

Multi-model ensemble projection of mean and extreme streamflow of Brahmaputra River Basin under the impact of climate change

Sarfراز Alam, Md. Mostafa Ali, Ahmmed Zulfiqar Rahaman and Zahidul Islam

ABSTRACT

The streamflow of Brahmaputra River Basin is vital for sustainable socioeconomic development of the Ganges delta. Frequent floods and droughts in the past decades indicate the susceptibility of the region to climate variability. Although there are multiple studies investigating the basin's future water availability, most of those are based on limited climate change scenarios despite the wide range of uncertainties in different climate model projections. This study aims to provide a better estimation of projected future streamflow for a combination of 18 climate change scenarios. We develop a hydrologic model of the basin and simulate the future water availability based on these climate change scenarios. Our results show that the simulated mean annual, mean seasonal and annual maximum streamflow of the basin is expected to increase in future. By the end of the 21st century, the projected increase in mean annual, mean dry season, mean wet season, and annual maximum streamflow is about 25, 178, 11, and 22%, respectively. We also demonstrate that this projected streamflow can be expressed as a multivariate linear regression of projected changes in temperature and precipitation in the basin and would be very useful for policy makers to make informed decision regarding climate change adaptation.

Key words | Brahmaputra River Basin, climate change, multivariate linear regression, streamflow, SWAT

HIGHLIGHTS

- Mean annual streamflow of the Brahmaputra River Basin (BRB) is expected to increase gradually over the 21st century.
- Annual maximum streamflow is projected to increase by about 22% indicating a higher peak in the future flood events.
- The projected mean annual, mean seasonal and annual maximum streamflow can be expressed as multivariate linear regression of projected changes in temperature and precipitation.

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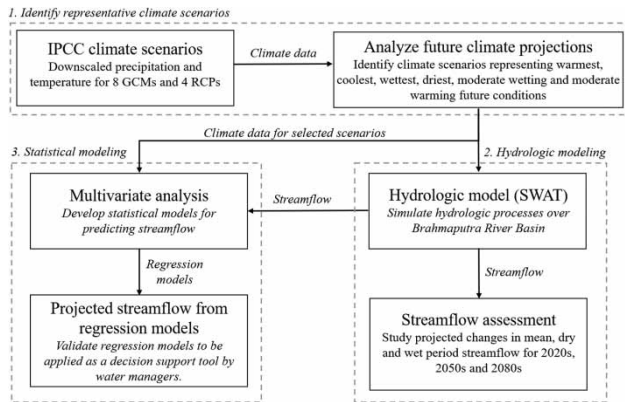
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GRAPHICAL ABSTRACT



INTRODUCTION

There is much scientific evidence of global warming and its association with hydrologic changes, for instance, changes in precipitation, streamflow, evapotranspiration, glacier retreat (García-Garizábal *et al.* 2014; Garrote *et al.* 2015). The change in the hydrologic cycle due to climate change poses a serious threat to Southeast Asia, a region where frequent floods and droughts are very common issues. Climate induced increase in streamflow during monsoon (a period of intense rainfall, generally May–September) can potentially worsen the flood damage, while the increase in evaporative losses (due to warmer temperature) during the dry period will intensify water scarcity in some regions. Any changes in streamflow can have major socioeconomic impacts on the lower riparian countries which have already been stressed by frequent prolonged flooding in the past few decades.

Brahmaputra River Basin (BRB), a sub-basin of Ganges, is one of the major river basins in Southeast Asia (Figure 1). The streamflow in BRB plays an important role in the socioeconomic development of the downstream countries, such as Bangladesh. Any significant changes in streamflow due to future climate can have a major hydrological impact. Low water availability, especially in the dry season (December–May) may result in depletion of groundwater storage and can lead to serious impacts on agriculture. On the other hand, excess water in the wet season (June–November) may increase the risk of flooding. In the past

few decades, the basin has gone through a series of flooding events (e.g. 1988, 1998, 2004, 2010, and 2017). However, water shortage is prominent in the northwest part of Bangladesh because of low water availability in the dry seasons. These extreme variations in water scarcity and abundance that the basin has been experiencing in the past will raise concerns about the basin's resiliency under the future potential climate changes (Gain *et al.* 2011). Climate change will potentially increase intense rainfall in this region leading to increased flooding phenomenon (UNFCCC 2007). Moreover, snowpack in the mountains is susceptible to warming temperatures and may cause a shift in snow melting time.

Several studies have been conducted on the hydro-climatological impacts on the streamflow of BRB (e.g. Mirza & Dixit 1997; Seidel *et al.* 2000; Mirza 2002; Mirza *et al.* 2003; Gain *et al.* 2011; Ghosh & Dutta 2012; Alam *et al.* 2016; Mohammed *et al.* 2017a, 2017b; Islam *et al.* 2018; Whitehead *et al.* 2018; Dutta *et al.* 2020). These hydrologic impact studies in BRB can be categorized into two distinct groups: synthetic climate change impact analysis (e.g. arbitrary changes in temperature and/or precipitation), and climate change impact analysis based on emission scenarios projected by IPCC (Intergovernmental Panel on Climate Change) assessment reports. Synthetic climate change studies by Seidel *et al.* (2000) and Alam *et al.* (2016) indicate that there will be about a 1.37% increase in mean annual streamflow for a 1% precipitation increase (in contrast to a

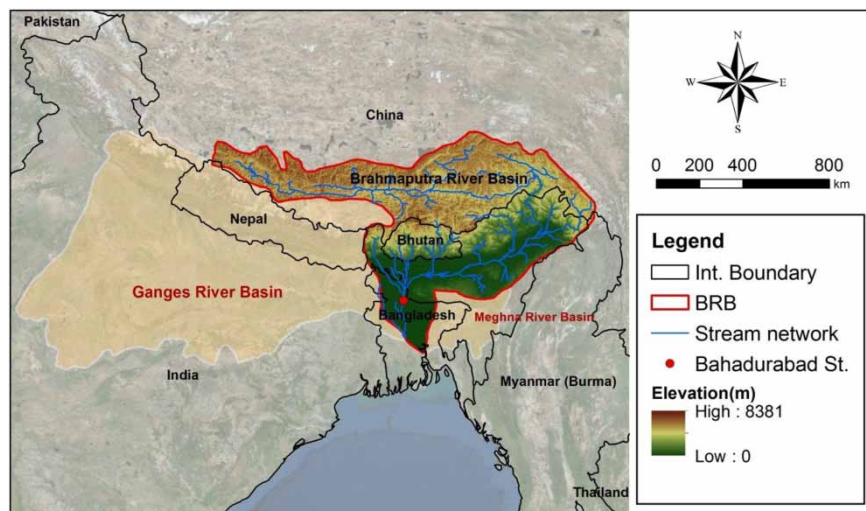


Figure 1 | Map of Brahmaputra River Basin (BRB) within the spatial extent of greater Ganges-Brahmaputra-Meghna (GBM) basin.

1.37% decrease for a 1 °C temperature increase), where flood peaks are relatively more sensitive to climate change (30% increase in monsoon flood peak for a 10% increase in precipitation and a 1.5 °C temperature increase). Similarly, [Mohammed *et al.* \(2017a, 2017b\)](#) assessed the impacts of 1.5 and 2 °C global warming on the extreme flows and water availability and found frequent flood flows and less frequent low flow events. Other than synthetic climate change studies, there are scenario-based studies conducted on BRB. [Ghosh & Dutta \(2012\)](#) used downscaled climate data for the A2 SRES scenario from PRECIS (Providing Regional Climates for Impacts Studies) and concluded that the pre-monsoonal peak discharge will increase by 12% at Tezpur (a hydrometric station in Bangladesh). [Masood *et al.* \(2015\)](#) used a macro scale global water resources model to simulate the streamflow of BRB for four General Circulation Models (GCMs) where the mean annual streamflow is estimated to increase (14%) for the increase in temperature (3%) and precipitation (14%).

The aforementioned studies significantly enhanced the understanding of the hydrologic process in a large watershed like BRB. However, future climate is highly uncertain and the projected climate scenarios vary widely depending on the choice of GCMs and emission scenarios (e.g. Representative Concentration Pathways or RCPs). Climate change will potentially have a wide range of impacts on water availability in the BRB. Few studies assessed the future changes in streamflow in BRB, most of them are

limited to a few GCM projections and RCP scenarios. For instance, [Mohammed *et al.* \(2018\)](#) estimated changes in a 100-year flood for a 1.5, 2, and 4 °C temperature increase. [Uhe *et al.* \(2019\)](#) estimated streamflow changes under 1.5 °C warming. [Mohammed *et al.* \(2017a\)](#) and [Haque *et al.* \(2020\)](#) used multiple GCM model outputs for streamflow projections. However, these studies were only limited to either RCP 8.5, or a combination of a few emission scenarios, indicating the results only demonstrate the projected changes due to high or limited emission scenarios. There is a great deal of interest and importance in understanding how much variability in projected streamflow is expected due to climate change. To address this issue, our study is the first of its kind that conducts a rigorous investigation of multiple climate change scenarios (combinations of GCMs and RCPs) and estimates streamflow changes for the most suitable combinations of climate change projections, considering different wetting/warming scenarios. Selecting suitable climate change scenarios makes it computationally efficient to predict climate change impacts on streamflow while making sure the full spectrum of variability is taken into account. The current study considered the investigation of projections from multiple GCM projections and RCP scenarios to identify a suite of scenarios that can capture the wide range of climate variability in BRB. The streamflow projections obtained from such an analysis provide an improved estimate of future changes expected in BRB.

