



## Impact analysis of climate change on near future streamflow using CORDEX-SA datasets in a hilly watershed

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**सार** – इस अध्ययन में पूर्वोत्तर भारत के बराक बेसिन में तापमान एवं वर्षा में अनुमानित वृद्धि के कारण नदी के प्रवाह पर पड़ने वाले प्रभाव का विश्लेषण किया गया है। वन-प्रधान तथा वर्षा-आधारित इस नदी बेसिन का क्षेत्रफल, बांग्लादेश की सीमा के निकट अन्नपूर्णा घाट (सिलचर) तक 19,004 वर्ग किमी है। वनावरण में कमी के कारण बेसिन में बाढ़ की घटनाओं में वृद्धि देखी गई है। अध्ययन में मृदा एवं जल आकलन उपकरण (Soil and Water Assessment Tool) जलवैज्ञानिक मॉडल का उपयोग करते हुए CORDEX-SA के छह क्षेत्रीय जलवायु मॉडलों (RCMs)—CNRM-CERFACS-CNRM-CM5, CCCma-CanESM2, IPSL-IPSL-CM5A-MR, MPI-M-MPI-ESM-MR, CSIRO-QCCCCE-CSIRO-Mk3-6-0 तथा NOAA-GFDL-GFDL-ESM2M—के बहु-मॉडल एन्सेम्बल माध्य (MME) के आधार पर निकट भविष्य (Near Future–NF; 2021-2050) के लिए जलवायु परिवर्तन के नदी प्रवाह पर प्रभाव का आकलन किया गया। इन मॉडल आँकड़ों में वितरण फलन (Distribution Function) के माध्यम से पूर्वाग्रह-संशोधन (Bias Correction) किया गया है। इस अध्ययन में RCP4.5 और RCP8.5 उत्सर्जन परिदृश्यों को ध्यान में रखा गया है। इस अध्ययन में SWAT मॉडल को वर्ष 2011 के भूमि उपयोग/भूमि आवरण (LULC) तथा 1990-2020 की प्रेक्षित जलवायु संबंधी आँकड़ों के आधार पर व्यवस्थित किया गया। आधारभूत मॉडल का अंशांकन (Calibration) एवं सत्यापन (Validation) वर्ष 1995-2020 के दो प्रेक्षित प्रवाह डेटा सेट का उपयोग करके किया गया। निकट भविष्य के लिए अनुमानित तापमान (Tmax तथा Tmin) में वृद्धि होने की संभावना है जबकि दोनों उत्सर्जन परिदृश्यों में मानसून के प्रथम चरण अर्थात् जून और जुलाई, तथा मानसूनोत्तर अवधि में वर्षा में वृद्धि, जबकि मानसून के द्वितीय चरण में वर्षा में कमी का अनुमान लगाया गया है। इसके विपरीत, RCP8.5 परिदृश्य के अंतर्गत मानसून-पूर्व अवधि में अनुमानित वर्षा, प्रेक्षित वर्षा की तुलना में अधिक है। प्रवाह दोनों उत्सर्जन परिदृश्यों में शुष्क शीत ऋतु के दौरान उल्लेखनीय कमी दिखाता है, जबकि मानसूनोत्तर अवधि में विसर्जन में वृद्धि पाई गई है। मानसून के दौरान RCP8.5 परिदृश्य में ऐतिहासिक रूप से प्रेक्षित विसर्जन की तुलना में विसर्जन में मामूली कमी देखी गई है। मासिक औसत नदी प्रवाह के वितरण का प्रतिरूप मुख्यतः वर्षा के अनुरूप पाया गया है, क्योंकि यह बेसिन मुख्य रूप से वर्षा-आधारित (Rain-fed) है।

**ABSTRACT.** The study analyses the impact of projected increases in temperature and rainfall on streamflow in the Barak Basin, Northeast India. The forest-dominated, rain-fed river basin up to Annapurna Ghat (Silchar), near the Bangladesh border, covers an area of 19004 sq. km. There has been an increasing occurrence of flood events in the basin due to decreasing forest cover. The study attempts to analyze the impact of climate change on river streamflow for the near-future (NF) (2021-2050) based on the multi-model ensemble mean (MME) of 6 Regional Climate Models (RCMs) from CORDEX-SA consisting of CNRM-CERFACS-CNRM-CM5, CCCma-CanESM2, IPSL-IPSL-CM5A-MR, MPI-M-MPI-ESM-MR, CSIRO-QCCCCE-CSIRO-Mk3-6-0, and NOAA-GFDL-GFDL-ESM2M, using the SWAT hydrological model. These model datasets are bias-corrected using the distribution function. Projection considered RCP4.5 and RCP8.5 emission scenarios. The study set up the SWAT model based on the LULC of 2011 and observed climate datasets for the period 1990-2020. The base model is calibrated and validated using two observed discharge datasets for the period 1995-2020. Projected temperature (Tmax and Tmin) increases in the near future, while rainfall increases in the first half of monsoon-June and July and post-monsoon and decreases in the second half of monsoon in both scenarios. In contrast, in the pre-monsoon, projected rainfall is in excess of observed under RCP8.5. The discharge shows a considerable decrease in both emission scenarios during the dry winter season, while the post-monsoon shows an increase in discharge. During the monsoon, the discharge marginally decreased with respect to the historically observed discharge under RCP 8.5. The monthly mean discharge distribution pattern closely follows the rainfall mainly because the basin is rain-fed.

**Key words** – SWAT model, Regional climate model projection, Emission scenarios-RCP4.5 and RCP8.5.

## 1. Introduction

River discharge is governed by rainfall and temperature patterns that are increasingly altered by climate change (Whitehead *et al.*, 2018). These alterations profoundly affect flow regimes, leading to more sustained, intense, and frequent hydrological extremes (Rodrigues *et al.*, 2020). Hydrological models serve as primary tools for investigating these potential impacts, particularly for quantifying changes in the magnitude and frequency of water-related extremes (Fowler *et al.*, 2007; Taye *et al.*, 2015). While global-scale assessments using coarse-resolution climate projections have provided valuable insights into large-scale future risks under warming scenarios (Hirabayashi *et al.*, 2013; Arnell and Gosling, 2016), such approaches often fail to capture critical regional and local-scale physical processes that significantly influence watershed flow characteristics (Xu *et al.*, 2017). Discharge variability, a fundamental component of hydrological systems, is driven not only by changing climatic conditions but also by population growth and land use/land cover (LULC) changes (Abera *et al.*, 2019; Guo *et al.*, 2020). Both climate and LULC have undergone unprecedented transformations globally, driven by increasing population pressures and socio-economic development activities (Yin *et al.*, 2017; Kim *et al.*, 2013). These changes have disrupted hydrological cycles even in remote regions, altering the frequency and spatial distribution of rainfall and intensifying the occurrence of floods and droughts, collectively reshaping regional flow regimes and runoff patterns (Aggarwal *et al.*, 2012; Tirupati and Shashidhar, 2020).

