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ANN based climate modeling of Jhelum river basin

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ABSTRACT

Artificial neural network technique was used to carry out the downscaling of the GCM predictors. The large scale GCM predictors were related to observed precipitation and temperature. So the future projections of climate were made under A1B and A2 scenario upto 21st century using CGCM3 model. At the end of the 21st century the mean annual temperature of the Jhelum river basin is predicted to increase by 1.43°C under A1B scenario and 1.56°C under A2 scenario using ANN technique whereas the average annual precipitation is predicted to decrease substantially by 30.88% and 35.32% respectively under A1B and A2 Scenario by ANN technique.

Introduction

Climate is a key parameter in earth's environment. Climate is usually defined as the average weather and in broad sense; it is the statistical description in terms of mean and variability of relevant quantities over a period of time ranging from months to thousands or millions of years (IPCC, 2008) [7]. The 21st century will face many challenges and one of them is a changing climate. Climate change affects the economy, infrastructure, health, and wildlife. Hence climate change has become one of the most important issues in the world as natural calamities, global warming, and extreme events appear to increase in frequency day by day. The United Nations Framework Convention on Climate Change (UNFCC) [12], in its article 1, defines climate change as "a change of climate which is attributed directly to human activity that alters the composition of global atmosphere and which is in addition to natural climate variability observed over comparable time periods" (IPCC, 2008) [7]. Climate change is measured by the change of temperature, wind, precipitation, sea level and snow cover. According to the Fourth Assessment Report of Intergovernmental Panel on Climate Change (IPCC AR4,2007) [6] has reported with a very high confidence that the impacts of climate change on freshwater systems and their management are mainly due to the observed and projected increases in temperature, sea level and precipitation variability. Accordingly, global surface temperature has risen by 0.74°C during the twentieth century and the warming trend has accelerated in the last 50 years [7].

General Circulation Models (GCMs) are widely accepted as a tool for predicting future climate change. However, output from GCMs cannot be used for local prediction directly because GCMs operate in large scale. It is necessary to bring output from GCMs down to small scale for local prediction. Downscaling is a method to derive local climate information from relative GCM output.

Two downscaling approaches that are commonly used are statistical downscaling and dynamical downscaling. Statistical downscaling assumes that relationships between large scale and local climate are constant. It combines GCM output with local observations in order to obtain their statistical relationships. Local climate forecast can then be determined from such relationships. Dynamical downscaling involves nesting regional climate model into an existing global climate model. Numerical meteorological modeling is used in dynamical downscaling approach.

Various methods have been employed to derive relationships in statistical downscaling to forecast different climate information in different parts of the world. Such methods include canonical correlation analysis, multiple linear regressions, artificial neural networks and support vector machine. The rest of this section summarizes some previous studies on statistical downscaling methods.

Dibike et al. compared two downscaling models—temporal neural network (TNN) model and regression-based statistical model. Models were to predict daily precipitation, daily minimum temperature and daily maximum temperature in northern Quebec, Canada. Six combinations of 6-7 predictors were evaluated. Thirty years of data (1961-1990) were used to construct the models. Seasonal model biases were discussed. It was found that the TNN model was more efficient in downscaling both daily precipitation and daily maximum and minimum temperatures.

Wilby et al., (1998) reported the use of weather generator and ANN as transfer functions. The weather generator performed better while simulating spell-length events and their duration. The weather generator's result shows only a small difference between the observed and the simulated precipitation. ANN seemed to perform poorly because of its inability to simulate the dry-wet occurrences well. Its poor performance was attributed to the model's tendency to produce many "wet days".

Bazartseren *et al.,* (2003) 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.

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They found that the NN and the neuro-fuzzy system were both superior to the linear statistical models.

Jain and Srinivasulu, (2004) have tried to integrate ANN with conceptual models. A forward artificial neural network has been used in Tisseuil et al., (2010) that is flexible and can be applied to various models and climate situations. The ANN was trained using a back-propagation algorithm that consists of a three layer architecture: the input layer, hidden layer and the output layer. Each neuron of a layer is connected with every other neuron of the last layer by weights that are constantly adjusted in each successive iteration. The back propagation algorithm adjusts the weights according to the back propagation error calculated between the observed and the simulated.

Ojha, etal., (2010) used multiple linear regression (MLR) and artificial neural networks (ANN) models for downscaling of precipitation for lake catchment in arid region in India. The results of downscaling models show that precipitation is projected to increase in future for A2 and A1B scenarios, whereas it is least for B1 and COMMIT scenarios using predictors.

In the present study the artificial neural network technique was employed to relate the GCM predictors with the predictands such as the locally observed precipitation and temperature at four meteorological observatories namely Srinagar, Pahalgam, Qazigund, and Gulmarg of Jhelum river basin which is located in the state of Jammu and Kashmir, India. The predictors were obtained from Canadian third generation Climate model (CGCM3).

