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A hybrid wavelet neural network (HWNN) for forecasting rainfall using temperature and climate indices

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Abstract. Rainfall forecasting plays an important role in water resources management and also for controlling the unusual events related to the rainfall. This study aims to forecast monthly rainfall from antecedent monthly rainfall, temperature and climate indices using a hybrid wavelet neural network (HWNN) model. The discrete wavelet transform is used incorporation with a conventional ANN model. The skilfulness of the proposed model is compared with the observed rainfall and the ANN model. The results show that the HWNN model provides a good fit with the observed rainfall data particularly in facing the extreme rainfall. The decomposed sub-series obtained by wavelet transform can extract invaluable information which is enormously useful for future rainfall prediction. The results confirm that the hybrid model considerably improves the neural network ability to predict future rainfall.

1. Introduction

Prediction of future rainfall is valuable for both the decision makers and water consumers. This is also very useful as the main input for various studies of stream-flow prediction, solute transfer study and managing unusual events such as flooding and drought prediction. Therefore, developing models with high accuracy have become essentially important to help the water resource managers to better control the impacts of rainfall anomalies. In the past decades, different methods have been developed to predict rainfall. The proposed models are categorized into dynamic and empirical methods. Dynamic modeling relies on some differential equations which sometimes are difficult to resolve. Nevertheless, empirical methods such as ANN and statistical methods are widely used methods and are dependent on historical observational data. The approach behind this method is to identify the features of past information and then to use them for predicting future phenomena [1]. There have been a number of attempts to find the most appropriate techniques for rainfall prediction. The broadly used empirical methods like regression, artificial neural network, fuzzy logic and have been applied in many rainfall predictions [2,3]. The main issue regarding almost all data-driven methods is the appropriate input data which plays an essential role in the performance of these models. In recent years, the use of hybrid approaches has been increased due to their ability to get better results in terms of accuracy. The Wavelet-ANN is one of the methods which is able to improve the results of ANN modeling. The wavelet analysis is a progressive tool in signal processing which is a good alternative for Fourier analysis [4]. Many studies in various fields used application of hybrid wavelet models. In hydrological modeling, ANN and wavelet method was used by Kim and Valdes [5]. They used wavelet transforms and neural network for forecasting drought in a river basin in Mexico. For modeling sediment discharge, Kisi used wavelet-ANN for assessing the ability of this method for calculating river sediment load [6]. In the mentioned studies, the performance of hybrid wavelet approach was compared with individual neural network and it was found that it is possible to take advantage of the neural network and wavelet analysis simultaneously. Partal and Cigizoglu applied wavelet-neural network for forecasting daily rainfall. They found that a combined model estimates superior results than conventional models [7].

The effect of temperature has been investigated in previous works. Recently, the relationship between extreme rainfall and daily maximum temperature was assessed by Herath *et al*. They analyzed different rainfall durations for evaluation rainfall-temperature scaling relationships by considering seven weather stations throughout Australia [8]. However, it has also been rarely addressed in Australia for projecting the rainfall. For example, Abbot and Morashy considered monthly rainfall, temperature and various climate indices for rainfall prediction in Queensland three-month ahead [9]. They also conducted appreciable research for improving the past models by modifying input data sets through the study of input selection by choosing a broad range of lagged values of rainfall, temperature and climate indices [10]. In their study, different data comprise of the unary, binary, ternary and quaternary input sets were used for calculating the rainfall for 1, 2 and 3 months lead times.

The goal of this work is to address the effect of temperature in forecasting rainfall using a hybrid wavelet-ANN model 1, 3 and 6 months in advance. The central interior of Queensland is used as a case study. The results are compared to the ANN and observed data obtained from Australian Bureau of Meteorology (BoM) by means of various statistical parameters such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Refined Index of Agreement (d_r).

2. Data and study area

To assess the performance of the proposed model and also the effect of temperature for calculating future rainfall, the information of the central interior of Queensland is used (figure 1). To consider the effect of ENSO on Queensland rainfall, the southern oscillation index (SOI) and Nino3.4 are used [11]. Monthly rainfall, southern oscillation index (SOI), minimum temperature and maximum temperature data were obtained from the Australian Bureau of Meteorology from nearby station of Ayrshire Downs (37001) and Richmond Post Office (30045) because of having long records of data with few missing values [12]. About 70 percent of data (the year 1908 to 1985) are used for calibration and remain (1985-2017) are used for testing the model. Nino3.4 is obtained from the Royal Netherlands Meteorological Institute (KNMI) Climate Explorer [13]. The different effective combinations of temperature, Nino3.4 and SOI are defined through model 1 to 6. Also, the twelve lagged values of rainfall, minimum temperature, maximum temperature, Nino3.4, and SOI plus current month values of each anomaly were used as input of the network.

