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Future Climate Projections Using SDSM and LARS-WG Downscaling Methods for CMIP5 GCMs over the Transboundary Jhelum River Basin of the Himalayas Region

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Abstract: Climate change is one of the leading issues affecting river basins due to its direct impacts on the cryosphere and hydrosphere. General circulation models (GCMs) are widely applied tools to assess climate change but the coarse spatial resolution of GCMs limit their direct application for local studies. This study selected five CMIP5 GCMs (CCSM4, HadCM3, GFDL-CM3, MRI-CGCM3 and CanESM2) for performance evaluation ranked by Nash–Sutcliffe coefficient (NSE) and Kling–Gupta Efficiency (KGE). CCSM4 and HadCM3 large-scale predictors were favored based on ranks (0.71 and 0.68, respectively) for statistical downscaling techniques to downscale the climatic indicators $T_{\max}$, $T_{\min}$ and precipitation. The performance of two downscaling techniques, Statistical Downscaling Methods (SDSM) and Long Ashton Research Station Weather Generator (LARS-WG), were examined using the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), bias, NSE and KGE with weights (W_i) for the validation period. The results of statistical measures proved SDSM more efficient (0.67) in comparison to the LARS-WG (0.51) for the validation time for the Jhelum River basin. The findings revealed that the SDSM simulation for $T_{\max}$ and $T_{\min}$ are more comparable to the reference data for the validation period except simulation of extreme events by precipitation. The 21st century climatic projections exhibited a significant rise in $T_{\max}$ (2.37–4.66 °C), $T_{\min}$ (2.47–4.52 °C) and precipitation (7.4–11.54%) for RCP-4.5 and RCP-8.5, respectively. Overall, the results depicted that winter and pre-monsoon seasons were potentially most affected in terms of warming and precipitation, which has the potential to alter the cryosphere and runoff of the Jhelum River basin.

Keywords: CMIP5; GCMs; LARS-WG; RCPs; statistical downscaling; SDSM

1. Introduction

Climate change is becoming a leading issue for the 21st century due to its devastating environmental and socioeconomic impacts. In the last few decades, the frequency and magnitude of extreme climatic events increased subsequently in response to the anthropogenic activities [1]. Anthropogenic activities, primarily socioeconomic (fossil fuels burning and land use/land cover changes), have influenced the amount of greenhouse gases which trigger climate change and extreme climate events. The occurrences of extreme events are not uniform across the globe; some regions are more susceptible to climate change. Particularly, Pakistan, has faced frequent heatwaves and floods in the last few years [2–4]. To cope with these extreme climatic events, the timely and effective monitoring of climate

change is required to make policies for adaptation and mitigation. The impacts of climate change on water resources and the hydrological cycle are of extreme importance because all socioeconomic and natural systems ultimately depend on water resources. The climatic changes can directly impact the availability and changing patterns of water resources such as flooding and droughts [3,5], and some indirect impacts on food, agriculture and energy production [6]. These climate change impacts may be worse for the transboundary river's basins such as Jhelum where management of the basin depends on different economic, political, and social interest of the countries. Jhelum River basin is an integral part of the Himalayas region where an increasing trend of temperature has been observed that increases glacial melting and precipitation, and affects the availability of water resources [7,8]. Climatic change studies in the Jhelum River basin is still at its infancy due to a lack of significant weather station data. To understand the impacts of climate change on the transboundary Jhelum River basin of the Himalayas region, GCMs have been used to assess the present and future climatic changes.

The GCMs provide projections of climate at a global scale for policymakers to adapt better strategies to cope with climate change. GCMs represent significant outputs at the global, hemispherical and continental scales by incorporating the complexity of the global system, however, these global dynamics cannot be represented at the local sub-grid level [9]. The efficiency of GCMs to project the future climate has been debated due to their uncertainties during the validation processes at the regional scale. Despite improvements in the GCMs to represent climate processes in better ways, these uncertainties cater to produce better climate projection but still remain a subject of ample concern at the regional/local level [10]. GCMs are widely used tools to assess the climate change impacts but their coarse spatial resolution restricts direct use for the sustainable management at the regional or local scale [11]. The downscaling techniques are essential to transform GCMs' spatial resolution from coarse to fine to allow their direct use at the local/regional scale [12]. The two widely used downscaling methods, statistical downscaling and dynamical downscaling applied to relate the GCMs' coarse resolution and local climatic variables [13]. Dynamic downscaling of GCMs are employed as a Regional Climate Model (RCM) at finer spatial resolution (10–50 km) to simulate regional climate by incorporating local features such as topography. Dynamic downscaling is an emerging and advanced method, but the advanced computational requirement and heavy data storage limit their use at regional scale [2]. Statistical downscaling is both a flexible and computationally efficient approach to downscale GCMs and to use fine resolution data for a climate impact assessment at the local/regional level [13]. Statistical downscaling has directly built a relationship between local observation, climatic variables and GCMs' output without requiring the physical knowledge of the local region [14]. Therefore, statistical downscaling methods have been extensively applied by the researchers to simulate climate projections at the local/regional scale for the climate impact studies [15].

The main theme of statistical downscaling is to develop the relationship among predictors (GCMs variables) and predictands (local scale variables) through statistical and mathematical techniques such as linear and non-linear regression models, and weather generators [13]. Among linear regression models, the Statistical Downscaling Method (SDSM) is a renowned statistical model developed by [16] that is frequently used by research to downscale GCMs [17]. SDSM is a hybrid model that employed the weather generators and regression models to downscale climatic variables. It facilitates the downscaling of long-term, low-cost, and rapid development of multiple daily weather parameters. The weather generator's technique, Long Ashton Research Station Weather Generator (LARS-WG), is a well-known stochastic weather generator technique used to simulate the weather data for a single weather station in the form of time series data for both present and future climatic conditions. The long-term time series data of a climate variables group e.g., $T_{\max}$, $T_{\min}$ and precipitation are simulated for the single weather station using the LARS-WG method [6].

SDSM and LARS-WG have been widely used techniques by the researchers to downscale the GCMs' data for local/regional basins [6,9]. These techniques have been used for three GCMs (BCC-CSM1-1, CanESM2 and MICRO5) and future projections depicted that mean annual temperature and precipitation for the future are on the rise [18]. These studies demonstrated statistical downscaling methods as a vigorous tool to analyze the futuristic climatic changes for the regional/local basin level. SDSM and LARS-WG have been used for the better assessment of climate changes in the Jhelum River basin using different GCMs. The study area is of key importance as it is part of the Indus basin and greater Himalayas that have permafrost mountain tops. The climate changes ultimately trigger the melting of snow/glacier at mountain tops. The recent study focused on examining the efficiency of these statistical downscaling techniques SDSM as a regression model and LARS-WG as weather generators for downscaling the T_{max} , T_{min} and precipitation data for the Jhelum River basin. The basin is the transboundary and conflicted region located at the greater Himalayas, therefore, future projections of T_{max} , T_{min} and precipitation will help to study the dynamics of hydrometeorological changes in the basin. The study designed a methodology to incorporate multiple GCMs for the basin based on local conditions. The selection of GCMs helped to downscale the long-term time series climatic data for the 21st century by using two different statistical downscaling techniques (SDSM and LARS-WG). The meteorological station's data of Jhelum River basin was applied to evaluate the accuracy of SDSM and LARS-WG. After evaluation of the statistical downscaling techniques, climate change projections were simulated for RCP 4.5 and RCP 8.5 using six GCMs for the 21st century.