2. Study Area and Data

In this paper, the catchment of Jhelum River has been chosen. River Jhelum is a major tributary of river Chenab which itself is a tributary of river Indus .The study area comprises of the Jhelum basin located in the state of Jammu and Kashmir, India. The catchment of the Jhelum River lies between 33°25' N to 34°40' N latitude and 73°55' E to 75°35'E longitude. The total geographical area of Jhelum basin upto Indo-Pakistan border is about 17622 Sq.Kms with the main channel length of 165 Kms.The average elevation of Jhelum basin is about 1830 metres above mean sea level. River Jhelum rises from Verinag Spring situated at the foot of the Pir Panjal in the south-eastern part of the Kashmir valley in India. It flows through Srinagar city and the Wular lake before entering Pakistan. It ends in a confluence with the Chenab. It covers almost all the physiographic divisions of the Kashmir Valley and is drained by the most important tributaries of river Jhelum. 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. Fig.1 shows the catchment map of river Jhelum.

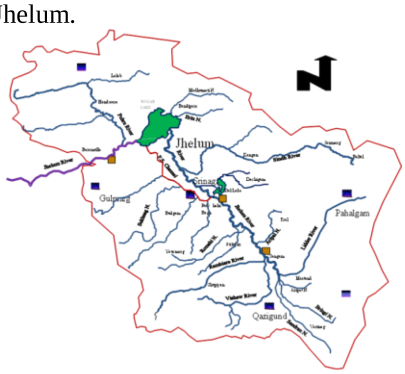

Figure 1. Catchment map of Jhelum river basin.

The monthly historical precipitation and temperature data for the study area were obtained from India Meteorological Department (IMD), Pune for four National Meteorological Observatory (NMO) stations namely Srinagar, Qazigund, Pahalgam, and Gulmarg for the period 1979 to 2013.

The predictor data of the GCMs ;mslpas (mean sea level pressure), tempas (mean temperature at 2m), humas (specific humidity at 2m),relative humidity(rhum), zonal velocity(u), meridional velocity(v) and 500 hPa geopotential height (p500) were obtained from Canadian third generation Climate Model (CGCM3) for A1B scenario for the grid location of 32°58'42" N to 35°08'02" N (latitude) and 73°23'32" E to 75°35'57" E (longitude). The above mentioned predictor data were downloaded for the period 1979 to 2100. For artificial neural network(ANN) technique the data set for the period 1979 - 2009 was used for calibration and that of 2010-2013 was used for validation purposes.

The average of the mean monthly precipitation and temperature recorded at the four meteorological stations were assumed to be the representative mean monthly precipitation and temperature of the Jhelum river basin. The ANN analysis was carried out to find the dependence relationship between temperature and precipitation and the appropriate GCM predictors

Table 1. List of large scale predictor variables from CGCM3.

S.No	Daily predictor variable description	code
1	Mean sea level pressure	mslpas
2	Mean temperature at 2m	tempas
3	Near surface specific humidity	shum
4	Near surface relative humidity	rhum
5	Zonal velocity component	u
6	Meridional velocity component	V
7	500 hPa geopotential height	p500

In this study, the third version of an Atmosphere General Circulation Model (AGCM) outputs from the CGCM3 were used for the generation of future climate scenarios. The Third Generation Coupled Global Climate Model (CGCM3) is a product of the Canadian Centre for Climate Modelling and Analysis. It updates the earlier Second Generation Coupled Global Climate Model with a new atmospheric component, the oceanic component remaining unchanged. It has been run at two resolutions, the T47 version with a 3.75 degree grid cell size for atmospheric horizontal resolution and 1.85 degree resolution for the oceanic component, and the T63 version has a 2.8 degree atmospheric resolution subdivided into 6 oceanic grid cells.

3. Methodology

3.1 Neural network (NN)

The ANNs can be defined as an interconnected network of many simple processing units called neurons and analogous to the biological neurons in the human brain. It is capable of identifying complex linear and non-linear relationships between input and output data sets without understanding the actual phenomena/study[9]. Neurons which have similar characteristics in an ANNs are arranged in groups called layers. The neurons in one layer are connected to those in the adjacent layers, but not to those in the same layer. The strength of connection between the two neurons in adjacent layers is named as “weight”. Normal ANNs consist of three layers, which are input, hidden and output layer. In this study, ANN architecture of MLP (multilayer perceptron) neural network model is used.

This type of ANN model is used because it is widely used in the field of hydrology particularly in climate change studies and runoff analysis [9]. The MLP network used is two-layer feed forward network trained with back propagation learning algorithm. The transfer function used in hidden layer is tan-sigmoid (tansig) and linear transfer function (purelin) at the output layer. The neurons in each layer are connected to the neurons in the subsequent layer by a weight, which were adjusted during training. Fig.2 illustrates the MLP network architecture. Detail of MLP network has been discussed by Demuth and Beale [3] and Kuok [9].

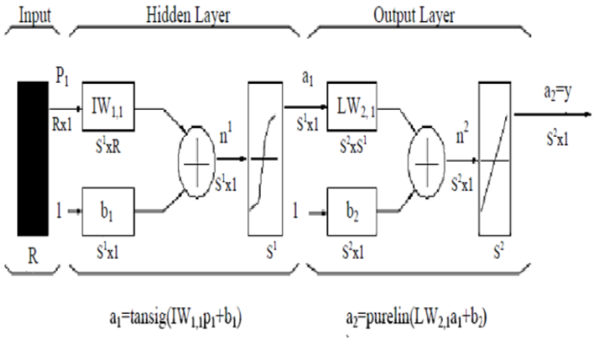

Figure 2. MLP network architecture[3].

