

Investigating the Influence of Remote Climate Drivers as the Predictors in Forecasting South Australian Spring Rainfall

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ABSTRACT: Australian rainfall is related with numerous key climate predictors namely El-Nino Southern Oscillation (ENSO), Indian Ocean Dipole (IOD) and Southern Annular Mode (SAM). Some studies have tried to discover the effects of these climate predictors on rainfall variability of different parts of Australia, particularly Western Australia, Queensland and Victoria. Nonetheless, clear association between separate or combined large-scale climate predictors and South Australian spring rainfall is yet to be established. Past studies showed that maximum rainfall predictability was only 20% considering isolated/individual effects of ENSO and SAM predictors in this region. The present study further explored these hypotheses by investigating two additional important aspects: investigating the relationship between lagged individual climate predictors with spring rainfall and linked (multiple combinations of ENSO and SAM) influences of significant lagged-climate indicators on spring rainfall forecasting using multiple regression (MR) modeling. Three stations were chosen as case studies for this region. MR models with combined-lagged climate predictors (SOI-SAM based models) showed better forecast ability in both model calibration and validation periods for all the stations. Results demonstrated that rainfall predictability significantly increased using combined climate predictor's influence compared to their individual effect. It was discovered that rainfall predictability increased up-to 63% using combined climate predictors compared to their single influences. The maximum attained rainfall predictability for the SOI-SAM based models was 47% for calibration period that significantly enhanced with combined predictors influence to 97% during validation period. Therefore, MR analyses delineated the capabilities and influences of remote climate drivers in forecasting South Australian spring rainfall.

Key words: ENSO, SAM, MR model, Correlation, Multicollinearity, Rainfall forecasting

INTRODUCTION

Rainfall variability is an important phenomenon and at times severely impacts our agricultural production, infrastructure as well as on the water resources management. It is the most studied hydro-climate variables because of its significance for sustainable water resources management, agricultural activities and ecological management. Global climate change is predicted to increase this variability which will only exacerbate these problems. Improved knowledge of expected rainfalls and subsequent flooding can significantly reduce the impacts of such floods. The ability to forecast rainfall several months or seasons in advance has been a goal of water resource managers for many decades. Such forecasting not only would assist in water resource management decision making, but would also be invaluable

for disaster management, emergency and evacuation planning. Forecasting rainfall is very essential in developing a water resource management strategy to check the balance of future water supply and demand to ensure proper water supplies to the people. A reliable rainfall forecast can be beneficial for the management of land and water resources systems (Anwar et al., 2008; Cuddy et al., 2005; Chiew et al., 2003; Abawi et al., 2001), particularly in Australia where the hydro-climatic variability is very high (Peel et al., 2001). For example, seasonal rainfall forecast might be supportive for water managers those who are making operational decisions on water allocation for competing end users, and forecasting the future events like rainfall would help for primary producers or farmers in man-

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aged and to take risk-based decisions for farm and crop management.

Many researchers have tried to establish the relationships between large-scale climate drivers and rainfall in different parts around the world (Niu, 2012; Grimm, 2011; Shukla et al., 2011; Chattopadhyay et al., 2010; Kim et al., 2008; Cheng et al., 2004; Yufu et al., 2002). Australian rainfall is highly variable both in space and time. The variability of Australian rainfall has been linked to several dominant large-scale climate predictors. It is well established that the occurrence of Australian rainfall is mostly influenced by several key climatic drivers based on Sea Surface Temperature (SST) and pressure differences anomalies originate from the Pacific, Indian and Antarctic or Southern Oceans. These large scale climate predictors including the ENSO, IOD and SAM were chosen as the best rainfall drivers over Australia based on the past studies such as Chowdhury and Beecham, 2013; Hasan & Dunn, 2012; Cai et al., 2011; Kirono et al., 2010; Chowdhury & Beecham, 2010; Risbey et al., 2009 and Meneghini et al., 2007. ENSO which is explained by the two different types of indicators: the Southern Oscillation Index (SOI) is characterized by Sea Level Pressure (SLP) anomalies between Tahiti and Darwin in the tropical western Pacific and the Sea Surface Temperature (SST) anomalies in the equatorial Pacific Ocean. The variation measured in average SST anomaly in the tropical eastern Pacific Ocean region from 50N-50S and 1500W-900W which is called Nino3, the region from 50N-50S and 1700W-1200W that indicates Nino3.4 and from 50N-50S and 1600E-1500W indicates Nino4 (Risbey et al., 2009; Suppiah, 2004; Wolter & Timlin, 1998; Drosowsky, 1993; Nicholls, 1989; McBride and Nicholls, 1983), the Indian Ocean Dipole (IOD) defined as a coupled ocean-atmosphere phenomenon in the equatorial Indian Ocean also known as the SST gradient between Indonesia and the central Indian Ocean (Saji & Yamagata, 2003; Saji et al., 1999), and the Southern Annular Mode (SAM) explains the dominant mode of rainfall variability in atmospheric circulation of the Southern Hemisphere land masses (Hendon et al., 2007; Cai & Cowan, 2006; Thompson & Solomon, 2002; Visbeck & Hall, 2004).