2. Materials and Methods

2.1. Study Area

The Jhelum River is the major tributary of the Indus basin located in the north of Pakistan. The basin is the transboundary conflicted region divided by the line of control (LoC) between India and Pakistan. The geographical extent of the region exists between 73–75.63° E and 33–35.1° N, covering a total area of about 34,475 km² (Figure 1). The river is fed by the glacier/snow melting of the drains from the top of the Himalayas mountains. The basin has a diverse altitudinal variation from 233 to 6178 m that covers the permanent snow-covered area in the north. The river basin has unique geomorphology and heterogeneous lithology with varied hydrological conditions which add up to the basin being more susceptible to climate change [19]. The climate of the basin has diversity in terms of spatio-temporal variability. The precipitation in the basin is dominant by the two seasonal rainfall regimes, monsoons during summer and western disturbances during winter. The details of the eleven meteorological stations of the basin are described in Table 1.

Table 1. Detail of the Meteorological Stations.

Station Name	Station ID	Lat (°N)	Long (°E)	Elevation (m) amsl	Annual Prec (mm)	Mean Teemp(°C)
Jhelum	A	33.1	73.74	614	1255	22.2
Kotli	B	33.5	73.89	1402	1423	17.5
Plandri	C	33.72	73.71	1676	1346	16.2
Rawlakot	D	33.87	73.68	2213	1780	12.8
Murree	E	33.92	73.38	845	1188	19.4
Garidopata	F	34.22	73.61	702	1388	20.6
Muzaffarabad	G	34.38	73.47	996	1693	18.3
Balakot	H	34.56	73.34	2363	1301	6.18
Naran	I	34.91	73.64	2220	1288	7
Astore	J	35.1	74.82	2168	448	6.56
Poonch	K	33.91	74.03	815	1516	19.4

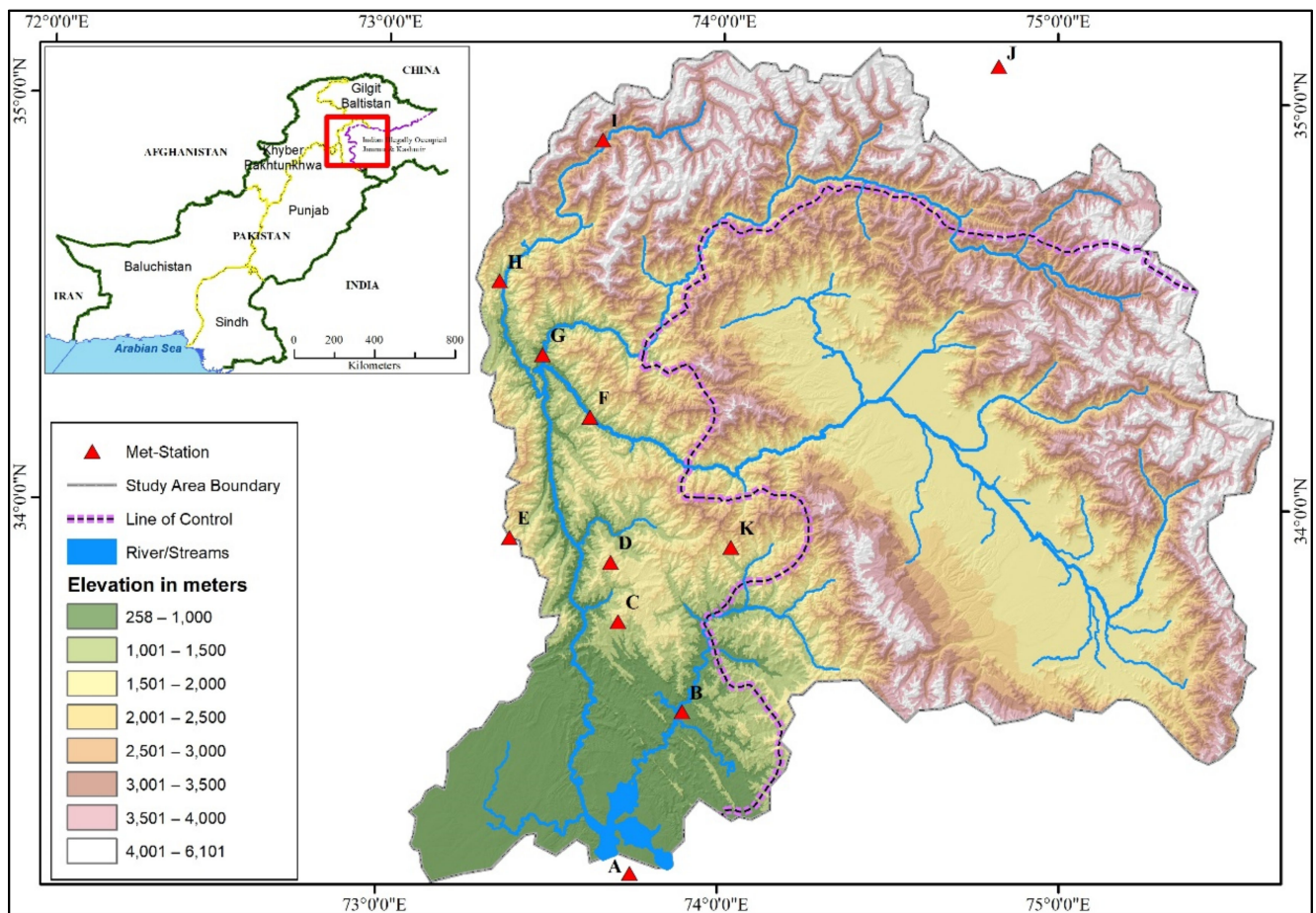


Figure 1. Geographical location of the Jhelum River basin.

2.2. Data Description

The predictands of daily time series data for $T_{\max}$ and $T_{\min}$ and precipitation were acquired from the Pakistan Meteorological Department (PMD) from 1976–2020. Few stations have some missing values that were replaced by using interpolation technique [15]. The datasets for 1976–2005 of eleven meteorological stations were applied for the evaluation of the GCMs and selection of the GCMs for the downscaling techniques. The thirty years of data (1976–2005) were used as the baseline data for statistical downscaling and bias correction of GCMs of the daily time series for the period 1976–2099.

