Chapter 2
Assessment of Climate Change Impacts on Floods and Low Flows of the Brahmaputra River

A. K. M. Saiful Islam, Khaled Mohammed, and G. M. Tarekul Islam

Abstract The Ganges-Brahmaputra-Meghna (GBM) river system plays a key role in the survival and development of more than 670 million people in South Asia. The extreme flows of the GBM rivers also dictate the occurrences of floods and hydrological droughts in Bangladesh, which lies at the delta of this river system. This study was undertaken to assess the impacts of high-end climate change on the extreme flows as well as the mean monthly flows of these rivers at their downstream locations inside Bangladesh. SWAT Hydrological modeling tools were used to simulate future flows using climate projections collected from the CORDEX initiative. The mean monthly flows are likely to increase in most months of the future in the GBM rivers, and the increases are likely to be largest in the Ganges River compared to the other two rivers in terms of percentage changes. Flood flows and low flows are projected to increase in all three rivers. The frequency of occurrence of flood flows is likely to increase and that of low flows are likely to decrease, especially near the end of this century. The projections presented in this article can be useful in adaptation planning as well as in supporting discussions on mitigation policies.

Keywords Climate change · Extreme flows · Ganges-Brahmaputra-Meghna (GBM) basins · SWAT model

2.1 Introduction

In conducting climate change impact assessments of river basins, the following modeling chain is usually adopted. First, climate models are used to project future meteorological variables for the desired years, typically for a duration of more than 30 years. Thereafter, these projected data are preprocessed, namely, by downscaling

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and bias correction. Finally, these preprocessed data are used as forcing to different hydrological models that are set up over a selected river basin to simulate hydrological variables for the future. In this chapter, all these elements of the modeling chain are briefly discussed, followed by an example of application of this modeling chain to assess the changes in future flows of the Brahmaputra River due to climate change. Climate models, also known as General Circulation Models (GCMs), are basically numerical weather prediction models that are run for a long time over a global domain at climatic scales of 30 years or more. Another difference of climate models from weather models is that while the atmospheric forcing of the weather models must be values as observed in reality, in the case of climate models, they can be different from the real-world scenario to investigate the response of the climate system to those different values. Since future forcings cannot possibly be known, a range of estimated values based on various possible scenarios are used to project future climates. A particular component of interest in these possible scenarios is the concentration of greenhouse gases in the atmosphere, which is the prime stimulant behind global warming. In the latest Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC), four Representative Concentration Pathways (RCPs) were defined based on four sets of socio-economic assumptions, namely, RCP2.6, RCP4.5, RCP6.0, and RCP8.5 (van Vuuren et al. 2011). RCP2.6 represents the lowest amount of global warming while RCP8.5 represents the highest.