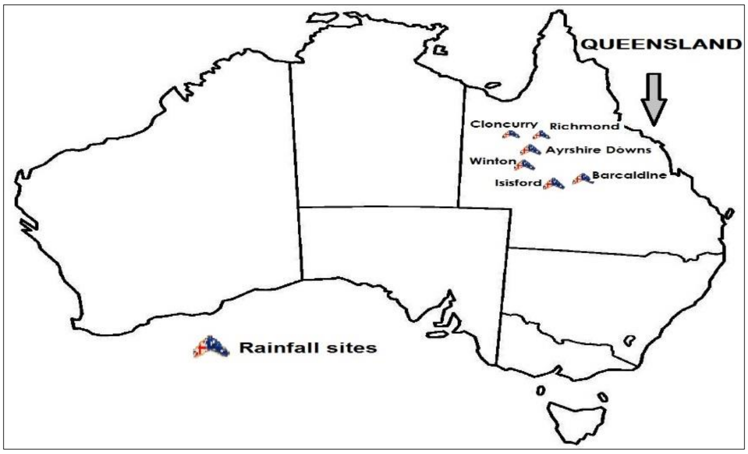

Figure 1. Study area and rainfall stations in the Central interior of Queensland.

The monthly mean rainfall, maximum and minimum monthly mean temperature in this region are 33 mm, 32.8 $C^{\cdot}$, and 16.7 $C^{\cdot}$ respectively.

For assessing the forecasting ability of each model, we consider lead times of 1, 3, and 6 months. The skilfulness of each model with different combinations of inputs is evaluated using various statistical parameters such as the Root Mean Squared Error (RMSE), Refined Index of Agreement (d_r), Mean Absolute Error (MAE) and correlation coefficient (R). The Refined Index of Agreement as a new parameter is defined as below:

$$d_r = \begin{cases} 1 - \frac{\sum_{i=1}^{n}|P_i - O_i|}{c\sum_{i=1}^{n}|O_i - \overline{O}|}, when \\ \sum_{i=1}^{n}|P_i - O_i| \le c\sum_{i=1}^{n}|O_i - \overline{O}| \\ \frac{c\sum_{i=1}^{n}|O_i - \overline{O}|}{\sum_{i=1}^{n}|P_i - O_i|} - 1,\ when \\ \sum_{i=1}^{n}|P_i - O_i| \ge c\sum_{i=1}^{n}|O_i - \overline{O}| \end{cases} \tag{1}$$

where, P is predicted or modelled values, and $\overline{O}$ represents observed mean value, c is scaling of the deviations to errors ratio, O is observed values and d_r is the refined index of agreement. ($c = 2$ is recommended) [14].

3. Artificial neural networks

Artificial neural networks are widely used black-box models throughout the worlds. An ANN consists of numerous nodes called neurons that are structured in one or more layers [15]. The ANN attempts to resemble human biological neural characteristic by some training rules. The most popular ANN is multilayer perceptron (MLP) feed-forward neural network with a back-propagation algorithm. It comprises one or more hidden layers between input and output. The number of hidden neurons can be obtained according to the complexity of the problem through trial and error process. A feed-forward neural network explicitly is described as follows [5]:

$$\hat{y}_k = f_0\left[\sum_{j=1}^{M} w_{kj} \cdot f_h\left(\sum_{i=1}^{N} w_{ji}x_i + w_{jo}\right) + w_{ko}\right] \tag{2}$$

where, w_{ji} stands for the hidden layer's weight which connects the ith neuron in the input layer with the j^{th} neuron in the hidden layer; f_o is the activation function for the output layer; w_{jo} is the bias for the j^{th} hidden neuron; w_{kj} represents the output layer's weight that connects jth neuron with the kth neuron in the output layer; w_{jo} is the bias for the k^{th} hidden neuron; f_h is activation function and $\hat{y}_k$ is the output of the feed forward neural network.