The projected climate changes are highly uncertain and rely on technological innovations and socioeconomic development to adapt clean technology against greenhouse gas emissions in the atmosphere. The Coupled Model Intercomparison Project Phase 5 (CMIP5) in accordance of the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) used RCPs that provide a wider picture of future climate change including a mitigation scenario (RCP-2.6), two medium stabilization scenarios (RCP-4.5 and RCP-6.0) and an extreme scenario (RCP 8.5). The five GCMs of CMIP5 for one medium stabilization scenario (RCP-4.5) and an extreme scenario (RCP-8.5) were downloaded (Table 2) from the Royal Netherlands Meteorological Institute's (KNMI) Climate Explorer [20].

Twenty different NCEP predictors applied for the screening purposes (Table 3) and based on the relationship among the NCEP predictors and local basin predictands ($T_{\max}$ and $T_{\min}$ and precipitation), following predictors selected for the SDSM.

Table 2. Selected GCMs from CMIP5 used for downscaling techniques.

Modelling Centre	GCM	Resolution
National Center for Atmospheric Research USA	CCSM4	$0.9^\circ \times 1.25^\circ$
UK Meteorological Office UK	HadCM3	$2.5^\circ \times 3.75^\circ$
Geophysical Fluid Dynamics Laboratory USA	GFDL-CM3	$2^\circ \times 2.5^\circ$
National Institute for Environmental Studies Japan	MRI-CGCM3	$1.12^\circ \times 1.12^\circ$
Canadian Centre for Climate Modelling and Analysis Canada	CanESM2	$2.79^\circ \times 2.8^\circ$
Beijing Climate Center, China	BCC-CSM1–1	$2.81^\circ \times 2.81^\circ$

Table 3. Description of NCEP predictor.

No.	Predictor	Code	No.	Predictor	Code
1	Mean sea level pressure	mslp	11	500 hPa meridional velocity	p5_v
2	500 hPa relative humidity	r500	12	Surface specific humidity	Shum
3	850 hPa vorticity	P8_z	13	Mean temperature at 2 m	temp
4	Surface zonal velocity	p_u	14	Surface airflow strength	p_f
5	500 hPa vorticity	p5_z	15	Surface meridional velocity	p_v
6	Surface vorticity	p_z	16	Surface wind direction	p_th
7	500 hPa wind direction	p5th	17	Surface divergence	p_zh
8	850 hPa relative humidity	r850	18	500 hPa airflow strength	p5_f
9	Surface zonal velocity	p_u	19	500 hPa zonal velocity	p5_u
10	850 hPa meridional velocity	p8_v	20	500 hPa geopotential height	p500

2.3. Mann–Kendall Trend Model

The Mann–Kendall trend test (MK) is a non-parametric model applied to assess the climatic trends in the long-term time series data [21]. MK trend model was applied on the $T_{\max}$, $T_{\min}$ and precipitation data for the baseline period using the following equations.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i), \quad (1)$$

where x_i and x_j are the orderly data records in the i and j years; n is the span of the time series data.

$$\text{where } \text{sgn}(x_j - x_i) = \begin{cases} +1, & (x_j - x_i) > 0 \\ 0, & (x_j - x_i) = 0 \\ -1, & (x_j - x_i) < 0 \end{cases} \quad (2)$$

$$\text{Var}(S) = \frac{1}{18} \left[n(n-1)(2n+5) \sum_{p=1}^q t_p(t_p-1)(2t_p+5) \right] \quad (3)$$

In Equation (3), q is the number of tied groups whereas t_p is the number of observations in the p th group.

2.4. Screening of the GCMs

The five GCMs were further evaluated based on the accuracy assessment to select two GCMs for the downscaling purposes because the study focused on the evaluation of the downscaling processes SDSM and LARS-WG that already made it intensive. The accuracy assessment of GCMs were carried out by using gridded $T_{\max}$, $T_{\min}$ and precipitation datasets cross-validated against the observed station data sets [22]. The gridded

$T_{\max}$, $T_{\min}$ and precipitation are interpolated using the kriging geospatial technique. The correspondence values of GCMs for climatic indicators ($T_{\max}$, $T_{\min}$ and precipitation) at the meteorological stations were used for the performance evaluation of GCMs. The indices were based on the simulated GCMs' values and the observed monthly time scale climatic indicators ($T_{\max}$, $T_{\min}$ and precipitation). The performance indicators between reference datasets and GCMs modeled data of climatic indicators by using Pearson's Correlation Coefficient (r), Kling–Gupta Efficiency (KGE) [19] and Nash–Sutcliffe coefficient (NSE) [20]. The detailed formulas of r , KGE and NSE are as follows:

$$r = \frac{\sum (x - \bar{x}_i)(x'_i - \bar{x}'_i)}{\sqrt{\sum (x_i - \bar{x}_i)^2 (x'_i - \bar{x}'_i)^2}} \quad (4)$$

$$KGE = 1 - \sqrt{(r - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \quad (5)$$

$$NSE = 1 - \frac{\sum_{i=1}^n (x_o - x_s)^2}{\sum_{i=1}^n (x_s - x_o)^2} \quad (6)$$

The description of 'x' are the climatic indicators ($T_{\max}$, $T_{\min}$ and precipitation) while subscripts s and o denoted the observed referenced values and simulated modeled values, respectively. Equation (4) represents the Pearson's correlation coefficient to measure the linear relationship between observed and simulated values. Equation (5) describes the KGE equation including values for r , β and γ while Equation (3) describes the NSE. The resultant values were normalized and rescaled between 0 and 1 and then finally summed up to generate rankings for each GCM.

2.5. Bias Correction

The bias correction method mean-based biased correction method (MB-BC) applied to eliminate errors from the modeled simulated data. The MB-BC method utilized the mean observed data and GCM simulation for the baseline period [21]. Following, the different Equations (7) and (8) were used for the bias correction of temperature and precipitation to avoid negative values for precipitation.

$$T_{\text{de-biased}} = T_{\text{sim}(2020-2099)} \times \left(\frac{T_{\text{sim}(1976-2005)} - T_{\text{obs}(1976-2005)}}{T_{\text{sim}(1976-2005)}} \right) \quad (7)$$

$$P_{\text{de-biased}} = P_{\text{sim}(2020-2099)} \times \left(\frac{P_{\text{obs}(1976-2005)}}{P_{\text{sim}(1976-2005)}} \right) \quad (8)$$

2.6. Statistical Downscaling Method

Two downscaling methods (SDSM and LARS-WG) were applied for the eleven meteorological stations of Jhelum River basin. The study aimed to compare the efficiency of the downscaling schemes for the selected GCMs. The three predictands ($T_{\max}$, $T_{\min}$ and precipitation) were considered against the GCM predictors to analyze the climate changes in the river basin for the 21st century.

