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FORECASTING LONG TERM PRECIPITATION USING CUCKOO SEARCH OPTIMIZATION NEURAL NETWORK MODELS

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Abstract

With anticipation of global warming and climate change, quantitative prediction of future precipitation trend is more important than ever. Global circulation models (GCMs) are widely used as the base for simulating climate change. However, due to their coarse resolution, researchers have been using various downscaling techniques to produce finer model for regional use. Recent advancements in metaheuristic algorithms have provided an alternative approach in downscaling. This paper introduces the application of a novel optimization algorithm, named as Cuckoo Search Optimization (CSO), to train Feedforward and Recurrent neural network to forecast long term precipitation. As benchmark, CSO was compared with Scaled Conjugate Gradient (SCG) and Levenberg-Marquardt (LM) methods. The models were evaluated through validation with historical precipitation; as well as their performance in Pearson correlation (r), root mean square error (RMSE), mean absolute error (MAE), and mean bias (MB). Results showed that CSO is capable of forecasting precipitation up to 90%~100% confidence level with an overall lower mean absolute error, root mean square error and mean bias; outperforming SCG and LM. Future precipitation forecasts revealed that the city will experience an increase of mean annual precipitation by 6~7% over Year 2071-2100. A regional climate model (RCM) with finer resolution was also investigated. Preliminary results revealed an underperformance of the regional climate model due to weaker correlation link between the predictors and historical precipitation.

Key words: climate change, cuckoo search optimization, neural network, precipitation forecasting, statistical downscaling

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1. Introduction

Since the pre-industrial age, global land and sea surface temperature has been changing. Observations of land-ocean temperature anomaly as well as land precipitation change over the years 1901 to 2010 (IPCC, 2013) have shown that these two major climate variables are in an unprecedented uptrend since the beginning of the 19th century. The main factor of such changes to the climate system is the increase of carbon dioxide (CO_2) concentration in Earth's atmosphere. According to NOAA (2014), recent global CO_2 concentration has reach 400ppm. (1ppm is equivalent to 7.81 gigatonnes of CO_2). A safe level of ppm is 350 (Hansen et al., 2008; Rockström et al., 2009). Based on observations over year 2004 to 2013, CO_2 concentration has been increasing at 2.0 ±0.1 ppm/year. This causes the atmosphere to become more proficient in trapping heat energy, therefore inducing further warming effect on Earth (Adger et al., 2003), resulting in a positive feedback loop.

With the global climate becoming exponentially warmer in recent years, local scale precipitation has been abrupt and holistic. This is because a warmer atmosphere is able to store more moisture and for a much longer duration of time. Hence precipitation of larger volume and drought of longer duration (prolonged wet and dry spells) are expected to become more frequent in the warming future. For example, the double occurrences of 100

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ARI (average recurrence interval) flood tragedy that hit Malaysia unexpectedly in December 2006 and January 2007. A 100 ARI flood was previously estimated to occur only once in every 100 years. An event of this magnitude occurring twice is a clear sign of the impact of climate change on regional and local precipitation pattern. Though the change in climate can no longer be avoided, it can and must be managed to ensure sustainability of the ecosystem and well-being of the community. A viable solution is to forecast future precipitation trend by taking into account the effect of climate change. Other solutions include elimination or minimization of fossil fuel consumption, commercialization of renewable energy, and commitment to reforestation, carbon capture, and carbon sequestration actions. The importance of having a quantitative forecast of long term precipitation is that it can serve as valuable insight for future water resource planning, stormwater management, early flood warning system, agricultural and industrial development, as well as tourism.

Unfortunately, precipitation is one of the most difficult elements of the hydrologic cycle to forecast (French et al., 1992) due to its tremendous range of variability over spatial and temporal dimension. One of the prominent methods to predict future climatology is through Global Circulation Models (GCMs). GCMs are global scale numerical models that characterize the physical processes in the atmosphere, ocean and land surface (IPCC, 2011). Although GCMs have been acknowledged as the best representing model of atmospheric change in response to increased greenhouse gases, they are not suitable for regional climate modelling due to their coarse resolution as a result of large spatial coverage. Resolution of GCMs is in the order of 100km (Wilks, 2012) which are larger than local atmospheric variables (typically 10 km or less). Therefore downscaling technique has been used extensively in climate studies to refine the resolution of GCMs.

