GCMs Derived Projection of Precipitation and Analysis of Spatio-Temporal Variation over N-W Himalayan Region

Dharmaveer Singh*[1], R.D. Gupta[2] and Sanjay K. Jain[3]

[1] *GIS Cell, Motilal Nehru National Institute of Technology Allahabad- 211004, India*

[2] *Department of Civil Engineering, Motilal Nehru National Institute of Technology, Allahabad-211004, Uttar Pradesh, India.*

[3] *Scientist-F, Water Resources Systems Division, National Institute of Hydrology, Roorkee- 247667, India.*

ABSTRACT

The ensembles of two Global Climate Models (GCMs) namely, third generation Canadian Coupled Global Climate Model (CGCM3) and Hadley Center Coupled Model, version 3 (HadCM3) are used to project future precipitation in a part of North-Western (N-W) Himalayan region, India. Statistical downscaling method is used to downscale and generate future scenarios of precipitation at station scale from large scale climate variables obtained from GCMs. The observed historical precipitation data has been collected for three metrological stations, namely, Rampur, Sunni and Kasol falling in the basin for further analysis. The future trends and patterns in precipitation under scenarios A2 and A1B for CGCM3 model, and A2 and B2 for HadCM3 model are analyzed for these stations under three different time periods: 2020's, 2050's and 2080's. An overall rise in mean annual precipitation under scenarios A2 and A1B for CGCM3 model have been noticed for future periods: 2020's, 2050's and 2080's. Decrease, in precipitation has been found under A2 and B2 scenarios of HadCM3 model for 2050's and slight increase for 2080's periods. Based on the analysis of results, CGCM3 model has been found better for simulation of precipitation in comparison to HadCM3 model.

Keywords: *CGCM3, HadCM3, Statistical downscaling method, Precipitation*

1. INTRODUCTION

Availability of abundant water on time is a prime concern for agriculture, energy and industrial sectors in India. The country has viewed increase in demand of water due to rapid growth in population and economy. Studies by various authors show that change in patterns of temperature and precipitation due to climate change may amend availability of water along with the risk of increased frequency of droughts and floods (Kumar and Jain 2010). The proper assessment of potential water resources is required in order to maintain continuous water supply to various sectors such as agricultural, industrial, energy and domestic in future (Gosain *et al*., 2011).

* Corresponding author : Dharmaveer Singh, E-mail:veermnnnit@gmail.com

Precipitation determines the magnitude of available water and is an important factor. Knowledge about past and future precipitation along with its variability has scientific as well as practical significance in climate change impact studies. Investigating how change in climate will alter future precipitation and its spatial and temporal variability is an area of active research (Basistha *et al*., 2009). Generally, assessment of likely future precipitation is done under a climate change scenario (Anandhi *et al.*, 2008). A climate scenario which refers to plausible future climate is a time series of synthetic weather data. These scenarios are based on future emission of greenhouse gases and used to study possible effects of human-induced climate change (Lapp *et al.*, 2009). Uncertainties associated with scenarios are an important issue in scientific communities as it is very intricate to determine nature of future concentrations of greenhouse gasses in atmosphere based on anthropogenic activities (Carter *et al*., 2001). Scenarios should not be taken as forecasts of future climate as these are constructed to provide sufficient quantitative measures of uncertainty represented with a range of plausible future paths (Lapp *et al.*, 2009). Anandhi *et al*. (2008) has strongly advocated for using a range of scenarios in climate change impact studies.

Global Climate Models (GCMs), the most credible available tools, are used to simulate state of the present and future climate using transient climate simulations. In a transient simulation, anthropogenic forcings, decided on the basis of IPCC climate scenarios, are changed gradually in a realistic fashion (Anandhi *et al*, 2008). The decrease in the accuracy of GCMs simulated climate variables has been observed from continental to local scale as they are unable to capture sub-grid scale features and physical dynamics due to their coarse (typically of the order 50,000km2) spatial resolution (Xu*.,*1999). This limits the direct applications of GCM's outputs in regional climate change impact studies (Ghosh, 2010; Raghavan *et al*., 2012; Wilby *et al.,* 2002). A methodology usually known as downscaling is introduced for bridging the gap between the scale of GCMs and required resolution for practical applications. Downscaling methodology broadly can be classified into statistical and dynamical methods (Ghosh, 2010).

