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Application of ANN for the Hydrological Modeling

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Abstract: Global climate change has been a burning problem for environmentalists since the middle of the 20th century. The application of artificial neural network (ANN) methodology for modeling climate change impact on river Jhelum basin in the State of Jammu & Kashmir, India is presented. In the present study ANN model was applied to monthly temperature and precipitation data for base time (1979–2009) at four different metrological stations viz. Srinagar, Pahalgam, Qazigund and Gulmarg of river Jhelum basin and then the future average annual temperature and precipitation predicted up to 2100. The large scale GCM predictors were related to observed precipitation and temperature and future projections of climate were made under A1B and A2 scenario upto 21st century. At the end of the 21st century the mean annual temperature of the Jhelum river basin is predicted to increase by 1.43°C whereas the total annual precipitation is predicted to decrease substantially by 30.88% ANN technique under A1B scenario. However, for A2 scenario average annual temperature increased by 1.56°C and total annual precipitation decreased by 35.32%.

Keywords: Artificial Neural Network, River Jhelum, Scenario, Temperature, Precipitation

I. INTRODUCTION

Artificial Neural Networks (ANNs) are analogous in application to multiple regression, with the added advantage that they are inherently non-linear, and particularly robust in finding and representing relationships in the presence of noisy data. The application of ANNs and utility for downscaling applications may be found in Sailor *et al.* [3]; Hewitson and Crane [12]; and Schoof and Pryor [25]. ANNs have proved particularly effective in downscaling precipitation and temperature, where there is a significant non-linear relationship that more traditional techniques such as regression do not capture well [25]. Artificial Neural Networks ANNs, use an input-output training set to learn the relationships from the data. Once the relationship is learned, the model is deterministic and can be used to make prediction from input data. Artificial neural networks (ANN) offer a relatively quick and flexible means of modeling and thus application of ANN based modeling are widely reported in literature. The American Society of Civil Engineers (ASCE) Task Committee [5]-[6] summarized application of ANN for the solution of many hydrological problems. Artificial neural networks have been used for stream flow forecasting and have been reported in literature. [8], [10], [13], [14], [17], [20], [28-29], to perform much better than the conventional models. The supremacy of the multilayer feed forward neural network (MLFN) over the regression model in terms of predictive power for the same data have been demonstrated [24]. Compared predictive results of NNs and a neuro-fuzzy approach to the predictions of two linear statistical models, auto-regressive moving average and auto-regressive exogenous input models have been reported ,with the neuro network and the neuro-fuzzy system both superior to the linear statistical models.

[9] An artificial neural network (ANN) is a data-driven process with a flexible mathematical algorithm capable of solving complex nonlinear relationships between input and output data sets. A neural network can be described as a network of simple processing nodes or neurons, interconnected to each other in a specific order, performing simple numerical manipulations. A neural network can be used to predict future values of possibly noisy multivariate time series based on past histories. ANNs have become popular in the last decade for hydrological forecasting such as rainfall-runoff modeling, streamflow forecasting, groundwater and precipitation forecasting, and water quality issues [Kisi, 2004; Sahoo and Ray, 2006; Adamowski, 2007, 2008a, 2008b; Banerjee et al., 2009; Pramanik and Panda,2009; Sreekanth et al., 2009; Sethi et al., 2010; Adamowski and Chan, 2011].[11] The most widely used neural network is the multilayer perceptron (MLP). In the MLP, the neurons are organized in layers, and each neuron is connected only with neurons in contiguous layers. A typical three-layer feedforward ANN is shown in Figure 1. The input signal propagates through the network in a forward direction, layer by layer. The mathematical form of a three-layer feedforward ANN is given as [Ozbek and Fidan, 2009]. A simple mathematical model in Figure 1 can be used in explaining a neuron quantitatively. The three basic elements of the neuronal model are: a set of synapses or connecting links, an adder and an activation function. This model also includes an externally applied bias, denoted by b_k.

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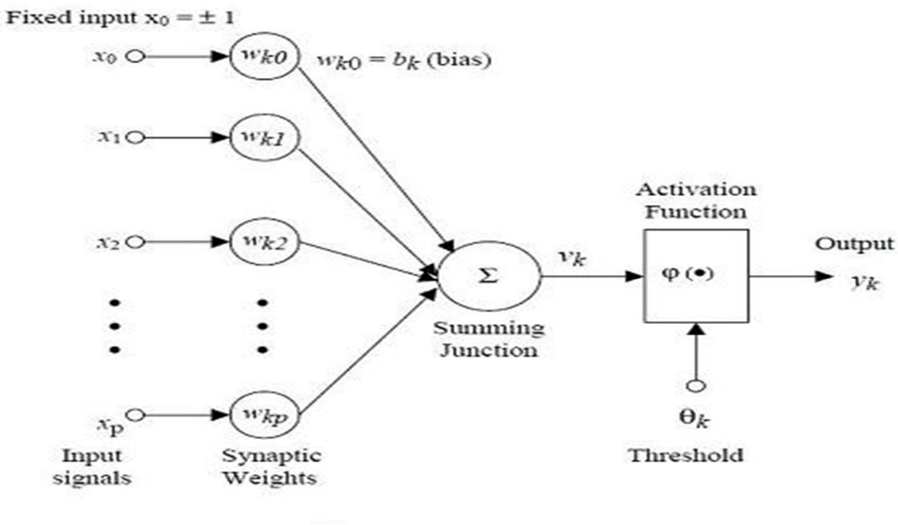

Fig.1 Non-linear model of a neuron

A network of neurons is formed when a neuron links with others via synapses which can be single layered or multi layered. A multilayer ANN contains an input layer of neurons, an output layer of neurons, and one or more hidden layer of neurons. The hidden layer aids in performing useful intermediary computations before directing the input to the output layer.