A number of researches in different parts of Australia tried to find out the relationship between the climate drivers and Australian rainfalls. Some of them covering the whole of Australia are Kirono et al., 2010; Risbey et al., 2009; Meneghini et al., 2007; Cai et al., 2001; Power et al., 1999; Drosowsky, 1993; McBride & Nicholls, 1983, while the others are more concentrated on a specific region like South West Western Australia (England et al., 2006; Ummenhofer et al., 2008), South Australia (Nicholls, 2010; Evans et al., 2009), South East Australia and East Australia (Murphy and Timbal, 2008;

Verdon et al., 2004). South Australia is one of the regions that so far did not show any good correlation of its rainfall and climate indices. According to Risbey et al. (2009) the South Australian rainfall predictability was limited to 20% considering individual effects of ENSO and SAM climate predictors. The more recent researches were conducted specifically on South Australian rainfall predictions including works of Chowdhury & Beecham (2013); Cai et al. (2011), which analyzed the impact of climate indices considering concurrent & separate role of single/isolate climate driver at a time. Furthermore the climate drivers were limited to ENSO and IOD only. However, a strong relationship between simultaneous/concurrent climate driver and rainfall does not principally prove that there also exists lagged relationship (Schepen et al., 2012), which is most important for future rainfall predictions.

Very limited studies have focused on the lagged climate predictors and rainfall relationship other than South Australia such as, Hasan & Dunn, 2012; Abbot & Marohasy, 2012; Schepen et al., 2012; Kirono et al., 2010; Drosowsky & Chambers, 2001. Hasan & Dunn (2012) investigated the separate correlation of climate indices with one month lag on Australian rainfall and showed that rainfall is significantly influenced by ENSO. Kirono et al (2010) is one of the few available publications who considered the maximum of two-month averaged lag relationship of climate indices and Australian rainfall. Abbot & Marohasy (2012) also used past values of climate indices for forecasting of rainfall in Queensland; however the climate indices they used was limited to generated from the Pacific Ocean and Indian Ocean lagged by 2 months. To the best of our knowledge, no study has been considered more than 2-months lagged-time effects of the climate indices to find the rainfall predictability. Also, previous research has not considered finding a multiple combination of these key climate indicators at a time in order to forecast future rainfall. These two important facts may be the reasons why the studies conducted on South Australia did not show good correlation among rainfall and climate indices. In many cases the relationships of climate predictors and rainfalls are much more complex and single predictors alone are unable to predict rainfall accurately. Such combined relationship with lagged-time effects of climate predictors has not previously been attempted in South Australia.

According to Keim & Verdon-Kidd (2009) south Australian rainfall variability is not determined by a single climate driver itself. Due to the geographical location of South Australia, single effects of ENSO and IOD are not much strong; the SAM climate driver might have much influence on rainfall variability in this region. Also, previous researches did not consider

lagged-time effects as well as multiple combinations (ENSO-SAM combined sets) of these key climate indicators at a time in assessing the rainfall predictabilities. These two important facts might be the reasons why the studies conducted on South Australia did not show good correlation. Therefore, this study would be the extension of the works conducted by Chowdhury & Beecham (2013); Cai et al., (2011) and Risbey et al. (2009). The outputs of the model were intended to be deterministic forecast means that can explore with quantitative measures which opposed to probabilistic forecast which can give results only above or below median value.

MATERIALS & METHODS

The historical monthly rainfall data in millimetres from January 1957 to December 2013 were obtained from the Australian Bureau of Meteorology website (www.bom.gov.au/climate/data/). The climate indices data were obtained from Climate Explorer website (<http://climexp.knmi.nl/>). Three rainfall stations were chosen as a case study from South Australia. The stations are Tarcoola (TC), Mount Eba (ME) and Millers Creek (MC) and the locations are shown in fig. 1. The stations were chosen based on their recorded length of data and the stations also had very few (less than 0.50%) missing value. To facilitate the analysis, the missing values were replaced by series means. Fig. 2 shows the intensity of ENSO and SAM during the study period. In general the positive phases of SOI (La Nina) brings more rainfall to the major parts of Australia, while the negative phases of SOI are more associated with drought events. Multiple Regression (MR) modelling was used to achieve the goal of this study. MR analysis is a linear statistical modeling technique that allows finding out

the best relationship between a dependent variable (predicant) and several other independent variables (predictor) through the least square method. The general equation of a multiple regression model can be expressed as follows (Montgomery et al., 2001).

$$Y = b_0 + b_1X_1 + b_2X_2 + c \tag{1}$$

Where, Y is the dependent variable (spring rainfall in this study), X₁ and X₂ are 1st and 2nd independent variables respectively (lagged ENSO and SAM indicators), b₁ and b₂ are the model coefficients of first and second independent variable respectively, b₀ is constant, and c is the error. The verification of multicollinearity among the predictors is an important stage in MR modeling. Multicollinearity occurs when the predictors are highly correlated which will result in dramatic change in parameter estimates in response to small changes in the data or the model. Tolerance (T) and Variance inflation factor (VIF) are the indicators used to identify the multicollinearity among the predictors.

