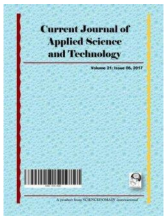

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Comparative Study of Different GCM Models for Stream Flow Prediction

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Authors' contributions

This work was carried out in collaboration between all authors. Authors MP and RKB designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors SK and MP managed the analyses of the study. Authors DL and NRB managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

Aims: The goal of this work was to provide comparative analysis of different GCM models for stream flow prediction. These models were prepared by training, validation, testing and mean square error. The specific objective of this study was to compare different GCM models for climatic analysis. Future stream flow was predicted by the best one.
Study Design: For the prediction of future flow, an artificial neural network model was developed for down scaling the GCM data. The ANN downscaling model was used to predict the future stream flow of the river.
Place and Duration of Study: This study was conducted in Ranganadi river which originates from the Nilam, Marta and Tapo mountain ranges in Arunachal Pradesh. The Ranganadi sub-basin spreads about 1749 sq. km. across the Lower Subansiri and Papum-Pare districts in Arunachal Pradesh and Lakhimpur district of Assam, where it joins with Subansiri-Brahmaputra river system at khichikagao. The study area was located between $94^{0}02'34''$ E longitude and $27^{0}14'01''$ N latitude in the Brahmaputra River basin of India. For this research, observed stream flow data from 1973-1983

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and 2001 to 2009 were used.
Methodology: Neural networks are mathematical representations of a process that operates nerve cells. Each network is made up of nodes and links like nerve cells. In this study the best model was decided by using the different algorithms and varying the number of hidden neuron from 1 to 15 with various combination of learning rate from 0.01 to 0.9 and momentum factor from 0.01 to 0.9. Forecasting was done in three clearly separate stages. They were training mode, validation and testing phase. In training mode, the output was linked to many of the input nodes as desired and the pattern was defined. The network was adjusted according to this error. The validation dataset was used at this stage to ensure that the model was not over trained. In testing phase, the model was tested using the dataset that was not used in training.
Results: In this work proposed the best GCM model for checking the future flow scenario of Ranganadi river using ANN model. For model prediction, stream flow data was used from 1973-1983 and 2001 to 2009. Mean and standard deviation (mapstd) function was used for scaling all input and target data using MATLAB. HadCM3 CGCM2 and GFDL model were used for comparative study of the best model. With each one of the GCM models, we had varied the seven different algorithms for achieving the best ANN model. The ANN model takes into consideration adaptive system with different layer of hidden neurons, so we also varied the number of neuron with each algorithm and each model. The best result was obtained for Levenberg-Marquardt algorithm with number of hidden neuron as 10. The Fig. 6. Showed that the value of correlation coefficient (R^2) and Mean square error (MSE) was the best as compared to other GCM models.
Conclusion: The main conclusion was that ANN was optimized in terms of various training algorithm, number of neurons in hidden layer and changes the various combinations of learning rate and momentum coefficient. By using various combinations of algorithm and number of neurons used to minimize the performance error, the best result was obtained for Levenberg-Marquardt algorithm with number of hidden neuron as 10. The Fig. 6. showed that the value of correlation coefficient (R^2) and Mean square error (MSE) was the best as compared to other GCM models. According to that the future stream flow was predicted for Ranganadi River which indicated an increasing trend in future.

Keywords: IPCC; GCM models climate change; Ranganadi River; stream flow.