Statistical downscaling method is supported by the view; the regional climate is conditioned by large scale climate state and regional/local physiographic features (*e.g.* topography, land-sea distribution and land use/land cover). In this method, large scale atmospheric variables (predictors) of GCMs are related to station-scale climate variables (predictands) based on empirical relationship (Kim *et al.*, 1984; Raje and Mujumdar, 2011; von Storch *et al.*, 2000). The statistical downscaling methods can be classified into 3 categories; weather typing, weather generator and regression method (Wilby and Wigley, 1997). In literature, the strength and weakness of each method is critically analyzed (Bárdossy *et al.*, 2005; Dubrovsky *et al.*, 2004; Fowler *et al.*, 2000; Hua *et al.*, 2010; Kilsby *et al.*, 2007; Mason, 2004; Tripathi *et al.*, 2006 Wilby *et al.*, 1999). In dynamical downscaling method physical processes are simulated at fine scale from host GCMs using a Regional Climate Model (RCM). A horizontal resolution of the order of tens of kilometers is obtained from RCMs over selected area of interests. RCMs accounts use of initial boundary conditions and time dependant lateral meteorological conditions derived from GCMs to provide information at high spatial and temporal scales (Giorgi, 1990; Jones *et al.*, 1995). The complex design and computationally expensive nature of

RCMs has limited their applications in climate change impact studies (Ghosh and Mishra, 2010; Hewitson and Crane 1996).

The Himalayan mountain systems which are birth place of many perennial river systems such as the Indus, the Ganga and the Brahmaputra have also a strong influence over the climate of Indian sub-continent (Bhutiyani *et al.,* 2007). Hence, a small change in the climate of the Himalaya has a potential to bring devastating effects on the socio-economic survival of millions of people living in these basins. Jain (2012) observed that trend analysis of past precipitation data in India has not revealed any significant extensive change in the patterns so far, but the simulated results derived from GCMs illustrate that in future these patterns are likely to change. These changes would not be uniform over space and time domain as some areas are expected to receive more precipitation and others less. There may be increase in frequency of extreme precipitation events.

Similar trend in precipitation has also been detected over Himalayan region. The north-east region along with eastern and central parts of the Tibetan Plateau has reveled increasing trend in annual precipitation while the western Tibetan region shows decreasing trend (Zhao *et al*., 2004; Xu *et al*., 2008). Similarly, the north-western Himalayan region (northern Pakistan) has experienced an increasing trend while Nepal exhibited no long-term trend in precipitation (Farooq and Khan, 2004; Shrestha *et al*., 2000). Increase in post-monsoon precipitation has been detected at Dehradun, Pithoragarh and other western Himalayan stations whereas decrease in winter (Pant *et al*., 1999). Kumar *et al*. (2005) found an increasing trend in annual precipitation but decreasing trend in monsoon precipitation over Himachal Pradesh, India. The modelled projections have shown a decrease of about 20% in monsoon precipitation in most parts of Pakistan and in south-eastern Afghanistan by the end of the century. The Tibetan plateau will exhibit increase (10–30%) in mean annual precipitation by 2080 (IPCC, 2007). Rupa Kumar *et al*. (2006) observed projected increase of 20 to 30% in precipitation for the western Himalayan region by the end of 21st century.

Keeping the above in mind, the objective of the present paper is to study the change in patterns of future precipitation under various emission scenarios over North-Western (N-W) Himalayan region, India. For this purpose, a software called Statistical Downscaling Model version 4.2 (SDSM 4.2) is used for downscaling of precipitation from large scale climate predictors obtained from third generation Canadian Coupled Global Climate Model (CGCM3) and Hadley Center Coupled Model, version 3 (HadCM3). India. SDSM 4.2 is used to generate single-sites scenarios of daily surface weather variables from large scale climate predictors simulated by GCMs (Wilby *et al.,* 2007). The future patterns and variability in precipitation under scenarios A2 and A1B for CGCM3 model, and A2 and B2 for HadCM3 model are analyzed under three different time periods: 2020's (2011-2040), 2050's (2041-2070) and 2080's(2071-2099).

2. STUDY AREA

The study area is a part of the Sutlej river basin and confined to the State of Himanchal Pradesh, India. The State shares its boundary with four Indian States namely, Jammu and Kashmir from North, Punjab from West, Haryana from South, Uttarakhand from South-East and has

