Comparison between Meteorological Drought Indices for Upper Seonath Basin using ANN

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Abstract— Drought forecasting plays a crucial role in drought risk management. The current development of artificial neural networks (ANN) has a remarkable impact on forecasting of drought indices. This paper explains an approach to simulate quantitative values of drought indices using Artificial Neural Network. Drought Indices are continuous function of rainfall, temperature and other hydro-meteorological measurable variables. In this research two meteorological drought indices Effective Drought Index (EDI) and the Standardized Precipitation Index (SPI) are calculated & compared for monitoring drought in Upper Seonath Basin, both indices are the continuous function of rainfall which measures the degree of dryness of any period. A number of different ANN models for both EDI & SPI with the lead time of 12 months and different combinations of past rainfall have been tested at several rainfall stations in the Upper Seonath Basin. The validation of simulate quantitative value done by the using R^2 & RMSE. The best models have R^2 values of 0.87-0.99 for a lead time of 12 months. The structure of the model inputs (previous year rainfall drought index) does not vary with lead time.

Key words: SPI, EDI, ANN

I. Introduction

Drought is a natural phenomenon that has significant impact on socio-economic, agriculture, and environmental spheres (Bhuiyan, 2004). It differs from natural hazards by its slow accumulating process and its indefinite commencement and termination. Being a slow process although drought often fails to draw the attention of the world community, its impact persists even after ending of the event (Bhuiyan, 2004). The droughts are broadly classified in three categories. They are Meteorological drought, Hydrological drought and Agricultural drought. Any one of these categories or combinations of these could generate a fourth category of drought called as Socio economic drought.

Several methodologies for drought characterization exist; however, using drought indices is prevalent (Tsakiris et al.2007). Drought indices are calculated from assimilating drought indicators into a single numerical value. A drought index provides a comprehensive picture for drought analysis and decision-making that is more readily usable compared with raw data from indicators (Hayes 2006).Some drought indices specifically reflect one type of impact or application, while others can be configured to correspond to varying impacts and thus drought type. For example, SPI, which is a meteorological drought, can be deployed for longer time scales to reflect agricultural and hydrological droughts/impacts.

An Artificial Neural Network (ANN) is an information processing system that resembles the structure and operation of the brain. Given sufficient data and complexity, ANN can be designed to model any relationship between a series of independent and dependent variables – inputs and outputs to the network respectively (Hassoun, 1995; ASCE Task Committee on Application of Artificial Neural Networks in Hydrology, 2000; Maier et al., 2010).

II. Study Area

A. General

The Seonath river basin is the longest tributary of the Mahanadi basin, and upper Seonath sub-basin is considered for study area. The Seonath River originates near village Panabaras in the Rajnandgaon district. It drains in three districts of Chhattisgarh namely Durg, Rajnandgaon and Bilaspur. The two districts Durg and Rajnandgaon are covered under study area.

Seonath basin has a tropical wet and dry climate; temperatures can be extremely hot from March to June, although it remains moderate throughout the year. A vast majority of it is contributed by monsoon season i.e. from June to early October, followed by post monsoon season (October to December). The mean annual rainfall in the basin varies from 1005 mm to 1255 mm. Seonath river basin comprises 25% of the catchment of the Mahanadi basin.

B. Location and Boundaries

The Basin is located between latitude 16' N to 41' N and Longitude 25' E to 35' E. The drainage area of the Seonath River basin is 30,761 Sq. km. The river traverses a length of 290 km. The main tributaries of Seonath river basin are Tandula, Kharun, Arpa, Hamp, Agar and Maniyari rivers.

C. Temperature

Both day and night temperatures are more or less uniform over the State, except at the coastal region and high elevated plateau. They generally decrease south-westwards over the State due to higher elevation and attain lower values at high level stations. April and May are the hottest months. In may mean maximum temperature rises to 48°C. November and December are the coldest month; it may fall to 5°C.

D. Rainfall

The Southwest monsoon arrives in 10^{th} -15^{th} month of June in the State. Chhattisgarh receives amount of rainfall with an average of 1292 mm. The completion of rainfall records 15^{th} June to 15^{th} September in the Southwest monsoon season and October to December from post monsoon season. The Upper Seonath river basin receives average rainfall of 40 mm.

