - 0.218 to 0.335, RMSE (training) - 0.289 to 0.382, RMSE (testing) - 0.275 to 0.429, NSE (training) - 0.813 to 0.893 and NSE (testing) - 0.723 to 0.886.

A. G. Salman, et. al. [11] proposed weather forecasting model using a combination of LSTMs and ARIMA models. The ARIMA model was used with the assumption that the time series data are generated using linear processes and LSTM was used because of its ability to adjust and improve the networks itself. Hence, a combination of these two models are used, along with Adam algorithm. The study shows that merged model gave a lower RMSE value than the ARIMA model. Performance evaluation accuracy measure for LSTM were 0.00007 to 0.00009 RMSE and for ARIMA were 0.948.

B. M. Dodamani, et. al. [3] suggested multiple linear regression models for drought modelling in the Krishna basin, with variables SPI and NDVI for one model and NDVI and sunspots for other model and output being current NDVI. They found out that the latter model, with NDVI and Sunspot as variables, has higher correlation with drought. It also suggested that predicted values of NDVI for the month of July, has much influence on the cropping patterns of the selected study area. The study proved that solar activity influences drought occurrence. The study also found out significant correlation between the current NDVI and SPI of various time lags. SPI 3 and 6 are highly correlated to vegetation cover. The coefficient of determination  $R^2$  was 92.49% (Assured rainfall zone) and  $R^2$  - 86.17% (Scarcity zone).

N. Laptev, et. al. [4] proposed a LSTM based model for predicting the number of completed trips during holidays. The system uses autoencoder and stacked LSTM. The autoencoder itself extracts a feature vector from the input, the feature vector is concatenated with new input and fed to stacked LSTM network for prediction. This combination of LSTM networks increased the accuracy up to 14%. The study showed that Vanilla LSTMs are not so efficient in terms of time series prediction. It also suggested that better results can be achieved by normalizing every minibatches of dataset and de-trending the data. Forecasting errors were SMAPE (mean) - 26.66 and SMAPE (median) - 22.62.

A. Chavdekar, et. al. [2] analyzed the history of droughts for the state of Maharashtra. The drought index used for was SPI. The state of Maharashtra was divided into four subdivisions i.e. Madhya Maharashtra, Vidarbha, Marathwada and Konkan and Goa. The SPI was computed using gamma distribution. The study suggested that precipitation is the regulating factor for droughts in the Central parts of Maharashtra. The paper showed that Madhya Maharashtra and Marathwada are most drought prone subdivisions of Maharashtra. It also concluded that years 1877, 1899, 1905, 1911, 1918, 1920, 1951, 1972, 1986, 1987, 2002, 2008 and 2012 reported most drought-prone conditions.

C.S. Murthy, et. al. [6] analyzed the spatial and temporal domain analysis of meteorological drought using SPI index. The study specifically focused on studying the uniqueness of the 2002 of drought by analyzing the widespread Area Under Dryness (AUD). The study analyzed drought for each month and computed AUD for each month for categorizing it into different drought categories. The study measured drought frequency by the number of years a grid experienced dryness (SPI<-1) and drought persistence was measured by the duration of drought over a period of time using Drought Persistence Score (DPS). The study showed different aspects of drought climatology in India.

O. Aiyelokun, et. al. [14] proposed an ANN model for determining the drought possibility, frequency, persistence and severity. The area of study is Ijube-Ode, Southwest Nigeria. The frequency was computed using SPI for 3, 6,9,12months' timescale. The study found a decreasing trend only for the month of April in 3 month timescale which indicated a possibility of drought. Hence, drought analysis was done for 3 step timescale for the month of April. The study also compared 2 Artificial Neural Networks and concluded that for this model, network with 1 hidden layer outperformed network with 2 hidden layer. The study suggested to compute SPI values for different timescales for better understanding of drought events. Forecasting accuracy was RMSE – 0.971.

### III. ANALYSIS

The following table is the summary of various research papers on Drought prediction and analysis methods using Deep Learning techniques.