1. INTRODUCTION

Stream flow is the event of hydrological cycle which contributes to huge amount of total rainfall and goes down to ocean without a proper use of it, so proper utilization of stream flow is a critical task. Forecasting of stream flow at various scales is most important for the efficient operation of a water resources system in India. In case of multipurpose reservoirs, stream flow forecasting is very important for efficient reservoir operation. Various studies have been performed for impact assessment of climate change on stream flow variation. [1] Patil, M, predicted the stream flow of ranganadi River using three GCM models and suggested that HadCM3 model is best as compare to other one. [2] according to Zealand et al. The utility of feed forward neural network model for stream flow forecasting was better than conventional model like regression analysis or linear model. Kirono et al. [3] worked with 14 GCMs model to simulate drought characteristic by various scenario of IPCC report, they used metrological parameter to find out the Reconnaissance Drought Index for different regions of Australia. The trend of drought magnitude and frequency has an increasing trend. Rainfall scenario has a decreasing trend of around 5% with increase of temperature and the evapotranspiration has also increased. [4] Blenkinso p and Fowler (2007), prepared a functions of six RCMs and four GCMs models to assess the average rainfall and drought statistics for 1961–1990 in the UK with two indices of drought severity, based on monthly rainfalls [5]. The worked estimated the uncertainty ranges occurs in future for A2 scenario of circulation model from 2071 to 2100. They suggested that the model RCMs are able to generate local cycle of annual rainfall in the UK, but observed frequency of the events could not generate by them. Similar finding have been recognized by Kumar et al. [6] for of the Hemavathi river basin. The trained network is used for both single step and multiple step forecasting. It was concluded that the recursive neural network perform well than FFN for forecasting monthly river flows in both single time step and multiple time steps. [7] Adam, P.P., Jaroslaw J., N. developed ANN model for mountain watershed and concluded that the selection of input variables, defined the strength of model learning process during calibration. Moreover, the results showed that the spring and summer monthly stream flow can be adequately represented; improving the results of calculations obtained using the other methods.

Some researchers used different emission scenario according to various conditions of the physiological and climatic factors. As such, the goal of this work is to provide comparative analysis of different GCM models for stream flow prediction. The model is prepared by training, validation, testing and mean square error is found out by various models. The results are then compared to show which model will be good for future work. Ranganadi is one of the tributaries of the Brahmaputra River. For the prediction of future flow, an artificial neural network model is then developed for down-scaling the GCM data [8,9]. The ANN downscaling model is then used to predict the future stream flow of the river. The specific objective is to compare different GCM models for climatic analysis. Future stream flow is also predicted by the best of model.

2. MATERIALS AND METHODS

2.1 Downscaling

Downscaling is a technique that takes the output from the model and adds the information at smaller scales [10,11]. Global climate models (GCMS) are run at coarser spatial resolution which cannot be used directly in the local impact studies due to cloud cover and other effects. To eliminate this problem, basic downscaling techniques are developed to obtain local-scale surface weather from regional-scale atmospheric variables which are provided by GCMs. Downscaling techniques can be classified into two types i.e. dynamic downscaling and statistical downscaling.

2.2 Dynamic Downscaling

Dynamic downscaling represents the use of high resolution Regional Climate Models (RCMs) which are nested with GCMs [12]. The RCMs are similar to GCMs, but RCMs generally improve with the higher order statics of metrological variables.

2.3 Statistical Downscaling

Statistical Downscaling has been used to observe the statistical relationship between large scale climate variables to local hydrological variables. This relation can be applied to future GCM outputs to obtain local and regional climate change factors.

2.3.1 Design of ANN model

[13] neural networks are mathematical representations of a process that operates like nerve cells. Each network is made up of nodes and links like nerve cells. In this study the best model has been decided by varying the different algorithms and varying the number of hidden neuron from 1 to 15 with various combination of learning rate from 0.01 to 0.9 and momentum factor from 0.01 to 0.9. [14] forecasting has been followed in three clearly separate stages. They are training mode, validation and testing phase. In training mode, the output is linked to as many of the input nodes as desired and pattern is defined. The network is adjusted according to this error. The validation dataset is used at this stage to ensure the model is not over trained. In testing phase, the model is tested using the dataset that was not used in training.

2.4 Downscaling Using the Artificial Neural Network

[15] neural network is one of the tools used for methodological analysis of hydrological forecasting. It can be thought of as a computational pattern that involves searching and matching procedures, which permits forecasting without an intimate knowledge of the physical process. The neural network seeks the relationship between input and output data and then creates its own equations to match the pattern in an iterative manner.

2.4.1 Artificial Neural Network (ANN)

[16] an ANN is a massively parallel-distributed information processing system that has certain performance characteristics resembling biological neural network of the human brain. Typically, a neural network is characterized by its architecture that represents the pattern of connection between neurons; its method of determining the connections weights and the activation function [17]. ANNs can be categorized by the number of layers. They can also be categorized based on the direction on information flow and processing. In most networks, the input layer receives the input variables for the defined problem and the last layer consists of values predicted by the network and thus represents the model output.