Warming climate will essentially change the volume and time of occurring peak streamflow, the estimate of which varies with climate models and scenarios. The RCPs, as developed by IPCC, indicate the cumulative measure of human emissions of greenhouse gases (GHGs) from all sources and represent a broad range of climate outcomes. Each RCP results from different combinations of economic, technological, demographic, policy, and institutional futures. Here, we use a calibrated and validated hydrologic model, Soil and Water Assessment Tool (SWAT), to estimate the impact of climate change on the streamflow of BRB. We consider a broader spectrum of possibilities through estimating future streamflow under various climate change scenarios (both extreme and nominal), which is the key contribution of this study. The current study will not only demonstrate the hydrologic impact of climate change on BRB, but also enhance our understanding of hydrologic responses of climate change on large watersheds. The impact of climate change on large watersheds is evident all over the world. Modelling large and complex watersheds for climate impact studies is a great challenge for scientists and engineers around the globe. These challenges are further complicated by various uncertainties in climate models, hydrologic models and streamflow monitoring.

Based on the aforementioned background, the main objectives of this study are:

- i. Select the most suitable combinations of RCP emission scenarios and GCMs to consider the wide spectrum of variability in wetting (precipitation) and warming (temperature) patterns for the 21st century.
- ii. Project future streamflow of BRB based on the selected future climate scenarios from objective (i).
- iii. Based on the combination of basin scale mean temperature and basin scale mean precipitation changes over the 21st century and projected streamflow, develop simple regression models for mean and extreme streamflow of BRB.

STUDY AREA

The BRB originates in high Himalayan mountains in the north and flows south through flat alluvium land to the

Bay of Bengal. Near the downstream end it meets two major rivers called Ganges and Meghna. In general, the basin can be classified into three elevation bands, viz. as the Tibetan Plateau (>3,500 m), the Himalayan Belt (100–3,500 m), and the floodplain (<100 m) covering 44.4, 28.6, and 27% of the entire basin, respectively (Immerzeel 2008). The majority of the precipitation (~60–70%) in this region occurs during the monsoon season (Immerzeel 2008). Historically (1981–2010), the annual average streamflow of BRB at the Bahadurabad station (located near the downstream end, see Figure 1) is about 21,250 m³/s. The mean dry season (December–May) and mean wet season (June–November) streamflow are about 7,565 and 30,840 m³/s, respectively, indicating distinctive seasonality in BRB streamflow. As climate changes, the seasonality shift of streamflow can increase the vulnerability of BRB, especially in the lower riparian regions of the basin.

RESEARCH APPROACH

Our methodology involves three key steps: (1) identifying representative climate scenarios, (2) hydrologic modeling for future streamflow projection, and (3) statistical modeling for future streamflow projection. Figure 2 shows a schematic of the research approach followed in this study. The first step is to analyze climate projections from multiple GCMs and RCPs to identify representative scenarios for streamflow investigation. The second step is to develop a hydrologic model and simulate the model for selected climate scenarios. The third step is to develop a statistical model using the outputs from steps 1 and 2 for predicting regional streamflow changes. In the following sections, we discuss each of these steps in further detail.

MODEL, DATA AND METHODOLOGY

Model

We used a physically based hydrologic model, Soil and Water Assessment Tool (SWAT), to simulate the hydrologic processes in BRB. SWAT is a semi-distributed hydrologic model that can run in a daily time step to simulate surface

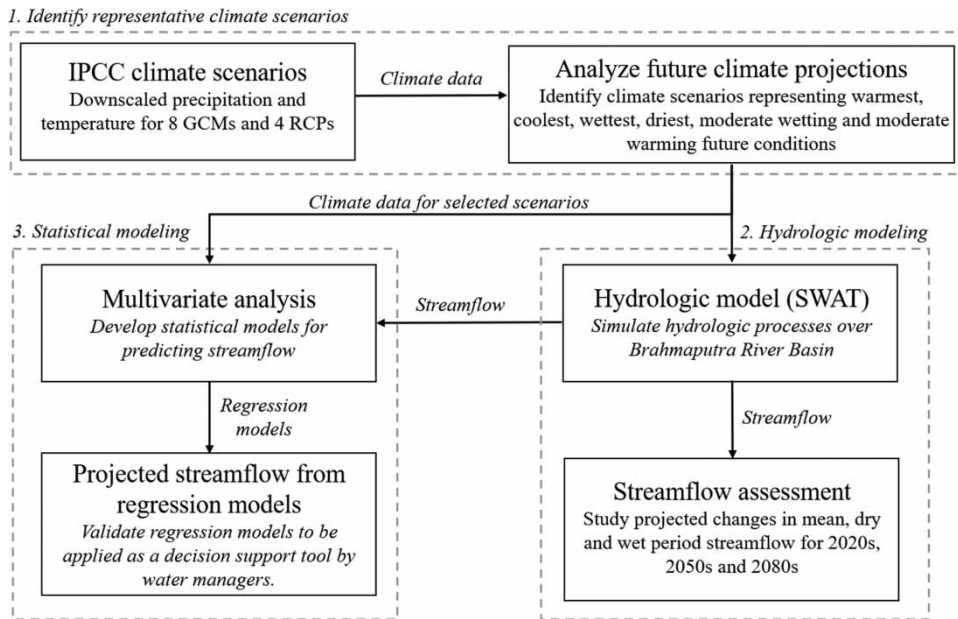


Figure 2 | Schematic of research approach.

runoff, evapotranspiration, infiltration, percolation, channel routing and aquifer flow (Arnold & Allen 1996). The model development requires multiple physiographical and meteorological datasets. SWAT solves the following water balance equation at each hydrological response unit (HRU), where HRU is the smallest spatial scale in the model that is created from unique combinations of land use, soil type and slope:

$$SWC_t = SWC_0 + \sum_{t=1}^t (P - R_{sup} - E - W_a - R_{sub}) \quad (1)$$

Note, SWC_0 and SWC_t are the initial and final (on day t) soil water content; precipitation, evapotranspiration, surface runoff, amount of water entering the vadose zone from the soil profile, and the amount of return flow on day t are denoted as P , E , R_{sup} , W_a , and R_{sub} , respectively.

Data

SWAT requires spatially distributed physiographical (e.g. topographical, soil, and landuse) data. The current study uses 90 m resolution Digital Elevation Model (DEM) data from the Shuttle Radar Topographic Mission (SRTM), 1 km resolution soil data from the Harmonized World Soil Database (HWSD), and 1 km resolution landuse data from the United States

Geological Survey (USGS). Figures S1–S3 of the supplemental information show the elevation, land use and soil map used for model development. SWAT also requires daily scale meteorological data (e.g. temperature and precipitation). Meteorological data for the historical period (climate normal: 1981–2010) was collected from the National Aeronautics and Space Administration (NASA) Prediction of Worldwide Energy (POWER) database. NASA-POWER is a reanalysis product of Modern-Era Retrospective Analysis for Research and Applications (MERRA), where MERRA uses Goddard Earth Observing System Data Assimilation System Version-5 (GEOS-5) (Schubert et al. 2008). The climate data for projected future scenarios (e.g. precipitation and temperature data for different combinations of GCMs, RCPs, and climate change periods of the 21st century) were collected from the Earth System Grid Federation (ESGF portal). The GCMs considered for the study are BCC-CSM1.1, BCC-CSM1.1 (m), GISS-E2-H, GISS-E2-R, HadGEM2-ES, MIROC-ESM, MIROC-ESM-CHEM and MRI-CGCM3. The GCMs are selected such that precipitation and temperature projection are available for all of the four RCPs (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5) for three different periods of the 21st century: 2011–2040 (2020s), 2041–2070 (2050s) and 2071–2100 (2080s). Streamflow data at the basin outlet is necessary for calibration and validation purposes. The streamflow (daily) of BRB at the Bahadurabad

station was collected from the Bangladesh Water Development Board (BWDB).

Model setup, calibration and validation

This process involved three major steps: (1) delineate the watersheds and identify HRUs, (2) simulate the model by forcing with meteorological variables, and (3) calibrate and validate the model by comparing with observed data. A brief summary of each step is presented below.