The most common climate models at present are the Atmosphere–Ocean General Circulation Models (AOGCMs) which couple the atmosphere with the ocean, land, and sea ice. An advancement over the AOGCMs is Earth System Models (ESMs) which further includes various biogeochemical cycles such as the carbon cycle, nitrogen cycle, or the sulfur cycle. There are many GCMs available at present that have been developed in countries from all over the world. About 39 models participated in the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al. 2012). Before running these models to project future climates, their parameters are calibrated in such a way so that they can reliably simulate the historically observed climate. The better a climate model can simulate the climate of the past, the more reliable it is assumed to be for simulating the climate of the future. A major problem in using the outputs of GCMs for hydrological predictions is their coarse resolution. A typical GCM can have a horizontal resolution of 2°, which is about 200 km near the equator. That means the outputs for a particular meteorological variable are provided as the spatially averaged values over an area of about 200 × 200 km. Obviously mesoscale processes like precipitation vary widely within a short span of location and so reasonable projections of hydrological variables cannot be expected using precipitation data that is spatially averaged over such a large area. This is where the concept of downscaling comes into play, which can convert these coarse resolution GCM outputs into finer scale information. Downscaling can be done either statistically or dynamically. Statistical downscaling simply relates the GCM outputs of the historical period with locally observed data using a statistical function and then uses this function to convert GCM outputs of the future at a local scale. Stationarity of the relationship between the GCM output and the local observation in the future period is therefore an inherent assumption of this process. On the other hand, dynamical downscaling is performed using Regional Climate Models (RCMs), which are very similar to GCMs. The difference is that the horizontal resolution of RCMs is very high (around 25–50 km or even less) and instead of running the models over the whole world, the RCMs are runover a limited area using lateral boundary conditions derived from the GCMs. Some of the most commonly used RCMs include the U.S. Regional Climate Model Version 3 (RegCM3), UK Met Office Hadley Centre's Regional Climate Model Version 3 (HadRM3), German Regional Climate Model (REMO), and the European Centre-Hamburg (ECHAM) model. Even though RCMs reduce the horizontal resolution of the climate simulations, simulated variables such as temperature and precipitation often show significant systematic biases. Using these values to simulate hydrological variables are likely to propagate the errors into hydrological simulations. That is why RCM outputs are almost always bias corrected before being used as forcings to hydrological models. Several bias correction methods are available which vary in complexity. Similar to statistical downscaling, bias correction methods assume that the relationship between the RCM outputs of the historical period and the observed values will remain stationary in the future periods. Some of the commonly used bias correction methods are linear scaling, power transformation, variance scaling, delta change correction, and quantile mapping (Teutschbein and Seibert 2012). Hydrological models are used to represent the hydrologic cycle and simulate its various components. The typical inputs required by these models are meteorological data such as precipitation, temperature and relative humidity, topographical information, soil information, land use/land cover information, and values of several parameters describing the hydrological processes of the study area. Hydrological models can generally be classified into three types: empirical models, conceptual models, and physically based models. Empirical models are data-driven models which are, as their name suggests, based on empirical relationships between various components of the hydrological cycle. Conceptual models use semi-empirical equations and have lumped parameters for describing hydrological processes. Physically based models use complex mathematical equations to calculate the different hydrological variables and use values of spatially distributed parameters. Examples of hydrological models include the Soil and Water Assessment Tool (SWAT), Variable Infiltration Capacity (VIC), Water–A Global Assessment and Prognosis (WaterGAP), and Joint UK Land Environment Simulator (JULES) (Kauffeldt et al. 2015).

2.2 The Study Area

The Brahmaputra is a transboundary river that has an annual average discharge of approximately 20,000 m^3/s (Jian et al. 2009), making it the fourth largest river in the world in terms of average discharge. Its drainage area of 520,000 km^2 encompasses China, India, Bhutan, and Bangladesh (Immerzeel 2008). It originates in southern Tibet of China and travels about 2900 km through China, India, and Bangladesh before ending in the Bay of Bengal (Gain et al. 2011). The climate of the northern

