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Complementary use of multi-model climate ensemble and Bayesian Model Averaging for projecting river hydrology in the Himalaya

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Abstract

This study aims to predictthe hydrology of the Jhelum basin under changing climatic scenarios based on Representative Concentration Pathways (RCPs). Six Global Circulation Models were dynamically downscaled for reliable climatic projections over the 21st century (2020-2080). To reduce the uncertainty associated with climate projections, multi-model ensemble estimations were refined using Bayesian Model Averaging (BMA). The assessment reveals that compared tothe baseline (1980-2010) values, the annual mean maximum temperature in the basin will rise by 0.41–2.31°C and 0.63–4.82°C and the mean minimum temperature will increase by 1.39–2.37 °C and 2.14–4.34 °C under RCP4.5 and RCP8.5respectively. While as, precipitation is expected to decreases by 7.2–4.57% and 4.75–2.4 7% under RCP4.5 and RCP8.5 correspondingly. BMA ensemble projections were used inthe Soil and Water Assessment Tool (SWAT)to simulate the future hydrological scenarios of the drainage basin. With the changing climate, the discharge of rivers in the Jhelum basin is expected to witness reductions by about 23–37% for RCP4.5 and 19–46% for RCP8.5. Moreover, the water yield of the basin may also exhibit decreases of 17–25% for RCP4.5 and 18–42 % for RCP8.5. The projected scenarios are likely to cause water stress, affect the availability of water for diverse uses, and trigger transboundary water sharing related conflicts. The impact of climate change on discharge demands early attention for the development of mitigation and adaptive measures at the regional level and beyond.

Keywords: *Climate change, Jhelum basin, RCP, Water balance, SWAT model,multi-model ensemble, BMA.*

1. Introduction

Changingclimatic regimes and their impact on water resources have attracted considerable attention in the contemporary world because of its tremendous environmental and socioeconomic implications (Jasper et al., 2004; Luo et al., 2019; Reshmidevi et al., 2018). Mounting evidence exists about the impact of increase in global mean temperatures on regional water budget (Huntington, 2006). Moreover, changing precipitation patterns and evapotranspiration rates projected under the climate change scenarios will further alterthe hydrological systems(Kundzewicz et al., 2008; Raneesh& Santosh, 2011).Therefore, while devising effective water management policies and adaptation strategies to offset the climate changeinduced stresses, it becomes quintessential to evaluate the hydrological responses and sensitivityof the riverine systems to the changing climate(Bhatta et al., 2019; Reshmidevi et al., 2018; Rodrigues et al., 2020).

Multiple studies have assessed the hydrological imprints to changing climate across the different river basins of the world (Bajracharya et al., 2018; Hao et al., 2018; Liu et al., 2011; Luo et al., 2019; Reshmidevi et al., 2018; Rodrigues et al., 2020; Tan et al., 2017; Vetter et al., 2017; Yu et al., 2018).Global circulation models (GCM) are the popular tools in use for projecting climate change under different emission scenarios. However, GCMs provide information on a coarse-scale with large grid sizes and insufficiently capture the regional heterogeneity that impact the hydrological processes on the basin scale.Regional climate models (RCMs) with a finer grid size have been developed to improve the outputs of GCMs. Although RCMs perform better in simulating the local climate; however, inherit significant error/biasfrom GCMs (Chen et al., 2013). As a result, using the RCM outputs directly into the hydrological models can yield significant deviations in the model outputs with respect to the observed data(de Oliveira et al., 2017). As a result, prior to any hydrological simulations, bias adjustment of the raw RCM results is critical (Luo et al., 2019). “Coupled Model Intercomparison Project Phase 5(CMIP5)”GCMs provide the outputs based upon the Representative concentration pathways (RCPs) that describe the net radiative forcing levels till 2,100 ranging from a mitigatingpathway (RCP2.6),

mediumstabilizing pathways (RCP4.5/RCP6), andextreme climaticpathway (RCP8.5)(Meinshausen et al., 2011; Taylor et al., 2012).

GCM output carries a substantial amount of uncertainty with it and must be taken in cognizance while carrying any impact assessment studies. The cascade of uncertainty is nestled in the range of socioeconomic or developmental pathways that the world may take in the future; incomplete knowledge or representation of the climatic system and its interactions; and the structural or the parametric differences in the GCMs. As such, the results from the single model must be interpreted with caution (Reshmidevi et al., 2018). To this end, ensemble projections have been proposed on account of their reliability and uncertainty assessment (Khan et al., 2021). In comparison to the outputs from separate models, the multi-model ensemble has demonstrated to be more effective in the representation and simulation of climatic variables (Gleckler et al., 2008; Knutti et al., 2010; Zhang & Huang, 2013). The ensemble techniques can vary from the simple arithmetic ensemble mean wherein each model is weightedequally irrespective of its performance, tothe weighted ensemble mean. BMA is a weighted ensemble method in which the relative competence of models is determined and model weights are optimized so that BMA ensemble projections closely match the observed data (Massoud et al., 2020). In this way, higher weights are applied to more skillful models as compared to low skillful models. BMA has been previously used for developing ensemble projections in studieslikeHuang, (2014), Khan et al., (2021), and Massoud et al., (2020).

Generally, hydrological models forced with climatic scenarios have been employed tosimulate the possible implications on the stream flows, catchment storage, and other water balance components. Different hydrological models that can replicate the hydrological properties and processes operating within a basin have already been developed (Krysanova&Hattermann, 2017). Soil and Water Assessment Tool (SWAT), is being widely used for evaluating the likelyimplications ofchanging climatic regimes on hydrological processes (Bajracharya et al., 2018; Bhatta et al., 2019; Rodrigues et al., 2020;Narsimlu et al., 2013; Touseef et al., 2021).

Climate change's potential implications are more noticeable in the mountainous regions likeHimalayas, particularly on water resources, where snowmelt and glacial ice melt are the major determinants of streamflow(Viviroli et al., 2007; Lutz et al., 2014; Immerzeel et al., 2013).Significant increases in the temperature along with the declining precipitation patterns have been reported for Jhelum basin (Ahsan et al., 2021a, b). Having established climate change

signals, it becomes obvious that the water resources will be most affected in this region.The imprints of the observed climatic variability are already visible over the hydrological regime of the Jhelum basin. For example, climate change is putting a lot of strain on the aquatic systems in the region (Alam et al., 2020).Lone et al., (2021) reported significant decreasing trends in the streamflow, driven by observed climate variability. Hence, climatic changesare likelyto further impact the water security of the region and challenge the existing management strategies. The hydrological consequences of the climatic changescan transmit to the overall prosperity of the region due to dependence of other sectors viz., irrigation,domestic, industrial, tourism, and hydropower generation on the water resource base.Limited studies have been attempted so far in the Jhelum basin that project the hydrological responses of changing climate e.g., SinghJasrotia et al., (2021). However, key limitations with this study are that it uses outputs of a single RCM and lacks any detailed assessment of water balance components. Hence, it is imperative to have a rigorous quantification of the hydrological responses to the projected changes in climatic regimes. For this purpose, the current study utilizes outputs from 6 GCMs under a medium stabilizing pathway (RCP4.5), and an extreme pathway (RCP8.5). The study primarily aims to developthe robust climaticprojections for the 21st century, using the multi-model ensemble based on Bayesian model averaging framework. The study subsequently employs the hydrological model SWAT coupled withthe climatic scenarios to project the changes in the streamflowand different components of water balanceover the 21st century. Nosuch comprehensive study has been attempted yet for the Jhelum basin; the present one canthus serve as a benchmark study while planning for the mitigation of hydrological implicationsascribed toclimate changeand pave the way for formulation of adaptivepolicy for sustainable water management.

2. Study area

The present studyis attemptedforJhelum basin (Fig 1) located in the lap of Himalaya with an area of about 15000 km^2. The trunk stream, Jhelumconstitutesaimportant tributary of the Indus River system forming an elongated bowl-shapedbasinthat originated from the collision between Indian and Eurasian plates(Alam et al., 2015, 2017). Based on stratigraphy and elevation, the basin can be divided into 3 major physiographic divisions viz., mountainous uplands, extensive plateaus of lacustrine deposits (Karewas), and valley floor with the numerousstreamsdraining into Jhelum(Bhat et al., 2018). The region's climatic regimeis controlled by two distinct weather

patterns viz., Western Disturbance in winter monthsand southwest Monsoons in the summer half. The impact of the latter is somewhat limited and the major proportion of the precipitation is received in the winter months, mainly in the form of snowfall. The winter precipitation feeds the glaciers and acts as a buffer in maintaining the streamflow of the river Jhelum during the dry periods. The climate of the region is moderate; however, the annual temperature variations of the region range from sub-freezing during the winter and can to high as 35 °C during the summer. The region supports a population of ~7 million persons with heavy reliance on water resources for sustenance.

3. Materials and methods

3.1 Observed hydroclimatic data

Observed climate data (1980-2016) for temperature and precipitation variables at a daily scale was procured from the Indian meteorological department, regional office Srinagar, J&K India. This data was utilized for the bias correction of the GCM data and also as input forthe baseline run of the SWAT model. For the other SWAT input climatic variables i.e., Relative Humidity, Wind Speed, and Solar Radiation,"Climate Forecast System Reanalysis (CFSR)" data were used. The observed streamflowdata for the 3 gauges on the trunk stream viz., Sangam, Asham, and Ram MunshiBaghwereusedstreamflow data was used in calibrating and validating the SWAT.