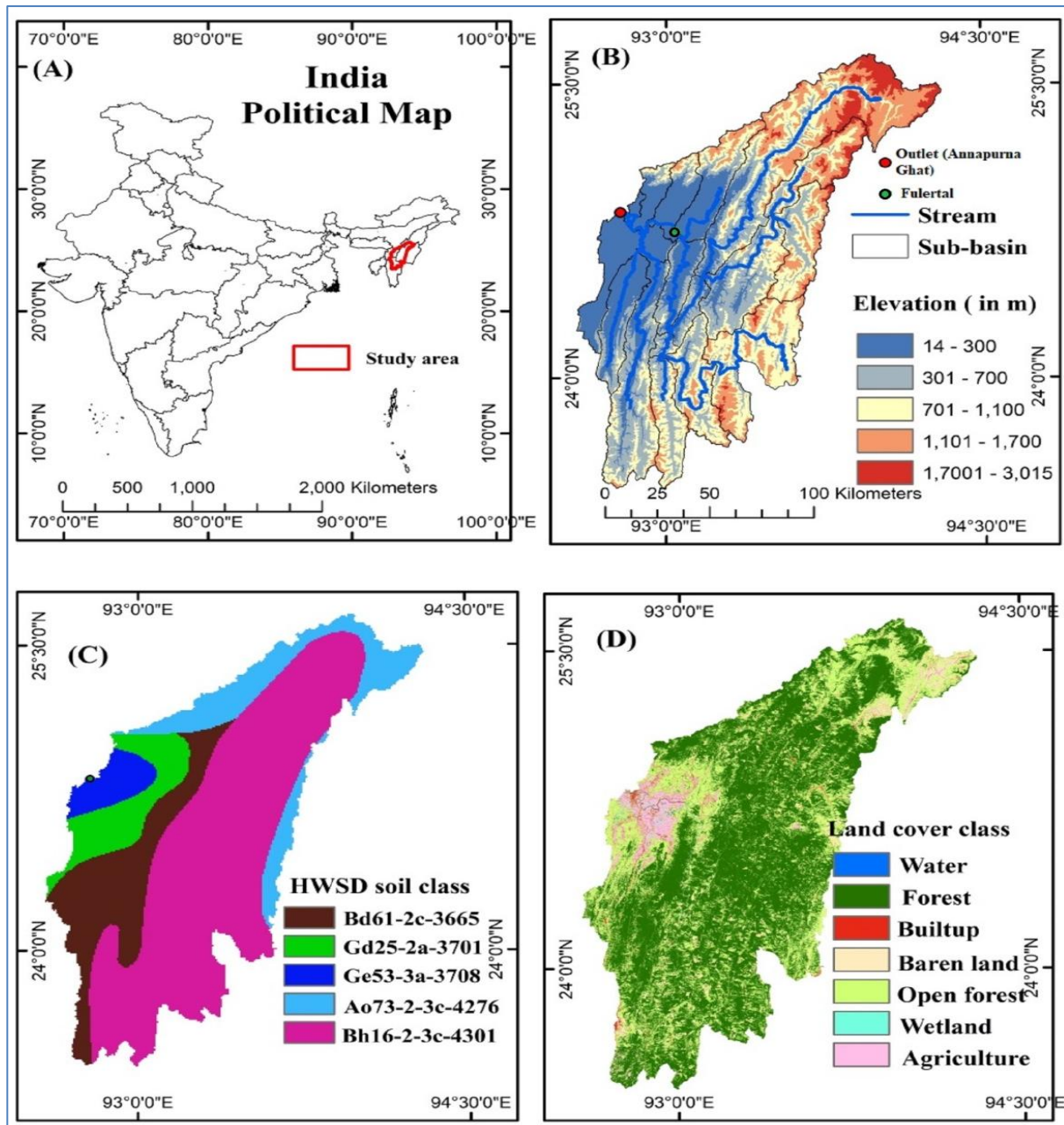
Various methodological approaches exist for climate-hydrology studies, including GCM-based methods (Githui *et al.*, 2009). Following the IPCC's Fifth Assessment Report (AR5), numerous studies have assessed climate change impacts on hydrological parameters, primarily leveraging GCM projections from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Shrestha *et al.*, 2018; Zheng *et al.*, 2018; Guo *et al.*, 2020). Among hydrological models, the Soil and Water Assessment Tool (SWAT) has emerged as the most widely deployed model for large-scale assessments of climate, LULC changes, and management practices on water resources, simulating basin water balance under various climate scenarios using both global and regional climate models (Arnold *et al.*, 1998; Dubey *et al.*, 2023).

Regional applications of SWAT across the Indian subcontinent demonstrate both the utility and evolving methodologies of hydrological modelling, showing flexibility to adapt to the data scarcity problem. Chanapathi

*et al.* (2018) analyzed extreme hydrological events across southern central India using CORDEX-South Asia RCMs under RCP4.5 and RCP8.5 scenarios. In eastern India, Gaur *et al.* (2020) employed high-resolution CORDEX-East Asia projections to assess flood characteristics in the Subarnarekha watershed, while Sinha *et al.* (2020) combined IMD gridded data with Climate Forecast System Reanalysis datasets for western India. In Southeast Asia, where floods and droughts pose persistent threats, climate-induced discharge increases during monsoons risk exacerbating flood damage, while elevated evaporative losses during dry periods intensify water scarcity, resulting in significant socioeconomic implications for lower riparian countries (Alam *et al.*, 2021). These studies have progressively addressed data limitations through climate reanalysis datasets and, in ungauged basins, parameter transfer from hydrologically similar gauged watersheds (Pandey *et al.*, 2016; Saharia and Sarma, 2018; Mengistu *et al.*, 2019).

Rainfed basins like the Barak basin (India-WRIS, 2014) are especially vulnerable to rainfall fluctuations in their intra-annual distribution, as they lack the buffering capacity provided by snowmelt and glacial meltwater sources (Singh and Bengtsson, 2005). The basin is vulnerable to climate-induced disasters owing to its location in the eastern Himalayan periphery, fragile geo-environmental setting, and economic problems. The hydrological and monsoon regime of the river is both a resource and a source of vulnerability (Jain *et al.*, 2012).

Consequently, quantifying climate change impacts on hydrological regimes is essential for projecting future flood and drought risks at the watershed scale (Kour *et al.*, 2016). Despite this extensive research activity with 110 SWAT-based studies documented across India between 2012 and 2022 (Dubey *et al.*, 2023), no comprehensive discharge variability analysis exists for the Barak River basin. This research gap is particularly critical given the basin's pronounced vulnerability. Therefore, this study focuses on the Barak basin upstream of Annapurna Ghat station (Silchar), where consistent discharge data for the baseline period 1990–2020 enable robust model development. The study aims to: (1) develop, calibrate, and validate a SWAT-based hydrological model for the basin; (2) project the changes in rainfall and temperature (maximum and minimum) using CORDEX-SA datasets; and (3) quantify climate change impacts on near-future discharge patterns. This integrated climate-hydrological modelling approach addresses a critical knowledge gap while providing essential information for flood risk management and water resource planning in this vulnerable basin.



**Figs. 1(A-D).** Location of study area and its physical characteristics used in SWAT model. (A) Location of the study area; (B) Elevation map derived from SRTM DEM; (C) Soil map from Food and Agriculture Organization (FAO); and (D) Land cover map derived using Landsat 5 TM

## 2. Data and methodology

### 2.1. Study area

The Barak basin (19,004 km<sup>2</sup>), encompassing areas of Cachar district (Assam), western Manipur valley, and northern Mizoram, is characterized by mixed LULC patterns dominated by forest and high-relief terrain, with urban concentrations in western plains (Fig. 1). As a rainfed system receiving approximately 300 cm of average annual

rainfall through orographic and cyclonic rainfall (Deb and Sil, 2019), the basin experiences severe flood vulnerability; four major floods occurred between 1986 and 2007 (Assam Disaster Management Authority, 2010). In Cachar district alone, 295 of 1,062 villages experience flooding 7–10 times per decade, conditions exacerbated by declining forest cover from prevalent slash-and-burn agricultural practices in hilly regions (Annayat *et al.*, 2022; Das *et al.*, 2021; India-WRIS, 2014) and concurrent decreasing rainfall with rising maximum temperatures

TABLE 1

Datasets used in the study

| Sl.no | Input data                 | Scale/resolution                                         | Description and Data sources                                                                                                                  |
|-------|----------------------------|----------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------|
| 1     | DEM                        | 30m                                                      | SRTM from ( <a href="https://earthexplorer.usgs.gov/">https:// earth explorer.usgs.gov/</a> )                                                 |
| 2     | Soil                       | 30 arc second (1000m)                                    | Harmonized World Soil Database (HWSD) ( <a href="https://iiasa.ac.at/models-tools-data/hwsd">https://iiasa.ac.at/models-tools-data/hwsd</a> ) |
| 3     | Daily weather (observed)   | Temperature (1° by 1°)<br>Rainfall (0.25° by 0.25°)      | IMD (1990-2020) ( <a href="https://cdsp.imdpune.gov.in/">https://cdsp.imdpune.gov.in/</a> )                                                   |
| 4     | Daily weather (reanalysis) | 0.5° by 0.5° for daily relative humidity, and insolation | MERRA-2 (Reinecker et al., 2011)                                                                                                              |
| 5     | Land use                   | 30 m                                                     | Landsat image 2011 ( <a href="https://earthexplorer.usgs.gov/">https:// earth explorer.usgs.gov/</a> )                                        |
| 6     | Discharge data             | Daily mean                                               | CWC India                                                                                                                                     |
| 7     | Projected climate data     | 0.44° by 0.44° degree                                    | 6 RCM models of RegCM4 hosted by IITM Pune, from CORDEX-SA                                                                                    |

(Sharma, 2003; Deb and Sil, 2019). The basin is covered predominantly by forest. The dense and open forest (degraded forest) covers about 80 per cent of the area of the basin (Annayat *et al.*, 2022).

#### 2.1.1. Data

The datasets used in the impact assessment comprise mainly climatic, land cover, soil, and elevation factors as given in Table 1. The rainfall datasets are taken from IMD (<https://cdsp.imdpune.gov.in/>), both gridded and station data. The gridded rainfall data are available at 0.25° by 0.25° spatial resolution (Pai *et al.*, 2015) and temperature at 1° by 1° (Srivastava *et al.*, 2009) for the period 1990-2020. The gridded datasets of daily insolation, relative humidity, and wind speed data at 0.5° by 0.5° resolution are obtained from the reanalysis datasets of MERRA-2 (Reinecker *et al.*, 2011), which are regridded into the IMD 0.25° grid resolution system as discussed in Sinha *et al.*, (2020). The study used the Harmonised World Soil Database (HWSD) v 1.2 obtained from FAO (<https://swat.tamu.edu/data/india-dataset/>). The future projected climate datasets of rainfall and temperature of CORDEX-SA datasets (Giorgi *et al.* 2012) are obtained from CCCR-IITM (Table A1). To reduce the inherent model uncertainties of six individual models, a multi-model ensemble mean is calculated.

