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Research Paper

Drought Forecasting, using Artificial Neural Network (ANN) and Predict Values of Drought Condition Derived using Enhanced Vegetation Index (EVI) Data

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Abstract —This paper focuses on drought forecasting, using Artificial Neural Network (ANN) and predicts the values of drought condition derived using Remote Sensing (EVI) data of Indore (M.P). We have used the EVI data as input data of ANN model for drought forecasting, and determine Standard Enhanced Vegetation Index (SEVI). Artificial Neural networks operate on the principle of learning from a training set. There is a large variety of neural network models and learning procedures. Two classes of neural networks that are usually used for prediction applications are feed-forward networks and recurrent networks. They often train both of these networks using back-propagation algorithm.

Keywords —Artificial Neural Network, Enhanced Vegetation Index.

1. Introduction

Artificial intelligence (AI) is a growing trend in computer automation systems. Several types of artificial intelligence technology are available. These include robotics, voice-recognition systems, and many smart computer systems. Artificial intelligence refers to any computer system that uses a logical process to learn and improve, based on the surrounding environment and prior mistakes. This technology is undergoing a great evolution, but is still far short of the capacity of the human brain. It may take several decades before computers will can actually use logic to determine the best approach for problem solving. The current AI systems can learn, but in a limited spectrum. This is because the human brain processes thousands of variables to solve a specific problem.

2. Artificial Neural Network

Neural networks provide a method for extracting patterns from noisy data. We have applied them to a wide variety of problems, including cloud classification (Bankert,[1], 1994) and tornado warnings (Marzban and Stumpf,[3], 1996) in a meteorological context. We discuss the advantages and disadvantages of neural networks in comparison to other statistical techniques for pattern extraction in (Marzban and Stumpf,[3] (1996)). We can find more detail about the construction of neural networks in (Marzban and Stumpf,[3] (1996)) and (Mu̓ller and Reinhardt,[4] (1991)) and references therein. The standard procedure for use of a neural network involves ‘‘training’’ the network with a large sample of representative data. The network has some number of input and output ‘‘nodes’’ representing the predictor and predict and variables, respectively. In between, there are a number of hidden nodes arranged in layers. The number of hidden nodes and layers is usually determined empirically to optimize performance for the particular situation. Each connection between nodes on a particular layer and the layer above it can be represented by a weight, viz. that indicates the importance of that connection between the i^{th} and j^{th} nodes. The training phase of the neural network is designed to optimize the weights so that the mean-squared error of the output is minimized. For each node at a particular layer, the input node values from the previous layer are multiplied by the weight of the connections between the nodes and then all of the different connections are summed to produce the value at that node. This process is repeated for all nodes and then for each layer. The network then can be used to make predictions based on new input values.

3. Use of Artificial Neural Networks (ANNs) for forecasting drought condition.

In recent decades artificial neural networks (ANNs) have shown exceptional ability in modelling and forecasting non-linear and non-stationary time series and in most of the cases especially in prediction of phenomena have showed excellent performance.

This discussion presents the application of artificial neural networks to predict drought in meteorological station Indore (M.P). In this paper, different architectures of artificial neural networks in Remote Sensing (EVI) Data have been used as inputs of the models. According to the results taken from this research, dynamic structures of artificial neural networks, including Recurrent Network (RN) and Time Lag Recurrent Network (TLRN) showed better performance for this application (because of higher accuracy of its outputs). Finally, TLRN network with only one hidden layer and hyperbolic tangent transfer function was the most appropriate model structure to predict drought for the next year. In fact, by a prediction of the Drought before its occurrence, it is possible to evaluate drought characteristics in advance. It was found that ANN is an efficient tool to model and predict drought events.

Artificial Neural networks operate on the principle of learning from a training set. Two classes of neural networks that are usually used for prediction applications are feed-forward networks and recurrent networks. We often train both of these networks using the backpropagation algorithm. An advantage of backpropagation is that it is simple. Prediction networks usually take the historical measured data, and after some processing stages, future condition is simulated. In this research, after evaluation and testing of different ANN Structures, TLRN and RN we selected networks because of their higher performance, and then between these two, TLRN network showed slightly higher abilities. Therefore, TLRN was the final selected ANN type for drought prediction in this study.