When a network had been constructed for a specific application, inputs and the corresponding targets are used to train a network until it learns to associate a particular input with a reasonable output. A network is ideally trained until the change in weights in a training cycle reaches a minimum value. After the network is properly trained, it has to be tested for its ability to produce accurate outputs. Large multilayered networks with multiple nodes in each layer are capable of memorizing data due to the vast number of synaptic weights available on such a network. Thus, generating correct outputs for input vectors encountered within the training process does not justify the ability of a network to generate accurate outputs.

Among the different types of neural networks, those which are mostly concentrated in this research work are Rosenblatt's perceptrons [21], also known as multilayer feed-forward neural networks. In these nets there is a layer of input units whose only role is to feed input patterns into the rest of the network. Next, there are one or more intermediate or hidden layers of neurons evaluating the same kind of function of the weighted sum of inputs, which, in turn, send it forward to units in the following layer. This process goes on until the final or output level is reached, thus making it possible to read off the computation. In the present study Artificial neural network (ANN) technique was employed for downscaling of monthly mean temperature and precipitation data of 4 national stations for base time (1979–2009) and then the future scenarios generated up to 2100. Future scenario was generated based on CGCM3 monthly data for A1B story line (IPCC 2007). The downscaled data has been tested, and it has shown a relatively strong relationship with the observed data for CGCM3.The predictors as obtained from Global Climate model (GCM) were: mslpas (mean sea level pressure), tempas (mean temperature at 2m), humas (specific humidity at 2m), relative humidity (rhum), zonal velocity component (u), meridional velocity component (v).

II. STUDY AREA

River Jhelum flows through India and Pakistan having a total length of about 725 kilometers. River Jhelum rises from Verinag spring situated at the foot of the Pir Panjal in the south-eastern part of Kashmir valley in India. It flows through Srinagar city, the capital of Jammu and Kashmir and the Wular lake before entering Pakistan. It ends in a confluence with the river Chenab. Srinagar city which is the largest urban centre in the valley is settled on both the sides of river Jhelum and is experiencing a fast spatial growth. The river Jhelum and its associated streams that drain the bordering mountain slopes together constitute the drainage network of the study area. They include the fairly developed systems like Sind, Rambiara, Vishaw and Lidder rivers as well as tiny rivulets such as the Sandran, Bringi and Arapat Kol. The study area chosen spatially lies between 33° 21' 54" N to 34 ° 27 ' 52" N latitude and 74° 24' 8" E to 75° 35' 36" E longitude with a total area of 8600.78 km2. Fig. 2 shows the catchment map of study area.

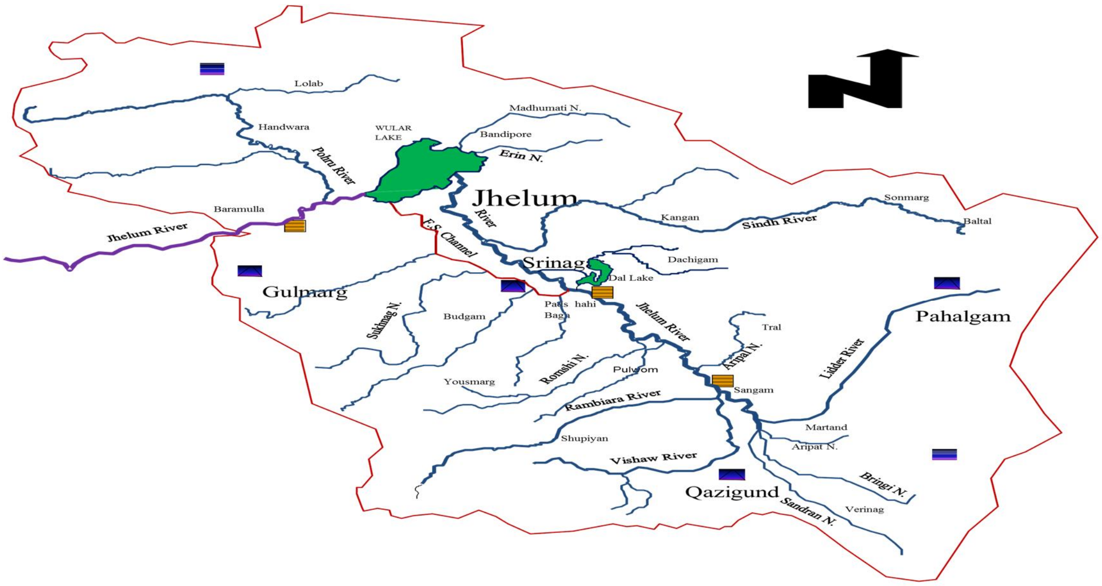

Fig.2 . Catchment map of Jhelum river basin

III. DATA USED

Meteorological data at four climate stations, viz Srinagar, Qazigund, Pahalgam, and Gulmarg of Jhelum catchment have been used in the analysis. This data, which was available for a period of 34 years (1979-2013) for Jhelum catchment, included: Monthly temperature and precipitation obtained from India Meteorological Department (IMD) Srinagar and NCDC (national climate data centre) website. The collected data was then be digitized.