The land cover maps are prepared from the Landsat 5 TM datasets for 2011 using the Maximum Likelihood method. The multi-sensor satellite imageries are obtained from NASA Earth-Explorer (<https://earthexplorer.usgs.gov/>) with a spatial resolution of 30 m. Shuttle Radar Topography Mission (SRTM) Digital Elevation Map (DEM) having a 30 m spatial resolution for the region is also obtained from NASA Earth-Explorer.

#### 2.1.2. Methods

##### 2.1.2.1. Pre-processing of the climate datasets

Before conducting the bias correction, the grid points of the model and observed data should be equally placed in space, *i.e.* they should have equal placement, equal projection (coordinate system), and hence equal spatial resolution (Mujumdar and Kumar, 2012). In the present study, all climate datasets with different grid resolutions are regridded based on the IMD rainfall grid *i.e.* 0.25° by 0.25° with *regular latitude/longitude* projection. The default grid system of CORDEX RCMs *i.e.* 0.44° by 0.44° *curvilinear* projection, is converted to IMD's using Climate Data Operator (CDO) (<https://code.mpimet.mpg.de/projects/cdo>). This is because in the SWAT modelling, the input climatic data should have the same grid position (station). Unit conversion and standardization of calendar are done using CDO (Table A1).

In the present study, distribution mapping or quantile-quantile mapping technique is used for statistical bias correction, which is considered the best method and is often used in climate impact assessment (Sinha *et al.*, 2020; Chanapathi *et al.*, 2018; Konda *et al.*, 2024). The goal of distribution mapping is to adjust the distribution function of RCM-simulated climate parameters to match the observed distribution function. This can be accomplished by developing a transfer function that shifts the distributions of rainfall and temperature (Sennikovs and Bethers, 2009). There are two mathematical distributions assumed to represent rainfall and temperature in natural occurrence *viz.* the Gamma distribution and Gaussian distribution (Teutschbein and Seibert, 2012). Gamma distribution (Equation 1) is assumed to be a suitable distribution to represent rainfall (Thom, 1958; Teutschbein and Seibert, 2012).

$$f_{\gamma}(x|\alpha, \beta) = x^{\alpha-1} \cdot \frac{1}{\beta^{\alpha} \Gamma(\alpha)} \cdot e^{-\frac{x}{\beta}}; x \geq 0; \alpha, \beta > 0 \quad (1)$$

where,  $f_{\gamma}$  is the distribution function of Gamma distribution,  $x$  is the independent variable, here rainfall;  $\alpha$  is the shape parameter and  $\beta$  is the scale parameter.

The shape parameter  $\alpha$  controls the profile of the distribution. (1) A Gamma distribution with a value of  $\alpha < 1$  is asymptotic at both axes. (2) An exponential distribution with  $\alpha = 1$  is a special case. (3)  $\alpha > 1$  results in a skewed unimodal distribution curve. The Gamma distribution's dispersion is determined by  $\beta$ . A smaller  $\beta$  results in a more compressed distribution and thus lower likelihood of extreme events. A larger  $\beta$ , on the other hand, results in a stretched distribution, implying a greater likelihood of severe events (Teutschbein and Seibert, 2012).

#### 2.1.2.2. Gaussian distribution

The temperature data is similar to the Gaussian distribution and is given in the Equation 2.

$$f_N(x|\mu, \sigma^2) = x^{\sigma-1} \cdot \frac{1}{\sigma \sqrt{2\pi}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}}; x \in \mathbb{R} \quad (2)$$

where,  $f_N$  is the distribution function of the Gaussian distribution;  $\mu$  is the mean which is the location parameter;  $\sigma$  is the standard deviation, which is the scale parameter;  $\mathbb{R}$  is a real number.

The scale parameter  $\sigma$  determines the standard deviation of the Gaussian distribution, indicating how much the range is stretched or compressed. A smaller  $\sigma$  number leads to a compressed distribution with fewer extreme values. A greater  $\sigma$  value suggests a stretched shape with more extreme values. The location parameter  $\mu$  determines the distribution's mean and thus its location (Teutschbein and Seibert, 2012).

#### 2.1.2.3. SWAT model setup

The SWAT model works on a daily time step and is a long-term, physically based distributed model developed to assess impacts of climate and land management on hydrological components, sediment loading, and pollution transport in watersheds (Arnold *et al.*, 1998). A watershed is divided into subbasins in the model. Based on soil and LULC, subbasins are further subdivided into a range of uniform hydrological response units (HRUs). Since water balance regulates all the processes like plant growth as well as the flow of nutrients, pesticides, pathogens, and sediments, it is the primary factor influencing all other

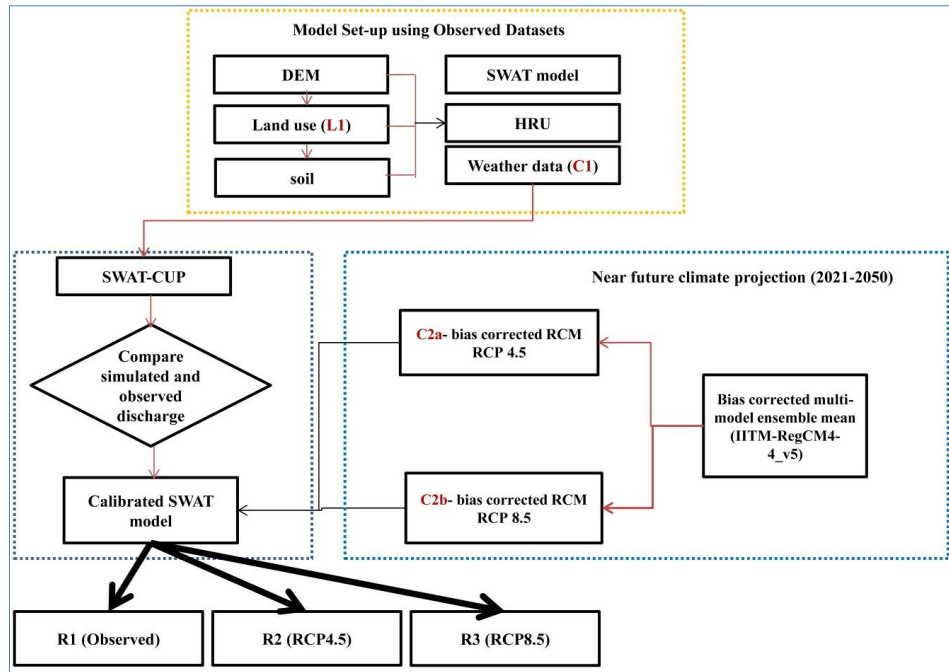
processes in the SWAT model (Arnold, 1998). Watershed hydrology simulation is divided into two phases: the in-stream or routing phase, which involves moving water and other materials through the watershed's network of channels to the outlet, and the land phase, which regulates the amount of water, sediment, nutrient, and pesticide loadings to each subbasin's main channel. The hydrological cycle was simulated in the SWAT model using the water balance equation (Equation 3).

$$SW_t = SW_0 + \sum_{i=1}^t (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \quad (3)$$

where,  $SW_t$  = soil water content after a time step  $t$  on a day  $i$  (mm);  $SW_0$  = initial soil water content on day  $i$  (mm);  $R_{day}$  = amount of precipitation on day  $i$ ;  $Q_{surf}$  = amount of surface runoff (mm);  $E_a$  = amount of evapotranspiration on day  $i$  (mm);  $W_{seep}$  = amount of water entering the vadose zone from the soil profile on day  $i$  (mm);  $Q_{gw}$  = amount of return flow as drainage to surface water (mm).

In the present study, SWAT model is set up in ArcGIS environment. Since inaccurate model set up or wrong model input cause unrealistic simulation results, the model setup and input dataset are pre-processed carefully in the ArcSWAT.

The hydrological model for the basin was developed using both spatial and non-spatial datasets (Fig. 2). A void-filled SRTM DEM was first employed to delineate the watershed boundary and define the drainage network, with the outlet specified at the Annapurna Ghat gauging station near Silchar town, Cachar district. Another gauging station Fulertal, on the Barak River, was also considered for sub-basin validation and discharge analysis. The delineation process divided the basin into 26 sub-basins, and the river network was generated accordingly. The study used the Penman–Monteith method (Penman, 1948; Monteith, 1965) for estimating the potential evapotranspiration (PET). Surface runoff was calculated using the Soil Conservation Service (SCS) Curve Number method (USDA, 1972), which relates runoff generation to land use, soil type, and antecedent moisture conditions. Three layers, namely land use and land cover (LULC), soil, and slope, were overlaid to define HRUs. Threshold values of 5% for land cover, 8% for soil type, and 10% for slope were applied during HRU creation to exclude minor combinations that contributed negligibly to basin hydrology. This ensured that HRUs remained sensitive to land-cover classes, important for scenario-based studies, while retaining the dominant soil and slope characteristics. The procedure resulted in 514 HRUs, which formed the fundamental modelling units for subsequent hydrological simulations. The model simulation was conducted for the period 1991 – 2020. The



**Fig. 2.** Workflow of hydrological modelling using SWAT to generate discharge for different climate scenarios

first five years (1991–1995) were set aside as a warm-up period (NYSKIP) to stabilize the model’s state variables.

