

Application of Artificial Neural Network for Seasonal Rainfall Forecasting: A Case Study for South Australia

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Abstract— Quantitative approaches are very useful tools in forecasting purposes among the hydrologists for enhanced decision making. Modelling accuracy is also another important aspect in selecting an appropriate forecasting technique. Compared to other regions, South Australia's seasonal rainfall forecasting models were not very accurate and satisfactory in regards to their forecasting skills. Past studies conducted on South Australia's rainfall variability have mostly used the linear methods and showed very low rainfall predictability through the individual effects of the concurrent climate predictors. Previous research had not considered the interactions/effects of multiple combinations (more than two) of the climate modes at a time in order to forecast rainfall across South Australia (SA). Moreover, lagged-time influences of the potential climate indices on rainfalls were ignored. Therefore, SA has been chosen as a case study to fill up the present research gap. The relationships among the rainfall and climate predictors are not linear; therefore in order to improve the predictability of rainfall multivariate non-linear Artificial Neural Networks (ANN) technique was used in this study. Seasonal rainfall is being forecasted with the effect of past values of the potential climate predictors such as El Nino southern Oscillation (ENSO), Southern Annular Mode (SAM) and Indian Ocean Dipole (IOD) by developing non-linear ANN models. The non-linear artificial intelligence technique, ANN has already been proved superior compared to other techniques in other regions of Australia. However, previously it has not been attempted for SA. In order to compare the forecasting ability by the ANN models, Multiple Linear Regression (MR) models were developed as a benchmark. Results revealed the superiority of multivariate non-linear ANN over traditional linear MR methods for seasonal rainfall forecasting by considering the effects of climate variables.

Index Terms—Artificial Neural Network (ANN), rainfall forecasting, climate predictors, ENSO, IOD, SAM

I. INTRODUCTION

FOR design, planning and development of water resources management strategies, rainfall forecasting is essentially important. It helps to evaluate the water balance between future supply and availability, which ensures proper strategic management of water resources. Rainfall is

the most studied

and most important hydro-climate variables among the climatologists all over the world because of its significance in sustainable water resources management, agricultural activities and ecological management. Therefore, rainfall forecasting several months or seasons has become one of the primary goals of the water resources managers for many decades. Many researchers have tried to establish the relationships between large-scale climate drivers and rainfall in different parts around the world using different linear and non-linear methods [1]. Reliable rainfall forecasting could be beneficial in the management of land, watershed and water systems [2], especially in Australia, where the hydroclimatic variability is extremely high [3]. Global climate change is predicted to increase the rainfall variability which will only exacerbate the water-related issues [4]. Australia is exposed to severe floods and droughts; therefore seasonal rainfall forecasting will be very helpful for water resources management, food production and mitigating flood risks.

The rainfall over Australia is extremely variable that varies both spatially and temporally. It is well established that the rainfall variability in Australia has been accompanied with several oceanic-atmospheric processes, which are classified by several remote climate modes/variables and in many parts of Australian rainfalls are significantly affected these remote climate variables [5]. The most important influence is thought to be from the tropical Pacific Ocean driver, i.e. the ENSO [6, 7]. It has been established that the climatic influences from the Indian Ocean also plays a vital role in rainfall variability in Australia which is known as IOD [6, 8]. Another important climate variable originating from the Southern Ocean is called SAM [9-11]. Several studies have tried to explore the association of climate predictors with the Australian rainfalls. Some of the past studies on hydro-climatic variability were generally focused on overall Australia [6, 10-11]. Some of the researches focused particularly on Eastern and South Eastern Australia [12-17]; whereas others were more concentrated on other regions such as South West Western Australia [18, 19].

However, very limited studies were found especially focusing on the variability of South Australian rainfall in association with the remote climate variables [6, 9, 20-22].

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Therefore further study is required to explore the relationships between the potential large scale remote climate drivers and SA's seasonal rainfalls to develop a reliable seasonal rainfall forecast model. To date, the studies being conducted on South Australian rainfall variability have used linear methods, though a recent study has considered non-linear threshold method for the same purpose but still failed to achieve the significant outcome due to the basic limitation of this method. In Australian climate at any particular locations, any individual climate index may explain only about 20% of the rainfall variability [23]. In another study [6] investigated the relationship between climate drivers and overall Australian rainfall and concluded that individual climate drivers can explored up to 20% variability of South Australian rainfall. Reference [6] used ENSO and SAM in their study as individual climate index respectively and explored that only a single climate index might not be sufficient to determine the maximum correlations between these climate features and rainfall.