The GCM data for the baseline period and the projection period were downloaded for selected GCM model and selected future scenario from Canadian Climate Data and Scenarios(CCDS) website http://ccds-dscc.ec.gc.ca/ and **www.cccsn.ec.gc.ca/**

IV. METHODOLOGY

Artificial Neural Network Tool Box of MATLAB 7.10.0 was used to develop Artificial Neural Network Model for impact of climate change in Jhelum river basin. Beginning with a network of single layer and pure-lin transfer function and a single neuron the training was started and model developed. The model didn't show good results. Then transfer function of tan-sig was used to develop the model which showed better results. To further get the best model, various combinations of the transfer functions were used while altering the number of hidden layers and number of neurons. The procedure for developing a neural network model is described below:

Data from MS-EXCEL was imported to MATLAB workspace. The selected data consisted of the monthly mean temperature and precipitation historical data and GCM predictors data arranged in separate horizontal rows. Before training, it is often useful to scale the inputs and targets so that they always fall within a specified range. The function premnmx can be used to scale inputs and targets so that they fall in the range [-1, 1], i.e. normalization of data to minimize the errors.

The following code illustrates the use of this function.

```
[pn,minp,maxp,tn,mint,maxt] = premnmx(p,t);
```

The original network inputs and targets were given in the matrices p and t. The normalized inputs and targets, pn and tn, that were returned all fall in the interval [-1,1]. The vectors minp and maxp contain the minimum and maximum values of the original inputs, and the vectors mint and maxt contain the minimum and maximum values of the original targets. Figure 5.2 shows the dialogue box with the vectors generated using command "premnmx". Also the sample matrix was made in MATLAB workspace named by "s" which consisted of the inputs for some years for which outputs were known to check the accuracy of network. The sample data was also normalized by using the command:

```
[sn,mins,maxs] = premnmx(s);
```

In this study, a single layer perceptron based feed forward ANN which uses back-propagation learning algorithm was initially applied for modeling and later double layered perceptron based feed forward ANN using back propagation learning algorithm was used. Two types of transfer functions namely; pure-lin and tan-sig were used to develop different types of networks. The first two

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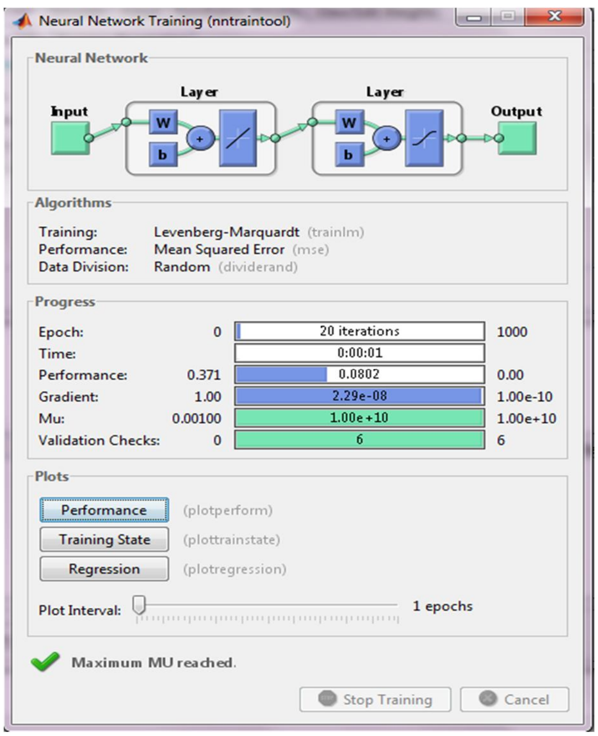
networks consisted of an input layer with 4 input parameters, one hidden layer consisting of 9 neurons and an output layer and pure-lin and tan-sig as transfer functions respectively. The latter two networks consisted of an input layer with ten input parameters, two hidden layers with 9 neurons in first hidden layer and a single neuron in second layer and the combination of pure-lin and tan-sig as transfer functions; on with pure-lin in first layer and tan-sig in second and the second with tan-sig in first and pure-lin in second respectively. The steps to the formation of the network are explained below:

A. The input and target matrices "p_1,p_2…" and "t_1,t_2…" of calibration data points; each of 4×8 and 1×8 were formed in the MATLAB 7.10.0 software using NN toolbox.
B. After normalizing the input, target and sample data; the workspace of MATLAB contains the all data in normalized form.
C. The normalized input, sample and target matrices i.e., pn, sn and tn respectively were imported to Network data manager of Matlab.
D. The network with the required specifications was generated.
E. The networks were trained with (6×8) input matrices and the corresponding (1×8) target matrices. The training process consisted of data sets of the years 1979-2009. The rest data were used for validation.
F. The networks were simulated with (3×4) sample matrices for checking the efficiency of network.

After starting the training it was observed that the performance increased with each set of data fed to the network. When the training was stopped the Training v/s Epoch plot of each of the designed networks showed the best performance.