#### 2.1.2.4. Calibration and validation

The Sequential Uncertainty Fitting algorithm (SUFI-2) was used to calibrate and validate SWAT in the SWAT-Calibration and Uncertainty Program (SWAT-CUP) (Abbaspour, 2013; Abbaspour *et al.*, 2015). SUFI-2 provides an iterative framework that simultaneously estimates optimal parameter values and quantifies associated uncertainties by linking directly to the SWAT master control file (.cio). Model parameters were first identified based on expert knowledge of watershed processes and formal sensitivity analysis (Arnold *et al.*, 2012). Each parameter was constrained within physically realistic ranges. In SWAT-CUP, parameters are modified using one of three operation modes: r\_\_ (relative, multiplicative adjustment), v\_\_ (replacement with a specified value), or a\_\_ (additive adjustment).

The calibration period (1991–2020) was divided into calibration (1995–2010) and validation (2011–2020) sub-periods with comparable statistical properties (mean and standard deviation) following Abbaspour *et al.* (2015). One important step in the initial calibration step is the sampling of the parameter values within the range values, which are set along with the three operation modes. This sampling of the parameter values is conducted using the Latin Hypercube Sampling (LHS), which divides each

parameter distribution into equal probability intervals to efficiently cover the parameter space (Abbaspour *et al.*, 2013). The calibration procedure used all-at-a-time (AAT) framework, in which all parameters changed simultaneously, allowing for parameter interactions to be accounted for and uncertainty to be reduced more realistically than with one-at-a-time approaches (Abbaspour, 2017). Thus, the results of AAT are adjusted to become reliable.

After each iteration, model performance based on the modification of parameter values was evaluated against observed discharge using objective functions including the Nash–Sutcliffe Efficiency (NSE), coefficient of determination ( $R^2$ ), and per cent bias (PBIAS) (which are discussed below). Parameter ranges were then updated based on the best-performing simulations until final simulation step. Following calibration, a global sensitivity analysis based on multiple regression was applied to quantify the relative importance of each parameter. This was achieved using statistical measures (t-statistics and p-values) that relate parameter variation to model performance, with all parameters assessed simultaneously (Abbaspour, 2013). The multiple regression used in the AAT framework for sensitivity analysis is given by Equation 4:

$$g = \alpha + \sum_{i=1}^n \beta_i b_i \quad (4)$$

TABLE 2

Matrices of objective function for the SWAT model

| Calibration (1995-2010) |                |      |       |          |          |
|-------------------------|----------------|------|-------|----------|----------|
| Station                 | R <sup>2</sup> | NSE  | PBIAS | p-factor | r-factor |
| Annapurna Ghat          | 0.79           | 0.77 | -7.2  | 0.74     | 0.67     |
| Fulertal                | 0.71           | 0.71 | 9.9   | 0.66     | 0.57     |
| Validation (2011-2020)  |                |      |       |          |          |
| Annapurna Ghat          | 0.77           | 0.75 | -9.4  | 0.62     | 0.36     |
| Fulertal                | 0.70           | 0.70 | 4.9   | 0.52     | 0.28     |

TABLE 3

Parameterization for calibration

| Parameter (change direction) | Methods* | Value before calibration the model | Modified factor or value after calibrating the model | Parameter description                                                     |
|------------------------------|----------|------------------------------------|------------------------------------------------------|---------------------------------------------------------------------------|
| CN2.mgt ↓                    | r        | 0.63 - 0.83                        | -0.04                                                | Initial SCS CN-2 value                                                    |
| ESCO.hru ↓                   | r        | 0.95                               | 0.36                                                 | Soil evaporation compensation factor                                      |
| GWQMN.gw ↑                   | a        | 1000                               | 1204.6                                               | Threshold water depth in shallow aquifer for flow                         |
| GW_REVAP.gw ↑                | v        | 0.02                               | 0.1                                                  | Ground water 'revap' coeff                                                |
| REVAMP.gw ↓                  | v        | 750                                | 380.1                                                | Threshold depth of water in the shallow aquifer for "revap" to occur [mm] |
| v__TLAPS.sub ↓               | v        | 0                                  | -1.1                                                 | Temperature lapse rate [°C/km]                                            |
| v__SLSUBBSN.hru ↑            | r        | 9.1 - 121.9                        | 53.8                                                 | Average slope length [m]                                                  |
| CANMX.hru ↑                  | r        | 0                                  | 51.06                                                | Maximum canopy storage [mm]                                               |
| ALPHA_BF.gw ↑                | v        | 0.048                              | 0.23                                                 | Baseflow alpha factor [days]                                              |
| CH_N2.rte ↑                  | v        | 0.014                              | 0.22                                                 | Main stream Manning 'n'                                                   |
| CH_K2.rte ↑                  | v        | 0                                  | 199.2                                                | Effective hydraulic conductivity [mm/hr]                                  |
| ALPHA_BNK.rte ↑              | v        | 0                                  | 0.6                                                  | Bank storage baseflow alpha factor [days]                                 |
| LAT_TTIME.hru ↑              | v        | 0                                  | 1.5                                                  | Lateral flow travel time [days]                                           |

where,  $g$  denotes the objective function value,  $\alpha$  is the regression constant,  $\beta$  represents the parameter coefficient and  $b$  represents each parameter. A t-test is applied to evaluate the statistical significance of each parameter coefficient. The reported sensitivities represent the average influence of changes in a given parameter on the objective function while other parameters are simultaneously changing.

### 3. Results and discussion

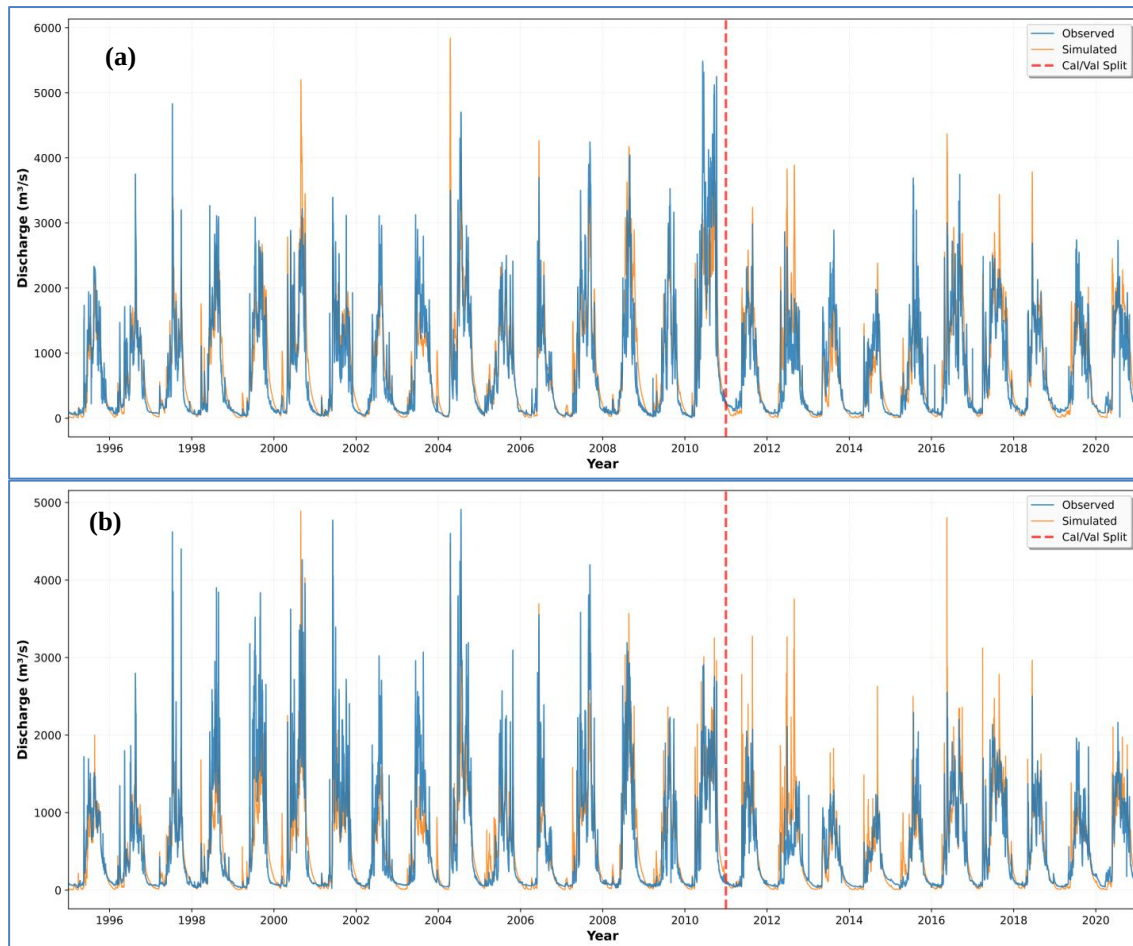
#### 3.1. Calibration and validation

The hydrological model was run for 31 years from 1990 to 2020, with a warm-up period of the initial 5 years. For more robust calibration, the model was calibrated and validated at the daily scale for the two stations viz. Annapurna Ghat (basin outlet) and Fuletal. Scores of the

objective functions during the best calibration are relatively high for these two stations (Table 2). The parameters used for calibration are explained in Table 3. The validation period (2011 to 2020) scored relatively high values for the objective function. This score matrix shows that the model fairly depicts the observed discharge of the watershed after calibration, according to the model skill score scale given by Moriasi *et al.*, 2015. (Fig. 3).