3.2 Climate scenario projections

The Coordinated Regional Climate Downscaling Experiment (CORDEX) was developed under the aegis of the World Climate Research Programme to stimulate climatic scenarios and improve regional impact assessment. CORDEX over the south Asian domain provides data for multiple GCM-RCM combinations at a gridsizeof 0.44° (~50 km). CORDEX-SA has previous successful applications in the Himalayan regionse.g., (Dimri et al., 2018; Krishnan et al., 2019). A total of 6GCMs (Table 1) downscaled dynamically using the RegCM4RCM (Giorgi et al., 2012)were used in the projection of the climatic scenariosunder RCP4.5and RCP8.5. The projected span (2006-2099) was split into 3 periods viz., 2011-2040 referred in the manuscript as 2020s,2041-2070 referred in the manuscript as 2050s, and2071-2099 referred in the manuscript as 2080s.The relative changes in mean climatology over the different spans of 21st century was computed from the baseline (1980-2010) climatology.

146 *3.3 Bias-correction of GCM/RCM data*

147 Prior to using the GCM/RCM data for the projection of climatic changes or its hydrologic
148 implications, it is necessary to apply the bias correction techniques because the data obtained
149 from the climate models inherit systematic biases(Luo et al., 2019). A wide range of bias-
150 correction techniques have been devised(Teutschbein& Seibert, 2012); and in the present study
151 Variance Scaling (VS) was used forbiascorrecting the temperature data, while a hybrid of power
152 transformation (PT) and local intensityscaling (LOCI) techniqueswas employed for bias
153 correcting the precipitation data.
154 Variance scaling is an effectivetechnique and has the advantage of correcting both the mean and
155 variance (Teutschbein& Seibert, 2012).Power transformation of the precipitation data also
156 corrects both mean and variance in the raw data. However, the limitation of the PT method is
157 that it doesn't correct the wet day frequency. Hence before its use, the wet day frequency is
158 adjusted using the local intensity scaling method. The details of thesebias correction techniques
159 are given inFang et al., (2015).To check the skill and efficiency of the RCM simulations, RCM
160 data (raw and bias-corrected) were compared with observational data on monthly time series
161 using the efficiency indicators like Coefficient of determination(R^2), percentage bias(PBIAS)
162 and Nash Sutcliffe efficiency (NSE). R^2 given by Eq.1 is a measure of goodness-of-fit among the
163 observed and model data ranging between0and1. R^2 values nearing 1 imply a higher agreement
164 among observed and model values. PBIAS (Eq.2) measures the model data's mean tendency to
165 be greater or lesserthan actual observations. PBIAS has an optimum value of 0 with positive
166 valuesdepicting underestimation and negative values depicting overestimation in model
167 simulations.NSE is a standardized statistic (Eq.3) that measures deviations among the modeled
168 and observed data normalized by the observational data variance (Takele et al., 2021).It values
169 between -∞ to 1 and NSE = 1 depicts modeled data are equal to that of the observed data(Nash &
170 Sutcliffe, 1970).
171

$$R^2 = \frac{\sum_{i=1}^{n} (O_i - \bar{O})(M_i - \bar{M})}{\sqrt{\sum_{i=1}^{n} (M_i - \bar{M})^2 \sum_{i=1}^{n} (O_i - \bar{O})^2}} \quad (1)$$

172

$$PBIAS = \frac{\sum_{i=1}^{n} (O_i - M_i) \cdot 100}{\sum_{i=1}^{n} (O_i)} \quad (2)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n} (O_i - M_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2} \quad (3)$$

Where, O_i are the observational data values and M_i are the model simulated values.

3.4 Bayesian model averaging (BMA) for *multi-model Ensemble*

On account of parametric and structural differences, GCMs/RCMs produce different outputs(Wallach et al., 2016). Hence, a single climate model's output may still be subject to uncertainty (Uusitalo et al., 2015).The bias-corrected RCM output with different GCM forcing's wereutilized to develop multi-model ensemble projections employing Bayesian model averaging (BMA)technique. BMA is an advanced statistical technique for deriving the multi-model ensemble and combines the individual models using optimized weights; weights being proportional to the relative skills of models in reproducing observed data.The regression model in BMA takes into account all conceivable combinations of variables (in this case, GCMs) before calculating a weighted average. The Posterior Model Probability (PMP) used as weight, is a measure of model's skillduring training(Raftery et al., 2005). Suppose we have *k* models; the maximum count of regression models is $s = 2^k$. Here in the study using 6models, the number of regression models is $s = 2^6 = 64$. PMP of *n*-th model$P(M_n \mid D)$,in 2^k candidate regression models is computed using Bayes theorem as given in Eq.4

$$P(M_n \mid D) = \frac{p(D \mid M_n) \cdot p(M_n)}{p(D)} \quad (4)$$

Where$p(D \mid M_n)$ is the observed data likelihood given *n*-thmodel, $p(M_n)$is the *n*-th regression model's prior probability and $p(D)$is a constant used for normalizing as given in Eq.5,

$$p(D) = \sum_{n=1}^{s} p(D \mid M_n) \cdot p(M_n) \quad (5)$$

Different forms of priors are available in the literature, and for this investigation, we selected a uniform prior distribution based on Khan et al., (2021), which gives equal weight to all possible regression models. For the likelihood function$p(D \mid M_n)$, Gaussian likelihood (Vogel et al., 2008) was used following Khan et al., (2021). Eq.6 gives the variable's conditional prediction PDF based on training data.

$$p(y \mid D) = \sum_{n=1}^{s} p(y \mid M_n, D) \cdot p(M_n \mid D) \quad (6)$$

Where $p(y \mid M_n)$ is the prediction PDF based on*n*-th regression model and $p(M_n \mid D)$ is the associated posterior probability and is being used as weight (Khan et al., 2021).

3.5 SWAT Model setup

Hydrological modeling is a key aspect in evaluating the hydrological implications of climatic changes(Praskievicz& Chang, 2009). The basin was modelled by employing the SWAT hydrological model to project the changes in streamflow and water budget components for the 21st century. The water balance in the model is governed by Eq.7 given below:

$$SW_t = SW_0 + \sum_{i=1}^{n} \left(R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw}\right) \quad (7)$$

Where SW_tdenotes thewater content of soil at *t*timestep, SW_0denotes the initialwater content of soil, R_{day} is daily precipitation, Q_{surf}denotes the surface runoff, $E_a$denotes the Evapotranspiration, w_{seep}denotes the percolation and Q_{gw}denotes the groundwater flow(Bajracharya et al., 2018). The units of all components are in millimeters (mm).

Snowmelt was incorporated in the runoff calculations andis governed by the Eq. 8,

$$SNOWmlt = \ bmlt * snowcov\left(\left(\frac{Tsnow + Tmax}{2}\right) - Tmlt\right) \quad (8)$$

where, *SNOWmlt*denotes the amount of daily snowmelt (mm), *bmlt*denotes the factor of daily melt (mm/day °C), *snowcov*denotes the fraction of snow-cover in HRU area, *Tmax*isthe day's maximum temperature., *Tsnow*isthe temperature ofsnowpack (°C) and *Tmlt*denotes the snowmelt thresholdtemperature (°C)(Bhatta et al., 2019).

SWAT uses various inputs viz., climate data, soil map/attributes,land use map/attributes, Digital Elevation Model (DEM), and the observed streamflow. The weather database for the calibrating and validatingSWAT model was prepared using the observed meteorological datafor Temperature (Tmax,Tmin) and Precipitation variables while for Solar Radiation, Wind Speed, and Relative Humidity, CFSR dataset was collated. For the elevation inputs, ALOS PALSAR DEMhaving a grid size of 12.5m was used (https://search.asf.alaska.edu/#/).Theland use/land cover data for the region was produced by the supervised classification of Landsat 8 OLI imagery acquired on 2013/06/03, in ArcGIS 10.2. The soil layer and the associated attributes for the study area wereaccessedthrough the SWAT website under India datasets (https://swat.tamu.edu/data/india-dataset/).

DEM was employed as an input in the *qswat* interface of the SWAT model to divide the catchment into sub-basins. A threshold of 10000 ha was used in the delineation of the drainage network andthe analysis identified 41 sub-basins in the Jhelum basin. The smallest model unit is the Hydrological Response Unit (HRU), which is defined by a unique fusion of soil type, slope class, and land use.(Romagnoli et al., 2017). Since the seasonal snowmelt determines the basin's hydrology, elevation bands were created to represent the snowmelt as well as the orographic controls of precipitation and temperature. SWAT model provides a maximum of 10 elevation bands for a particular sub-basin and in the present analysis 5 elevation bands were set for the sub-basins having a significant attitudinal range whereas for sub-basins with less orographic differences only one elevation band was used e.g., Bajracharya et al.,(2018).

3.6 SWAT model calibration and validation

Multi-site calibration and validation were carried for the 3 gauges on the trunk stream viz., Sangam, Asham, and Ram MunshiBagh. Observed monthly streamflow data for 10yrs (2002-

2011) were used in calibration while as 5yrs (2012-2016) were used in the validation of the model. Before the calibration of the model, sensitivity analysis was carried to filter the most influential parameters determining the streamflow variations. The parameters were ranked as per their sensitivity towards the streamflow using the global sensitivity analysis embedded in the SUFI-2. It employs the p-stat and t-statto determine the most sensitive parameters, having lower p-values and higher t-values (Bhatta et al., 2019). The SWAT-CUP considers the parameter uncertainty, model uncertainty, input error, and yields uncertainty measures like 95% prediction uncertainty (95PPU),r-factor and p-factor. The p-factor refers to percentage of the observed data series that is encompassed by the 95PPU, and ranges between 0 to 1.Similarly, the r-factor, which runs from 0 to1, is the mean width of the 95PPU divided with the standard deviation of the observational datasets. The higher p-factor values (towards 1) and lower r-factor values (towards 0) imply the better simulation of the hydrology and thus stream flows (Uniyal et al., 2015). Statistical indicators such as R^2, PBIAS, and NSE were also utilized to assess model performance. Moriasi et al., (2007) and Almeida et al., (2018) have defined the thresholds of satisfactory and acceptable model performance for $0.50 < R2 \leq 0.60$, $\pm 15 < PBIAS \leq \pm 25$, and $0.36 < NSE \leq 0.60$.

