A Soft-computing Ensemble Approach (SEA) to forecast Indian Summer Monsoon Rainfall

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Extended Abstract

Agriculture is the backbone of the Indian economy and contributes to ~16% of the Gross Domestic Product (GDP) and ~10% of the total exports. Over 60% of the land is arable making India the second largest country in terms of the total crop grown area. About 2/3 of this cultivated land depends on monsoon rainfall. As a result, the economic growth of the country largely depends on the accurate prediction of the monsoon rainfall. While predicting the rainfall, more emphasis is given to the southwest monsoon rainfall as 90% of the total rain falls in this season. Even a slight deviation from the average rainfall of 887.5 mm significantly influences the Indian economy. Gadgil and Gadgil (2006) report that the negative impact of drought, on food grain production, is far greater than the positive impact of surplus rain. In addition, heavy rainfall or floods can also damage the food production. Thus, both deficit and excess rainfall affects the Indian economy. Hence, accurate and timely forecasting of monthly Indian Summer Monsoon Rainfall (ISMR) is very much in demand for economic planning and agricultural practices.

Several methods and models, comprising of dynamical, statistical and combination of the two, exist for monsoon forecasting. With the availability of supercomputing facilities, the atmospheric modelers have been running the models with different initial conditions giving different forecasts. Their forecasts are then used to generate one ensemble forecast. An ensemble forecast consists of multiple runs of dynamical models with either different initial conditions or with different numerical simulations of the atmospheric phase (Gneiting and Raftery 2005). In the single model ensemble method, forecasts of a model with different initial conditions are used whereas in the multi-model ensemble approach, forecasts of many models with different initial conditions are used. The initial error, though very small, could grow very fast into different scales as the integration time increases (Lorenz 1982). Using ensemble forecast, instead of a single deterministic forecast, reduces this forecasting error (Zhu, 2005).

Krishnamurti et al. (1999) used multi-model super ensemble model for climate prediction using the multiple regression technique. They reported that their super ensemble model outperformed all model forecasts for different scales of weather and hurricane forecasts. Since Artificial Neural Networks (ANN) outperform multiple regression technique (Pao 2008, Swain et al. 2014), we used ANN techniques in place of multiple regression to develop a Soft-computing Ensemble Algorithm (SEA).

For this purpose, we used 57 members from 6 models from 1982 – 2016 from IRI/LDEO Climate Data Library with 1^0 x 1^0 spatial resolution. Besides rainfall from model predictions, we also use measured rainfall from NOAA Earth System Research Laboratory (ESRL) from 1982 to 2014, having a spatial resolution of 0.5^0 x 0.5^0 degree. Then, the model forecasts and the observations are collocated, after bringing both the observations to the same resolution. Since our aim is to predict the ISMR, we analyze the data from June to September of every year. Initially, the model forecasts given in January for June, July, August and September (JJAS) are collocated with the ESRL measured rainfall of the JJAS on monthly basis, thus creating four sets of data for the four monsoon months.

Out of six models, arithmetic averages of three models predicted more than normal and three predicted below normal rainfall, for 2016. To remove the model biases, we consider all the six models in developing a Soft-computing Ensemble Approach (SEA) using Artificial Neural Network (ANN) approach. We developed 4 ensemble models using different combinations of the 6 model forecasts and found that the estimated errors are minimal if all the 57 members of the six models are used as the independent variables and observation as the dependent variable. The % deviations of rainfall predicted using SEA and from India Meteorology Department (IMD) for the season as a whole during 1982 – 2015 (Figure 1), show a very good agreement between the estimations and the observations. Since we predicted rainfall at each grid point, we studied the efficiency of the model at different locations, by computing the scatter index (SI: defined as the RMSE normalized to observed mean) at each grid point. The model performance is considered good if the SI is less than 100%. This criteria is met in 77.3%, 83.8%, 85.4% and 86.8% of the total grid points during June, July, August and September respectively.

SEA predicted an excess rainfall of 108% for 2016 compared to the long period average of 887.5 mm. However, the Indian Ocean dipole and the El Niño/La Niña conditions have changed rapidly. La Niña has not developed as predicted/expected and the negative IOD has been very strong. As a result, the all India monsoon rainfall could be normal. The aim of the present paper is to present another method of predicting rainfall. Obviously, solving the monsoon prediction problem, which has been continuing for many years, is not the objective of the present study. Further, development of model physics as well as improvements in the initial conditions is required to improve the ISMR prediction skill. Ali et al. (2015) suggested a relook into the input parameters for cyclone studies. Similarly, re-examination of the input parameters for monsoon forecasting may help improve the predictability.

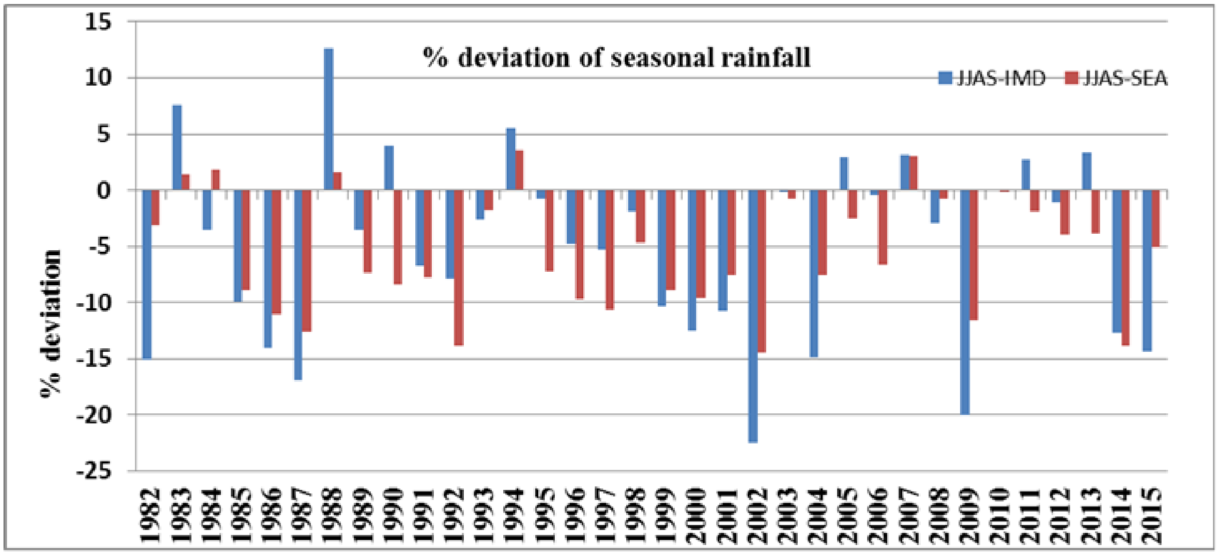

Figure 1: The % deviation of rainfall predicted using SEA and from IMD observations for the season as a whole during 1982 – 2015.

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