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Southern Indian Ocean SST indices as early predictors of Indian summer monsoon

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Four indices of quarterly mean sea surface temperature (SST) values extracted for Southern Indian Ocean (SIO) region for which the maximum correlation with All India Rainfall Index (AIRI) was found with a lag up to 7 seasons w.r.t. the onset of monsoon. The Artificial Neural Network (ANN) technique has been used to study the predictability of the Indian summer monsoon with four indices individually as well as in various combinations. It has been found that two combinations of SST indices of SIO region, SIOI + ACCI and CSIOI + NWAI + SIOI + ACCI, show best predictive skill when used collectively. It has been found that the performance of the ANN model is better than the corresponding regression model in the prediction of ISMR indicating that the relationship between ISMR and SST indices are non-linear in nature.

[**Key words:** Artificial neural networks, error back propagation, monsoon, Southern Indian Ocean, sea surface temperature indices, Indian summer monsoon, predictors]

1. Introduction

The Indian summer monsoon (ISM), which takes place from June to September, is one of the most important and widely studied monsoon systems. It is associated with winds blowing from the southwest in India and adjacent areas with very heavy rainfall. The ISM affecting the Indian Subcontinent is much more severe as compared to the North American monsoon in terms of total precipitation, total area covered and the total number of people affected. The western and central India receives more than 90% of their total annual precipitation while southern and northwestern India receives about 50%-75% of their total annual rainfall during the ISM. On the national level, ISM accounts for 80 % of the rainfall in the country. Indian agriculture (which accounts for 25 % of the GDP and employs 70 % of the population) is heavily dependent on the rains. The failure of monsoon brings famine whereas strong monsoon result in devastating floods on the other. A delay of a few days in the arrival of the monsoon can, and does, badly affect the economy, as evidenced in the numerous droughts in India during the 90s. Thus a better understanding of monsoon is not only of scientific importance but it also has social and economic implications. But, the long-term prediction of monsoon is still a challenge.

Gradients of Sea Surface Temperature (SST) are important in determining the position of precipitation over the tropics including monsoon regions[1]. It is supposed that the SST Anomaly (SSTA) over Indian Ocean plays a major role in determining the monsoon rainfall variability[2, 3]. The empirical studies show a positive correlation between Arabian Sea SSTA and Indian summer rainfall with a leading time scales of 1 to 4 months[4, 5].

Earlier attempts of finding the relationship between Indian Ocean SSTA and monsoon has been limited only in equatorial and tropical Indian Ocean region. But some of the recent studies have also investigated the Southern Indian Ocean (SIO) SST variability for south central African rainfall[6]. Southeast Indian Ocean SST (72°E to 122°E and 4°S to 26°S) anomalies setup during boreal winter provides well defined precursory signal for Indian summer monsoon rainfall (ISMR)[7] and plays primarily a role in the transition of the whole monsoon-ENSO system[8, 9]. It has been proposed that the SST variability in autumn (three seasons before the monsoon) and winter (two seasons before the monsoon) may be better monsoon precursor[10]. In a recent study, Mascarene high has been shown to play a major role on east Asian summer monsoon whereas Australia high is of secondary importance[11].

Recently, Artificial Neural Network (ANN) [12] has been used to study various oceanic and meteorological phenomena such as prediction of

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Tsunami travel time in the Indian Ocean[13], predictability of sea surface temperature[14, 15], Indian summer monsoon rainfall[16], sea ice classification[17], relation between the tropical pacific sea level pressure and the sea surface temperature[18], nonlinear principal component analysis[19] and Arctic and Antarctic sea ice[20].

In the present communication, we have studied the predictability of the Indian summer monsoon using ANN technique. It has been found that two SST indices of extreme SIO region show best predictive skill when used collectively.

2. Data

The extended reconstructed SST (ERSST, version 2.0) [21] has been used in the present study. This data set contains global record of monthly SST from years 1871 to 2003. But, due to the uncertainties and data scarcity in the earlier data set of 19th century, we have considered the temporal coverage only from 1950 to 2003. Further, the monthly data set of 2°x2° grid has been interpolated on a grid resolution of 1°x1° and the spatial coverage is limited to the SIO region (5°S to 60°S and 30° to 120°E) only. The monthly mean climatology has been subtracted from the data to remove seasonal and monthly cycles (if any) from the data under consideration. The All India Rainfall Index (AIRI) has been constructed by calculating anomaly series averaged over the summer season i.e. June-July-August-September (JJAS) after removal of annual cycle from the monthly ISMR data[22] for the period 1871-2003.