In this paper, two observed data have been used for ANN model, which are rainfall and temperature. Performance of ANN model is measured using coefficient of determination (R^2), root mean square error coefficient (RMSE) and mean absolute deviation:

4. Result and Discussion

After a satisfactory calibration is obtained, the ANN model is validated using data outside the period for which the model is calibrated. The obtained results are shown in Figures 3 and 4.

The non-linear model used in this study is the multi-layer feed forward NN. NNs are able to perform non-linear mapping between input and target values. Training is accomplished by presenting a set of input-output pairs of vector values to the NN and subsequently modifying the internal parameters of the network until the output generated is close to observed values (Zhang & Govindaraju 2000) [14]. A two layer feed-forward NN can approximate arbitrarily well any continuous non-linear function given a set of inputs and a sufficient number of hidden neurons (Hornik et al. 1989) [4]. The two-layer NN used in this work includes one hidden layer containing nine neurons and one output layer with one neuron. The transfer function associated to the neurons in the hidden layer was a hyperbolic tangent sigmoid transfers function. To the output neuron, it was associated a linear transfer function. All NN were trained using gradient descent backpropagation.

To define the optimum moment for stopping the training procedure, early stopping was used. The early stopping technique prevents the NN to over-fit by stopping the training if the network performance on a test vector (a reserved part of the training subset) fails to improve (Demuth & Beale 1994) [3]. To avoid instabilities, as suggested by Hsieh & Tang (1998) [5] among others, an ensemble of nine runs was generated, each one starting from different initial conditions. The ensemble average was considered as the final output of the NN. All NN tests were performed using Matlab.

Prediction accuracy of temperature was higher than that of rainfall for both A1B and A2 scenario. Fig.3. shows the validation of temperature model and Fig.4.shows the validation of precipitation model over the period 2010 to 2013.

From Fig.3. it is clear that the observed and predicted values of temperature varied in the same direction throughout the validation period. Furthermore, the future mean monthly temperatures of the Jhelum basin for the period 2001-2100 were predicted by ANN model and are shown in Fig.5.1 to Fig. 5.12. It was observed that the mean monthly temperature over the 21st century based on ANN predictions, depict an increasing trend except for the months of October and November. The variation of average annual temperature for Jhelum river basin was also determined using ANN model and is shown in Fig.7. The average annual temperature also shows an increasing trend and by the end of 21st century it is predicted to increase by 1.43°C and 1.56°C for A1B and A2 scenario respectively.

Similarly, the future mean monthly precipitation of the Jhelum basin for the period 2001-2100 were predicted by ANN model and are shown in Fig.8.1 to Fig.8.12. It was observed that the mean monthly precipitation of Jhelum basin is expected to decrease continuously over the 21st century. This decrease in monthly total precipitation is more pronounced for the months of January, March, and May. The total annual precipitation of Jhelum basin during the period 2001-2100 was also predicted using ANN model. Fig.10 represents the variation of this annual precipitation over a 100 year period of 2001-2100 and shows that annual precipitation is expected to decrease by 30.88% and 35.32% respectively under A1B and A2 scenario by ANN technique.

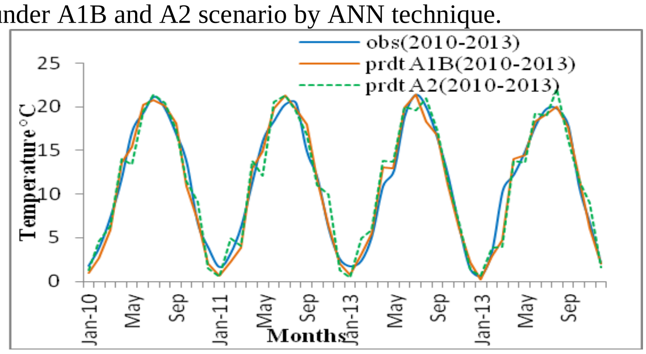

Figure 3.Validation of mean monthly temperature of Jhelum river basin for the period 2010-2013 using ANN.

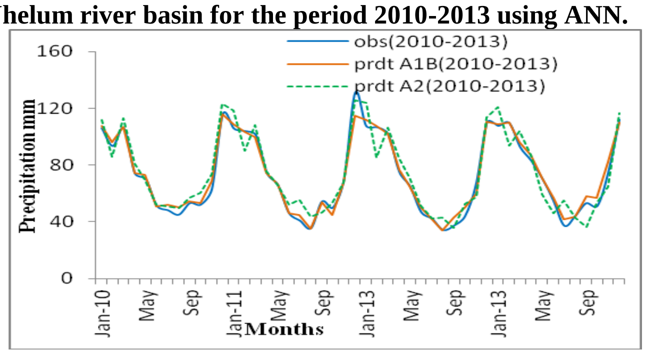

Figure 4.Validation of monthly total precipitation of Jhelum river basin for the period 2010-2013 using ANN.