First, the watershed boundary of the BRB was delineated using a 90-m digital elevation model and the basin was divided into 149 smaller sub-basins. Then, the soil layer, landuse, and slope class were overlaid to generate 1,020 HRUs (area 687 km² on average) of the BRB.

Second, the streamflow was simulated by running the model using daily climate forcing data, i.e. precipitation, maximum temperature and minimum temperature. The Soil Conservation Service Curve Number (SCS-CN) procedure (USDA-SCS 1972) was applied to estimate surface runoff volumes, the Hargreaves method was used to estimate the potential evapotranspiration and channel routing was performed using a variable storage method.

Finally, the model was calibrated and validated using monthly streamflow data at Bahadurabad station, a hydro-metric station in Bangladesh and considered as the basin outlet of BRB. The calibration period is 1981–1995, excluding a warmup period of three years (1978–1980), and the validation period is 1996–2010. We conducted sensitivity analysis using regressing Latin Hypercube generated parameters against objective function values to identify

parameters that show sensitivity to streamflow (Abbaspour 2012). We selected 11 parameters and found that streamflow is most sensitive to curve number (CN2). Table S1 in the supplementary information provides a detailed description of the parameters and the optimum values. Figure 3 compares the simulated versus observed streamflow at Bahadurabad station for both calibration and validation periods, which indicates a very good agreement with observed data.

The performance of the model simulation is evaluated using four Goodness-of-Fit statistics: the Nash–Sutcliffe Efficiency value (*NSE*), the coefficient of determination (*R*²), percent bias (*PBIAS*) and the ratio of the root mean square error between the simulated and observed streamflows to the standard deviation of the observations (*RSR*) (Equations (2)–(5)):

$$NSE = 1 - \left[\frac{\sum_i^n (xobs(i) - ymod(i))^2}{\sum_i^n (xobs(i) - \overline{xobs})^2} \right] \quad (2)$$

$$PBIAS = \left[\frac{\sum_i^n (xobs(i) - ymod(i))}{\sum_i^n xobs(i)} \right] \quad (3)$$

$$RSR = \left[\frac{\sqrt{\sum_i^n (xobs(i) - ymod(i))^2}}{\sqrt{\sum_i^n (xobs(i) - \overline{xobs})^2}} \right] \quad (4)$$

$$R^2 = \left[\frac{\left[\sum_i^n (xobs(i) - \overline{xobs})(ymod(i) - \overline{ymod}) \right]^2}{\left[\sum_i^n (xobs(i) - \overline{xobs})^2 \sum_i^n (ymod(i) - \overline{ymod})^2 \right]} \right] \quad (5)$$

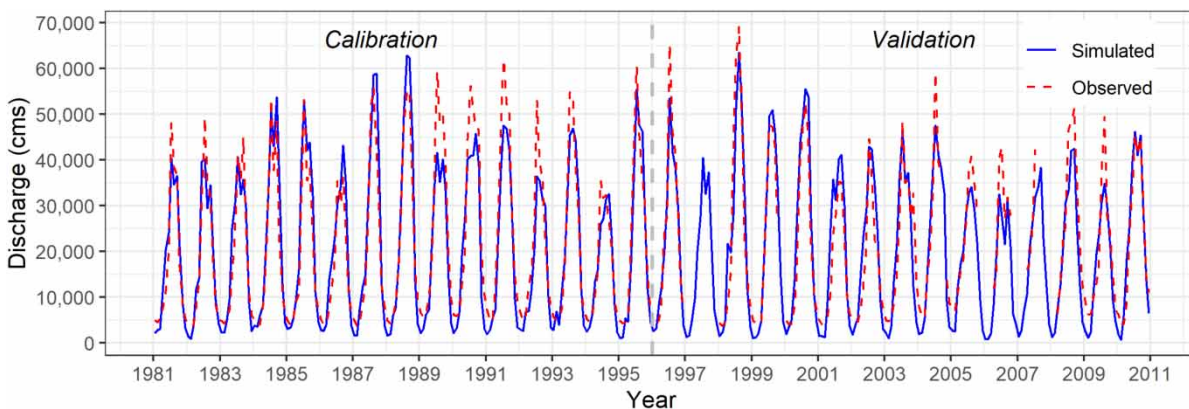


Figure 3 | Comparison of SWAT simulated and observed streamflow at Bahadurabad Station for the calibration (1981–1995) and validation (1996–2010) period.

where x_{obs} = observed flow and y_{mod} = model/simulated flow. The NSE , R^2 , $PBIAS$ and RSR for the calibration and validation periods are 0.90 and 0.86, 0.90 and 0.87, 3.49 and 3.28 and 0.28 and 0.34, respectively. The performance evaluation metrics demonstrated that the SWAT model developed for the BRB generally performed well during the historical simulation period, which establishes the basis for conducting climate change studies using the developed SWAT model, assuming the basin's physical conditions remain unchanged. Although the model is parameterized to effectively represent the streamflow at the downstream location (Bahadurabad), we acknowledge that the model may have limited capability to represent upstream storage and streamflow diversions.

Selection of climate change scenarios

We compared the projected changes in temperature (absolute changes, ΔT °C) and precipitation (percent changes, ΔP %) with respect to the climate normal period (1981–2010) for eight GCMs and four RCPs (RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5). The GCMs considered for analysis are BCC-CSM1.1, BCC-CSM1.1(m), GISS-E2-H, GISS-E2-R, HadGEM2-ES, MIROC-ESM, MIROC-ESM-CHEM, and MRI-CGCM3. Figure 4(a) shows the projected changes in temperature for three future periods (2020s, 2050s, and 2080s). We find that the uncertainty in the projected increase in temperature doubles from the 2020s to the 2080s. The median increase in temperature from the 2020s to the 2080s

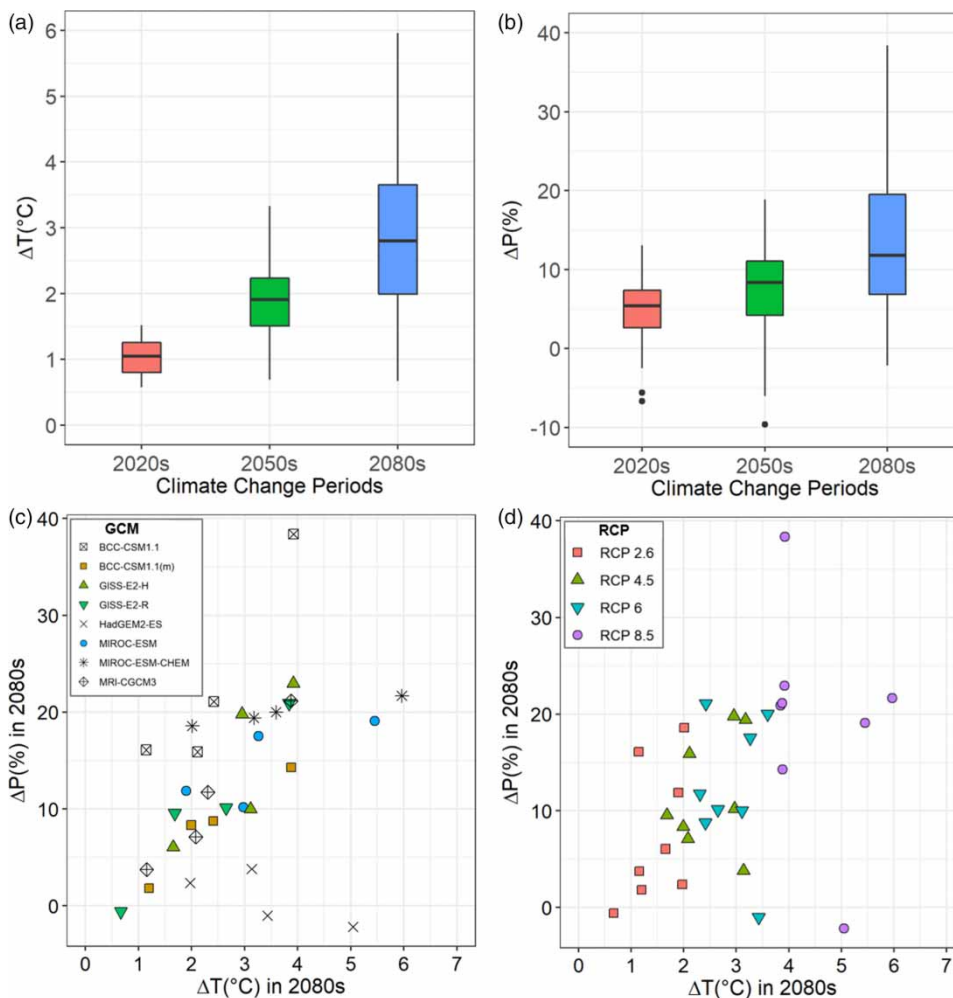


Figure 4 | Boxplots at the top row show projected changes in (a) temperature and (b) precipitation for three climate changes period (2020s, 2050s, and 2080s) based on eight GCMs and four RCP scenarios. Scatterplots at the bottom row show percent changes in precipitation versus absolute changes in temperature during the 2080s for different (c) GCMs and (d) RCPs.

is around 1.5 °C. Figure 4(b) shows the projected changes in precipitation for three future periods. The median change in precipitation shows an increasing trend and the uncertainty increases significantly from the 2020s to the 2080s.

