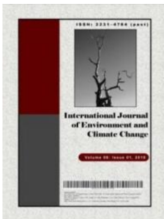

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Modeling Climate Change Projections for Ferozpur Sub-catchment of Jhelum Sub-basin of Kashmir Valley

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Authors' contributions

This work was carried out in collaboration between all authors. Author SRA designed the study, performed the statistical analysis. Authors SRA and JNK performed the mapping tasks. Authors SRA, JNK, MUDD and SAB wrote the protocol and wrote the first draft of the manuscript. All authors managed the analyses of the study. Authors SMF, MS and IM managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

Aims: The study aimed at modeling the climate change projections for Ferozpur subcatchment of Jhelum sub-basin of Kashmir Valley using the SDSM model.
Study Design: The study was carried out in three different time slices viz Baseline (1985-2015), Mid-century (2030-2059) and End-century (2070-2099).
Place and Duration of Study: Division of Agricultural Engineering, SKUAST-K, Shalimar between August 2015 and July 2016.
Methodology: Statistical downscaling model (SDSM) was applied in downscaling weather files (T_{max}, T_{min} and precipitation). The study includes the calibration of the SDSM model by using Observed daily climate data (T_{max}, T_{min} and precipitation) of thirty one years and large scale atmospheric variables encompassing National Centers for Environmental Prediction (NCEP) reanalysis data, the validation of the model, and the outputs of downscaled scenario A2 of the Global Climate Model (GCM) data of Hadley Centre Coupled Model, Version 3 (HadCM3) model for the future. Daily Climate (T_{max}, T_{min} and precipitation) scenarios were generated from 1961 to 2099 under A2 defined by Intergovernmental Panel on Climate Change (IPCC).
Results: The results showed that temperature and precipitation would increase by 0.29°C, 255.38 mm (30.97%) in MC (Mid-century) (2030-2059); and 0.67°C and 233.28 mm (28.29%) during EC (End-century) (2070-2099), respectively.

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Conclusion: The climate projections for 21st century under A2 scenario indicated that both mean annual temperature and precipitation are showing an increasing trend.

Keywords: Climate change; IPCC; Ferozpur subcatchment; SDSM.

1. INTRODUCTION

Water is indispensable for life, but its availability at a sustainable quality and quantity is threatened by many factors, of which climate plays a leading role. The Intergovernmental Panel on Climate Change (IPCC) defines climate as "the average weather in terms of the mean and its variability over a certain time span and a certain area" and a statistically significant variation of the mean state of the climate or of its variability lasting for decades or longer, is referred to as climate change. There is a growing evidence that global climate is changing. The Intergovernmental Panel on Climate Change (IPCC) estimates that the global mean surface temperature has increased 0.6 ± 0.2°C since 1861, and predicts an increase of 2 to 4°C over the next 100 years. Global sea levels have risen between 10 and 25 cm since the late 19th century. As a direct consequence of warmer temperatures, the hydrologic cycle will undergo significant impact with accompanying changes in the rates of precipitation and evaporation. Predictions include higher incidences of severe weather events, a higher likelihood of flooding, and more droughts. The impact would be particularly severe in the tropical areas, which mainly consist of developing countries, including India. The warming trend for the last 30 years period is roughly three times that for the past 100 years as a whole [1,2] and it is expected that global temperature will continue to rise between 1.4 and 5.8°C by 2100 due to the emission of greenhouse gases [3].

Coupled atmosphere-ocean global climate models (GCMs) are used to estimate changes in climate. These physically-based numerical models simulate synoptic-scale climate and hydrological processes, and are forced with greenhouse gas and aerosol emission scenarios. A wide diversity of GCMs (CGCM2, CSIRO, BCC-CSM1,+ HadCM2, HadCM3 etc.) developed by leading climate centres are available for other researchers to evaluate potential impacts of climate change. To ensure that the predictive elements from a GCM are realistic, a statistical downscaling technique should be employed to bridge the local-scale and synoptic-scale processes. Statistical downscaling uses a correlation between predictands (site measured variables, such as observed temperature and precipitation) and predictors (region-scale variables, such as GCM variables).

Climate models are the main tools available for developing projections of climate change in the future. Changing climate poses an unprecedented challenge for hydrology. The quantification of knowledge on occurrence, circulation and distribution of the waters of the earth becomes increasingly complex under climate projections because of uncertain effects due to anthropogenic emissions. According to the sixth Intergovernmental Panel on Climate Change (IPCC) Technical Paper on Climate Change and Water [4], changes in the large-scale hydrological cycle have been related to an increase in the observed temperature over several decades.

The advantage of computationally-demanding GCMs over simpler models is that GCMs can provide geographically distributed and physically consistent estimates of climate change. Recently, the study [5] gave details of obtaining the future climate data of Ludhiana in central Indian Punjab from three GCMs (Hadley Center Coupled Model Version 3 (HadCM3), Australia's Commonwealth Scientific & Industrial Research Organization Mk2 (CSIRO-Mk2) and Second Version of Canadian Center for Climate Modeling and Analysis Coupled Global Climate Model (CCCMA-CGCM2). Jalota et al. (2011) used this data for predicting climate change and its impact on crop productivity of rice-wheat cropping system for the years 2020, 2050 and 2080. However, the performance of GCMs is usually poor at the scale of the grid cell, while the impacts of climate change are often of interest at grid scale or sub-grid scale, such as a hydrological catchment, a city or a farm [6].

Downscaling of the GCM data is often required for climate change impact studies. Downscaling approaches can for convenience be divided into two categories: dynamical downscaling, in which physical dynamics are solved explicitly and empirical (statistical) downscaling [7]. Statistical downscaling (SD) generally encompasses the derivation of local scale meteorological data from

GCMs/RCMs with the help of statistical models fitted to present observations. These statistical models describe the relationship between large-scale atmospheric variables (predictors) and local or regional climate variables (predictands), which can be expressed as a stochastic and/or deterministic function [8]. Predictor sets are typically derived from sea level pressure, geopotential height, wind fields, absolute or relative humidity, and temperature variables [9]. The fundamental concept of SD is that regional climates are largely a function of the large-scale atmospheric state [8]. Statistical downscaling model (SDSM) was used to downscale future climate change scenarios, which were obtained from the UK HadCM3 climate model. The downscaled climate was used as input to the WetSpa hydrological model for impact studies in the upper Scezibwa catchment, Uganda [10].