2.6.1. SDSM

SDSM is the hybrid scheme, a combination of Stochastic Weather Generators (SWG) and Multiple Linear Regression (MLR). MLR was used to develop the relationship between the predictands ($T_{\max}$, $T_{\min}$ and precipitation) and NCEP predictors (large-scale climate data) by yielding regression parameters. These regression parameters were further used for screening and calibration of NCEP predictors. After screening, the NCEP predictors were established on the correlation analysis of large-scale predictors with the local scale predictands. The screening of the GCM's large-scale predictors is the key to success of the

SDSM and yields through regression parameters were established on the correlation matrix and absolute partial correlation [8].

The regression parameters, NCEP predictors and GCM data (CCSM4 and HadCM3) were further used by the SWG scheme to simulate the time series data for the 21st century [13]. The precipitation projections were challenging as compared to the temperature due to its complex nature. The precipitation was modeled by using a conditional sub model and SWG conditioned and applied on the predictors. The conditional sub model was designed for the precipitation [22] as it occurs on each day t or not by using the following equation:

$$P_t = \alpha_0 + \sum_{i=1}^n \alpha_i u_t^{(i)} + \alpha_{t-1} w_{t-1} \quad (9)$$

The P_t is the conditional processes for precipitation of each day t ; $u_t^{(i)}$ is used to normalized predictor, while α_i is regression parameter; α_{t-1} and w_{t-1} are the conditional possibilities for precipitation occurrence on day $t - 1$.

2.6.2. LARS-WG Model

LARS-WG is the stochastic weather generator that was applied for the simulation of weather data for both the present and future climatic conditions. The synthetic weather data were generated for three timelines: model calibration (1976–2005), model validation (2006–2020) and scenario generation (2021–2099). For model calibration (1976–2005), the daily observed series data for $T_{\max}$, $T_{\min}$ and precipitation were applied to examine parameters for probability distribution. The observed weather data ($T_{\max}$, $T_{\min}$ and precipitation) were used in LARS-WG to generate time series of erratic length by selecting random values from the stations' distributions [9]. LARS-WG was based on the semi-empirical distribution that used cumulative probability distribution function to approximate probability of dry and wet series for $T_{\max}$ and $T_{\min}$ and dry and wet days for the precipitation [13]. The future climate scenarios were generated for the period (2021–2099) for selected RCPs based on the LARS-WG baseline parameters (1976–2005). In LARS-WG, the differences in current and future climatic changes were incorporated by using bias correction [23], which is the difference of the mean monthly changes of $T_{\max}$, $T_{\min}$ and precipitation. The following equations are used for ΔT_i and ΔP_i :

$$\Delta T_i = (T_{2021-2099} - T_{1976-2005}) \quad (10)$$

$$\Delta P_i = \left(\frac{P_{2021-2099}}{P_{1976-2005}} \right) \quad (11)$$

The ΔT_i and ΔP_i are to represent long term changes of each month ($1 \leq i \leq 12$), for temperature and precipitation, respectively.

2.6.3. SDSM and LARS-WG Performance Evaluations

SDSM and LARS-WG performance evaluations were assessed by using statistical techniques. The statistical errors (Equations (12)–(14)); mean absolute error (MAE), root mean square error (RMSE) and bias were used along with NSE and KGE. The NSE and KGE are hypersensitive to extreme values and inconsiderable to the proportional and additive differences that exist between the observation and model simulations. The equations for NSE and KGE were described in the above section (Equations (4) and (5)). Following are the equations for MAE, RMSE and bias:

$$MAE = \frac{\sum_{i=1}^n |X_o - X_s|}{n} \quad (12)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (X_o - X_s)^2} \quad (13)$$

$$\text{Bias} = \frac{\sum_{i=1}^n x_o}{n} - \frac{\sum_{i=1}^n x_s}{n} \quad (14)$$

X_o and X_s are the observation and simulated data in the above equations by statistical downscaling, respectively, and n is the number of all samples. Additionally, weight technique is used for performance matrices incorporating all the measurements errors to avoid discrepancies. More weight (0.5) was assigned to measurement errors (MAE, RMSE and bias) while less weight (0.15) was applied to the NSE and KGE due to their oversensitivity to extreme values [6]. Equation (15) is used to rank the SDSM and LARS-WG model based on the weights assigned to the different measurement errors. The performance evaluation of the downscaling methods were summarized by using summation of the weights of each measurement error by using Equation (15).

$$W_i = W_{MAE} \frac{MAE_i}{MAE_{max}} + W_{RMSE} \frac{RMSE_i}{RMSE_{max}} + W_{Bias} \frac{Bias_i}{Bias_{max}} + W_{KGE} \frac{KGE_i}{KGE_{max}} + W_{NSE} \frac{NSE_i}{NSE_{max}} \quad (15)$$

where the i index represents to the downscaling model; W_i refers to the overall performance measure.

3. Results and Discussion

3.1. Temperature and Precipitation Trend Analysis for the Baseline Period

The Mann–Kendall trend model was applied on the eleven meteorological stations of the Jhelum River basin. In this test, the Kendall's tau denotes the strength of the monotonic trend where the value of Kendall's tau ranges from $-1 \leq \tau \leq 1$. The positive Kendall's tau indicated an increasing trend whereas the negative values denoted decreasing. Based on a 95% significance level, the p value is ≤ 0.05 and indicated the presence of a significant trend while p value ≥ 0.05 verified that there was no trend in the time series data. The results found that there were different trends for all stations. The significant trend for T_{max} depicted for Station D station have a p value less than 0.05, while the rest of the stations showed no significant trend (Table 4).

Table 4. Mann–Kendall test results for T_{max} for Meteorological stations.

Station ID	Mann–Kendall Statistics	Kendall's Tau	Variance (S)	p Value (Two Tailed Test)
A	38	0.2000	950	0.2300
B	−32	0.1684	950	0.3145
C	54	0.2842	950	0.0855
D	88	0.4632	950	0.0048
E	7	0.0369	949	0.8456
F	16	0.0842	950	0.6265
G	16	0.0842	950	0.6265
H	−44	−0.1534	950	0.2845
I	24	0.187	950	0.0756
J	26	0.094	950	0.5265
K	33	0.048	950	0.2651

The Mann–Kendall trend for T_{min} predicted in line trend results of T_{max} . The meteorological stations D, I and another station, K, have shown a statistical trend. Other stations represented an insignificant trend for the historical time series data (Table 5).

The Mann–Kendall statistics results for precipitation illustrated no significant trend for most of the basin during the historical period. The three stations B, H and K depicted a negative trend for precipitation (Table 6).

Table 5. Mann–Kendall test results for $T_{\min}$ for Meteorological stations.

Station ID	Mann–Kendall Statistics	Kendall’s Tau	Variance (S)	p Value (Two Tailed Test)
A	36	0.1895	950	0.2561
B	44	0.2316	950	0.1630
C	−68	−0.3579	950	0.0297
D	93	0.4908	949	0.0028
E	36	0.1895	950	0.2561
F	−20	−0.1053	950	0.5376
G	27	0.2571	408	0.1982
H	−34	−0.197	860	0.2131
I	58	0.2876	950	0.0341
J	34	0.1951	950	0.261
K	45	0.3161	950	0.130

Table 6. Mann–Kendall test results for Precipitation for Meteorological stations.