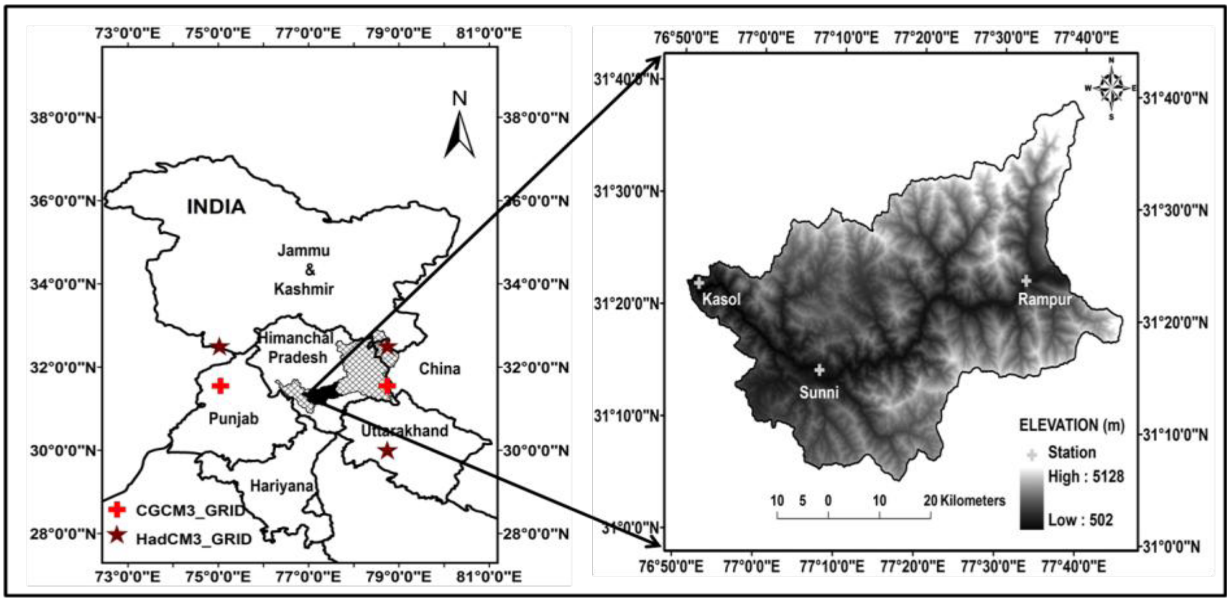

Figure 1: Location map of study area

international border with China (Tibet). It covers a geographical area of 2457km2 lying between 31°05’00”N to 31°39’26”N latitudes and 76°51’11”E to 77°45’17”E longitudes (Figure 1).

Sutlej river basin is drained by the Sutlej river which originates from Mansarovar- Rakastal lakes near Darma pass in the western Tibet at an elevation of 4,570 m. The basin is characterized by steep slope, dissected topography and high relief features. The altitude in the basin (study area) ranges in between 502 m to 5128 m. The slope gradually decreases downstream. The major part of the study area exhibits the characteristics of warm and temperate climate. The mean annual rainfall and temperature is 103cm and 21.23°C respectively.

3. DATA SETS

The data acquired from various sources are used throughout the downscaling procedure. The climate station precipitation data (predictand) which is available on daily time step is procured from Bhakra Beas Management Board (BBMB), India for three stations namely, Kasol, Sunni and Rampur. These stations have data series covering the period 1963-2000 for Kasol and 1970-2000 for Sunni and Rampur respectively. Figure 1 also shows the location of stations.

The observed and modelled predictors are obtained from the National Centre for Environmental Prediction/ National Centre for Atmospheric Research (NCEP/ NCAR) reanalysis (Kalnay *et al.*, 1996) and from CGCM3 and HadCM3 models respectively. The NCEP/NCAR reanalysis data sets have a grid-spacing of 1.9° latitude × 1.9° longitude whereas CGCM3 and HadCM3 have grid resolution of 3.75° latitude × 3.75° longitude and 2.5° latitude × 3.75° longitude respectively . The re-gridding of the NCEP/NCAR reanalysis predictors have been performed to conform to the grid-spacing of CGCM3 and HadCM3 models. The standardization of predictors is carried out before statistical downscaling to minimize biases in mean and variance of CGCM3 and HadCM3 predictors with respect

Table 1: Selection of NCEP/ NCAR predictors using partial correlations and P value statistics

