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Impact of Climate Change on Jhelum River Basin

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ABSTRACT

Mean temperature and precipitation are sensitive indicators of climate change. The present study examines the effect of climate change on temperature and precipitation regimes of Jhelum river basin using the predictor data of the global climate models (GCMs) and the local historical weather data. Multiple linear regression technique was used to carry out the downscaling of the GCM predictors. At the end of the 21st century the mean annual temperature of the Jhelum river basin is predicted to increase by 2.37°C, whereas the average annual precipitation is predicted to decrease substantially by 38.56%.

Introduction

Climate change is a change in the statistical distribution of weather patterns when that change lasts for an extended period of time (i.e., decades to millions of years). It refers to any change in climate over time, whether due to natural variability or as a result of human activity [1]. Global surface temperature has risen by 0.74°C during the twentieth century and the warming trend has accelerated in the last 50 years [1]. The past two decades were the warmest [2]. The discussions are more or less supported by the outputs from Global Climate Models (GCMs) under different emission scenarios that are usually used in impact assessments. The GCMs are mathematical models which have been developed to simulate the present climate and implemented to predict future climatic change under various Green House Gas (GHG) concentrations. These models are also regarded as principal tools for accounting the complex set of processes which will produce future climate change. Based on the simulation results of GCMs there is evidence that anthropogenic emissions of GHGs have altered the large scale patterns of temperature over the twentieth century. Among other outputs from GCMs, precipitation and temperature data are the most frequently used variables to force impact models (e.g., hydrological models). Beside this, both precipitation and temperature are the most dynamic atmospheric characteristics affected by the GHG emissions. For instance, the Fourth Assessment Report of Intergovernmental Panel on Climate Change (IPCC AR4) 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 mean surface temperatures have reported to be increased by0.74°C±0.18°C over the last 100 years (1906-2005) and recently the year 2010 is reported as one of the top three warmest years since 1850 and and rainfall has decreased over much of the Northern hemisphere sub-tropical regions by about 0.3% per Decade during the 20th century [1]. While temperature is predicted to increase everywhere over land and during all seasons of the year with different increments, precipitation is expected to increase in some river basins, but to decrease in the others. GCMs perform reasonably well in simulating climatic variables at larger spatial scale of (3.75°lat. × 3.75°long.). GCMs thus demonstrate significant skill at the continental and hemispheric spatial scales, and incorporate a large proportion of the complexity of the global system, they are inherently unable to represent local sub grid scale features and dynamics [3] and [4]. This mismatch in system representation is due to the difference in resolution and referred to as the scale issues. The conflict between GCM performance at regional spatial scales and the needs of regional scale impact assessment is largely related to model resolution in such a way that the GCM accuracy decreases at increasingly finer spatial scales and that the needs of impact researchers conversely increase with higher resolution. As a means of bridging this gap, downscaling is commonly used to assess the impact of climate change on water resources at basin scale. The basic assumption of downscaling is that the large scale atmospheric characteristics highly influence the local scale weather, but that in general the reverse effects from local scales upon global scales are negligible and thus can be disregarded.

Downscaling is the general name for a procedure to take information known at large scales to make prediction at local scales. It can be achieved in two ways such as statistical downscaling and dynamic downscaling.

Statistical downscaling is a two-step process consisting of (a) the development of statistical relationships between local climate variables (e.g., surface air temperature and precipitation) and large-scale predictors (e.g., pressure fields), and (b) the application of such relationships to the output of Global climate model (GCM) experiments to simulate local climate characteristics in the future. Dynamic downscaling involves the nesting of a higher resolution regional climate model (RCM) within a coarser resolution GCM.

The dynamic downscaling is performed by Regional Climate Models (RCMs) or Limited Area Models (LAMs) at 0.5°×0.5° or even higher Resolutions that parameterizes the atmospheric processes. The noteworthy limitations of dynamic downscaling, which restricts its use in climate change impact studies, is its complicated design and being computationally as

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demanding as GCMs. RCMs are also inflexible in the sense that expanding the region or moving to a slightly different region requires redoing the entire experiment. Various studies have been carried out to derive predictor-preictand relationship.

Kazmi,etal.(2014) employed Statistical Downscaling Model (SDSM) for downscaling of daily minimum and maximum temperature data of 44 national stations of Pakistan region for base time (1961–1990) and then the future scenarios generated up to 2099 [5]. Generally, the southern half of the country is considered vulnerable in terms of increasing temperatures, but the results of this study projects that in future, the northern belt in particular would have a possible threat of increasing tendency in air temperature.

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 [6]. 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.

Haylock,et al.(2006) used six statistical and two dynamical downscaling models for downscaling heavy precipitation over the united kingdom [7]. Models based on non-linear artificial neural networks (ANNs) were found to be the best at modeling the inter-annual variability of the indices; however, their strong negative biases implied a tendency to underestimate extremes.

In the present study the multiple linear regression 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 as obtained from Canadian third generation Climate model (CGCM3) 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).

Multiple Linear Regression (MLR)

Multiple regression has three primary uses :(a) Understanding which input variables have the greatest effect on the output. (b) Knowing the direction of the effect of the input variables on output variable (c) Using the model to predict future values of the output variable when only the input variables are known.