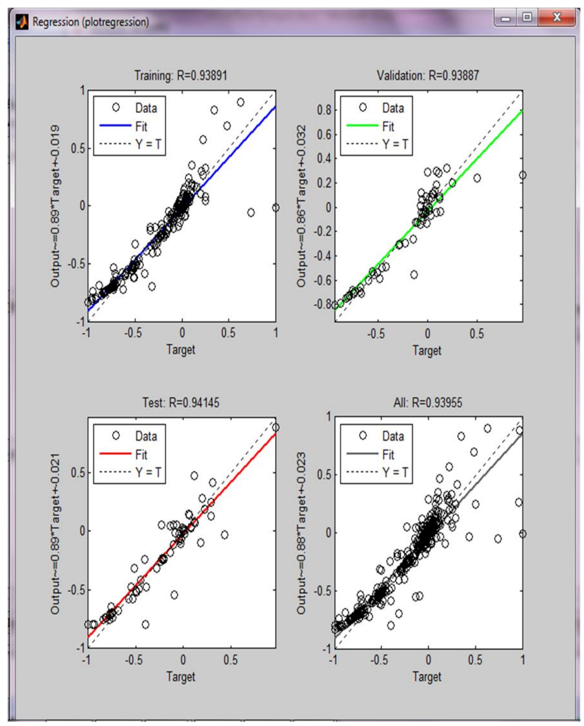


Fig.3 Dialogue box showing performance training

Fig.4 Dialogue box showing regression during during training

The training was continued till the errors were minimum and regression R^2 was maximum.

B. Model Performance Evaluation

The performance of the predictions resulting from training and testing was evaluated by measures of goodness of fit i.e. mean squared error MSE or root mean squared error RMSE, coefficient of determination R2 and mean absolute deviation MAD expressed in the following equations;

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_p - y_a)^2 \quad (1)$$

$$RMSE = (MSE)^{\frac{1}{2}} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_p - y_a)^2}{\sum_{i=1}^{n}(y_a - y_m)^2} \quad (3)$$

$$\text{MAD} = \frac{1}{n}\sum_{i=1}^{n}|x_i - \mu| \quad (4)$$

where ya represents the actual observed value; yp is predicted value and n represents the number of observations considered. Additionally a multiple linear regression model as an alternate method was applied for evaluating the models performance statistically. The model having minimum RMSE, minimum MAD and maximum R^2 is considered as the best model.

V. RESULTS AND DISCUSSION

In ANN technique projections of future climate were done for two SRES scenarios namely A1B and A2. Figure 5 shows the validation of temperature model and Figure 6 shows the validation of precipitation model over the period 2010 to 2013. From Figure 5 it is clear that the observed and predicted values of temperature varied in the same direction throughout the validation period.

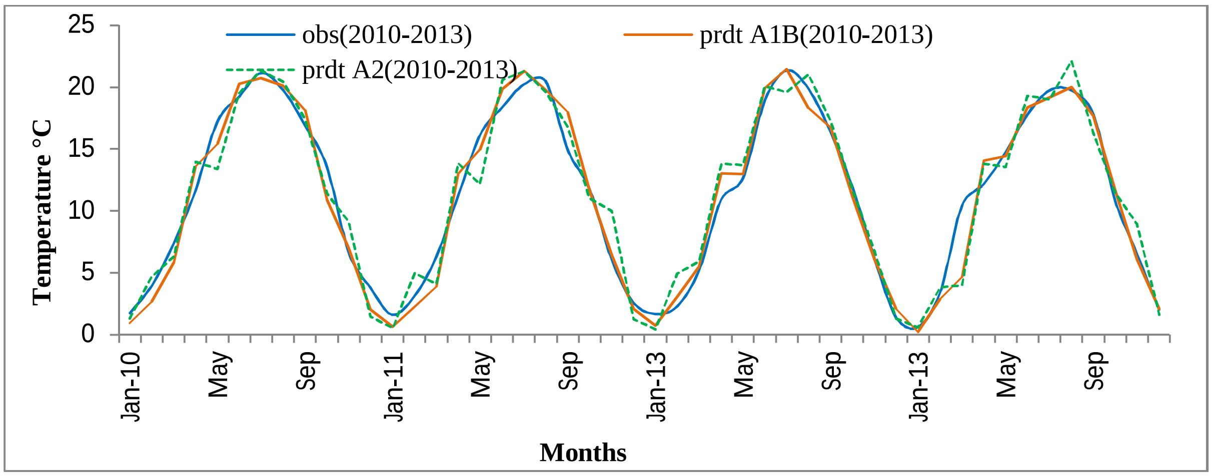


Fig.5 Validation of mean monthly temperature of Jhelum river basin for the period 2010-2013 using ANN

Table 1: Statistical parameters of ANN validation for temperature using CGCM3 model for A1B scenario

Month	MSE	RMSE	MAD
January	0.001259	0.035480	0.021521
February	0.002368	0.048658	0.025765
March	0.018746	0.136916	-0.077500
April	0.003382	0.058152	-0.049690
May	0.00681	0.082525	-0.023970
June	0.020214	0.142178	-0.088110
July	0.044278	0.210424	0.081197
August	0.012225	0.110567	-0.047500
September	0.009688	0.098426	-0.041860
October	0.008527	0.092344	0.007558
November	0.031696	0.178033	-0.072740
December	0.011327	0.106430	0.048770

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Table 2: Statistical parameters of ANN validation for temperature using CGCM3 model under A2 scenario

