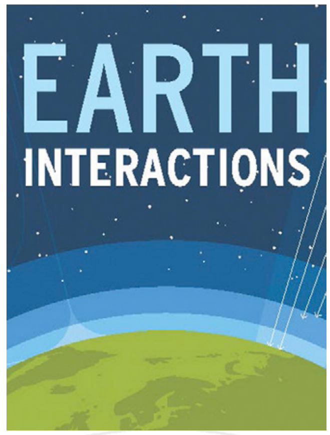

Satellite Precipitation Data–Driven Hydrological Modeling for Water Resources Management in the Ganges, Brahmaputra, and Meghna Basins

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ABSTRACT: The Ganges–Brahmaputra–Meghna (GBM) river basins exhibit extremes in surface water availability at seasonal to annual time scales. However, because of a lack of basinwide hydrological data from in situ platforms, whether they are real time or historical, water management has been quite challenging for the 630 million inhabitants. Under such circumstances, a large-scale and spatially distributed hydrological model, forced with more widely available satellite meteorological data, can be useful for generating high resolution basinwide hydrological state variable data [streamflow, runoff, and evapotranspiration (ET)] and for decision making on water management. The Variable Infiltration Capacity (VIC) hydrological model was therefore set up for the entire GBM basin at spatial scales ranging from 12.5 to 25 km to generate daily fluxes of surface water availability (runoff and streamflow). Results indicate that, with the selection of representative gridcell size and application of correction factors to evapotranspiration calculation, it is possible to significantly improve streamflow simulation and overcome some of the insufficient sampling and data quality issues in the ungauged basins. Assessment of skill of satellite precipitation forcing datasets revealed that the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA) product of 3B42RT fared comparatively better than the Climate Prediction Center (CPC) morphing technique (CMORPH) product for simulation of streamflow. The general conclusion that emerges from this study is that spatially distributed hydrologic modeling for water management is feasible for the GBM basins under the scenario of inadequate in situ data availability. Satellite precipitation forcing datasets provide the necessary skill for water balance studies at interannual and interseasonal scales. However, further improvement in skill may be required if these datasets are to be used for flood management at daily to weekly time scales and within a data assimilation framework.

KEYWORDS: Precipitation; Hydrologic models; Land surface model; Model evaluation/performance

1. Introduction

The Ganges–Brahmaputra–Meghna (GBM) river basins represent one of the largest set of basins with land areas from Bangladesh, India; Nepal; Bhutan; and
F1 China (Nishat and Rahman 2009; Figure 1). The total drainage area is about 1.72 million km^2, with a population of at least 630 million. The most downstream country (i.e., Bangladesh) occupies only 8% of GBM basin area with 100% of basin streamflow flowing through the country and discharging into the Bay of Bengal (Nishat and Rahman 2009).

The GBM basin exhibits extremes in surface water availability, making water resources management quite challenging at seasonal to annual time scales. For example, annual rainfall in the GBM ranges from 990 to 11 500 mm (Shah 2001). On the other hand, streamflow in the downstream regions of the Brahmaputra and Ganges Rivers can vary from 5000 m^3 s^{-1} in winter to 80 000 m^3 s^{-1} during the monsoon season (Mirza 2004). Such wide-ranging interannual variation exceeding by an order of magnitude can be explained by the Himalayan and Vindhya Ranges that are the key sources of water for these rivers (including Meghna River). The Himalayan Range covers about 15 000 glaciers, which stores about 12 000 km^3 of freshwater (Dyurgerov and Meier 2005). Hence, annual water distribution in the GBM basin is highly dominated by the storage of precipitation (snow and ice) over