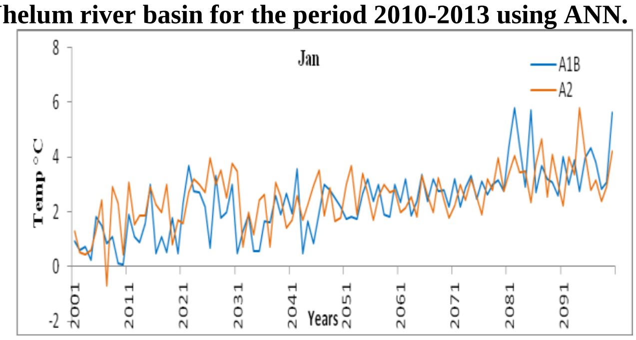

Figure 5.1.Variation of mean monthly temperature of Jhelum river basin for January during 2001-2100.

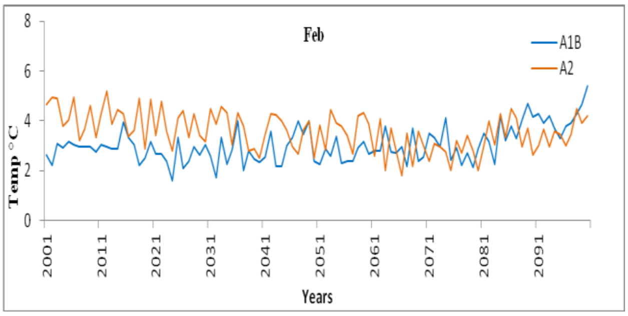

Figure 5.2. Variation of mean monthly temperature of Jhelum river basin for February during 2001-2100.

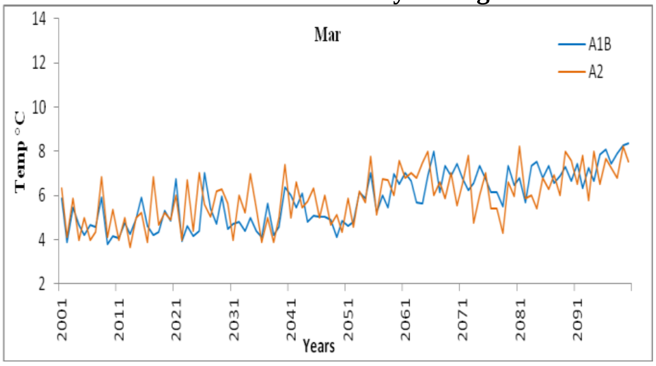

Figure 5.3 Variation of mean monthly temperature of Jhelum river basin for March during 2001-2100.

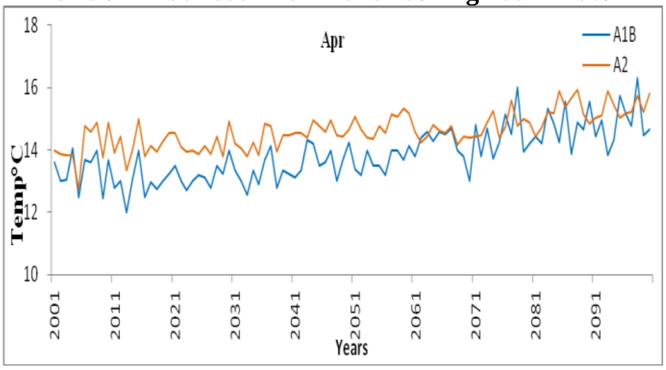

Figure 5.4. Variation of mean monthly temperature of Jhelum river basin for April during 2001-2100.

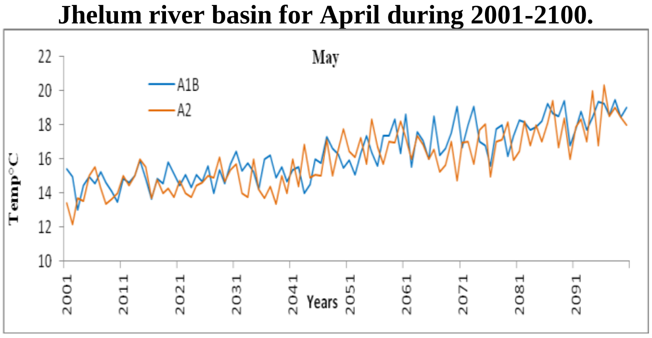

Figure 5.5.Variation of mean monthly temperature of Jhelum river basin for May during 2001-2100.

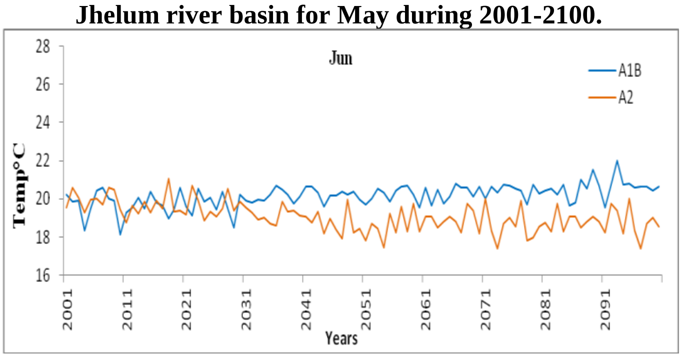

Figure 5.6.Variation of mean monthly temperature of Jhelum river basin for June during 2001-2100.