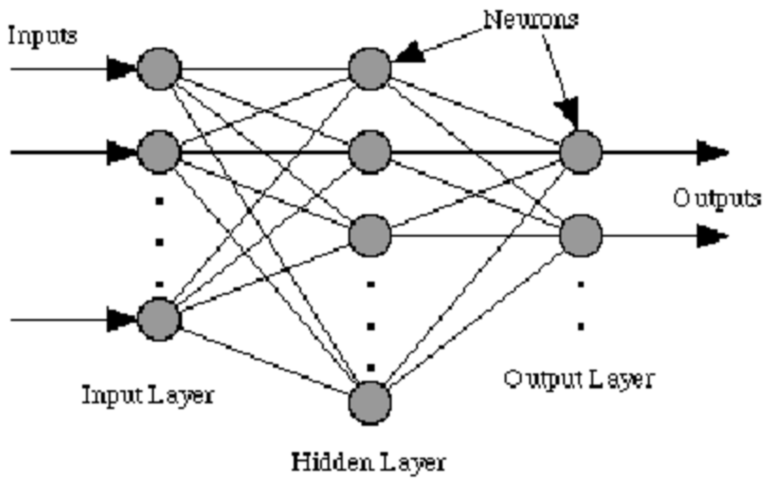

Fig. 1. ANN functioning

Finally, the output signal is sent through all the output connections to other neuron as through synapses in case of biological neuron.

$$y_j = f(w_j, x_j) - \theta_j$$

The function f is called as an activation function. The activation function enables a network to map any non-linear process. The most commonly used function is the sigmoid function expressed as:

$$f(x) = \frac{1}{1+e^{-x}}.$$

2.5 Levenberg - Marquardt Algorithm (trainlm)

[18] the Levenberg-Marquardt algorithm was designed to approach second order training speed without having to compute the Hessian matrix. When the performance function has the form of sum of squares, then the Hessian matrix can be approximated as

$$H = J^T J$$

And the gradient can be computed as

$$g = J^T e$$

Where, J is the jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is the vector of network errors. The Jacobian matrix can be computed by standard back-propagation method that is much less complex than computing the Hessian matrix. The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton like

$$X_{K+1} = X_K - [J^T J + \mu I]^{-1} J^T e$$

When µ is zero, this is just Newton's method, using approximate Hessian matrix. When µ will be large, this becomes gradient descent with bit step size. In practice LM is much faster and better for a variety of the problems but they require much memory to run.

Selection of Predictors: [19] the predictor selection has been done by Pearson correlation. Pearson correlation is a simple correlation between predictor and predictant. In the correlation test, "0" represent weak correlation whereas "1" represents strong correlation. The data is normalized before entering into the neural network. Due to the nature of the algorithm, large values slow down training process. This is because of the gradient of the sigmoid function at extreme values approximate to zero. Mean and Standard Deviation (mapstd), an approach for scaling the network inputs and targets so as to minimize the mean and standard deviation of the training set. The function mapstd normalizes the inputs and targets so that they will have zero mean and unity standard deviation. The original network inputs and targets are given in matrices p_n and t_n. They effectively become a part of the network, just like the network weights and

Table 1. Correlation between observed stream flow data and HadCM3 GCM simulated data

Sl. no.	HadCM3 Predictors	Correlation of HadCM3 with observed runoff at point 1
1	Sea level pressure	0.2396
2	Relative humidity	-0.0459
3	Relative humidity@200 hpa	0.0789
4	Relative humidity@500 hpa	0.2088
5	Geo-potential height @200 hpa	0.0186
6	Geo-potential height @500 hpa	0.0088
7	short wave radiation flux	0.2471
8	Humidity mixing ratio	0.1030
9	Temperature	0.1971
10	Temperature@850 hpa	0.2147
11	Maximum temperature	0.2053
12	Minimum temperature	0.1688

biases. After this, the outputs are converted back into the same units. Table 1 showed the relation between the observed and model data for model preparation.

According to this Table 1, the predictor that shows the best correlation value will be used in the next step.

Table 3 showed the relations of observed and CGCM2 data.