$$\text{Tolerance} = 1 - R^2, \text{ VIF} = \frac{1}{\text{Tolerance}}, R^2 = \frac{\text{SSR}}{\text{SST}} = 1 - \frac{\text{SSE}}{\text{SST}} \tag{2}$$

Where, R² is the coefficient of multiple determinations, SST equal to the total sum of squares, SSR equals the regression sum of squares and SSE is the error sum of squares. Lin (2008) identified that the value of tolerance less than 0.20-0.10, meaning that the VIF values greater than 5-10 indicates a multicollinearity problem among the predictors. In conducting the MR modelling it is very important to investigate for the independency of the residuals, meaning that no autocorrelation exists

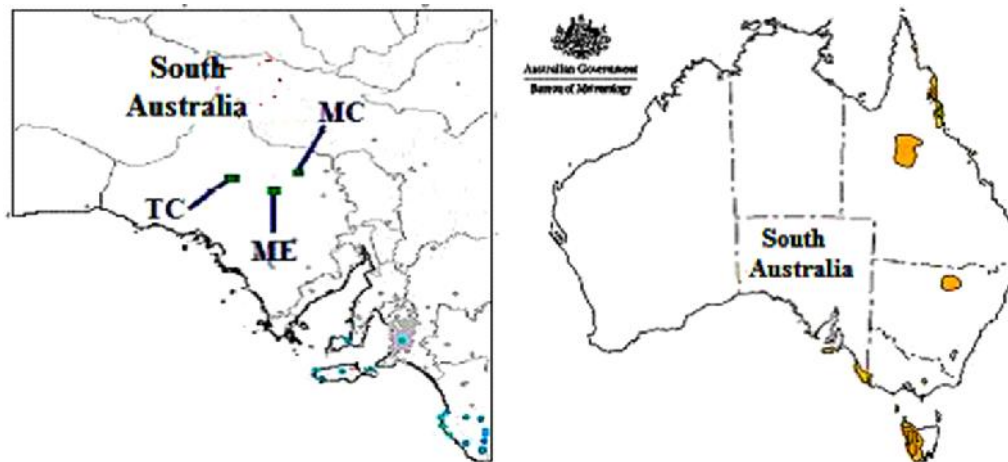


Fig. 1. Map showing the study area with selected locations (Source: www.bom.gov.au)

