

Bat optimisation neural networks for rainfall forecasting: case study for Kuching city

King Kuok Kuok, Sze Miang Kueh and Po Chan Chiu

ABSTRACT

This paper presents a novel metaheuristic artificial neural network (ANN) model, named as Bat optimisation neural network (BatNN), for spatial downscaling of long-term precipitation. This novel BatNN was developed due to the inefficiency of traditional ANNs in spatial downscaling of large-scale outputs from climate models. Input data are predictors from three climate models including HadCM3, ECHAM5 and HadGEM3-RA combined with observed precipitation collected from Kuching airport rainfall station. The output is the forecasted precipitation. Data from 1961 to 1990 were used for model training, while data from 1991 to 2010 were used for validation. Square root of correlation of determination (r), root mean square error (RMSE), mean absolute error (MAE) and Nash–Sutcliffe coefficient (E) are used to evaluate the models' performance. Results showed that through global and local searches, BatNN is able to avoid local optima trappings. The average r , RMSE, MAE and E for three climate models were yielded to 0.96, 1.69, 1.40 and 0.84, respectively. This reveals that BatNN is able to optimise and forecast long-term precipitation accurately.

Key words | Bat optimisation neural network, climate model, precipitation, predictands, predictor

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INTRODUCTION

Climate change has proven to have significant impacts on ecosystems, economies and communities on the planet. For Malaysia, the major concern related to climate change is the response of precipitation under an increasingly warming climate. Presently, the most acknowledged method to estimate future climate change is through global circulation models (GCMs). However, it is impractical to establish any significant implication from GCM projections for hydrological risk assessments (Willems & Vrac 2011) since the resolution of GCMs range from 100 km to 300 km. It is too coarse to be directly applied onto a local study site of below 5 km. As a result, spatial downscaling techniques were adapted to refine the resolution of GCMs.

The two common statistical downscaling approaches are statistical downscaling model (SDSM) and conventional artificial neural networks (ANNs). SDSM is mainly incorporated with climate data generated by Hadley Centre Coupled Model version 3 (HadCM3) and National Centres for

Environmental Prediction (NCEP) reanalysis data (Wilby *et al.* 2002). As a result, SDSM lacks the flexibility to be incorporated with data outputs from other GCMs (Wilby & Dawson 2013). Besides, Nguyen *et al.* (2007) also stated that SDSM is expected to underestimate actual precipitation, especially extreme events. Meanwhile, Wilby *et al.* (2002) and Karamouz *et al.* (2009) reported that ANNs grounded with backpropagation (BP), scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM) algorithms underperform more than SDSM. These gradient-based algorithms have been reported to be susceptible to local optima trapping (Gupta & Sexton 1999; Deb 2001; Risi *et al.* 2009).

One possible way to overcome these limitations is by using a metaheuristic algorithm that is nature-inspired (Glover 1986). The main advantage of metaheuristic algorithms is their ability to avoid local optima by conducting a global search (Yang 2010) and the ability to solve a variety of problems (Blum & Roli 2003; Silberholz & Golden 2010;

Gandomi *et al.* 2013). The metaheuristic technique proposed in this study is Bat algorithm, which was introduced by Yang (2010). The superiority of Bat algorithm against other conventional optimisation algorithms has been demonstrated in terms of solving nonlinear problems and finding globally optimal solutions (Yang 2010, 2011; Yang & Gandomi 2012; Yang *et al.* 2012; Bozorg-Haddad *et al.* 2014; Omar & Saida 2014; Reddy & Subramanyam 2014). Therefore, this paper attempts to integrate a newly developed Bat algorithm into ANN for spatial downscaling of precipitation, hereafter forming the Bat optimisation neural network (BatNN).

STUDY AREA

The study area is Kuching, the capital and the fourth largest city of Malaysia (refer to Figure 1). The city is situated at the southwest tip of the state of Sarawak on the island of Borneo and covers an area of 431 km² (166 mile²) with a population of about 705,546 (Sarawak Population 2016). Kuching enjoys sunshine throughout the year except for the monsoon season which runs from November to February. The average total annual precipitation in Kuching is

about 4,096 mm and the maximum daily precipitation can reach up to 485.4 mm based on collected precipitation data from 1958 to 2010.

With such high precipitation intensity, it is not uncommon for the urban city to be hit by major flash floods, especially during the northeast monsoon. Climatic studies have reported that it is likely that precipitation within the region will increase by 10% due to climate change (NC2 2010). Therefore, it is essential to develop a feasible tool to estimate Kuching's future precipitation change.

BAT OPTIMISATION (BAT) NEURAL NETWORKS

The Bat algorithm (BA) was originally developed by Yang (2010). The main idea behind the algorithm is the echolocation ability of bats for communication, navigation and predatory purposes. The rules in developing the algorithm are as follows:

1. Bats use echolocation to sense distance and have the ability to differentiate between prey and obstacles.
2. Bats fly with random velocity (v_i) at position (X_i). Their sonar has a fixed minimum frequency (f_{min}), with varying



Figure 1 | Locality map of Kuching and Kuching airport rainfall gauge station with latitude of 1.4847 and longitude of 110.3469 (Kuok *et al.* 2015).

wavelength (λ) and loudness (A) when searching for prey. Bats have the ability to adjust their sonar frequency and the rate of pulse emission (R) in relation to the proximity of their target. Normally, A will decrease as the bat gets nearer to a prey, while R increases to improve its accuracy.