Table 2. List of selected predictors

Location	Predictands	Predictors
Point	Runoff	Mean sea level pressure Surface air temperature Air temp.@850 hpa Relative humidity@500 hpa Short wave radiation

Performance Indicator: The Model is prepared by using Artificial Neural Network (ANN) with the best predictor's .for satisfactory the correlation coefficient (R) and Mean square error (MSE) has been used as model performance for modeling.

$$R^2 = \frac{n\sum(xy)-\sum(x)\sum(y)}{n[\Sigma x^2-(\Sigma x)^2].[(n\Sigma y^2)-(\Sigma y)^2]}$$

$$MSE= \frac{1}{n}\sum_{i=1}^{n}(Yp - Yo)^2$$

3. RESULTS AND DISCUSSION

[20] in this work the best GCM model is proposed for checking the future flow scenario of Ranganadi river using ANN model. For this, research observed stream flow data from 1973-1983 and 2001 to 2009 are used. Observed and predicted stream flow is compared with the best model to check stream flow trend. Mean and standard deviation (mapstd) function is used for scaling all input and target data using MATLAB. HadCM3 CGCM2 and GFDL model are used for comparatively study of the best model. With each one of the GCM models, we have varied the

Table 3. Correlation between CGCM2 and observed

Sl. no.	CGCM2 predictors	Correlation of CGCM2 with observed runoff at point 1
1	U component of velocity	0.0129
2	Dew point depression	0.1643
3	Temperature	0.1672
4	Geo-potential height	- 0.0227
5	Geo-potential height @500 hpa	-0.221
6	Stream function	-0.0485
7	short wave radiation flux	-0.2790
8	Total precipitation	0.1760
9	Maximum temperature	0.1686
10	Minimum temperature	0.1657

seven different algorithms for achieving the best ANN model. The ANN model takes into consideration adaptive system with different layer of hidden neurons, so we have also varied the no of neuron with each algorithm and each model.

Table 4. List of selected predictors

Location	Predictands	Predictors
Point	runoff	Mean sea level pressure Surface air temperature Maxi. temperature Mini. Temperature Total precipitation

Table 5. Correlation between GFDL and observed data

GFDL predictors	Correlation of GFDL with observed runoff at point 1
Short wave	-0.1991
Perceptible water	0.0193
Total precipitation	-0.0256
Pressure	0.0220
Temperature	0.0701
Dew point depression	0.1585

Table 6. List of selected predictors

Location	Predictands	Predictors
Point	runoff	Total precipitation Temperature Dew point depression Perceptible water

3.1 Evaluation of the Best Optimization Algorithms and Optimum Number of Hidden Neurons of the ANN Model for HadCM3 GCM

Initially, the single GCM point available near the study area is used for predicting the future flow of the river Ranganadi. The Table 7 shows the comparative study with levenberg-marquardt algorithm. It can be seen that MSE is 0.064 when number of hidden neurons is 8. Table 8 shows that the MSE is 0.101 when number of hidden neurons is 8 with batch gradient descent algorithm. The Table 9 shows that the minimum MSE occurs when number of hidden neurons is 6 and its value is 0.0405 with variable learning rate algorithm. It shows result that minimum MSE is 0.077 for number of neurons equal to 11. Different combination of algorithm it is found that levenberg-marquardt algorithm is the best algorithm to train the network in this case.

From the Table 7 it can be seen that learning function ‘trainlm’ is the best as per the training algorithms are concerned. Selection of optimum numbers of neurons is an essential part of ANN model development. The trainlm used for training the model with 50% observed data and remaining 50% for validation and testing has been evaluated for optimum number of neurons. Number of hidden neurons has been varied from 1-15. The performance of ANN model with N=8 is shown in Table 7. It is seen that the MSE is minimum, with a value of 0.064, with training =0.711, validation =0.789 and testing value is 0.7016.

The Fig. 2 shows the regression curve indicating training, validation, testing, and all R value,

Table 7. Performance of neural network with levenberg-marquardt algorithm

No of neuron (trainlm)	Training *R*	Validation *R*	Testing *R*	All *R*	M S E
N3	0.7766	0.580	0.8173	0.716	0.057
N4	0.7674	0.7041	0.6438	0.6984	0.08
N5	0.7629	0.6065	0.8437	0.7139	0.065
N6	0.7916	0.5957	0.6157	0.7081	0.10
N7	0.8770	0.5608	0.5756	0.769	0.11
N8	**0.7115**	**0.7890**	**0.7016**	**0.695**	**0.064**
N10	0.9430	0.4894	0.50561	0.8069	0.128
N11	0.9690	0.4918	0.5713	0.8556	0.084
N12	0.9267	0.6067	0.5993	0.8161	0.098
N13	0.9618	0.5810	0.6219	0.8777	0.063
N14	0.97464	0.4419	0.6579	0.8658	0.102
N15	0.9622	0.6060	0.7255	0.8727	0.074