The variability of ISMR rainfall vis-à-vis SIO SST variability and SST-AIRI relationship is examined by correlating the SST time series at each month and at each grid point in the SIO region with the AIRI beginning with June and 24 months (8 seasons) prior to the AIRI. We have defined some of the indices for quarterly mean SST values extracted for SIO region for which the maximum correlation with AIRI was found and is tabulated in Table 1. These indices are the area averaged values. The indices, thus defined are CSIOI (A), NWAI (B), SIOI (C) and ACCI (D). The multilayer feed forward neural network with error back propagation learning algorithm with delta learning rule[23-25] has been used to study the predictability of ISMR with the indices A, B, C and D. These indices have been used individually as well as in various combinations: (CSIOI, NWAI, SIOI, ACCI, CSIOI+NWAI, SIOI+ACCI, CSIOI + NWAI + SIOI + ACCI). Thus, altogether seven combinations have been used to study the predictability of ISMR.

The covariability of SST indices has been checked and it has been found that indices of southern latitudes (C and D) are correlated among themselves but SST indices of extreme southern latitudes (C and D) and southern latitudes (A and B) are independent. Since indices A and B are independent with indices C and D so the combinations A+C, A+D, B+C, B+D, A+C+D, B+C+D have been discarded and only combinations A+B, C+D have been taken. We have also taken the combination A+B+C+D to see the performance of predictability of monsoon by combining all the indices of Indian Ocean by ANN. Thus, altogether seven combinations have been used to study the predictability of ISMR (A, B, C, D, A+B, C+D, A + B + C + D).

3. Artificial Neural Networks

Artificial Neural Network (ANN) is a mathematical model that simulates the behavior of human brain[12]. These computing networks are far simpler than their biological counterparts. It is composed of simple processing units, called synthetic neurons[25], which were first formally defined by McCulloh & Pitts[26].

Artificial neural networks (ANNs) are especially useful for classification and mapping problems where direct mappings cannot be easily obtained. In conventional data analysis, such as multivariate linear regression and modeling methodologies, failure of one component of the analysis usually means the

Table 1—Quarterly mean SST Indices

Index	Region	Area	Months	Lag of SST Index w.r.t. AIRI (in season/year)
CSIOI (A)	Central Southern Indian Ocean (CSIO)	22°S - 24°S, 79°E - 81°E	MAM	1/0
NWAI (B)	Northwest of Australia (NWA)	14°S - 17°S, 114°E - 116°E	DJF	2/0
SIOI (C)	Southern Indian Ocean (SIO)	41°S - 40°S, 82°E - 85°E	DJF	6/2
ACCI (D)	Antarctic Circumpolar Current (ACC)	38°S - 42°S, 64°E - 68°E	SON	7/2

CSIOI = Central Southern Indian Ocean Index, NWAI = Northwest of Australia Index,
SIOI = Southern Indian Ocean Index, ACCI = Antarctic Circumpolar Current Index

failure of the entire analytic system. ANN, on the other hand is a 'shooting' technique that searches for an optimum solution in the parameter space. The noise patterns and chaotic components are better tolerated by the neural networks than by other statistical methods[27]. This is because the noise is not repetitive and it can be taken care of if the "overfitting" is avoided with "intelligent" design[24]. While comparing the prediction capabilities of all statistical models, the ANN model proved to be better than all other models for almost all the data sets[28]. Predictive skills of ANN vis-a-vis other statistical models have been reported recently[16]. It has also been shown that ANNs have better prediction and classification skills[29]. Further, it has been found that the ANN model is capable of making good forecasts even in the case when the multivariate linear regression models fail to make any forecast[14].

4. Model Description

Our ANN is a multilayer feed forward neural network as shown in Figure 1, with error back propagation learning algorithm and delta learning rule. The error backpropagation algorithm strives for the minimum of the cost function (RMS error between model output and observed values) with respect to the weight matrix[23]. For simplicity we have taken only one hidden layer (with four neurons) as it has been mathematically established that one hidden layer is sufficient to model arbitrary non-linearity in the data[30]. The number of neurons in the hidden layer has been decided using the approach adopted by Tripathi et. al[14]. Thus for all the seven combinations of the data sets, the ANN architecture consists of one neuron in the input layer that accepts the SST index, one neuron in the output layer that gives the precipitation and four neurons in the hidden layer for learning the non-linearity in the input and output relation.