3. Loudness of the sonar is assumed to vary from a large initial A , to a minimum but constant A_{min} .

In optimisation analogy, the positions or locations of bats are the candidate solutions. In the initial phase, the frequency (f), R and A of sound pulses emitted by the bats are defined. The movements of bats towards new solutions are generated by varying f , along with v_i and X_i of bats. The best solution is selected among candidate solutions and a local solution is generated around the selected best solution. Concurrently, a new solution is generated randomly. The fitness of the new solution is evaluated and it will be accepted if the solution accuracy is better than the previous one. For bats, the emitted frequency of their sound pulses is typically within the range of a few metres (Richardson 2008). In Bat algorithm, the frequency has been simplified to range between zero and one.

Bat algorithm has the ability to conduct local search and global search via random walk. The local search component is an enactment of elitism strategy where once a possible solution is found, the algorithm converges towards that point. Meanwhile, global search is the component which promotes further exploration beyond the convergent point. This particular component is essential to avoid local optima trappings.

In this study, Bat optimisation algorithm was integrated into neural network to form a novel Bat optimisation neural network. In this newly developed neural network, R has been modified to be low enough while A has been set to be high enough during the initial stage to fully exploit the search space. As more iteration passes, A gradually decreases while R increases in order to perform local search, where both parameters automatically update themselves as the bat gets nearer to the desired solution. This optimisation process can be simplified using Equations (1) and (2):

$$R = 1 - (0.9 \exp(-\alpha i_n)) \quad (1)$$

$$A = 0.9 \exp(-\alpha i_n) + 0.1 \quad (2)$$

where α = velocity factor and $i_n = n^{\text{th}}$ iteration ($n = 1, 2, 3, \dots$).

The optimisation sequence of BatNN can be summarised as follows:

1. The initial loudness ($A_{initial}$), pulse rate ($R_{initial}$) and pulse frequency ($f_{initial}$) are determined. Weights and biases are randomly assigned to a population of bats. These bats represent candidate solutions.
2. The fitness of the current population of bats is evaluated. The bat with the best fitness is determined and stored in the memory.
3. The bats are ranked according to their fitness. The bat with the lowest error is stored as 'globalbestbat'.
4. New bats are generated based on the current pulse frequency (f_i), velocity (v_i) and position of bats (X_i).
5. If a randomly generated number from the range of [0, 1] is larger than the current pulse rate (R_i), a random walk is performed around the current position of the bat. Otherwise, no change will be undertaken.
6. New bats are randomly generated via Lévy flight.
7. Step 2 is repeated to find the fitness of these new bats.
8. 'globalbestbat' is updated based on two criteria:
 - a. The fitness of new bats is greater than the current fitness of 'globalbestbat'.
 - b. A randomly generated number from the range of [0, 1] is larger than the current loudness, A_i .
9. If the two criteria are met, the new bat with best fitness becomes the new 'globalbestbat'. A_i and R_i are then updated based on Equations (1) and (2). If the criteria are not met, no change will be undertaken.
10. Steps 4 to 9 are repeated until the desired minimum error is found or maximum iteration reached.

METHODOLOGY

Climate data from three climate models have been used throughout the research, namely, HadCM3, ECHAM5 and HadGEM3-RA. HadCM3 stands for Hadley Centre Coupled Model version 3 developed by the Met Office Hadley Centre (MOHC), UK (Met Office 2014). ECHAM5 was developed

by the Max Planck Institute for Meteorology (MPIM), Germany in 2005. HadGEM3-RA is a regional climate model (RCM) based on Hadley Centre Global Environment Model version 3 (HadGEM3) developed by the MOHC, UK.

Spatial downscaling requires two types of data input, namely, predictand and predictors. For this research, the predictand data are the historical observation of daily precipitation in Kuching. The data were obtained from Kuching airport rainfall station. The predictand data were divided into two periods. The first period, from 1961 to 1990, was used for model training. The second period, from 1991 to 2010, was used for validation.

All the three climate models will be trained using BatNN. The selected input data are as follows:

- Predictand: observed monthly mean precipitation over 1961–1990.
- Predictors over 1961–1990:
 - HadCM3 SRES A2a: *r850*, *shum*, *r500*, *temp* and *mslp*.
 - ECHAM5 20C3M: *ts*, *tas*, *ta850*, *ta500*, *ta200*, *hur850* and *hur200*.
 - HadGEM3-RA 'historical r1i1p1': *va200*, *tas*, *tasmax*, *rlus*, *vas* and *rsut*.

Validation data set for the three climate models are:

- Predictand: observed monthly mean precipitation over 1991–2000.
- Predictors over 1991–2010:
 - HadCM3 SRES A2a: *r850*, *shum*, *r500*, *temp* and *mslp*.
 - ECHAM5 20C3M: *ts*, *tas*, *ta850*, *ta500*, *ta200*, *hur850* and *hur200*.
 - HadGEM3-RA 'historical r1i1p1': *va200*, *tas*, *tasmax*, *rlus*, *vas* and *rsut*.