Station	Precipitation (CGCM3 Model)			Precipitation (HadCM3 Model)		
	Predictors	Partial Correlation(r)	P value	Predictors	Partial Correlation(r)	P value
Kasol	p__v	0.027	0.2860	**msl**	-0.114	0.0000
	p500	0.076	0.0021	**p5_f**	0.094	0.0006
	p5zh	0.073	0.0032	**rhum**	0.149	0.0000
	s850	0.122	0.0000			
	shum	0.081	0.0010			
	temp	0.091	0.0002			
Sunni	p_f	0.011	0.5168	**p__z**	-0.059	0.0418
	p500	-0.14	0.0000	p__th	-0.022	0.3911
	p_th	-0.080	0.0047	pzh	0.038	0.1925
	shum	0.208	0.0000	p5_u	-0.036	0.2152
				p500	-0.086	0.021
				p8_th	0.048	0.0973
				rhum	0.115	0.0000
				temp	0.095	0.0006
Rampur	**msl**	0.062	0.0293	**p5_v**	-0.061	0.0149
	p_th	-0.041	0.1570	**temp**	0.064	0.0110
	p500	-0.153	0.0000			
	p8_z	0.120	0.0000			
	p8zh	-0.117	0.0000			
	s850	0.126	0.0000			
	temp	0.089	0.0012			

to that of NCEP/ NCAR reanalysis data. All the predictor variables are normalized over baseline periods *i.e.,* 1961-1990 periods.

The re-gridded and standardized predictors used as the SDSM model input are directly downloaded from the Data Access Integration (DAI) website (http://loki.qc.ec.gc.ca/DAI/predictors-e.html) for CGCM3 model and Canadian Climate Impacts Scenarios (CCIS) website (http://www.cics.uvic.ca/scenarios/index.cgi) for HadCM3 model. The predictor variables are available for period 1961-2100 for CGCM3 model, 1961-2099 for HadCM3 model and 1961-2001 for NCEP/ NCAR. The predictors are simulated under A2 historical GHG (Greenhouse Gas) and aerosol concentration experiment (20C3M) as well as Special Report on Emission Scenarios (SRES) A2 and A1B emission scenarios for future run for CGCM3 model and A2 and B2 emission scenarios for HadCM3 model respectively.

4. METHODOLOGY

The SDSM 4.2 software, invented by R.L. Wilby and C.W. Dawson (Wilby *et al*., 2002) has been used to downscale and generate future scenarios of precipitation. It is a windows based decision support tool that is based on statistical downscaling method. In this software, the multiple liner regression is used to establish empirical relationship between predictors and predictands whereas downscaled data is generated stochastically. Therefore, SDSM

Table 2: Cross correlation between predictors of NCEP/NCAR (CGCM3model)

Station		Predictors						
Kasol		p__v	**p500**	**p5zh**	**s850**	**shum**	**temp**	
	p__v	1	-0.01	0.14	-0.10	0.20	0.14	
	p500	-0.01	1	-0.54	-0.12	-0.32	-0.33	
	p5zh	0.14	0.54	1	0.03	0.04	0.01	
	s850	-0.10	-0.12	0.03	1	0.87	0.67	
	shum	0.20	-0.32	0.04	0.87	1	0.70	
	temp	0.14	-0.33	0.01	0.67	0.70	1	
Sunni		p_f	**p500**	**p_th**	**shum**			
	p_f	1	0.10	0.34	0.63			
	p_th	0.10	1	0.37	0.29			
	p500	0.34	0.37	1	0.81			
	shum	0.63	0.29	0.81	1			
Rampur		**ms**l	p_th	**p500**	**p8_z**	**p8zh**	**s850**	**temp**
	msl	1	-.03	-0.10	-0.10	-0.08	-0.11	0.05
	p_th	-.03	1	-0.20	-0.58	0.36	-0.26	-0.82
	p500	-0.10	-0.20	1	-0.16	0.12	0.82	0.90
	p8_z	-0.10	-0.58	-0.16	1	-0.19	-0.35	-0.28
	p8zh	-0.08	0.36	0.12	-0.19	1	0.23	0.17
	s850	-0.11	-0.26	0.82	-0.35	0.23	1	0.89
	temp	0.05	-0.82	0.90	-0.28	0.17	0.89	1

is a hybrid downscaling model comprising a stochastic weather generator and a regression method (Chen *et al.,* 2010). The development of SDSM tool and its characteristics are discussed in literature (Wilby *et al*., 1998, 1999, 2002; Wilby and Dawson, 2007). The predictor variables selected for downscaling daily precipitation used in the study are shown in bold in Table 1. Further, cross correlation between predictors of NCEP/NCAR is also investigated and it is shown in Table 2 for CGCM3 model. A high positive correlation is observed between predictors such as shum, s850 and temp. This indicates mutual dependency of these predictors with each other.

5. RESULTS AND DISCUSSIONS

This section describes the development of SDSM 4.2 for downscaling of precipitation from predictors of NCEP/ NCAR and GCMs. The performance of the model along with downscaled results is discussed for future periods (2020's, 2050's and 2080's) under various emission scenarios (A2, A1B and B2).