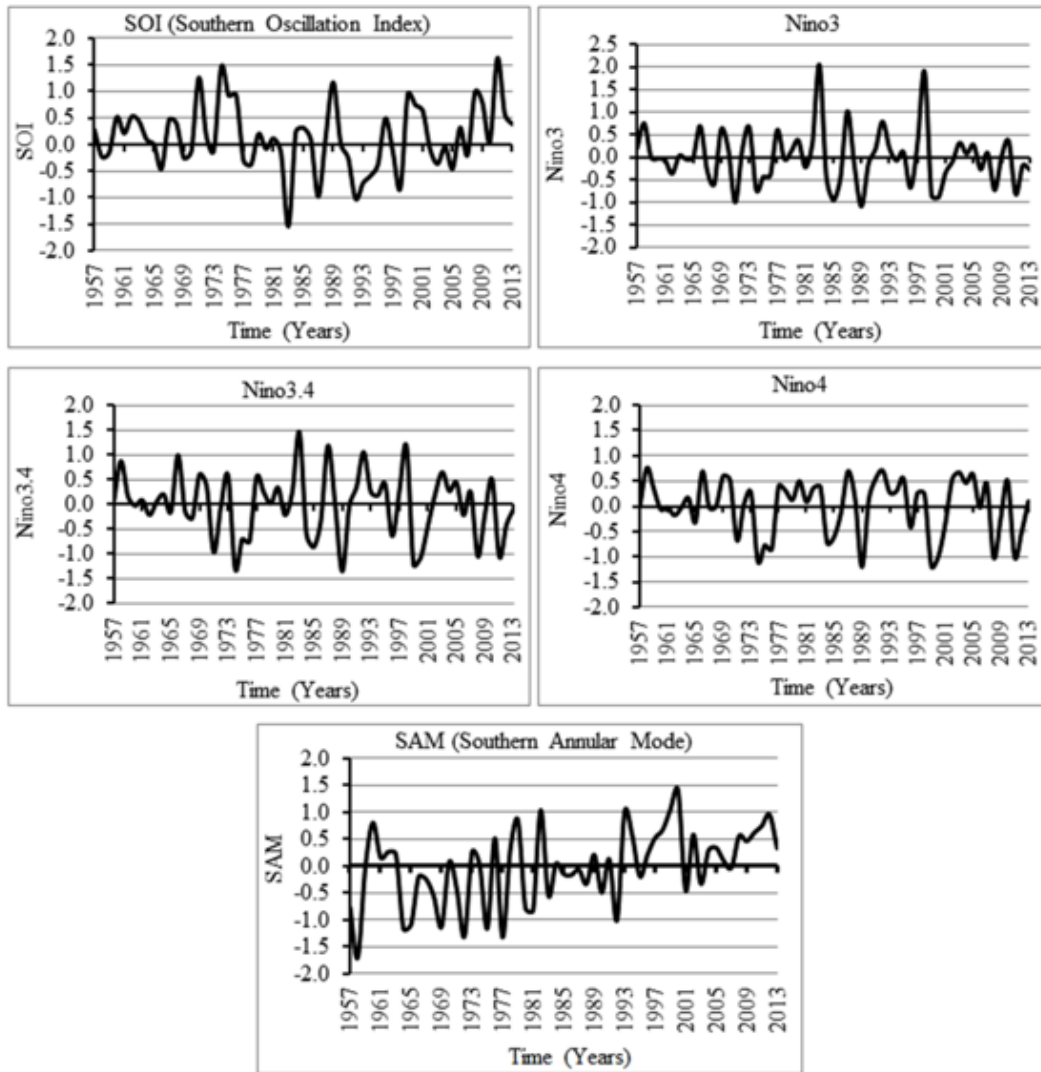


Fig. 2. The intensity of climate indices during the study period; ENSO indicator (SOI, Nino3, Nino3.4 and Nino4) and SAM (Southern Annular Mode) index

among the residuals and the model has fit the data well enough. If any autocorrelation exists among the residuals then the models fails to capture all the relationship between the inputs and the output. So, investigating the residual pattern is another vital performance of evaluating the goodness-of-fit of the prediction models. Durbin-Watson test statistics (D-W) is widely used criterion to evaluate for serial correlations between residuals or errors. This test statistics have a values range from 0 to 4. Field (2009) specified that the D-W values less than 1 or greater than 3 are definitely the matter of concern of autocorrelation among the residuals. The SPSS statistical software was used to accomplish the single and multiple regression correlation analysis. The correlations which were statistically significant at 1% and 5% level were considered in this study. The data were divided into two sets, years from 1957-2009 were

used for calibration of the models. Later four years from 2010-2013 were selected as the out-of-sample test set to evaluate the generalization ability of the developed forecasting models and all the model evaluation parameters were computed separately for both model calibration and validation period. The performances of MR models were evaluated by adopting several error indices and other important statistical performance test parameters which are widely used for the evaluation of prediction model. To evaluate data agreement or disagreement, some statistical methods are widely used. These includes: (i) Root mean square error (RMSE), (ii) Mean absolute error (MAE), (iii) Mean Absolute Percentage Error (MAPE%), (iv) Relative Error (RE), (v) Pearson correlation coefficients (R), (vi) Willmott index of agreement (d), (vii) Variance inflation factor (VIF), (viii) Durbin-Watson statistics (D-W), and (ix) F-test

and t-test. RMSE and MAE indices are very important which is called the "best" overall measures of model performance among other test because they precisely indicate the average difference in the same units of observations and modeled data (Fox, 1981). Although the RMSE and MAE values of 0 indicate a perfect fit which is almost impossible in reality, so lower the RMSE the better the model performance (Singh et al., 2004). The mean absolute Percent error (MAPE) is widely used to validate the forecast models. The closer the MAPE values to 0.0, the better the forecasting results (Saigal & Mehrotra, 2012). MAPE gives very meaningful results only if all observations (O_i) values are positive (Ramanathan, 1995). RE measures the relative size of the error in the modeled values with respect to observed values. RE value is zero for an ideal case that indicates the developed model is perfect, which is not possible in practical case. However, lesser RE value showed the better performance by the developed model. To assess the goodness of the model to fit the observation data, the Pearson multiple correlation coefficients (R) are used. Those traditional measures are not always ideal for assessing the data agreement or disagreement. For example, R merely indicates the linear co-variation between two datasets rather than the actual difference; RMSE and MAE are dimensional measures of disagreement, thus are not independent of data scale and unit. To overcome the shortcomings accompanying with R, MAE, and RMSE; Willmott (1981, 1982) developed the index of agreement (d), which was used for further assessment and validating the developed forecasting models. The optimum value of d is 1, which means that all the modeled values fit the observations (Willmott 1981, 1982). Moreover, Willmott's measure is more appropriate for the investigation of model validation, where observed and model-predicted values need to be compared. The index of agreement (d) expressed as:

$$d = 1 - \left(\frac{\sum(P_i - O_i)^2}{[\sum(|P_i - \bar{O}| + |O_i - \bar{O}|)^2]} \right) \quad (3)$$

Where, P_i is model predicted value of the ith observation and O_i is observed value of ith observation.