To identify representative climate change scenarios for hydrologic simulation, we compare the projected precipitation and temperature changes by each GCM and RCP in the later part of the century: 2080s (Figure 4(c) and 4(d)). Figure 4(c) shows the precipitation and temperature changes projected by GCMs, and Figure 4(d) shows the changes under different RCP scenarios.

From these comparisons we identify the six climate change scenarios (a combination of GCMs and RCPs): (i) 'Warmest' (projecting the highest temperature increase by the 2080s), (ii) 'Coolest' (projecting the lowest temperature increase by the 2080s), (iii) 'Driest' (projecting the lowest precipitation increase or highest precipitation decrease by the 2080s), (iv) 'Wettest' (projecting the highest precipitation increase or lowest precipitation decrease by the 2080s), (v) 'Moderate Warming' (projecting the median temperature increase changes by the 2080s), and (vi) 'Moderate Wetting' (projecting the median precipitation changes by the 2080s). Table 1 shows a list of these selected scenarios, relevant GCMs, RCPs and changes in temperature and precipitation. Although these climate change scenarios were selected based on the projected climate in the 2080s, they were applied to drive the hydrologic model for all three climate change periods (2020s, 2050s, and 2080s) so that they can be compared to each other.

Climate data for future scenarios

SWAT, the selected hydrological model of BRB, was simulated for selected scenarios with high resolution projected

climate data. Since this study aimed to quantify streamflow changes for a wide range of climate projections, it is computationally challenging to apply dynamic downscale techniques, for instance using regional climate models, for a wide range of GCMs. Therefore, we use a relatively computationally efficient method, namely pattern scaling, to generate high resolution future climate data. This technique has been applied for different geographic regions and time periods (Mitchell et al. 1999; Tebaldi & Arblaster 2014) and has been found valid for both temperature and precipitation (Mitchell 2003) despite underlying limitations and assumptions (Tebaldi & Arblaster 2014; Herger et al. 2015). In pattern scaling, the anomaly of a variable (V) in a grid at a given time is obtained from the product of a scalar (S) with a response pattern (V'). Here, S is obtained from the global mean temperature anomaly for a given forcing scenario and V' is obtained from GCMs.

In the current study we used the tool 'Marksim' by the Consortium of International Agricultural Research Centers (CGIAR) to obtain pattern scaled temperature (max and min) and precipitation at 0.5° resolution for the projected scenarios. Marksim generates precipitation using a third order Markov chain to define wet days and acquire parameters from climate clusters that have been fitted to data from more than 9,200 stations globally (Schuol & Abbaspour 2007). Marksim relies on the interpolated surface generated from multiple weather stations. On the other hand, daily maximum and minimum temperatures are generated using the Decision Support System for Agrotechnology Transfer (DSSAT) weather generator (Pickering et al. 1994), based on the routines of Richardson (1985) and Geng et al. (1988). More detail on model formulation is well presented by Jones & Thornton (1993, 1997, 1999, 2000). Although there are limitations of using Marksim, it is a

Table 1 | Selection of climate change scenarios

Scenarios	Criteria (2080s climate)	GCM	RCP	ΔT (°C) (2080s)	ΔP (%) (2080s)
Warmest	$\Delta T = \text{Maximum}$	MIROC-ESM-CHEM	8.5	5.96	21.70
Coolest	$\Delta T = \text{Minimum}$	GISS-E2-R	2.6	0.67	-0.58
Driest	$\Delta P\% = \text{Minimum}$	HadGEM2-ES	8.5	5.04	-2.16
Wettest	$\Delta P\% = \text{Maximum}$	BCC-CSM1.1	8.5	3.92	38.38
Moderate Warming	$\Delta T = \text{Median}$	GISS-E2-H	4.5	2.95	19.80
Moderate Wetting	$\Delta P\% = \text{Median}$	MRI-CGCM3	6	2.31	11.74

useful and efficient way to obtain projected climate data when any study considers wide varieties of GCMs and RCP scenarios. Moreover, we were able to generate an uncertainty band for extreme and moderate cases which is another strength of following this approach.

DISCUSSION

The water balance equation in SWAT considers precipitation as input to the sub-basins, evapotranspiration and deep percolation as loss, and surface and subsurface runoff as outflow from the system. In BRB, 66% of the total basin precipitation converted to surface runoff, sub-surface runoff and shallow groundwater flow into the river; 24% of the precipitation converted to evapotranspiration; and 2% moved to deep percolation. More than two-thirds of total streamflow comes from the combination of sub-surface runoff and lateral inflow (72%), and the rest from surface runoff (28%). The SWAT model was simulated with climate variables for multiple climate change scenarios. We understand that changes in future landuse may have some impact on the hydrological processes of the BRB. However, the changes in basin hydrology due to changes in landuse are not within the scope of this study. Therefore, the projected streamflows estimated in this study are due to the future changes in basin scale climatic conditions.

Mean annual streamflow

The SWAT model was run with the downscaled climate data for six climate change scenarios (Warmest, Coolest, Driest, Wettest, Moderate Warming, and Moderate Wetting) and three climate change periods (2020s, 2050s, and 2080s). The simulated streamflow of BRB for these scenarios were then compared with climate normal period observed streamflow (1981–2010) at Bahadurabad station. We use scatterplots to analyze outputs from the hydrologic model. Scatterplots presented in the article primarily show how a variable, for instance streamflow, varies with various GCM outputs of temperature changes or precipitation changes from the climate normal period of 1981–2010. They are a very common demonstration of hydrologic responses resulting from climatic changes and are found to be very useful to understand the sensitivity or trend of that response variable. Figures 5(a) and 6(a) show the scatterplots of projected mean annual streamflow of the BRB versus the future changes in temperature and precipitation, respectively; Figure 7(a) shows the boxplot of these projected streamflows. The projected changes in mean annual streamflow with respect to the climate normal period observed streamflow (1981–2010) are presented in Table 2 along with the uncertainty analysis of such projections (95% confidence interval of median changes, and 95% bootstrap confidence interval of means). Figure 8(a) shows the bootstrap mean

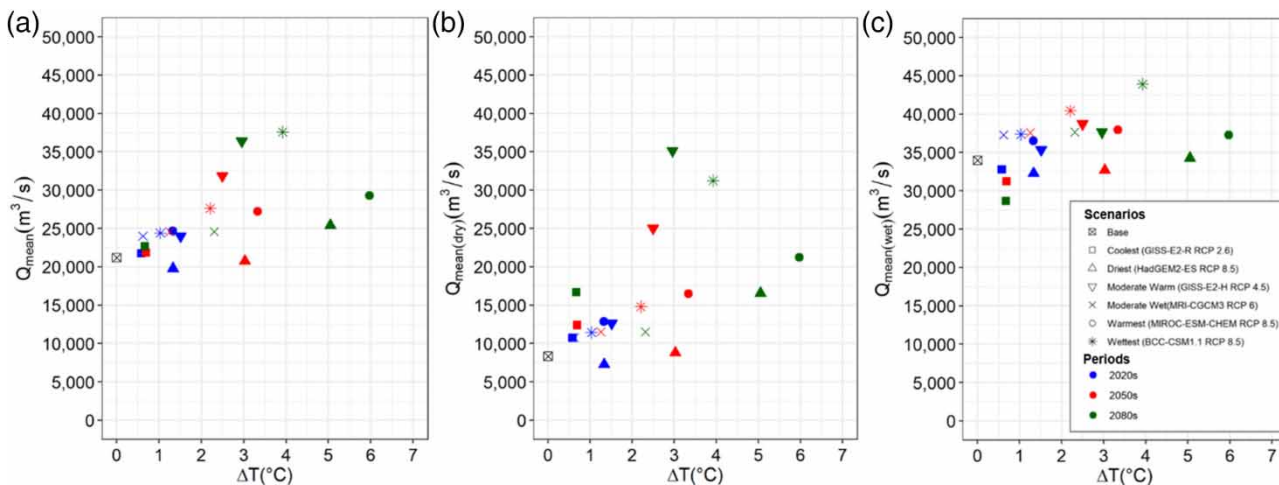


Figure 5 | Scatterplots showing Soil and Water Assessment Tool (SWAT) simulated (a) mean annual, (b) mean dry season, and (c) mean wet season streamflow of Brahmaputra River Basin at Bahadurabad of Bangladesh for the projected changes in temperature (ΔT °C) based on six selected climate change scenarios for the 21st century.