The IPCC has developed a number of socio-economic scenarios that describe future Green House Gases and sulphur emissions. These projections of future emissions are called IPCC SRES Scenarios (Special Report on Emissions Scenarios) and are based on a number of assumptions in driving forces [11]. The SRES team defined four narrative storylines describing different social, technological, economic, demographic and environmental developments, which are labeled A1, B1, A2 and B2. A2 and B2 scenarios project CO_2 concentrations of approximately 850 ppm and 600 ppm, respectively. Based on these scenarios, a number of general circulation models (GCMs) have been developed.

2. MATERIALS AND METHODS

2.1 Site Location

Ferozpur sub-catchment falls in western part of Kashmir Valley in Baramulla District. The study area is bounded between North latitude 34° 03′ and 34° 07′ and East longitude 74° 31′ and 74° 39′ (Fig. 1). The sub-catchment is bounded by Gunder watershed from north and Sukhnag watershed from south and east. The geographical area of the sub-catchment is 58.4 sq. kms.

2.2 Climate

The Climate of the Ferozpur sub-catchment is Temperate cum Mediterranean type. Average minimum and maximum temperature varies from 6.77 to 19.59°C. The winter season starts from the middle of the November and severe winter conditions continues till the middle of February/March. The study area receives an average annual precipitation of about 825 mm in the form of rain and snow for about 60 days.

2.3 Observed and Future Climate Data

In many of the earlier studies [12,13] future climate was predicted in relation to the modeled climate data of baseline (1961-1990) without considering the observed data. While present study is considering the observed/station data.

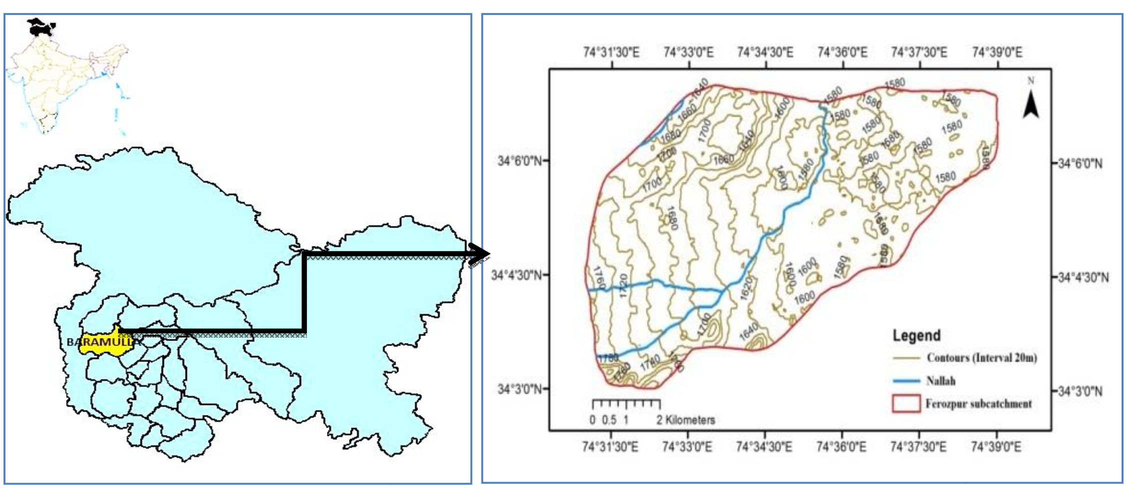


Fig. 1. Location map of study area with contour interval

Climate station data/observed historical data (predictands): Long-term observed daily $T_{max,}$ T_{min} and precipitation data from Division of Agronomy, SKUAST-K, from (1985-2015) were collected and used for the generation of weather files in the Statistical Downscaling Model (SDSM) for the observed period of the study.

Large-scale atmospheric variables (predictors): Statistical Downscaling Model (SDSM) version 4.2.9 was used for climate modeling. $T_{max,}$ T_{min} and precipitation was forecasted up to year 2099 using GCM data. GCM data were downloaded from Canadian Climate Scenarios Network. National Centers for Environmental Prediction (NCEP_1961-2001) data set was used to calibrate and validate the model. Then for future $T_{max,}$ T_{min} and precipitation predictions, Hadley Centre Coupled Model, Version 3 (HadCM3) data sets for A2 scenario (H3a2a_1961-2099) was used.

Future forecasts of annual maximum daily $T_{max,}$ T_{min} and precipitation and monthly averaged total precipitations was made under A2 scenario of IPCC.

2.4 Statistical Downscaling Model (SDSM)

SDSM deals with generation of synthetic series of daily weather data at a local site based on empirical relationships between local-scale predictands (daily temperature and precipitation) and large-scale predictors (atmospheric variables). SDSM predictors were obtained for the given area from courtesy of a data portal maintained by the Canadian Climate Impacts Scenarios Group.

2.4.1 Development of SDSM model

The observed daily maximum temperature, minimum temperature and precipitation data was then transformed & converted into *.dat* format to be recognized, accepted & executed in the SDSM software. Data used in any other format may either not be recognized or can lead to system errors due to inappropriate data or the production of non-sensible output.

Before downscaling, a check was made to ensure the correct date ranges, type and integrity of all input data. Since, the model to be used here was a HadCM3 model having model years consisting of 360 days therefore, the default year length was set to 360 days in scenario generation. The “Standard Start Date” was set for 01/01/1961 and “The Standard End Date” for 31/12/2099 while in case of Observed data (predictand) the default “Calendar (366)” allows 29 days in February every fourth year (i.e., leap years) was set. As, temperature consists of negative values, negative values were allowed by using the checkbox against “Allow Negative Values”. The “Event Threshold” was kept 0 for temperature but for precipitation was kept around 0.3 mm/day to treat trace rain days as dry days.