For each index, the 53-year data set has been divided into three sets: training, cross-validation and test[27]. The last 8-year data is taken as the test set for real hindcast. The remaining 45-year data is divided in two sets: estimation (35 years) and cross-validation

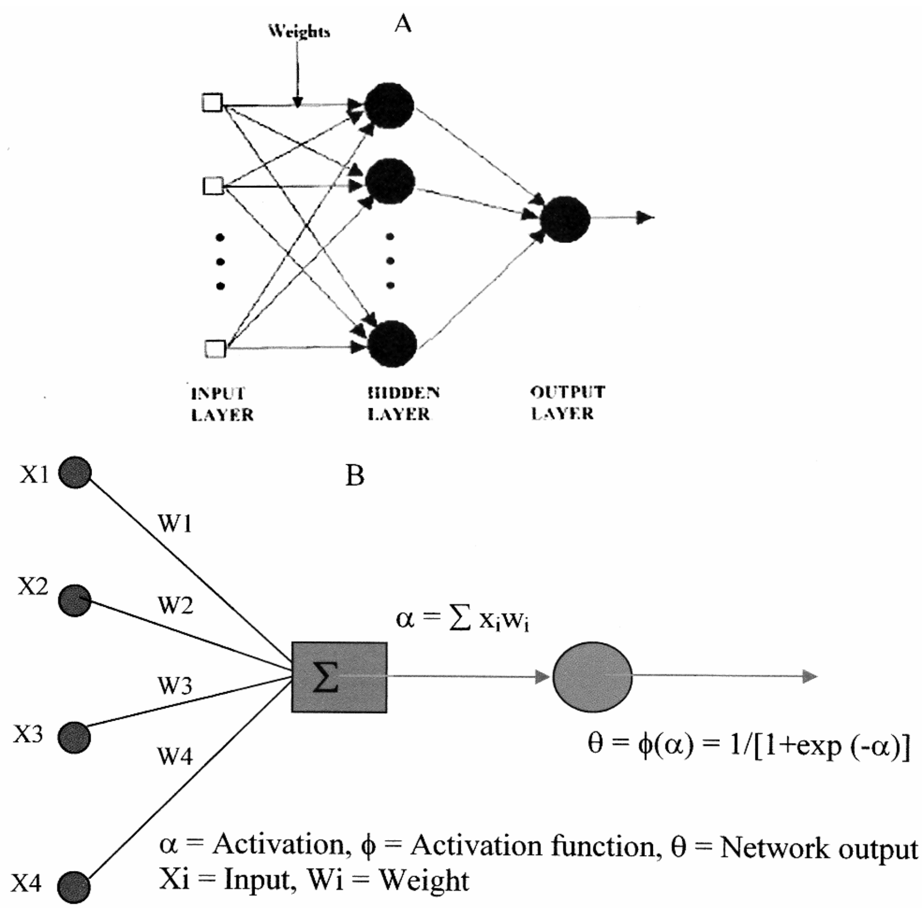

Fig. 1—(A) Schematic diagram of ANN architecture, (B) Working of an artificial neuron

(10 years) randomly. The estimation set is used for the estimation of weights and the cross-validation set is used in conjunction with the estimation set for the on-line evaluation of the performance of the model on unseen data. In short, the algorithm proceeds as follows:

Till 1000 cycles

Train the network for 10 cycles and adjust the weights

Evaluate the performace on the validation set. (No adjustment of weights is done in this phase)

It is to be noted that the test set and the validation set are different sets. While the test set is completely ignorant of the training procedure, the validation set is indirectly used in the training. The training is stopped after every 10 cycles and the performance is evaluated on the validation set. The network which performs best on the validation set is selected. The final evaluation is done on the test set[24].