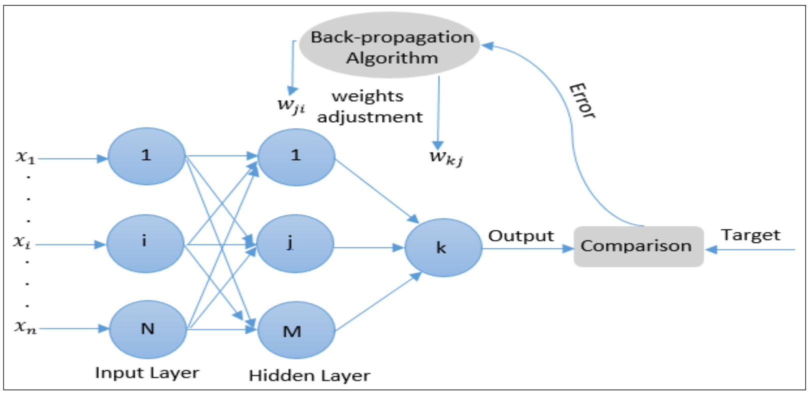

Figure 2. Schematic representation of a three-layered feed-forward network with a back-propagation training algorithm.

The network described by mathematical equations can be shown visually in figure 2. In this study, the Levenberg–Marquardt (LM) algorithm is used for training the network. In every ANN model, the overtraining is inevitable which can cause poor predictive results. Thereby, some techniques are used to avoid this problem. The early stop technique is used in this study. In other words, the training process is halted when validation error starts to increase in spite of diminishing the training set error. Also, allocating some data as a testing set can be applied for validating the model. These data have not already been used in the network for calibration purpose. It is noteworthy that in this study, the number of hidden neurons was chosen based on trial and error using Back-Propagation algorithm. It was found that the efficient number of neurons for ANN modeling is 11 and for HWNN is 13.

4. Wavelet analysis

The wavelet transform, initially, was introduced as an alternative to the Fourier transform and has been used widely in communications, image processing, and computer science. Fourier transforms are able to break down a signal into continuous sine waves in different frequencies which are not temporally and spatially localized. Thereby, the Fourier transform cannot capture the sudden variation of the time series. Consequently, a new technique for localizing the signal in time and space is needed. This procedure is defined through wavelet transform. A wavelet is a limited duration wave with a mean value of zero. In wavelet analysis, the main time series is decomposed into different lower resolution levels through shifting and scaling factors of a basic wave called mother wavelet (The wavelet function). Scaling refers to the process of stretching or shrinking the signal in time and shifting is proceeding and delaying a wave along the signal. Selecting a proper wavelet coefficient is the essential part of the wavelet analysis and it affects the accuracy of the results. There are few widely used mother wavelets such as Daubchies, Morlet, Discrete Meyer and Haar wavelets. In continuous wavelet transform (CWT), the wavelet coefficients describe accurately the time-scale view of the signal. Nevertheless, calculating wavelet coefficients at every single scale is inefficient and creates a huge amount of information. Hence, for prediction purpose, it is not possible to use CWT. In this study, a discrete form of the wavelet is used. The discrete wavelet transform (DWT) converts the signal from the time domain into the time/frequency domain. It accepts the following form [16]

$$f(a,b) = a^{-1/2}\int_{-\infty}^{\infty} f(t)\,\varphi\left(\frac{t-b}{a}\right)dt \quad a\epsilon R, \qquad b\epsilon R, a \neq 0 \tag{3}$$

where $\varphi(t)$ is the basic wavelet with length (t) which is normally much shorter than the main time series $f(t)$, a is the scale parameter, b defines positithe on of the wavelet that demonstrates sliding of the wavelet over $f(t)$. The main signal is decomposed into approximation and detail components and can be described by:

$$f(t) = D_1 + D_2 + D_3 + \cdots + D_i + A_i \tag{4}$$

where D and A represent detail and approximation, respectively. i is the level of decomposition (highest level). Each low-pass filtered component (A) can be decomposed into a high-pass filtered and a low-pas filtered component. For example A_1 is a low-pass filter which can generate A_2 (a low-pas filtered component) and D_2 (a high-pass filtered component). The output (targets) value of the network is considered the observed time series at $t + T$ for predicting the rainfall in T lead-time.