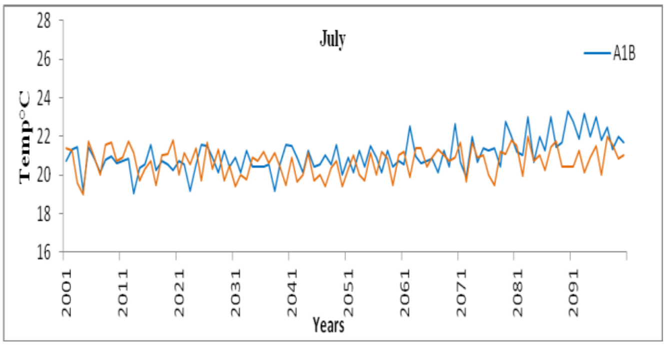

Figure 5.7.Variation of mean monthly temperature of Jhelum river basin for July during 2001-2100.

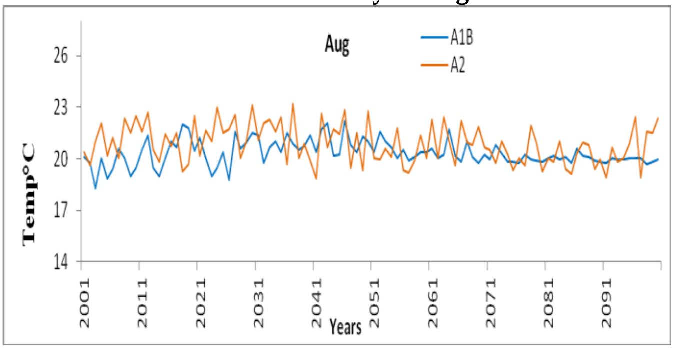

Figure 5.8. Variation of mean monthly temperature of Jhelum river basin for August during 2001-2100

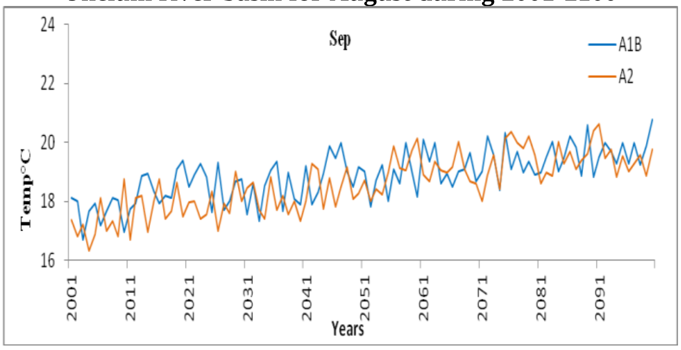

Figure 5.9.Variation of mean monthly temperature of Jhelum river basin for September during 2001-2100 .

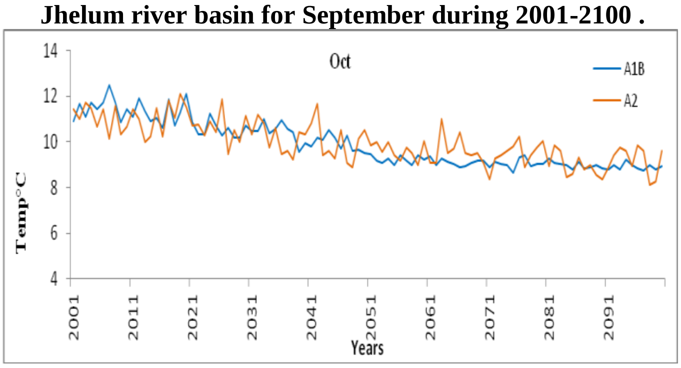

Figure 5.10.Variation of mean monthly temperature of Jhelum river basin for October during 2001-2100 .

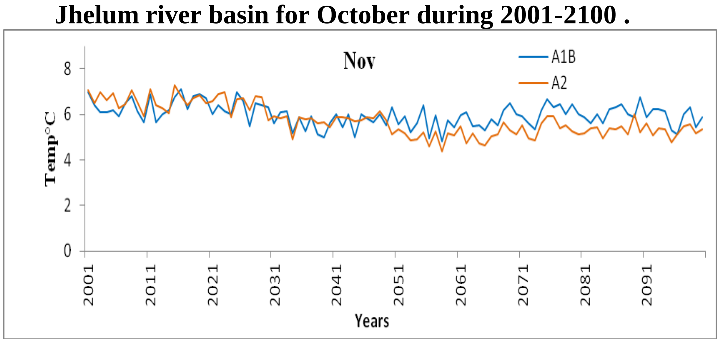

Figure 5.11.Variation of mean monthly temperature of Jhelum river basin for November during 2001-2100 .

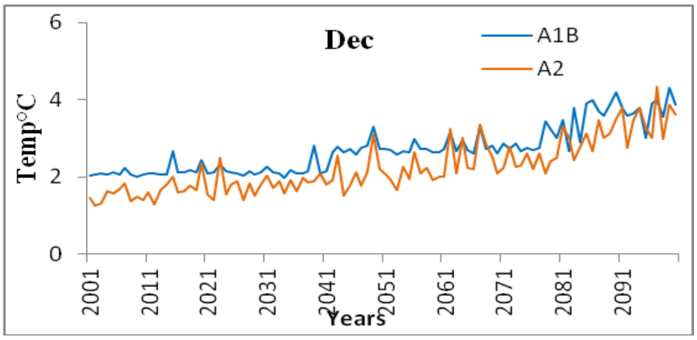

Figure 5.12 Variation of mean monthly temperature of Jhelum river basin for January during 2001-2100.