Artificial Neural networks (ANNs) or neural networks (NNs) have been researched on as an alternative to downscale GCMs. Also known as a ‘black box’, NNs are capable of distinguishing inherent patterns from a large amount of data (Hall et al., 1999). French et al. (1992) had developed a NN model to forecast one hour ahead of rainfall intensity fields; Hewitson and Robert (1992) and Cavazos (1999) had implemented NN in downscaling daily and monthly precipitation in Mexico; Xiao and Chandrasekar (1997) had developed NN based algorithm to estimate rainfall from radar observation; Kuligowski and Barros (1998) experimented on using NN to forecast short term precipitation; Coulibaly and Dibike (2005 and 2006) applied temporal concept onto NN to downscale climate extremes; Hong et al. (2004) used NN as a system to classify clouds from remotely sensed imagery to predict precipitation; Ramírez et al., (2005) applied NN to forecast rainfall in São Paulo region; and Karamouz et al., (2009) had predicted long lead rainfall through NN. Moreover, NNs are proven by Hornik (1989), Musavi et al., (1994), Huang (1996) and Kak (1998) for their generalization and learning ability, even with incomplete data input.

The objective of this paper is to implement a novel training method, named as Cuckoo Search Optimisation (CSO) into Feedforward NN and Recurrent NN to downscale GCM outputs; as well as evaluating their performance against widely used Scaled Conjugate Gradient (SCG) and Levenberg-Marquardt (LM) method. CSO was chosen as it has been successful in solving structural optimization problems (Gandomi et al., 2011; Yang and Deb, 2010); as well as forecasting flood events (Chaowanawatee and Heednacram, 2012). Unfortunately, thus far there has been no research on implementing CSO into NN to forecast long term precipitation. As such, the main contribution of this paper is the implementation of CSO into NN models and their application in forecasting long term future precipitation.

The paper is structured in five sections. Section 1 introduces the threat of climate change, and discusses the use of NN as a highly accurate forecasting tool for future climate. Section 2 will disclose the location and the data used in for this study, as well as research methodology. The cuckoo search algorithm as well as time lagged concept will be explained here. Performance indicators used to evaluate the accuracy of the models are also included in this section. Section 3 documents the methodology and workflow of the study. Section 4 compiles the results and discussions from the study. The conclusions of the study can be found in Section 5, along with recommendations for future research.

2. Location of study and data

2.1. Location of study

The study area selected is Kuching City, located on $1^0$33’N $110^0$20’E. Like any other cities in Malaysia, Kuching is warm and humid all year round. The annual precipitation of the city is about 4000mm (based on observed annual rainfall data over Year 1958 to 2010). Weather in Kuching is influenced by two distinct monsoons, namely the Northeast and Southwest monsoon.

The former occurs from November to March; while the latter starts in May and end in September. April and October are known as the inter-monsoon period where the transition between the two monsoons takes place. Based on historical records, the monthly mean precipitation during Northeast monsoon is 15.57mm (wetter season); while Southwest monsoon carries 7.11mm (drier season).

2.2. Data

NN models require input data for training/calibration to facilitate the model to distinguish inherent patterns amongst the input data and learn its characteristics. For this study, input data are monthly averages of GCM climatological variables (predictors), and observed local monthly average precipitation data (predictand). The predictand data was obtained from Kuching Airport Rainfall Station. On the other hand, predictors were obtained from IPCC website which contains various GCM models generated by different meteorological institutes around the world. The GCM predictor data are only available in monthly means, and were downloaded from http://www.ipcc-data.org/. For this study, scenario A2 was selected as the predicting scenario for future precipitation.

The scenario tells the story of a future with increasing CO_2 emission, high population growth, less concern for rapid economic expansion, but slow technological advancement (CICS, 2006; IPCC, 2011). ECHAM5 model from Max-Planck-Institut for Meteorology (MPI-M), Germany were selected to be used in this study as data from other models were incomplete and of coarser resolution. ECHAM5 predictors have a resolution of 1.9^0 x 1.9^0, or 210 x 210km (IPCC, 2011). Regional climate models (RCMs) variables from HadGEM3-AO with resolution of 50km were used to compare with variables from GCM outputs. The data can be downloaded from http://cordex-ea.climate.go.kr/main/mainPage.do.

3. Methodology

3.1. Brief description on neural networks

NNs were first inspired by studies of the neural system of biological organism. They are the mathematical bio-mimicries of how the nervous system transmits information (input) to the brain for processing, in which the resulting response (output) is transmitted back to the relevant nerves for appropriate reactions. Two distinct NN types used in this study are: Feedforward neural network (FNN) and Recurrent neural network (RNN). FNN (illustrated in Fig. 1) is a simple, direct input to hidden layer and to output layer structure; whilst RNN (illustrated in Fig. 2) introduces a loop inside the NN model, which can be considered as another weight within the hidden layer. Input, hidden, and output layers are connected by transfer functions.

For this study, the hyperbolic tangent sigmoid equation is used as the transfer function, f_1, to connect the input layer to hidden layer; while pure linear equation is used as transfer function, f_2, to connect the hidden layer to output layer. Weights, W_i, and biases, B_i, are generated randomly during the initial iteration. NN models are trained iteratively to learn the connections or patterns between the inputs based on the training algorithm during each pass of iteration. After the initial iteration, the global error is calculated and propagated back to the network, in which the weights and biases are adjusted accordingly with the aim of reducing the overall error between the desired outputs and simulated data (Crane and Hewitson, 1998).