Multiple linear regression model of the general form represented by “Eq. (1)” was used in the data analysis for the present study.

$$y = a_0 + a_i x_i + \varepsilon \qquad (1)$$

Where, y is the dependent (or response, output) variable, x_i is independent (or predictor, input) variable and $\mathcal{E}$ is the error term

The intercept a_0 and the regression coefficients a_i were obtained using Minitab software.

Statistical Downscaling

Statistical downscaling methodologies can be broadly classified into three categories [8] : weather generators, weather typing and transfer function.

Weather generators are statistical models of observed sequences of weather variables that replicate the statistical attributes of a local climate variable (such as the mean and variance) but not the observed sequence of events There are two basic types of daily weather generators, based on the approach to model daily precipitation occurrence: the Markov chain approach and the spell-length approach [9]. Weather typing approaches involve grouping of local, meteorological variables in relation to prevailing patterns of atmospheric circulation [10]. Future regional or local climate scenarios are constructed either by resampling from the observed data (variable) distribution (conditioned on the circulation pattern produced by a GCM), or by first generating synthetic sequences of weather pattern and then resampling from the generated data. The mean or frequency distribution of the local climate is then derived by weighing the local climate states with the relative frequencies of the weather groups or classes.

Transfer-function [3] downscaling methods rely on empirical relationships between local scale climate variables (predictands) and the variables containing the large scale climate information in the form of GCM outputs (predictors). Individual downscaling schemes differ according to the choice of mathematical transfer function, predictor variables or statistical fitting procedure. To date, linear and nonlinear regression, Artificial Neural network (ANN), canonical correlation, etc. have been used to derive predictor–predictand relationship.

The statistical downscaling techniques involve developing quantitative relationships between large scale atmospheric variables (the predictors) and local surface variables (the predictands). Thus, in this method, the predictand predictor relationship can be given by “Eq. (2)”

$$R=F(X) \qquad (2)$$

Where R is predict and (local climate variable that is being downscaled), X stands for predictor (i.e., set of large scale climate variables) and F represents a deterministic or stochastic function that relates the two. The F function is typically established by training and validating historical ground observation or reanalysis of the data. Thus, the success of the downscaling method is dependent on the relationship used and choice of predictor variables, whose performance can be evaluated through quantification of error in mean and explained variances. Moreover, the predictability and skill of downscaling is reported to vary seasonally, regionally and between different periods of record, as well as the variable considered. Common to both statistical and dynamical downscaling methods, The key assumptions of these methods include (1) the predictands are functions of synoptic forcing and the predictors are variables of relevance that are realistically modeled by the GCM (2) the transfer function remains valid under changing climate conditions ; and (3) the predictors fully represent the climate change signal.

In the present study, the GCM predictors of tempas, rhum, u and v were used as dependent variables for temperature and those of mslpas, tempas, u and humas for precipitation. The choice of selection of same predictor variables for temperature and precipitation has also been reported in [11] and [12].

Study Area

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 mountains 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 location map of Kashmir Valley whereas Fig.2 shows the catchment map of Jhelum river basin.