5.1. Development of SDSM Downscaling Model

The selected predictors from sets of NCEP/ NCAR reanalysis data as given in Table 2 are used to train SDSM 4.2 model. The model is calibrated and validated for downscaling precipitation using 20 years (1963-1982 for Kasol) data, 16 years (1970-1985 for Sunni and Rampur) and 18 years (1983-2000 for Kasol), 15 years (1986-2000 for Sunni and Rampur) data respectively. The statistical parameters such as the monthly average percentage of explained variance (E) and the monthly

Table 3: Performance statistics of SDSM model during calibration period

Station	Precipitation (CGCM3)				Precipitation (HadCM3)			
	E (%)	SE (mm)	R^2	RMSE (mm)	E (%)	SE (mm)	R^2	RMSE (mm)
Kasol (1963-82)	11.20	0.082	0.63	3.17	5.00	0.87	0.61	3.43
Sunni (1970-85)	6.40	0.088	0.41	2.13	7.30	0.88	0.37	2.42
Rampur (1970-85)	13.60	0.79	0.46	1.18	8.30	0.081	0.30	1.45

Table 4: Performance statistics of SDSM model during validation period

Station	Precipitation (CGCM3)				Precipitation (HadCM3)			
	E (%)	SE (mm)	R^2	RMSE (mm)	E (%)	SE (mm)	R^2	RMSE (mm)
Kasol (1983-2000)	10.40	0.084	0.58	3.54	4.80	0.87	0.57	3.34
Sunni (1986-2000)	5.90	0.088	0.49	1.89	7.10	0.87	0.34	2.25
Rampur (1986-2000)	13.90	0.79	0.37	1.34	9.90	0.080	0.31	1.46

average standard error (SE) are used to reflect downscaling results of daily precipitation at each site in the basin. To evaluate the efficiency of model performance during calibration period, coefficient of determination R^2 and Root Mean Square Error (RMSE) statistics are used.

The results obtained from calibration show small values of E (%) and R^2 which reveal the complexity of downscaling station scale precipitation from predictor variables (Table 3). The monthly average value of E (%) for precipitation has been found in between 6.40% to 13.60% for CGCM3 model and 5.00(%) to 8.30(%) for HadCM3 model respectively. The results gained during validation are listed in Table 4.

A comparison of observed daily precipitation with downscaled precipitation has been shown in Figure 2 and 3 for calibration and validation period. The results show that a moderate to poor agreement has been observed between observed and downscaled precipitation values.

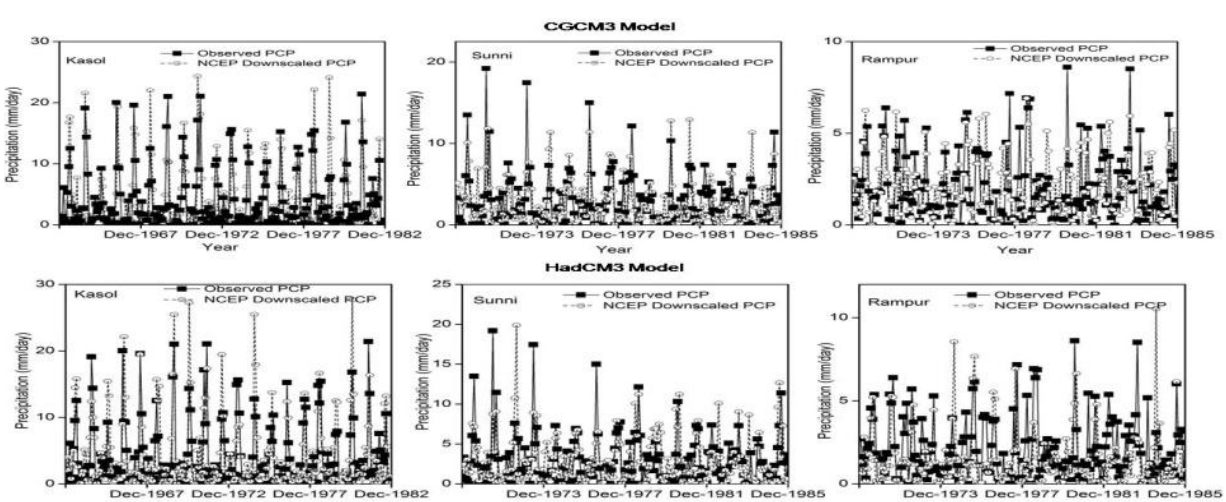

Figure 2: Comparing observed and downscaled values of precipitation for all three stations during calibration period for CGCM3 and HadCM3 models