3.2. Cuckoo search optimization algorithm

Cuckoo search algorithm (CSA) is a mathematical interpretation of the reproductive behaviour of 'Cuckoo' bird species.

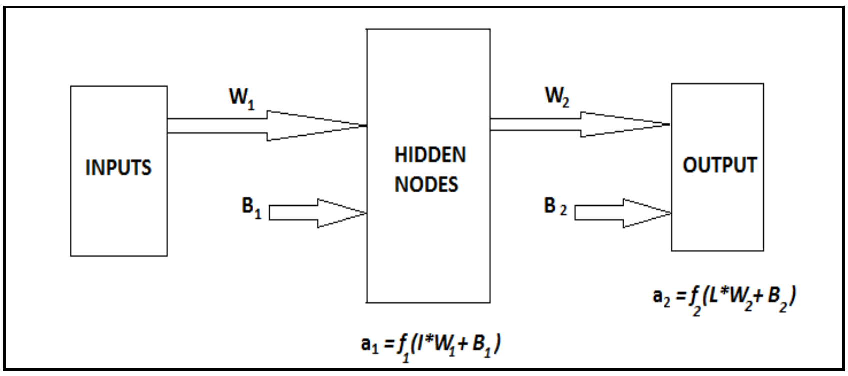

Fig. 1. Structure of FNN

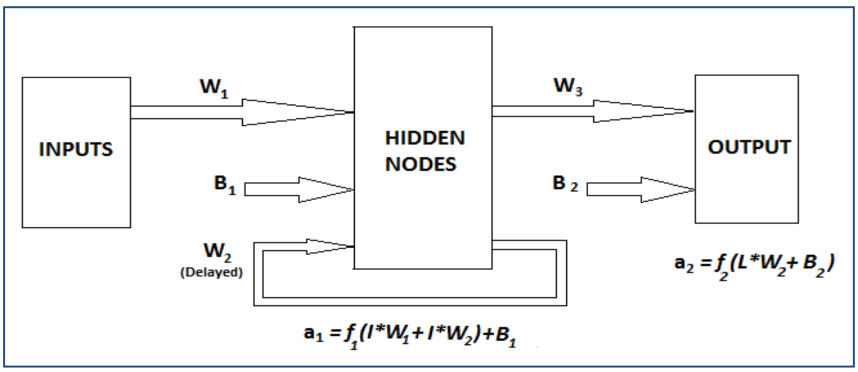

Fig. 1. Structure of RNN

Studies revealed that Cuckoos demonstrate a brood parasitic conduct in their breeding behaviour (Fossøy et. al., 2012; Rajabioun, 2011), in which Cuckoos (the parasite) will lay their eggs into the nests of other bird species (the host). In order to increase the survivability of their eggs, the Cuckoos' eggs are modified to visually resemble the eggs of its hosts. The algorithm uses Lévy flight to define the search pattern of Cuckoos. Its advantage over most metaheuristic algorithm is that it is controlled by only two variables - the number of nests and discovery rate of the eggs by the host. CSA is available online at: http://www.mathworks.com/matlabcentral/fileexchange/29809-cuckoo-search-csalgorithm.

The pseudo code for CSA is as follows (Yang and Deb, 2009):

- objective function, $f(x)$, $x = (x_1,\ldots,x_d)^T$
- generate initial population of n host nests, x_i, $(i=1,2,\ldots,n)$
- while (t < *Max Generation*) or (stop criterion)
- get a cuckoo randomly by Lévy flights and evaluate its fitness, F_i;
- choose a nest among n (say, j) randomly
- if ($F_i > F_j$),
- replace j by the new solution;
- End
- a fraction (p_a) of worse nests is abandoned and new ones are built;
- keep best solutions;
- rank and choose best solution;
- End while

The original CSA fixed two variables: fraction of worst nest to be abandoned, p_a and the steps-size of Lévy flights, α as a constant. Valian et al., (2011) stated the drawback of fixing both variables: a small p_a with large α will lead to poor performance, therefore requiring more iteration runs; while a large p_a but small α will increase the speed of convergence but might fail to find the best solution. Hence, Valian et al., (2011) proposed Improved Cuckoo Search (ICS) algorithm where p_a and α are imposed as variables. After each training iteration, p_a and α will decrease according to Eqs.1-3. In their paper, Valian et al., (2011) have successfully proved that ICS performs better than CSA in terms of accuracy, mean and SD criteria. For this study, trial and error method was used by to determine the optimal value for both variables. It was found that during the initial iteration, the values of p_a and α should be large enough in order to increase the generalization or diversification of the solution vectors.