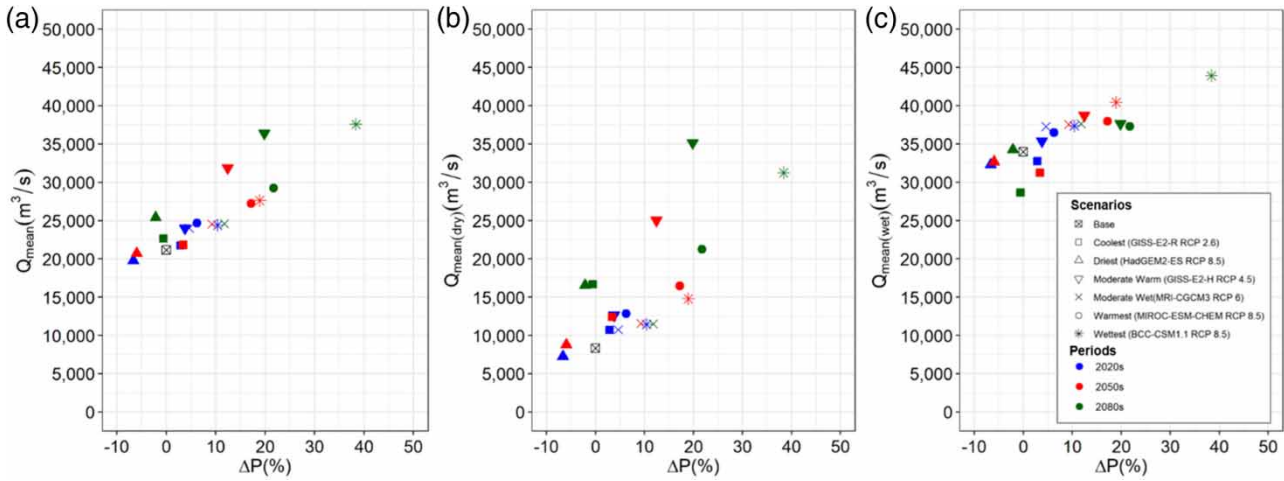


Figure 6 | Scatterplots showing Soil and Water Assessment Tool (SWAT) simulated (a) mean annual, (b) mean dry season, and (c) mean wet season streamflow of Brahmaputra River Basin at Bahadurabad of Bangladesh for the projected changes in precipitation (ΔP) based on six selected climate change scenarios for the 21st century.

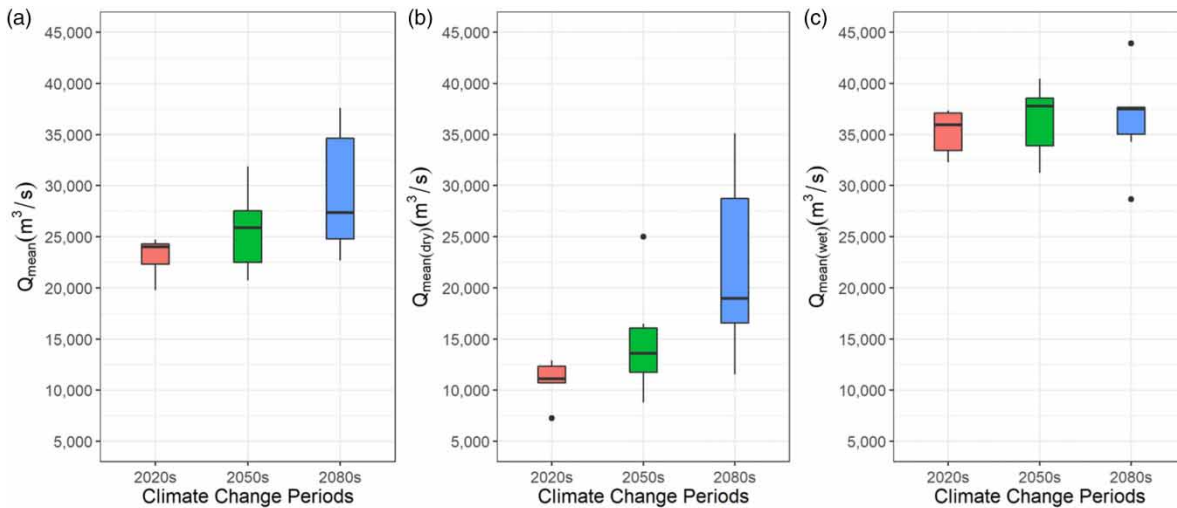


Figure 7 | Boxplots showing Soil and Water Assessment Tool (SWAT) simulated (a) mean annual, (b) mean dry season, and (c) mean wet season streamflow of Brahmaputra River Basin at Bahadurabad of Bangladesh for the three climate change periods of the 21st century.

and associated confidence interval (95%) for the projected changes in mean annual streamflow.

In the early 21st century (2020s, or 2011–2040) most of the scenarios project an increase in the mean annual streamflow of the BRB. Only the Driest (HadGEM2-ES RCP 8.5) scenario projects a minor decrease (3%) in mean annual streamflow. The projected increase in mean annual streamflow ranges from about 1% (Coolest scenario) to about 15% (Warmest scenario) with a median increase of about 11% (95% confidence interval of -3 and 15%), and a mean

increase of about 8% (with a 95% bootstrap confidence interval of 2 and 12%).

In the mid-21st century (2050s, or 2041–2070) all the scenarios project an increase in the mean annual streamflow of the BRB. The projected increase in mean annual streamflow ranges from about 2% (Coolest scenario) to about 32% (Moderate Warming scenario) with a median increase of about 20% (95% confidence interval of 2 and 32%), and a mean increase of about 17% (with a 95% bootstrap confidence interval of 8 and 26%).

Table 2 | Soil and Water Assessment Tool (SWAT) simulated projected changes in mean annual (ΔQ_{mean} %), mean dry season ($\Delta Q_{\text{mean (dry)}}$ %), and mean wet season ($\Delta Q_{\text{mean (wet)}}$ %) streamflow of Brahmaputra River Basin at Bahadurabad of Bangladesh for the projected changes in temperature and precipitation based on six selected climate change scenarios for the 21st century

Scenarios	Model & RCP	ΔQ_{mean} (%)				$\Delta Q_{\text{mean (dry)}}$ (%)				$\Delta Q_{\text{mean (wet)}}$ (%)			
		2020s	2050s	2080s	2080s	2020s	2050s	2080s	2080s	2020s	2050s	2080s	2080s
Warmest	MIROC-ESM-CHEM (RCP 8.5)	15	26	30	187	74	139	187	10	17	16	16	
Coolest	GISS-E2-R (RCP 2.6)	1	2	-1	140	46	91	140	-3	-6	-13	-13	
Driest	HadGEM2-ES (RCP 8.5)	-3	3	19	174	12	49	174	-5	-1	6	6	
Wettest	BCC-CSM1.1 (RCP 8.5)	11	27	47	189	31	77	189	9	23	35	35	
Moderate Warming	GISS-E2-H (RCP 4.5)	10	32	39	336	80	232	336	4	16	14	14	
Moderate Wetting	MRI-CGCM3 (RCP 6)	12	13	14	41	33	42	41	10	11	11	11	
Median (95% confidence interval)		11 (-3, 15)	20 (2, 32)	24 (1, 46)	180 (58, 339)	40 (17, 85)	84 (46, 235)	180 (58, 339)	7 (-5, 10)	13 (-5, 22)	12 (-11, 33)	12 (-11, 33)	
Mean (95% bootstrap confidence interval)		8 (2, 12)	17 (8, 26)	25 (11, 37)	178 (118, 271)	46 (29, 70)	105 (64, 172)	178 (118, 271)	4 (-1, 9)	10 (1, 17)	11 (0, 24)	11 (0, 24)	

At the end of the 21st century (2080s, or 2071–2100) except for the ‘Coolest’ scenario, all other scenarios project an increase in the mean annual streamflow of the BRB. The projected increase in mean annual streamflow ranges from about 14% (Moderate Wetting scenario) to about 47% (Wet-test scenario) with a median increase of about 24% (95% confidence interval of 1 and 46%), and a mean increase of about 25% (with a 95% bootstrap confidence interval of 11 and 37%).

Mean dry season (December–May) streamflow

Figures 5(b) and 6(b) show the scatterplots of projected mean dry season streamflow of the BRB versus the future changes in temperature and precipitation, respectively; Figure 7(b) shows the boxplot of these projected seasonal streamflows. The projected changes in mean dry season streamflow with respect to the climate normal period observed streamflow (1981–2010) are presented in Table 2 along with the uncertainty analysis of such projections (95% confidence interval of median changes, and 95% bootstrap confidence interval of means). Figure 8(b) shows the bootstrap mean and associated confidence interval (95%) for the projected changes in mean dry season streamflow.