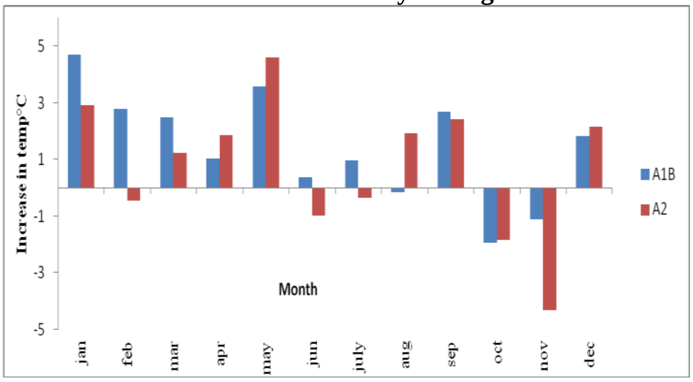

Fig.6.Change in the mean temperature of the Jhelum basin at the end of 21st century from 2001

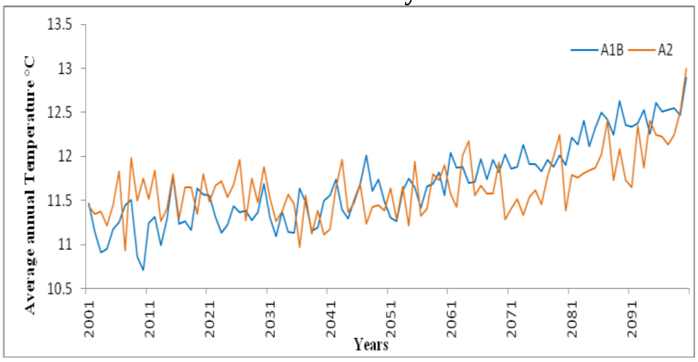

Fig.7.Variation of ANN predicted average annual temperature of Jhelum river basin during 21st century.

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 7).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.

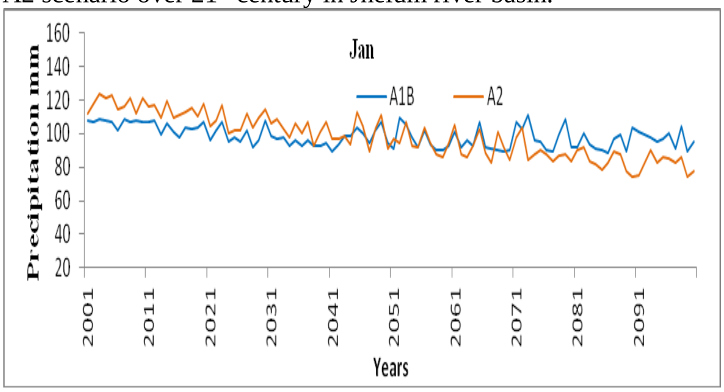

Figure 8.1 Variation of mean monthly precipitation of Jhelum river basin for January during 2001-2100.

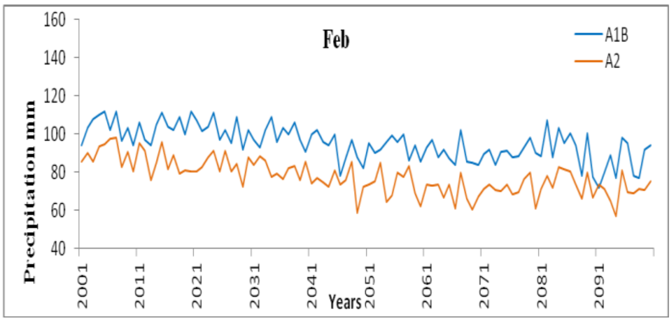

Figure 8.2 .Variation of mean monthly precipitation of Jhelum river basin for February during 2001-2100.

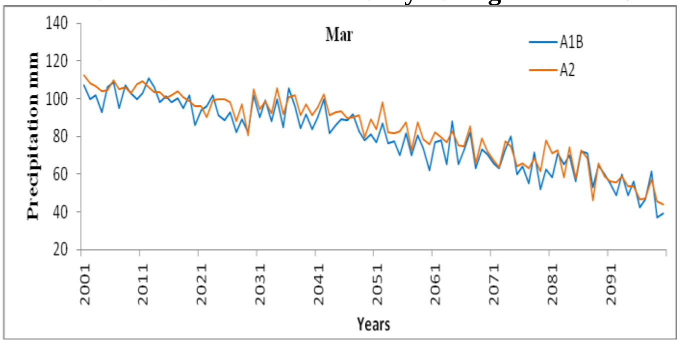

Figure8.3.Variation of mean monthly precipitation of Jhelum river basin for March during 2001-2100.