RESULTS & DISCUSSION

For evaluating the rainfall predictability, single/individual correlations between south Australian spring rainfall(S-O-N) at any year 'n' with lagged monthly values of ENSO and SAM climate predictors (Nino3, Nino4, Nino3.4 and SOI were chosen as ENSO predictors) from Dec_{n-1}-Aug_n ('n' being the year for which spring rainfall is predicted) were investigated. The correlations of rainfall with single predictor within the limits of statistical significance level and multicollinearity among the predictors were chosen for further MR analysis. It was observed that the maximum three months (i.e. June, July and August) lagged SOI, Nino34 and Nino4 climate predictors has significant correlation with spring rainfall, whereas maximum five months of significant lagged relation was found with SAM predictor. Results also demonstrated that the highest and significant correlations were achieved between spring rainfall and single climate indices with maximum of three month lagged for ENSO and five months lagged for SAM predictors. Moreover there is no further significant relationship more than lag five for South Australia. Correlations of different lagged-time effects of individual climate predictors and SA spring rainfall are presented in Table 1.

Statistical performances showed good consistency with the previous findings (Chowdhury & Beecham, 2013; Cai et al., 2011; Nicholls, 2010; Meneghini et al., 2007). It is seen that Millers Creek is showing better correlations of SOI and SAM than other two stations. In Mount Eba both Nino34 as well as Nino4 predictors are showing better correlations with spring rainfall compared to Tarcoola and Millers Creek. Spring rainfall is significantly influenced by SOI, particularly in July and August, but its influence is reduced in June. Moreover, the spring rainfall is also found significantly correlated by SAM driver in April in this region. The other phases

Table 1. Correlations of different lagged time effects of single climate predictors with spring rainfall

Station	Lagged climate indices								
	SAM _{Apr}	SOI _{Jul}	SOI _{Aug}	Nino3.4 _{Jun}	Nino3.4 _{Jul}	Nino3.4 _{Aug}	Nino4 _{Jun}	Nino4 _{Jul}	Nino4 _{Aug}
Tarcoola	0.28*	---	0.33*	-0.30*	-0.31*	---	-0.32*	-0.37**	-0.31*
Mount Eba	0.29*	0.30*	---	-0.33*	-0.36**	-0.32*	-0.36**	-0.42**	-0.39**
Millers Creek	0.33*	0.35*	---	-0.35*	-0.35*	-0.32*	-0.32*	-0.37**	-0.41**

*: correlations are statistically significant at the 1% level, **: correlations are statistically significant at the 5% level

of ENSO that is Nino34 and Nino4 having much influence compared to other climate predictors. Subsequently, the combined lagged-predictor model sets were organized based on the single and separate significant lagged relationship of ENSO and SAM climate predictors obtained from Table 1. ENSO-SAM based combined predictor input sets were then used for further assessment in multiple regression modelling. The MR model input sets with the combinations of combined significant lagged climate predictors are shown in Table 2. The developed combined predictors model sets includes maximum of nine months lagged ENSO-SAM combined sets which was further used for MR modeling, the multiple climate indices sets also ensure that there is no agreement among the predictor variables on which the indices can better represent this ocean-atmospheric phenomenon. MR modeling was then performed in order to investigate the predictability of spring rainfall using significant combined-lagged relationships

of SOI-SAM, Nino34-SAM and Nino4-SAM predictors as shown in Table 2.

F-test and t-test statistics has conducted to evaluate the significance level of MR models and regression coefficients. Among the developed predicted models the ones that follow all the limits of statistical significance level were selected, models having lower error were chosen as the best model for rainfall forecasting. Table 3 shows the summary of the best multiple regression models developed among the three stations mentioning the values of the multiple regression coefficients, VIF and Durbin-Watson statistics (D-W) of the best models. VIF indicators for the selected models are one and thus there is no multicollinearity problems exist among the predictors. Moreover, D-W test statistics fall around a value of two which elucidate that the residuals of the predicted models have no autocorrelation and they are independent that confirmed the goodness-of-fit of the models.

Table 2. MR model input sets with the combinations of combined significant lagged climate predictors

Station	SOI _x -SAM _y model sets	Nino3.4 _x -SAM _y model sets	Nino4 _x -SAM _y model sets
Tarcoola	Aug-Apr	Jun-Apr, Jul-Apr	Jun-Apr, Jul-Apr, Aug-Apr
Mount Eba	Jul-Apr	Jun-Apr, Jul-Apr, Aug-Apr	Jun-Apr, Jul-Apr, Aug-Apr
Millers Creek	Jul-Apr	Jun-Apr, Jul-Apr, Aug-Apr	Jun-Apr, Jul-Apr, Aug-Apr

*x and y are the lagged months of the different climate predictors

Table 3. Summary of the best developed MR models (statistically significant at least 5% levels are shown)

Station	Models	Coefficient					VIF	DW
		Const.	SOI _{Jun}	SOI _{Jul}	SOI _{Aug}	SAM _{Apr}		
Tarcoola	SOI _{Aug} -SAM _{Apr}	16.19	---	---	4.64	1.95	1.00	1.82
Mount Eba	SOI _{Jul} -SAM _{Apr}	11.68	---	3.36	---	1.50	1.00	1.84
Millers Creek	SOI _{Jul} -SAM _{Apr}	10.59	---	3.97	---	1.74	1.00	1.89