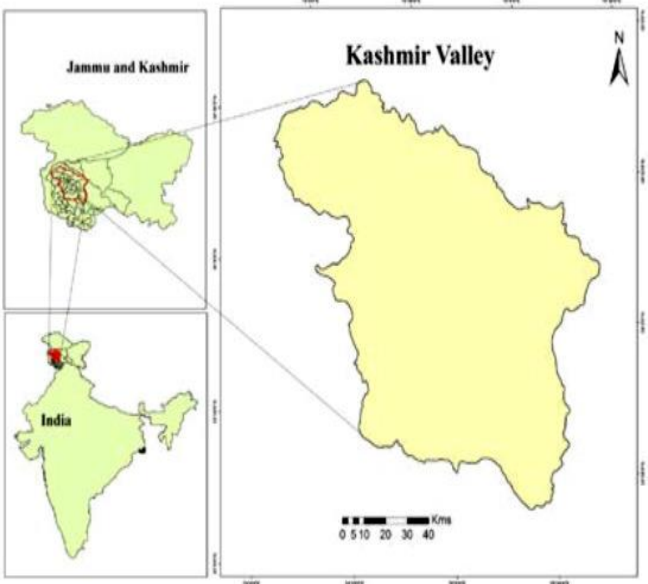

Figure 1. Location map of study area

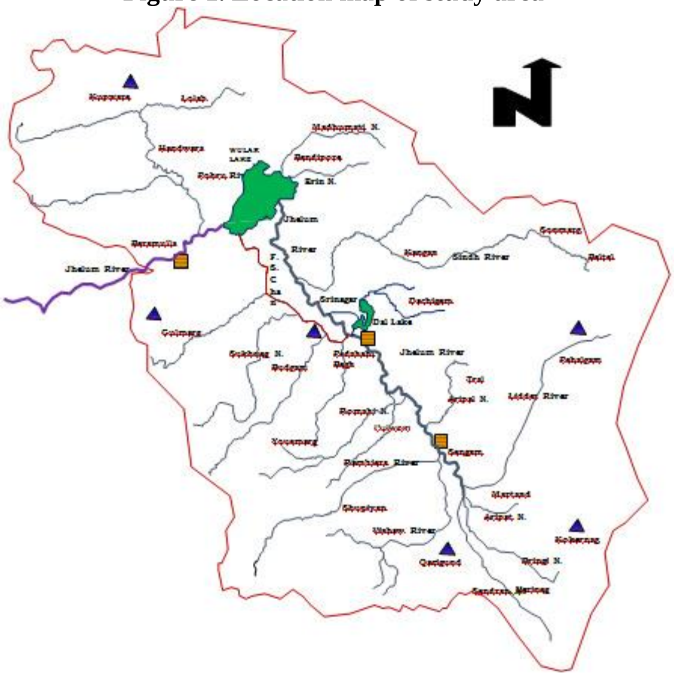

Figure 2. Catchment map of Jhelum river basin

Data Analysis

Monthly precipitation and temperature data (1970– 2004) for four National Meteorological Observatory (NMO) stations namely Srinagar, Qazigund, Pahalgam, and Gulmarg for the period 1970 to 2004 were obtained from India Meteorological Department (IMD), Pune.

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) 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 downscaled using MLR technique. For multiple linear regression (MLR) analysis the data set for the period 1970 -2000 was used for calibration and that of 2001-2004 was used for validation purposes.

The average of the mean monthly temperature and monthly precipitation totals recorded at the four meteorological stations were assumed to represent the basin wide averages. The MLR analysis was carried out to find the dependence relationship between temperature and precipitation and the appropriate GCM predictors.

Results and Discussions

The MLR model was applied on the spatially averaged mean monthly temperature and monthly rainfall of Jhelum river basin. The historical precipitation data for the period 1970 to 2000 was used for calibrating the regression model, whereas the data for the period 2001-2004 was used for validating the model. The regression statistics for temperature and precipitation are given in table 1. Prediction accuracy of temperature was higher than that of rainfall for A1B scenario. Fig.3 shows the validation of temperature model and Fig.4 shows the validation of precipitation model over the period 2001 to 2004.

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 MLR 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 MLR 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 MLR model and is shown in Fig.6. The average annual temperature also shows an increasing trend and by the end of 21st century it is predicted to increase by 2.37°C.

Similarly, the future mean monthly precipitation of the Jhelum basin for the period 2001-2100 were predicted by MLR model and are shown in Fig.7.1 to Fig.7.12. 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 MLR model. Fig.8 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 about 38.56% by the end of 21st century.

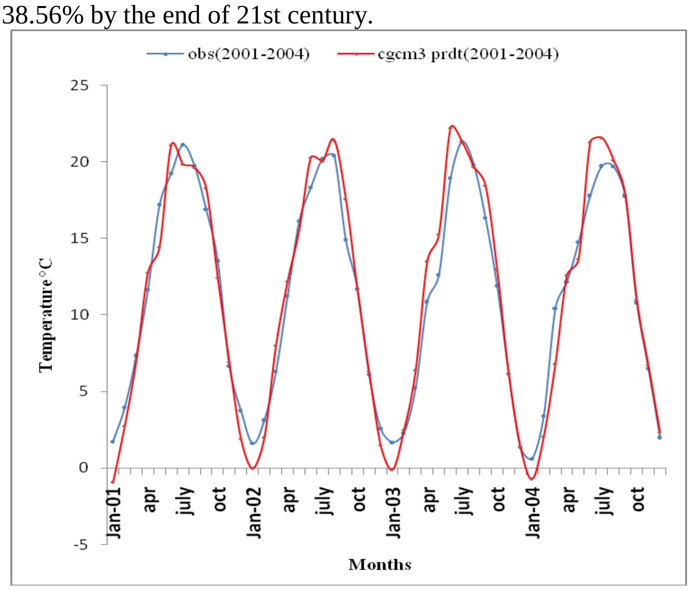

Figure 3. Validation of mean monthly temperature of Jhelum river basin for the period 2001-2004 using MLR

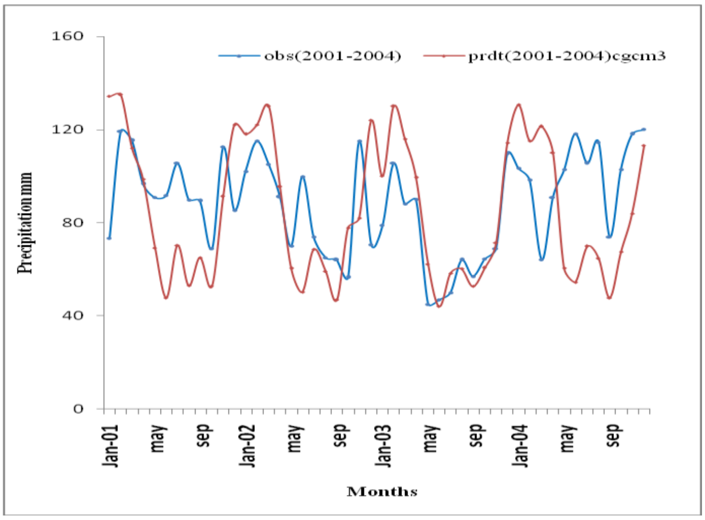

Figure 4. Validation of monthly total precipitation of Jhelum river basin for the period 2001-2004 using MLR