There are generally two steps in the training process:

1. Downscaling climate data
2. Statistical downscaling

   a. Predictand data quality control
   b. Screening downscaling predictors
   c. SDSM Model Calibration
   d. Scenario Generation

2.4.2 Downscaling climate data

Downscaling climate data was done by using Statistical Downscaling Model (SDSM 4.2.9). The HadCM3 was employed for A2 and B2 emission scenarios. A2 is medium-low emission scenario and B2 is Medium-High emission scenario.

2.4.3 Statistical downscaling

SDSM [14] is a decision support tool that facilitates the assessment of regional impacts of global warming by allowing the process of spatial scale reduction of data provided by large-scale GCMs. Statistical downscaling Model (SDSM 4.2.9) developed by Wilby et al. (2008) was downloaded freely from http://www.sdsm.org.uk. It establishes statistical relationships between output from GCM at large-scale (i.e. predictors) and observed data from meteorological stations at local-scale (i.e. predictands) climate based on multiple linear regression techniques. The general procedure used to downscale from GCM output data is presented in the flowchart. Daily maximum and minimum temperature and precipitation are downscaled by using the following discrete processes. These are predictand data quality control; predictor variables selection; model calibration; weather generation and scenario generation using climate model predictors. The procedures applied in the section below were adapted from the SDSM 4.2.9 manual [15].

2.4.4 Predictand data quality control

Data collected from meteorological stations may not be 100% complete and/or accurate. In SDSM, quality control of time series data is very crucial step to handle missing or imperfect data. For all meteorological stations daily data quality was checked to manage missed, suspected values and outliers of the predictand before screening of the predictor variables.

2.4.5 Screening downscaling predictors

Screening predictors is central and the most challenging stage in statistical downscaling because it determines the character of the downscaled climate scenario. Its main purpose is to assist the user in the selection of appropriate downscaling predictor variables. The selection of predictors (Table 1) in SDSM is described as is an iterative process and partly based subjective judgment of the user's. In this study, predictors with relatively high correlation and partial correlation value and P value less than 0.05 were selected [6]. The partial correlation is defined as "the correlation between two variables after removing the linear effect of the third or more other variables" [16].

The statistical test (i.e. t-test) used to calculate a p-value, which is used to accept or reject the hypotheses that the two sets of data (i.e. observed and simulated) could have similar or the same statistical properties. Significant differences between the simulated and observed climate data may be arise from the errors in the observed data, model smoothing of the observed data or random error.

The higher correlation and partial correlation values show strong association between predictor and predictand whereas smaller P values indicate that the occurrence of this association is less likely by chance. The correlation and partial correlation statistics and P values shows the strength of the association between predictor and predictand. The association strength of individual predictors varies on a monthly basis and the most appropriate combination of predictors was by looking at the analysis output of the twelve months. P value less than 0.05 is consistently used as the cut-off. However, even if P is less than 0.05 the result can be statistically significant but not be of practical significance. When there is high correlation and low P value, the scatter plot was used to evaluate whether this result is due to few outliers, or is a potentially useful downscaling relationship. The Scatter plot may also reveal that one (or both) of the variables should by modified using the "transform operation", to make linear relationship. The predictor variables are normalized with respect to their means and standard deviations.

Table 1. Large-scale atmospheric variables (Predictors) used as potential inputs in SDSM

No.	Predictors	Description	No.	Predictors	Description
1	tempas	mean temperature at 2 m	14	p500as	500hpa geo-potential height
2	shumas	surface specific humidity	15	p5_zas	500hpa velocity
3	rhumas	near surface relative humidity	16	p5_vas	500hp meriodinal velocity
4	r850as	relative humidity at 850hpa	17	p5_zhas	500hpa divergence
5	r500as	relative humidity at 500 hpa	18	p5_uas	500pa zonal velocity
6	p8zhas	850 hpa divergence	19	p5_fas	500hpa air flow strength
7	p8thas	850hpa wind direction	20	p_zhas	surface divergence
8	p850as	850hpa geo-potential height	21	p_zas	surface velocity
9	p8_zas	850 hpa velocity	22	p_vas	surface meridian velocity
10	p8_vas	850 hpa meriodinal velocity	23	p_uas	surface zonal velocity
11	p8_uas	850hpa zonal velocity	24	p_thas	surface wind direction
12	p8_fas	850hpa airflow strength	25	p_fas	surface air flow strength
13	p5_thas	500hpa wind direction	26	mslpas	men sea level pressure

2.4.6 SDSM model calibration

By calibrating of the SDSM, the downscaling model is build based on multiple linear regression equations, daily predictand data (i.e. meteorological station data) for GCM predictor variables. In this study calibration is done by using selected Screen Variables (See Tables 3, 4 and 5) and level of the variance in the local predictand of daily precipitation, maximum and minimum temperature of Local station data for the period of 1985-2015 are used. This 31 period is served as the baseline for this study. During model calibration, conditional for precipitation while unconditional process for maximum and minimum temperature was applied. In unconditional process, a direct link assumed between the predictors and predictand whereas conditional processes are done with intermediate process.

2.4.7 Weather generation

The Weather Generator operation generates ensembles of synthetic daily weather series given observed (or NCEP re-analysis) atmospheric predictor variables. The procedure enables the verification of calibrated models (using independent data) and the synthesis of artificial time series for present climate conditions. The User selects a calibrated model and SDSM automatically links all necessary predictors to model weights. The user must also specify the period of record to be synthesized as well as the desired number of ensemble members. Synthetic time series are written to specific output files for later statistical analysis, graphing and/or impacts modeling.

2.4.8 Generation

The Scenario Generation process produces daily base data for maximum temperature, minimum temperature and precipitation for the period 1961-2099. Each predictand (i.e. precipitation, maximum and minimum temperature) scenario is generated based on the calibration result and the daily atmospheric predictors of the HadCM3 (See Tables 3, 4 and 5). The calibration result is used based on assumption that predictor-predictand relationships under the current condition remain valid under future climate conditions too.