For connecting ANN with wavelet, the values of approximation and details are used as input of the ANN. In other words, after decomposition the signal into detail and approximation, the value of approximation in the last level and values of detail at all levels are used as the input of the ANN. Figure 3 shows the input values including rainfall, maximum temperature, minimum temperature, SOI and Nino3.4 index. It is evident that if the signal is decomposed into higher levels, more information will be provided for the network. However, it might increase the computations dramatically which is not required in most problems. Hence, selecting an optimum level of decomposition can result in the reduction of computations. Similarly, selecting the appropriate mother wavelet is an essential part of designing the model. In other words, according to the intrinsic nature of the signal (*e.g.* shape or rapid fluctuations), the most similar mother wavelet to the main signal should be selected to capture the useful hidden information in the signal. In this study, after trial and error, it was found that the Dmey wavelet produces better results with respect to the other wavelet functions. Also, in this study, the main signal is decomposed into 3 level which is the optimum level number for the current problem.

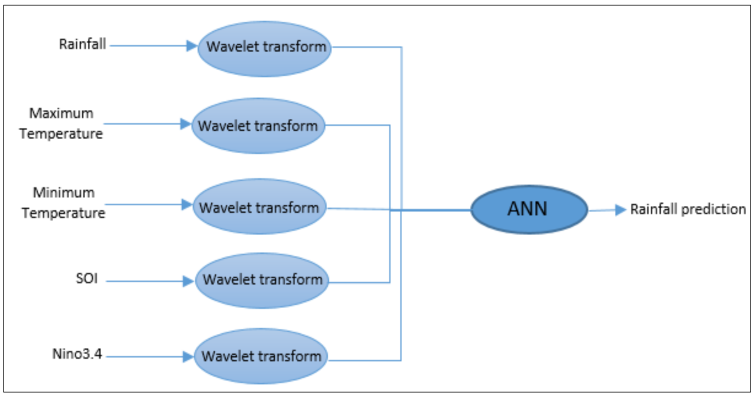

Figure 3. The wavelet and artificial neural networks conjunction.

The decomposed sub-series of approximations and details through calibration (training) period for rainfall and minimum temperature as a signal decomposition instance are depicted in figure 4.