Month	MSE	RMSE	MAD
January	0.060246	0.245451	-0.013
February	0.226462	0.47588	-0.361
March	0.173756	0.416841	-0.15875
April	0.283164	0.532131	-0.3116
May	0.237875	0.487724	0.3025
June	0.437941	0.66177	-0.37937
July	0.022373	0.149575	0.066727
August	0.079143	0.281324	-0.10324
September	0.035625	0.188746	0.1625
October	0.260574	0.510465	-0.05411
November	0.019462	0.139505	-0.0187
December	0.074943	0.273757	0.164841

From the statistical parameters of temperature validation using ANN model, value of MSE ranges from 0.001259-0.044278 for A1B scenario and 0.019462 -0.437941 for A2 scenario. Similarly the value of RMSE for A1B scenario ranges from 0.035482-0.210424 for A2 scenario. The value of MAD is more for A1B scenario than that of A2 scenario. Thus MSE and RMSE works out to be least for CGCM3 A1B scenario and is thus more accurate simulation of climate. Thus projections of future climate worked under A1B scenario using CGCM3 predictors give more accurate results than under A2 scenario.

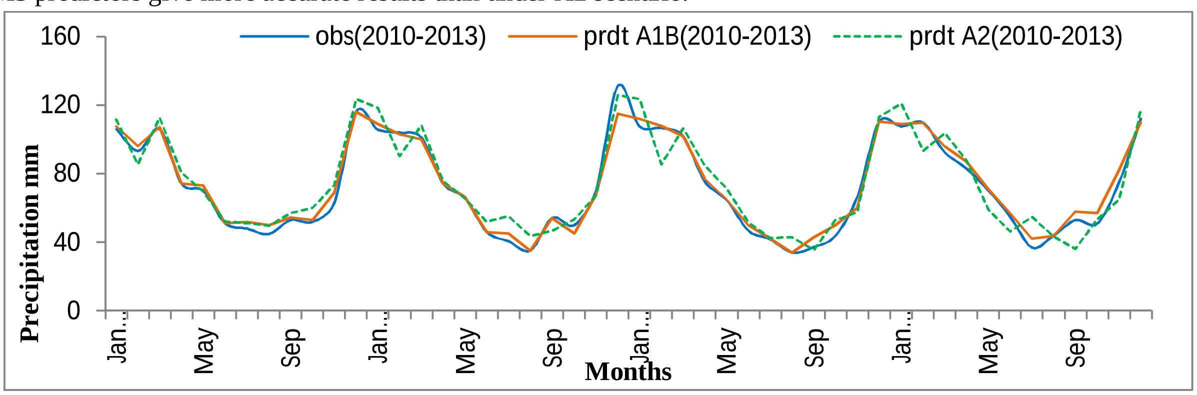

Fig.6. Validation of monthly total precipitation of Jhelum river basin for the period 2010-2013 using ANN

Table 3: Statistical parameters of ANN model validation for precipitation using CGCM3 predictors for A1B scenario

Month	MSE	RMSE	MAD
January	0.550001	0.741620	-0.85179
February	0.555556	0.745356	-0.33321
March	0.558400	0.747262	-0.16000
April	0.016172	0.127170	-0.10063
May	0.171383	0.413984	-0.30533
June	0.474336	0.688721	0.46576
July	0.438580	0.662254	0.41128
August	0.344438	0.586888	-0.10334
September	0.550001	0.741620	-0.75236
October	0.300002	0.547724	0.01038
November	0.575100	0.758353	0.95709
December	0.400609	0.632937	-0.46965

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Table 4: Statistical parameters of ANN model validation for precipitation using CGCM3 predictors for A2 scenario

Month	MSE	RMSE	MAD
January	0.691003	0.831266	-2.08382
February	0.555556	0.745356	3.500085
March	0.85893	0.926785	-3.50014
April	0.272351	0.521873	-3.75009
May	0.144734	0.380439	1.379169
June	0.474336	0.688721	-0.78445
July	0.43858	0.662254	-2.52188
August	0.800001	0.894428	-3.43162
September	0.550001	0.74162	2.355614
October	0.300002	0.547724	-3.43642
November	0.5751	0.758353	2.834638
December	0.547614	0.74001	-2.48785

From the statistical parameters of precipitation validation using ANN technique, value of MSE ranges from 0.016172-0.575100 for CGCM3 A1B scenario and 0.144734-0.858930 for CGCM3 A2 scenario. Similarly the value of RMSE for CGCM3 A1B scenario ranges from 0.127170-0.758353 and for CGCM3 A2 scenario ranges from 0.380439-0.894428. The value of MAD is more A1B scenario than that for A2 scenario. Thus MSE and RMSE works out to be least for CGCM3 A1B scenario and is the best climate model selected