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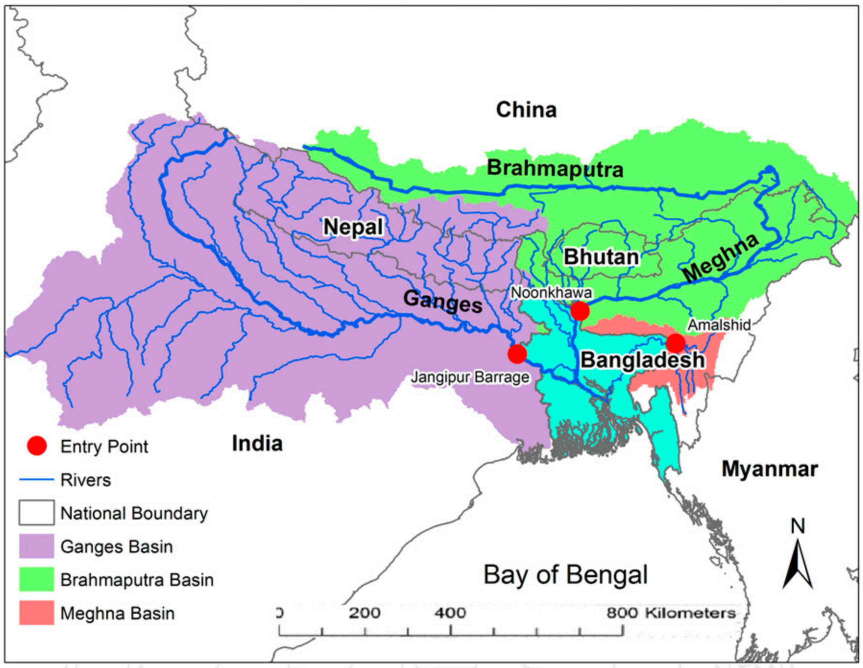

Figure 1. The Ganges–Brahmaputra–Meghna river basins of South Asia. The red circle indicates the location of entry points inside Bangladesh.

a long period in the Himalayas (Chowdhury and Ward 2004). In addition, elevations of the Vindhya Range in the south, at an elevation from 450 to 1100 m (Figure 1), contribute significant amount of orographic precipitation to nourish the southern tributaries of the Ganges–Yamuna system. After the Amazon and Congo Rivers, the GBM river system represents the largest freshwater outlet to the World Ocean (Chowdhury and Ward 2004).

Water resource management is the activity of planning, developing, distributing, and managing the optimum use of water resources (Biswas 2008). As such, water management therefore includes management of flood, drought, crop, and water quality. Among them, flood forecasting is probably more important for the GBM basin inhabitants, since it is relatively more devastating, particularly in the downstream regions, such as Bangladesh (Mirza 2003). To reduce vulnerability to water extremes (e.g., floods and droughts), access to basinwide hydrological data such as precipitation (rainfall and snow), river flow, river water stage, surface runoff, and soil moisture, especially from upstream nations of GBM, is very critical for effective water resources management.

The most reliable method of acquiring hydrological data has historically been through ground instrumentation. However, in situ monitoring stations have declined rapidly around the world, particularly for precipitation and streamflow measurement (Shiklomanov et al. 2002; Vörösmarty 2002). The ground observation network is also not dense in large parts of the world, and there is no universal way to collect and share streamflow worldwide on a real-time basis. The GBM

Fig(s). 1 live 4/C

basin is no exception. Hydrological data collection and sharing of that hydrological information among riparian nations are known to be fundamentally intractable issues (Bakker 2009; Balthrop and Hossain 2010). Because of the lack of basinwide hydrological data, whether it is real time or historical, water management at the basinwide scale has been quite challenging.

To address the absence of routine and basinwide hydrological data needed for water management, hydrological modeling of the basin has often been used as an alternative approach. Through such modeling, hydrological variables, such as runoff, infiltration rate, evapotranspiration, and streamflow, which are important for water management, can be routinely generated in a spatially distributed manner at the expense of equally routine but easier to measure meteorological forcing data (e.g., precipitation, wind speed, temperature). A hydrological model can yield information on water availability at closer space–time resolutions, where it is very hard to place gauges. Thus, a hydrological model can bridge gaps in in situ measurement as well as keep track of the terrestrial component of the dynamic water cycle.

As there is a general lack of in situ meteorological data availability for forcing a hydrological model, there is often a need to use the more widely available satellite-based forcing products (Gebregiorgis et al. 2012; Gebregiorgis and Hossain 2011, 2013; Hong et al. 2004; Khan et al. 2012; Nijssen and Lettenmaier 2004; Kamal-Heikman et al. 2007). Given the challenging size, scale, and makeup by five riparian nations with no mechanism to share hydrological or meteorological forcing data (Katiyar and Hossain 2007), satellite estimated data such as precipitation, temperature, and wind are likely to be the more realistic source for forcing a hydrologic model for water management.