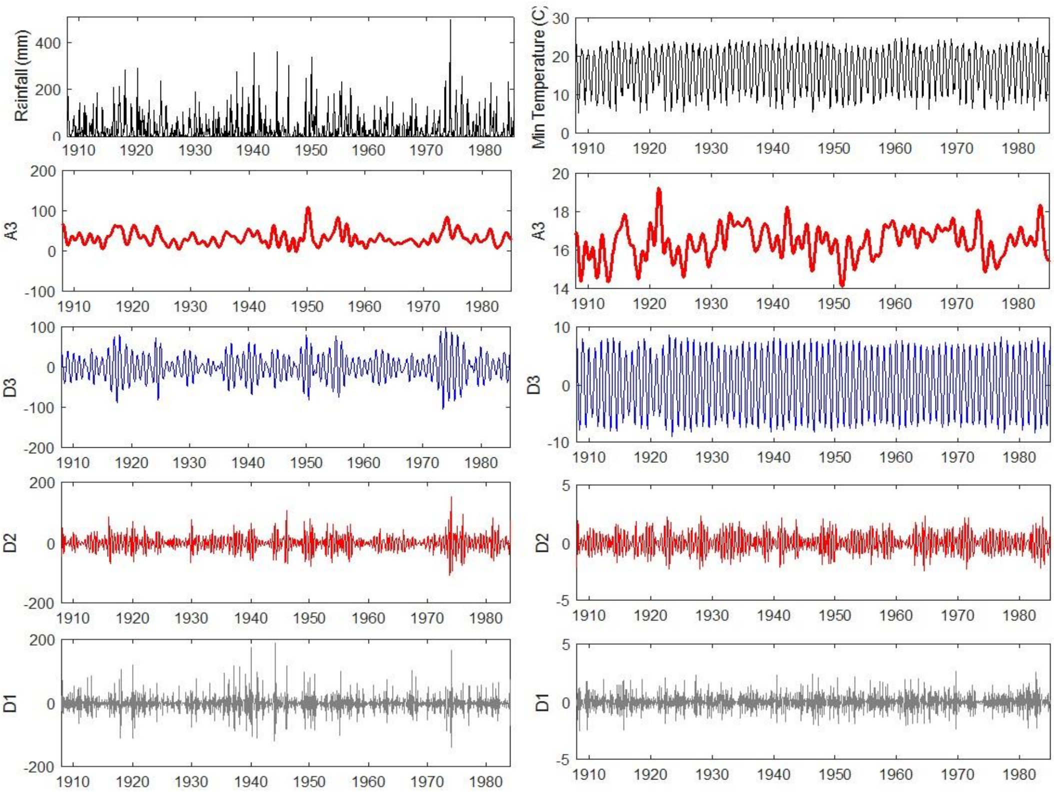

Figure 4. The rainfall and minimum temperature decomposition into detail and approximation sub-series during the calibration period.

It is seen that D1 contains very meticulous information of the original signal and can capture trivial events like sudden changes which cannot be detected easily in the main signal. Moreover, A3 presents information regarding the general properties of the signal.

5. Result and discussion

Six various models are defined for evaluation of temperature impact on rainfall and also for assessing HWNN model. The first model is the unary model with one input which is defined as a base model for comparing with other models. The forecasting is done in three different lead-times including 1, 3 and 6 months. The results for calibration (training) and testing period are shown in table 1, table 2 and table 3. In table 1 prediction is done for 1 month ahead rainfall. It is evident that in the HWNN modeling, the first model can release better outcomes with respect to the other models.

To the best of our knowledge, in Wavelet-ANN modeling, when the same types of inputs and outputs are selected, the exact results are created by the Hybrid model compared with other models. For example, when the input and output of the network are rainfall data, projection the future rainfall would be most accurate. In other words, since in wavelet analysis the main signal is decomposed into some sub-signals, the superior similarities are found between the input and output of the network when input and output are of the same type. However, this is not true for ANN modeling. It is seen that in ANN modeling, the differences between model 1 and other models are not high and they generate results with the relatively same precision. The best model in ANN is the fourth model with the RMSE=45.11 and MAE=29.68. Conversely, the RMSE and MAE values for HWNN is 4.63 and 1.85, respectively that are very lower than the ANN result for this lead time. The best-combined model in HWNN modeling is the fourth model. Therefore, it seems that for forecasting the rainfall 1 month in advance, the combination of minimum temperature and maximum temperature can estimate the rainfall more accurate than other combined models. This is owing to the presence of better correlations between minimum temperature and maximum temperature with the rainfall. The prediction of rainfall three months ahead is shown in table 2.

It is clear that the lower RMSE of 18.88 in model 1 and the RMSE value of 42.31 in the fourth combined model are obtained by HWNN. Also, the correlation between observed rainfall and modeled rainfall is perfect in model 1 and is comparatively high in model 4 in the three months lead time. However, the values of RMSE in six various models are in the same range and fluctuate between 47 and 50 for the ANN. One can see that the model with the input of minimum temperature can generate better results than other models. Additionally, according to table 2 and correlation analysis, the better correlations between real rainfall and forecasted rainfall would not be higher than 0.46 for ANN modeling.

Table 1. Skilfulness of HWNN versus ANN model forecast model for one month lead time during calibration and testing period. (The two lowest RMSE values are highlighted).

Model Input		Calibration				Testing			
		RMSE	MAE	d_r	R	RMSE	MAE	d_r	R
				ANN					
1	Rainfall	49.03	33.4	0.54	0.47	47.97	31.71	0.56	0.43
2	Min Temp/Min Temp/Nino	45.33	27.27	0.63	0.54	46.89	30.62	0.58	0.47
3	Max Temp/Min Temp/SOI	48.72	30.07	0.59	0.5	47.64	29.07	0.6	0.45
4	Max Temp/Min Temp	46.54	29.94	0.59	0.54	**45.11**	29.68	0.59	0.52
5	Min Temp	47.89	30.64	0.58	0.50	**46.16**	30.05	0.58	0.49
6	Max Temp	47.37	30.35	0.58	0.51	46.86	29.68	0.59	0.47
				HWNN					
1	Rainfall	3.01	1.50	0.98	0.99	**4.63**	1.85	0.97	0.99
2	Min Temp/Min Temp/Nino	45.01	29.17	0.60	0.57	45.72	32.1	0.56	0.51
3	Max Temp/Min Temp/SOI	36.73	24.55	0.67	0.76	42.10	29.4	0.6	0.63
4	Max Temp/Min Temp	39.16	25.28	0.65	0.70	**38.36**	24.5	0.66	0.73
5	Min Temp	44.35	27.49	0.62	0.60	44.57	37.7	0.62	0.56
6	Max Temp	36.28	22.58	0.70	0.75	39.91	24.2	0.67	0.68

Table 2. Skilfulness of HWNN versus ANN forecast model for six months lead time during calibration and testing period. (The two lowest RMSE values are highlighted).