Multi-model ensemble climatic projections were coupled with the calibrated and validated model to simulate the hydrological implications of changing climatic patterns in the Jhelum basin. After ascertaining the robustness of BMA projections, these were utilized as an input to project the streamflow at Ram MunshiBagh, Asham, and Sangamgauges under RCP4.5 and RCP8.5. Moreover, the impact of climatic changes was assessed separately on the different components of catchment water balance viz., evapotranspiration, snowmelt, surface runoff, and water yield. Due to paucity of observed data, the SWAT simulated output for these components during the baseline run (2001-2010) was used as reference to estimate the relative changes over the 21st century (Bajracharya et al., 2018).

4. Results

4.1 Bias -correction of the GCM/RCM output

The competenceof the bias correction techniques was evaluated by the comparisonRCM data (raw & BC) with the observational data on a monthly scale,using efficiency metrics viz., R^2,

PBIAS, and NSE (Table 2). For Tmax and Tmin, R^2values were high before bias correction but PBIAS and NSE got significantly improved. The raw Tmax (Tmin) displayed substantial biases and bias correctionminimized the PBIAS from -60.6 – -37.40 (-135 – -47.2) to 1.9 – 3.9(2.3 – 6.5). Likewise, the NSE values for Tmax (Tmin) in raw RCM were of the order -0.84 – 0.06 (-0.29 – 0.55) andbias correction improved the values to 0.89 – 0.91 (0.92 – 0.95). In contrast to this, GCMs tend to resolve the precipitation poorly as indicated by lower values of efficiency metrics. However, thebias correctioncould improve the match among the simulated and the observational data (Table 2). Furthermore, Taylor Diagrams (Taylor, 2001) are used to display the RCM's performance (raw and BC) (Fig 2).

Considering the uncertainty in the single RCM output, multi-model ensemble projections were derived using BMA and were also compared with the baseline data.The BMA ensemble data matched closely with the observed data than any of the individual RCMs, supported by the increased values of the efficiency indicators (Table 2).The PBIAS in the BMA estimates of climatic variables reduced to 0 along with further improvements in R^2 and NSE. Fig 3 depicts the performanceof the BMA technique during the training period.

4.2 Climate change projections for 21st century

Theprojections from the individual models and the BMA ensemble for the Jhelum basin are presented inTable 3. The resultsinfer substantialwarming inthe annualmean maximum (Tmax) and minimum (Tmin) temperatures with varying rates of warming among the different GCMs. Multi-model ensemble projections show that under RCP4.5 the Tmax (Tmin) of the region will increase by 0.41 (1.39) °C during 2020s, 1.80 (2.12) °C during 2050s, and 2.31 (2.37) °Cduring 2080s. The rate of the warming for Tmax (Tmin) enhances under the RCP8.5 forcing levels by increments of 0.63 (2.14) °C during 2020s, 2.56 (3.12) °C during 2050s, and 4.82 (4.35) °Cduring 2080s. While comparing the magnitude of changesimulated by the different models, it varied substantially e.g., for Tmax,it varied from 0.81°C(CNRM-CM5) to 1.42°C (MPI-ESM-MR) for the 2020s,1.59°C (CNRM-CM5) to3.01°C (CSIRO-Mk3) for 2050s, and 2.17°C (CNRM-CM5) to 3.66°C (CSIRO-Mk3) for 2080s under RCP4.5 forcing levels. CNRM -CM5 shown consistently least amount of the change for Tmax and Tmin during the different spans of the 21st century under both RCPs. The station scale BMA projections (Table 4)reveal higher warmingrates inTmax and Tmin for the Gulmarg while the lowest warming rates were found

299 forSrinagar (Tmax) andPahalgam (Tmin). Moreover, ensemble estimates project enhanced night-
300 time warming in the region over the 21st century pinpointed by the higher warming rates of
301 Tminas compared to the Tmax. The asymmetrical warming patterns of Tmax and Tmin exist
302 even between models and also among the different spans of the 21st century e.g., the CSIRO-
303 Mk3 model projects higher rates of warming in Tmin than Tmax for the 2020s and vice versa
304 during the 2050s and 2080s. The BMA projections for the Tmax and Tmin in the Jhelum basin
305 are shown graphically in Fig 4a and Fig 4brespectively.

306 Precipitation projections for the Jhelum basin show reductionsover the 21st century vis-a-vis the
307 baseline (1980-2010). The BMA estimates projectdecreases of order 7.2- 4.57 % (RCP4.5) and
308 4.75-2.47 % (RCP8.5) during the different periods of the 21st century. Despite the fact that
309 precipitation tends to increase from the 2020s to the 2080s (Fig 4c), there is a net decrease when
310 compared to baseline values. The diminishing patterns of precipitation rhyme across all
311 theindividual modelsalthough with higher magnitudes than BMA estimates (Table 3), except
312 IPSL-CM5A-LR which projects an increase of 9.6 % in the precipitation of the Jhelum basin
313 duringthe 2080s under RCP8.5. The station scale BMA estimates (Table 4) show enhanced
314 decreases for Kokernag (RCP4.5 and 8.5),Kupwara (RCP4.5 and 8.5), andGulmarg (RCP8.5). In
315 contrast to this, stations like Gulmarg (RCP4.5), and Qazigund (RCP 8.5) witness increases in
316 the precipitation while the Srinagar shows almost no change (< 1%) over the 21st century when
317 compared with the baseline precipitation.

318 *4.3 SWAT model calibration and validation*

319 Any hydrological model must be adequately calibrated and validated before adopting its outputs
320 for further analysis. The SUFI-2 algorithm, embedded within the SWAT-CUP was employed to
321 calibrate and validate SWAT. Multi-site calibration was done for Sangam, Asham, and Ram
322 MunshiBagh gauges, located on the trunk stream using the observedmean monthly streamflow
323 values for 2000-2010. The model was validated using 5yr (2011-2016) streamflow data. Prior to
324 that, sensitivity analysis was executedto limit the count of parameters. Table 5shows the 11most
325 sensitive parametersas well as their p-value and t-stat,important in the estimation of streamflow
326 variability.The model conformity during its calibrating and validating process was assessed using
327 3 statistical indicators viz., R^2, PBIAS, and NSE. Furthermore, uncertainty ofthe model outputs
328 wasevaluated using the r-factor and p-factor. Table 6 shows the performance metrics of the

SWAT model and the values reflect thatmodel performancewas well within the acceptable limits.The close agreement between actual and modelled streamflow (Fig5) reveals that the validated model could be employed with considerable confidence and accuracy to model hydrologic responses to climatic changes.

4.5 Projection of streamflow's under climate change scenario's

After the calibration and validation,SWATwas employed to translate the climatic change signals into streamflow responses using the multi-model ensemble climatic projections obtained using BMA.The relative changes in the streamflow during the different spans of 21stcentury was compared with the baseline (2001-2010)values for 3 gauges (Sangam, Asham, and Ram MunshiBagh) located along the course of the trunk stream (Table 7). Inthe wake of rising temperatures and declining precipitation patterns, the Jhelum basin is going to witness substantial reductions in streamflow over the 21st century. Under RCP4.5 forcing levels, the decreases are of the order 23-27% during 2020s, 30-35% during 2050s, and 31-37% during 2080s. With intensifications in the radiative forcing level under RCP8.5, the reductions also get enhanced with magnitudes of 19-25% during 2020s,31-37% during 2050s, and 40-46% during2080s. In comparison to the baseline values, seasonal streamflow tended to decline over time. Summer (JJA) witnesses most of the decreases followed by Winter (DJF) and Spring (MAM) under both RCPs. Summer shows a maximum reduction during the 2080s,by about 46-52% under RCP4.5 and 61-67% under RCP8.5.Moreover, Autumn (SON) is the least affected and shows only minimal changes in streamflow's over the 21st century.For illustrative purposes, the projectedvariations in mean monthly, annual and, seasonal streamflow's of river Jhelum at Ashamgauge under both the RCPs are shown in Fig 6.

4.6 Projection of water budget components under climatic change scenario's

The variations in the streamflow are governed and linkedwith thedifferent components of water balance like precipitation, evapotranspiration, surface runoff, snowmelt, etc. After having the precipitation projections for the 21st century, the current study also intended to assess the relative changes in other water balance components viz., Actual Evapotranspiration (ET), Potential Evapotranspiration (PET),Snowmelt, Surface runoff (SurQ), and Water yield (Wyield) under climate change scenarios. These components were simulated using the SWAT model for the

baseline period (2001-2010) from the observational climate data and BMA ensemble climatic projections were employed for the future simulations. Due to lack of observed data, the SWAT simulated output for these components during the baseline run (2001-2010) was used as reference data(Bajracharya et al., 2018). The percentage changes in the water budget components throughout various time periods in the 21stcentury, under both RCPs were calculated by comparing them to baseline values.Fig 7 shows the projected changes in the Jhelum basin's average annual hydrological components over different time periods in the future.

ET was estimated from the Hargreaves method (Hargreaves and Samani, 1985),and it witnessed increasesover the 21st century in the Jhelum basin.Actual ET shows increases of order 18 (20) during 2020s, 28(30) during 2050s, and 31(40) %during 2080s under RCP4.5 (RCP8.5). The changes in the ET for different sub-basins over 21st century under both RCPs is shown in Fig 8. ET projectionsshow a progressive increase for the future, determined by levels of radiative forcing and time viz., near, mid or endcentury.This increase in the ET aligns with the projected increase in the temperatures driven by the enhanced radiative forcing levels.Due to the continuously rising temperatures, the ET values show a consistent rise over the 21st century. ET constitutes a major abstraction in the water balance which reduces the net water availability for the runoff and is a measure of the irrigation water requirements.