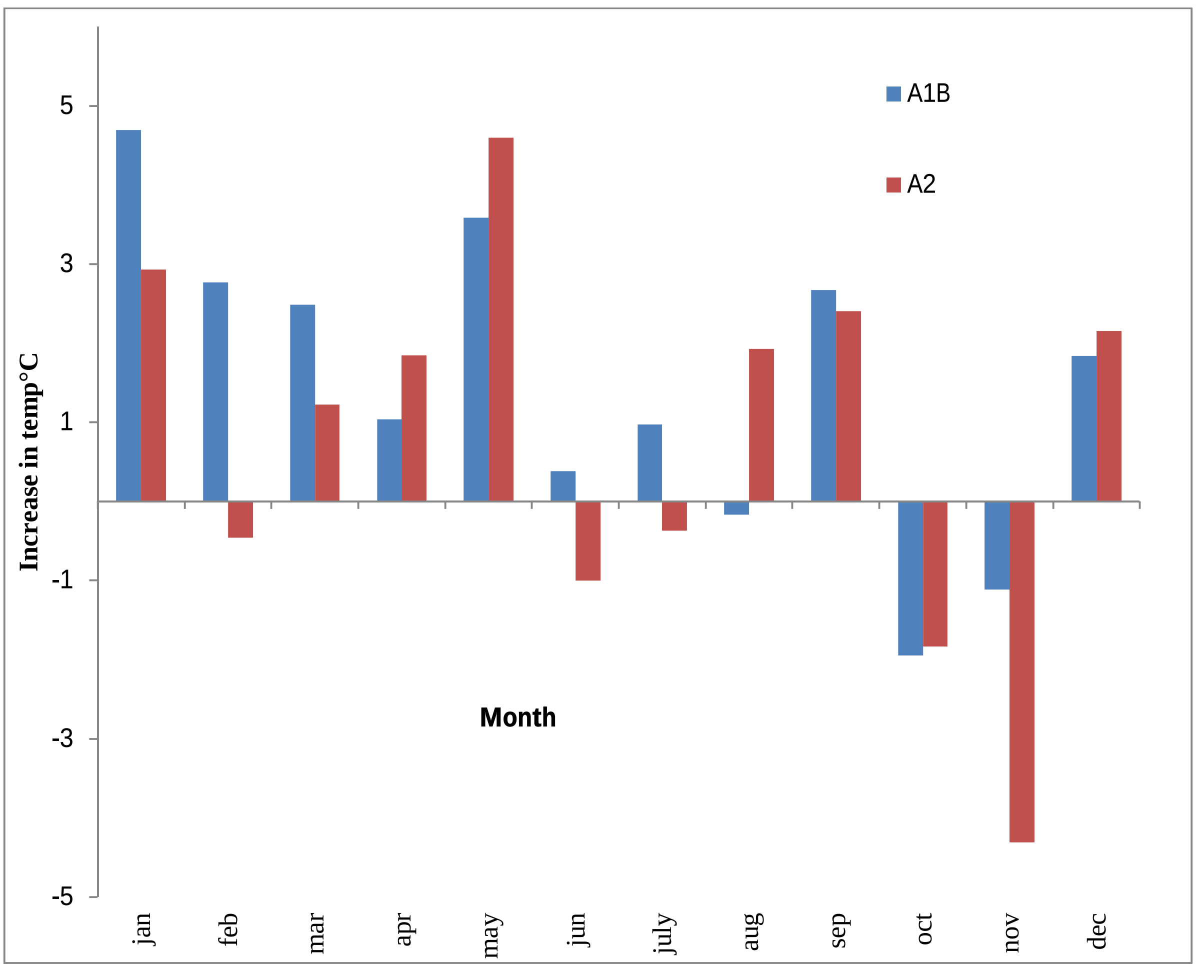

Fig.7 Change in the mean temperature of the Jhelum basin at the end of 21st century from 2001

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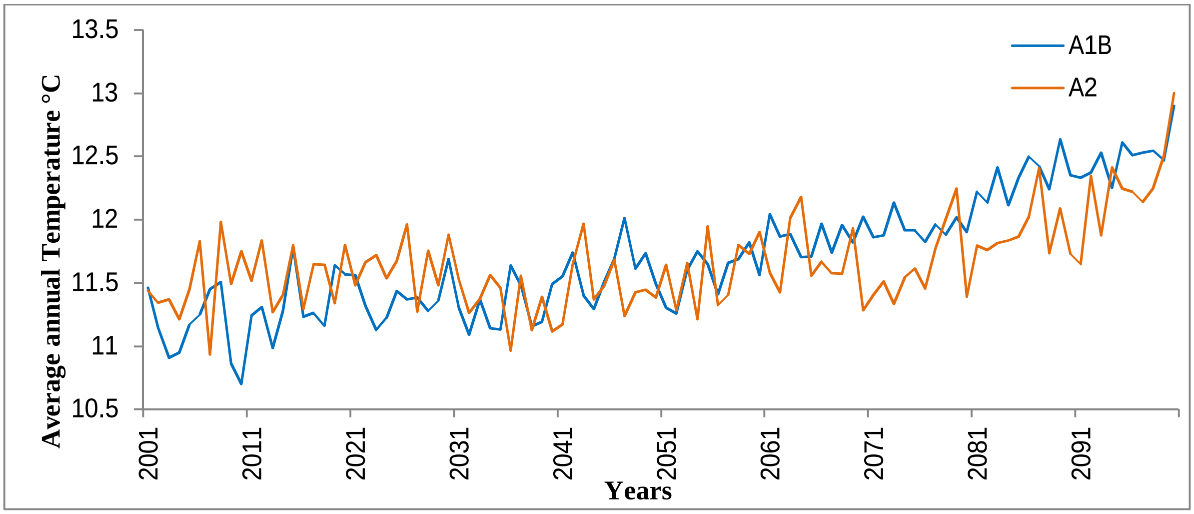

Fig. 8.Variation of ANN predicted average annual temperature of Jhelum river basin during 21st century

The downscaled monthly mean temperature shows an increasing trend in all months except for October and November for the period 2001–2100 for both A1B and A2.Also for the months of February, June and July temperature decreases for A2 scenario only. In general, the annual mean temperature shows an increasing trend in both A1B and A2 scenarios (Figure 8).The average annual temperature will increase by 1.43°C for A1B and 1.56°C for A2 scenario over 21st century in Jhelum river basin.