#### 3.2. Sensitivity analysis

The parameters used during calibration are checked for their individual influence on the simulations of the model. The global sensitivity analysis of the SWAT-CUP model identified the key parameters whose changes are sensitive to streamflow simulation and its change in the basin. It is computed based on t-statistics and p-values as discussed in the methodology. Among all parameters



**Figs. 3(a-b).** Calibration and validation of SWAT hydrological model– Annapurna Ghat(a), and Fulertal (b)

selected, curve number (CN2) emerged as the most sensitive, indicating that surface runoff generation plays a dominant role in the basin's hydrological response. Other highly sensitive parameters in the discharge of the basin include CANMX (canopy interception storage), SLSUBBSN (slope length) GW\_DELAY (lag time for aquifer recharge), ALPHA\_BNK (bank storage recession rate) LAT\_TTIME (lateral subsurface flow travel time), ALPHA\_BF (baseflow recession constant), CH\_N2 (channel roughness affecting flow velocity), and CH\_K2 (channel hydraulic conductivity controlling transmission losses). This indicates an important role of channel processes, topography, and vegetation interception on flow routing and flood dynamics. They are moderately sensitive with p-value 0.04-0.05. Parameters related to groundwater re-evaporation (GW\_REVAP.gw, REVAPMN.gw), temperature lapse rate (TLAPS.sub), threshold depth for groundwater flow (GWQMN.gw), and soil evaporation compensation factor (ESCO.hru) are statistically non-significant (p-value > 0.05) (Table 4).

Overall, the sensitivity pattern indicates that the hydrology of the basin is primarily controlled by runoff coefficient and channel routing processes, in this high-rainfall, monsoon-dominated basin. Accordingly, calibration efforts were prioritised toward the most sensitive surface runoff, channel, and vegetation-related parameters to improve model performance. Temperature lapse rate (*TLAPS*) in the elevation band is not very sensitive to the model due to the use of gridded climatic datasets in which the region is spread out with the individual grids uniformly (Abbaspour, 2013) (Table 4).

### 3.3. Bias correction

The RCM datasets, which are dynamically downscaled, have default systematic bias. The performances of the raw and bias corrected climate data against the observed IMD historical data are shown for rainfall (Fig. 4 -A0 and A1),  $T_{max}$  (Fig. 4 - B0 and B1) and  $T_{min}$  (Fig. 4- C0 and C1). Due to the inherent complexity of the climate system, rainfall exhibits high uncertainty

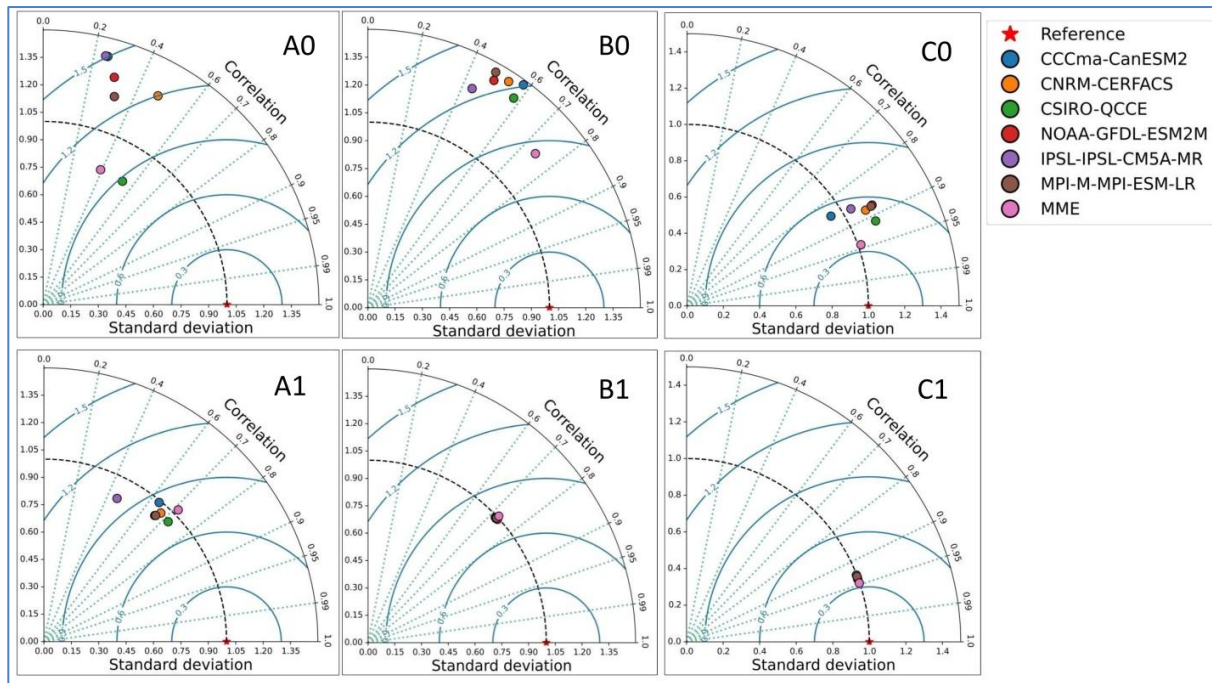


Fig. 4. Comparison of raw (A0, B0, C0) and bias-corrected (A1, B1, C1) rainfall, maximum Tmax, and Tmin with observed datasets

TABLE 4

Sensitivity analysis of the parameters

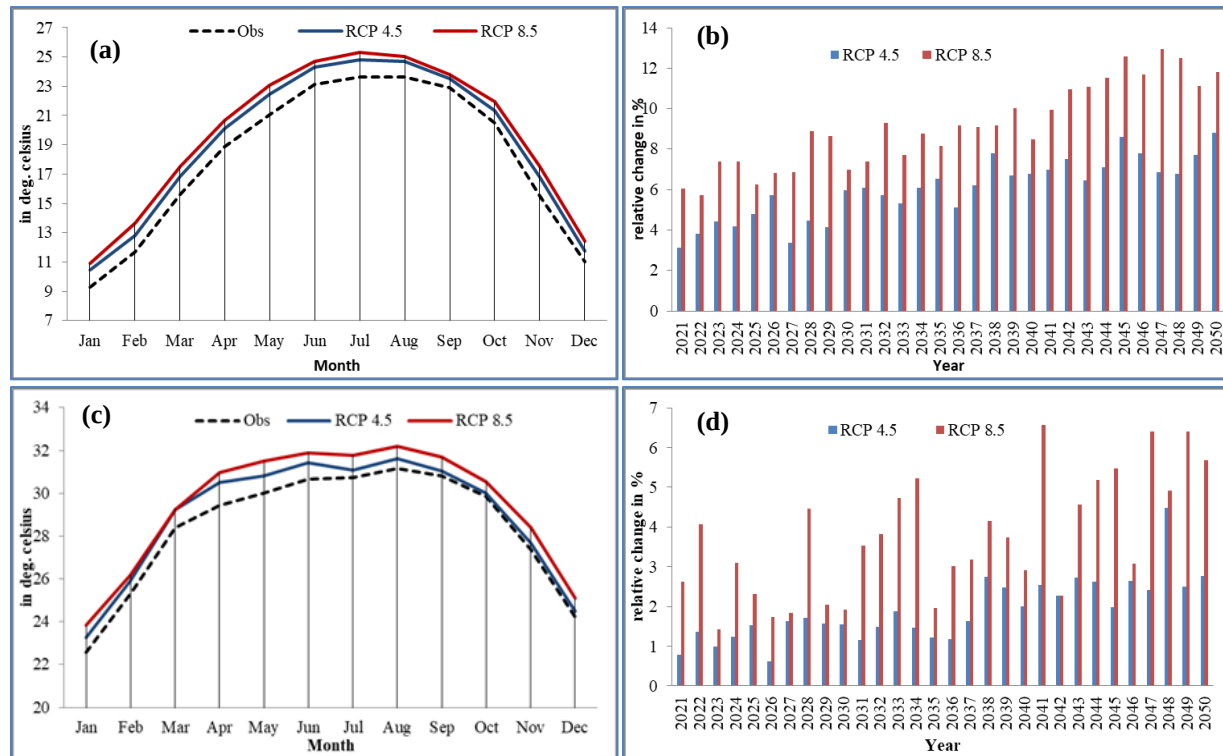
| Parameter Name   | t-Stat  | P-Value |
|------------------|---------|---------|
| V__GW_REVAP.gw   | 0.27    | 0.79    |
| V__REVAPMN.gw    | -0.50   | 0.62    |
| V__TLAPS.sub     | 0.69    | 0.49    |
| V__GWQMN.gw      | 0.70    | 0.48    |
| V__ESCO.hru      | -1.79   | 0.07    |
| V__CH_K2.rte     | 2.14    | 0.03    |
| V__CH_N2.rte     | 2.39    | 0.02    |
| V__ALPHA_BF.gw   | -2.78   | 0.01    |
| V__LAT_TTIME.hru | 8.22    | 0.00    |
| V__GW_DELAY.gw   | -9.72   | 0.00    |
| V__SLSUBBSN.hru  | 10.47   | 0.00    |
| V__CANMX.hru     | 22.70   | 0.00    |
| V__ALPHA_BNK.rte | -50.28  | 0.00    |
| R_CN2.mgt        | -132.71 | 0.00    |

(Schaller *et al.*, 2011), which is reflected in the relatively low model performance scores for rainfall. In contrast, Tmax and Tmin show comparatively better performance. As illustrated in Fig. 4, the standard deviation is reduced after bias correction. The correlation coefficient has improved, with values closer to 1 indicating better agreement. The centre root mean square error (distance from the reference point) quantifies overall error in pattern representation; smaller values indicate better performance.