Recently, Reference [20] used the non-linear threshold method for investigating the variability and forecasting capability of South Australian seasonal rainfall with the aid of climate predictors where maximum of two climate drivers were used instead of single and found some successes regarding correlations and rainfall variability. Reference [20] suggested that the seasonal rainfall variability skill is largely depends on the influences and association of the multiple combination (more than two at a time) of climate drivers. However, there was a basic drawback of threshold method used in their study; it was not able to explore the complex rainfall-climate predictor's relationships with the combinations of more than two climate drivers due to the limitations of this method. Because, the threshold method applied in the study was unable to derive mathematical model involving more than two climate drivers at a time. Reference [20] also suggested that a new statistical non-linear multi-variate ANN approach which is free from such limitations of input variables should be used with the threshold method in using the number of combinations of input variables at a time. Some studies have already shown that the multivariate non-linear ANN technique is able to map the complex rainfall-climate driver's relationships with higher predictability compared to the threshold method used in the study of [20]. Such an emerging non-linear artificial intelligence technique was very rarely used for rainfall forecasting purposes in Australia using the large scale climate drivers as potential predictors. Few studies found are limited to some particular regions of Australia including the Queensland [14] and Victoria [5, 12-13]. For Victorian rainfalls, ANN models were developed for the seasonal rainfall forecasting and the ANN outputs were found to be superior compared to other techniques [5, 12-13].

So far, no study has established rainfall forecasting model for South Australia using the non-linear multivariate ANN approach considering multiple combinations (more than two) of potential climate variables. Moreover, the current model outputs will be deterministic meaning that it can explore with quantitative forecasting, in opposed to

probabilistic forecast that usually gives results only above or below median value.

II. DATA AND METHODS

A. Rainfall and Climate predictor variables data

The historical monthly rainfall data was obtained from the Australian Bureau of Meteorology website. As a case study of South Australia, Mount Bold Reservoir (MBR) rainfall station has been chosen. Figure 1 shows the location details of the rainfall station considered in this study. Seasonal spring (September-October- November) rainfall was obtained from monthly rainfall data from January 1957 to December 2013 (www.bom.gov.au/climate/data/). The monthly values of Nino3, Nino3.4, Nino4 and SOI were used as the representation of ENSO climate predictor variables. A measure of IOD is the Dipole Mode Index (DMI) from the Indian Ocean and SAM climate index from the Southern Ocean were considered. ENSO, IOD and SAM indices were obtained from Climate Explorer website <http://climexp.knmi.nl/>. A robust multivariate non-linear Artificial Neural Network (ANN) modelling technique will be used as a new technique to accomplish the goal of this study. In order to compare the forecast skill of non-linear ANN models, traditional Multiple Linear Regression (MR) linear models were used as a benchmark.

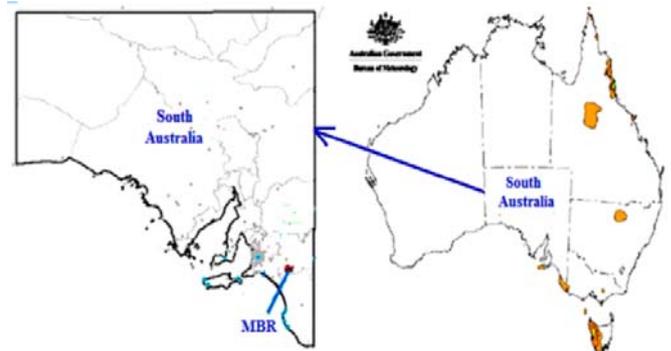


Fig. 1. Map showing the study area with selected location as a case study (Source: www.bom.gov.au).