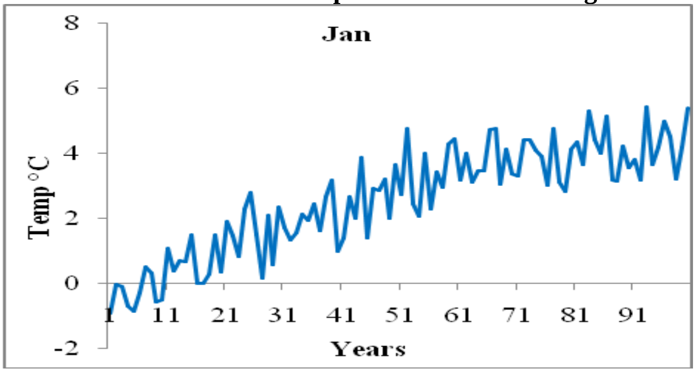

Figure 5.Variation of mean monthly temperature of Jhelum river basin for January during 2001-2100

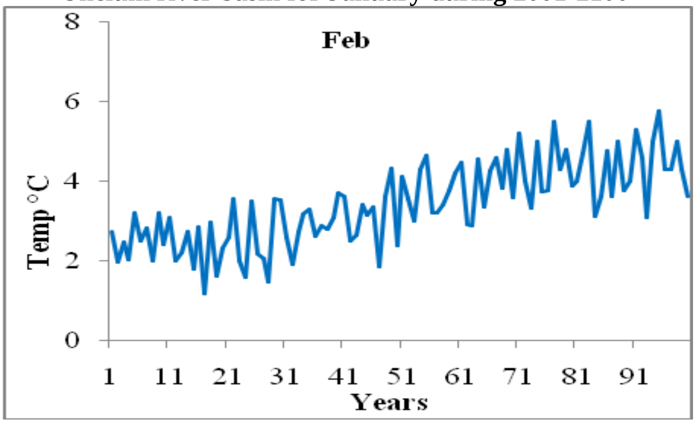

Figure 6. Variation of mean monthly temperature of Jhelum river basin for February during 2001-2100

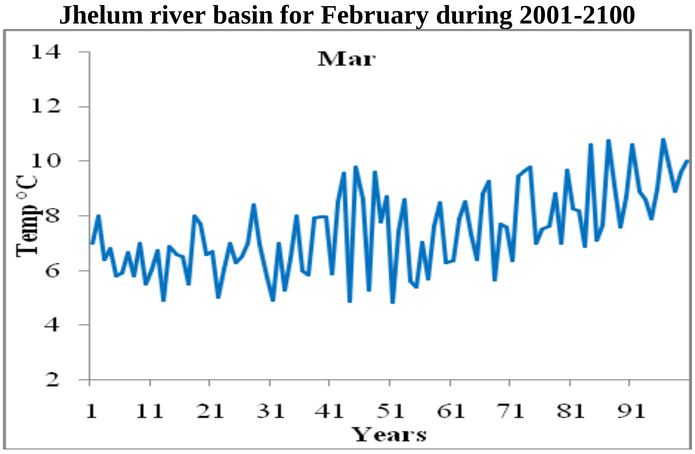

Figure 7. Variation of mean monthly temperature of Jhelum river basin for March during 2001-2100

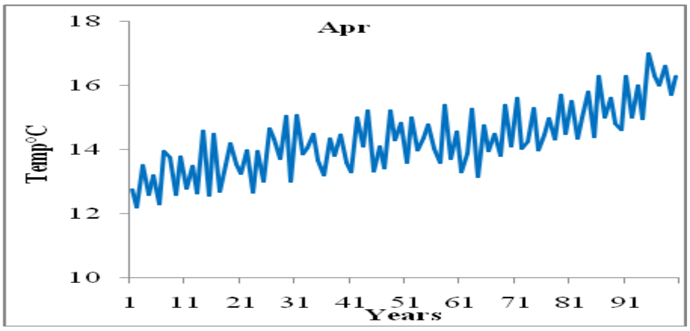

Figure 8. Variation of mean monthly temperature of Jhelum river basin for April during 2001-2100

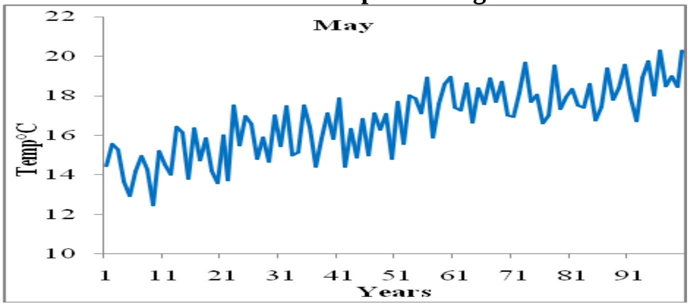

Figure 9.Variation of mean monthly temperature of Jhelum river basin for May during 2001-2100