HadCM3 has two emission scenarios A2 and B2. For A2 emission, scenario twenty ensembles of synthetic daily time series data were produced for 139 years. The stochastic component of SDSM allows the generation of up to 100 ensembles. Where ensemble data has the same statistical characteristics but vary on a day-to-day basis. Selection of only twenty ensembles is done due to reasonably match between observed and simulated daily temperature and precipitation. In addition, large number of ensembles notably did not improve and subjective for large deviation among ensembles output, only 20 individual ensemble outputs are averaged to improve the performance of model for future time horizon. For time horizons 1961-2099, the A2 emission scenario precipitation, maximum and minimum temperature outputs are generated.

Data for the time slices representing periods 1985-2015 (baseline), mid-century (MC) climate change projection (2030-2059), and end century (EC) projection (2070-2099) were used for further analysis.

3. RESULTS AND DISCUSSION

3.1 Calibration and Generation of Future Climate Scenarios for Ferozpur Subcatchment

3.1.1 Selection of potential predictor variable

The first step in the downscaling procedure using SDSM was to establish the empirical relationships between the predictand variables (maximum temperature, minimum temperature, and precipitation) collected from station and the predictor variables obtained from the NCEP re-analysis data for the current climate. This was involved in the identification of appropriate predictor variables that have strong correlation with the predictand variable. The next step was the application of these empirical predictor-predictand relationships of the observed climate to downscale ensembles of the same local variables for the future climate. Data supplied by the HadCM3 for the A2 and B2 emission scenarios for the period of 1961-2099 for Ferozpur subcatchment. This is based on the assumption that the predictor-predictand relationships under the current condition remain valid under future climate conditions too. Therefore, according to the above procedure the potential predictors selected for maximum temperature, minimum temperature, and precipitation for the study area are listed in Table 2.

Table 2. List of selected predictor variables that gave better correlation results at p<0.05

Predictand	Predictor variable	Description	Cor. coefficient	Partial cor.
T_{max}	ncepp500as.dat	500 hPa geopotential height	0.773	0.449
	ncepshumas.dat	Surface specific humidity	0.701	0.069
	nceptempas.dat	Mean temperature at 2m	0.765	0.435
T_{min}	ncepp500as.dat	500 hPa geopotential height	0.756	0.410
	ncepshumas.dat	Surface specific humidity	0.771	0.182
	nceptempas.dat	Mean temperature at 2m	0.812	0.434
Precipitation	ncepp5_fas.dat	500 hPa airflow strength	0.051	0.050
	ncepp5_vas.dat	500 hPa meridoinal velocity	0.066	0.038
	ncepp8_zas.dat	850 hPa vorticity	0.040	0.027

The partial correlation coefficient (r) shows the explanatory power that is specific to each predictor. All are significant at p ≤ 0.05. 2hpa: is a unit of pressure, 1 hPa = 1 mbar = 100 Pa = 0.1 kPa. Correlation matrix was used to investigate intervariable correlations for specified analysis period (annual). SDSM also reports partial correlations between the selected predictors and predictand. These statistics help to identify the amount of explanatory power that is unique to each predictor.

3.1.2 Model calibration

The Model calibration process constructs downscaling models based on multiple regression equations, given daily T_{max}, T_{min} and precipitation data of the study area (the predictand) and regional-scale, atmospheric (predictor) variables. SDSM optimizes the model using either dual simplex or ordinary least squares optimization in the advanced settings of SDSM 4.2. The model structure was arranged as monthly as sub models required by unconditional and conditional settings for temperature and precipitation respectively (Tables 3, 4 and 5).

3.1.3 Weather generator

Ensembles of synthetic daily weather series were generated and given observed (or NCEP re-analysis) atmospheric predictor variables. The procedure enables the verification of calibrated models (using independent data) and the synthesis of artificial time series for present climate conditions of the study area (7305 days) (Table 6).

3.1.4 Maximum and minimum temperature

Monthly average of 20 years (1985-2004) of the observed weather data and SDSM weather generated values using calibration OUT file (NCEP data) maximum temperature (T_{max}) and minimum temperature (T_{min}) for the location showed that the observed values were same as the weather generated values using calibrated OUT file in SDSM (Figs. 2 and 3). The average R^2 value for both T_{max} and T_{min} cases during calibration period was 0.99.

3.1.5 Precipitation

In case of precipitation, the weather generated precipitation was greater than observed precipitation during all months from January to December (Fig. 4). The analysis of the statistical parameter revealed that the mean (μ) of weather generated precipitation was 17 per cent more than that of the observed precipitation and the average R^2 value was 0.97.

3.2 Future Climate Predictions

This section presents the annual and monthly trends of T_{max}, T_{min} and Precipitation for present (from 1985-2015), future scenarios MC and EC.

3.2.1 Maximum temperature

The annual and monthly trends in maximum temperature during different years of Baseline, mid-century (MC) and end-century (EC) is presented in Tables 7 and 8 and their graphical representation is shown in (Fig. 5). Average annual T_{max} of 19.59°C for the Baseline would increase to 19.77°C in MC and 20.26°C in EC. This implies that in MC and EC, increase in T_{max} would be 0.18 and 0.67°C respectively in future. In MC, the change in T_{max} would be positive in the month of January, April, May, June and August negative in the month of February, March, July, September, October and December and no change in the month of November. Highest positive change would be of 2.77°C in the month of January and negative change of 0.97°C in the months of March and September.

In EC, the change in T_{max} would be positive in the month of January, April, May, June, August, October, November and December and negative in the month of February, March, July and September. The maximum positive change would be 3.20°C in the month of January and negative change of 0.68°C in the month of March.