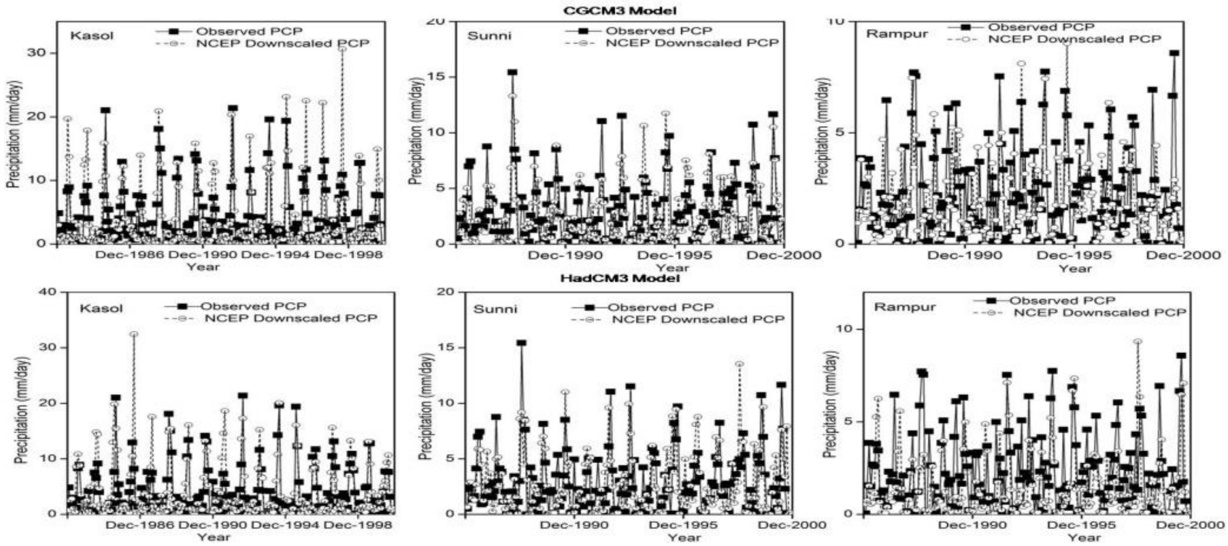

Figure 3: Comparing observed and downscaled values of precipitation for all three stations during validation for CGCM3 and HadCM3 models

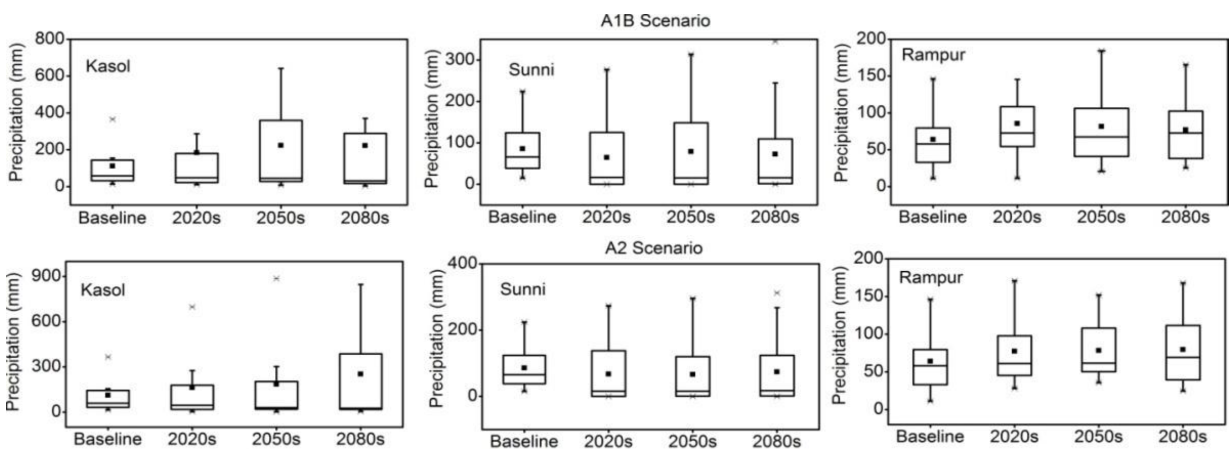

Figure 4: Box plots results from SDSM based downscaling model for the projected precipitation (CGCM3 model). The horizontal line in the middle of the box represents median value while darkened square represents mean value of precipitation data

5.2. Spatial and Temporal Patterns of Downscaled Precipitation for Future Periods

The calibrated SDSM model is used to downscale and generate future scenarios of precipitation from predictors of CGCM3 (SRES A2 and A1B) and HadCM3 (SRES A2 and B2) models in the study region. The pattern of downscaled precipitation is investigated for future periods with a box plot. For this study, the future period is grouped into three time slices; 2020's (2011–2040), 2050's (2041–2070) and 2080's (2071–2099) and each corresponds to span of 30 year periods respectively. The downscaled precipitation is compared with baseline precipitation (1970-2000) to observe change in patterns of precipitation.