The performance of the multi-model ensemble mean (MME) is in tune with observed rainfall and temperature (Fig. 4) during bias correction (Gaur *et al.* 2020; Xu *et al.*, 2021; Konda *et al.*, 2024).

### 3.4. Climate projection

To project the rainfall and temperature, the RCP4.5 and RCP8.5 emission scenarios were considered for the



**Figs. 5(a-d).** Climate projection of NF - Tmin – (A) monthly and annual (C) relative change and Tmax – (B) monthly and annual relative change (D) w.r.t. the average observed Tmin and Tmax (1990-2020)

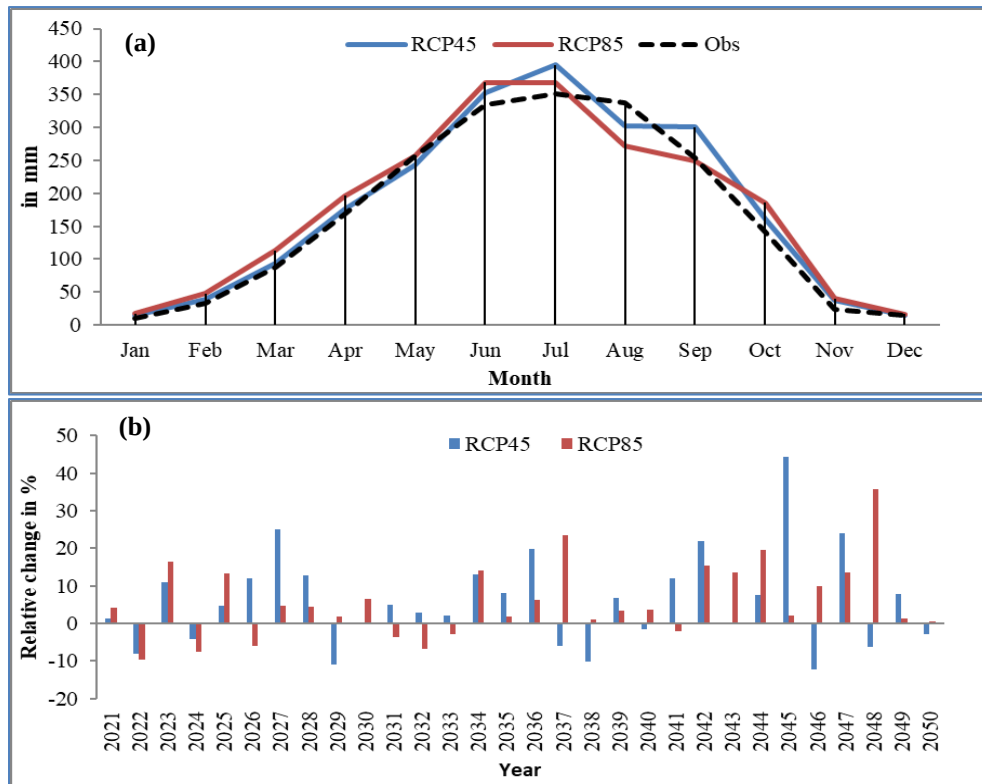
2021-2050 (NF). Both the RCP 4.5 and RCP 8.5 emission scenarios showed similar warming patterns for temperature projections in the near future (NF) period relative to the base period 1961-2020, with the latter consistently higher than the former. For Tmin, an overall increase of approximately 1 °C is projected throughout the year, with the highest warming occurring during June-July, reaching approximately 24-25 °C under both emission scenarios compared to observed values of around 23 °C. The winter months show warming from approximately 9-11 °C to 11-13 °C. Similarly, Tmax shows an overall increase across the NF period. Peak Tmax values during summer months increase from 31 °C in the observed long-term mean to approximately 32 °C under both scenarios, with the difference between the two being maximum during the month of JJAS for both parameters  $T_{min}$  and  $T_{max}$  (Fig. 5 (A & B)). March-July (Fig. 5B).

In terms of relative change percent with respect to the normal observed temperature, Tmin shows a higher increase. Fig. 5C demonstrates a consistent upward trend with RCP 8.5 showing more warming, particularly after 2027, reaching changes of up to 12% by 2050, while RCP 4.5 shows relatively moderate increases of approximately 7-8%. Similarly, for Tmax, the relative change percent is positive for all years, with higher values for RCP 8.5 than RCP 4.5 (Fig. 5D). The projections reveal that Tmax

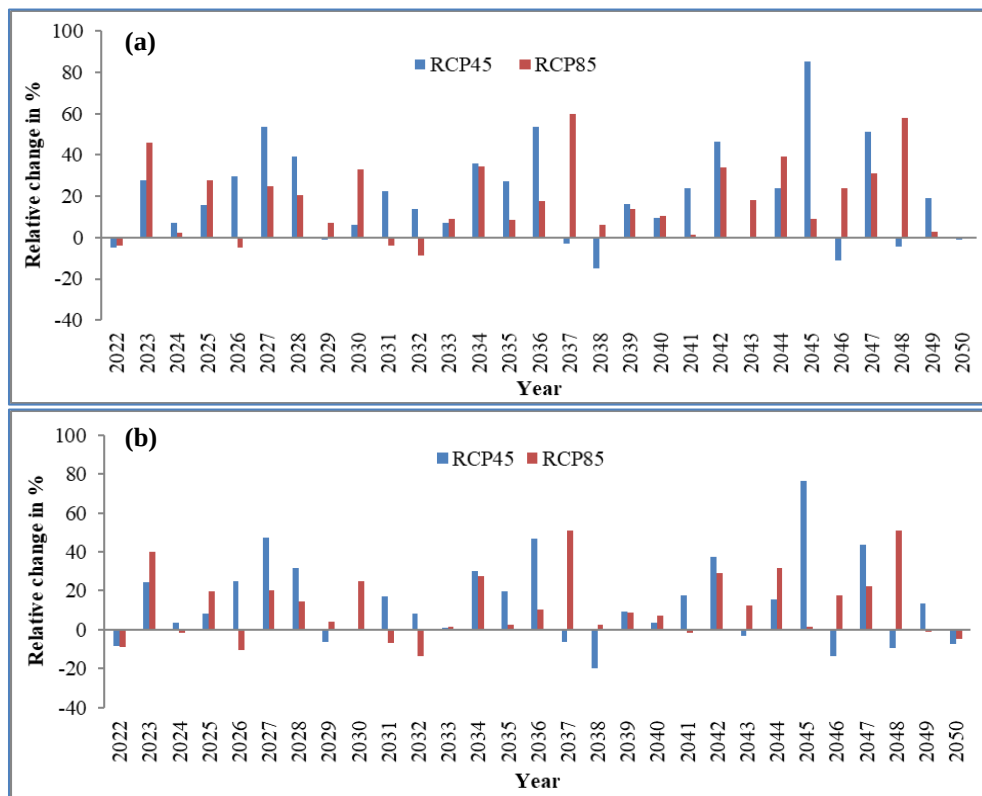
increases progressively over time, with RCP 8.5 projecting increases up to 6-7%, approximately 2-3% higher than RCP 4.5. The divergence between the two scenarios becomes more pronounced after 2035, indicating differential impacts of the two emission scenarios (Fig. 5 (C & D)).

Both climate scenarios, RCP4.5 and RCP8.5, project high inter-annual variability of rainfall relative to historical observations. However, the monthly distribution shows that both scenarios maintain the monsoon pattern with minimal changes to the dry season. During the peak monsoon period, both RCP4.5 and RCP8.5 scenarios project similar rainfall maxima in July (approximately 400 mm), which slightly exceed historical observations and follow the same seasonal pattern. Both scenarios show a dip in mid-monsoon rainfall, especially for RCP8.5 scenario in August (Fig. 6 A). Also, the monthly rainfall is increasing during the pre-monsoon in the RCP8.5 scenario. Both scenarios show increasing rainfall during the post-monsoon period.