All of the climate change scenarios for future periods, irrespective of GCMs and RCP scenarios, project an increase of the dry season streamflow of the BRB. In the early 21st century, the projected increase in mean dry season streamflow ranges from about 12% (Driest scenario) to about 80% (Moderate Warming scenario) with a median increase of about 40% (95% confidence interval of 17 and 85%), and mean increase of about 46% (with a 95% bootstrap confidence interval of 29 and 70%). By the mid-21st century, the projected increase in mean dry season streamflow ranges from about 42% (Moderate Wetting scenario) to about 232% (Moderate Warming scenario) with a median increase of about 84% (95% confidence interval of 46 and 235%), and mean increase of about 105% (with a 95% bootstrap confidence interval of 64 and 172%). At the end of the 21st century, the projected increase in mean dry season streamflow ranges from about 41% (Moderate Wetting scenario) to about 336% (Moderate Warming scenario) with a median increase of about 180% (95% confidence interval of 58 and 339%), and mean increase

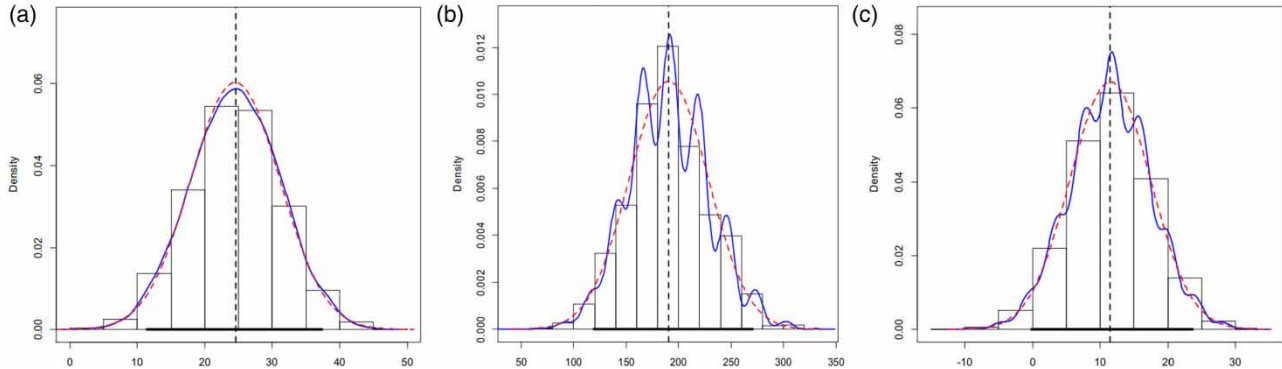


Figure 8 | Bootstrap mean and associated confidence interval (95%) for the projected changes in (a) mean annual streamflow, (b) mean dry season streamflow and (c) mean wet season streamflow. The red dotted line shows the normal density, the blue line shows the kernel density, black vertical dotted line shows modeled mean streamflow, and thick black horizontal line shows the 95% confidence interval of the mean modeled streamflow.

of about 178% (with a 95% bootstrap confidence interval of 118 and 271%). These relatively high increases in dry season streamflow compared to the mean annual streamflow are presumably attributed to enhanced snowmelt at the headwaters due to the increase in temperature.

Mean wet season (June–November) streamflow

Figures 5(c) and 6(c) show the scatterplots of projected mean wet season streamflow of the BRB versus the future changes in temperature and precipitation, respectively; Figure 7(c) shows the boxplot of these projected seasonal streamflows. The projected changes in mean wet season streamflow with respect to the climate normal period observed streamflow (1981–2010) are presented in Table 2 along with the uncertainty analysis of such projections (95% confidence interval of median changes, and 95% bootstrap confidence interval of means). Figure 8(c) shows the bootstrap mean and associated confidence interval (95%) for the projected changes in mean wet season streamflow.

At the early, mid and end of the 21st century, except for the ‘Coolest’ and ‘Driest’ scenarios, all four other scenarios projected an increase in mean wet season streamflow. The projected increase in mean wet season streamflow ranges from about 4% (Moderate Warming scenario) to about 10% (Warmest and Moderate Wetting scenarios) with a median increase of about 7% (95% confidence interval of –5 and 10%), and mean increase of about 4% (with a 95% bootstrap confidence interval of –1 and 9%). By the mid-21st century, the projected increase in mean wet season streamflow

ranges from about 11% (Moderate Wetting scenario) to about 23% (Wettest scenario) with a median increase of about 13% (95% confidence interval of –5 and 22%), and mean increase of about 10% (with a 95% bootstrap confidence interval of 1 and 17%). At the end of the 21st century, the projected increase in mean wet season streamflow ranges from about 6% (Driest scenario) to about 35% (Wettest scenario) with a median increase of about 12% (95% confidence interval of –11 and 33%) and a mean increase of about 11% (with a 95% bootstrap confidence interval of 0 and 24%).

Multivariate regression analysis of mean and seasonal streamflow

Multiple linear regression is used to model the relationship between multiple predictor variables and a response variable by fitting a linear equation. In this study, multivariate linear regression models (MVR) have been developed using SWAT simulated streamflow (from multiple scenarios) as response variable and climate change parameters (ΔT and ΔP) as predictors. Three types of MVR models were developed to represent annual and seasonal streamflow, i.e. mean annual, mean dry season and mean wet season streamflow. The fitted regressions are given by:

$$Q_{\text{Mean}}(m^3/s) = 21,535 - 575*\Delta T + 349*\Delta P\% \quad (6)$$

$$Q_{\text{Mean(Dry)}}(m^3/s) = 9,551 + 1,109*\Delta T + 428*\Delta P\% \quad (7)$$

$$Q_{\text{Mean(Wet)}}(m^3/s) = 33,518 + 41*\Delta T + 271*\Delta P\% \quad (8)$$

where ΔT and ΔP are changes in basin scale mean temperature ($^{\circ}\text{C}$) and basin scale mean precipitation (%) with respect to the climate normal period (1981–2010), respectively; Q_{Mean} , $Q_{\text{Mean(Dry)}}$, and $Q_{\text{Mean(Wet)}}$ are the mean annual, mean dry season, and mean wet season streamflow at Bahadurabad for the future periods.

These MVR equations are developed based on 18 data points (six selected climate change scenarios by a combination of GCMs and RCPs to demonstrate different wetting and warming patterns, and then multiplying by three climate change periods: 2020s, 2050s, and 2080s). Because of the limited data points, it was necessary to run statistical significance tests to assess the performance of the regression models (Table 3). First, we analyzed the t-statistics, which is a measure of the likelihood that the actual value of the exponent and intercept of a regression equation is not zero (Islam & Seneka 2019). For the MVR of mean annual streamflow (Equation (6)), the t-statistics for the intercept, ΔT and ΔP , were found to be 20.34 (P -value: 2.46×10^{-12}), 1.33 (P -value: 2.03×10^{-1}), and 5.78 (P -value: 3.61×10^{-5}), respectively. The higher t-statistics and associated lower P -values indicate that it is less likely the actual value of the

parameter could be zero. While performing the F-test, we noticed that the F-value and associated P -value for the MVR of mean annual streamflow are 25.94 and 1.35×10^{-5} , respectively. The low P -value associated with the F-value indicates the validity of the regression equation in fitting the modelled results zero (Islam & Seneka 2019). A statistical significant test for the other two models (MVR of mean dry season streamflow, MVR of the mean wet season streamflow) provides similar results (see Table 3 for details).