The BatNN parameters investigated are bat population (b), maximum and minimum pulse frequency (f_{max} , f_{min}), velocity factor (α), hidden nodes (HN), iteration (IN) and learning rate (LR). f_{min} is effectively zero, hence only f_{max} requires parameter configuration. The optimal configuration for each parameter was determined through trial and error. Table 1 shows the parameters of BatNN to be investigated.

The model performance is evaluated using square root of correlation of determination (r), root mean square errors

Table 1 | Investigation on parameters of BatNN

Parameter	Trial configurations
B	5, 10, 15, 20, 25, 30, 35 and 40
f_{max}	1, 2, 4, 6, 8 and 10
α	1, 1×10^{-1} , 1×10^{-2} , 1×10^{-3} , 1×10^{-4} , 5×10^{-1} , 5×10^{-2} , 5×10^{-3} and 5×10^{-4}
HN	5, 10, 15, 20, 25, 50, 75, 100, 150, 200, 250 and 300
IN	100, 200, 400, 600, 800, 1,000, 1,500, 2,000, 2,500, 3,000, 3,500, 4,000, 4,500, 5,000, 5,500 and 6,000
LR	0.01, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1

(RMSE), mean absolute error (MAE) and Nash–Sutcliffe coefficient (E), as presented in Equations (3)–(6), respectively.

$$r = \frac{N \left(\sum_{i=1}^N O_i S_i \right) - \sum_{i=1}^N O_i \sum_{i=1}^N S_i}{\sqrt{\left[N \sum_{i=1}^N O_i^2 - \left(\sum_{i=1}^N O_i \right)^2 \right]} \sqrt{\left[N \sum_{i=1}^N S_i^2 - \left(\sum_{i=1}^N S_i \right)^2 \right]}} \quad [\text{Ideal} = 1 \text{ or } -1] \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (O_i - S_i)^2}{N}} \quad [\text{Ideal} = 0] \quad (4)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |O_i - S_i| \quad [\text{Ideal} = 0] \quad (5)$$

$$E = 1 - \frac{\sum_{i=1}^N (O_i - S_i)^2}{\sum_{i=1}^N (O_i - \bar{O}_i)^2} \quad [\text{Ideal} = 1] \quad (6)$$

where O_i = observed values, \bar{O}_i = mean of observed values, S_i = simulated or predicted values and N = sample size.

The optimal configuration of BatNN obtained from three different climate models will be utilised to forecast future precipitation.

RESULTS AND DISCUSSION

Accuracy of BatNN model was evaluated based on r , RMSE, MAE and E . Evaluation is conducted on the validation set. Validation set refers to prediction of both models compared

to observed precipitation over 1991–2000. The details of the validation results are presented below.

Optimal bat population (b)

Table 2 presents the validation results of BatNN trained with various b , simulated using selected predictors of HadCM3, ECHAM5 and HadGEM3-RA. All three climate models revealed that as b was increased from 5 to 20, BatNN showed increasing accuracy. The best accuracy was recorded when $b = 20$. Thereafter, increasing b resulted in slightly lower accuracy. Hence, the optimal b for BatNN was 20 for simulation based on HadCM3, ECHAM5 and HadGEM3-RA climate data. The optimum validation results of BatNN based on HadCM3 are $r = 0.96$, $RMSE = 1.74$, $MAE = 1.50$ and $E = 0.84$. Meanwhile, $r = 0.97$, $RMSE =$

1.38, $MAE = 1.19$ and $E = 0.88$ were obtained for optimum validation based on ECHAM5. Lastly, optimum validation results of BatNN based on HadGEM3-RA yielded $r = 0.96$, $RMSE = 1.95$, $MAE = 1.51$ and $E = 0.80$.

Optimal maximum pulse frequency (f_{max})

Subsequently, the optimal configuration of parameter f_{max} of BatNN was determined. Table 3 presents the validation results for BatNN trained on various f_{max} , simulated using selected predictors of HadCM3, ECHAM5 and HadGEM3-RA. It was found that increasing f_{max} from 1 to 4 produced increasingly better accuracy. When $f_{max} = 4$, BatNN showed the best results for all three climate models. Subsequent attempts to increase f_{max} from 6 to 10 resulted in reduced accuracy. Hence, the optimal f_{max} for

Table 2 | Accuracy of BatNN trained with various b , based on HadCM3, ECHAM5 and HadGEM3-RA

b	HadCM3				ECHAM5				HadGEM3-RA			
	r	RMSE	MAE	E	r	RMSE	MAE	E	r	RMSE	MAE	E
5	0.88	2.04	2.18	0.74	0.94	1.83	1.59	0.85	0.90	2.33	1.89	0.73
10	0.90	1.92	1.86	0.78	0.95	1.77	1.50	0.86	0.93	2.10	1.64	0.77
15	0.96	1.77	1.55	0.84	0.95	1.77	1.49	0.86	0.94	2.06	1.60	0.77
20	0.96	1.74	1.50	0.84	0.97	1.38	1.19	0.88	0.96	1.95	1.51	0.80
25	0.96	1.79	1.54	0.84	0.96	1.70	1.45	0.88	0.96	1.98	1.58	0.80
30	0.95	1.87	1.58	0.83	0.97	1.74	1.47	0.87	0.96	1.99	1.38	0.78
35	0.94	1.93	1.62	0.82	0.97	1.74	1.48	0.87	0.95	2.09	1.40	0.77
40	0.93	1.96	1.64	0.82	0.95	1.77	1.50	0.86	0.95	2.09	1.40	0.78

Note: Bold numbers are optimal b values obtained.