$$P_a(gn) = P_{a_{max}} - \frac{gn}{NI}\left(P_{a_{max}} - P_{a_{min}}\right) \tag{1}$$

$$\alpha(gn) = \alpha_{max}\exp(c.\,gn) \tag{2}$$

$$c = \frac{1}{NI}Ln\left(\frac{\alpha_{min}}{\alpha_{max}}\right) \tag{3}$$

Time lagged neural network (TLNN) uses sliding time window method to produce supervised training examples (Donate and Cortez, 2011, and Kote and Jothiprakash, 2008). It is introduced into NNs because simply training NN using designated data from a constrained time interval will cause the network to lose its time dimensioning ability (Dibike and Coulibaly, 2006). Saharia and Bhattacharjya (2012) had implemented time lagged data feed into NN models to allow the network to learn temporal patterns of local precipitation trend through past data.

In this study, the predictand period, t, starts from Year 1961 to 1990, totalling 30 years, was used as the input. The input sequence is shown in Eq. 4, where "*obs(t)*" denotes the current predictand data from Year 1961 to Year 1990; while "*obs(t-1)*" denotes the predictand data from Year 1960 to 1989, and henceforth.

$$I = \{obs(t), obs(t-1), obs(t-2), \ldots, obs(t-4)\} \tag{4}$$

3.4. Workflow

Predictand and predictor data over Year 1961 to 1990 was selected for model calibration. According to World Meteorological Organization, this 30-year-period (Year1961-1990) is suitable for model calibration as it best describe the mean and variance of meteorological parameters that affects local weather. GCM predictors from scenario '20CM3' which were produced based on observed CO_2 emission from the 20^{th} century. Simulations for future climate change were conducted by feeding the trained network with GCM predictors from scenario A2, which are available from Year 2001 to 2100.

In line with the objective of this paper, the proposed CSO was implemented in Feedfoward NN (named CSOFNN) and in Recurrent NN (named CSORNN). Its results will be benchmarked with simulation results by SCG and LM optimisation methods. Trained models were compared with the observed monthly precipitation for two decades: Year 1991-2000 and Year 2001-2010, for the purpose of evaluating their performance. Both testing sets were not included as input during the training phase of the network. This is to ensure that the dataset used for validation are completely separated from the dataset used for training, hence removing credence doubt of generalization for the trained model (Elshorbagy et al., 2010).

3.5. Measuring the performance of models

The performance of the models will be evaluated through several accuracy indicators, which are: root mean squared error (RMSE), mean absolute error (MAE), mean bias (MB), and correlation coefficient (R). RMSE is the square root of the sum of each squared errors over N (total number of outputs). MAE is the summation of absolute error values divided by N (Willmott and Matsuura, 2005). MB shows the mean forecast error of forecast against observed values (Fekete et al., 2004; Ramirez, 2005). A positive value indicates overestimation and vice versa. The workflow of this study was as structured in Figure 3. The formula for each performance indicator and the ideal/optimal point are as follows (Elshorbagy et al., 2010):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(O_i - S_i)^2}{N}} \quad (5)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|O_i - S_i| \quad (6)$$

$$MB = \frac{1}{N}\sum_{i=1}^{N}(O_i - S_i) \quad (7)$$

$$R = \frac{\sum_{i=1}^{N}(O_i - \overline{O_i})(P_i - \overline{P_i})}{\sqrt{\sum_{i=1}^{N}(O_i - \overline{O_i})^2 \sum_{i=1}^{N}(P_i - \overline{P_i})^2}} \quad (8)$$

where: O_i = Observed values; P_i = Predicted values; $\overline{O_i}$ = mean of observed values; $\overline{P_i}$ = mean of predicted values.

4. Results and discussions

4.1. Correlation analysis of GCM predictors

Before training of NN was initiated, predictor data from Year 1961-2000 were normalized and examined for their relative correlation with observed precipitation data.

Only highly correlated predictors will be selected for training as inputting low correlating predictors can induce undesired noise into the network (Gorp et al., 1998). GCM predictors were tested for their correlation coefficient, r and p value in order to determine their relative significance with respect to the observed precipitation data. A high 'r' value indicates that the predictor holds some degree of importance to the local climate. 'p' value indicates the coincidental probability of getting high 'r' value even if there is no correlation. For this study, any 'p' value higher than 0.05 is considered a false correlation.

Predictors with p value higher than 0.05 were discarded from the training process. A negative value correlation only indicates that there is anti-correlation or an inverse relationship between the predictor and predictand. The correlation analysis revealed that ECHAM5 predictors are better correlated to locally observed rainfall than HadGEM3-RA predictors.