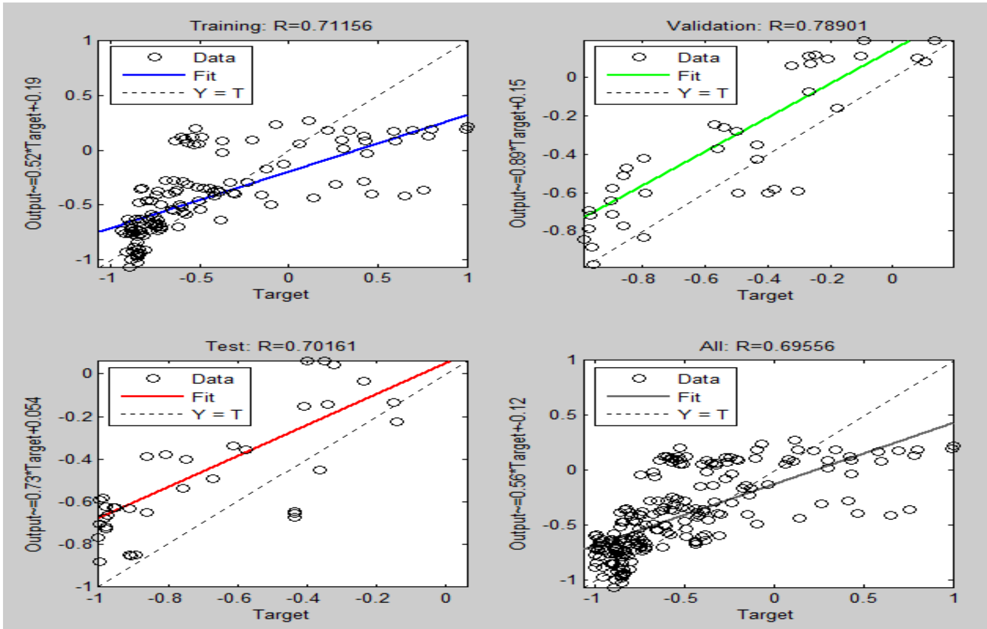

Fig. 2. Regression curve for training, validation, testing using Hadcm3 data

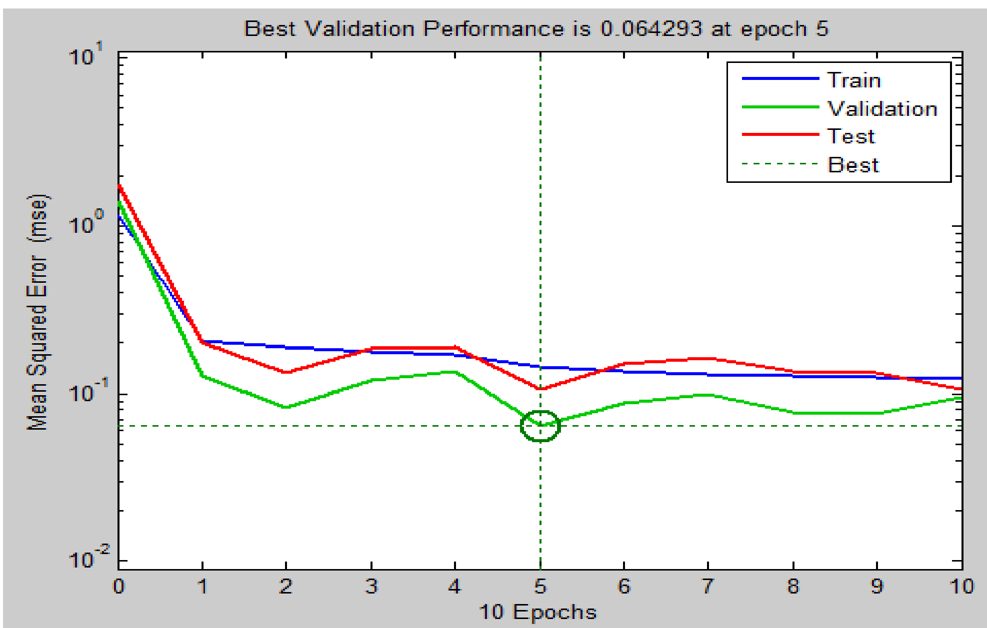

Fig. 3. Performance curve using Hadcm3 data

where data is varying between the training, validation, testing line and the best fit line. Our purpose is to set the data along the best fit line so that we achieve the best regression value. In the Fig. 2, validation data is very close to the best fit line. The performance curve in Fig. 3 shows the MSE for training, validation and testing. For epoch 3, the Fig. 4. clearly shows that the validation line is very close to the best fit line. If these two lines overlap, it means that the MSE value has been minimized. After this, the average value of five HadCM3 points which are in and around study area is taken and the regression and MSE value are obtained for prediction of stream flow. The average value of five points giveas optimum result for training and validation but performance MSE value is not acceptable as shown in Table 8.