4. Study Area and Data Source

Fig.1. Indore

The geographical location of Indore is 22.2 - 23.05o North Latitude and 75.25 - 76.16o East Longitude. It is the largest city of the Central-Indian state of Madhya Pradesh; with an area of 3898 sq km, and is situated on the Malwa Plateau. The location of Indore makes it central to the Indian subcontinent. The city once used to serve as the summer capital of the former state of Madhya Bharat. The location of Indore is just south of the Satpura range, at an altitude of 553 meters above sea level.

The strategic location of Indore on the western fringes of the state of Madhya Pradesh has been instrumental in determining the climatic conditions of the city. Summer in Indore spans between the months of April and June and the temperatures soar as high as 45 degrees Celsius during the month of May. Summer temperatures in Indore usually vary between 35 degrees to 40 degrees centigrade. However, an interesting feature about the Indore summer is that although the summer days are scorching hot, the evenings are much cooler and pleasant. Indore, being located on the southern extremity of the Malwa Plateau is subject to the bracing wind of the Shab-e- Malwa during the early evening.

Rainfall in Indore is quite sparse and the city receives 35 to 40 inches.i.e. approximately 80 cm rainfall annually from the southwest monsoon downpours. Winters are fairly cold with the average night temperature being around 10 degrees centigrade. Often during winter, the mercury dips as low as 2 degrees centigrade, the lowest mark ever being 1.5 degrees Celsius.

5. Enhanced Vegetation Index (EVI)

The Enhanced Vegetation Index (EVI) was developed to improve the distinction in vegetation from satellite images. It is an 'optimized' index designed to enhance the vegetation signal with improved sensitivity particularly in the high biomass regions like the forests. It reaches improved vegetation monitoring by getting a better view through the canopy layer of the trees and by reducing the atmospheric influences.

In other words, where the Normalized Difference Vegetation Index (NDVI) is only chlorophyll sensitive, the EVI is dependent of canopy structural variations. These variations are the Leaf Area Index (LAI), canopy type, plant appearance, and the canopy structure. Another difference between the NDVI and the EVI is that in case of snow the values of NDVI decrease while EVI values increase with all its consequences. The EVI additionally separates the soil and atmospheric influences from the vegetation signal by including a feedback term for simultaneous correction.

It was developed by the MODIS Science Team to take full advantages of the sensor capabilities. In order to increase the sensitivity to the vegetation signal, the index makes use of measurements in the red and near infrared bands (as in the case of NDVI), and also in the visible blue band, which allows for an extra correction of aerosol scattering. EVI also performs better than NDVI over high biomass areas, since it does not saturate as easily.

The enhanced vegetation index (EVI) was developed as an alternative vegetation index to address some of the limitations of the NDVI. The EVI was specifically developed to: be more sensitive to changes in areas having high biomass (a serious shortcoming of NDVI), reduce the influence of atmospheric conditions on vegetation index values, and correct for canopy background signals.

EVI tends to be more sensitive to plant canopy differences like leaf area index (LAI), canopy structure, and plant phenology and stress than does NDVI which generally responds just to the amount of chlorophyll present. With the launch of the MODIS sensors, NASA adopted EVI as a standard MODIS product that is distributed by the USGS. EVI is calculated as

$$EVI = 2.5 * \frac{(NIR-RED)}{(NIR+ C_1*Red- C_2*BLUE+L)}$$

Where NIR, RED, and BLUE are atmospherically-corrected (or partially atmospherically corrected) surface reflectance's, and C_1, C_2, and L are coefficients to correct for atmospheric condition (i.e., aerosol resistance). For the standard MODIS EVI product, L=1, C_1=6, and C_2=7.5.