The GCM predictors used for this paper were: hur200, hur850, ts, tas, ta200, ta500, and ta850. RCM predictors used are: va200, tas, and tasmax. Adding more predictors, in the case of RCM, reduces the accuracy of the trained NN model significantly.

Table 1 and Table 2 show the predictors available from ECHAM5 and HadGEM3-RA models along with their correlation analysis. For this study, RCM predictors were not included to the NN models based on: i) the correlation analysis showed that HadGEM3-RA predictors do not correlate well with historical precipitation compared to ECHAM5 predictors; ii) initial runs of NN model trained with HadGEM3-RA did not perform up to par with NN model trained with ECHAM5 predictors.

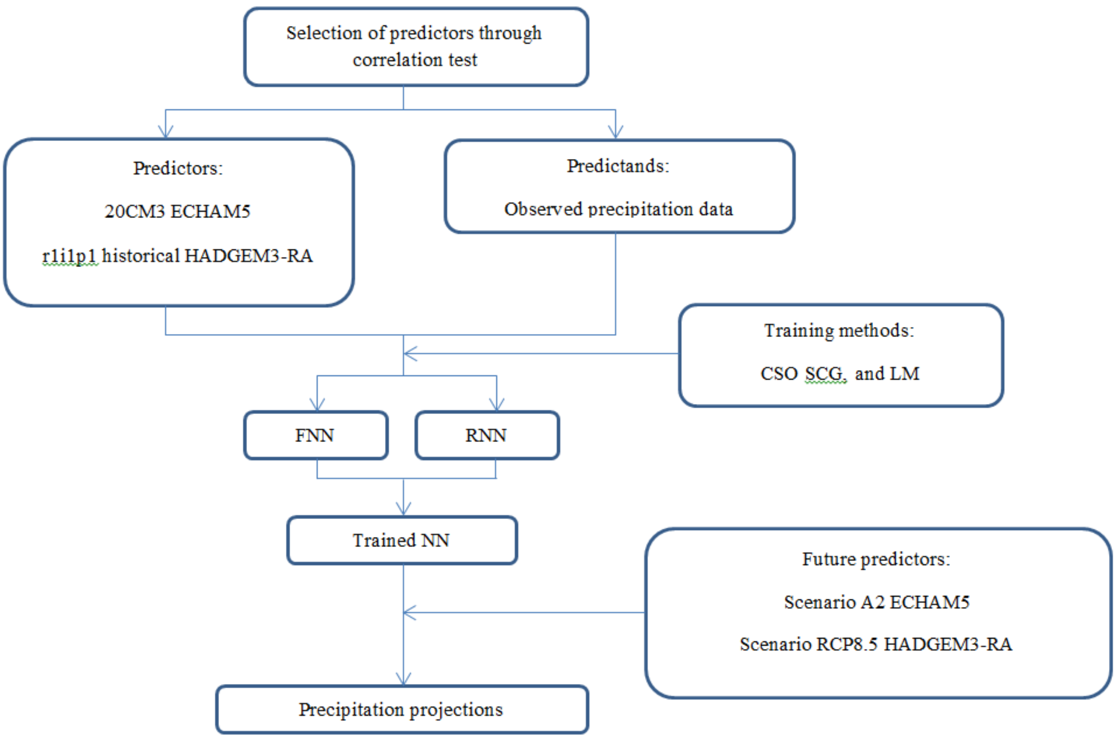

Fig. 2. Workflow structure for this research

4.2. Model validation and performance analysis of NN models

It is essential for calibrated NN models to be validated with two or more independent datasets (Elshorbagy et al., 2010; Trigo and Palutikor, 1999). The NN models for this study were named as CSOFNN, CSORNN, SCGFNN, SCGRNN, LMFNN, and LMRNN. All NN models were validated with observed precipitation data from two decades: Year 1990-2000 (validation test 1); and Year 2001-2010 (validation test 2). Additionally, the performance of each model was evaluated through four indicators – R, RMSE, MB, and MAPE. The model was trained for 1000 iterations with its hidden nodes set to 100 and learning rate at 0.9 as this configuration provides better results without overtraining the model.

Results from five trial runs were averaged and taken as the simulation results. For simplicity of comparison, the observed data are denoted as "OBS"; while "SIM" indicates simulated data. The line graph signifies the mean precipitation level during the base period. It was found that CSO models have the tendency of overestimating mean precipitation by approximately 20%, especially during the first half of the year. This overestimation fault was also present in the benchmarked models. It is capable of achieving Pearson's correlation, r of 1.0~0.9; MAE of 0.1~0.5; RMSE of 0.06~2.18; and MB of -0.4~0.66. This can be attributed to the ability of CSO to conduct global and local search to find optimal results. This advantage which does not exist in the benchmarked models enables it to avoid being trapped in a local minima/maxima point, where NN might falsely identify it as optimal point.