Satellite-based geodetic and remote sensing platforms are increasingly common in collecting hydrological measurements (Brakenridge et al. 1994; Birkett 1998; Al-Khudhairy et al. 2001). The ability to collect data and monitor rivers by using satellite-based techniques is likely to become increasingly necessary. There are also satellite-based precipitation products like the Climate Prediction Center (CPC) morphing technique (CMORPH; Joyce et al. 2004; Joyce and Xie 2011), Precipitation Estimation from Remotely Sensed Imagery Using Artificial Neural Networks (PERSIANN; Hsu et al. 1997; Hong et al. 2004; Hsu et al. 2010), and Tropical Rainfall Measuring Mission (TRMM)-based 3B42RT (Huffman et al. 2010). There are also new satellite missions proposed for enhancing the availability of such hydrological data, such as precipitation [Global Precipitation Measurement (GPM) mission; Smith et al. 2007], streamflow [Surface Water and Ocean Topography (SWOT) mission; Alsdorf et al. 2007], and soil moisture [Soil Moisture Active and Passive (SMAP) mission; Entekhabi et al. 2010]. Fairly high spatial (0.25°) and temporal resolution (3 hourly) satellite precipitation data are already routinely available.

Integration of satellite remote sensing forcing data in GBM-scale hydrologic modeling is therefore worthy of exploration for water management for the inhabitants. For example, during flood management, remote sensing can provide information on flood extent, water stage, and surface runoff contributing to river flow in a cost-effective manner via distributed hydrological modeling (Nishat and Rahman 2009). In addition, remote sensing derived hydrologic modeling variables such as runoff, baseflow, and evapotranspiration (ET) are useful for water resources

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management. Such a large-scale hydrologic model, if it is spatially distributed, can overcome the key challenges to water resources management in the GBM basin.

Although a hydrological model can be a potential tool for simulation of water management variables (runoff and streamflow), good quality modeling at a continental scale spanning more than 1 million km^2 and five nations, such as the GBM basins, has not been reported in literature. To the best of our knowledge, the only GBM-wide hydrologic model currently in existence for water management is that reported by Nishat and Rahman (2009). Although the application of a hydrologic model provided the necessary platform for understanding the challenges of basinwide modeling for the GBM, the monthly simulation scale along with the lumped (at the subbasin scale) nature of the model used in Nishat and Rahman (2009) offered very limited potential for water management. On the other hand, the nearby basin of the Irrawaddy River has experienced water management with hydrological modeling. A reasonable agreement between simulated and observed streamflow at the Pyay station on the Irrawaddy River was reported by Chavoshian et al. (2007). The model-simulated streamflow was underestimated by 15% and 40% for high- and low-flow seasons, respectively. Satellite-based precipitation data (GPCP) were used along with other public domain available data such as global coverage topographic data land cover and soil types. Similarity between different catchments was analyzed to identify proxy catchment for transferring parameters. AU1 A parsimonious version of the Block-Wise Use of TOPMODEL (BTOPMC) hydrologic model was applied to simulate streamflow of the Irrawaddy River using the Mekong basin as a proxy. Shamsudduha et al. (2012) used two data sources (satellite gravimetric observations and hydrological modeling) for in situ groundwater table measurements for understanding annual water groundwater storage variations in Bangladesh.

In this regard, there are two scientific questions that motivate this study: 1) How well can we model the hydrological state variables for the GBM basin using a large-scale hydrological model forced with satellite meteorological datasets? 2) How can we advance the application of satellite datasets, notably precipitation, to improve the hydrologic modeling for decision making on GBM basin water management?

Our study therefore had two key objectives: 1) to develop, calibrate, and validate a macroscale, spatially distributed hydrologic model for the GBM basins and 2) to evaluate the performance of key satellite precipitation forcing datasets in a manner that can be useful for further improvement of satellite precipitation data development. In general, the GBM basin, like many other regions, is vulnerable to water resources availability that often manifests as shortage (drought or upstream and unilateral extraction by dams or diversion projects), excess (floods), and crop damaging natural disasters (cyclones and river flooding). Among various options to build resilience against this vulnerability, one of the most cost-effective strategies with a proven benefit-to-cost ratio is to institutionalize a near-real-time visualization system that can monitor and provide early warning of the potential changing dynamics of water cycle parameters as well as provide accurate postdisaster (or predisaster) assessment. For example, recent rural household surveys in Bangladesh have revealed that a doubling of the flood forecasting range from 3 to 7 days can potentially minimize losses further from 3% to 20% for the Bangladesh economy (CEGIS 2006). Such a comprehensive near-real-time visualization system could

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provide routine and early information to management agencies with a mandate for improving resilience against water-related vulnerability. This study on the development of a satellite data–based large-scale hydrological model for the GBM basins will therefore shed light on the improvements needed for hydrological modeling and satellite datasets for decision making.