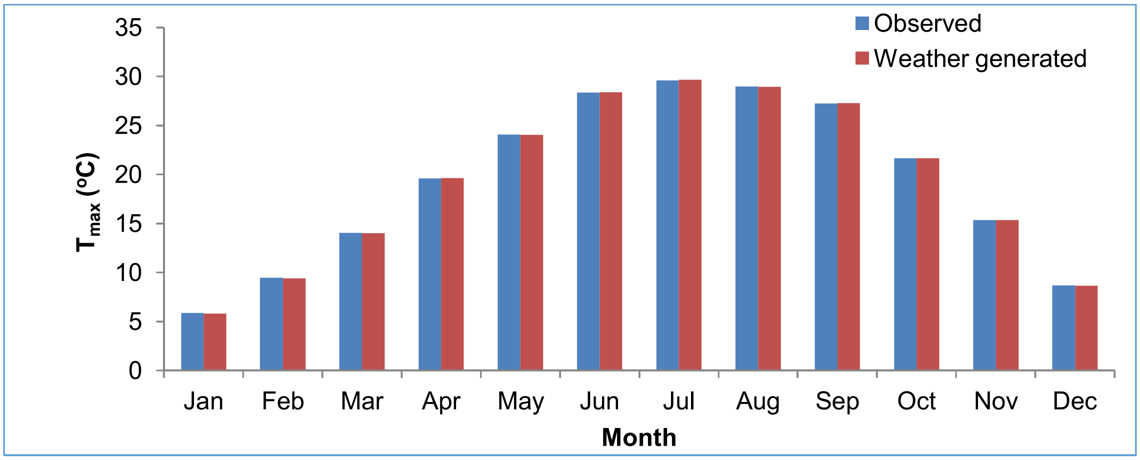


Fig. 2. Mean monthly observed T_{max} and weather generated T_{max} (1985-2004)

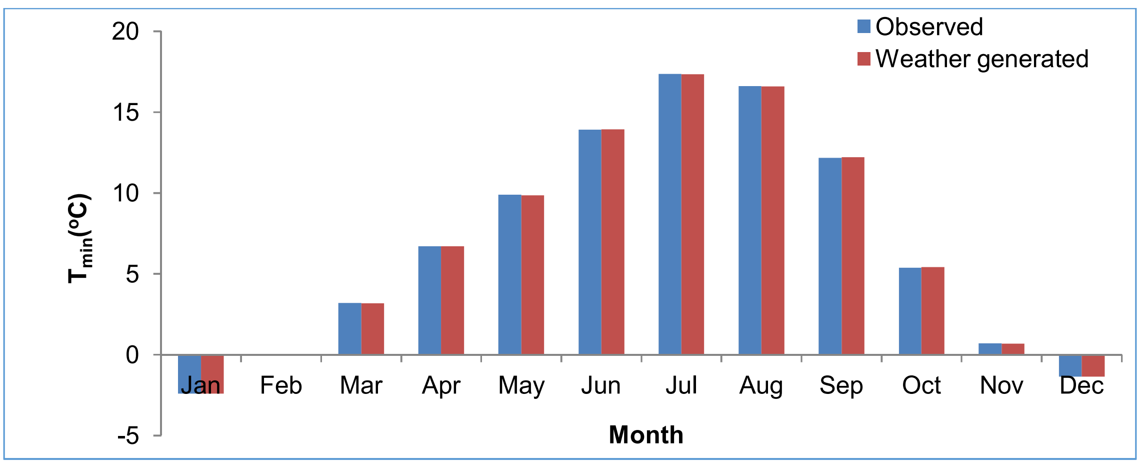


Fig. 3. Mean monthly observed T_{min} and weather generated T_{min} (1985-2004)

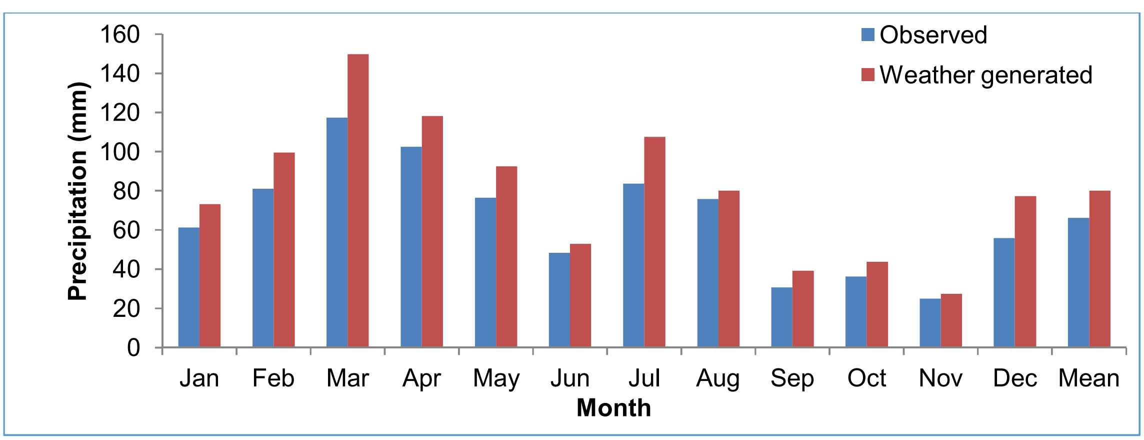


Fig. 4. Mean monthly observed precipitation and weather generated precipitation (1985-2004)

Table 3. Calibration statistics of daily maximum temperatures

Predictor variable	R square value													
	Statistical measure	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**Mean**
ncepp500as.dat	R^2	0.025	0.008	0.012	0.022	0.057	0.008	0.011	0.007	0.042	0.041	0.093	0.026	0.029
ncepshumas.dat	Standard Error	4.024	3.418	4.454	4.568	4.743	3.886	3.406	3.227	3.390	3.661	3.804	3.489	3.839
nceptempas.dat	Durbin-Watson statistics	0.321	0.632	0.555	0.589	0.513	0.547	0.861	0.957	0.709	0.498	0.392	0.405	0.582

Table 4. Calibration statistics of daily minimum temperatures

Predictor variable	R square value													
	Statistical measure	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**Mean**
ncepp500as.dat	R^2	0.021	0.019	0.027	0.073	0.035	0.069	0.019	0.022	0.124	0.093	0.086	0.042	0.053
ncepshumas.dat	Standard Error	3.069	2.259	2.550	2.397	2.381	2.542	2.388	2.145	2.737	2.593	2.222	2.545	2.486
nceptempas.dat	Durbin-Watson statistics	0.427	0.615	0.632	0.846	0.713	0.476	0.659	0.543	0.443	0.346	0.571	0.479	0.563