Table 3 | Accuracy of BatNN trained with various f_{max} , based on HadCM3, ECHAM5 and HadGEM3-RA

f_{max}	HadCM3				ECHAM5				HadGEM3-RA			
	r	RMSE	MAE	E	r	RMSE	MAE	E	r	RMSE	MAE	E
1	0.91	2.05	1.72	0.79	0.93	1.53	1.65	0.83	0.94	2.10	1.66	0.76
2	0.93	1.99	1.65	0.81	0.95	1.47	1.30	0.85	0.94	2.06	1.59	0.80
4	0.96	1.74	1.50	0.84	0.97	1.38	1.19	0.88	0.96	1.95	1.51	0.80
6	0.96	1.74	1.57	0.84	0.97	1.43	1.25	0.86	0.95	1.98	1.61	0.78
8	0.95	1.97	1.66	0.81	0.94	1.51	1.59	0.82	0.93	2.20	1.88	0.74
10	0.92	2.19	1.79	0.79	0.94	1.52	1.60	0.82	0.93	2.21	1.90	0.74

Note: Bold numbers are optimal f_{max} values obtained.

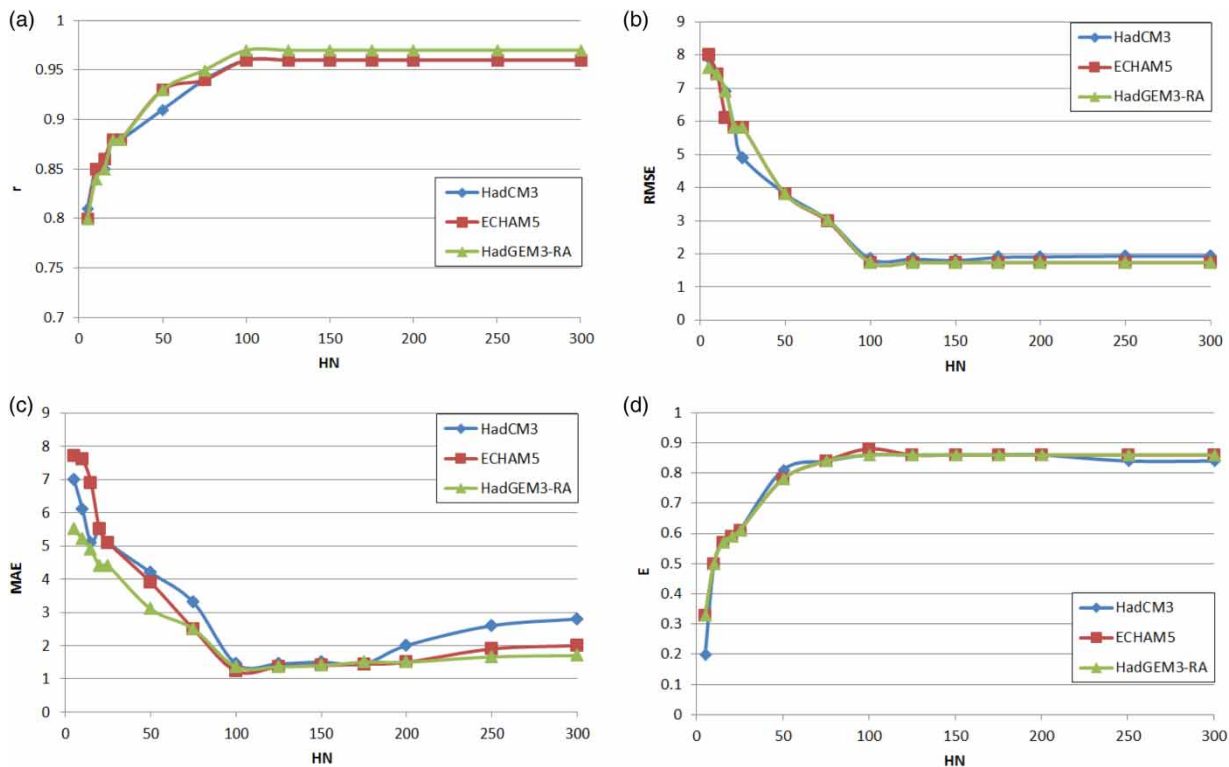
Table 4 | Comparison between BatNN trained with various α , based on HadCM3, ECHAM5 and HadGEM3-RA