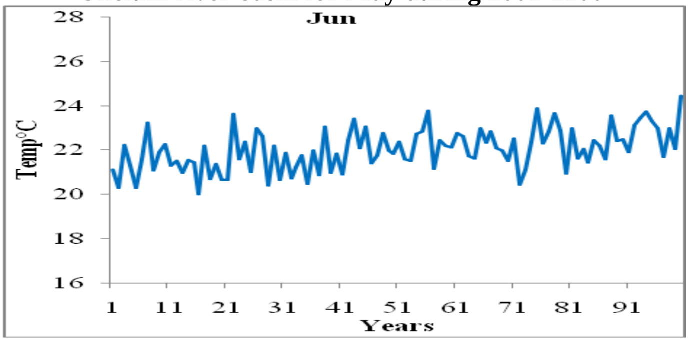

Figure 10.Variation of mean monthly temperature of Jhelum river basin for June during 2001-2100

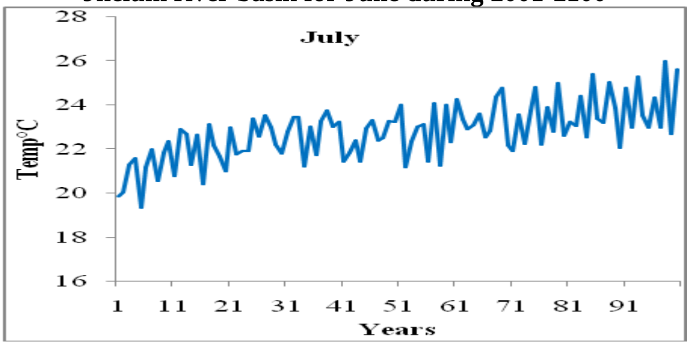

Figure 11.Variation of mean monthly temperature of Jhelum river basin for July during 2001-2100

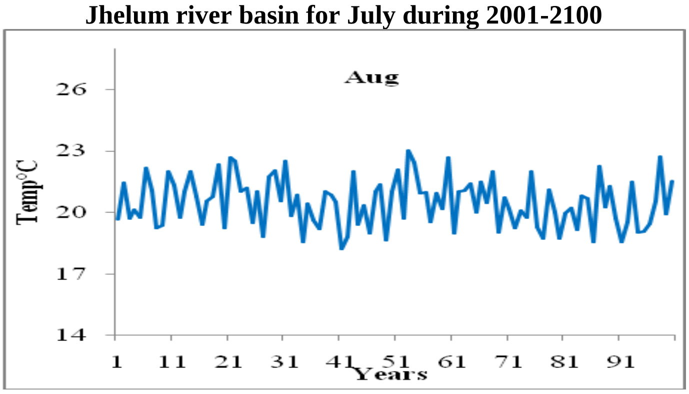

Figure 12. Variation of mean monthly temperature of Jhelum river basin for August during 2001-2100

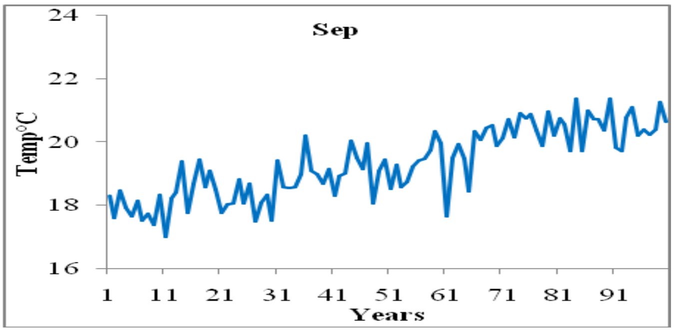

Figure 13.Variation of mean monthly temperature of Jhelum river basin for September during 2001-2100

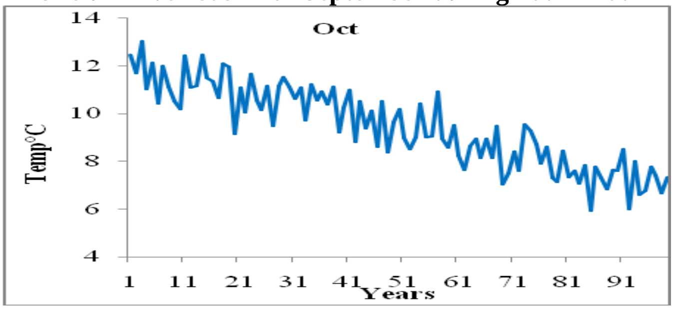

Figure 14.Variation of mean monthly temperature of Jhelum river basin for October during 2001-2100

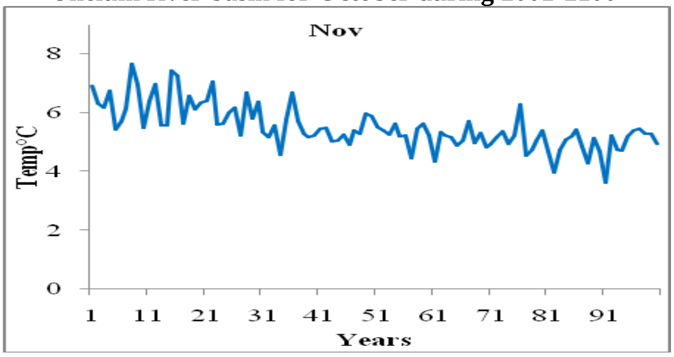

Figure 15.Variation of mean monthly temperature of Jhelum river basin for November during 2001-2100