Snowmelt contribution in the Jhelum basin witnessed significant decreasesin future under the changing climatic regimes. The snowmelt shows substantial reductions by about 53(50) % during 2020s, 58(62) % during 2050s, and 60(72) % during2080s under RCP4.5 (RCP8.5). Moreover, Fig 9 reveals that most of the decreases will be observed in the sub-basins situated in the lower elevation. The decrease in Snowmelt contribution may be attributed to the declining precipitation trends over the 21st century. Jhelum basin is projected to witness decreases in the overall precipitation, and this would mean a reduction in the winter season precipitation toothat is in the form of snowfall. Significant decreasing trends are already ominous in the winter season precipitation of the Jhelum basin (Ahsan et al., 2021a).Furthermore, the warming temperatures would also reduce the precipitation amount falling as snow and there will be more liquid precipitation.

Water yield is a measure of the cumulative water delivered to streamflow by sub-basins/HRUs, and includes baseflow, lateral flow, and surface runoff (Andrade et al., 2021; Jain et al., 2017).The average water yieldwithin the Jhelum basinwitnessed a decline over 21st century. For the RCP4.5 (RCP8.5), the water yield witnesses' reductions by 17.7(18.4) % during 2020s, 24 (32) % during 2050s, and 25 (42) % during 2080s. Fig 10 shows the spatial variations in the projected water yield of different sub-basins for different spans of the future. The projected decreases in the water yield can be attributed to the enhancement of the ET levels and decreases in the snowmelt contribution over the 21st century.The progressive decline in the water yield during the 21st century infers that water availability will get reduced significantly and will aggravate the water scarcity and stresses in the basin.

5. Discussions

The water resources of the mountainous basins are highly exposed to climatic changes wherein the regional hydrology is dependent on the glacial ice melt and seasonal snowmelt characteristics. The present study is attempted in the Jhelum basin- nestled in the complex folds of North-Western Himalayas and forms important headwaters ofthe Indus River system. The imprints of global climate change are well established from the observational datasets in the Jhelum basin and its impacts are already being felt(Ahsan et al., 2021a). Few studies e.g., (Ahsan et al., 2021b) have also attempted to estimate the magnitude of climatic changes over the 21st century. However, these studies are limited in scope because the projections are based on a single GCM.It has been found that GCM outputs inherit considerable uncertainty in them and thus use of a single GCM can yield inaccurate results(Khan et al., 2021). For modeling the hydrological consequences of climatic changes, the development of rigorous and robust climate change projections is a primary requirement. To this end,6 GCMs dynamically downscaled by the RegCM4 RCM from the CORDEX-SA experiments under a medium stabilizing forcing level (RCP4.5) and an extreme forcing level (RCP8.5), were collated for the present study. The use of RCM output is preferred for the basin-scale assessment than the GCM due to their higher resolution and the local sub-grid processesare parametrized better(Seager&Vecchi, 2010). However, the raw RCM outputs may still contain significant biases particularly over mountainousareas(Fowler et al., 2007).As a result, bias correcting the RCM ouputs is critical, and in this work, temperature was bias-corrected using the VS approach, and precipitation was

bias-corrected using a mix of LOCI and PT techniques. The bias correction significantly improved the performance indicators and yielded an overall better match between the observational data and the RCM simulation results duringthe baseline (1980-2010). Furthermore, to narrow theuncertainty, multi-model ensemble climate change projections were developed using the Bayesian Model Averaging (BMA) technique. There is consensus among the climate modeling community that by using the multi-model ensemble climatic projections,the uncertainty can significantly reduce, given the fact that individual models may simulate different aspects of the climate system well and the errors get canceled or reduced in the process (Brient, 2019). Moreover, it has been reported that by using the multiple simulations from a given RCM for different GCM forcings andemission scenarios,accuracy of climaticprojectionscan be further improved (Raisanen et al., 2004; van den Hurk et al., 2005; Salathe, 2005).

The climate change projections from all the GCMs and BMA estimates show unequivocalwarming for the Jhelum basin over 21st century. The increments in temperature are progressive over time and varies directly with levels of radiative forcing levels. BMA estimatesproject warming of Tmax by 0.41-2.37 (0.63-4.82) during the various spans of the future under RCP4.5(RCP8.5). Tmin is getting warmer at a relatively higher rate vis-a-visTmaxand increases are of the order 1.39-2.37 ^{o}Cunder RCP4.5 and 2.14-4.35^{o}Cunder RCP8.5. Precipitation in the Jhelum basin witnessed reductionsby varying amounts across different GCMs. These changing climatic regimes are going to triggerseveralimplications for key sectors viz., water resources, agriculture, energy consumption, or human health (Ahsan et al., 2021a). The possibleimplications on the streamflow and water budget of the basinwere assessed by coupling the climate change scenarios into the SWAT model. SWAT model performed quite well in simulating the basin hydrology as inferred by high values of the model skill metrics. The streamflow of the river Jhelum is projected to witness substantial reductions over the 21st century under both RCP's. The decreases aggravate over time and forcing levels with the highest decrease of about 40-46% for the 2080s under RCP8.5.These reductions in streamflow are driven by influences of climaticchanges on thedifferent components of water budget like Evapotranspiration and snowmelt. Both potential and actual ET are showing a rise over 21st century in response to the projected warming.Actual ET in the Jhelum basin witnessed amaximum increase of31% under RCP4.5 and 40% under RCP8.5 during 2080s. Increases in the ET under climatic warming has beenstated in other relevant studies likeAndrade et al.,

448 (2021),Bajracharyaet al., (2018) andReshmidevi et al., (2018). Snowmelt is another important
449 component of regional hydrology and sustains the streamflowsin Jhelum basin during the dry
450 months(Jeelani et al., 2012). Under the changing climate, snowmelt witness a reduction of 50-
451 70% over the 21st century. The decrease in the snowmelt may be attributed to the coupled impact
452 of warming temperatures and diminishing precipitation. Higher temperatures particularly during
453 the winter would cause more precipitation in the form of rain than snow and would ultimately
454 decrease the snowmelt contributions. The decreasing snow and increasing rainproportion in the
455 precipitation are already being observed in the basin as reported by Romshoo et al., (2018). This
456 will also lead to the enhanced ablation of the glacial reserves in the basin. The glacial recession
457 has amplified significantly in the region during the last few decades (Murtaza&Romshoo,
458 2016).Another important aspect of the snowmelt characteristic driven by the increasing
459 temperatures is the earlier melting of the snowpacks.This impact is discernible during the 2080s
460 under RCP8.5 where the peak streamflow month is showing a shift from May to March (Fig
461 6c).This shifting of peak streamflow has been reported in the numerous other snow-fed basins of
462 the world and tends to create issues for water resource management due to shifting of peak
463 streamflow period away from peak demand season(Barnett et al., 2005). The combined impacts
464 of the ET and snowmelt are yielding a decrease in water yield of the basin and hence
465 streamflow's.

466 **6. Conclusions**

467 The discharge from the rivers in the Jhelum basin is of tremendous importance from the
468 perspective of ecology, environmental health, and water security. The river waters aregenerally
469 tapped for irrigation, hydropower generation,domestic consumption, and recreation purposes.
470 Hence, any changes in hydrological conditions induced by the climatic changes will entail a
471 profoundinfluence on the environment andthe society. With the application of multiple
472 downscaled GCMs, the present study projects the magnitude of climatic changes and its
473 hydrological repercussions in the Jhelum basin for the 21st century. The changes are projected for
474 the annual mean maximum and minimum temperatures, precipitation percentages and river
475 discharge. This analysis found that the maximum temperature may rise up to 4.82°C and
476 minimum temperature may go up by4.35°C coupled withreduction in the precipitation to the
477 maximum of 7.2% in the given time period. Consequent to the changes in temperature and
478 precipitation conditions, the discharge of the rivers is likely to fall by 17 to 42%. The increase in

temperature, decline in the precipitation, and the huge decrease in the seasonal flow of rivers may result in dwindling aquatic ecosystems, loss of biodiversity, reduced productivity, and conflicts in water sharing agreements e.g., Indus Water Treaty. The deliverables of the study may therefore serve as a guidefor foreseeing the future challenges and developing policies to mitigate and adapt to the changing climate and the flow regimes of the river basins in the Himalaya.

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Conflict of interest

The authors declare that there is no conflict of financial or personal interests or beliefs that could affect the objectivity of this research.

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On behalf of all authors

Data Availability Statement

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Akhtar Alam
On behalf of all authors

Author Contributions Statement

Shafkat Ahsan has been primary involved in modelling part and writing; M. Sultan Bhat developed the idea and contributed in writing; Akhtar Alam performed some simulations, contributed in writing and overall editing of the manuscript; Hakim Farooq coordinated the work and was responsible for literature review and compilation of the results; and Hilal A. Sheikh did the artwork.