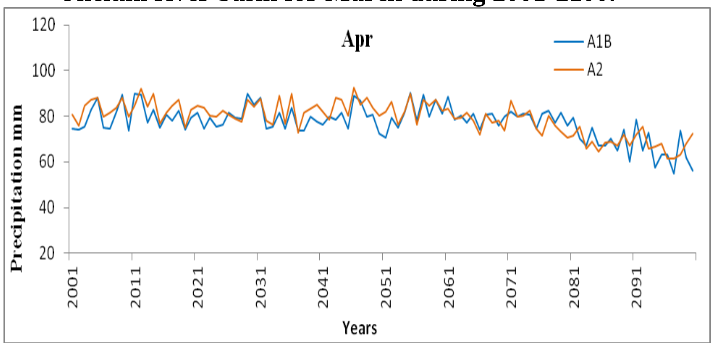

Figure 8.4. Variation of mean monthly precipitation of Jhelum river basin for April during 2001-2100.

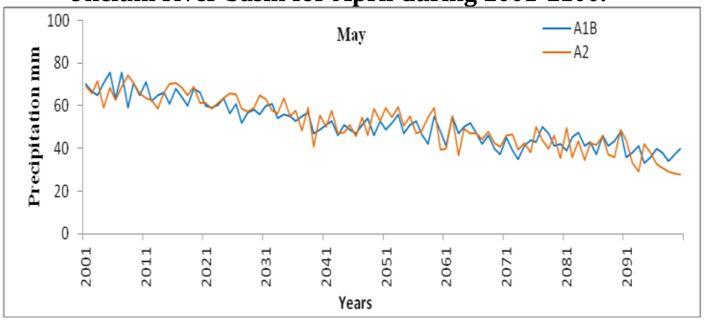

Figure 8.5. Variation of mean monthly precipitation of Jhelum river basin for May during 2001-2100.

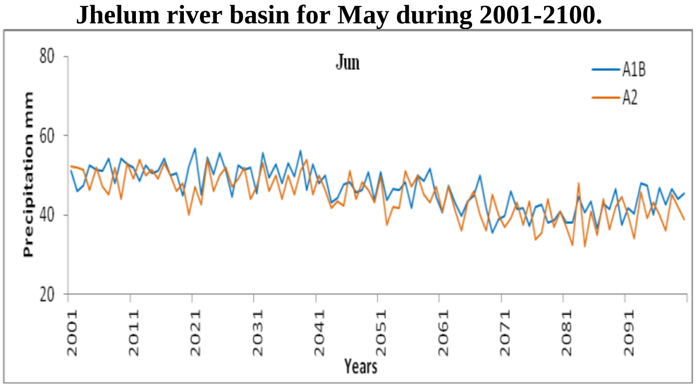

Figure 8.6.Variation of mean monthly precipitation of Jhelum river basin for June during 2001-2100.

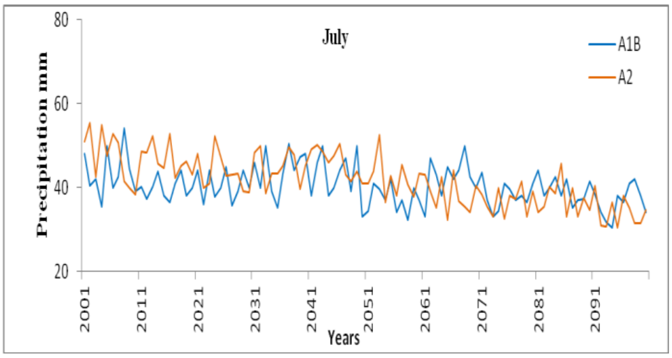

Figure 8.7. Variation of mean monthly precipitation of Jhelum river basin for July during 2001-2100

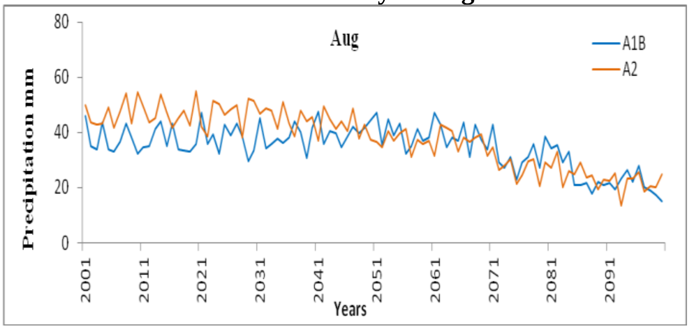

Figure 8.8.Variation of mean monthly precipitation of Jhelum river basin for August during 2001-2100

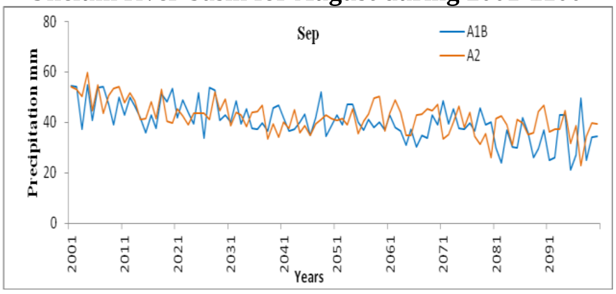

Figure 8.9.Variation of mean monthly precipitation of Jhelum river basin for September during 2001-2100