B. Artificial Neural Networks

The Artificial Neural Network (ANN) approach is a non-linear statistical technique that has become popular among scientists as an alternative technique for predicting and modelling complicated time series, weather phenomena and climate variables (Mekanik et al., 2013). ANN has been used in many hydrological and meteorological applications; it has also been used for many cases of rainfall forecasting [24-26]. The parameters for ANN modelling are basically network topology, neurons characteristics, training and learning rules. A typical architecture and working layout of an artificial neural network (ANN) is shown in the figure 2.

In most of the studies the applications related to rainfall forecasting utilized feed forward neural network (FFNN) that incorporates the standard static multilayer perceptron (MLP) trained with the back-propagation algorithm [14]. The number of input and output neurons is based on the number of input and output data. Basically, the input layer only serves as receiving the input data for further processing in the network. The hidden layers are a very important part

in a MLP since they provide the nonlinearity between the input and output sets.

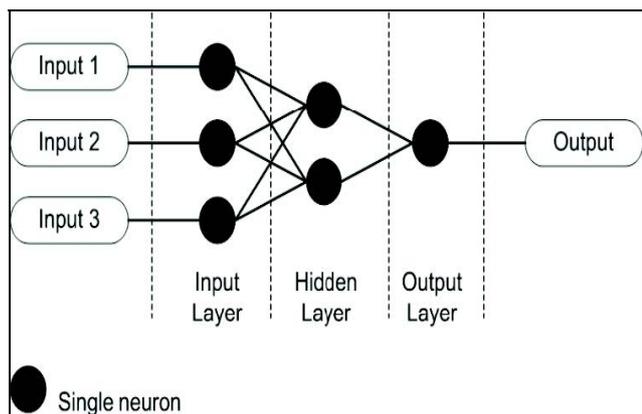


Fig. 2. Typical architecture and working layout of an artificial neural network (ANN).

Mathematically, the network illustrated in figure 2 can be expressed by using the following equation:

$$Y_t = f_2 \left[\sum_{j=1}^J w_j f_1 \left(\sum_{i=1}^I w_i x_i \right) \right] \quad (1)$$

Where, Y_t is the output of the network, x_i is the input to the network, w_i and w_j are the weights between neurons of the input and hidden layer and between hidden layer and output respectively; f_1 and f_2 are the activation functions for the hidden layer and output layer respectively. In this study f_1 is considered tansigmoid function which is a nonlinear function and f_2 is considered the linear purelin function. The ANN models were trained based on Levenberg-Marquardt algorithm. Number of hidden neurons was chosen based on trial and error procedures considering the different number of hidden nodes.

C. Multiple Regression Modelling

Multiple Regression (MR) is a linear statistical modelling technique that predicts a dependent or predictant variable based on the several other independent or predictor variables through the least square method. MR model can be presented by using the following general equation:

$$Y = a + b_1 X_1 + b_2 X_2 + e \quad (2)$$

Where,

Y = Dependent variable (spring rainfall)

X_1 = First independent variable or predictor (i.e. ENSO representative)

X_2 = Second independent variable or predictor (i.e. SAM, IOD representatives)

b_1 = Coefficient of first independent variable, X_1

b_2 = Coefficient of second independent variable, X_2

a = Constant or intercept

e = Error

The models were evaluated using Pearson correlation (R), root mean square error (RMSE), and index of agreement (d), which is widely used for the evaluation of prediction model. The optimum value of d is 1 is considered the better

model meaning that all the modelled values fit the observations [27]. The correlations which are statistically significant at 1 and 5% levels were considered in this study.

III. RESULTS AND DISCUSSIONS

This study attempts to model the seasonal spring rainfall which includes September, October and November (S-O-N). For this purpose, from December to August month's Nino3, Nino3.4, Nino4, SOI, DMI and SAM climate predictor's variables have been selected to be used in the non-linear ANN and linear MR modelling of seasonal spring rainfall (S-O-N). Thus, the single linear correlations of these months' (December to August) climate variables with Mount Bold Reservoir (MBR) rainfall were calculated and the months with highest significant correlation were chosen to be used in the modelling which is shown in table I. It can be seen that not all the lags have significant relationship with rainfall; the maximum correlation of 0.44 is achieved for DMI-August. For different indices different months have significant relationship with rainfall, however July and August months are having the highest correlation with rainfall. It was observed that the maximum three months' (June, July and August) lagged SOI, DMI and SAM climate predictors have significant correlation with spring rainfall.