Stations ID	Mann–Kendall Statistics	Kendall’s Tau	Variance (S)	p Value (Two Tailed Test)
A	14	0.0737	950	0.6732
B	−20	−0.1053	950	0.5376
C	34	0.1789	950	0.2843
D	36	0.1895	950	0.2561
E	38	0.2000	950	0.2300
F	54	0.2842	950	0.0855
G	−19	−0.1810	408	0.3731
H	−24	−0.1245	450	0.4786
I	28	0.1345	950	0.2785
J	16	0.0973	950	0.5732
K	−13	−0.131	950	0.3761

3.2. Selection of GCMs

It was difficult to perform statistical downscaling (SDSM and LARS-WG) for all five GCMs for the river basin. Therefore, the selection of GCMs were made by using Equations (4)–(6) and the best GCMs were chosen for further processing based on ranks described in Table 7. The best proved GCMs were CCSM4 and HadCM3, in relationship to the reference data ($T_{\max}$, $T_{\min}$ and precipitation), with 0.71 and 0.68 ranking, respectively (Table 7).

3.3. Screening Predictor Variable of SDSM

The twenty predictors (Table 2) analyzed by absolute partial correlation coefficient (abs P) between the predictors and predictands are summarized in Figure 2. Among the selected thirteen predictors, 500 hPa vorticity ($p5_z$) depicted the highest relationship for $T_{\max}$, $T_{\min}$ and precipitation while the predictor surface divergence (p_zh) showed the weakest relationship for the predictands. The best predictor for $T_{\max}$ was surface vorticity (p_z) with highest value (0.59) and minimum relationship (0.22) of predictor with 500 hPa geopotential height ($p500$). The best predictor for $T_{\min}$ was 500 hPa vorticity ($p5_z$) and for precipitation was 850 hPa relative humidity ($r850$). The weakest relationship of $T_{\min}$

existed with predictor mean temperature at 2 m (temp) and of precipitation with surface divergence (p_zh). These thirteen predictors were further used in the downscaling process and the selection criteria, based on the previous studies [24].

Table 7. Selection of GCMs.

GCM Models	Pearson's Correlation Coefficient (r)			KGE			NSE			Rank
	T _{max}	T _{min}	P	T _{max}	T _{min}	P	T _{max}	T _{min}	P	
CCSM4	0.82	0.93	0.79	0.47	0.49	0.42	0.78	0.89	0.79	0.71
GFDL-CM3	0.49	0.56	0.61	0.39	0.34	0.21	0.51	0.68	0.57	0.48
HadCM3	0.72	0.83	0.77	0.47	0.39	0.32	0.88	0.79	0.91	0.68
MRI-CGCM3	0.59	0.67	0.51	0.29	0.33	0.27	0.61	0.58	0.64	0.49
CanESM2	0.62	0.57	0.49	0.29	0.34	0.37	0.71	0.67	0.64	0.52
BCC-CSM1-1	0.77	0.81	0.67	0.49	0.43	0.33	0.78	0.89	0.81	0.66

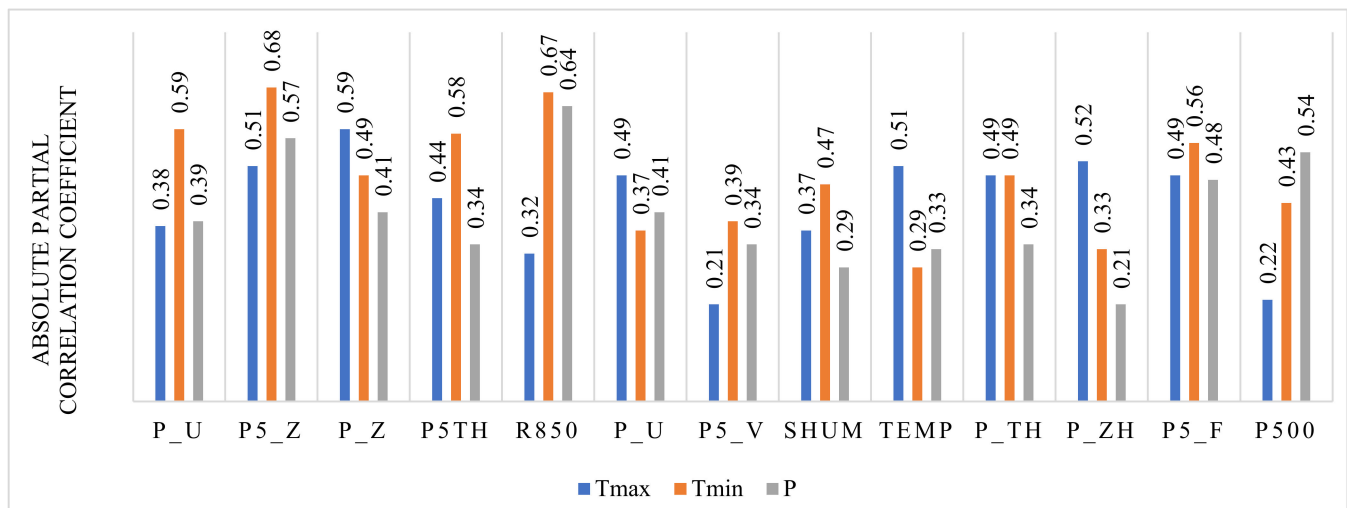


Figure 2. Selected predictors against predictands (T_{max}, T_{min} and precipitation).

3.4. Calibration and Validation of SDSM and LARS-WG

The GCMs' (CCSM4 and HadCM3) data were downscaled by using statistical downscaling methods (SDSM and LARS-WG) during the calibration period (1976–2005). The results of calibrations are plotted against the observed referenced data in Figure 3. The calibration results depicted that SDSM yields more accurate and good quality time series data for T_{max} and T_{min} against the observations for the calibration period. On the contrary, LARS-WG predicted more accurate precipitation time series data. The precipitation is the complex indicator and LARS-WG proved to be more accurate in recording extreme events and precipitation distribution. The results of the calibration period simulated against RCP-4.5 were more accurate in comparison to the RCP-8.5, as the later simulation were more exaggerated from the former one (Figure 3). The precipitation for the summer months i.e., June, July and August (JJA) were underestimated while for winter months, namely, December, January and February (DJF) were overestimated. The simulated results of T_{max} for the calibration period were more accurate as compared to the T_{min} which was a bit exaggerated for the winter months (Figure 3).