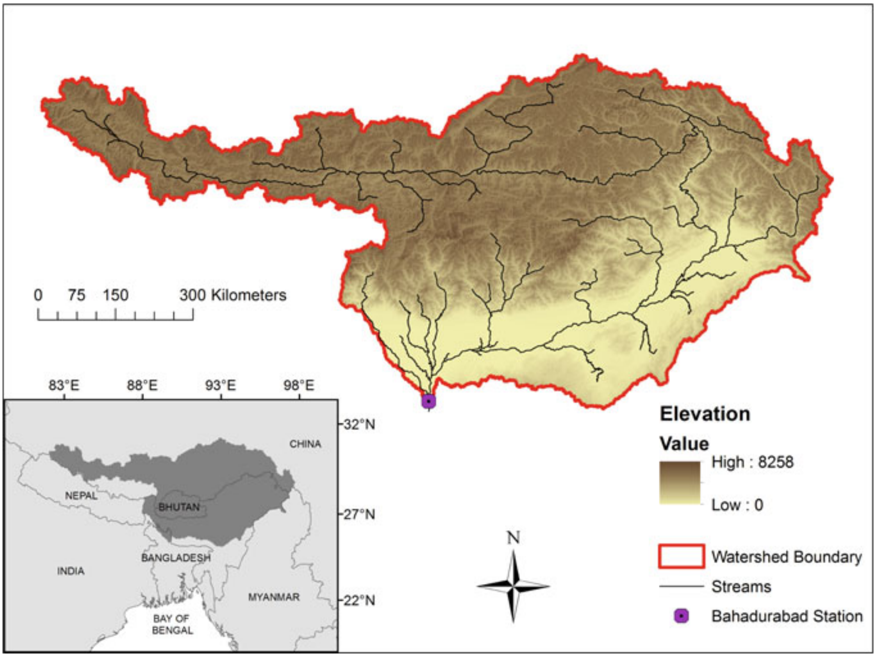

Fig. 2.1 Location and details of the Brahmaputra River Basin

part of the basin that is located over Tibetan Plateau with elevations above 3500 m is cold and dry. The remaining parts of the basin are mostly located on the low-lying floodplains with elevations below 100 m. This southern part has a warm and humid tropical monsoon climate. The mean annual precipitation in the basin is around 2300 mm and about 60–70% of this falls in the monsoon season (June to September). The Brahmaputra River Basin is shown in Fig. 2.1.

2.2.1 Database and Methodology

Daily precipitation and temperature data were collected from 11 different climate projections. The reason for using an ensemble of projections in climate change assessments is that the climate models available at present often disagree with one another in the projected values of different variables at different locations. Therefore, by using an ensemble of projections instead of a single projection, the uncertainties that are inherent in the different GCMs and RCMs can be partly accounted for. The 11 selected projections were generated using 10 GCMs of CMIP5 and later dynamically downscaled using 3 RCMs by the Coordinated Regional Climate Downscaling Experiment (CORDEX) (Giorgi and Gutowski 2015). A list of the projections are

Table 2.1 CORDEX—South Asia climate projections used in the study

Institute	GCM	RCM
CSIRO	ACCESS1.0	CCAM-1391M
CSIRO	CCSM4.0	CCAM-1391M
SMHI	CNRM-CERFACS-CNRM-CM5	RCA4
CSIRO	CNRM-CM5	CCAM-1391M
SMHI	ICHEC-EC-EARTH	RCA4
CSIRO	MPI-ESM-LR	CCAM-1391M
MPI-CSC	MPI-M-MPI-ESM-LR	REMO2009
SMHI	MPI-M-MPI-ESM-LR	RCA4
SMHI	NOAA-GFDL-GFDL-ESM2M	RCA4
SMHI	IPSL-CM5A-MR	RCA4
SMHI	MIROC-MIROC5	RCA4

given in Table 2.1. All the projections have a horizontal resolution of 0.5° and were bias corrected with a Multi-segment Statistical Bias Correction (MSBC) method as described in Grillakis et al. (2013). The MSBC method used here is of the family of quantile mapping correction methods. The reference dataset used for the bias correction was the WFDEI dataset (WATCH Forcing Data methodology applied to ERA-Interim data) (Weedon et al. 2014).

The topographic information of the area was collected in the form of a Digital Elevation Model (DEM), namely, the hydrologically conditioned version of the Shuttle Radar Topography Mission (SRTM) DEM of 90 m resolution from the HydroSHEDS database of the United States Geological Survey. A global land use/land cover map of 300 m resolution called GlobCover prepared by the European Space Agency for the year 2009 was collected and the Digital Soil Map of The World prepared by the Food and Agriculture Organization of the United Nations was collected as soil information. Finally, observed discharges of the Brahmaputra River at Bahadurabad gauging station were collected from the Bangladesh Water Development Board (BWDB) for the years 1980–2009. The location of the station is shown in Fig. 2.1. The Soil and Water Assessment Tool (SWAT) was used as the hydrological model. SWAT is a physically based, semi-distributed, watershed-scale, computationally efficient, continuous-time hydrological model that operates on a daily time step. It divides a basin into sub-basins by overlaying a land use/land cover map, a soil map, and a DEM. The sub-basins are further divided into lumped units called hydrologic response units (HRU) which are the percentage of a sub-basin area that has a unique combination of soil, land use/land cover, and slope properties. Using moisture and energy inputs provided by the user, the model then predicts the hydrology at each HRU using a water balance equation which consists of daily precipitation, runoff, evapotranspiration, percolation, and return flow components. The generated flow of all the HRUs in a sub-basin is then summed together and routed through the channels, ponds, and reservoirs to the basin outlet. Detailed descriptions of the model can be found in Arnold et al. (1998).