Table 5. Calibration statistics of daily precipitation

Predictor variable	R square value													
	Statistical measure	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**Mean**
ncepp5_fas.dat	R^2	0.011	0.002	0.029	0.000	0.023	0.000	0.060	0.020	0.013	0.056	0.100	0.083	0.033
ncepp5_vas.dat ncepp8_zas.dat	Standard Error	10.652	13.369	12.485	12.197	8.766	9.917	13.925	13.123	9.255	11.257	9.499	17.916	11.863

3.2.2 Minimum temperature

Average annual T_{min} of 6.77°C for the Baseline would increase to 7.18°C in MC and 7.43°C in EC (Table 7). These results indicate that the increase in T_{min} would be 0.41 and 0.66°C in MC and EC (Fig. 6) respectively in future. In MC, the change in T_{min} would be positive in the month of January, March, April, May, June, November and December negative in the month of February, July, August, September and October (Table 8). Highest positive change would be of 2.24°C in the month of December and negative change of 1.1°C in the month of September. In EC, the change in T_{min} would be positive in the month of January, February, March, April, May, June, November and December and negative in the month of July, August, September and October. The maximum positive change would be 2.62°C in the month of December and negative change of 0.47°C in the month of September (Fig. 6).

The above data indicates that under A2 scenario mean annual temperature would increase by 0.29°C in MC and 0.67°C in EC compared to that of the Baseline period.

3.2.3 Precipitation

The precipitation showed an increasing trend on annual basis, in Baseline the average annual precipitation is 824.52 mm which is likely to increase to 1079.9 mm in MC and 1057.8 mm in EC (Table 7) and (Fig. 7). These results indicate that in MC the precipitation would increase by 255.38 mm (30.97%) and in EC by 233.28 mm (28.29%) respectively. Monthly trends (averaged over years in each time slice) showed that change in precipitation would be positive in all the months of MC and EC compared to that of the Baseline, except in months of August and September (Fig. 7). The highest positive change in precipitation would be in the month of July, which was computed as 90.25 mm in MC and 74.16 mm in EC.

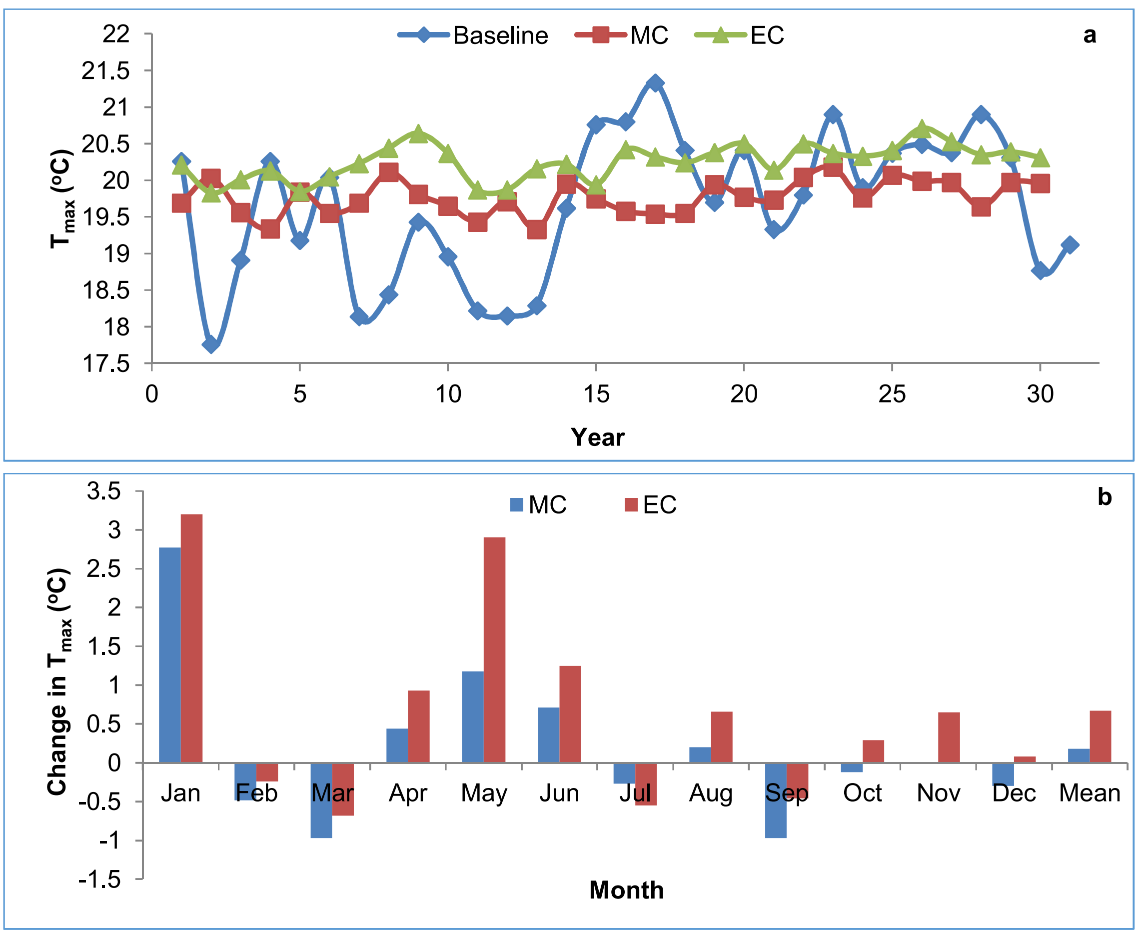


Fig. 5. Annual (a) and monthly (b) maximum temperature trends in Baseline, mid-century (MC) and end century (EC)