TABLE I
SIMPLE LINEAR CORRELATION OF SEASONAL SPRING RAINFALL AND DIFFERENT LAGGED-TIME INFLUENCES OF INDIVIDUAL CLIMATE PREDICTORS (CORRELATIONS AT EITHER 1 OR 5% SIGNIFICANT LEVELS ARE SHOWN WITH ASTERISK)

Month	Pearson correlation with individual climate predictors		
	DMI	SOI	SAM
Dec	---	---	---
Jan	---	---	---
Feb	---	---	---
Mar	---	---	---
Apr	---	---	---
May	---	---	---
June	---	---	-0.33*
July	-0.38**	0.33*	---
Aug	-0.44*	---	---

The combined lagged-predictor model sets were organized based on the significant single and separate lagged relationship obtained in table 1 with ENSO, IOD and SAM climate predictors. Then, ENSO-DMI-SAM based combined model input sets were used for further linear MR and non-linear ANN modelling to investigate the predictability of rainfall. Among the developed models the ones that follow the limits of statistical significance level were selected, the models having lower error were chosen as the best model for rainfall prediction. The combinations of these significant lagged indices were further examined in MR modelling. It can be seen that combined climate indices significantly increased the correlation up to 0.46 in calibration and 0.56 in testing phase with DMI (Jul)-SAM (Jun) combination. The traditional linear MR model was

used to forecast seasonal rainfall with correlation 0.56 which is the improvement of linear MR model by 44% with the combination of maximum two climate predictors. Attempts have been made to use all the possible combined lags as predictors in MR modelling, but most of the combined-lagged predictor's model was not statistically significant. Therefore, those insignificant models were not reliable in rainfall forecasting. Even though some of the lags of the predictors were not linearly correlated with the rainfall, however for non-linear ANN modeling all the lagged indices were used as predictors (Dec. to Aug.). The reason behind of taking all these lags due to the concept of ANN which is capable of finding the nonlinear relationship between the predictors and rainfall. Table II shows the result of non-linear ANN modeling on both training-validation and testing set using the combination of two as well as multiple climate predictor's model to figure out the best combination of the forecasting model. The number of hidden neurons giving the least error, maximum correlation as well as maximum data agreements between observed and modelled rainfall was 4.

TABLE II
COMPARISON BETWEEN THE CORRELATIONS OF SEASONAL SPRING RAINFALL WITH LINEAR AND NON-LINEAR MODELS

Combine d models	Correlation			
	Training-Validation	Testin g	Training-Validation	Testin g
	Linear Regression model		Non-linear ANN model	
DMI-SAM	0.46	0.56	0.62	0.82
SOI-SAM	0.45	0.34	0.70	0.41
DMI-SOI-SAM	Model is not able to explain the multiple combination of variables		0.75	0.93

Multivariate non-linear ANN models are showing much higher correlations and statistical performances for both the combination of two and three climate predictors' models. The correlation in ANN models are significantly higher than the maximum correlation found in MR models, which was 0.56. However using ANN approach the correlations were improved significantly using combination of two climate predictors which is found 0.82, the improvement of ANN model was observed by 46%. Further analyses with the non-linear ANN model was carried out by using three climate predictors (i.e. DMI-SOI-SAM), which was the basic input limitations in linear models. The results demonstrated further improvement of the forecasting ability of the multivariate ANN methods and the correlation was found up to 0.93, which is a significant improvement (by 66%) over the correlation achieved by the best liner regression model incorporating two predictors. Figure 3 shows the comparisons of observed and predicted rainfalls using linear MR and non-linear ANN models. It can be seen that the MR models is modeling around the mean of the series and is not capable of capturing the peaks and minimum values. On the other hand ANN is smoothly fitting the series capturing

most of the peaks and minimum values.