3.2 Evaluation of the Best Optimization Algorithms and Optimum Number of Hidden Neurons of the ANN Model for CGCM2 GCM

The study is also carried out considering CGCM2 data and in this case also, the point data available near to the study area is considered as the input of the ANN model. Table 9 shows the result with levenberg marquardt algorithm, the minimum MSE being 0.045 with number of neurons as 6. Levenberg marquardt algorithm shows the best minimum MSE value as compared to other algorithms with CGCM2 model. Table below shows the results of each algorithm.

So far, we have used the GFDL model parameters as inputs in ANN model. In the table below, the results of GFDL have been shown and precise result of each algorithm has been highlighted. Levenberg-marquardt algorithm shows training = 0.8298, validation = 0.8204, testing= 0.7299, over all R= 0.7973 with the MSE= 0.0357 which is the minimum MSE out of all three models and seven algorithms. Finally the performance of these three GCM models, the results focus that the GFDL model is the best for stream flow prediction of this area.

3.2 Simulation of Future Runoff of River Ranganadi

The above analysis reveals that the GFDL model gave the best performance out of the three GCM model considered in the study is the GFDL GCM model. As such the GFDL model is used in the study to predict the future flow scenario of the river. The ANN model trained With Levenberg-Marquardt algorithm and also with hidden neuron of 10 is used for predicting the future discharge of the river. Fig. 8 prediction plot indicates increasing trend of stream flow

Table 8. Performance of ANN at average of five points with different number of neurons

No of neuron (trainlm)	Training *R*	Validation *R*	Testing *R*	All *R*	MSE
N3	0.7726	0.490	0.7275	0.6957	0.10
N4	0.92415	0.6545	0.6298	0.7563	0.12
N5	0.82666	0.4065	0.7789	0.665	0.20
N6	0.8153	0.4378	0.6618	0.6284	0.103
N7	0.9582	0.6517	0.730	0.595	0.129
N8	**0.9445**	**0.6525**	**0.7029**	**0.7401**	**0.101**
N9	0.9353	0.5861	0.565	0.5148	0.16
N11	0.956	0.498	0.7118	0.6300	0.31
N12	0.935	0.553	0.2089	0.382	0.15

Table 9. Performance of ANN with CGCM2 data using Levenberg-Marquardt algorithm

No of neuron (trainlm)	Training *R*	Validation *R*	Testing *R*	All *R*	M S E
N3	0.7584	0.65993	0.555	0.6843	0.0666
N4	0.7705	0.69935	0.6485	0.7186	0.0621
N5	0.7902	0.6195	0.4925	0.67181	0.06999
N6	**0.8762**	**0.7712**	**0.6898**	**0.80001**	**0.04545**
N7	0.8133	0.6725	0.622	0.7134	0.06846
N8	0.8802	0.7097	0.5997	0.7385	0.06951
N9	0.7994	0.6887	0.5816	0.7118	0.06267
N10	0.7396	0.5528	0.4584	0.63032	0.07680
N11	0.81384	0.6773	0.4456	0.6892	0.06591
N12	0.8229	0.4680	0.3953	0.6029	0.08867
N13	0.8028	0.5401	0.5281	0.63877	0.06643
N14	0.9019	0.6534	0.3685	0.6973	0.08589