In order to assess the performance of these fitted regression equations, the mean annual streamflow and mean seasonal streamflow (at different temperature and precipitation changes for the six climate change scenarios selected for this study) estimated using Equations (6)–(8) were plotted against the SWAT simulated streamflows (Figure 9). Also, statistical performance was checked through coefficient of determination (R^2) and the error bound as a form of 95% confidence interval of fitted values (e.g. intercept, ΔT and ΔP) (see Table 3 for details). It appears that the fitted equation for mean annual streamflow and mean wet season streamflow (Equations (6) and (8)) is in good

Table 3 | Statistics of Multivariate Regression (MVR) models of mean annual (Q_{Mean}) and mean seasonal ($Q_{\text{Mean(Dry)}}$ and $Q_{\text{Mean(Wet)}}$) streamflow developed in this study

Statistics		Model		
		Q_{Mean} to ΔT and $\Delta P\%$	$Q_{\text{Mean (Dry)}}$ to ΔT and $\Delta P\%$	$Q_{\text{Mean(Wet)}}$ to ΔT and $\Delta P\%$
R^2		0.78	0.57	0.72
F Value		25.94	10.05	19.04
P Value		1.35×10^{-5}	1.70×10^{-3}	7.66×10^{-5}
Intercept	Estimate	21,535	9,551	33,518
	t Value	20.34	4.27	38.80
	P Value	2.46×10^{-12}	6.73×10^{-4}	$<2 \times 10^{-16}$
	Lower 95 CI%	19,279	4,782	31,677
	Upper 95 CI%	23,791	1.43×10^{-4}	35,360
ΔT	Estimate	575	1,109	41
	t Value	1.33	2.22	0.12
	P Value	2.03×10^{-1}	2.43×10^{-1}	9.09×10^{-1}
	Lower 95 CI%	-345	-836	-710
	Upper 95 CI%	1,495	$3.05 \times 10^{+3}$	792
$\Delta P\%$	Estimate	349	428	271
	t Value	5.78	3.35	5.50
	P Value	3.61×10^{-5}	4.39×10^{-3}	6.13×10^{-5}
	Lower 95 CI%	221	155	166
	Upper 95 CI%	478	700	376

ΔT = Absolute changes in temperature, $\Delta P\%$ = Percentage changes in mean precipitation, CI = Confidence interval.

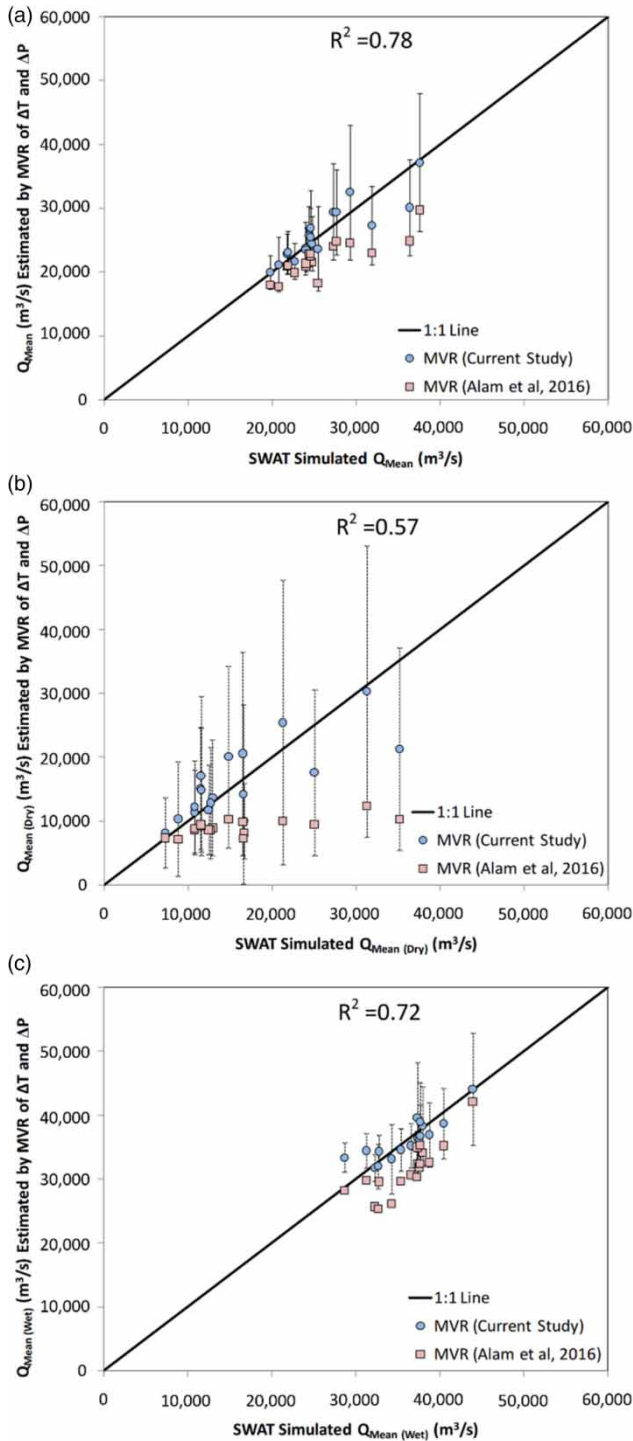


Figure 9 | Comparison of SWAT simulated streamflow with the estimated streamflow using Multivariate Regression (MVR) model of ΔT and $\Delta P\%$ of current study and the study of Alam *et al.* (2016) for (a) annual, (b) dry, and (c) wet conditions. Error bar represents 95% confidence interval on estimated streamflow.

agreement with the simulated flow with higher R^2 and less uncertainty (comparatively narrow bound of 95% confidence interval). However, the fitted equation for the mean dry season streamflow shows more scattering and more uncertainty (relatively wide 95% confidence interval).

The fitted MVR models for the mean annual, mean dry season, and mean wet season streamflow were also compared with a previous study where synthetic climate change scenarios (arbitrary perturbed temperature and precipitation) were used to simulate projected changes in mean and extreme streamflow (Alam *et al.* 2016). It was found that the MVR models based on the actual projected changes in temperature and precipitation changes generally perform better. We acknowledge that such a simple regression model may not be an ideal tool to estimate streamflow of BRB. However, it can be a useful tool for policy makers or operational engineers for a quick estimation of basin average flow, which is often critical for water managers and planners for adaptation planning.

Maximum annual streamflow

The Ganges delta is one of the world's most flood-prone areas. Hence, an analysis of SWAT simulated annual maximum streamflow for the climate change scenarios was performed and then compared with the climate normal period observed maximum streamflow (1981–2010) at Bahadurabad station. Figure 10(a) and 10(b) show the scatterplot of projected maximum annual streamflow of the BRB versus the future changes in temperature and precipitation, respectively; Figure 10(c) shows the boxplot of these projected streamflows. The projected changes in future annual maximum streamflow with respect to the climate normal period observed streamflow (1981–2010) are also presented in Table 4 along with the uncertainty analysis of such projections (95% confidence interval of median changes, and 95% bootstrap confidence interval of means).

Except for a few scenarios (Coolest scenario, Driest scenario), all the other scenarios project an increase in annual maximum streamflow over the 21st century. The projected increase in annual maximum streamflow is

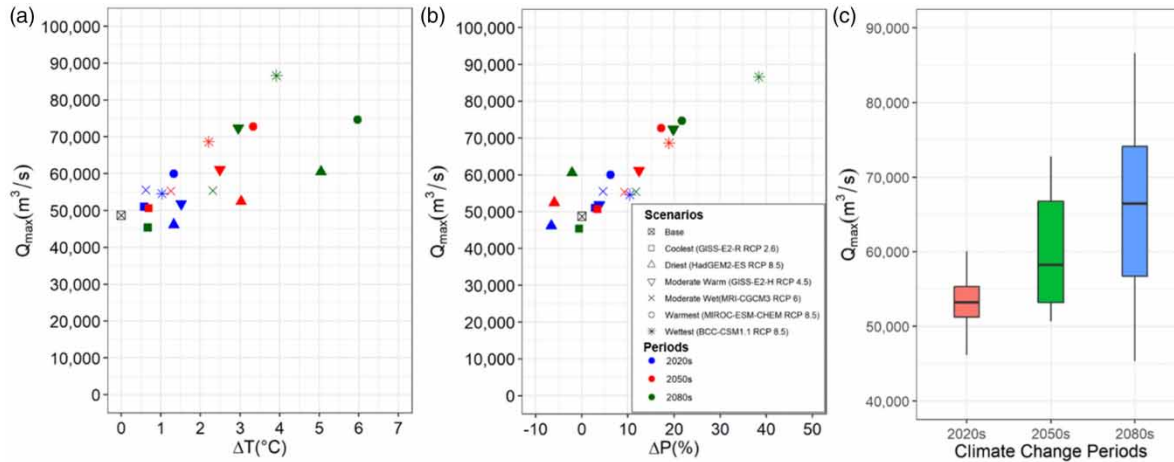


Figure 10 | Scatterplots showing Soil and Water Assessment Tool (SWAT) simulated maximum annual streamflow of Brahmaputra River Basin at Bahadurabad of Bangladesh for the projected changes in (a) temperature (ΔT °C), and (b) precipitation (ΔP %) based on six climate change scenarios for the 21st century; and (c) Boxplot of the SWAT simulated annual maximum streamflow and the associated uncertainties for the three climate change periods.