The projected precipitation for the future periods (2020's, 2050's and 2080's) has been shown in Figure 4 for the CGCM3 model.

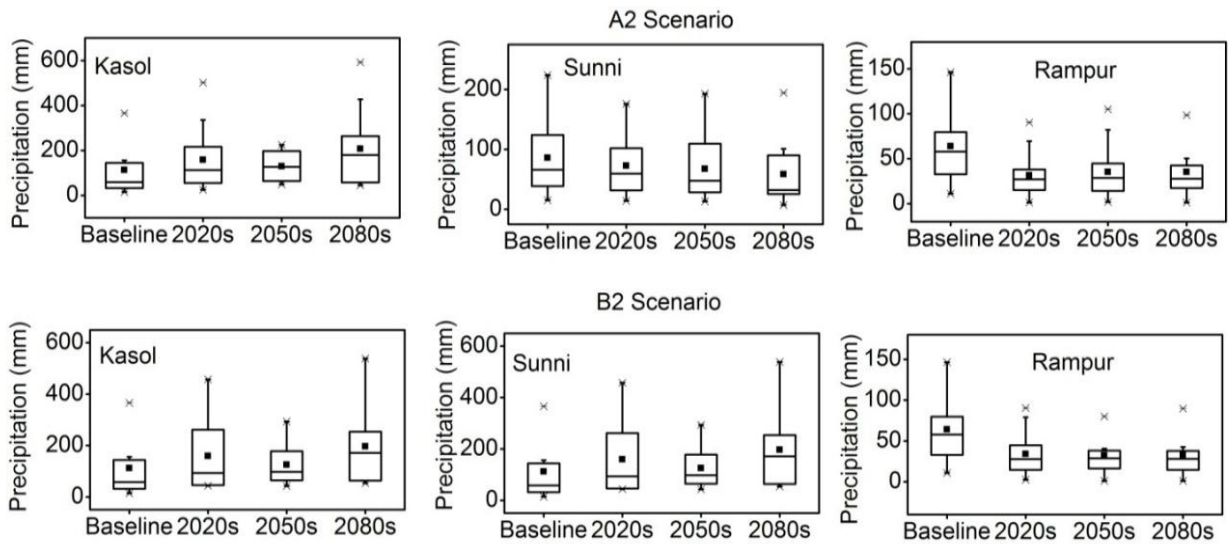

Figure 5: Box plots results from SDSM based downscaling model for the projected precipitation (HadCM3 model). The horizontal line in the middle of the box represents median value while darkened square represents mean value of precipitation data

The increase in future precipitation has been observed at Kasol and Rampur while decrease has been found at Sunni for SRES A2 and SRES A1B scenarios. An overall increase of 5.67%, 8.52% and 18.25% has been computed in mean annual precipitation in the study area under A1B scenario during 2020's, 2050's and 2080's whereas it is 9.21%, 11.23% and 13.91% under A2 scenario respectively. The increase in projected precipitation is higher for A2 scenario as compared to A1B scenario.

The results obtained from HadCM3 model is shown in Figure 5. The decline in amount of simulated precipitation has been found at Sunni and Rampur whereas increase at Kasol for SRES A2 and SRES B2 scenarios. The net change in amount of mean annual precipitation has been computed over study area under SRES A2 and SRES B2 scenarios. The results show increase in magnitude of precipitation under A2 and B2 scenarios for 2080's and decrease for 2050's respectively. This has been found 5.24% under A2 scenario and 4.57% under B2 scenario for 2080's and 3.77% under A2 and 4.08% under B2 for 2050's. For 2020's, no change in mean annual precipitation has been noticed under A2 whereas it is 0.92% under B2 scenario. The poor results obtained during calibration and validation suggests that predictors of HadCM3 model are not well simulated. Further, these are unable to capture regional climate dynamics and hence, poorly projected by SDSM model as compared to CGCM3 model.

The seasonal patterns of projected precipitation have been studied and presented in Table 5 for CGCM3 model. The large increase in projected precipitation has been found at Kasol and significant decrease at Sunni during JJA (June, July, August) periods. The unexpected results have been observed at Rampur. The increase in projected precipitation has been shown during JJA periods for A1B emission scenario and decrease for A2 scenario accordingly. The model predicts increase in projected precipitation under SON (September, October, November) periods for all three stations.

