

Prediction of Monsoon Rainfall Using Large Scale Climate Signals: A Case Study

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Abstract

In this paper, a comprehensive investigation on application Artificial Neural Networks in long-term rainfall forecasting is presented. A variety of ANN-models have been developed to process and train a system with large scale climate signals for the summer precipitation spells. The summer monsoon is one of the most dynamic climate systems that controls rainfall variation in some Asian countries such as India and Pakistan and delivers a component of annual rainfall in these regions. The sum of rainfall during July, August and September is called summer monsoon rainfall.

In order to quantify the effects of large scale climate signals on the precipitation in the study area, long-term records of SST (Sea Surface Temperature) and SLP (Sea Level Pressure) over Oman Sea, Arabian Sea and Indian Ocean have been examined. The SSTs over west coast of India as well as the SSTs over the Oman Sea shows a high correlation with monsoon rainfall in Iran. Also SLP over the Northern part of India shows a significant correlation with recorded rainfall at different points of the region. These signals can be used as useful predictors for monsoon rainfall at the south-eastern part of Iran. The results show that considering a set of predictors developed in this study could significantly increase the accuracy of long-lead precipitation forecasting in the study area using ANN models.

Keywords: Monsoon Rainfall, Climate Signals, Rainfall Predictors, SLP, SST, Forecasting, Artificial Neural Network (ANN)

1- Introduction

The summer monsoon is one of the dynamic climate systems and the livelihood of more than 60 percent of the world's population depends on them. Furthermore, the Asian summer monsoon is a key component of the earth's climate system, having important teleconnections with global weather and climate in Iran and delivers a component of annual rainfall in the southeastern part of Iran. The sum of rainfall during the month of July, August and September is the seasonal monsoon in southeastern part of Iran. Many investigations have been done to understand the relation between monsoons and other global phenomenas and large scale climate signals such as El Nino southern oscillation, (SST), (SLP) and other large scale climate signals. (Karamouz et al., 2006)

Following the Great Indian Drought of 1877, Blanford, who established the Indian Meteorological Department in 1875, forecasted Indian monsoon rainfall in 1884. Later, in the early part of the 20th century, Walker initiated extensive studies of global teleconnections which led him to the discovery of Southern Oscillation. Walker introduced the concept of correlation for long-range forecasting of Asian summer monsoon and his findings are relevant even today (Krishna Kumar et al., 2004). The models established later by Gowariker et al. (1989), Thapliyal (1990), and Sahai et al. (2003) belong to the category of Walker's studies. Among these, the model of Sahai et al. (2003), which links global SST with Indian monsoon seasonal data, appears to be the most successful.

Artificial Neural Networks (ANNs) have proven to be an efficient alternative to traditional methods for modeling qualitative and quantitative water resource variables (Karunanithi et al. 1994; Smith and Eli 1995; Maier and Dandy 1996; Shamseldin 1997; Clair and Ehrman 1998). A successful work of ANNs application in rainfall forecasting is the study done by French et al. (1992), who applied a neural network to forecast one-hour-ahead, two-dimensional rainfall fields on a regular grid. Toth et al. (2000) investigated the capability of ANNs in short-term rainfall forecasting using past rainfall depths as the only input information.

In the present study, the emphasis is on long-lead rainfall forecasting which is referred to forecasts as 1 month to 6 month ahead forecast. Most of ANNs applications in hydrology have used feed forward neural networks, namely the standard multilayer perceptron (MLP) trained with the back-propagation algorithm (Coulibaly et al., 1999). MLP is a static and memoryless network and even though it is the most widely used for water resource variables prediction which often yields suboptimal solutions. In fact, the MLP model does not perform temporal processing and the input vector space does not consider the temporal relationship of the inputs (Giles et al. 1997).

In this study, attempts have been made to explore the relationship between Iran summer monsoon rainfall and SLP at certain points in India, Arabian Sea, Oman Sea, Pakistan and Iran to find predictors for forecasting precipitation in the study area. After finding predictors of Iran summer monsoon rainfall, static and dynamic ANN models have been developed for rainfall forecasting based on these predictors.