Table 4. Performance of the developed MR models during calibration and validation period

Station	Models	Results for calibration period (1957-2009)					Results for model validation period (2010-2013)				
		R	RMSE	MAE	RE	MAPE (%)	R	RMSE	MAE	RE	MAPE (%)
Tarcoola	SOI _{Aug} -SAM _{Apr}	0.44	10.06	7.91	0.47	0.90	0.94	11.99	7.91	0.78	1.57
Mount Eba	SOI _{Jul} -SAM _{Apr}	0.40	8.24	6.43	0.55	1.05	0.83	12.07	10.17	0.60	1.20
Millers Creek	SOI _{Jul} -SAM _{Apr}	0.47	8.00	6.16	0.58	1.11	0.97	8.33	6.21	0.57	1.14

The performances evaluation statistics such as RMSE, MAE, MAPE (%), RE, R and d of the best MR models for the three regions are shown in table 4. SOI-SAM based models demonstrated statistically significant with better predicting ability for south Australian spring rainfall, with R= 0.44 for Tarcoola, 0.40 for Mount Eba and 0.47 for Millers Creek. After calibrating the models an out-of-sample tests were carried out on the years from 2010-2013 to evaluate the future rainfall predicting ability of the developed models. MR model in validation stage is showing better generalization ability for all stations; however the ability of MR models to forecast out-of-sample sets improves significantly for Tarcoola with R= 0.97. The RMSE, MAE and RE values of the testing sets for MR models are compatible in compared to the calibration stage. The MAPE value varies 0.90 to 1.11% in calibration, and 1.14 to 1.57% in validation stage, which are very low and compatible compared to the calibration stage indicating that the models are capable of forecasting spring rainfall with better accuracy.

It can be seen from the table 4 that after combining the climate predictors, it significantly increased the rainfall predictability up to 97% for Millers Creek with SOI_{Jul}-SAM_{Apr} combination of predictors. The best one among the three predicted models considering the correlation coefficient, statistical performance parameters and lower error is shown by the following equation 4:

$$Rainfall = 3.97 \times SOI(July) + 1.74 \times SAM(Apr) + 10.59 \quad (4)$$

Fig. 3 shows the best developed MR model's time series outputs for the three stations. Using lagged climate indices as potential predictors, multiple regressions were able to model the observed rainfall in a way that the models follow the pattern of rainfalls several years in advance with very good accuracy. Willmott (1981, 1982) developed an additional criteria, an index of agreement (d), which were used further assessment of the model performance especially for validating the developed forecasting models. While Pearson correlation shows how well the models are following the trend of the actual observations, Willmott index of agreement

"d" shows how well the models are fitting the observed data series; the value of "d" is close to 1 indicates the better fitted model with higher model accuracy.

Table 5 shows the 'd' values for the three stations. Mount Eba is having higher d value in validation sets than other regions however the error values are bit higher than other two stations. All the 'd' values in the validation/test sets are nearly 0.50 confirming that the SOI-SAM based combined climate predictor models are capable of forecasting south Australian spring rainfall with better accuracy.

To further evaluate the ability of MR models, the peaks and trough values of the MR predicted spring rainfall and actual spring rainfall were cross plotted in fig. 4, where upper values with square boxes are represents peaks and lower values are troughs. Table 6 shows the correlation coefficient values for the model peaks and troughs. It can be seen from the table 6 that MR models are able to capture the peaks with a correlation of 0.59 for Tarcoola, 0.36 for Mount Eba and 0.51 for Millers Creek. Other than Mount Eba with a weak correlation of 0.21, Tarcoola and Millers Creek models were able to forecast the troughs with a correlation of R = 0.36 and 0.33 respectively. In general, the models were able to forecast the peaks much better than the trough values with correlations of R = 0.36 to 0.59.

The simulation results, various performance evaluation parameters as well as statistical significances demonstrated that the developed SOI-SAM based combined climate predictors' models are capable of forecasting South Australian spring rainfall. The developed MR model in general, showing an underestimation of the actual observed data series. To further asses this matter mean and standard deviation of the models were evaluated which is shown in the Table 7. It is evident from table 7 that the models have a mean very close to the mean of the series however the standard deviation of the models are lower indicating an underestimation of the observations. Moreover, the models in validation period are showing a bit overestimation of the actual observation that means the developed SOI-

Table 5. Index of agreement (d) values for the MR models in calibration and validation stage

Station	Models	d (calibration period)	d (validation period)
Tarcoola	SOI _{Aug} -SAM _{Apr}	0.55	0.51
Mount Eba	SOI _{Jul} - SAM _{Apr}	0.50	0.55
Millers Creek	SOI _{Jul} - SAM _{Apr}	0.58	0.49