Fig. 4 shows the results from validation test 1 and test 2. Fig. 5 shows the performance for CSO models and its benchmarks, SCG and LM models in which CSO showed better overall performances.

4.3. Simulated future precipitation scenarios by CSOFNN and CSORNN

Future precipitation scenarios simulated by CSOFNN are presented in this section. Fig. 6 shows the future precipitation forecasts for three decadal periods, namely from Year 2011-2040; Year 2041-2070; and Year 2071-2100. The monthly percentage increase/decrease relative to the base period (Year1961-1990) is shown to provide a clearer perspective of future precipitation change.

It should be noted that both CSOFNN and CSORNN simulations showed a higher mean precipitation for March and July. Both models seem to project higher precipitation trend when compared to the base period. In particular, the Southeast monsoon (which encompasses May, June, July, August and September), which is traditionally a drier season, was predicted to receive higher precipitation volume.

5. Conclusions and recommendations

This research was conducted on the intention of providing an alternate forecasting method and to explore higher accuracy methods in forecasting long term future precipitation in Malaysia.

Table 1. ECHAM5 GCM model predictors and their correlation, r and p value

Predictor	r	p	*Predictor*	r	p	*Predictor*	r	P
pr	-0.151	0.001	***uas***	0.024	0.593	***ua500***	0.001	0.68
hur850	-0.544	0	***vas***	-0.275	0	***ua200***	0.075	0.1
hur500	-0.114	0.013	***ta850***	0.614	0	***psl***	0.067	0.143
hur200	-0.544	0	***ta500***	0.583	0	***va850***	-0.350	0
ts	0.624	0	***ta200***	0.545	0	***va500***	0.134	0.03
tas	0.624	0	***ua850***	0.171	0	***va200***	0.077	0.09

Table 2. HadGEM3-RA RCM model predictors and their correlation, r and p value

Predictor	r	p	*Predictor*	r	p	*Predictor*	r	P
tas	-0.473	0	***rsds***	-0.396	0	***ta200***	0.052	0.224
tasmax	-0.447	0	***rsus***	0.395	0.071	***vas***	-0.425	0
tasmin	-0.360	0	***rsut***	0.402	0	***mrro***	0.246	0
pr	0.377	0	***ua850***	-0.078	0	***mrros***	0.241	0
psl	-0.071	0.1	***ua500***	-0.225	0	***hfls***	-0.318	0
huss	0.008	0.86	***ua200***	0.240	0	***hfss***	-0.223	0
clt	0.265	0	***uas***	0.185	0	***sfcWind***	-0.217	0
rlus	-0.443	0	***va500***	0.292	0	***sfcWindmax***	-0.210	0
rlut	-0.232	0	***va200***	0.525	0			
rsdt	-0.232	0	***ta500***	0.165	0			

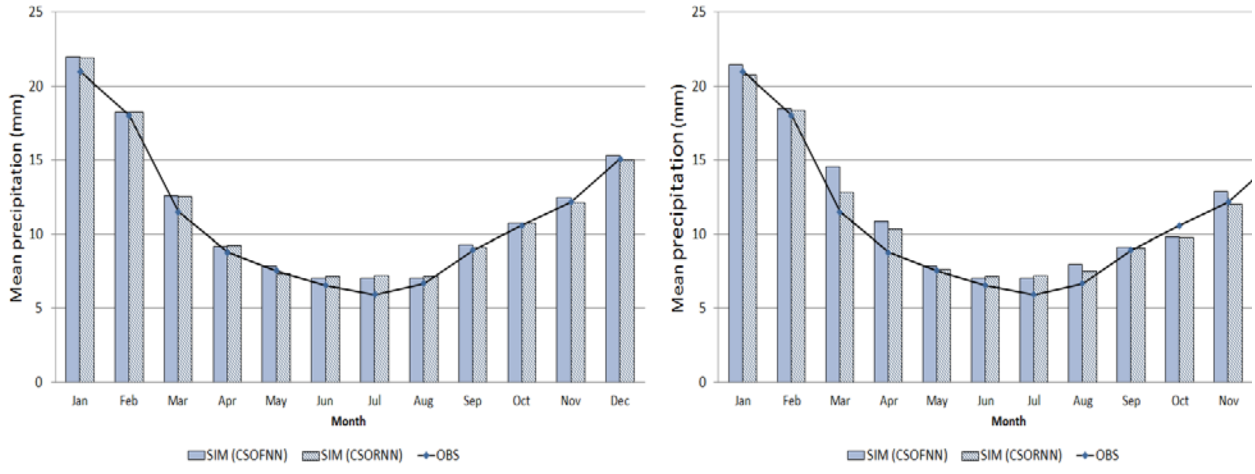

Fig. 3. Validation test 1 and 2 results for CSOFNN and CSORNN for two decadal period: Year1991-2000 (left); and Year2001-2010 (right)