2- Study area

The study area (South Baloochestan watershed) lies between 60° and 62° Northern latitude and 25° and 27° Eastern longitude, in the south-east part of Iran in an area of about 25000 square kilometers. There are 6 meteorological stations at the region including: Kagdar, Ghasre-Ghand, Rask, Bahookahalt, Pishin, Chabahar. The average precipitation of the region has been calculated using the Kridging method. The average annual precipitation in South Baloochestan watershed is about 180 mm. Figure1 shows the summer rainfall variation in the study area during 1973 through 2002 in which rainfall data are available with 3 month average of 22.8 mm.

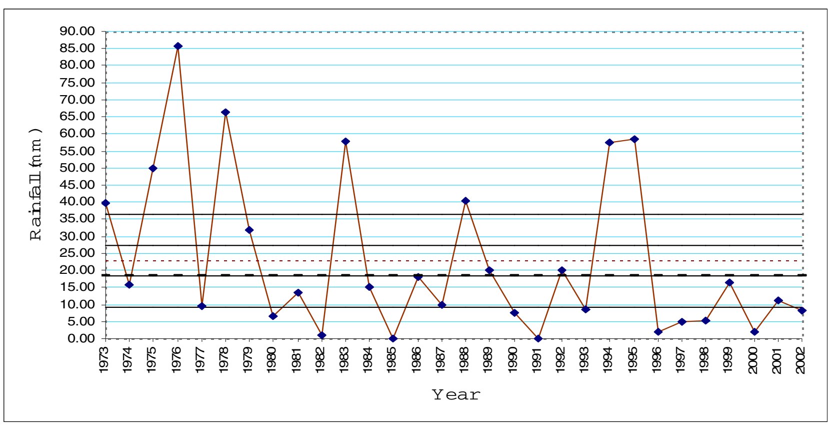

Figure 1: Summer Rainfall Variation in the South Baloochestan

3. Large scale climate signals

In order to quantify the effects of large scale climate signals on the precipitation, long-term records of SST (Sea Surface Temperature) and SLP (Sea Level Pressure) over Oman Sea, Arabian Sea and Indian Ocean have been examined. The study of

SLP and ΔSLP effects on precipitation of study area is discussed in Karamouz et al. (2006) and its summary is presented in section 3.1. In the following section, the correlation between monsoon precipitation in the study area and SSTs over a part of Indian Ocean and Oman Sea is discussed. Data of these signals are available from 1973 to 2002.

3.1. Sea level pressure (SLP)

Karamouz et al. (2006) considered Southeastern parts of Iran, Oman Sea, Pakistan, northwest of India, the Arabian Sea and the Indian Ocean for determining long-lead rainfall predictors. They investigated the relation between long-term records of SLP in the months July of previous year through June of the following year in selected locations and the total average area precipitation in the months of July through September. The result of the best correlation obtained for each studied climate signal and considered water surfaces, are presented in Table 1. In this study the following indexes considered as indicators of summer precipitation in the study area.

Table 1: Correlation of each climate signals at different locations (Karamouz et al., 2006).

Signal	Name of considered area	Monsoon Rainfall Predictor characteristics			
		location		Month of effectiveness signal	CC*
		Latitude	Longitude		
SLP	Central Iran (P1)	25^{o}	55^{o}	April-May	0.53
	Pakistan & northern India (P2)	25^{o}	67.5^{o}	March-May	-0.50
	Northern India (P3)	20^{o}	62.5^{o}	March-May	-0.46
SLP difference	Indian Ocean-Study area	0^{o}-25^{o}	70^{o}-61^{o}	April-May	0.47
	Indian Ocean-Northern India	0^{o}-25^{o}	70^{o}-80^{o}	April-May	0.43

* Correlation Coefficient

3.2. Sea surface temperature (SST)

The Oman Sea, Arabian Sea and the east of Oman Sea are selected for determining long-lead rainfall predictors. The relation between long-term records of SST in the months of July to June of the following year at selected points and the total average precipitation in the proceeding months of July through September in the study area is investigated. The sea surface pressures (SSTs) of selected area have been determined over 1×1 degree grids. As an example, Figure 2 shows the correlation map over the Arabian Sea showing the relationship between monsoon rainfall of the study area and

SST for March. Coordinates of selected SST areas are presented in Table 2. This table also shows the maximum correlation between SST of studied regions and monsoon rainfall of the study area. According to Table 2, the SST of Eastern part of the Oman Sea in the months of March and April has the highest correlation with Iran monsoon rainfall.