**TABLE 1**  
**ANALYSIS TABLE**

Sr. No.	Title of paper	Techniques used	Datasets used	Performance Measure
1.	Time-series extreme event forecasting with Neural Networks at Uber [4]	LSTM	Own dataset created.	SMAPE (mean) - 26.66 SMAPE (median) - 22.62
2.	EMD-Based Predictive Deep Belief Network for Time Series Prediction: An Application to Drought Forecasting [7]	Empirical Mode Decomposition (EMD) and Deep Belief Networks (DBN)	Colorado River Basin Natural Flow and Salt Data	RMSE - 0.006 to 0.01 MAE - 0.004 to 0.008 NSE - 0.99
3.	Drought forecasting using data-driven methods and an	Imperialist Competitive Algorithm-	Not mentioned.	R (ICA-RLMP) - 0.967 RMSE (ICA-RLMP) - 0.484 MSE (ICA-RLMP) - 0.322

	evolutionary algorithm [8]	Recursive Multi-layer Perceptron (ICA-RMLP) and Imperialist Competitive Algorithm-Recursive Support Vector Regression (ICA-RSVR)		R (ICA-RSVR) - 0.969 RMSE (ICA- RSVR) - 0.278 MSE (ICA- RSVR) - 0.186
4.	Application of recurrent neural networks for drought projections in California [5]	Recurrent Neural Network (RNN)	Global Historical Climatology Network (GHCN) nClimDiv data set	R - 0.610 to 0.434
Sr. No.	Title of paper	Techniques used	Datasets used	Performance Measure
5.	Historical Drought Analysis of Maharashtra State by Using SPI Index [2]	Gamma Distribution	India Meteorological Department (IMD)	-
6.	Agricultural Drought Modeling Using Remote Sensing [3]	Multiple Regression Model	Earthexplorer	$R^2 - 92.49\%$ (Assured rainfall zone) $R^2 - 86.17\%$ (Scarcity zone)
7.	Agricultural drought prediction using climate indices based on Support Vector Regression in Xiangjiang River basin [10]	Support Vector Regression (SVR)	Climate Prediction Centre (CPC) and National Oceanic and Atmospheric Administration (NOAA)	MSE (training) - 0.223 to 0.303 MAPE (testing) - 0.218 to 0.335 RMSE (training) - 0.289 to 0.382 RMSE (testing) - 0.275 to 0.429 NSE (training) - 0.813 to 0.893 NSE (testing) - 0.723 to 0.886
8.	Weather Forecasting Using Merged Long Short-Term Memory Model (LSTM) and Autoregressive Integrated Moving Average (ARIMA) Model [11]	LSTM and ARIMA	Weather Underground	RMSE - 0.00007 to 0.00009
9.	Spatiotemporal Analysis of Meteorological Drought Variability in the Indian Region Using Standardized Precipitation Index [6]	Pearson III Distribution	India Meteorological Department (IMD) and National Climatic Data Centre (NCDC)	-
10.	Reducing Vulnerability to Climate Variability: Forecasting Droughts in Vidarbha Region of Maharashtra, Western India [13]	DST (Decision support Tool)	Not mentioned	-

11.	Assessment and monitoring of Agricultural Droughts in Maharashtra using meteorological and remote sensing based indices [1]	-	India Meteorological Department (IMD)	-
12.	Prediction of drought-induced reduction of agricultural productivity in Chile from MODIS, rainfall estimates, and climate oscillation indices [9].	Optimal linear regression (OLR) and multi-layer feedforward neural network (DL)	Moderate Resolution Imaging Spectroradiometer (MODIS) sensor	RMSE - 0.21 (OLR) R <sup>2</sup> - 0.95 (OLR) RMSE - 0.20 (DL) R <sup>2</sup> - 0.96 (DL)
13.	Artificial Neural Network-Based Crop Yield Prediction Using NDVI, SPI, VCI Feature Vectors [15]	EBPNN	International Research Institute for Climate and Society	RMSE reduced by 62.39% Relative error reduced by 33% Testing time decreased by 38.2%
14.	An artificial intelligence based drought predictions in part of the tropics [14]	ANN	Nigeria Meteorological Agency (NIMET)	RMSE - 0.971

**Abbreviations:**

**SMAPE:** Symmetric Mean Absolute Percentage Error, **MAE:** Mean Absolute Error, **RMSE:** Root Mean Squared Error, **NSE:** Nash-Sutcliffe model efficiency coefficient, **MAPE:** Mean Absolute Percentage Error, **R:** Correlation Coefficient, **R<sup>2</sup>:** Coefficient of Determination

The various models used for drought prediction and modelling are summarized in the above analysis table. From the table it can be seen that LSTM presents better results as compared to other approaches.

**IV. CONCLUSION**

Due to the overwhelming impact of drought over climate as well as on agriculture, predictions for both – meteorological and agricultural drought have been done. The need for developing such a system was the onset and prevalence of drought every year during summer in the Central region of Maharashtra, increasing suicide rates among farmers, influence on the health of humans and livestock and lack of enough attention from ministries and governing bodies. The variables SPI and NDVI are found efficient for the prediction of drought. In this paper, various statistical techniques and deep learning techniques have been studied and analyzed. It is evident from the studied papers that the deep learning models provide more accuracy than the statistical models.

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