α	HadCM3				ECHAM5				HadGEM3-RA			
	r	RMSE	MAE	E	r	RMSE	MAE	E	r	RMSE	MAE	E
1	0.86	2.40	2.20	0.78	0.89	2.00	1.79	0.80	0.84	2.64	1.91	0.70
1×10^{-1}	0.90	2.21	1.89	0.80	0.92	1.90	1.73	0.82	0.90	2.51	1.72	0.77
1×10^{-2}	0.94	1.98	1.60	0.83	0.94	1.83	1.62	0.85	0.94	2.14	1.61	0.79
1×10^{-3}	0.96	1.74	1.50	0.84	0.97	1.38	1.19	0.88	0.96	1.95	1.51	0.80
1×10^{-4}	0.96	1.94	1.59	0.83	0.96	1.47	1.23	0.86	0.96	2.07	1.59	0.80
5×10^{-1}	0.86	2.30	2.10	0.78	0.91	2.10	1.83	0.79	0.82	2.74	2.00	0.70
5×10^{-2}	0.94	2.02	1.73	0.82	0.92	1.89	1.64	0.83	0.86	2.55	1.65	0.76
5×10^{-3}	0.94	1.97	1.64	0.82	0.94	1.81	1.59	0.84	0.90	2.23	1.61	0.78
5×10^{-4}	0.95	1.95	1.60	0.84	0.95	1.59	1.33	0.86	0.95	2.00	1.59	0.80

Note: Bold numbers are optimal α values obtained.

BatNN was 4 for simulation based on HadCM3, with $r = 0.96$, RMSE = 1.74, MAE = 1.50 and E = 0.84. For BatNN simulated based on ECHAM5, the optimum results obtained are $r = 0.97$, RMSE = 1.38, MAE = 1.19 and E = 0.88. Subsequently, validation results yielded $r = 0.96$, RMSE = 1.95,

MAE = 1.51 and E = 0.80 as BatNN was simulated with HadGEM3-RA climate data. It is interesting to note that validation results by all three climate models agree that the optimal configuration for f_{max} parameter of BatNN was 4.

**Figure 2** | Accuracy of BatNN in (a) r , (b) RMSE, (c) MAE and (d) E, based on various HN.

Optimal velocity factor (α)

The optimal configuration of α was determined via trial and error. Table 4 shows the simulations of BatNN trained with various α , simulated using selected predictors of HadCM3, ECHAM5 and HadGEM3-RA. It can be observed that decreasing α from 1 to 1×10^{-3} resulted in increasingly higher accuracy of BatNN. The best accuracy of BatNN was observed when $\alpha = 1e-3$. Further reduction of α to $1e-4$ resulted in reduced accuracy, as can be clearly seen by the higher RMSE and MAE. Moreover, simulations based on all three climate models agreed that the optimal value for α was $1e-3$.

Optimal hidden node (HN)

Lastly, the optimal configurations of HN, IN and LR for BatNN were determined through trial and error. The accuracy of BatNN trained with various configurations of HN is shown in Figure 2. It can be seen that increasing HN from

5 to 100 resulted in higher accuracy. BatNN achieved the best accuracy when HN = 100. Further increment of HN did not improve the results. In fact, higher HN seemed to increase the MAE of BatNN, as shown in Figure 2(c). Hence, the optimal HN for BatNN was determined to be 100.

Optimal iteration number (IN)

Figure 3 presents the validation results of BatNN trained with various IN. Analysis of the results revealed that from IN of 100 to 1,000, the model showed increasingly better accuracy. The best accuracy was observed when IN = 1,000. Subsequent attempts to increase IN to 6,000 resulted in slight reduction of accuracy. Therefore, it was decided that IN = 1,000 was optimal for BatNN.

Optimal learning rate (LR)

Figure 4 compiles the validation results of BatNN trained with various LR. It can be observed that increasing LR