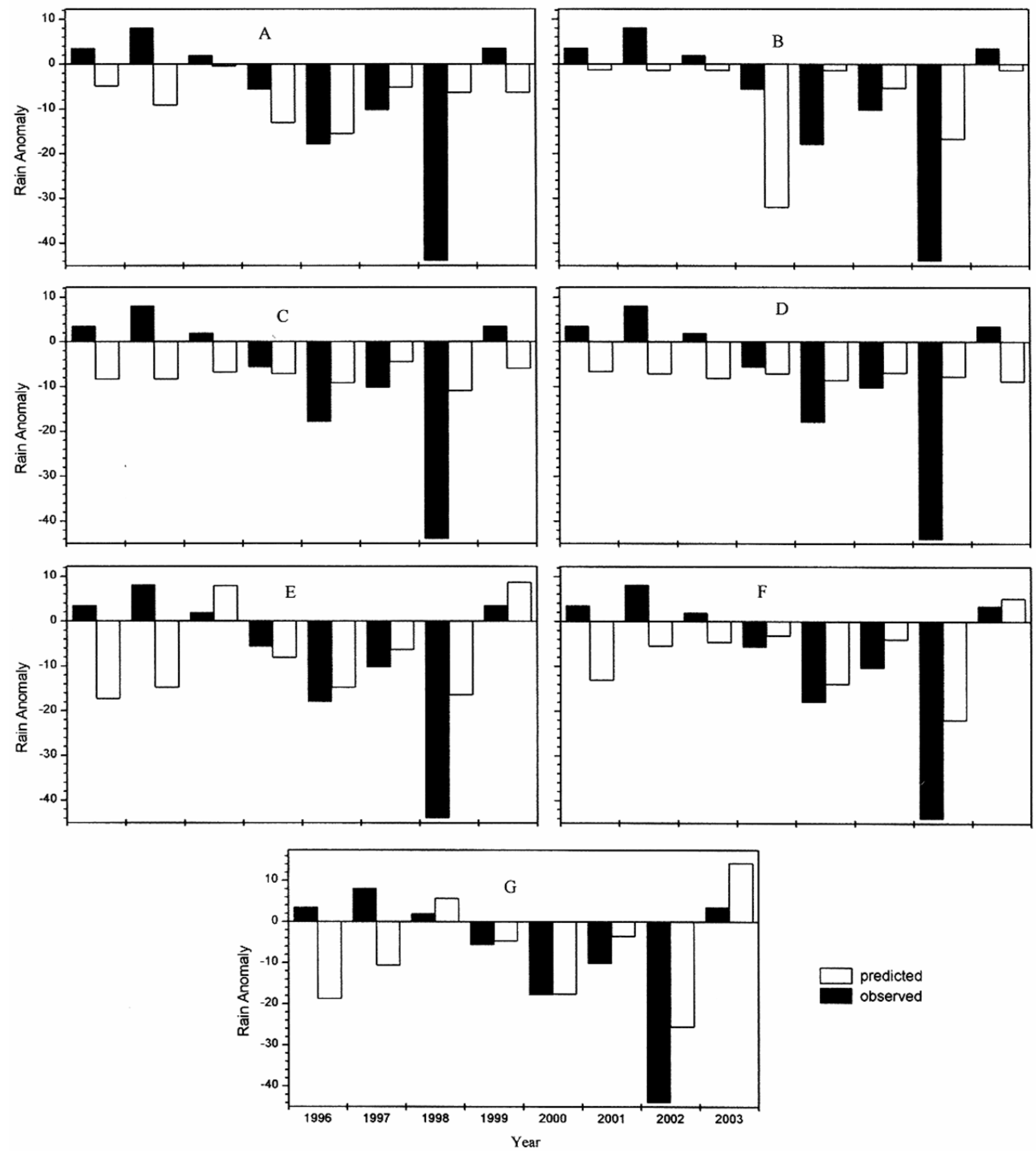

Fig. 2—ANN model output with: (A) CSIOI as a predictor, B= NWAI as a predictor, C= SIOI as a predictor, D= ACCI as a predictor, E= CSIOI+NWAI as a predictor, F= SIOI+ACCI as a predictor, G= CSIOI+NWAI+SIOI+ACCI as a predictor

The inputs and the output have been normalized separately in the range 0.2 to 0.8 using the following equation,

$$X_n = 0.6 * [(X - X_{min})/(X_{max} - X_{min}) + 0.2 \quad (1)$$

where X is the input for the respective network, X_{max} is the maximum value of the SST index for the input and the maximum value for the precipitation for the output, X_{min} is the minimum value of SST index for the input and minimum value of precipitation for the output, X_n is the normalized value of the SST for the input and normalized value of precipitation for the output. The factors of 0.6 and 0.2 are included so that the normalized values are not 0.0 or 1.0 because as X_n approaches these extreme values, the derivative of the sigmoid function becomes 0 and no learning occurs[31]. The sigmoid function[27]

$$F(x) = 1 / [1 + \exp(-x)] \quad (2)$$

has been used for the activation function for neurons in the hidden layer. For the neurons in the output layer the identity function[19]

$$f(\alpha) = \alpha \quad (3)$$

has been used as the activation function.