Table 5: Change in projected precipitation during different seasons for CGCM3 model

Station	Season	Change in Precipitation (cm)					
		SRES A2 Scenario			SRES A1B Scenario		
		2020's	2050's	2080's	2020's	2050's	2080's
Kasol	DJF	-0.76	-1.95	-2.74	0.41	1.42	2.14
	MAM	-2.48	-2.79	-2.69	1.25	2.24	2.70
	JJA	19.15	28.75	49.24	25.90	29.90	41.68
	SON	4.13	5.01	12.24	4.78	18.54	7.24
Sunni	DJF	1.27	0.06	0.38	0.50	2.13	0.50
	MAM	-3.40	-3.36	-3.39	3.52	3.56	3.43
	JJA	-10.73	-10.46	-8.42	10.07	7.85	9.26
	SON	5.37	5.97	6.63	5.33	6.50	7.98
Rampur	DJF	1.42	0.44	7.26	1.29	1.74	1.22
	MAM	3.63	8.92	4.40	0.20	1.20	1.81
	JJA	-0.18	-6.24	-5.83	5.29	4.23	2.17
	SON	0.47	2.60	0.41	1.91	2.27	3.60

Table 6: Change in projected precipitation during different seasons for HadCM3 model

Station	Season	Change in Precipitation (cm)					
		SRES A2 Scenario			SRES B2 Scenario		
		2020's	2050's	2080's	2020's	2050's	2080's
Kasol	DJF	19.37	5.11	37.75	18.72	2.39	36.73
	MAM	22.13	6.22	9.99	24.04	6.59	8.78
	JJA	-23.99	-6.99	-23.52	-24.52	-5.84	-23.06
	SON	1.03	2.48	13.78	0.57	2.13	11.38
Sunni	DJF	-0.023	-2.02	-3.37	-0.65	-1.51	-2.23
	MAM	4.78	3.22	0.89	4.55	2.78	2.61
	JJA	-7.98	-6.86	-6.62	-6.57	-5.14	-6.34
	SON	-1.89	-1.60	-1.87	-1.83	-1.77	-1.80
Rampur	DJF	-3.19	0.20	-2.91	-3.20	-3.01	-3.16
	MAM	-2.30	-1.94	-2.21	-1.66	-2.19	-2.36
	JJA	-5.02	-4.32	-4.12	-4.85	-5.14	-4.92
	SON	-2.41	-2.13	-2.12	-2.32	-2.23	-2.20

On contrary, the projected precipitation obtained from HadCM3 model (Table 6) show significant differences in results that are obtained from CGCM3 model. The amount of precipitation is reduced significantly during JJA periods at Kasol. The decrease in projected precipitation has been observed for future periods at Sunni and Rampur respectively.

6. CONCLUSION

In the present paper, a multiple regression based statistical downscaling tool popularly known as SDSM 4.2 is successfully applied to downscale and generate future scenarios of precipitation from predictors of CGCM3 and HadCM3 models in a part of North-Western

(N-W) Himalayan region, India. The change in projected precipitation has been studied for the time periods; 2020's, 2050's and 2080's for SRES A2 and A1B scenarios (CGCM3 model) and for SRES A2 and B2 scenarios respectively. The seasonal patterns of precipitation are also examined and changes with respect to baseline period are shown.

The results of precipitation downscaling using SDSM are found to be poor for HadCM3 model as compared to CGCM3 model. The results obtained from CGCM3 model predict an overall increase in precipitation while decrease in precipitation is predicted by HadCM3 model for the future periods in the region. Based on the analysis of results, CGCM3 model has been found better for simulation of precipitation in comparison to HadCM3 model.

APPENDIX: 1

Abbreviations used in Table 1

Predictors	Description
msl	Mean sea level pressure
p_f	Surface air flow strength
p__v	Surface meridional velocity
p__z	Surface vorticity
p_th	Surface wind direction
pzh	Surface divergence
p5_f	500 hpa airflow strength
p5_u	500 hpa zonal velocity
p5_v	500 hpa meridional velocity
Predictors	Description
p500	500 hpa geopotential height
p5zh	500hpa divergence
p8_z	850 hpa vorticity
p8_th	850 hpa wind direction
s850	Relative/Specific humidity at 850 hpa
p8zh	850 hpa divergence
rhum	Near surface relative humidity
shum	Surface specific humidity
temp	Mean temperature at 2 m

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