Using the collected DEM of the study area, the automatic watershed delineation command of SWAT defined a stream network and delineated the outline of the complete basin given the location of the basin outlet (Fig. 2.1). The SWAT model was run at a daily time step for all purposes, i.e., for calibration, validation, and simulation of future discharges. The first 20 years (1980–1999) of the observed discharge data were used for calibration and the remaining 10 years (2000–2009) were used for validation. Calibration was done for only the SWAT parameters that were found to be the most sensitive to Brahmaputra River's discharges by a separate tool called SWAT-CUP (Calibration and Uncertainty Program). Before simulating the future discharges of a particular climate projection, the SWAT model was calibrated and validated using the baseline period of that same climate projection. The Sequential Uncertainty Fitting II (SUFI-2) algorithm of SWAT-CUP was used for calibration.

2.3 Results

To analyze future river discharges, four time slices were considered. These are the baseline period (1980–2009), the 2020s (2010–2039), the 2050s (2040–2079), and the 2080s (2080–2099). The mean monthly discharges of the Brahmaputra River in these time slices are shown in Fig. 2.2 as boxplots. Each box includes data from all the 11 climate projections. Large uncertainties can be seen in the projections. Based on the change in median values of these boxes, the months from March to July will see an increase in mean monthly discharge for all future time slices. The months from September to December will see a decrease in mean monthly discharge for all future time slices. The largest increase for all three future time slices is in March, with values of 41, 86, and 147% during the 2020s, 2050s, and 2080s, respectively. The largest decrease for all three future time slices is predicted in December, with values of 13, 28, and 39% during the 2020s, 2050s, and 2080s, respectively.

Parametric frequency analyses were performed on the annual maxima and minima of the simulated discharges. The Generalized Extreme Value distribution and the Weibull distribution were used to fit the maxima and minima datasets, respectively. The return period curves as estimated by the parametric frequency analysis performed on the annual maxima are shown in Fig. 2.3. Four shaded regions, one per time slice, show the range of return periods estimated by the 11 climate projections. The uncertainty range in the annual maximum discharge is seen to increase with the return period. The solid lines show the ensemble means. Based on the ensemble means, the annual maximum discharges at different return periods are predicted to increase during the 2020s, 2050s, and 2080s compared to the baseline period and the increase is slated to be highest during the 2080s. For instance, the annual maximum discharge with a 100-year return period will increase by 47% during the 2080s compared to the baseline period.

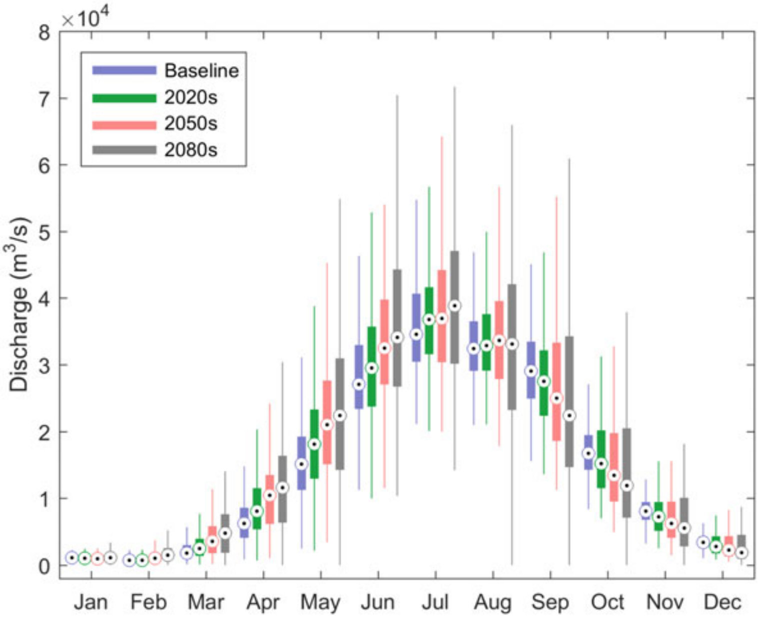

Fig. 2.2 Mean monthly discharges of the Brahmaputra River at different time slices