The study is organized as follows: Section 2 provides a brief overview of the GBM basin hydrologic, terrain, land use/land cover (LULC), soils, and vegetation features followed by a basic description of the macroscale model used. Section 3 describes the calibration and validation of the hydrologic model. Section 4 presents the assessment of the skill of satellite precipitation data for basinwide hydrologic modeling of streamflow along with the potential underlying physical reasons for the skill. Finally, section 5 provides the findings and conclusions of this study and recommendation for future study.

2. The GBM basin, data, and hydrologic model

2.1. The river basins

The geographical location of GBM basin is between 21°68′ and 31°43′N and between 73°43′ and 97°68′E. The Ganges, Brahmaputra, and Meghna Rivers are the three major rivers in GBM basin. The Himalayan and Vindhya Ranges are the sources of these three rivers (Nishat and Rahman 2009). The area of Himalayas is F2 1.089 million km^2 and the highest elevation is 8848 m (Figure 2). The Himalayas are comprised of more than a hundred mountains exceeding 7200 m in height. Elevations of the Vindhya Range are from 450 to 1100 m.

2.2. Data

The following types of data were collected, processed, and analyzed for setting up the GBM basin model: 1) topographic data, 2) meteorological forcing data, 3) vegetation data, and 4) soil data. For topographic data, a digital elevation model (DEM) was created for the GBM river basins by collecting elevation data from the Shuttle Radar Topographic Model (SRTM) (http://www2.jpl.nasa.gov/srtm/dataprod.htm). The resolution of this DEM was 90 m. The elevation of GBM basins ranged from −37 to 8840 m (above mean sea level). The DEM of GBM basins is shown in Figure 2 (top). Using the SRTM DEM of GBM basins, the corresponding stream network was generated. The Arc Hydro software was used for this purpose. The generated stream network of the GBM basins is shown in Figure 2 (middle).

Precipitation data was collected from Global Summary of the Day (GSOD) of the U.S. National Climatic Data Centre (NCDC). This data source was augmented with data collected from the International Centre for Integrated Mountain Development (ICIMOD) located in Nepal. The daily precipitation data for the period of 2002–10 were collected for entire GBM basins. Stations with more than 50% missing data were discarded. The missing data were replaced with precipitation data provided by a newly quality controlled dataset called Asian Precipitation—Highly-Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE) that is built specifically for the Asian region