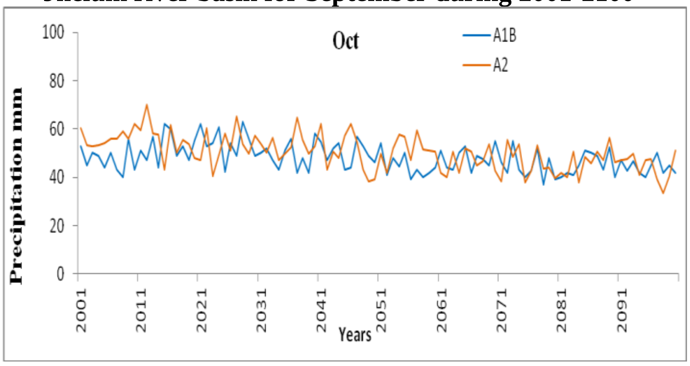

Figure 8.10.Variation of mean monthly precipitation of Jhelum river basin for October during 2001-2100

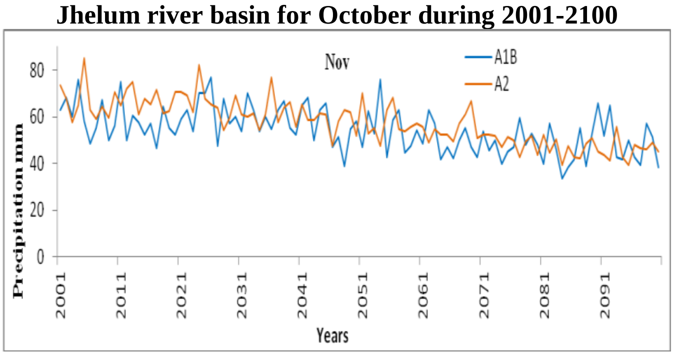

Figure 8.11. Variation of mean monthly precipitation of Jhelum river basin for November during 2001-2100

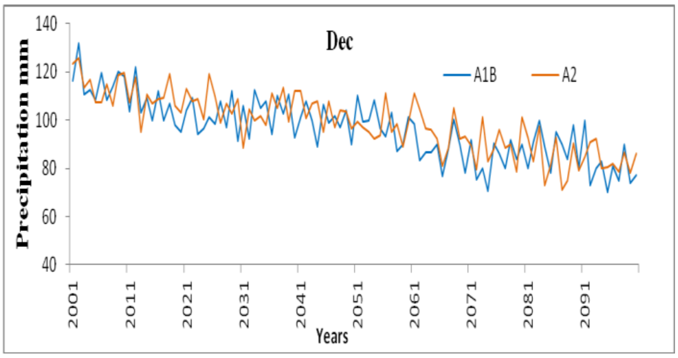

Figure 8.12.Variation of mean monthly precipitation of Jhelum river basin for December during 2001-2100

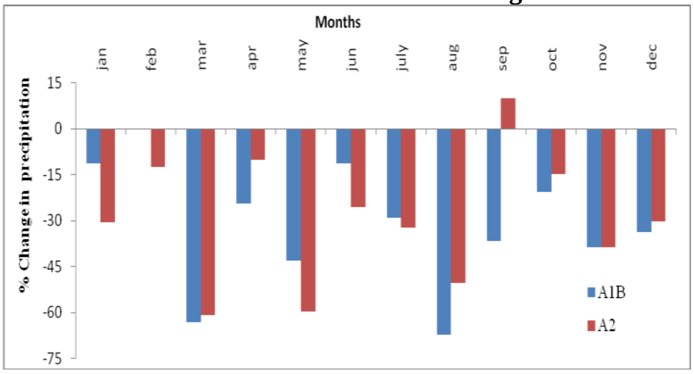

Figure 9. Change in the total precipitation of the Jhelum basin at the end of 21st century

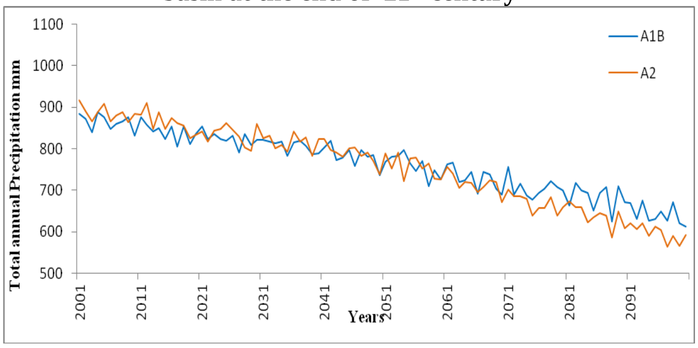

Figure. 10.Variation of MLR predicted total annual precipitation of Jhelum river basin during 21st century.

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).

Table 2.1. Statistical parameters of ANN validation for temperature using CGCM3 model for A1B scenari.

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

Table 2.2. 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

Table 2.1 and 2.2 shows the regression statistics values of mean square error(MSE), root mean square error(RMSE) and mean absolute deviation (MAD) of ANN model for validation period of 2009-2013 for temperature. 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.

Table 3.1. 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

Table 3.2. 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

Table 3.1 and 3.2 shows the regression statistics values of mean square error(MSE), root mean square error(RMSE) and mean absolute deviation (MAD) of ANN model for validation period of 2009-2013 for precipitation. 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.

5.Conclusion

Based on the results the following main conclusions can be drawn:

1) 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.

2)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.

3) 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.

4) 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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