Model Input		Calibration				Testing			
		RMSE	MAE	d_r	R	RMSE	MAE	d_r	R
ANN									
1	Rainfall	49.81	29.74	0.59	0.45	49.53	29.44	0.59	0.38
2	Min Temp/Min Temp/Nino	45.31	28.08	0.61	0.58	48.24	29.96	0.58	0.45
3	Max Temp/Min Temp/SOI	46.37	29.59	0.59	0.54	48.14	30.56	0.57	0.44
4	Max Temp/Min Temp	48.26	30.62	0.58	0.51	**48.02**	29.92	0.58	0.45
5	Min Temp	47.88	29.58	0.59	0.52	**47.05**	31.80	0.55	0.46
6	Max Temp	48.13	29.17	0.6	0.5	50.71	30.66	0.57	0.32
HWNN									
1	Rainfall	17.62	12.35	0.83	0.95	**18.88**	13.22	0.81	0.94
2	Min Temp/Min Temp/Nino	41.44	28.30	0.61	0.66	46.87	33.08	0.54	0.52
3	Max Temp/Min Temp/SOI	44.16	29.51	0.59	0.60	46.84	31.91	0.55	0.50
4	Max Temp/Min Temp	36.89	21.77	0.70	0.77	**42.31**	24.88	0.66	0.65
5	Min Temp	45.65	28.79	0.60	0.56	46.57	28.27	0.61	0.50
6	Max Temp	39.82	23.76	0.68	0.69	42.89	24.03	0.67	0.63

Finally, the rainfall prediction six months ahead is done and results are shown in table 3. It is evident that although RMSE and MAE values in this lead time are higher than the previous lead time in HWNN modeling, it is relatively lower than the ANN modeling. In HWNN modeling, the best model is still the first model and then the model consists of minimum and maximum temperature (model 4). Similarly, in ANN modeling, the fourth model shows better performance compared to other models. It is evident that the HWNN models can release superior results in terms of errors and correlations than the ANN models. Besides, it is seen that the Nino index and SOI do not have effective influence in rainfall in different lead time in the central interior region of Queensland. However, the effect of Maximum temperature and minimum temperature for predicting future rainfall is higher than the climate indices.

Table 3. Skilfulness of HWNN versus ANN forecast model for six months lead time during calibration and testing period. (The two lowest RMSE values are highlighted).

Model Input		Calibration				Testing			
		RMSE	MAE	d_r	R	RMSE	MAE	d_r	R
ANN									
1	Rainfall	50.64	31.12	0.57	0.41	49.91	30.66	0.57	0.35
2	Min Temp/Min Temp/Nino	47.93	30.19	0.57	0.51	48.19	30.42	0.57	0.41
3	Max Temp/Min Temp/SOI	47.46	29.08	0.6	0.53	48.46	28.57	0.6	0.45
4	Max Temp/Min Temp	48.39	29.87	0.59	0.49	**46.66**	28.65	0.6	0.46
5	Min Temp	47.82	29.79	0.59	0.5	**47.15**	29.82	0.58	0.46
6	Max Temp	48.33	29.98	0.59	0.51	49.39	31.96	0.55	0.44
HWNN									
1	Rainfall	30.39	21	0.71	0.83	**32.16**	21.8	0.71	0.79
2	Min Temp/Min Temp/Nino	47.77	29.3	0.6	0.5	48.14	30.2	0.58	0.43
3	Max Temp/Min Temp/SOI	43.42	28.6	0.61	0.61	45.48	31.3	0.56	0.57
4	Max Temp/Min Temp	41.8	24.93	0.66	0.67	**42.38**	26.1	0.63	0.64
5	Min Temp	48.51	30.6	0.58	0.48	47.93	31.2	0.57	0.48
6	Max Temp	42.25	25.8	0.61	0.64	43.72	26	0.64	0.58