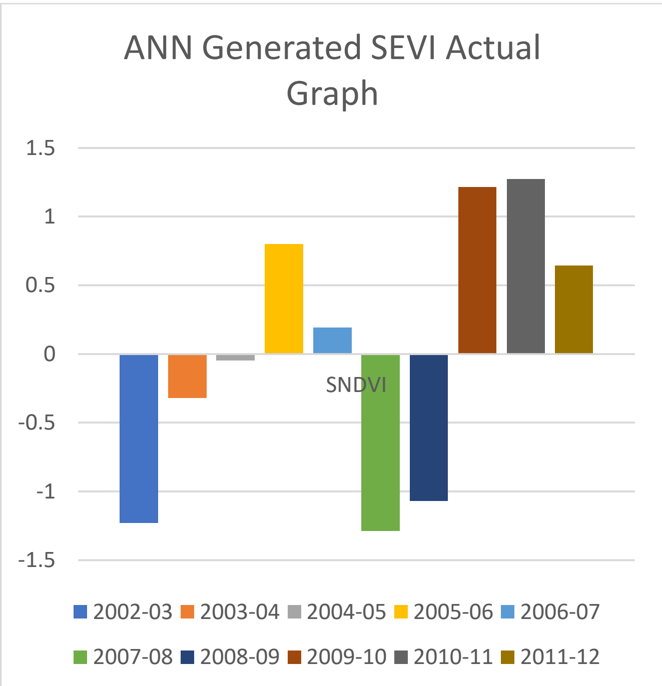
In this study first calculate SEVI by this given formula:

$$SEVI = \frac{EVIi - EVIm}{\sigma}$$

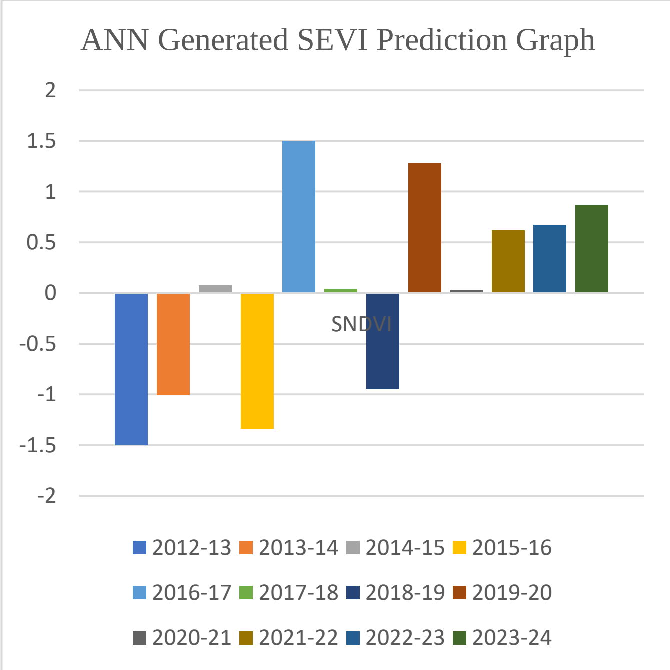
And calculate the drought category result from the SEVI value using ANN model

And also according to the previous year predict drought year using the Artificial Intelligence algorithm and generate the SEVI data value

6. ANN Generated Graph



Graph.1. ANN Generated Actual Graph



Graph.2. ANN Generated Prediction Graph

7. Conclusion

Initially, the ANN model has been conducted on the whole dataset. We have performed graphical visualization in order to make it easier to understand the data itself graph 1and 2 shows it.

The SEVI graph generates by ANN model indicate that meteorological drought appears in the Indore region in a random fashion. From graph 1 the negative bars in years 2002-03, 03-04,05-06 ,08-09, show over all poor vegetation condition in these years, while 2002-03 depict extremely dry condition and remaining years show mild meteorological drought occurrence. The positive bars in years 09-10, 10-11, 11-12 show that good vegetation condition. Higher positive values indicate to good vegetation.

Similarly, from prediction graph 2 the negative bars in years 2012-13, 13-14, 15-16, 18-19, show poor vegetation condition occurrence in these years. The positive bars in years 19-20, 20-21, 21-22, 22-23, 23-24 show that good vegetation condition. It is observed that the actual result is very close to the predicted result in concerned area.

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