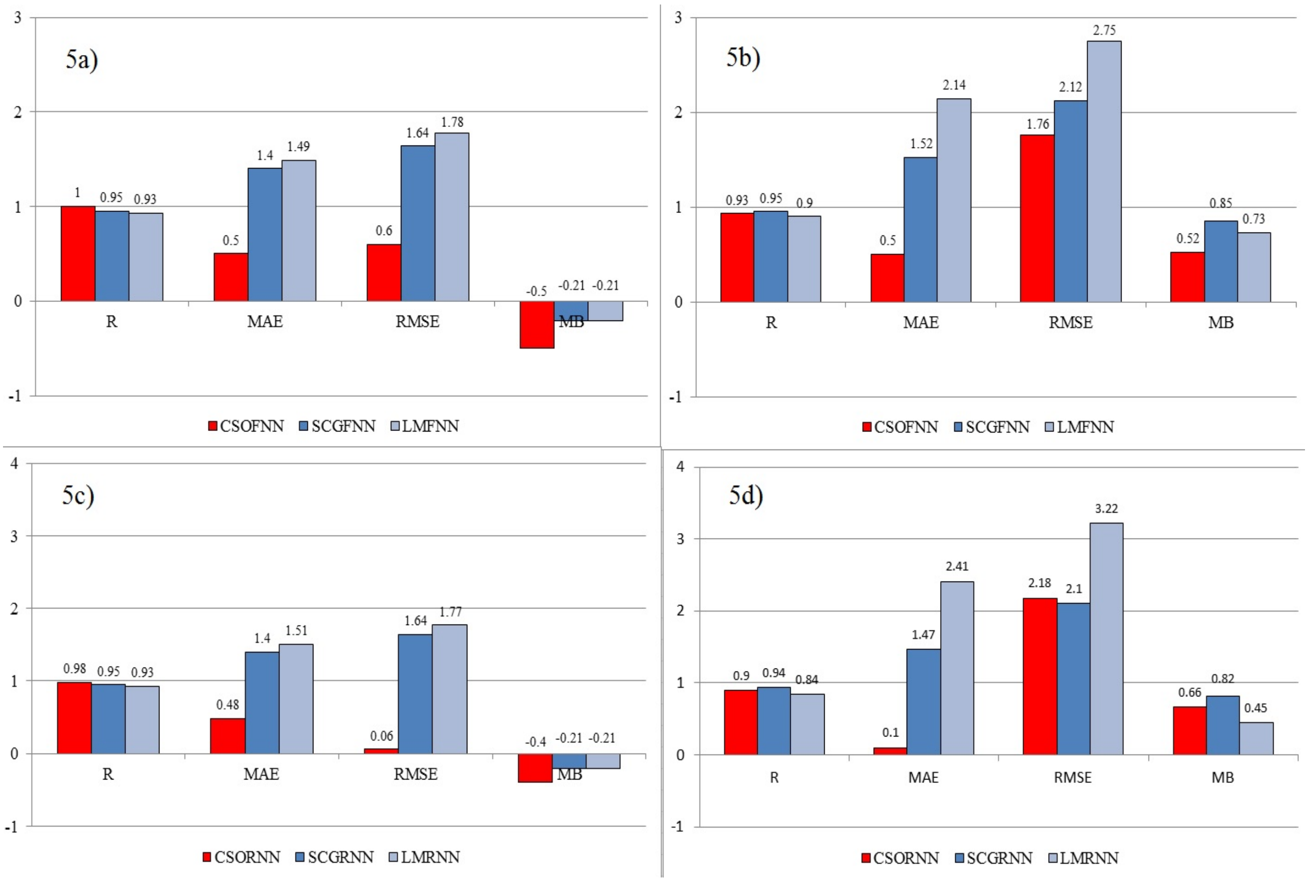

Fig. 4. Performance of CSO, SCG and LM optimization methods over Year 1991-2000 for a) FNN model, c) RNN model; as well as over Year 2001-2010 for b) FNN model, and d) RNN model