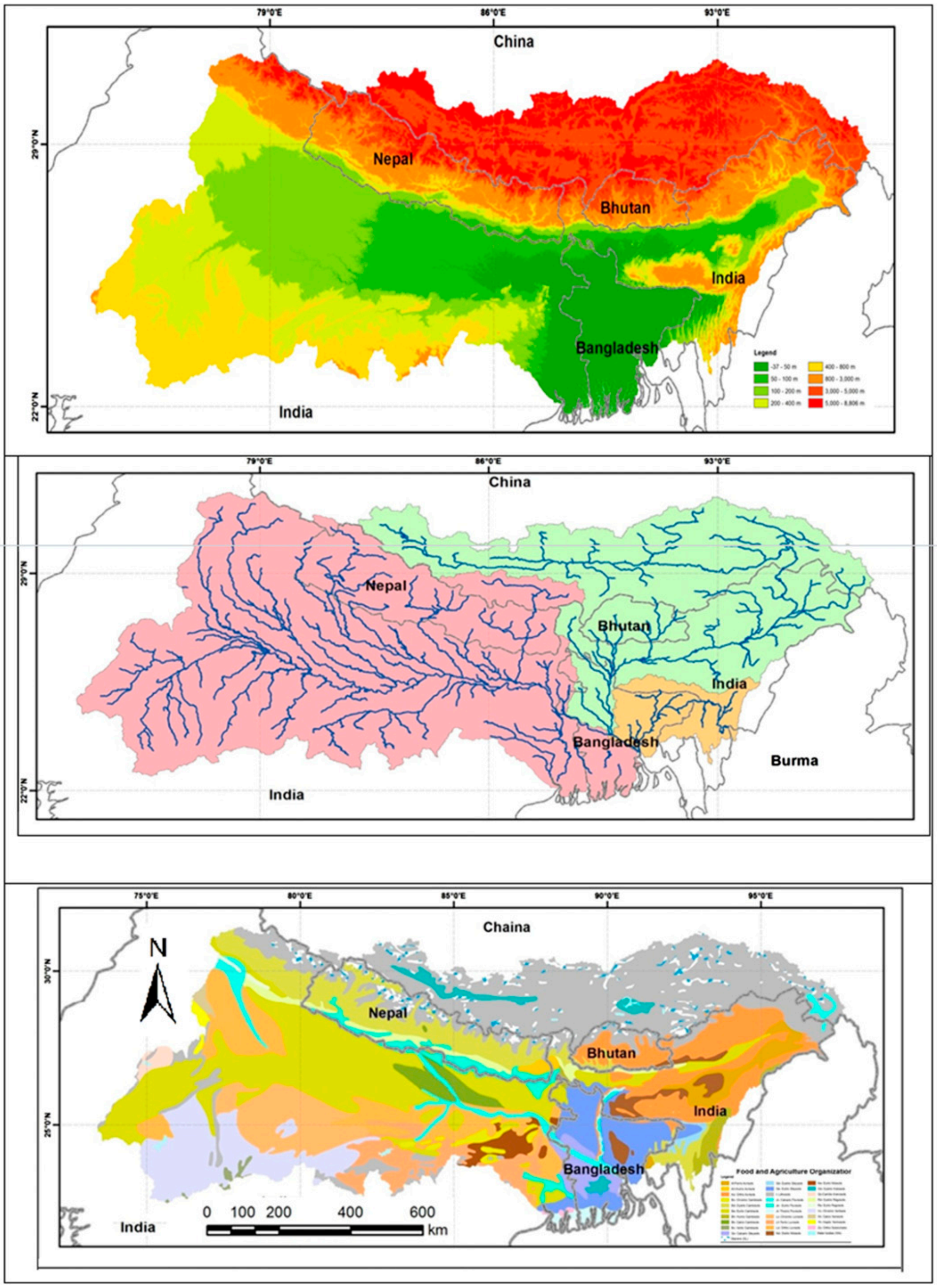

Figure 2. (top) Topographic map of GBM basin derived from SRTM elevation data, (middle) stream network of GBM basins derived from SRTM DEM data, and (bottom) soil type for the GBM river basins as obtained from the Food and Agriculture Organization. Maps are intentionally qualitative (no color coding) to represent the overall diversity in geophysical features.

(http://www.chikyu.ac.jp/precip/; Yatagai et al. 2012). However, APHRODITE datasets extend only up to the end of 2007 (at the time of writing this manuscript). Thus, the TRMM (3B42, version 7; Huffman et al. 2010) was used for replacing the F3 missing precipitation data from 2008 to 2010. Figure 3a shows the station locations used for in situ forcing precipitation data.

Daily temperature (maximum and minimum) and wind speed data were also collected from NCDC (http://gis.ncdc.noaa.gov) pertaining to 104 stations located within the GBM basins area (that registered less than 30% missing data). Snow depth data were from the Interim European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-Interim; daily, 1.5° resolution; http://data-portal.ecmwf.int/data/d/interim_daily/). Snow extent data were from Moderate Resolution Imaging Spectroradiometer (MODIS) data collected on board the National Aeronautics and Space Administration (NASA) *Terra* and *Aqua* platforms (8-day sampling and 500-m resolution). The snow depth data were resampled to the resolution 0.125° and 0.25° for integrated in the hydrologic model. Figure 3b shows the location of NCDC hourly weather stations. Vegetation data such as the leaf area index (LAI) are also important input to hydrologic model. The LAI data were obtained from *Terra* MODIS LAI and regridded to 0.125° and 0.25° grid cells for integration in the hydrologic model. Finally, soil type data were collected from Food and Agriculture Organization (FAO; http://www.fao.org/nr/land/soils/harmonized-world-soil-database/en/; Batjes 2009). In FAO, soil type data are available all over the world. This also included soil parameters such as porosity and saturated hydraulic conductivity, which are needed for hydrologic model parameter calibration. Figure 2 (bottom) shows the soil type for the GBM basins.

2.3. Hydrological model

The Variable Infiltration Capacity (VIC) model, first developed by Liang et al. (1994), was used as the macroscale distributed hydrological model. VIC is a large-scale, semidistributed macroscale hydrological model. It is capable of solving full water and energy balances. The basic structure of the VIC model is described in detail by Liang et al. (1994); many subsequent papers have described various updates to the model [e.g., Cherkauer et al. (2003) for cold land process updates, Andreadis et al. (2009) for snow model updates, Bowling and Lettenmaier (2010) for lakes and wetlands]. The model has been widely applied for purposes such as seasonal hydrological forecasting, climate change impacts studies, and water and energy budget studies, among various other applications. VIC's distinguishing hydrologic features are its representation of the role of subgrid variability as a control on soil water storage and in turn runoff generation and its parameterization of base flow, which occurs from a lower soil moisture zone as a nonlinear recession (Dumenil and Todini 1992).