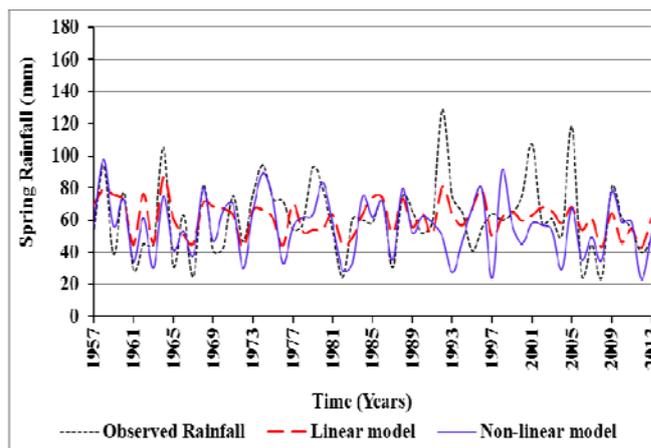


Fig. 3. Comparison between non-linear ANN model with linear model's output for spring rainfall, (1957-2008=training-validation period, 2009-2013=testing period)

The Index of agreement (d) an additional criterion has been chosen for model comparison and for the better assessment of the model's performance (Willmott, 1981). It is seen from table III that non-linear ANN revealed the least error and better fitted model regarding RMSE and 'd'.

TABLE III
EVALUATION OF MODEL PERFORMANCE USING 'RMSE' AND 'd' VALUES FOR THE BEST MODELS

Models		Model Performance			
		Training-Validation	Testing	Training-Validation	Testing
Linear Regression		RMSE		d	
	DMI-SAM	20.91	11.95	0.59	0.70
	SOI-SAM	21.00	13.36	0.56	0.46
	DMI-SOI-SAM	---	---	---	---
Non-linear ANN	DMI-SAM	16.35	9.04	0.72	0.81
	SOI-SAM	15.82	14.64	0.61	0.59
	DMI-SOI-SAM	14.06	8.04	0.67	0.93

Therefore, depending upon the correlation and model's RMSE and d values, ANN models output with the multiple combinations such as DMI-SOI-SAM is the better predictors of SA's seasonal rainfall. The second most reliable ANN models output is obtained using DMI-SAM combinations. Therefore, it seems that DMI and SAM is more reliable rainfall predictors than other indices affecting South Australian seasonal rainfalls significantly.

IV. CONCLUSIONS

The aim of this research was to investigate the combined lagged effects of the potential climate predictors for South Australian seasonal spring rainfall predictions using multiple regressions as a linear method compared to Artificial Neural Networks (ANN) as a nonlinear method in order to investigate the predictability of spring rainfall using

lagged DMI-ENSO-SAM climate combinations. Previous studies were focusing on finding the effect of these climate indices individually on SA's rainfalls and were unable to achieve the rainfall predictability with good statistical correlations. ANN models have shown to be an effective, general-purpose approach for pattern recognition, classification, clustering, and especially time series prediction with a high degree of accuracy. This study elaborated the improvement of the generalization ability of complex relationships between rainfall and climate predictors by using the multi-variate non-linear ANN modelling approach in predicting the seasonal rainfall in South Australia.

The traditional linear MR model using combined predictors (DMI-SAM) was found to provide the maximum correlation of 0.56, which is an improvement of model correlations by 44% compared to linear models' performances using single predictor. The attained correlations of ANN models are significantly higher than the maximum correlation found in MR models ($R=0.56$). Using ANN approach the correlations were improved significantly; with the combination of two climate predictors (DMI-SAM) the maximum correlation found was 0.82 (an improvement of 46% compared to MR model using two predictors) and with the combination of three predictors (DMI-SOI-SAM) the maximum correlation achieved was 0.93 (an improvement of 66% compared to MR model using two predictors). ANN with combined-lagged climate predictors was able to model the observed rainfall in a way that the models can predict the pattern of rainfalls several months in advance with very good accuracy (least error and model correlation up to 0.93). Therefore, depending upon the correlation as well as other model performances evaluation parameters such as RMSE and d values, ANN model output with the multiple combinations of predictors (DMI-SOI-SAM) is the best model for the predictions of SA's seasonal rainfall compared to any other available technique/model. This study concluded that non-linear artificial intelligence modelling technique is able to provide higher correlations and lower error to forecast rainfall compared to linear methods and it would be a suitable prediction tool for the prediction of South Australian spring rainfall. There is a need to further investigate this method on other rainfall stations in this region to generalize the forecasting model which will be covered in future studies.

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