E. Precipitation Data and Selected Drought Indices

To quantify drought using the SPI & EDI monthly precipitation data was used in this study. The data set for the Upper Seonath Basin was for the period from January 1980 to December 2013. Observed monthly and daily rainfall data from eighteen meteorological stations located in different parts of the Upper Seonath Basin, have been selected for this study.

III. METHODOLOGY

Commercial Microsoft window-based artificial neural network software, MATLAB version 7.6.0(ANN toolbox) is used in the present study with a personal computer. Artificial neural network model so developed was implemented under MATLAB meteorology is used in this work. MATLAB is a software package for high performance numerical calculations and visualizations. It provides an iterative environment with an extensive library of built-in functions (for example: tan-sigmoid and linear transfer function) for technical computations, graphics and animation. It is because MATLAB provides a very convenient computing to handle calculations for derivations of the artificial neural networks.

A. Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) was developed by McKee et al (1993). The SPI is based only on precipitation. The SPI assigns a single numeric value to the precipitation, which can be compared across regions and time scales with markedly different climates. Jain et al. (2010) reported that there are a number of indices to quantify drought using meteorological data; however, the SPI is most widely used index. SPI can be calculated at different time scales and hence can quantify water deficits of different duration. SPI was designed to show that it is possible to simultaneously experience wet conditions on one or more time scales and dry conditions at another time scale. These time scales reflect the impact of a drought on the availability of the different water resources. The Standardized Precipitation Index (SPI) is not a tool which was developed primarily for defining and monitoring drought. It allows an analyst to determine the rarity of a drought at a given time scale (temporal resolution) of interest for any rainfall station with historic data. It can also be used to determine periods of anomalously wet events.

Mathematically, the SPI is based on the cumulative probability of a given rainfall event occurring at a station. The historic rainfall data of the station is fitted to a gamma distribution, as the gamma distribution has been found to fit the precipitation distribution quite well. This is done through a process of maximum likelihood estimation of the gamma distribution parameters, α and β. In simple terms, the process described above allows the rainfall distribution at the station to be effectively represented by a mathematical cumulative probability function. Therefore, based on the historic rainfall data, an analyst can then tell what is the probability of the rainfall being less than or equal to a certain amount. Thus, the probability of rainfall being less than or equal to the average rainfall for that area will be about 0.5, while the probability of rainfall being less than or equal to an amount much smaller than the average will be also be lower (0.2, 0.1, 0.01 etc, depending on the amount). Therefore if a particular rainfall event gives a low probability on the cumulative probability function, then this is indicative of a likely drought event. Alternatively, a rainfall event which gives a high probability on the cumulative probability function is an anomalously wet event.

B. Effective Drought Index (EDI)

Effective drought Index (EDI) (Byun and Wilhite, 1999) in its original form used daily rainfall data to analyze drought severity and duration. It is a function of the rainfall needed for return to normal (R_n) condition, signifying the precipitation necessary for recovery from accumulated deficit since the beginning of the drought.

The original and proposed forms used to analyze the monthly data for EDI computation are discussed below.

The first step is to calculate effective rainfall (EP), defined as a function of summed value of monthly precipitation with a time-dependent reduction function. Similarly, in the case of a daily time step, it is defined as the current month's rainfall and weighted rainfall over a defined preceding period. Equation is applied to compute monthly depletion of water resources for the study area:

$$EP = \sum_{m=1}^{N} \left[\left(\sum_{i-1}^{m} P_m \right) / m \right]$$

Where, i is the summation duration (SD; dry duration added to 12 on month), Pm is the monthly precipitation of m-1 month before, and n is the periods of whose precipitation data are averaged for. EP is derived from the concept that precipitation m-1 month before is added in the form of average precipitation from (month 1) to (month n).