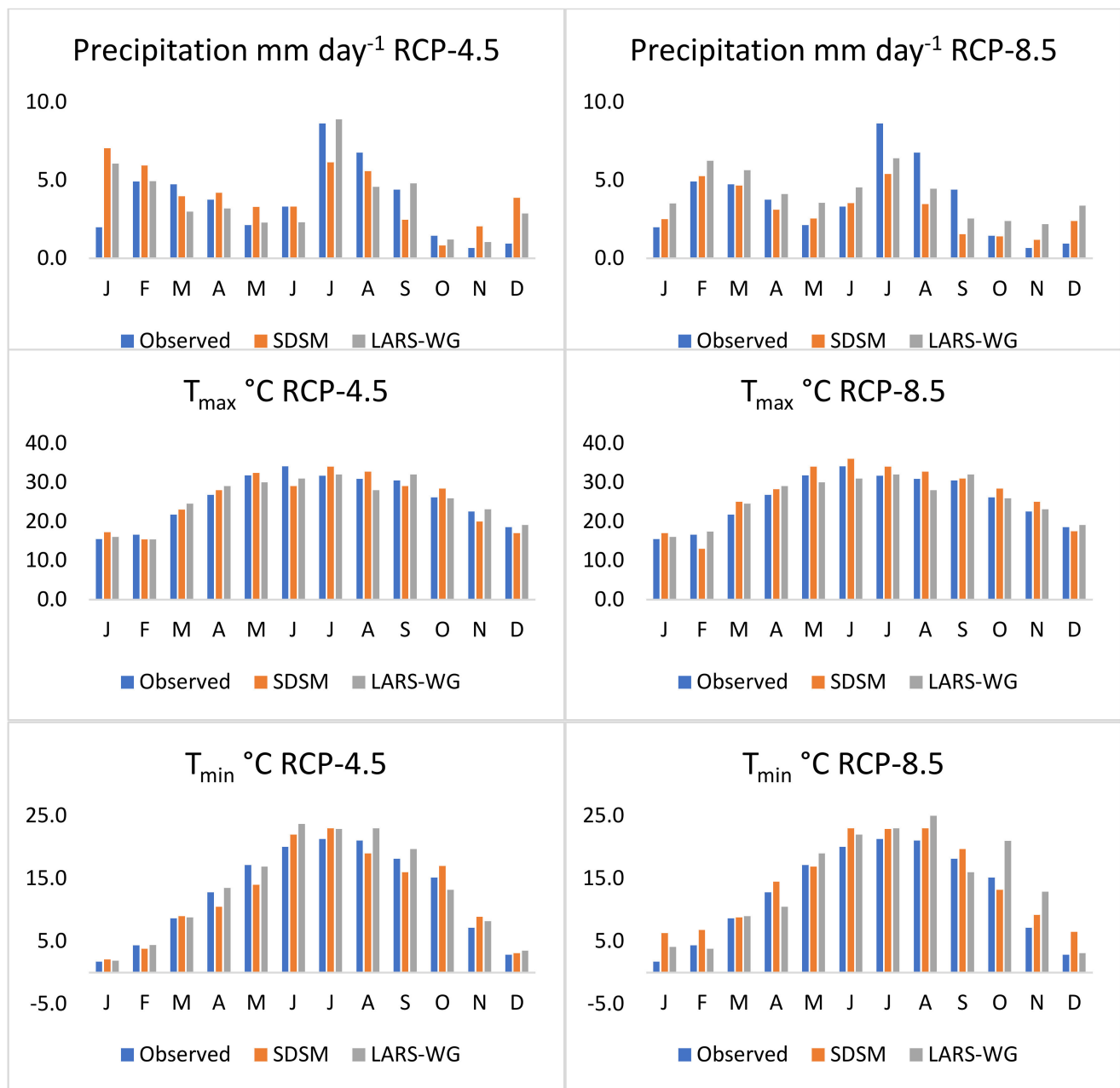


Figure 3. Calibration results of SDSM and LARS-WG models (1976–2005).

The statistical downscaling models (SDSM and LARS-WG) were validated for the period of (2006–2020) by using statistical measures MAE, RMSE, bias, KGE and NSE. These measures were weighed as discussed in the Materials and Methods section following Equation (15). The values for the statistical errors were rescaled between 0–1 to avoid negative values for the precipitation. The performance assessment of the models for the validation for each of the climatic parameters are described in Table 8. The results of statistical measures proved SDSM as more efficient (0.67) in comparison to the LARS-WG (0.51) for the validation period for the Jhelum River basin. SDSM was further applied to generate future climate changes for the 21st century due to its better performance. The validation results for RCPs were in line with the calibration period and RCP-8.5 was exaggerated in comparison to the RCP-4.5 (Table 8). The simulated indicator T_{max} proved best during the validation and precipitation was depicted the least accurate due to its complex nature (Table 8).

Table 8. Performance of the models during the validation period (2006–2020).

Models	MAE			RMSE			Bias			KGE			NSE		
	T _{max}	T _{min}	P	T _{max}	T _{min}	P	T _{max}	T _{min}	P	T _{max}	T _{min}	P	T _{max}	T _{min}	P
CCSM4 RCP-4.5															
SDSM	0.72	0.93	0.79	0.5	0.69	0.42	0.78	0.89	0.79	0.68	0.53	0.48	0.61	0.72	0.42
LARS-WG	0.49	0.56	0.61	0.9	0.42	0.72	0.51	0.68	0.57	0.48	0.58	0.62	0.62	0.57	0.69
CCSM4 RCP-8.5															
SDSM	0.52	0.65	0.67	0.4	0.92	0.51	0.73	0.53	0.65	0.42	0.59	0.61	0.44	0.57	0.59
LARS-WG	0.3	0.49	0.39	0.89	0.84	0.56	0.68	0.62	0.64	0.5	0.46	0.55	0.36	0.38	0.41
HadCM3 RCP-4.5															
SDSM	0.79	0.77	0.51	0.41	0.43	0.32	0.61	0.58	0.64	0.49	0.5	0.54	0.59	0.67	0.58
LARS-WG	0.62	0.57	0.49	0.21	0.67	0.71	0.71	0.67	0.64	0.52	0.71	0.65	0.69	0.71	0.65
HadCM3 RCP-8.5															
SDSM	0.64	0.81	0.51	0.53	0.81	0.53	0.65	0.57	0.71	0.67	0.64	0.52	0.73	0.69	0.55
LARS-WG	0.65	0.59	0.47	0.76	0.79	0.45	0.29	0.28	0.62	0.51	0.73	0.54	0.63	0.67	0.61

3.5. Future Climate Projections

The projected annual and seasonal changes for T_{max}, T_{min} and precipitation under both RCPs (RCP-4.5 and RCP-8.5) for the mid-century (2021–2060) and end-century (2061–2099) over the Jhelum River basin are summarized in Table 9. Overall, an annual increase in temperature (T_{max} and T_{min}) was observed for both RCPs, however, the temperature rise for RCP-8.5 (4.48 °C) was expected to be more significant than RCP-4.5 (2.52 °C) (Table 9). The rate of increase in temperature and precipitation are in line with the previous studies in the basin [25]. As the climate change triggered changes in the river basin by making it hot and wet for the upcoming century, it can trigger other physical changes in the basin by altering the balance of glaciation, deglaciation and flooding.