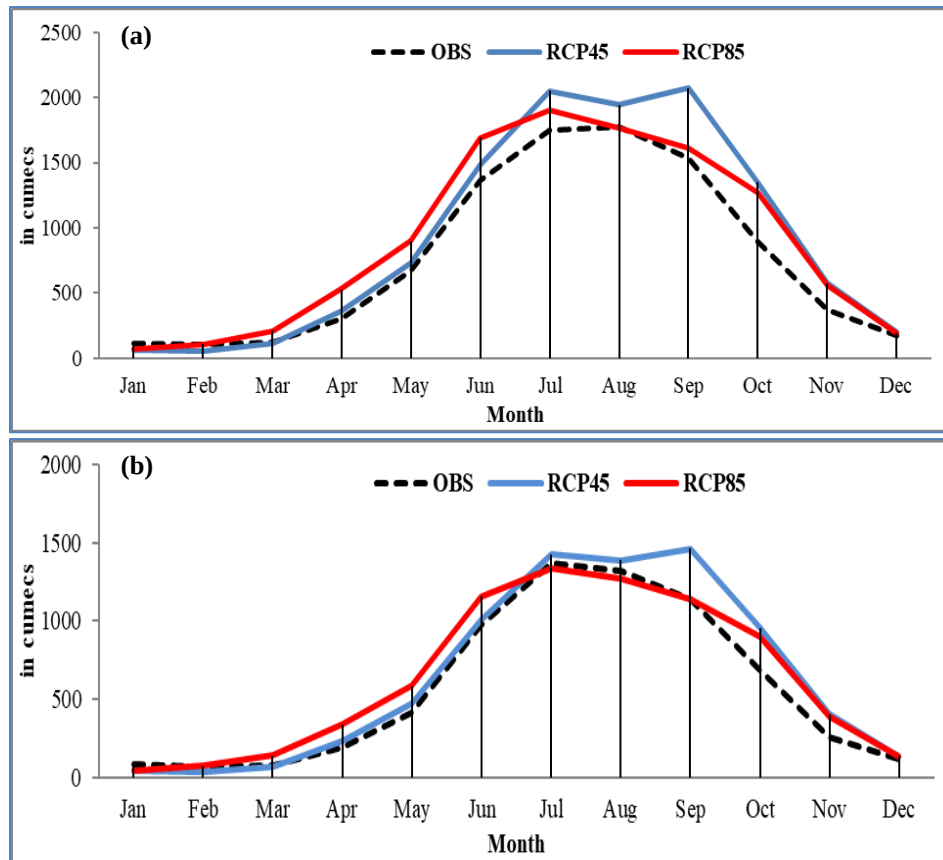
The annual relative change analysis reveals substantial variability between years (Fig. 6 B). The RCP4.5 scenario shows a particularly high positive anomaly (exceeding 40%) around 2045, indicating substantially wetter conditions projected for that period. Both scenarios display high variability between years, with RCP8.5 showing greater magnitude in variations,



**Figs. 6(a&b).** Projected rainfall for the NF (2021-2050) under RCP4.5 and RCP8.5 –(A) mean monthly; (B) annual relative change per cent



**Figs. 7(a&b).** Annual relative change per cent of discharge (A) for RCP4.5 and (B) for RCP8.5 w.r.t. mean annual observed discharge (1990-2020)



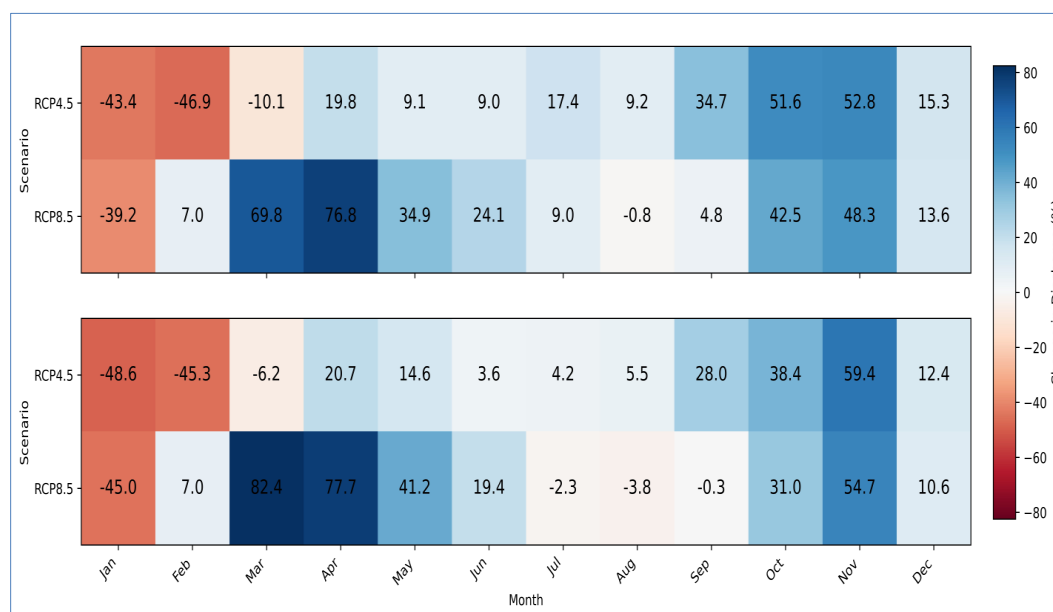
**Figs. 8(a&b).** Mean monthly discharge for observed (1990-2020), RCP4.5 and RCP8.5 for (A) Annapurna Ghat and (B) Fulertal

particularly in the 2040s. The RCP8.5 scenario exhibits larger inter-annual variability with notably high positive values (approximately 35-45%) around 2045-2048. The projections show both positive and negative anomalies throughout the time series, with variations ranging from approximately -15% to +45%, indicating increased year-to-year variability rather than a consistent trend toward wetter conditions. This suggests greater uncertainty and potential for both extreme wet and dry years under future climate scenarios, with RCP8.5 demonstrating more pronounced swings between wet and dry periods.

The annual relative change analysis for the near future shows high annual variability under both climate scenarios of RCP4.5 and RCP8.5 at both stations. At Annapurna Ghat, discharge projections show mostly surplus discharge changes across NF, with RCP4.5 showing a peak increase of approximately 85% in 2045, while RCP8.5 exhibits a peak increase of around 60% in 2023 and 2037 (Fig. 7 A). At Fulertal, similar patterns can be observed as the RCP4.5 scenario-based discharge shows the greatest positive change of approximately 77% in 2045 (Fig. 7 B). Both scenarios occasionally project negative discharge changes, particularly notable around 2038, where RCP4.5 shows

approximately -15% change at Annapurna Ghat. The inter-annual variability appears more prominent in the RCP4.5 scenario than that of RCP8.5 as can be seen in CV in Table A2

At Annapurna Ghat, observed discharge follows a typical monsoonal pattern, increasing from approximately 100 cumecs in January to peak at 1,750 cumecs in July, then declining to reach the low in December. RCP4.5 projects consistently higher flows throughout most months, with peak discharge reaching approximately 2,050 cumecs in July. RCP8.5 exhibits a different pattern, with substantially higher pre-monsoon flows (March-May) but an earlier peak in July, approximately 1,800 cumecs. By August, RCP8.5 flows fall below RCP4.5 levels, aligning with regional findings by Saharia and Sarma (2018) and Whitehead *et al.* (2018) for an early onset of monsoon under high emission scenarios (Figure 8A). At Fulertal, observed discharge peaks at approximately 1,375 cumecs in July. RCP4.5 shows a post-monsoon increase. RCP8.5 shows more moderate increases, peaking at approximately 1,425 cumecs in July, and post-monsoon flows follow close to observed patterns (Fig. 8B).



**Fig. 9.** Monthly relative change per cent of discharge for RCP8.5 and RCP4.5 w.r.t. the long observed monthly mean at (A) Annapurna Ghat and (B) Fulertal