These results commensurate with the previous findings [17] indicating significant warming and increasing rainfall over India towards the end of the 21st century using PRECIS under A1B scenario [17] and with [18] who used multi model outputs for climate projections indicating northern India, particularly states of Rajasthan, Madhya Pradesh, Uttar Pradesh, Uttaranchal, Himachal, Delhi, Punjab and Haryana are projected to experience higher levels of warming than the rest

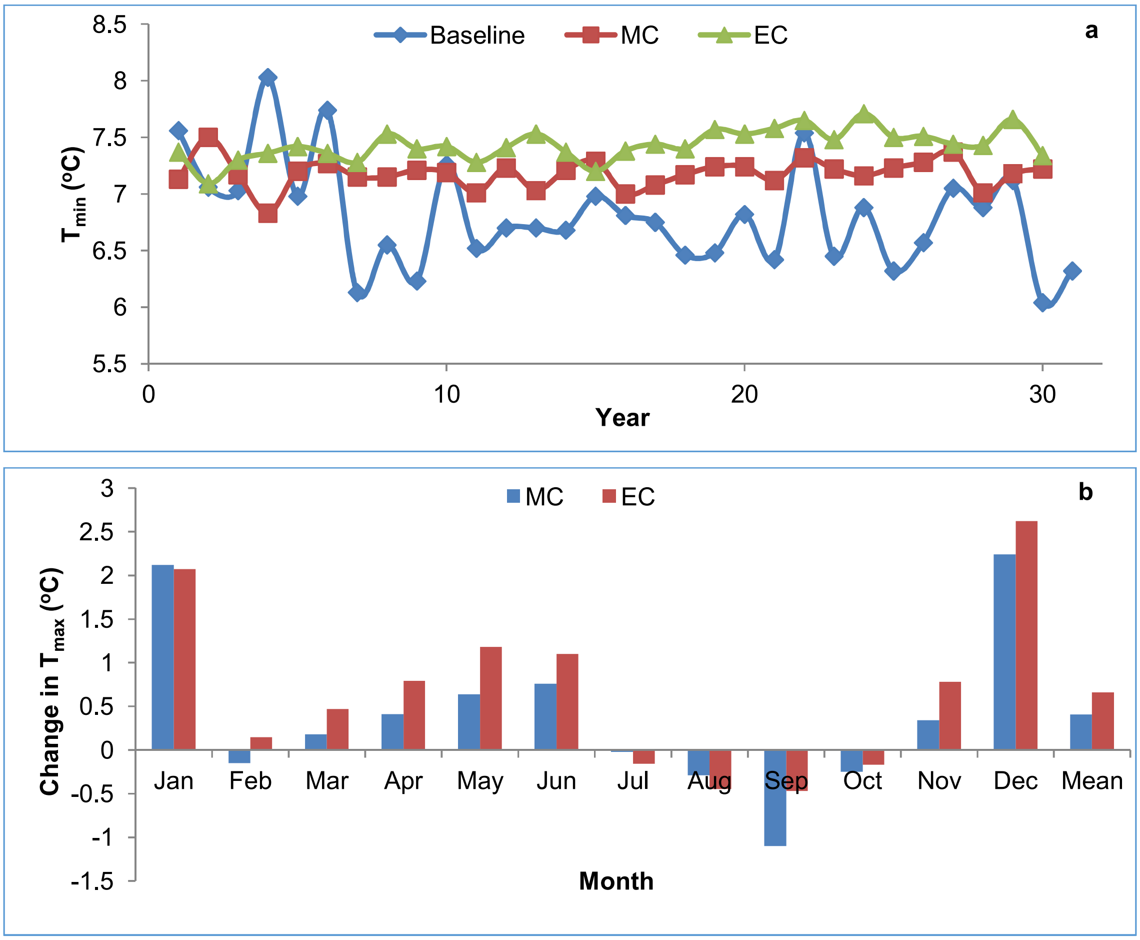
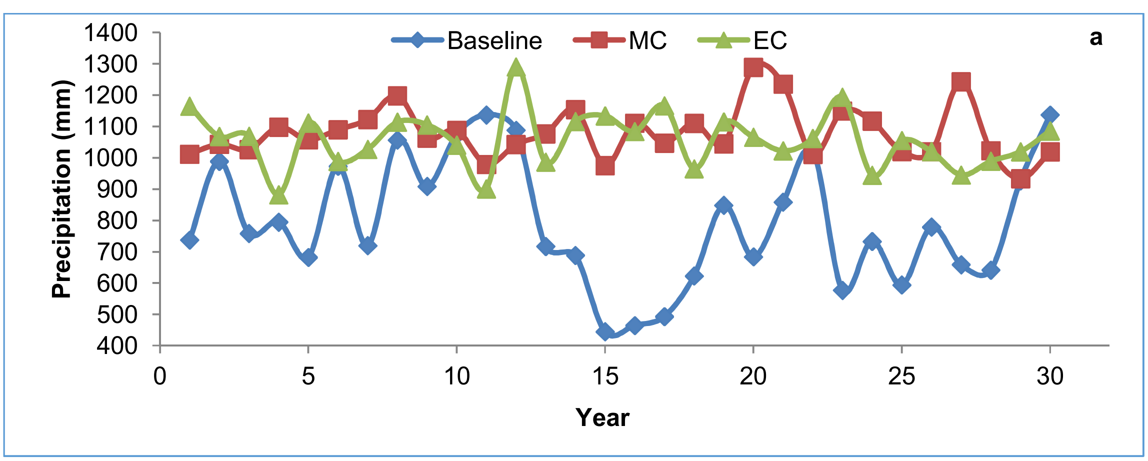


Fig. 6. Annual (a) and monthly (b) minimum temperature trends in Baseline, mid-century (MC) and end century (EC)