Table 4 | Soil and Water Assessment Tool (SWAT) simulated projected changes in annual maximum (ΔQ_{Max} %), maximum dry season ($\Delta Q_{Max (Dry)}$ %), and maximum wet season ($\Delta Q_{Max (Wet)}$ %) streamflow of Brahmaputra River Basin at Bahadurabad of Bangladesh for the projected changes in temperature and precipitation based on six selected climate change scenarios for the 21st century

Scenarios	Model & RCP	ΔQ_{Max} (%)		
		2020s	2050s	2080s
Warmest	MIROC-ESM-CHEM (RCP 8.5)	17	37	41
Coolest	GISS-E2-R (RCP 2.6)	-4	-4	-13
Driest	HadGEM2-ES (RCP 8.5)	-2	-1	14
Wettest	BCC-CSM1.1 (RCP 8.5)	8	30	64
Moderate Warming	GISS-E2-H (RCP 4.5)	1	16	18
Moderate Wetting	MRI-CGCM3 (RCP 6)	5	8	6
Median (95% confidence interval)		3 (-3, 16)	12 (-4, 36)	16 (-10, 61)
Mean (95% bootstrap confidence interval)		4 (-1, 10)	14 (2, 27)	22 (3, 42)

gradual (e.g. mean and median increase of 4 and 3%, 14 and 12, and 22 and 16% at the early, mid, and end of 21st century, respectively), and the uncertainty associated with these projected changes increases in the future periods (Figure 10(c) and Table 4). At the end of the 21st century (2080s, or 2071–2100) the projected increase in annual maximum streamflow ranges from about 6% (Moderate Wetting scenario) to about 64% (Wettest scenario) with a median increase of about 16% (95% confidence interval of -10 and 61%), and mean increase of about 22% (with a 95% bootstrap confidence interval of 3 and 42%).

Multivariate regression analysis of annual maximum streamflow

The SWAT simulated annual maximum streamflow obtained for different RCP scenarios has been used to develop multivariate linear regression models between changes in the climatic input (ΔT and ΔP) and the annual maximum streamflow of the BRB. The fitted regressions are given by:

$$Q_{Max}(m^3/s) = 47,110 + 2,655 * \Delta T + 731 * \Delta P\% \quad (9)$$

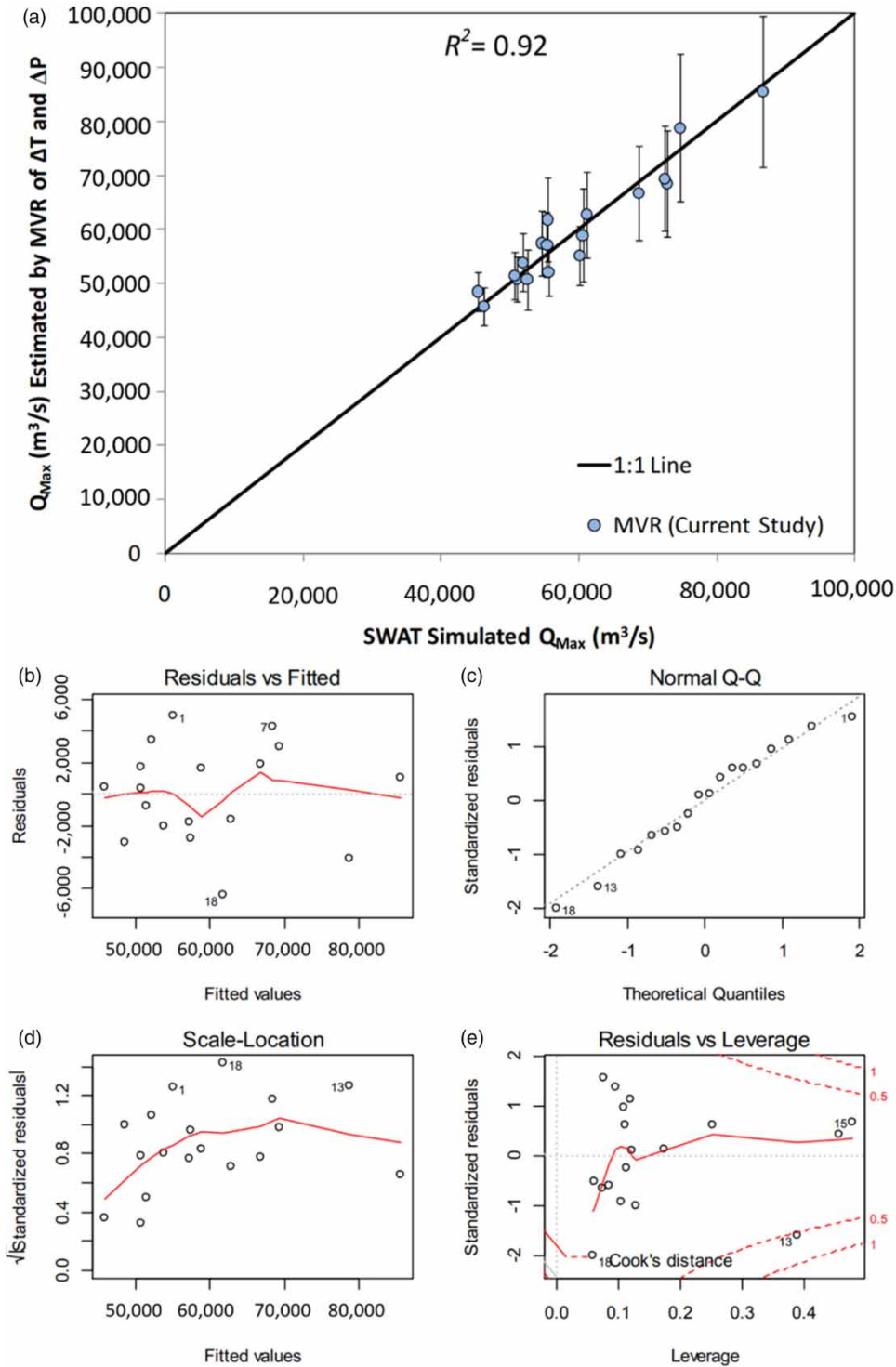


Figure 11 | (a) Comparison of SWAT simulated annual maximum streamflow with the estimated annual maximum streamflow using Multivariate Regression (MVR) model of ΔT and $\Delta P\%$ (error bar represents 95% confidence interval on estimated streamflow); (b)–(e) represents residual statistics for the MVR.

where ΔT and ΔP are the changes in basin scale mean temperature ($^{\circ}\text{C}$) and basin scale mean precipitation (%) from the climate normal period (1981–2010), respectively and Q_{Max} is the annual maximum streamflow of Brahmaputra at Bahadurabad for the future periods.

The results of the statistical significance test performed for Equation (9) are satisfactory. The t-statistic (and associated probability, or P -value) for the intercept, ΔT and ΔP , were found to be 34.24 (P -value: 1.17×10^{-15}), 4.73 (P -value: 2.68×10^{-4}), and 9.31 (P -value: 1.26×10^{-7}), respectively. The F-value and associated P -values for the MVR of annual maximum streamflow were found to be 91.29 and 4.01×10^{-9} , respectively. In order to assess the performance of these fitted regression equations, annual maximum streamflow (at different temperature and precipitation changes for the six climate change scenarios) estimated using Equation (9) were plotted against the SWAT simulated annual maximum streamflow (Figure 11). Also, statistical performance was checked through coefficient of determination (R^2) and the error bound as a form of 95% confidence interval of fitted values (e.g. intercept, ΔT and ΔP). It appears that the fitted equation is in good compliance with the simulated flow with higher R^2 (0.92) and less uncertainty (comparatively narrow bound of 95% confidence interval).

CONCLUSIONS

- (1) The mean annual streamflow of the basin is expected to increase gradually over the 21st century. By the end of the 21st century, the projected increase in mean annual streamflow, with respect to the 1981–2010 climate normal period, ranges from about 14 to 47%, with a median and mean of about 24 and 25%, respectively. However, the uncertainty associated with these projected changes grows as we progress to the distant future.
- (2) The mean dry season streamflow of the basin is expected to increase at a much higher rate than the mean wet season streamflow. By the end of the 21st century, the median and mean projected increase in dry season streamflow is about 180 and 178%, respectively. However, the median and mean projected increase in wet season streamflow is only about 12 and 11%, respectively. This relatively high increase in dry season

streamflow compared to the mean annual or mean wet season streamflow is presumably attributed to the enhanced snowmelt at the headwaters due to increase in temperature.

- (3) By the end of the 21st century, the annual maximum streamflow is projected to increase by about 22% (ranges from about 6 to 64%).
- (4) The projected mean annual, mean seasonal and annual maximum streamflow can be expressed as a multivariate linear regression of projected changes in basin scale mean temperature and basin scale mean precipitation. The fitted equations for the annual maximum streamflow result in higher statistical goodness ($R^2 = 0.92$) and lower uncertainty. The fitted equations for the mean annual streamflow ($R^2 = 0.78$) and mean wet season streamflow ($R^2 = 0.72$) also show satisfactory results. However, the fitted equations for the mean dry season streamflow demonstrate lower statistical goodness ($R^2 = 0.57$) and higher uncertainty.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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