Table 9. Projected changes in mean T_{max} (°C), T_{min} (°C) and total precipitation (%) on annual and seasonal bases under future scenarios (RCP-4.5 and RCP 8.5) for mid-century (2021–2060) and end-century (2061–2099) in comparison to the baseline period (1976–2005) over the Jhelum River basin.

Season/ Period	RCP-4.5						RCP-8.5					
	CCSM4		HadCM3		Average		CCSM4		HadCM3		Average	
	2021–2060	2061–2099	2021–2060	2061–2099	2021–2060	2061–2099	2021–2060	2061–2099	2021–2060	2061–2099	2021–2060	2061–2099
T _{max} °C												
Annual (J–D)	1.36	2.46	1.22	2.62	1.29	2.54	2.34	4.61	2.41	4.71	2.37	4.66
Winter (D–F)	1.46	2.59	1.35	2.76	1.4	2.67	2.59	4.8	2.62	4.71	2.6	4.75
Pre-monsoon (A–J)	1.5	2.54	1.26	2.86	1.38	2.7	2.34	4.71	2.51	4.58	2.42	4.64
Monsoon (J–S)	1.12	2.1	1.06	2.24	1.09	2.17	2.09	4.34	2.1	4.56	2.09	4.45
T _{min} °C												
Annual (J–D)	1.35	2.54	1.22	2.52	1.96	2.53	2.43	4.53	2.52	4.51	2.47	4.52
Winter (D–F)	1.48	2.76	1.36	2.75	1.42	2.75	2.66	4.65	2.72	4.61	2.69	4.63
Pre-monsoon (A–J)	1.56	2.54	1.25	2.46	1.40	2.5	2.34	4.59	2.51	4.57	2.42	4.58
Monsoon (J–S)	1.02	2.34	1.06	2.36	1.04	2.35	2.29	4.36	2.35	4.36	2.32	4.36
Precipitation (%)												
Annual (J–D)	6.77	12.62	6.17	12.51	6.47	12.56	7.41	10.58	7.4	12.5	7.4	11.54
Winter (D–F)	5.49	13.56	4.84	14.9	5.1	14.23	6.51	11.68	7.45	14.5	6.98	13.09
Pre-monsoon (A–J)	6.52	11.45	5.78	10.89	6.15	11.17	7.53	9.53	6.65	10.4	7.09	9.96
Monsoon (J–S)	8.3	12.87	7.89	11.76	8.09	12.3	8.21	10.55	8.1	12.6	8.1	11.57

The 21st century projection for $T_{\max}$ was about 2.54 °C–4.66 °C and for $T_{\min}$ was about 2.53 °C–4.52 °C for RCP-4.5 and RCP-8.5 for the whole basin. The seasonal change in projected $T_{\max}$ and $T_{\min}$ depicted the highest temperature changes for the winter season (DJF) followed by the pre-monsoon (AMJ) period (Table 9) under both scenarios for mid-century and end-century. This warming of the winter season may trigger the earliest deglaciation period due to a rise in critical temperature by changing the hydrologic cycle. The rise in critical temperature during the winter season may alter the precipitation form from snow to rainfall, consequently shrinking the snow/glacier-covered area in the Jhelum River basin that leads in a reduction of summer river discharge. In addition, the temperature increase for the pre-monsoon period could generate early and rapid snow/glacier melting from a high altitude/elevation of the basin that might cause shrinking of the glacier/snow-covered area of the basin. The temperature increase for RCP-8.5 simulations were more intense than RCP-4.5, which could generate more severe consequences for the cryosphere and hydrosphere of the river basin.

The precipitation projection depicted an increase for both scenarios, but a slight decrease was observed for RCP-8.5 in comparison to the RCP-4.5. The rise in precipitation ranges were between 6–12% over the basin. The rate of increase in precipitation were more considerable for the winter and monsoon season for both scenarios [25]. The minimum increase in precipitation was observed for the pre-monsoon period. The spatial distribution of $T_{\max}$, $T_{\min}$ and precipitation was immensely significant due to the powerful impacts of significant climatic patterns [26,27]. The spatial patterns for precipitation and temperature for the mid- and end-century for both GCMs under climate scenarios are presented in Figures 4 and 5. The spatial distribution of precipitation changes is extremely important because the basin is influenced by two contrasting climatic systems: monsoon during summer and westerlies circulation pattern during winters. The projected rise in winter precipitation is due to the southwest side of the basin that is affected by the westerlies while the rise in precipitation in the northeastern region of the basin is due to the monsoon precipitation during the summer season (Figure 4). The precipitation spatial pattern is heterogenous in the basin and, overall, depicted a rise for both RCPs for the 21st century.

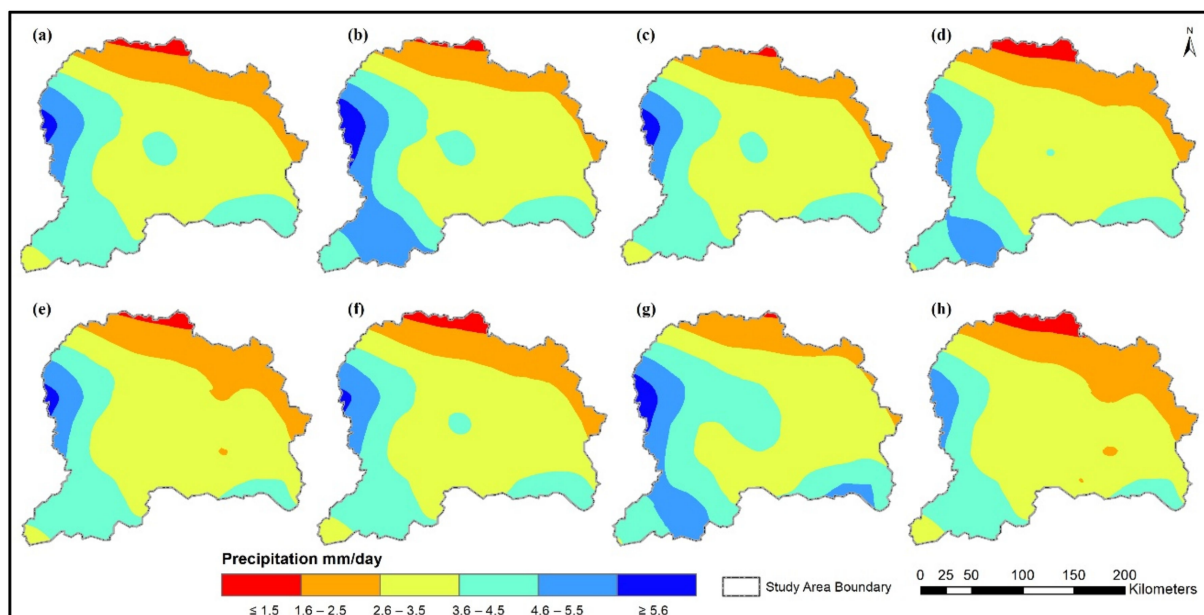


Figure 4. Spatial projections of precipitation (mm/day): (a) CCSM4 RCP-4.5 2021–2060; (b) CCSM4 RCP-4.5 2061–2099; (c) CCSM4 RCP-8.5 2021–2060; (d) CCSM4 RCP-8.5 2061–2099; (e) HadCM3 RCP-4.5 2021–2060; (f) HadCM3 RCP-4.5 2061–2099; (g) HadCM3 RCP-8.5 2021–2060; (h) HadCM3 RCP-8.5 2061–2099.