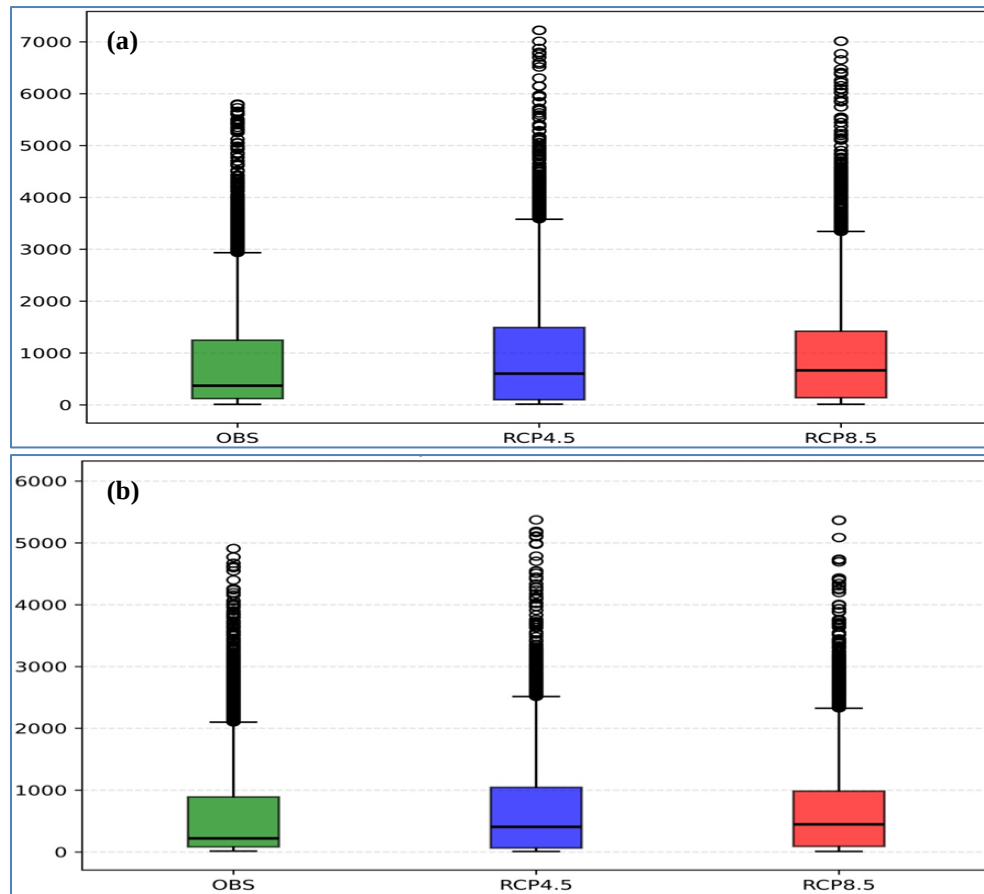
At Annapurna Ghat, discharge shows deficits for January-February as relative change. It ranges from -43.4% to -46.9% under RCP4.5; -39.2% to +7.0% under RCP8.5. March shows contrasting patterns; the relative change is -10.1% under RCP4.5 against +69.8% under RCP8.5. April exhibits substantial increases under both scenarios (+19.8% and +76.8% respectively), indicating a shift toward higher pre-monsoon flows, particularly under high emissions (Fig. 9 A). The monsoon season shows low relative changes, as projected discharge under RCP4.5 increases from +9.0% to +17.4% and that of RCP8.5 from -0.8% to 9.0%. Thus, RCP8.5 shows a lower increase in monsoon discharge but a higher increase during pre-monsoon and post-monsoon periods. Fulertal also follows a similar pattern to that of the Annapurna Ghat. Here, winter deficits reached up to -48.6% under RCP4.5 and -45.0% under RCP8.5 in January. March shows a similar contrasting pattern of relative change, with discharge under RCP8.5 showing an increase of about 82% while under RCP4.5 shows a deficit of -6.2% (Fig. 9 B). Notably, mid-monsoon months of July-September under RCP8.5 show slight decreases at -2.3% to -0.3%, contrasting with downstream patterns and suggesting complex basin-scale processes.

The boxplot analysis shows important statistical properties of discharge under different scenarios at both stations. At both Annapurna Ghat and Fulertal, the median discharge values show slight increases from observed conditions under RCP4.5 and RCP8.5, with the latter producing a higher median value. However, significant

differences emerge in other statistical properties of the discharge distributions (Table A2). Both climate scenarios exhibit enhanced interquartile ranges compared to observed conditions, with RCP4.5 showing slightly higher median values and wider boxes than RCP8.5 at both stations. This increased spread suggests more variable discharge conditions and potentially more challenging water management conditions under future climate scenarios.

Both under RCP4.5 and RCP8.5 scenarios, discharge shows higher peak flows compared to historical observations. At Annapurna Ghat, peak flows under both scenarios are near or above 7,000 cumecs, substantially exceeding the maximum outliers in the historical (Figure 10A). At Fulertal, the pattern is similar, with both future scenarios' peak flow reaching around 5,500 cumecs compared to around 5,000 cumecs in the observed period (Fig. 10B). This finding aligns with climate change projections that predict more extreme rainfall events and subsequent high-flow conditions under elevated emission scenarios. The comparable pattern in extreme peak flows between RCP4.5 and RCP8.5 suggests that even under moderate emissions pathways, the basin may experience substantially increased flood risks.

The minimum values remain relatively similar across all scenarios at both stations, indicating that low-flow conditions may not change dramatically, though the winter discharge reductions noted in the seasonal analysis suggest potential concerns during specific months.



**Figs. 10(a&b).** Comparison of discharge scenarios w.r.t. observed discharge for (a) Annapurna Ghat and (b) Fulertal

#### 4. Conclusions

The hydrological model SWAT is fairly accurate in depicting the baseline flow regime. The calibration & validation show relatively high agreement with the observed discharge. Monthly temperature, both  $T_{min}$  and  $T_{max}$ , show higher mean temperatures than the baseline temperature. Similarly, in terms of relative change per cent, both maximum and minimum temperature show an increase. The analysis of future rainfall and discharge patterns in the watershed reveals significant transformations in the regional hydrological regime under both RCP4.5 and RCP8.5 emission scenarios. These projections consistently indicate an overall wetter future with an increase in early pre-monsoon rainfall and post-monsoon seasons likely to alter traditionally dry season conditions. However, the winter season is likely to be drier than usual. While both scenarios project higher rainfall and discharge values, they differ notably in their temporal distribution patterns. RCP4.5 suggests more extreme variability with higher peak flows but greater fluctuations between years, whereas RCP8.5 indicates an earlier onset of monsoon conditions,

higher early-monsoon season discharge, and more consistent year-to-year increases. The comparative analysis of discharge distribution using box plot analysis further confirms the likelihood of more extreme high-flow events, particularly under RCP8.5, with maximum discharge values approaching 8,000 cumecs. The mean monthly discharge pattern closely follows that of the rainfall as the basin is rain-fed. These projected increases in discharge and peak flow demand comprehensive adaptation strategies for water infrastructure, agricultural planning, and disaster management in the watershed, as communities need to navigate both the opportunities presented by increased water availability during traditionally dry periods and the challenges posed by potentially more intense flooding events and greater hydrological unpredictability in a changing climate.

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**Disclaimer:** The contents and views expressed in this research article are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

#### Authors' Contributions

Indrakumar Laishram: Developed the research idea and methods, collected and curated the data, carried out analysis and prepared the draft manuscript. (email: [rachalaishram@gmail.com](mailto:rachalaishram@gmail.com)).

S. Sreekesh: Contributed to the development of the research idea and methods, evaluated and validated the results, and edited, reviewed and finalised the manuscript.

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## Appendix

**TABLE A1**  
**CORDEX South Asia RCM outputs available on ESGF under CCCR-IITM**

| CORDEX South Asia RCM            | RCM Description                                                                                                                         | Contributing CORDEX Modeling Center                                                               | Driving CMIP5 AOGCM (see details at <a href="https://verc.enes.org/data/enes-model-data/cmip5/resolution">https://verc.enes.org/data/enes-model-data/cmip5/resolution</a> ) | Contributing CMIP5 Modeling Center                                                                        |
|----------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------|
| IITM-RegCM4 (6 ensemble members) | The Abdus Salam International Centre for Theoretical Physics (ICTP) Regional Climatic Model version 4.4.5 (RegCM4; Giorgi et al., 2012) | Centre for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM), India | CanESM2                                                                                                                                                                     | Canadian Centre for Climate Modelling and Analysis (CCCma), Canada                                        |
|                                  |                                                                                                                                         |                                                                                                   | GFDL-ESM2M                                                                                                                                                                  | National Oceanic and Atmospheric Administration (NOAA), Geophysical Fluid Dynamics Laboratory (GFDL), USA |
|                                  |                                                                                                                                         |                                                                                                   | CNRM-CM5                                                                                                                                                                    | Centre National de Recherches Mé'té'orologiques (CNRM), France                                            |
|                                  |                                                                                                                                         |                                                                                                   | MPI-ESM-MR                                                                                                                                                                  | Max Planck Institute for Meteorology (MPI-M), Germany                                                     |
|                                  |                                                                                                                                         |                                                                                                   | IPSL-CM5A-LR                                                                                                                                                                | Institut Pierre-Simon Laplace (IPSL), France                                                              |
|                                  |                                                                                                                                         |                                                                                                   | CSIRO-Mk3.6                                                                                                                                                                 | Commonwealth Scientific and Industrial Research Organization (CSIRO), Australia                           |

TABLE A2

Descriptive statistics discharge under different climate scenarios

| Annapurna Ghat |                      |                    |                    |
|----------------|----------------------|--------------------|--------------------|
|                | Observed (1990-2020) | RCP4.5 (2021-2050) | RCP8.5 (2021-2050) |
| <b>Mean</b>    | 777.7                | 919.8              | 904.6              |
| <b>Median</b>  | 371.7                | 603.5              | 665.9              |
| <b>Std</b>     | 878.3                | 959.1              | 911.8              |
| <b>IQR</b>     | 1126.8               | 1391.8             | 1282.1             |
| <b>CV</b>      | 112.8                | 104.               | 100.7              |
| Fulertal       |                      |                    |                    |
| <b>Mean</b>    | 566.7                | 640.3              | 630.3              |
| <b>Median</b>  | 221                  | 406.5              | 447.4              |
| <b>Std</b>     | 682.5                | 681.4              | 656.1              |
| <b>IQR</b>     | 807.9                | 980.6              | 894.4              |
| <b>CV</b>      | 120.4                | 106.4              | 104.1              |