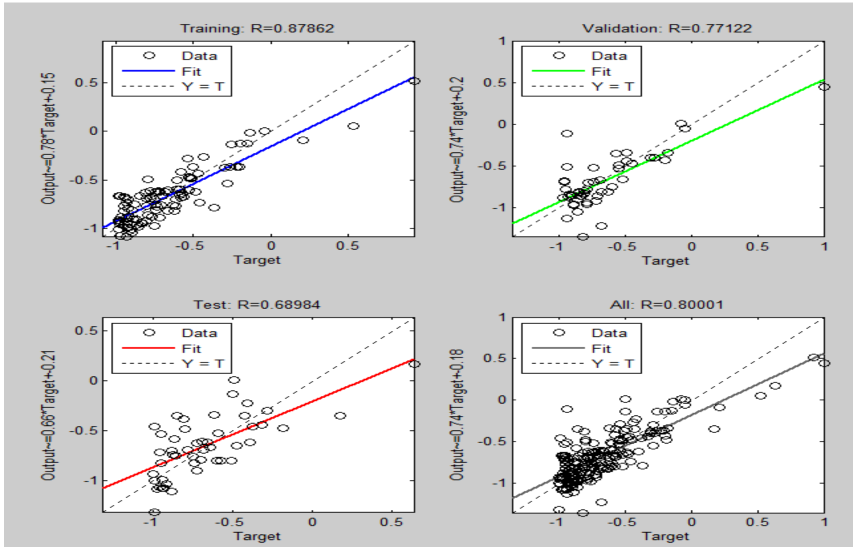

Fig. 4. Regression curve for training, validation, testing using cgcm2 data

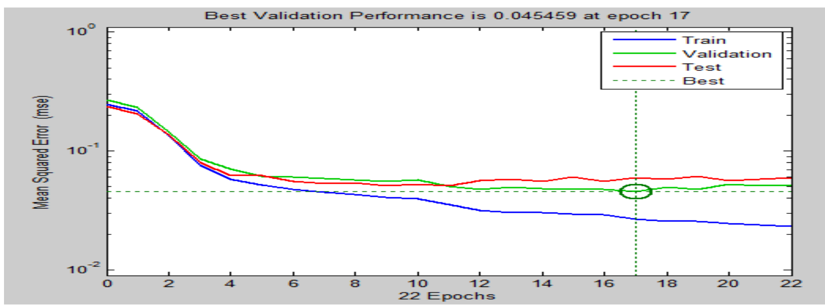

Fig. 5. Performance curve using cgcm2

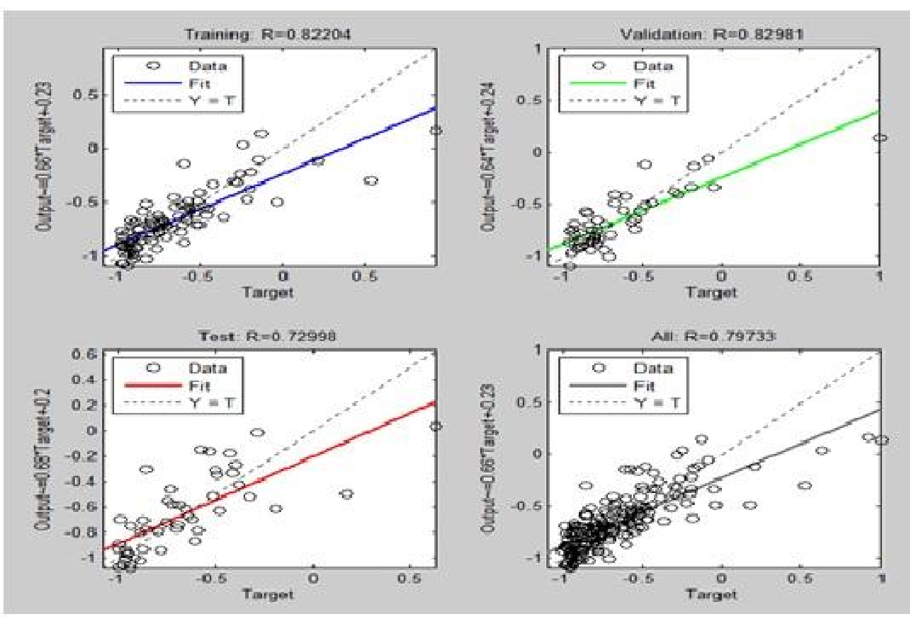

Fig. 6. Regression curve for training, validation, testing using

Table 10. Performance of neural network with GFDL data using Levenberg-Marquardt algorithm