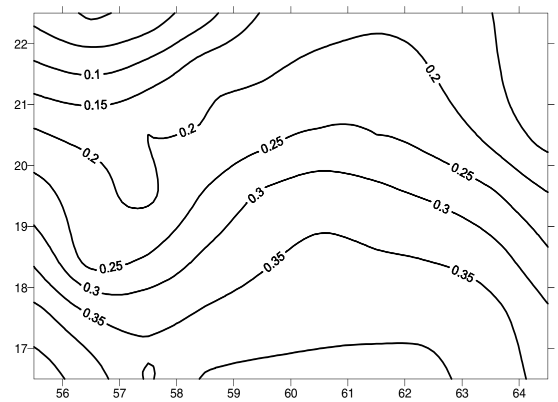

Figure 2: The correlation map of Arabian Sea showing the relationship between monsoon rainfall of the study area and SST for March.

Table 2: Characteristics of SST at selected points and correlation with monsoon rainfall

Area			Maximum Correlation			
Name	Latitude	Longitude	Latitude	Longitude	Period	CC
Oman Sea	$23.5^\circ N$ - $24.5^\circ N$	$55.5^\circ E$ - $64.5^\circ E$	$23.5^\circ N$	$59.5^\circ E$	March-April	0.43
Arabian Sea	$19^\circ N$ - $23^\circ N$	$55^\circ E$ - $65^\circ E$	$16.5^\circ N$	$55.5^\circ E$	May	0.48
Eastern part of Oman Sea	$19.5^\circ N$ - $25.5^\circ N$	$65.5^\circ E$ - $72^\circ E$	$20^\circ N$	$72.5^\circ E$	March-April	0.58

3.3. Summer precipitation Indicators

Results show that the following indices can be considered as indicators of summer precipitation in the study area:

1. SLP of central Iran (P1)
2. SLP of Pakistan & Northern India (P2)
3. SLP of Northern India (P3)
4. SLP difference between Indian Ocean and study area, and
5. SLP difference between Indian Ocean and Northern India
6. SST of Oman Sea
7. SST of Arabian Sea

8. SST of Eastern part of Oman Sea

The above signals have high correlation with summer monsoon in the study area and combinations of them are considered as ANN model inputs.

4- Results of monsoon summer rainfall forecasting

A thirty year time series of summer Monsoon rainfall and large scale signals found as Monsoon predictors (including SST, SLP and ΔSLP), from 1973 to 2002 are used for developing an ANN model for precipitation forecasting in the study area. The first twenty two years data from 1973 to 1994 are used for model calibration and the remaining 8 years of data are used for validation of the ANN model. The ANN model inputs are time series of different combinations of Monsoon predictors and their outputs are the Monsoon rainfall time series. Several different types of ANN models including MLP, RNN and IDNN have been developed and compared to find the model with the best performance. Each type of ANN models has been trained with different parameters and combination of signals until the best model has been obtained. The best structure of each type of considered ANN models has been shown in Table 3. Input data of ANN models are signals discussed in section 3.3. To quantify the ANNs performance, RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) have been calculated (Table 2). These two statistics show that MLP model has better performance.

Table 3: Structure of different ANN Models and their errors

ANN Model	no. of neurons in hidden layer	TDL (Time Delay Line)	RMSE	MAE
MLP	8	-	15.33	5.60
RNN	11	-	19.47	8.96
IDNN	8	1	10.49	5.09

The results of summer Monsoon rainfall forecasting with the selected ANN model, has been shown in Figure 3. This figure shows the acceptable ability of these three ANN models for rainfall prediction. But it must be noted that some times models predictions are overestimated. To better understand model performance, some error tolerances are defined. For this purpose, error is calculated as follows:

$$Error_i = \frac{|obs_i - for_i|}{obs_i} \qquad (1)$$

where obs_i and for_i stand for observed and forecasted rainfall, respectively. The percentages of predicted Monsoon rainfalls which lie within different error ranges are calculated and summarized in Table 4 for different ANN models.