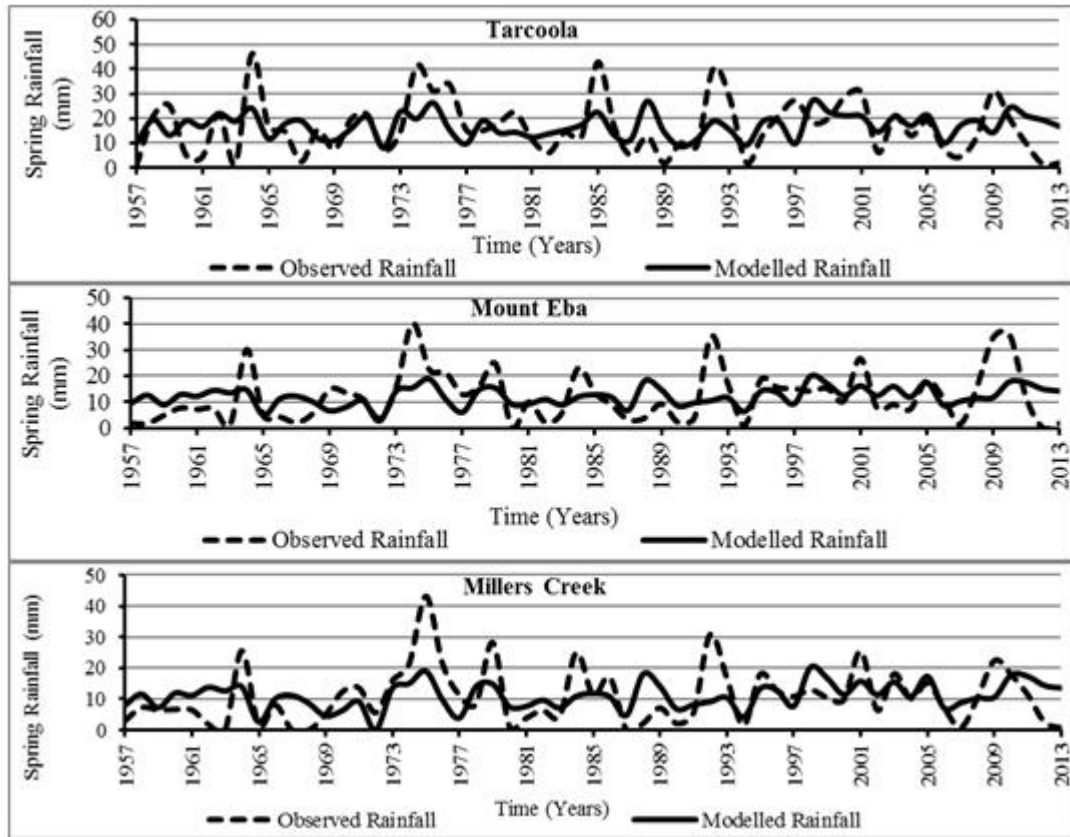


Fig. 3. Comparison of MR model's output for rainfall forecasting for the three stations (1957-2009: elibration and 2010-2013: validation period)

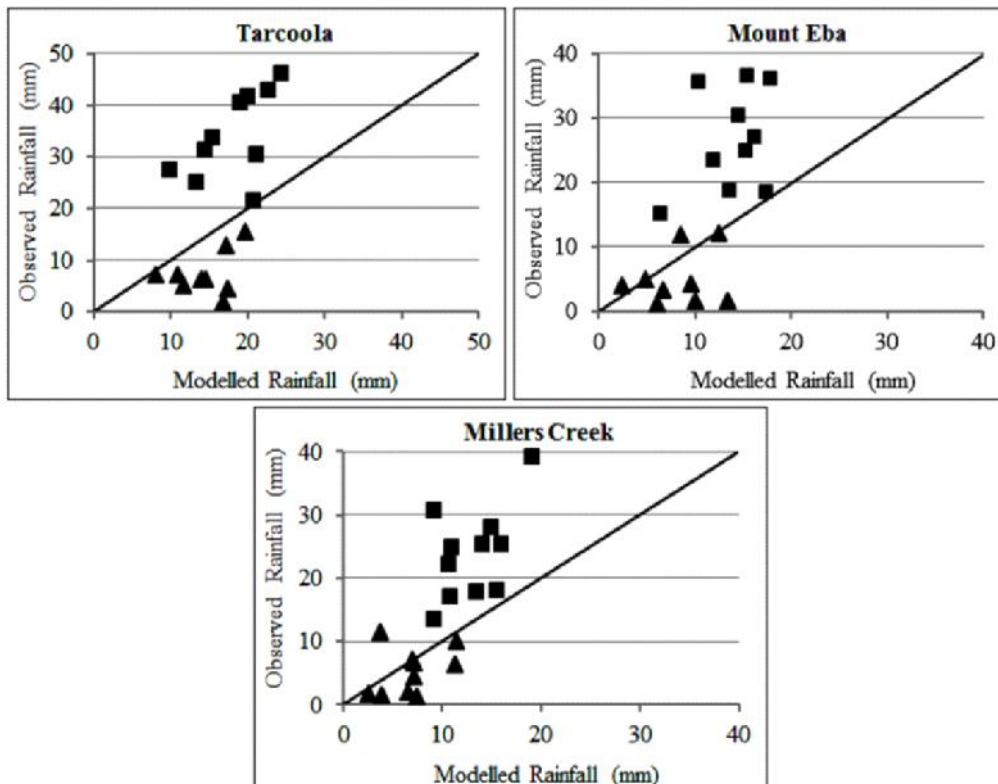


Fig. 4. Performance evaluation of the developed MR models in regards to the peaks and troughs