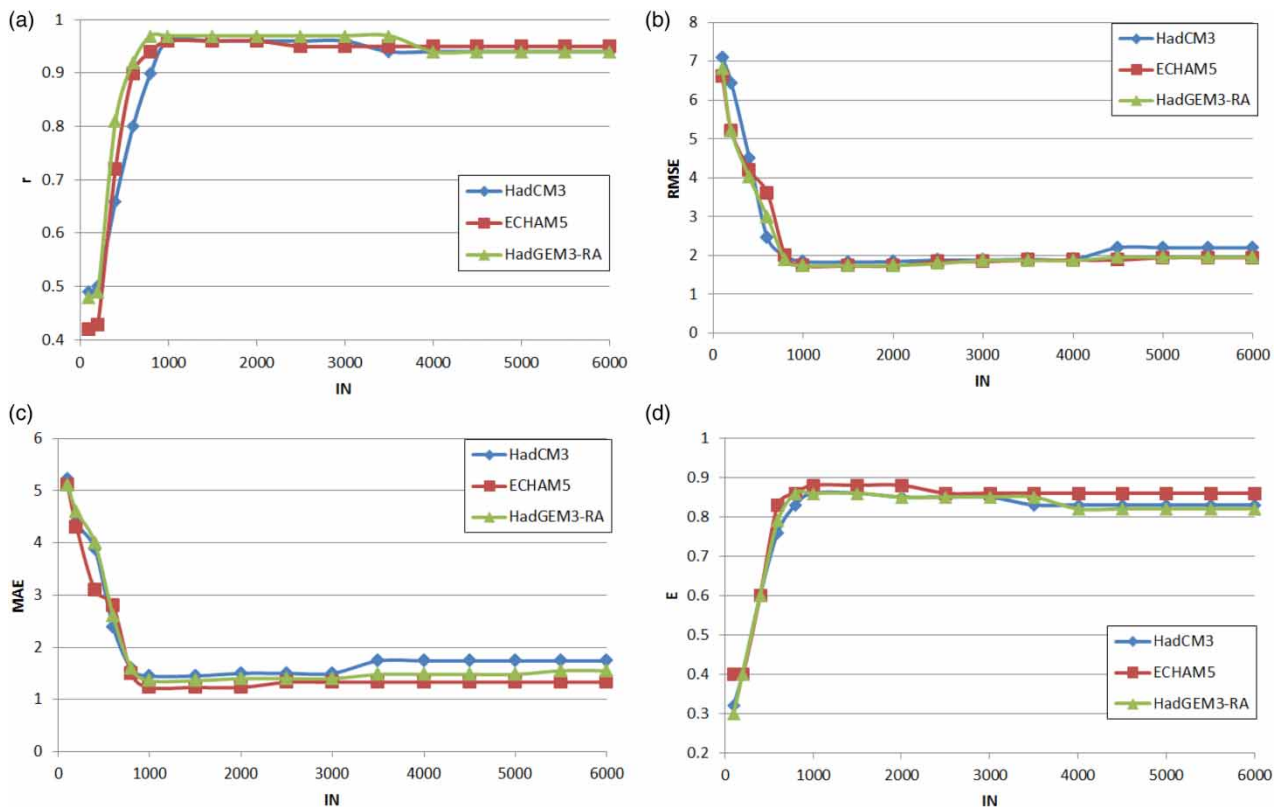


Figure 3 | Accuracy of BatNN in (a) r , (b) RMSE, (c) MAE and (d) E , based on various IN.

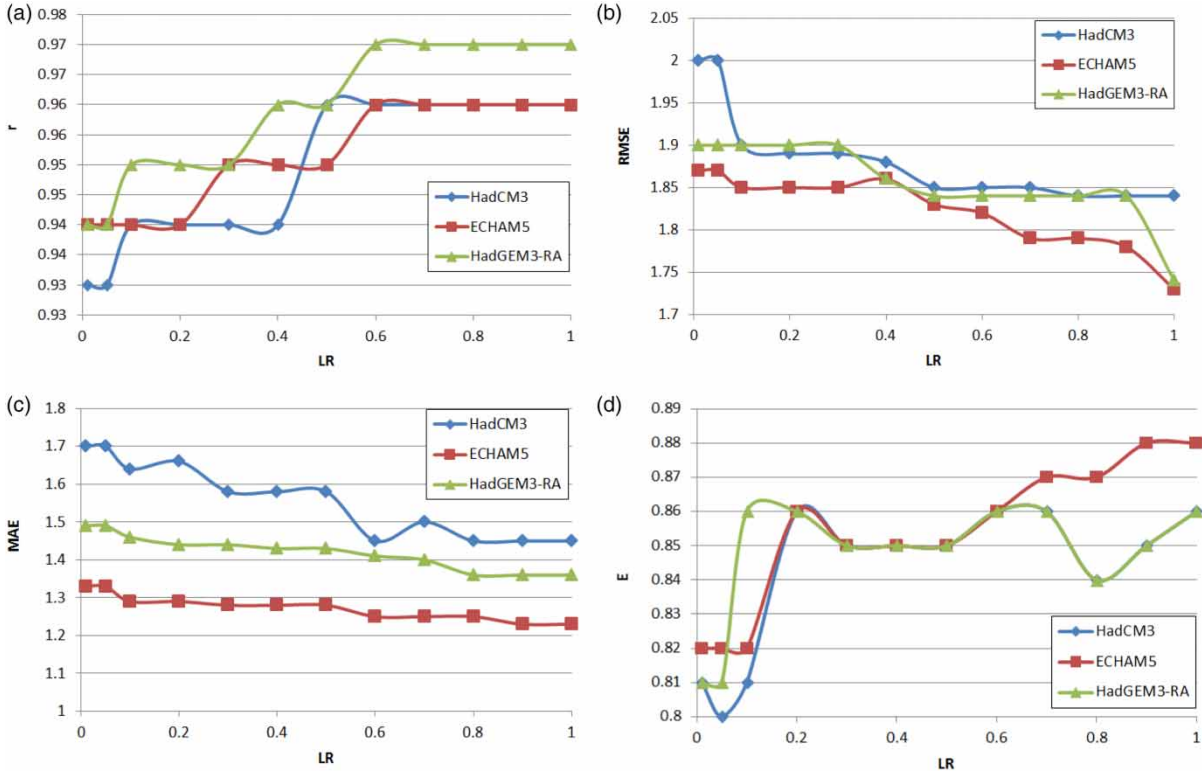


Figure 4 | Accuracy of BatNN in (a) r , (b) RMSE, (c) MAE and (d) E , based on various LR.