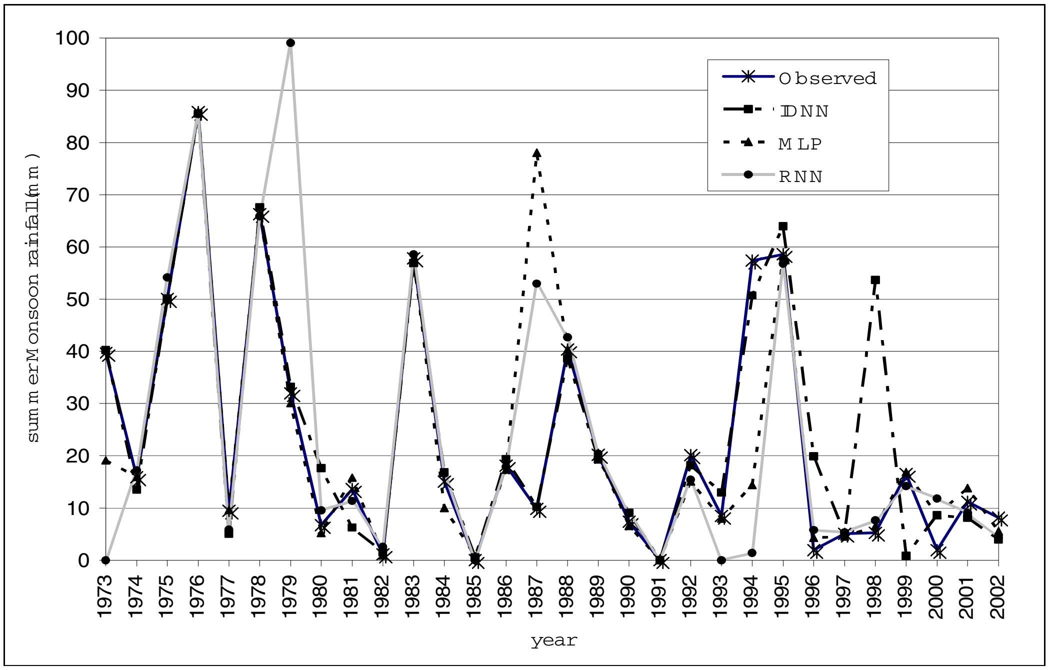

Figure 3: Comparative forecasted and observed summer Monsoon rainfall

According to Table 4, MLP can predict 50% of time within 30% of the observed rainfall. This range could be reduced for the months of August and September once the rainfall data for July is observed.

Table 4: Percentage of occurrence of predicted values within different error ranges

ANN Model		Tolerance		
		± 10%	± 20%	± 30%
MLP	Calibration	48	64	76
	Validation	33.33	33.33	50
RNN	Calibration	45.45	63.63	72.73
	Validation	12.5	25	25
IDNN	Calibration	54.55	68.18	77.73
	Validation	25	25	37.5

5. Conclusion

This study is an extension of Karamouz et al. (2006) which studied the relations between SLP and ΔSLP with Iran monsoon rainfall. SST signals are combined with

SLP signals in this paper to develop a forecasting model. Three regions including the Oman Sea, Arabian Sea and Eastern parts of the Oman Sea are selected and SST signals have been studied. Each region is divided into 1 × 1 degree grids and the correlation of SST in each zone with average rainfall of the study area has been estimated.

Different ANN models including MLP, RNN and IDNN with different architectures and different combinations of input predictors have been developed for Iran monsoon rainfall prediction. The models are tested and compared using MAE and RMSE statistics. The MLP model has the best performance and can predict rainfall patterns with acceptable accuracy.

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