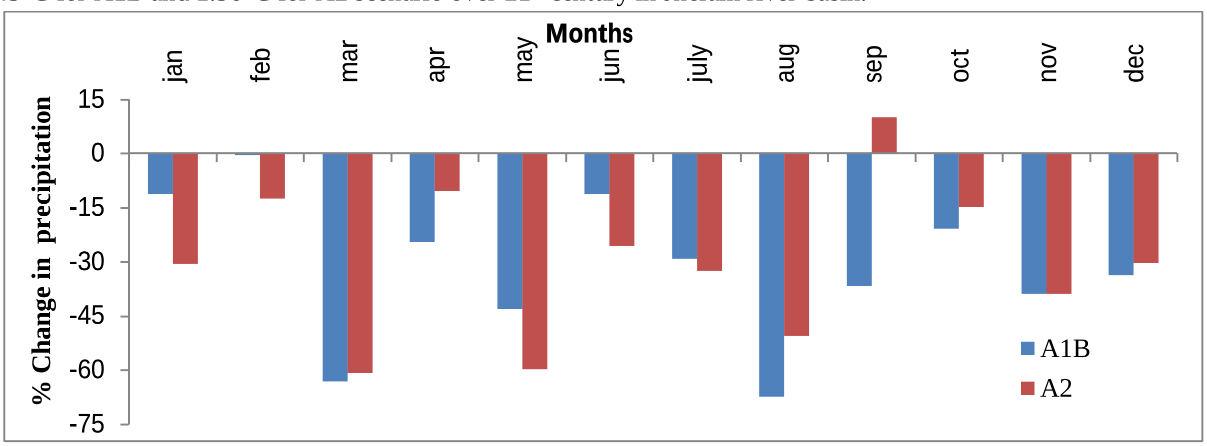

Fig.9 Change in the mean temperature of the Jhelum basin at the end of 21st century

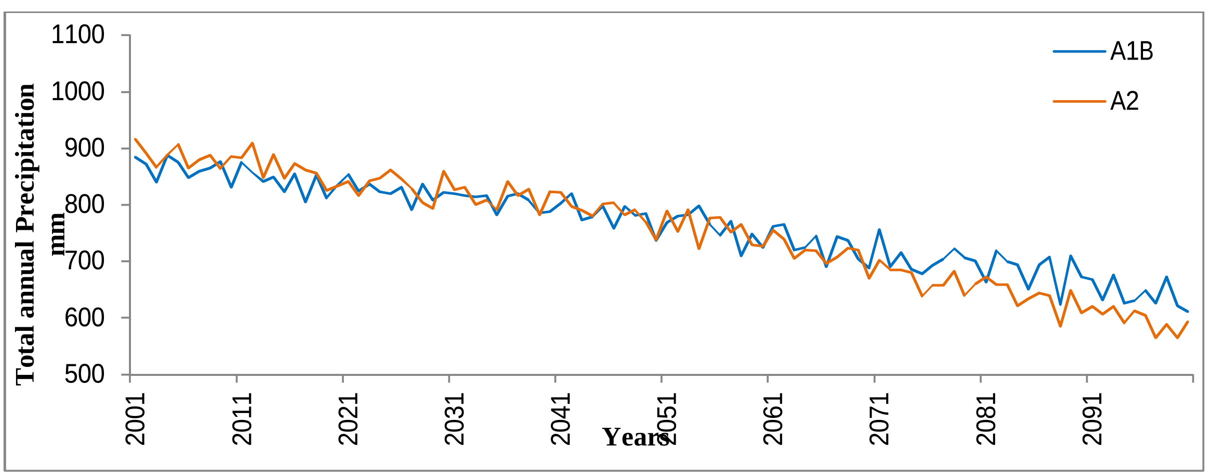

Fig. 10 Variation of MLR predicted total annual precipitation of Jhelum river basin during 21st century

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The rainfall amounts generally show a decreasing trend throughout the year with a pronounced decrease in the months of March, May and August for both A1B and A2 scenarios and a little increase for the month of September for the period 2001–2100 for the CGCM3 data for A2 scenario. The total annual precipitation will decrease by 30.88% and 35.32% respectively for A1B and A2 scenario over 21st century using CGCM3 model data (Figure 10).