Akhtar Alam
On behalf of all authors

Figures

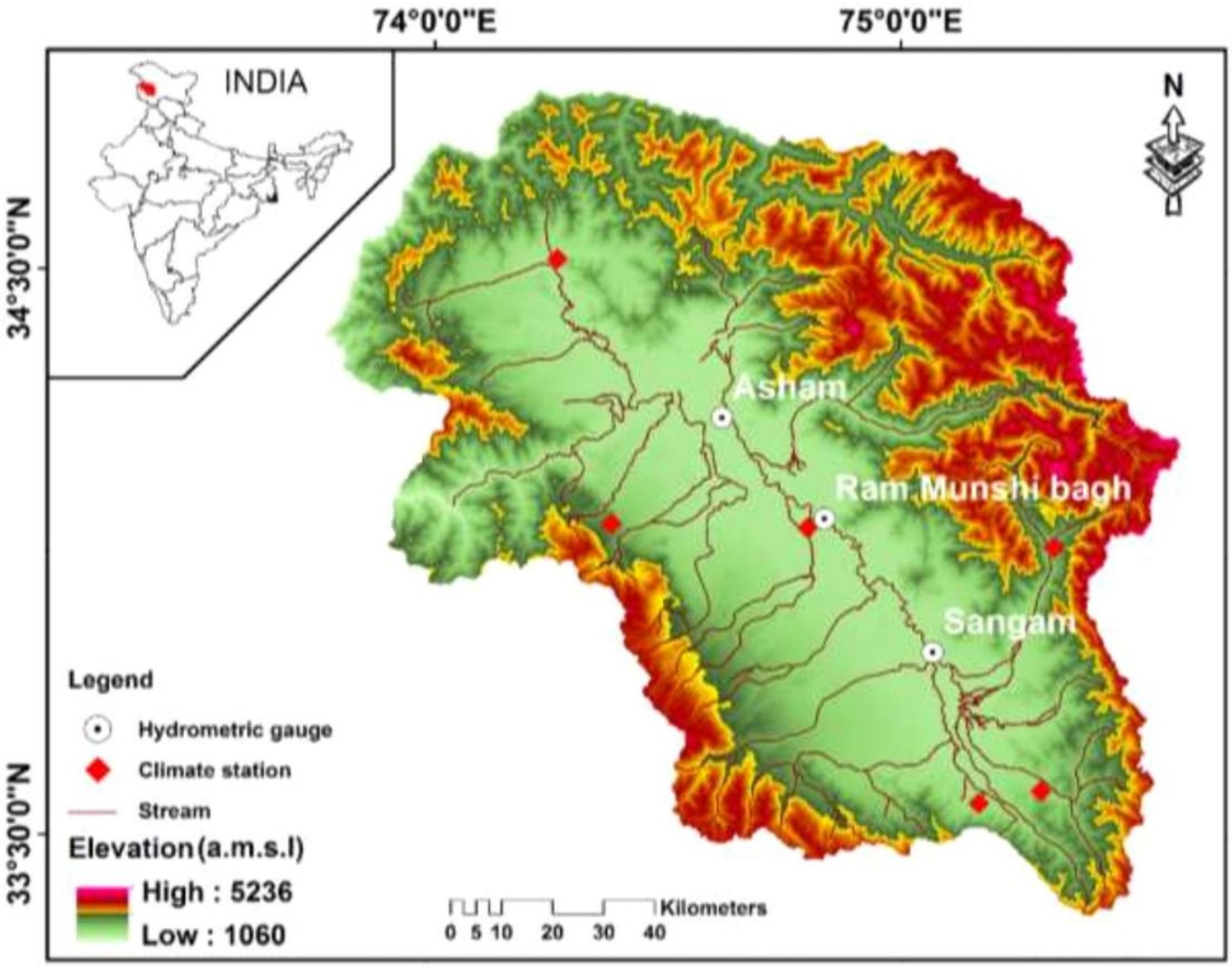

Figure 1

Location map of the Jhelum basin with the major streams, climatic stations and the river gauges.

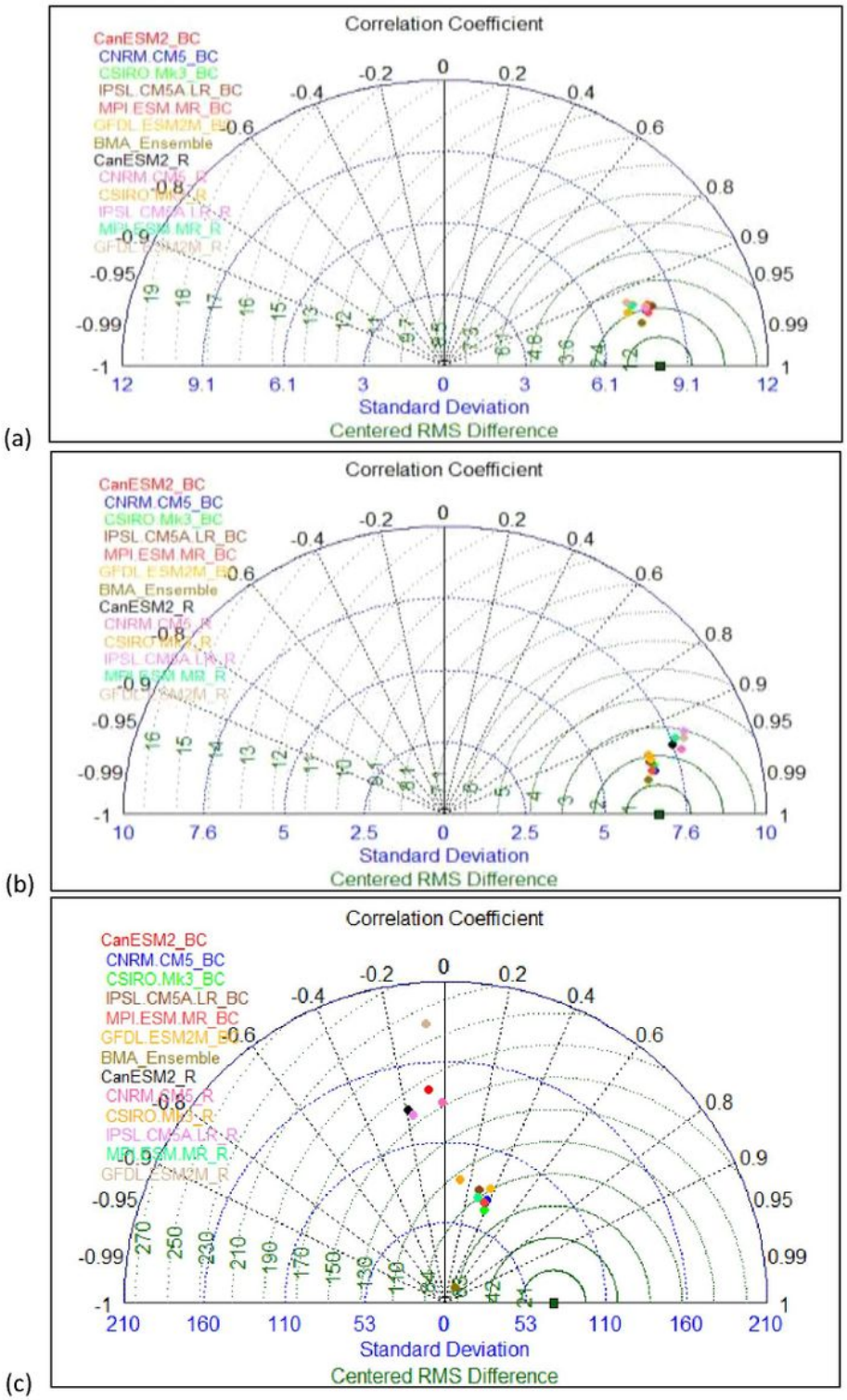

Figure 2

Performance of GCMs and BMA ensemble during training period (1980-2005); (a) mean maximum temperature, (b) mean minimum temperature and (c) precipitation. BC = bias corrected GCM output, R= raw GCM output.

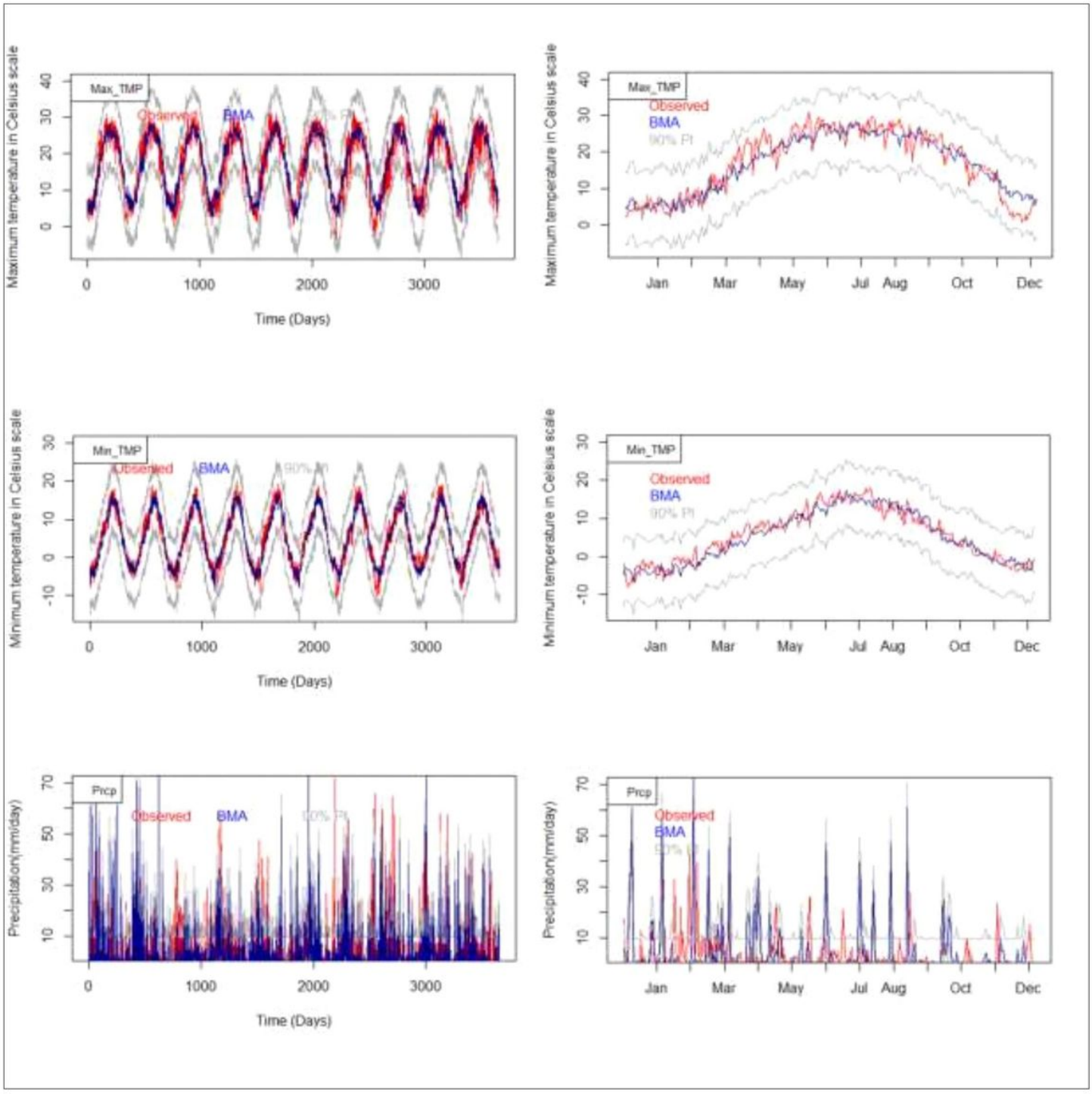

Figure 3

Performance of the BMA during training period, left - daily data for 10yrs and right - data for only 1yr for detailed visualization. Max_TMP = mean maximum temperature, Min_TMP = mean minimum temperature, and Prcp = Precipitation.