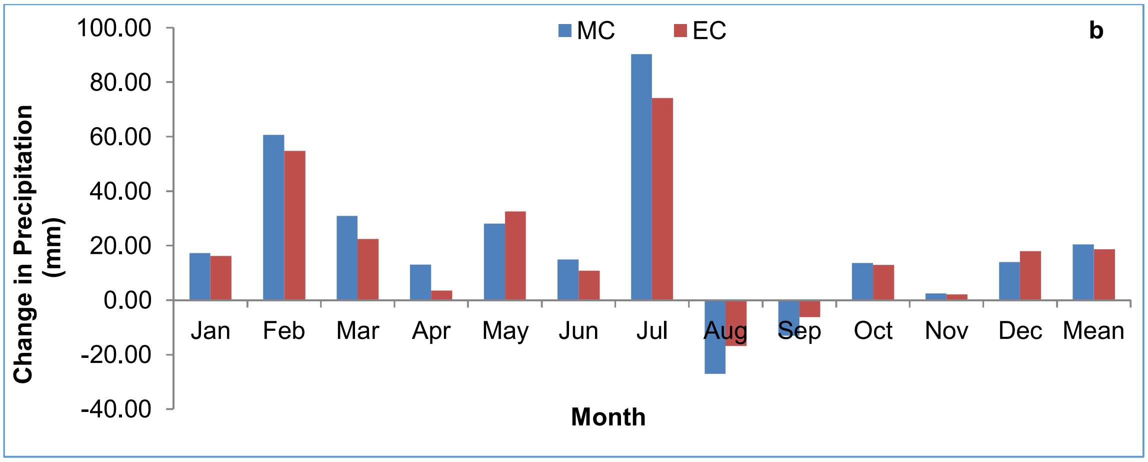


Fig. 7. Annual (a) and monthly (b) precipitation trends in Baseline, mid-century (MC) and end century (EC)

Table 6. SIM file produced by the weather generator operation

Predictor variable	Line order and representation	
ncepp500as.dat ncepshumas.dat nceptempas.dat	Order	Representation
	[1]	the number of predictor variables (in this case 3 screened predictor variables)
	[2]	the season code (1=annual, 4=seasonal, 12=monthly);
	[3]	the maximum number of days in a year (here a calendar year is used, so there are up to 366 days in leap years);
	[4]	the start date of the data used for model calibration (1/1/1985)
	[5]	the number of days simulated (7305 days in our case)
	[6]	Model fitting start date(1/1/1985)
	[7]	Number of days used in the model fitting (7305 days)
	[8]	Whether the model is conditional (True) for temperature and unconditional (False) for precipitation
	[9]	Transformation (1=none, 2=fourth root, 3=natural log, 4=lognormal) in this case none (1)
	[10]	Ensemble size (20)
	[11]	Auto-regression indicator (True or False)
	[12]	Predictand file name
	[13]	Predictor filenames (in this case five)
	[14]	Model parameters; the first 6 columns in this example are the parameters (including the intercept), the last two columns are the SE and r-squared statistic
	[15]	The root directory of the predictand file

of the country. Indo-Gangetic plains is likely to experience a 0.5-1°C rise in average temperatures during MC and 3.5-4.5°C rise in EC, and increased frequency of extremely wet rainy seasons from PRECIS climate model [19]. In future, though temperature would increase but increased temperature would shorten crop duration [6,20].

Table 7. Annual based Climate predictions for the three time slices of the future weather for Ferozpur subcatchment

Temperature	Baseline (1985-2015)	Mid Century (2030-2059)	End Century (2070-2099)
Annual T_{max} (°C)	19.59	19.77	20.26
Annual T_{min} (°C)	6.77	7.18	7.43
Mean (°C)	13.18	13.47	13.85
Precipitation (mm)	824.52	1079.9	1057.8

Table 8. Monthly based maximum and minimum temperature and precipitation values averaged under three different time slices for Ferozpur subcatchment

Month	T_{max} (°C)			T_{min} (°C)			Precipitation (mm)		
	1985-2015	2030-2059	2070-2099	1985-2015	2030-2059	2070-2099	1985-2015	2030-2059	2070-2099
Jan	6.48	9.25	9.68	-2.29	-0.17	-0.22	67.95	85.20	84.11
Feb	9.42	8.94	9.18	0.11	-0.04	0.26	94.59	155.30	149.37
Mar	14.63	13.66	13.95	3.3	3.48	3.77	123.03	153.96	145.47
Apr	19.74	20.18	20.67	6.59	7.0	7.38	100.27	113.31	103.84
May	24.16	25.34	27.06	9.76	10.4	10.94	71.65	99.79	104.15
June	28.24	28.95	29.49	13.64	14.4	14.74	48.75	63.71	59.66
July	29.73	29.46	29.18	17.17	17.15	17.01	86.83	177.08	160.99
Aug	29.22	29.42	29.88	16.65	16.36	16.2	83.11	56.10	66.29
Sep	27.12	26.15	26.66	11.97	10.87	11.5	43.10	30.02	36.88
Oct	21.96	21.84	22.25	5.38	5.13	5.21	32.44	46.05	45.37
Nov	15.37	15.37	16.02	0.7	1.04	1.48	25.94	28.37	28.01
Dec	9.0	8.7	9.08	-1.69	0.55	0.93	46.85	60.82	64.82
Mean	19.59	19.77	20.26	6.77	7.18	7.43	824.52	1079.9	1057.8

4. CONCLUSION

The framework was used for generation of climate change projections for the Ferozpur subcatchment of Jhelum sub-basin of Kashmir Valley. The specific conclusions in this context are:

In case of T_{max} and T_{min} three among twenty six predictor variables viz ncepp500as, ncepshumas and nceptempas were having maximum correlation and partial correlation with observed data/predictand and in case of precipitation ncepp5_fas, ncepp5_vas and ncepp8_zas were having maximum correlation and partial correlation with observed data.

Monthly average as well as annual average T_{max} and T_{min} observed and weather generated for calibration results were same with R^2 value of 0.99 in all cases while as in case of precipitation both mean monthly and average annual weather generated results were little higher than observed with R^2 value of 0.97.

The climate projections for 21st century under A2 scenario indicated that mean annual temperature would increase by 0.29°C in MC and 0.67°C in EC and precipitation would increase by 255.38 mm (30.97%) during MC and 233.28 mm (28.29%) during EC.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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