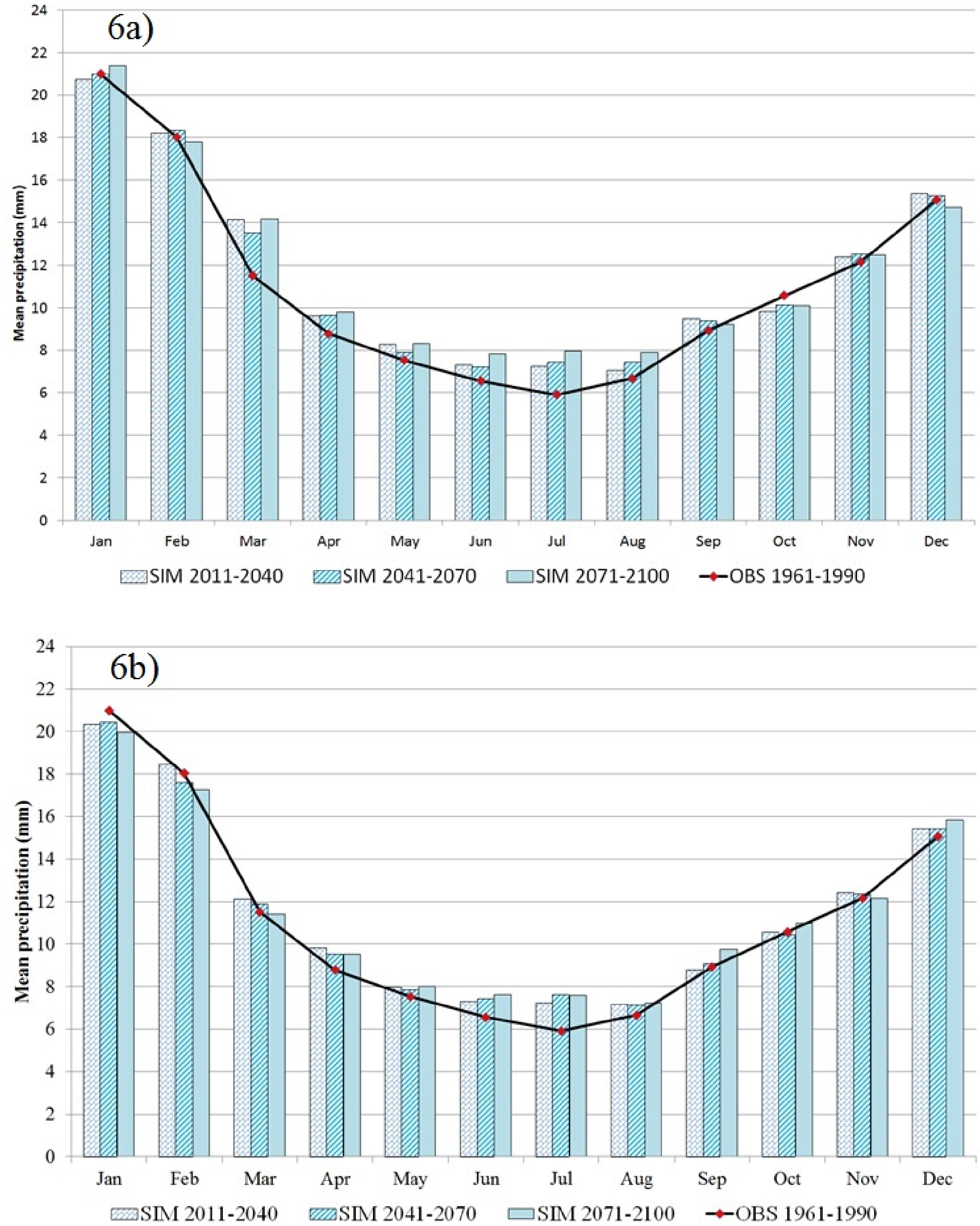

Fig. 5. Forecasts of long term future precipitation using ECHAM5 predictors by 6a) CSOFNN; and 6b) CSORNN for Year2011-2040, Year2041-2070, and Year2071-2100

The paper implemented cuckoo search algorithm into NN as a training function, named CSO, to downscale GCM outputs to climate parameters to local scale. CSO algorithm was trained in FNN and RNN. As benchmark, CSO was compared with conventional NN training method – SCG and LM. Time-lagged concept was introduced into the NN models through inputting antecedent data, show NN performance trained with lagged and no lag data hence improving the accuracy of forecasts. Simulated results were validated with historical mean monthly precipitation data for two decadal periods: Year 1991-2000 and Year 2001-2010. RCM predictors with finer resolution (50km) were also selected for NN training. Preliminary results showed NN model trained using RCM predictors did not performed better than those trained with GCM predictors. This can be attributed to a weaker link as revealed through correlation analysis. The comparison between CSO, SCG and LM optimization methods proved that CSO has better performance. The simulated forecasts by CSOFNN and CSORNN indicate slightly higher mean precipitation when compared to the base period. The former predicted an average increase of 5%~7%; while the latter predicted 3%~4% increase in mean precipitation over the century. The forecasts also provide an insight to a wetter Southwest monsoon season, especially during June, July and August. As recommendation for future research, other metaheuristic optimization algorithms can be implemented in ANN to forecast precipitation. GCM predictors from other meteorology model can be used by ANN to forecast future precipitation in order to further confirm the general trend of changes. Other scenarios, such as scenario A1, B1, and B2 can be used to simulate future precipitation. This will help in establishing a general range of precipitation variance in the future.

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