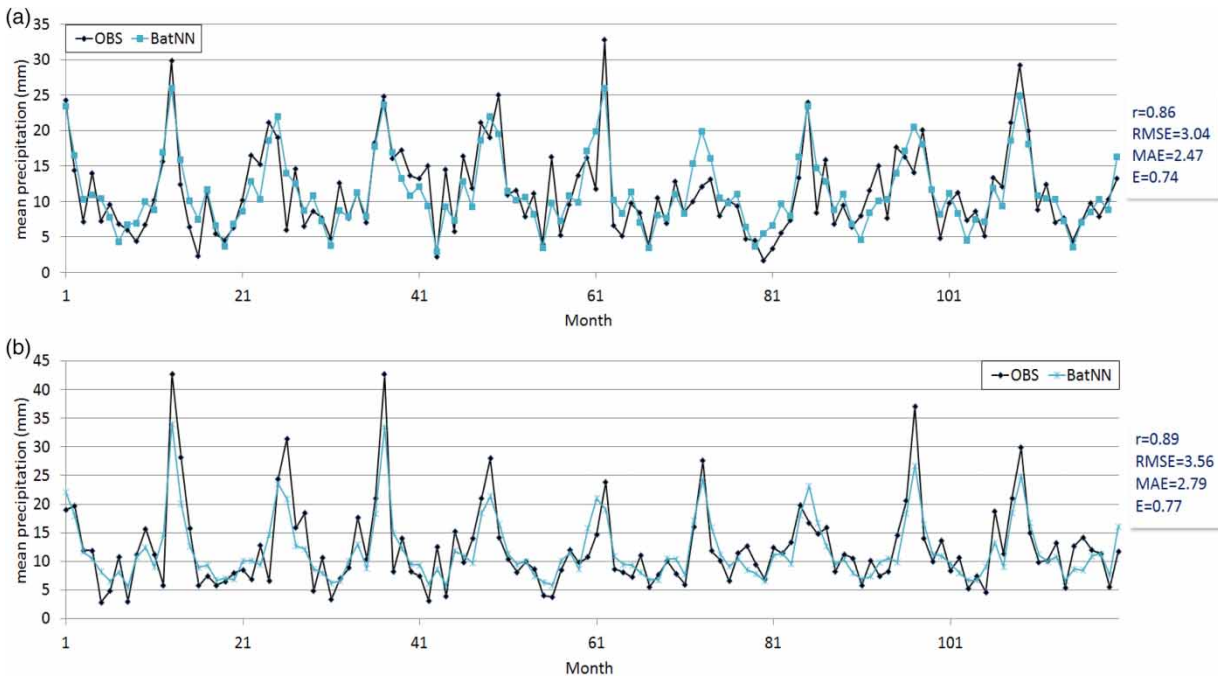


Figure 5 | Comparison of observed and predicted monthly mean precipitation over 1991–2010 for BatNN simulated using HadCM3. (a) Validation period 1991–2000, (b) validation period 2001–2010.

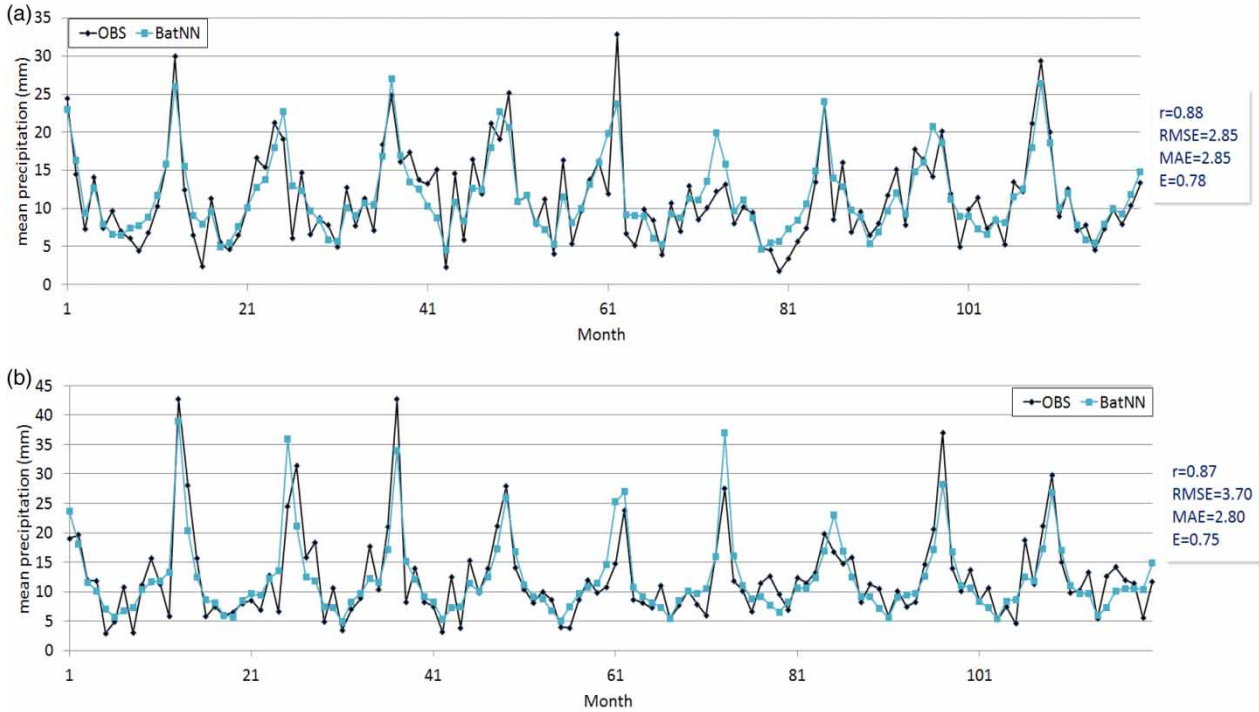


Figure 6 | Comparison of observed and predicted monthly mean precipitation over 1991–2010 for BatNN simulated using ECHAM5. (a) Validation period 1991–2000, (b) validation period 2001–2010.