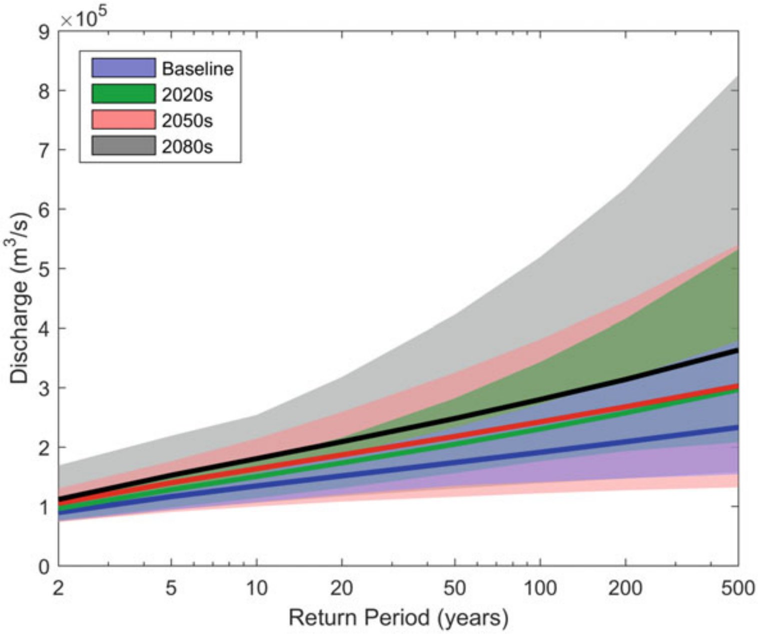

Fig. 2.3 Return period curves of annual maximum discharges at different time slices

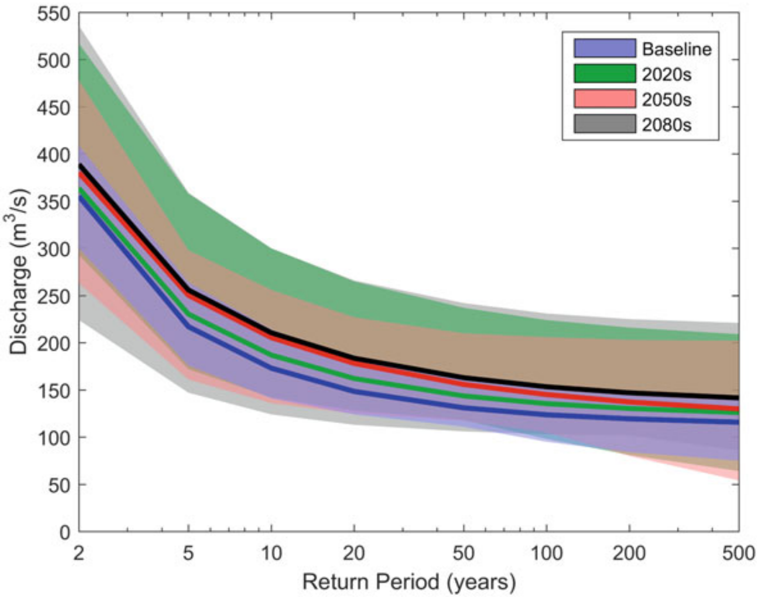

Fig. 2.4 Return period curves of annual minimum discharges at different time slices

Similarly, the return period curves as estimated by the parametric frequency analysis performed on the annual minima are shown in Fig. 2.4. Based on the ensemble means, the annual minimum discharges at different return periods will increase during the 2020, 2050, and 2080s compared to the baseline period and the increase is maximum during the 2080s. For instance, the annual minimum discharge with a 100-year return period will increase by 24% during the 2080s compared to the baseline period.

2.4 Summary and Conclusions

Using an ensemble of 11 bias corrected and downscaled climate projections to force the SWAT hydrological model, an assessment was made of the possible future changes of flows in the Brahmaputra River. Results show that the pre-monsoon months will see an increase and the post-monsoon months a decrease in mean monthly discharges for all future time slices. The month of March has been predicted to register the largest increase and December the largest decrease in mean monthly discharge compared to the other months. By the end of the century, floods are likely to become more frequent in the future and their magnitude is slated to become more severe. Low flows are projected to become less frequent in the future and their magnitude is likely to become less severe.

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