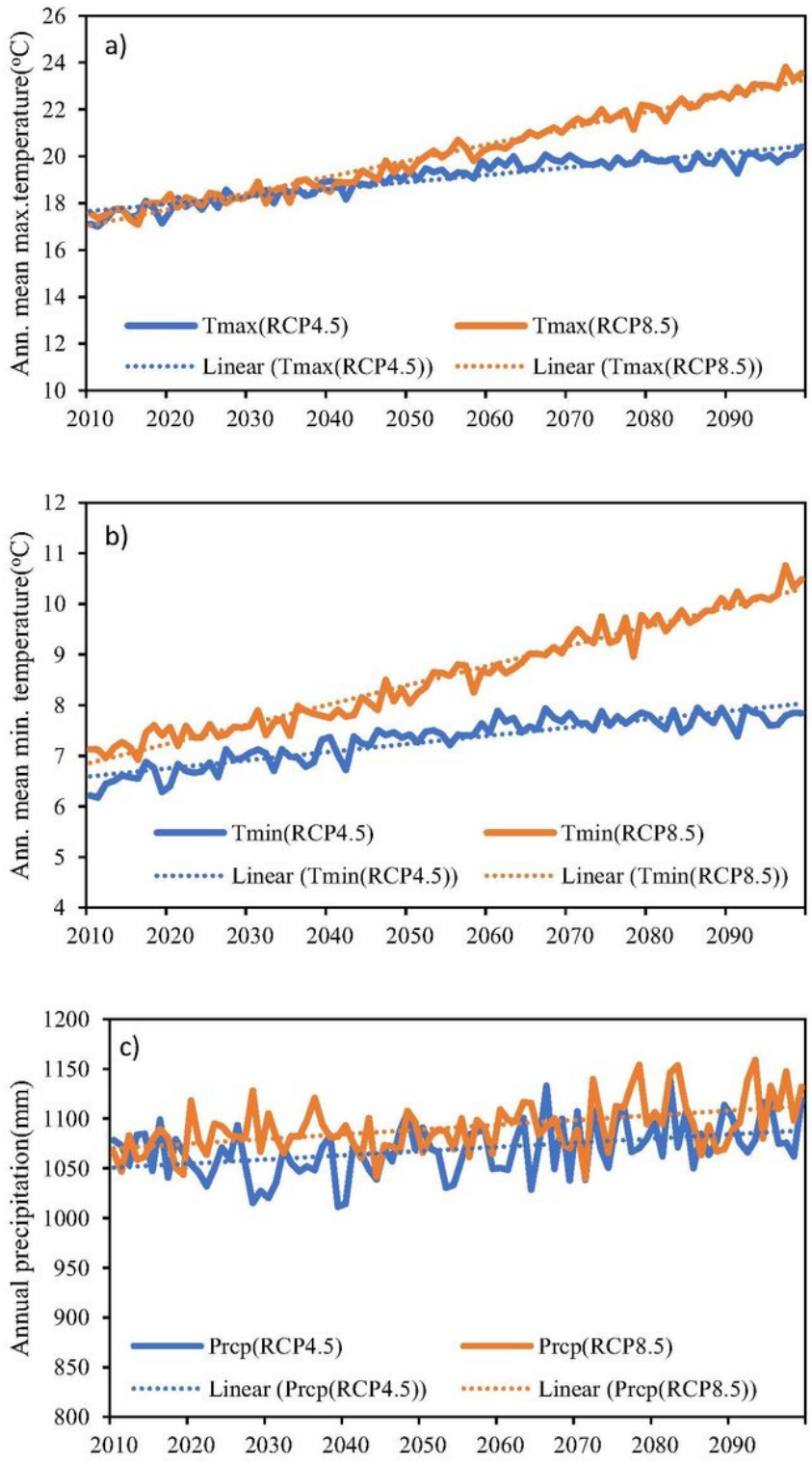

Figure 4

BMA based projected changes in annual mean maximum temperature (a), mean minimum temperature (b), and precipitation (c) under RCP4.5 and RCP8.5, with respect to the baseline (1980-2010) values for Jhelum basin.

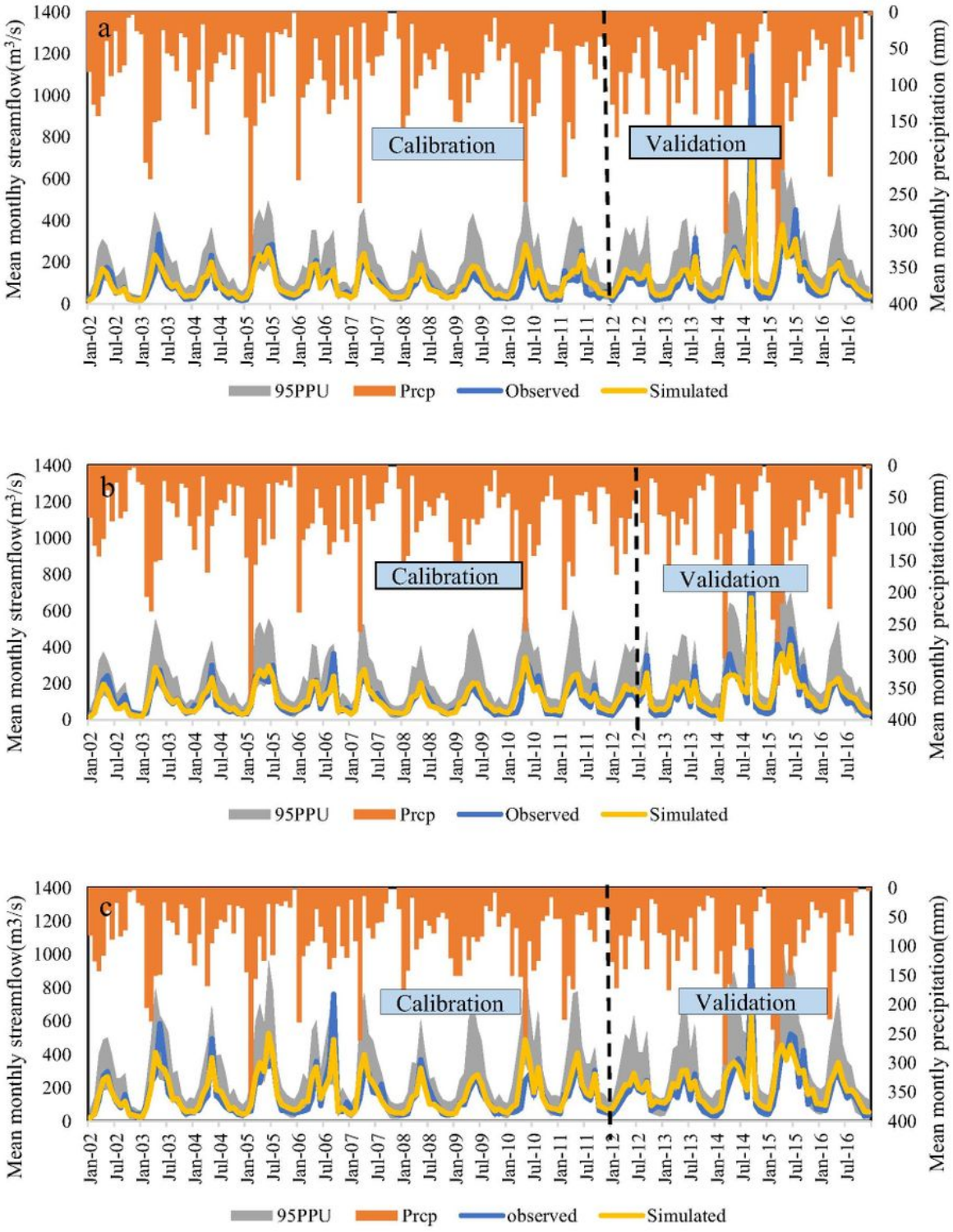

Figure 5

Multi-site evaluation of the SWAT model during calibration (2002-2011) and validation (2012-2016) periods at Sangam gauge (a), Ram Munshi Bagh gauge (b) and Asham gauge (c) sttions.