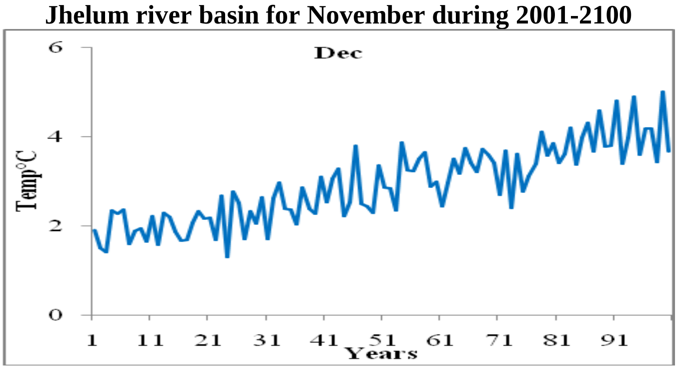

Figure 16. Variation of mean monthly temperature of Jhelum river basin for January during 2001-2100

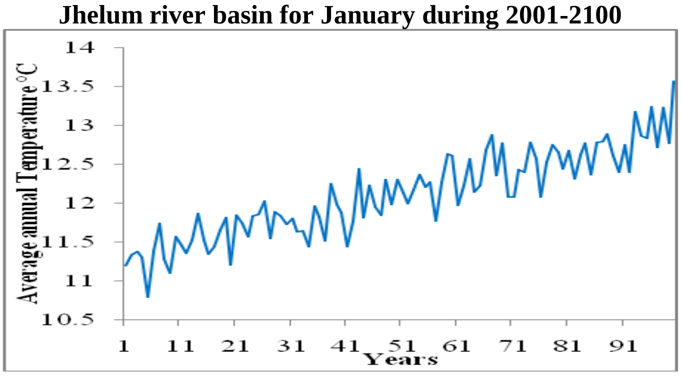

Figure 17.Variation of MLR predicted average annual temperature of Jhelum river basin during 21st century

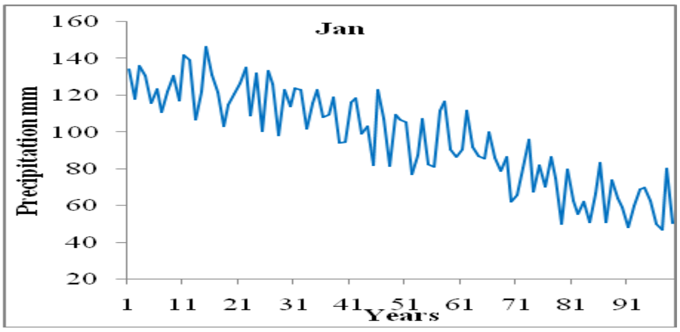

Figure 18. Variation of monthly precipitation of Jhelum river basin for January during 2001-2100

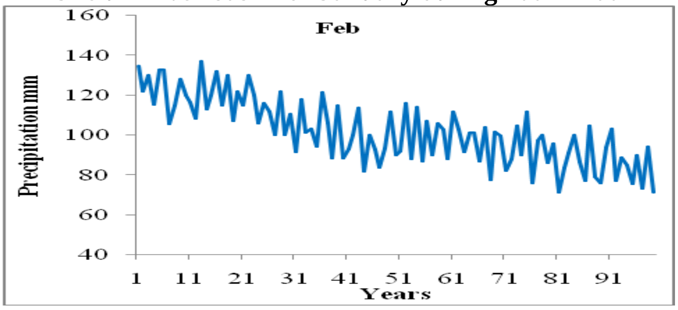

Figure 19. Variation of monthly precipitation of Jhelum river basin for February during 2001-2100

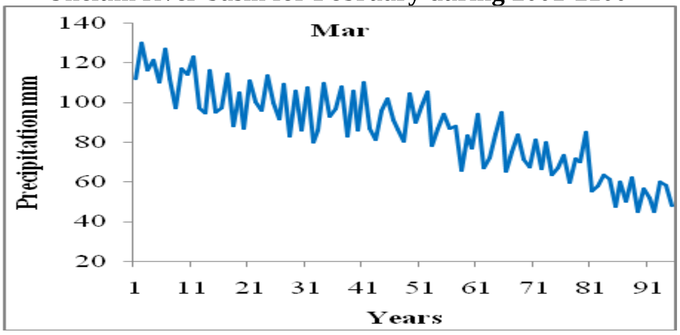

Figure 20. Variation of monthly precipitation of Jhelum river basin for March during 2001-2100