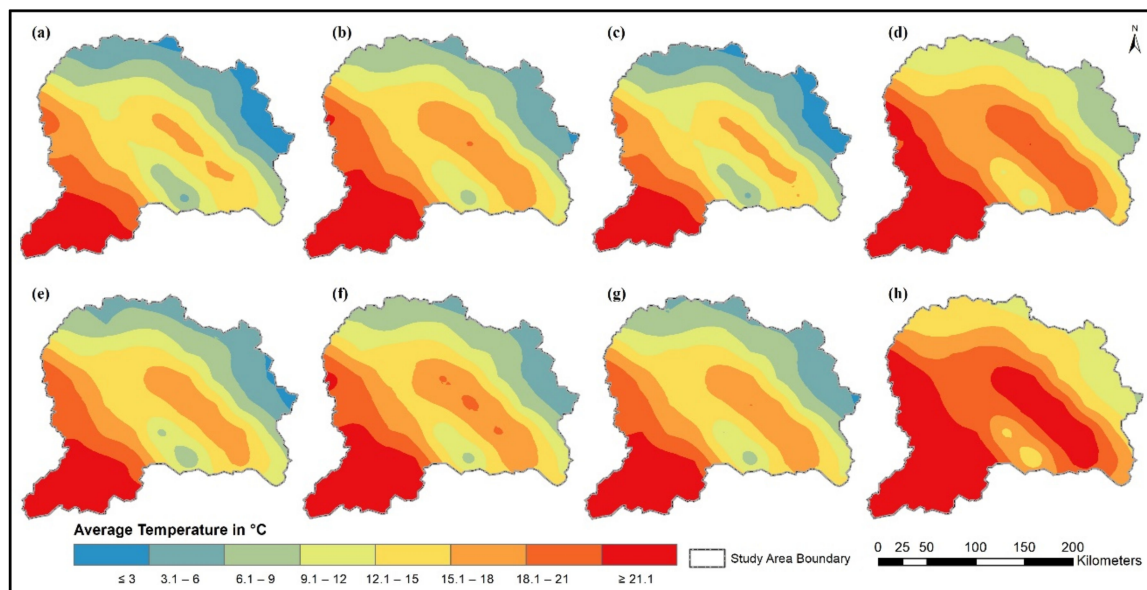


Figure 5. Spatial projections of average temperature (°C): (a) CCSM4 RCP-4.5 2021–2060; (b) CCSM4 RCP-4.5 2061–2099; (c) CCSM4 RCP-8.5 2021–2060; (d) CCSM4 RCP-8.5 2061–2099; (e) HadCM3 RCP-4.5 2021–2060; (f) HadCM3 RCP-4.5 2061–2099; (g) HadCM3 RCP-8.5 2021–2060; (h) HadCM3 RCP-8.5 2061–2099.

The spatial distribution of temperature projections (Figure 5) depicted that the north-eastern part of the basin was more affected from a rise in temperature for both GCMs under climate scenarios. The southeastern part of the basin was noticed to be least impacted for a rise in temperature for 21st century. The transition in class boundaries was observed, especially in the northern part of the basin, which may cause deglaciation due to a rise in temperature in the high altitudinal (4000–6000 masl) areas of the basin. The temperature changes in the northern mountainous region might disturb the balance of the cryosphere and hydrosphere by altering the permanent snow-covered area of the Jhelum River basin. The temperature changes are considered a more significant variable because they trigger changes in precipitation forms and snow/glacial reserves. The projected changes in precipitation and temperature may accelerate the surface runoff during the mid-century and can introduce recurrent droughts in the end-century due to disturbance in the hydrosphere and cryosphere. These changes in temperature and precipitation patterns from the mid-(2021–2060) to the end-century (2061–2099) were more prominent and severe for RCP-8.5 than RCP 4.5.

4. Conclusions and Remarks

This study focused on the climatic changes for the transboundary mountainous region by using CMIP5 GCMs and climate scenarios. The Jhelum River basin is the part of the Himalayas mountains which are affluent in glaciers after polar regions and climate changes can induce tremendous, unexpected variabilities in the basin. GCMs are the most reliable mathematical tools to project climatic changes as it is a global phenomenon and linked through permanent circulations such as atmospheric winds and oceanic currents. The GCM projections for the local/regional basin may cause uncertainties due to the influence of the micro/regional climate. To overcome the uncertainties, five GCMs from CMIP5 project were selected for the study and two GCMs, CCSM4 and HadCM3, were chosen based on the relationship with the reference observed data. The large-scale GCM predictors were downscaled by using two statistical downscaling methods (SDSM and LARS-WG) that can relate large-scale predictors with the local climatic variables (T_{max} , T_{min} and precipitation).

SDSM was proved to be a more effective and efficient method than LARS-WG in downscaling the climatic variables for the validation period, except for a bit in improved

performance of LARS-WG for precipitation due to its wet and dry spells. Both climatic indicators of temperature and precipitation projected a rising trend for the 21st century, but the change was more pronounced for RCP-8.5 than RCP-4.5, which depicted the storyline of the climatic scenario. The seasonal changes depicted that the winter season was more threatened and became warmer and wetter with time which may disturb the existing snow cover. After winter, the pre-monsoon season predicted a rising trend for temperature that may introduce early deglaciation by disturbing the balance of the cryosphere and hydrosphere of the basin.

The study area is a transboundary conflicted region and has a limited number of weather stations that affect the accuracy of the climatic projections. Multiple GCMs can be used to check the most suitable location for the study area but it can make the research more intensive as the focus is on the multiple task of first selecting the GCMs then downscaling by using two comparable methods. The dynamic downscaling can also be used but it is a very intensive and computer-oriented downscaling method difficult for the individual researcher. Two climatic scenarios: one medium stabilization scenario RCP 4.5 and the other, a high emission scenario RCP 8.5, were selected to project climatic changes. The other two RCP-2.5 and RCP-6.0 can be used for future projections.

Author Contributions: S.M. designed the methodology and conceptualization in writing and editing, G.R. worked on the GCMs to select the suitable ones for the study area. M.M. worked on SDSM; S.M and N.A.-A. worked on LARS-WG; K.U. worked on statistical analysis for SDSM and LARS-WG. While M.F.U.M. worked on spatial projections, M.F.U.M. and N.A.-A. helped in data curation, visualization, writing review and editing. N.T.T.L. supervised the research, review and editing. All authors have read and agreed to the published version of the manuscript.

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