For further investigation, the plot of observed rainfall and forecasted rainfall in different lead times are depicted in figure 5 and figure 6 for the testing period in ANN modeling based on best input combinations. It should be noted that although the best model in HWNN is the first model, for predicting the rainfall using temperature anomaly in this study, we consider the best model which is composed of at least one of the temperature parameters (minimum or maximum temperature). From this figure, it is seen that the HWNN is able to predict the rainfall exact than the ANN and particularly can predict the rainfall with good precision a few months in advance. It is also seen that the extreme (peak) rainfall is predicted better by HWNN. This is due to the hidden characteristics of wavelet transform in extracting the beneficial information from the main signal which cannot be seen easily in the original signal before this investigation.

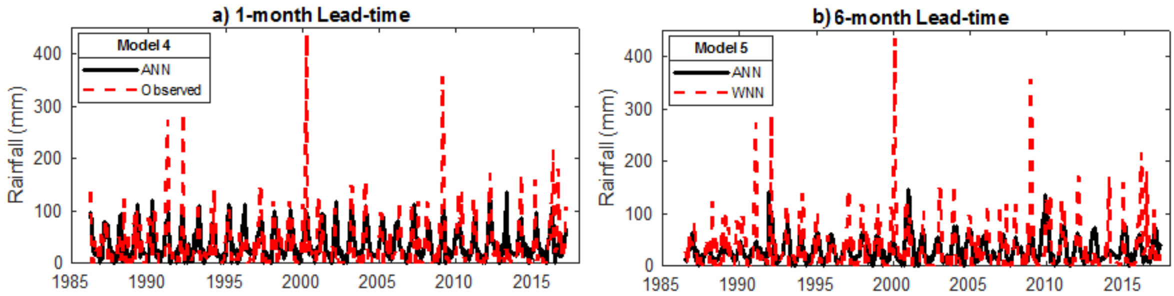

Figure 5. Observed and forecasted rainfall using ANN modeling for one and six months lead times.

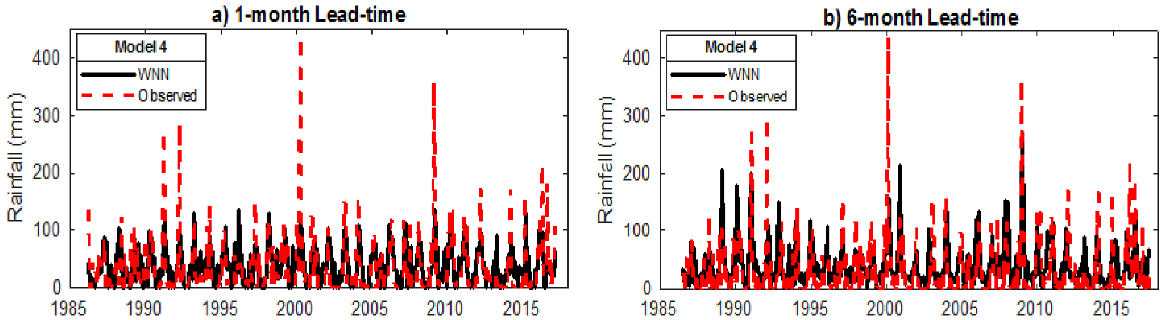

Figure 6. Observed and forecasted rainfall using HWNN modeling for one and six months lead times.

The scatter plot between forecasted and observed rainfall for prediction the rainfall 1 month ahead is shown in figure 7.