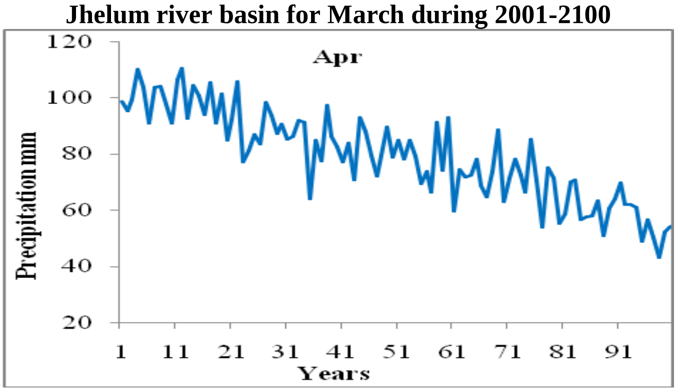

Figure 21. Variation of monthly precipitation of Jhelum river basin for April during 2001-2100

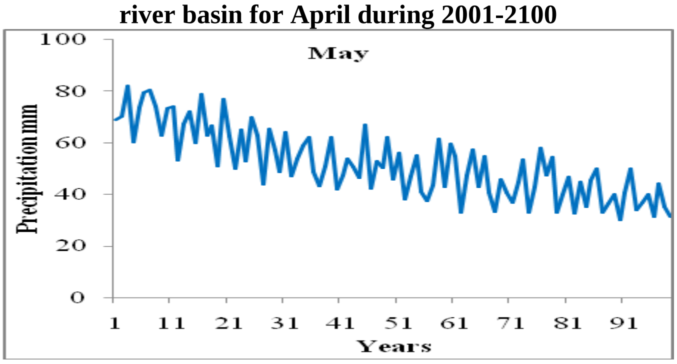

Figure 22. Variation of monthly precipitation of Jhelum river basin for May during 2001-2100

Table 1. Regression statistics of MLR model

Variable	Std. error of estimate	Std. deviation of residuals	Multiple Correlation Coeff.	Coeff. of multiple Determination
Temperature	1.91°C	2.00 °C	0.97	0.93
Precipitation	32.06 mm	33.56 mm	0.73	0.40

Table 2. Variation of temperature and precipitation over 21st century from 2001-2100

Month	Increase in mean monthly Temp°C over 21st century	%age Decrease in monthly Precipitation over 21st century
January	6.33	62.51
February	0.87	42.74
March	3.00	64.27
April	3.53	31.63
May	5.86	68.50
June	3.33	25.53
July	5.72	42.48
August	1.85	28.57
September	2.34	25.06
October	-5.10	26.97
November	-1.96	23.20
December	1.76	37.28

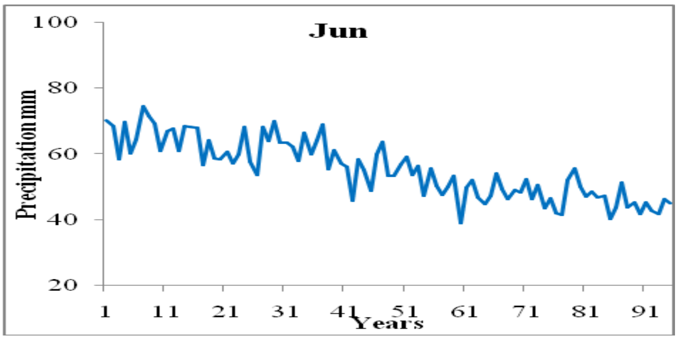

Figure 23.Variation of monthly precipitation of Jhelum river basin for June during 2001-2100

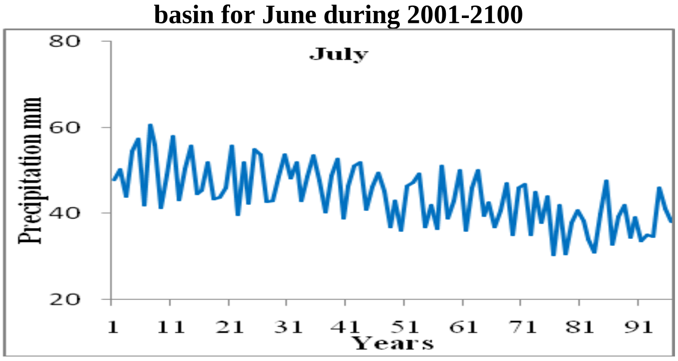

Figure 24. Variation of monthly precipitation of Jhelum river basin for July during 2001-2100

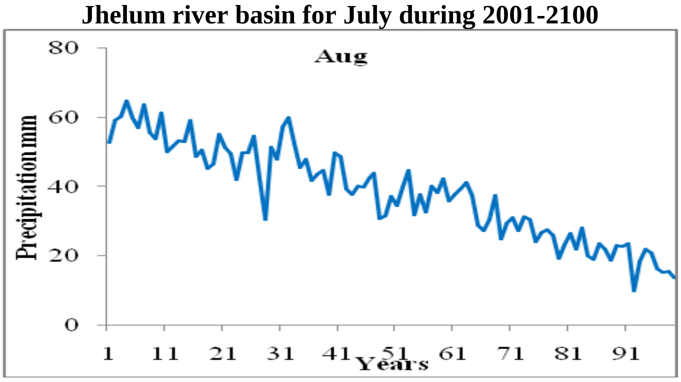

Figure 25.Variation of monthly precipitation of Jhelum river basin for August during 2001-2100