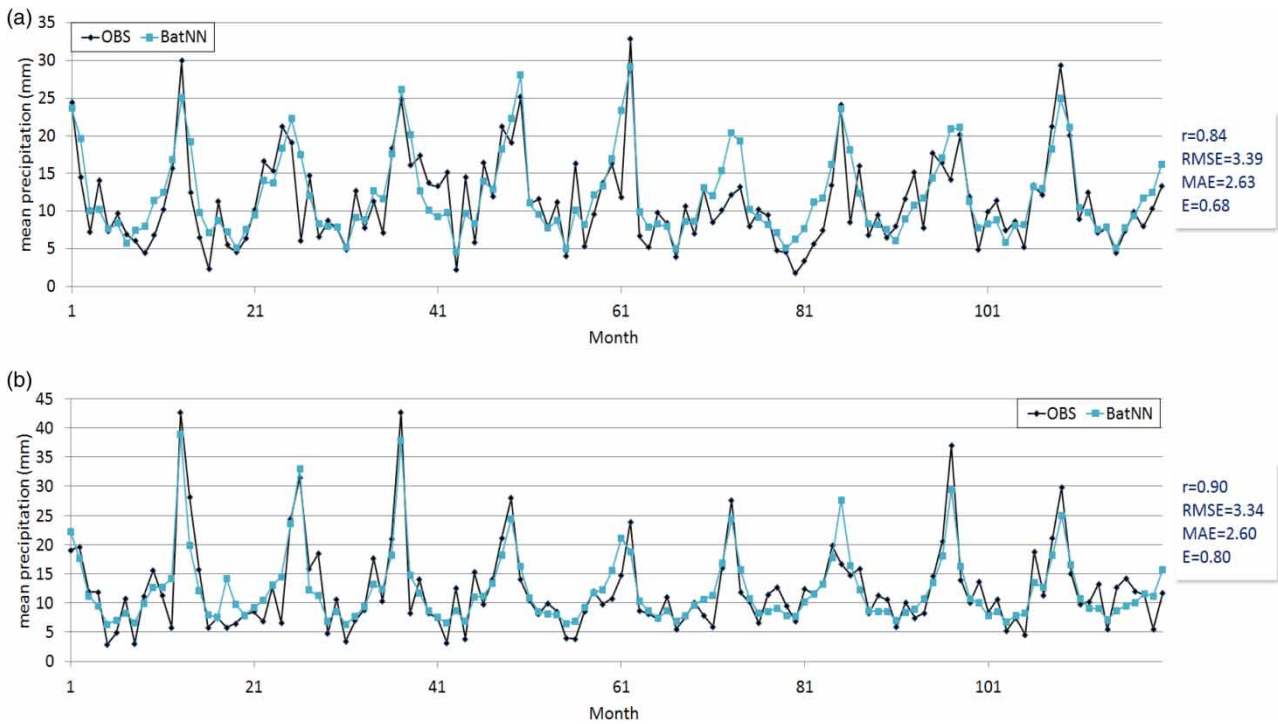


Figure 7 | Comparison of observed and predicted monthly mean precipitation over 1991–2010 for BatNN simulated using HadGEM3-RA. (a) Validation period 1991–2000, (b) validation period 2001–2010.

from 0.01 to 1 resulted in increasingly better accuracy and decreased error, as clearly shown in Figure 4(b) and 4(c). The best accuracy was recorded when $LR = 1$, hence it was adopted as the optimal configuration for BatNN.

Summary of optimal configuration for BatNN

In summary, the best parameter configurations of BatNN for spatial downscaling and projection of long-term future precipitation in Kuching were as follows:

- I. $b = 20$
- II. $f_{max} = 6$
- III. $\alpha = 1e-3$
- IV. $HN = 100$
- V. $IN = 1,000$
- VI. $LR = 1$

These configurations will be used in BatNN for spatial downscaling and prediction of long-term future precipitation in Kuching. Comparison of observed and predicted monthly mean precipitation over 1991–2010 for HadCM3, ECHAM5 and HadGEM3-RA are presented in Figures 5–7, respectively.

CONCLUSION

The results revealed that the newly developed BatNN is able to downscale and simulate precipitation accurately with average $r = 0.96$, average $RMSE = 1.69$, average $MAE = 1.40$ and average $E = 0.84$ across the three climate models. This is because BatNN incorporates global search function in the training process, aside from local search, which diversifies the search range and promotes broader exploration within the search space. As such, BatNN is able to avoid local optima trappings to find the global optimum, and extreme precipitation can be estimated with better accuracy. Knowledge about the changes in extreme precipitation events is beneficial for policy-makers, in terms of providing valuable input for mitigation and adaption strategies, as well as water resources management.

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