Table 6. Correlation coefficients of the MR models for the peaks and troughs

Station	Models	Peak	Trough
Tarcoola	SOI _{Aug} -SAM _{Apr}	0.59	0.36
Mount Eba	SOI _{Jul} - SAM _{Apr}	0.36	0.21
Millers Creek	SOI _{Jul} - SAM _{Apr}	0.51	0.33

Table 7. Mean and Standard deviation of the models and observations

Station	Mean		Standard Deviation	
	Observation	Model	Observation	Model
Tarcoola	16.93	16.93	11.31	4.97
Mount Eba	11.75	11.75	9.09	3.67
Millers Creek	10.67	10.67	9.16	4.30

SAM based model with combined climate drivers is capable of predicting spring rainfall; however other climate influence may also be involved and which would be taken into account for more accurate predictions in future studies.

CONCLUSION

The emphasis of this study has been concentrated on investigating the influences of remote climate drivers such as the effects of El Nino Southern Oscillation (ENSO) and Southern Annular Mode (SAM) as potential predictors, more precisely study focused on investigating the influences of single and combined lagged ENSO and SAM climate predictors on South Australian spring rainfall prediction. In addition, a comparative study was made for finding rainfall predictability between individual as well as combined lagged climate models. Three regions (Tarcoola, Mount Eba and Millers Creek) from South Australia were chosen as a case study. The correlations of rainfall with single predictor within the limits of statistical significance level and multicollinearity among the predictors were chosen for further MR analysis. It was observed that the maximum three months (i.e. June, July and August) lagged SOI, Nino3.4 and Nino4 climate predictors has significant correlation with spring rainfall, whereas maximum five months of significant lagged relation was found with SAM predictor. Results also demonstrated that the highest and significant correlations were achieved between South Australian spring rainfall and single climate indices with maximum of three month lagged for ENSO and five months lagged for SAM predictors. Millers Creek is showing better correlations of SOI and SAM than other two stations. In Mount Eba both

Nino3.4 as well as Nino4 predictors is showing better correlations with spring rainfall compared to Tarcoola and Millers Creek. Spring rainfall is significantly influenced by SOI, particularly in July and August, but its influence is reduced in June. Moreover, the spring rainfall is also found significantly correlated by SAM driver in April in this region. The other phases of ENSO that is Nino3.4 and Nino4 having much influence compared to other climate predictors.

Furthermore, the combinations of significant lagged predictor variables were examined in MR modeling to investigate the predictability of spring rainfall. The errors of the testing/validation sets for multiple regression models are generally lower compared to the calibration sets. The RMSE, MAE and RE values of the testing sets for the MR models are compatible in compared to the calibration stage. The MAPE value varies 0.90 to 1.11% in calibration stage, and 1.14 to 1.57% in validation stage, which are very low and compatible compared to the calibration stage indicating that the models are capable of forecasting spring rainfall with better accuracy. Mount Eba is having higher index of agreement value (d) in validation sets than other regions however the error values are bit higher than other two stations. All the 'd' values in the validation/test sets are nearly 0.50 confirming that the SOI-SAM based combined climate predictor models are capable of predicting south Australian spring rainfall. Results demonstrated that rainfall predictability significantly increased using combined climate predictors compared to predictability with individual effects of predictors. The attained combined model predictabilities are 44% for Tarcoola, 40% for Mount Eba and 47% for Millers Creek during calibration pe-

riod. The predictabilities were significantly enhanced during model validation; the results are 94% for Tarcoola, 83% for Mount Eba and 97% for Millers Creek. Therefore, MR model discovered that combined lagged climate predictors significantly increased the rainfall forecasting ability up to 97% with SOI_{Jul}-SAM_{Apr} combination in forecast out-of-sample test sets for Millers Creek. However, these predictabilities were limited to 33%, 30% and 34% respectively considering the influences of single/individual climate predictors. In general, the influences of SOI-SAM based combined lagged-climate predictors' models showed good generalization ability for all the three stations. Therefore, SOI-SAM based combined climate predictor's influences demonstrated statistically significant relationships with better forecasting ability for south Australian spring rainfall. The statistical analyses outlined the capabilities of combined-lagged climate predictors in compared with their single/individual influences for forecasting spring rainfall using multiple regressions modeling. Moreover, further investigation of this method is necessary with other rainfall stations in this region to suggest generalize model for rainfall forecasting which will be covered in future studies.

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