The mean and standard deviations of the EP values for each month are then calculated and the time series of EP values is converted to deviations from the mean (DEP). PRN values are then calculated as:

$$PRN = DEP / \sum (\mathbf{1/N})$$

The summation term is the sum of the reciprocals of all the months in the duration N (i.e. for N = 3 months, this term will be equal to: 1/1 + 1/2 + 1/3). Average precipitation deficit (APD) and PRN are superior to EDI in the description of drought intensity. Since APD and PRN depend on the background climatology, EDI is often needed for universal drought assessment. It is expressed as

EDI = PRN/Std (PRN) ……..….……………..…….. (4.3)

IV. ARETIFICIAL NEURAL NETWORK

In ANN relationship the input and the output, depends on a historical observations set, named the training set, used for network 'learning'. The training set is a data collection related to past situations and associated with them, the neural network correct answer or a variable closely related to the unknown correct answer.

During the training phase the ANN will 'learn' the underlying relationship between the inputs and outputs by means of a learning algorithm that compares the networks outputs with the real outputs. The learning algorithm used was the back propagation algorithm. (Rumelhart et al. 1986; Chauvin et al. 1995). After the training phase, when the ANN works with a new situation, it will behave in line with the learning set. So ANNs become interesting in unknown or complex structure data source phenomenon forecasting. As the relationship between input variables and output or target variables, in this case meteorological features of the area, may change over time, it is useful to re-train the ANN periodically, increasing the training set with new data that reflect the changes in the variables with time.

The architecture of a network consists of a description of how many layers a network has and the number of neurons or nodes in each layer. The commonest type of artificial neural network consists of three layers of units; a layer of "input" units is connected to a layer of "hidden" units, which in turn is connected to a layer of "output" units.

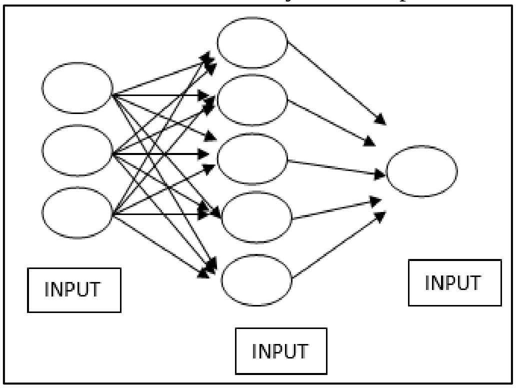

Fig. 1: Network Layers

- The activity of the input unit represents the raw information that is fed into the network.
- The activity of each hidden unit is determined by the activities of the input units and the weights on the connection between the input and the hidden units.
- The behaviour of the output units depend on the activity of the hidden units and the weights between the hidden and the output links.

In this study Back-Propagation learning technique is used to develop a ANN model. Back-propagation is a supervised learning technique used for training artificial neural networks. Back-propagation is commonly applied to feed-forward multilayer networks. This is a learning rule in which weights and biases are adjusted by error derivative vectors. Input vectors (input data) and corresponding target vectors (output data) are used in this work to train network until it can approximate a function. Standard back-propagation method uses a gradient decent algorithm. Back propagation refers to the manner in which the gradient is computed for non-linear multilayer networks. The simplest implementation of back-propagation learning updates the network weights and biases in the direction in which the performance function decreases most rapidly i.e. along the negative of the gradient .One iteration of this algorithm can be written as

$$\mathbf{X_{K+I} = X_K - \propto_K g_K}$$

Where, X_K is a vector of current weights and biases, $\propto_K$ is the learning rate, and g_K is the current gradient.

V. Conclusions

For each station of the Upper Seonath River Basin, showed the best performance results for model is presented below. In this study 12-months lead time of SPI & EDI were calculated to determine the effectiveness of the model over different indices. The models exhibited better results for simulates of 12-month lead time. Simulation of SPI 12 and EDI 12, for this model, had better performance results than in terms of R2, RMSE. The best 12-month lead time simulates of SPI 12 & EDI 12 had results of 0.986, 0.120 & 0.974, 0.125 in terms of R2, RMSE respectively. Each station has a different climatology, there does not seem to be a clear trend linking climatology with forecast accuracy. It seems that the reason behind the best models in various stations is linked with the characteristics of the individual station and not the characteristics of the basin as a whole. In the case of SPI 12, EDI 12 each individual month has less impact on the total and the index is not as sensitive to changes in precipitation from one month to the next. The fact that short term lead time is more sensitive to changes in precipitation results in less accurate forecast results than long term term lead time.

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