No of neuron (trainlm)	Training *R*	Validation *R*	Testing *R*	All *R*	M S E
N3	0.8190	0.7134	0.6621	0.7477	0.04913
N4	0.8880	0.69277	0.6971	0.7844	0.0468
N5	0.7679	0.7099	0.572	0.6915	0.0572
N6	0.8655	0.7312	0.6719	0.7676	0.0483
N7	0.9253	0.7722	0.7764	0.8430	0.03434
N8	0.8825	0.6563	0.7736	0.7966	0.05378
N9	0.8911	0.5797	0.7585	0.7738	0.06466
N10	**0.8298**	**0.8204**	**0.7299**	**0.7973**	**0.0357**
N11	0.8622	0.4004	0.5978	0.6380	0.0715
N12	0.7836	0.5082	0.5334	0.6449	0.0674
N13	0.9488	0.6647	0.7439	0.8012	0.0495
N14	0.9413	0.4830	0.5648	0.6689	0.0650

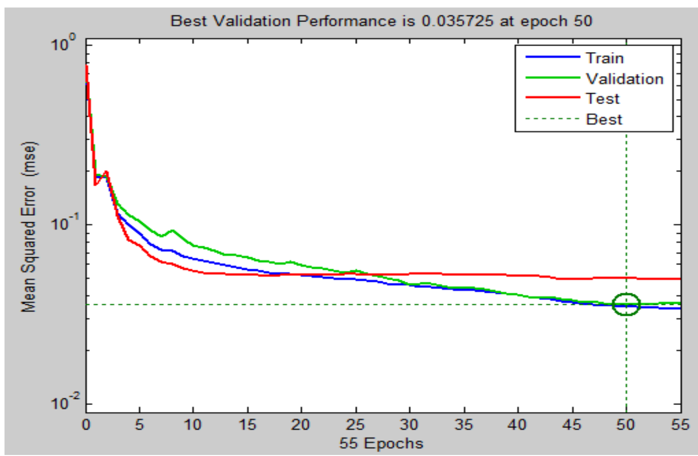

Fig. 7. Performance curve using GFDL data

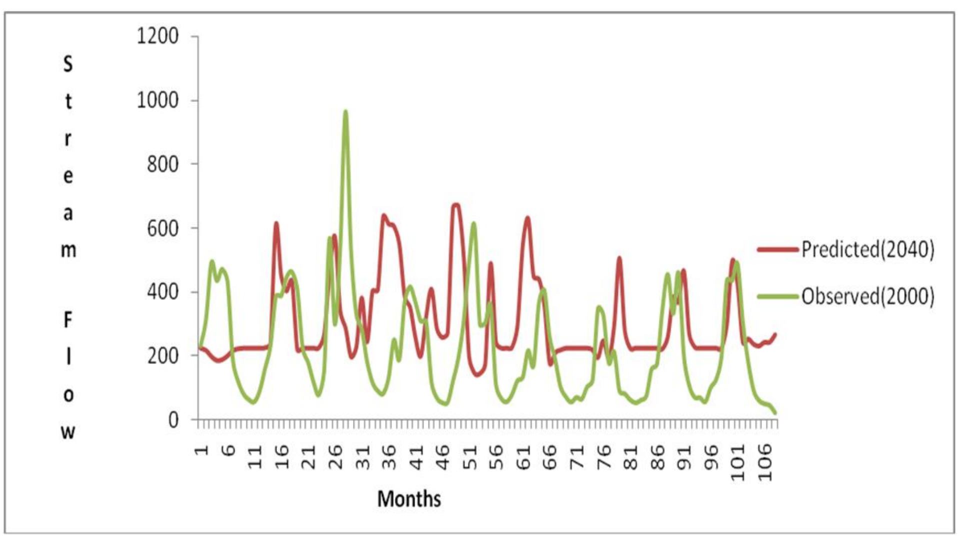

Fig. 8. Performance curve of observed and predicted

4. CONCLUSION

In this work, the comparative study of different GCMs was done for proposing the best model for possible future stream flow prediction of Ranganadi River. The prediction was done by downscaling, using artificial neural network. The main concept was to optimize ANN in terms of various training algorithm, number of neurons in hidden layer and changes the various combinations of learning rate and momentum coefficient. By using various combinations of algorithm and number of neurons used to minimize the performance error, the best result was obtained for Levenberg-Marquardt algorithm with number of hidden neuron as 10. The Fig. 6. showed that the value of correlation coefficient (R^2) and Mean square error (MSE) was the best as compared to other GCM models. According to that the future stream flow was predicted of Ranganadi river, which indicated increased trend in future.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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