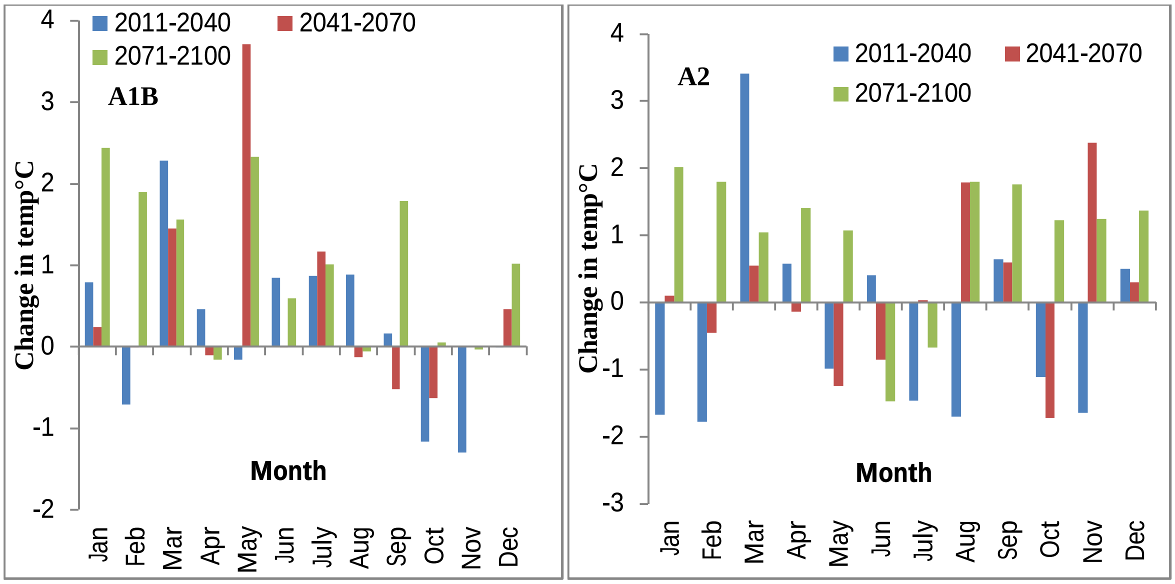

Fig.11. Change in the mean temperature over 21st century from 2010 for Jhelum river basin under A1B and A2 scenario using ANN

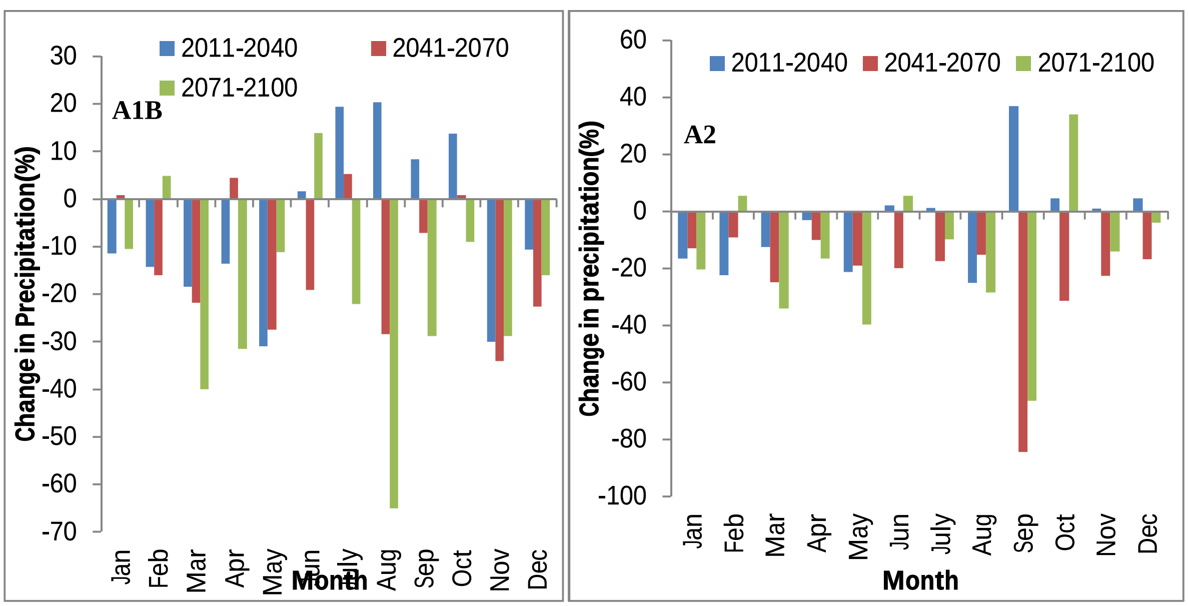

Fig.12. Percentage change in monthly precipitation over 21st century from 2010 for Jhelum river basin under A1B and A2 scenario using ANN

VI. CONCLUSIONS

The following conclusions were made after analyzing the results:

A. ANN model with tansig function in first layer and purelin in second layer gave better results than others; making apparent the fact that by increasing the number of hidden layers with more neurons in the layer with tan-sig transfer function showed superior results in projecting climate change compared to the neural network with single layer and more number of neurons with pure-lin transfer function.

B. The model results show that by increasing the number of hidden layers doesn't have significantly high effect on improving the predictability, while as by increasing the number of neurons in the hidden layer with tan-sig transfer function, the predictability could be increased significantly.

C. The downscaled monthly mean temperature using ANN technique showed an increasing trend in all months except for October and November for the period 2001–2100 for both A1B and A2. Also for the months of February, June and July temperature decreases for A2 scenario only.

D. The average annual temperature increased by 1.43°C for A1B and 1.56°C for A2 scenario over 21st century in Jhelum river basin, using ANN technique.

E. The rainfall amounts showed a decreasing trend throughout the year with a pronounced decrease in the months of March, May and August for both A1B and A2 scenarios and a little increase for the month of September for the period 2001–2100 for the CGCM3 data for A2 scenario.

F. The total annual precipitation decreased by 30.88% and 35.32% respectively for A1B and A2 scenario over 21st century using ANN technique for CGCM3 model data.

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