5. Results and Discussion

Figure 2 shows the plots of the precipitation against various indices of the SST. It can be seen that the year of the largest anomaly corresponds to the drought of 2002. It can be seen that this drought is best modeled when the indices A+B, C+D and A+B+C+D are used as predictors. Table 2 depicts the performance of the regression and the ANN models when these indices are used as predictors for the ISMR. It may be seen that the RMS error is smallest for both the linear and non-linear models in the last three cases. The RMS errors fall significantly for the cases when C+D and A+B+C+D are used as predictors than when other combinations are used. This indicates that C+D and A+B+C+D are better predictors of the ISMR than the individual predictors and the predictors A and B combined.

It is seen that the RMS errors for all the indices and for both the ANN and linear regression models are always smaller than the standard deviation of the training data. The comparison between RMS error with the standard deviation of the training data is important to be able to say that the predictions made are better than the mean value of the past data. The RMS errors of the ANN models are smaller than the standard deviation of the test data, which is not the case with the linear model. This once again establishes the better modeling capability of the ANN model because this indicates that the model is flexible enough to accommodate the possible variation in the mean. The RMS error of the regression model for the case when C + D and A + B + C + D are used as predictors are also smaller than the standard deviation of the test data.

The results of the correlation analysis between these predictors and the ISMR are also shown in Table 2. Earlier it has been shown that the combined indices are better predictors for ISMR[32]. The regression analysis was also done to establish these results. However, linear regression being a linear

Table 2—Performance of the regression and the ANN models when these indeces are used as predictors for the ISMR. It may be seen that the RMS error is smallest for both the linear and non-linear models in the last three cases. The RMS error falls significantly for the cases when C+D and A+B+C+D are used as predictors than when any other combination is used. This indicates that C+D and A+B+C+D are better predictors of the ISMR than the individual predictors and the predictors A and B combined.

Index	Corr. Between observed and predicted rain (ANN)	Corr. Between observed and predicted rain (Regression)	RMS error between observed and predicted rain (ANN)	RMS error between observed and predicted rain (Regression)
A	0.19	0.19	15.68	18.04
B	0.38	0.36	15.33	17.92
C	0.57	0.59	14.91	16.92
D	0.14	0.15	15.81	17.42
A+B	0.40	0.42	15.00	16.74
C+D	0.74	0.75	11.48	12.98
A+B+C+D	0.60	0.62	13.04	13.97

Standard Deviation of the observed precipitation for the training case = 21.74 and that for the test case = 15.90.

model is negligent towards any non-linearity that may be present in the relationship. Hence the non-linear ANN model was used to determine the predictability of the ISMR with these indices. This would account for any non-linearity that may be present in the input-output relationship.

It may be seen that the correlation coefficients between the observed and predicted rainfalls improves significantly for the cases when C, C + D and A + B + C + D are used as predictors. Although the correlation coefficient when C is used as predictor is better, this is not considered a good predictor in this study because the variance of the predicted rainfall is very small. It can be seen from Figure 2C that the model makes almost the same prediction for all the years.

6. Conclusion

It may be concluded that the indices SIOI+ACCI and CSIOI+NWAI+SIOI+ACCI may act as better predictors of the ISMR. This shows the enhancement of predictability by including the SST predictors of SIO region with tropical Indian Ocean. It is also pertinent to note that the SST index of SIO region is for the 6-7 seasons prior to onset of Indian summer monsoon. It has been established that the performance of the ANN model is better than the corresponding regression model in the prediction of ISMR with the above indices indicating that the relationship between ISMR and SST indices are non-linear in nature.

It will be too early to propose exact physical mechanisms behind this predictability and the exact nature of such an influence requires more detailed study for which this work can provide some basis. There is also a need to address the exact mechanism of this connection by Coupled General Circulation Model (CGCM) experiments. The plausible reason may be largely attributed to Atmosphere-Ocean interaction of temperate-tropical regions. The process responsible for such an interaction may be either due to enhancement of southeasterlies west off Australia by increase in evaporation and Upper Ocean mixing during positive south dipole event[6] or atmospheric forcing on SST and vice-versa. The warming (cooling) may be linked to changes in surface fluxes in responses to changes in surface winds. They may also be connected through other chain reactions among various atmospheric and oceanic processes.

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