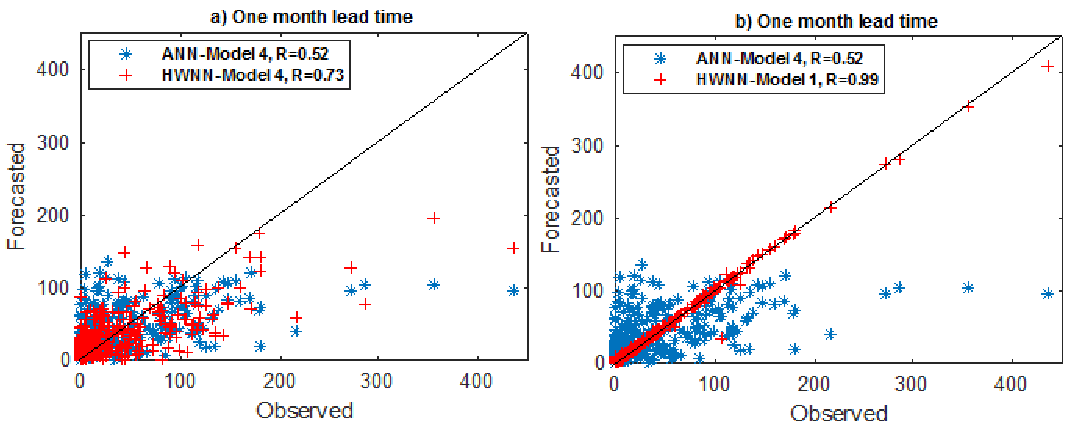

Figure 7. Scatter plot between observed and forecasted rainfall through the testing period for one month lead time.

The models 1 and 4 in HWNN modeling are depicted separately in figure 7a and figure 7b for better understanding the differences between these models. It is observed that the results from the HWNN model are perfectly close to the 45 degrees line with the correlation coefficients of 0.99, 0.72 for model 1 and model 4. However, the best correlation obtained by ANN modeling for this lead time is 0.52. Also, the scatter plot of modeled and real rainfall for forecasting the rainfall 3 months in advance is depicted in figure 8. While the correlation coefficient for HWNN is 0.65 for the fourth model, it is 0.46 for the fifth model in ANN. Besides, as one can see in figure 8b, a better correlation can be acquired using HWNN through model 1.

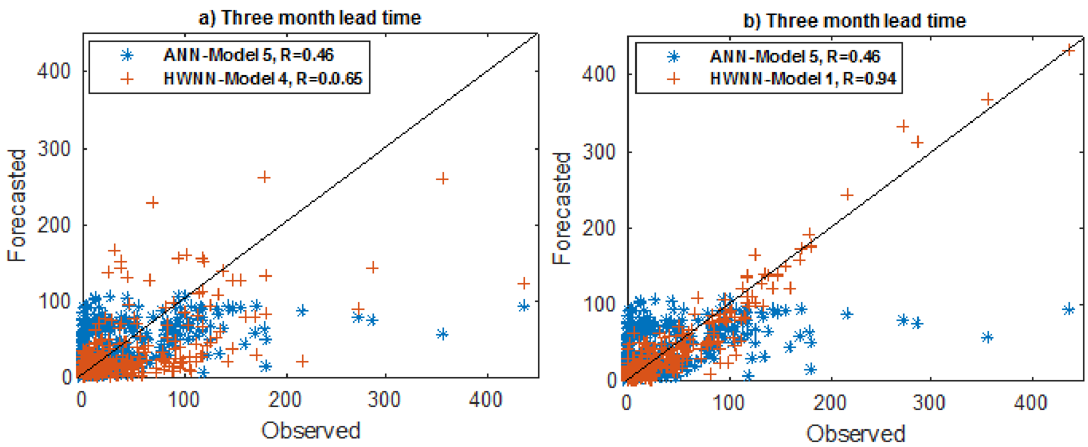

Figure 8. Scatter plot between observed and forecasted rainfall through the testing period for three months lead time.

6. Conclusions

In this study, a hybrid neural network for forecasting rainfall 1, 3 and 6 months in advance was presented. The different six models comprised of rainfall, Nino index, SOI, maximum temperature and minimum temperature as the input of the network were defined. The model was calibrated with the data of 77 years and was tested with the remaining 32 years. The developed model was applied to the central interior of Queensland, Australia. The results confirm that HWNN model outperforms the ANN model.

The skilfulness of the model was evaluated by RMSE, MAE, refined index of agreement and correlation coefficient. It was found that the models consist of minimum temperature and maximum temperature have more influence on predicting future rainfall than the climate indices. It was also found that the wavelet transform can enhance the results and is a superior method for estimating the extreme rainfall in various lead-times. Moreover, the ability of this approach is improved more when the input and output of the network are chosen from the same type. The HWNN can estimate the accurate future rainfall because the wavelet transform is able to capture the hidden valuable information of the time series by decomposing it into approximation and detail components. This method is beneficial for optimizing the calculations and is a useful tool for enhancing the precision of the results.

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