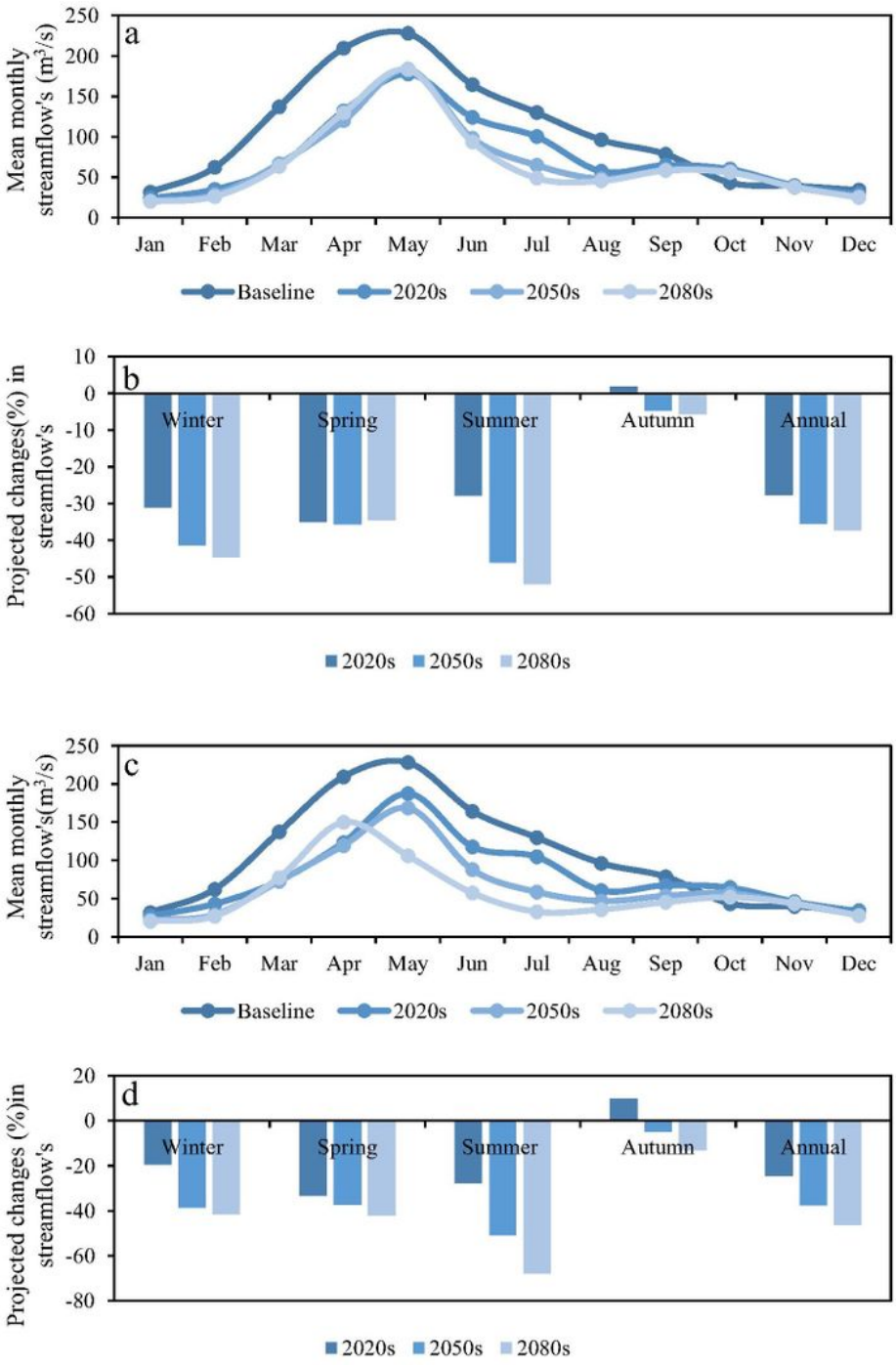

Figure 6

Projected changes in mean monthly and seasonal streamflow of Jhelum at Sangam gauge under RCP4.5 (a, b) and RCP8.5 (c, d) over 21st century

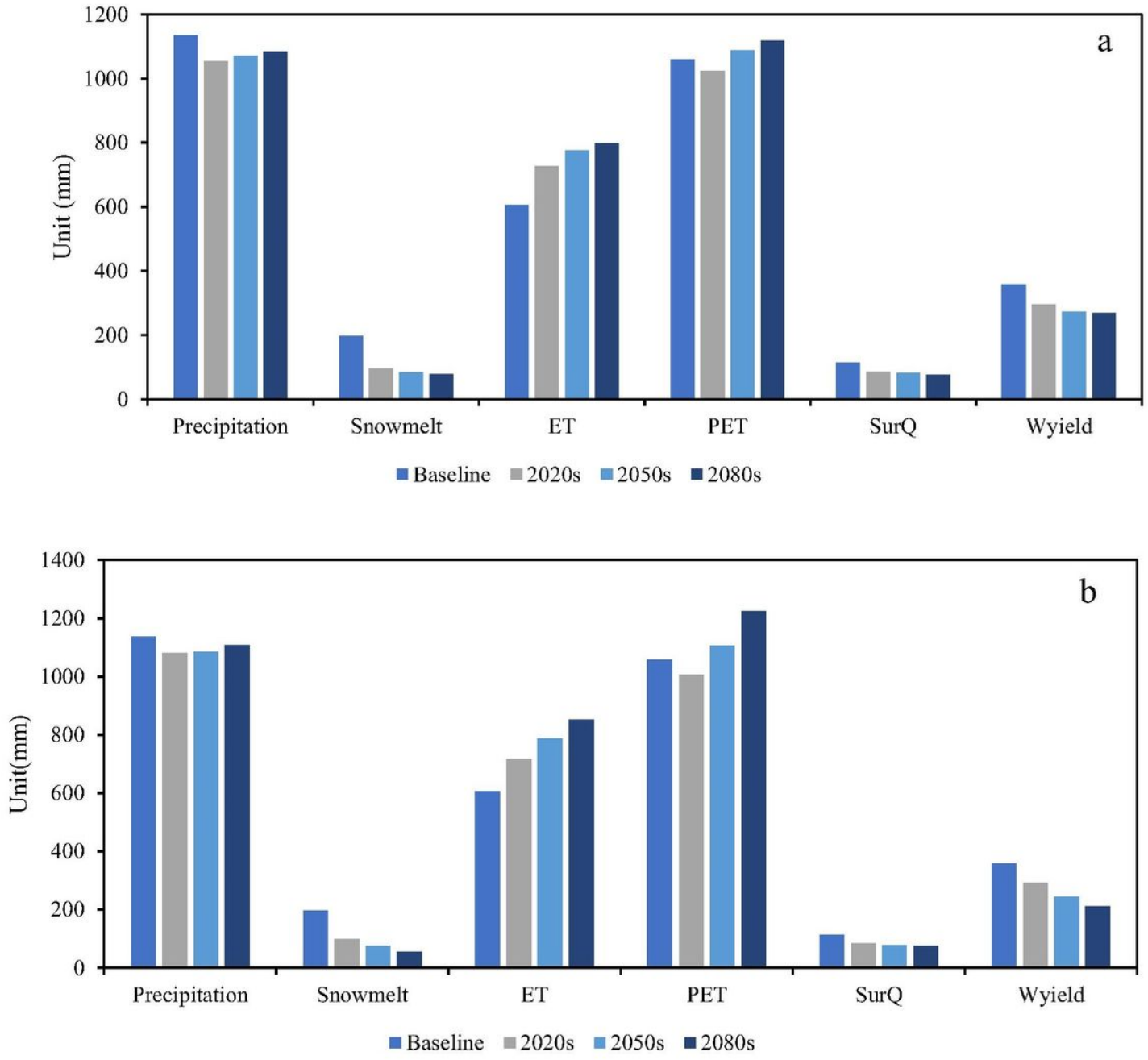

Figure 7

Projected changes in the annual average water balance components of the Jhelum basin under RCP4.5 (a) and RCP8.5 (b) over 21st century.