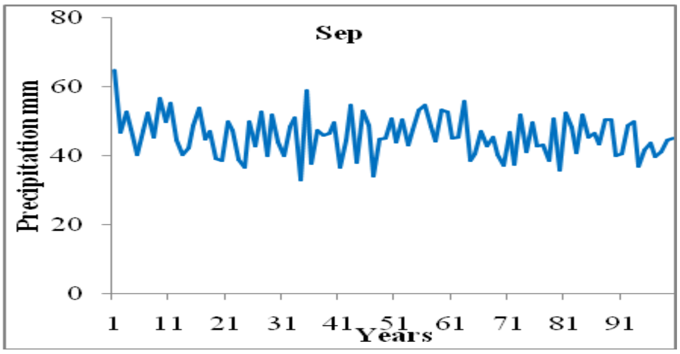

Figure 26.Variation of monthly precipitation of Jhelum river basin for September during 2001-2100

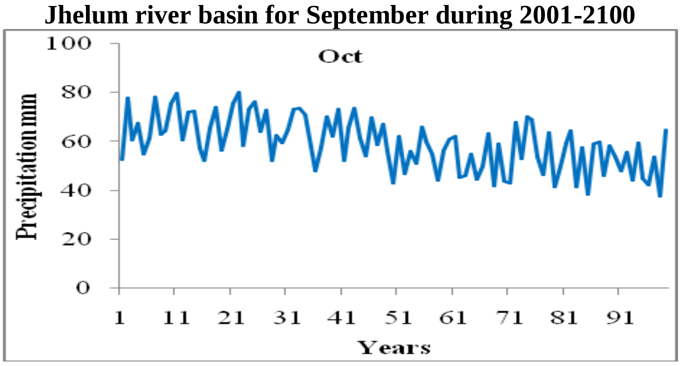

Figure 27.Variation of monthly precipitation of Jhelum river basin for October during 2001-2100

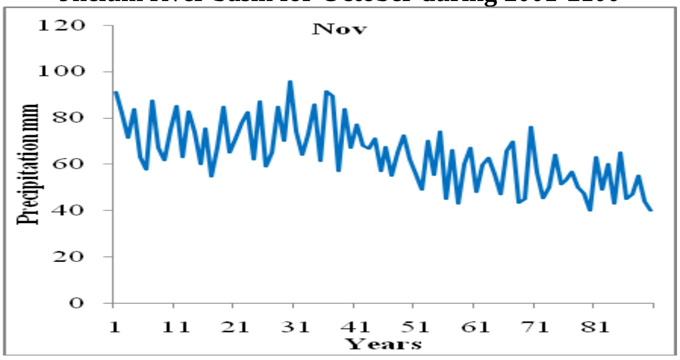

Figure 28. Variation of monthly precipitation of Jhelum river basin during 2001-2100

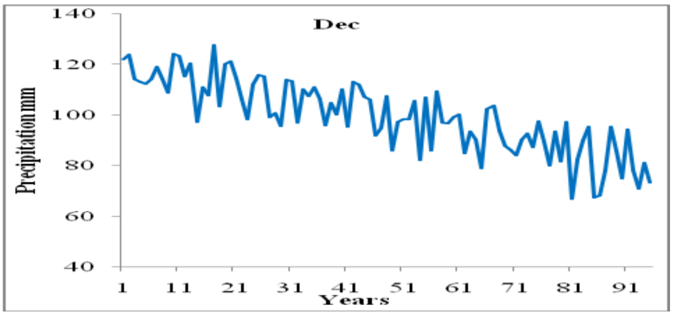

Figure 29.Variation of monthly precipitation of Jhelum river basin during 2001-2100

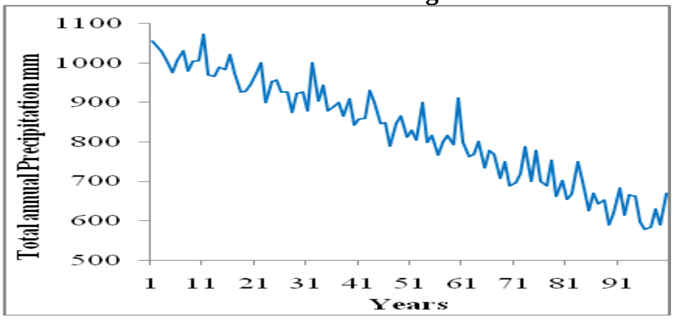

Figure 30.Variation of MLR predicted total annual Precipitation of Jhelum river basin during 21st century

The summary of the expected variation in mean monthly temperatures and monthly precipitation amounts for Jhelum river basin over the 21st century are given in table 2.

Conclusion

From the analysis of results the following conclusions were drawn:

1) The MLR model predicts an increase in mean monthly temperature of Jhelum river basin over the 21st century except for the months of October and November.

2) The monthly total precipitation of Jhelum river basin was found to decrease by MLR model. However, the MLR model predicted a pronounced decrease in the January, March and May months.

3) The MLR model predicts that the total annual precipitation of the valley is expected to decrease substantially by about 36.53% and average annual temperature is expected to increase by 21.15% by the end of 21st century.

4) The MLR model predicts that the total annual precipitation of the valley is expected to decrease substantially by about 38.563% and average annual temperature is expected to increase by 2.37°C by the end of 21st century.

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