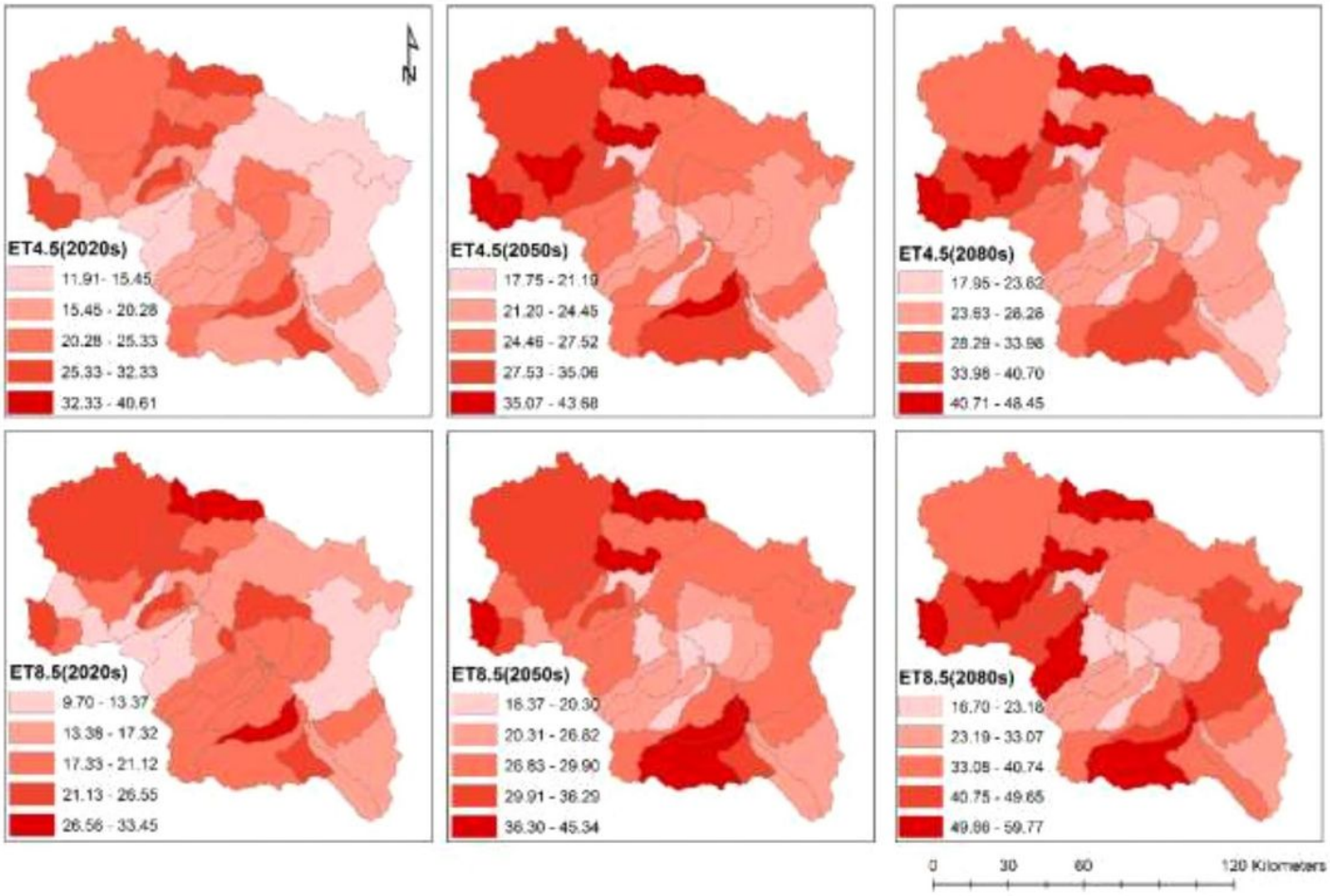

Figure 8

Spatial distribution of the projected changes (%) in evapotranspiration of the Jhelum basin under RCP4.5 (top) and RCP8.5 (bottom).

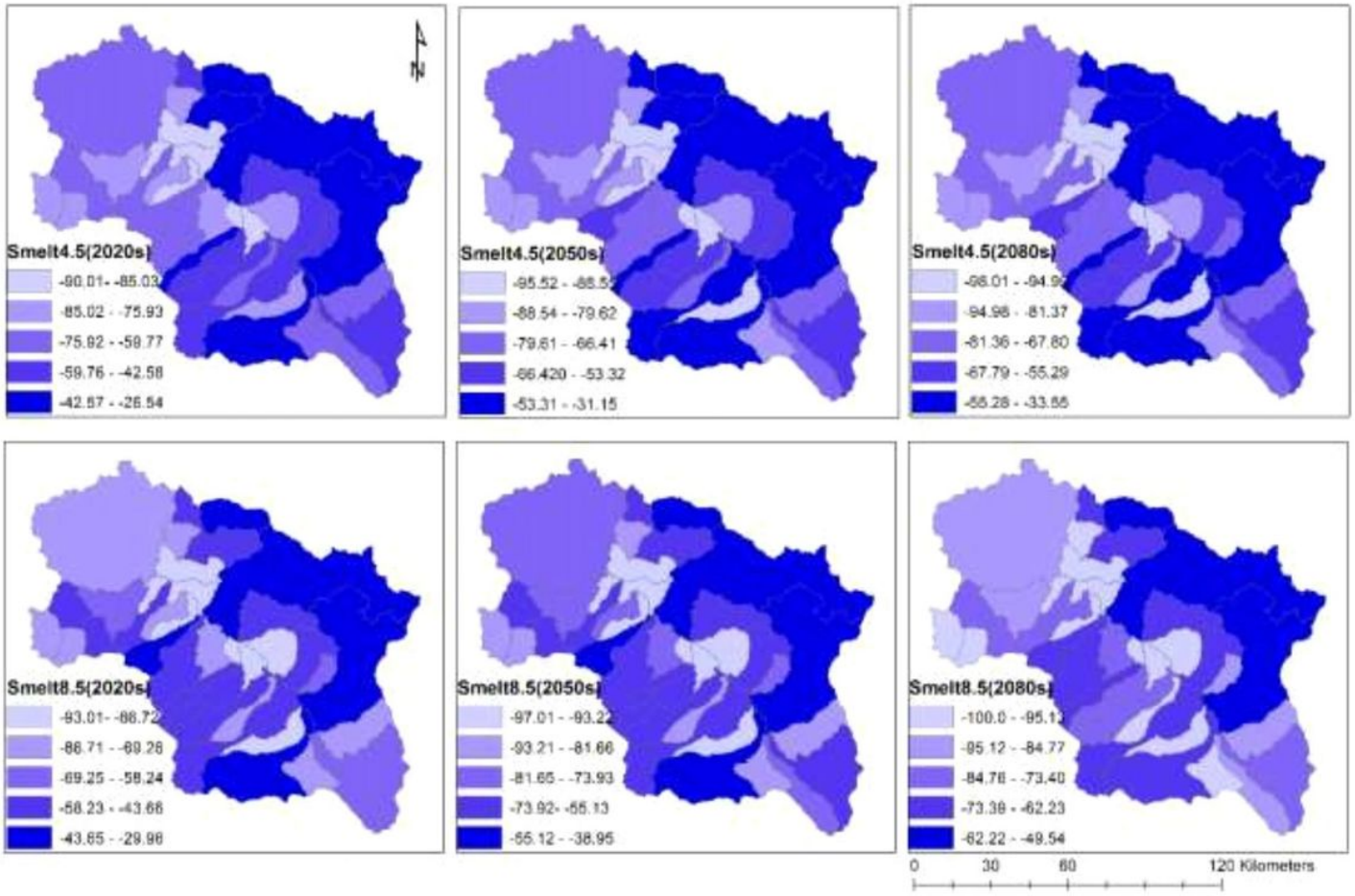

Figure 9

Spatial distribution of the projected changes (%) in the snowmelt of the Jhelum basin under RCP4.5 (top) and RCP8.5 (bottom)

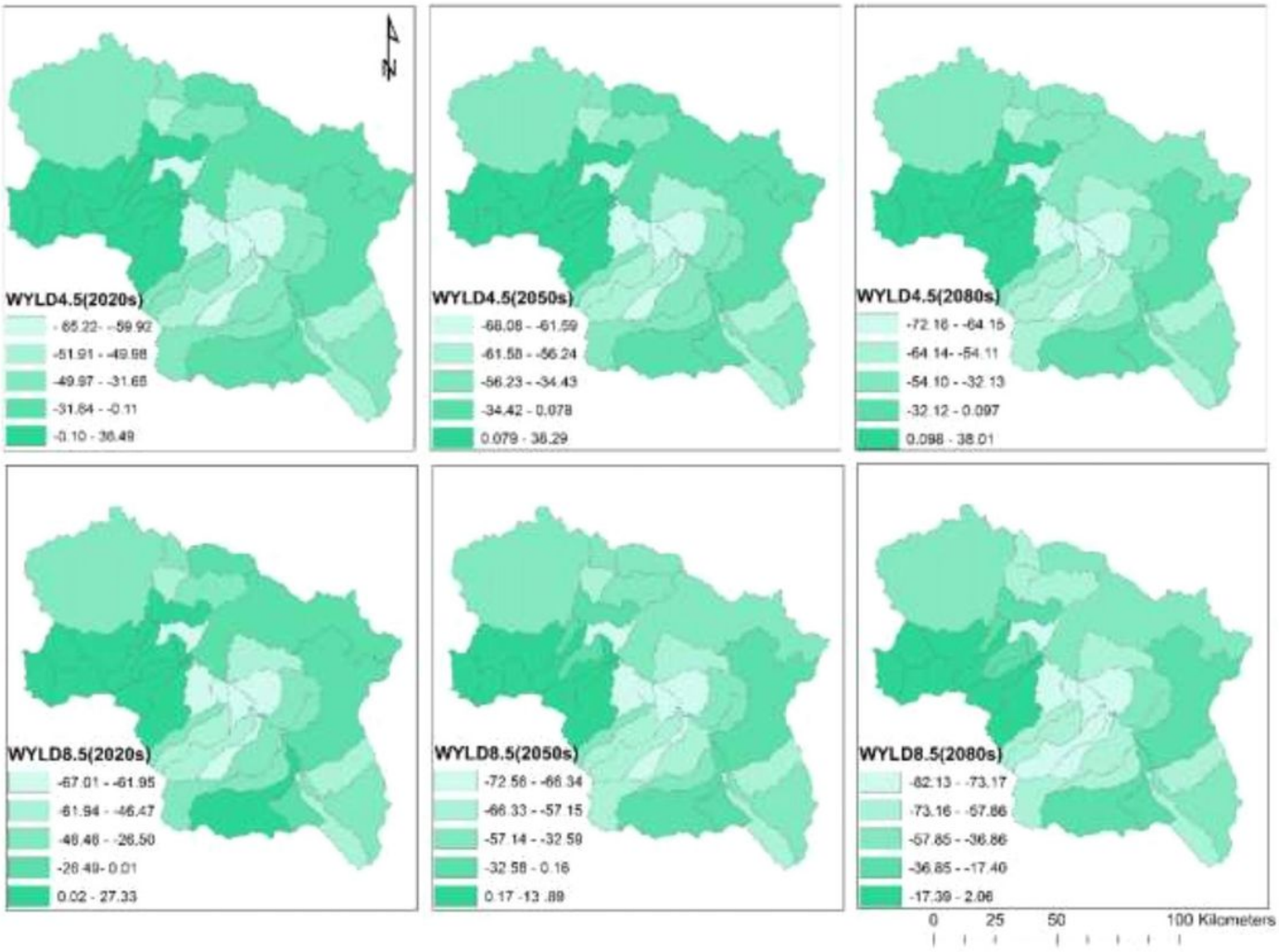

Figure 10

Spatial distribution of the projected changes (%) in the water yield of the Jhelum basin under RCP4.5 (top) and RCP8.5 (bottom).