The basic model features of VIC are as follows: 1) the land surface is modeled as a (lumped) grid of large (>1 km), flat, uniform cells; 2) inputs to the model are time series of daily or subdaily meteorological drivers (e.g., rainfall, snow, air temperature, wind speed); 3) land–atmosphere fluxes and the water and energy balances at the land surface are simulated at a daily or subdaily time step, and water

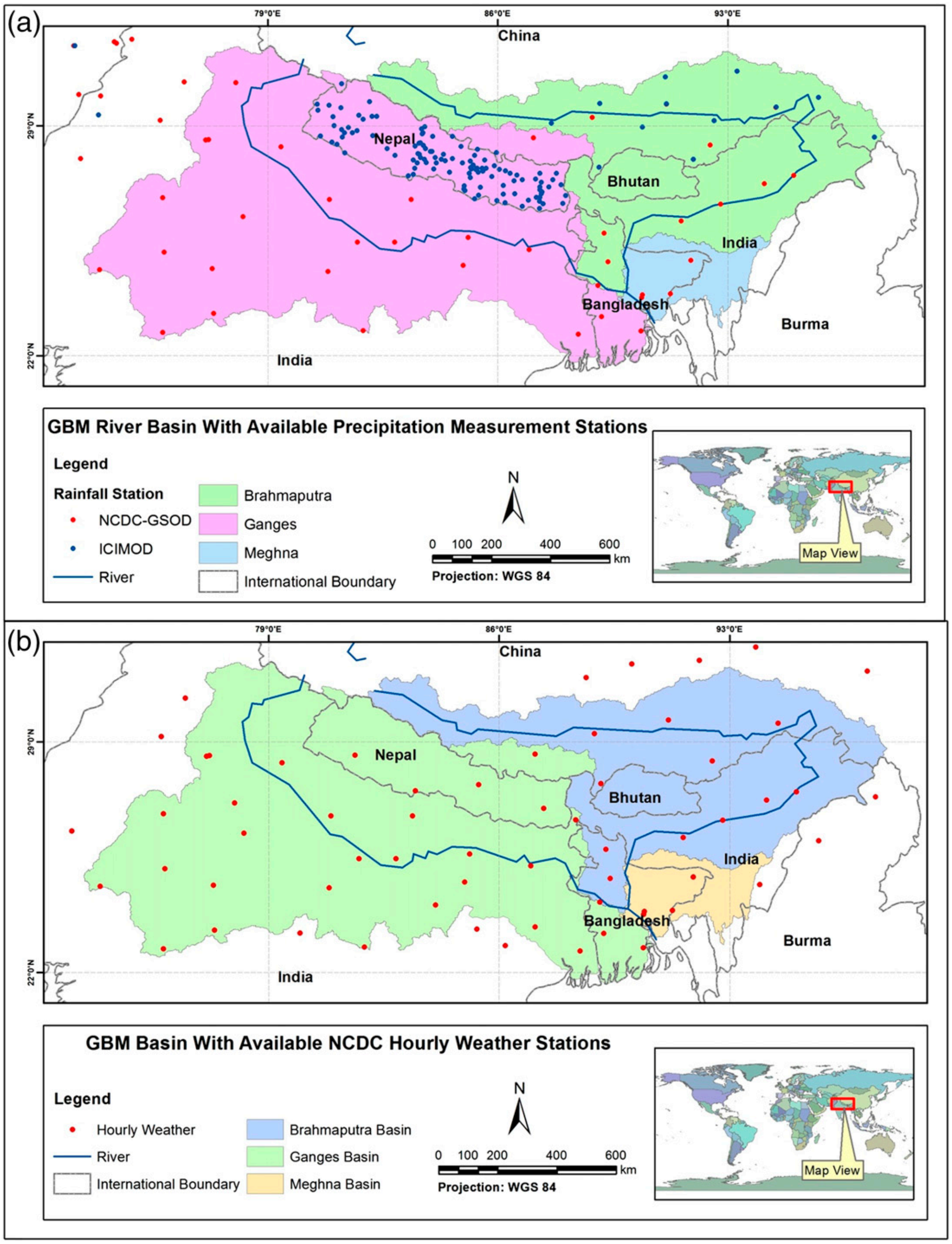

Figure 3. (a) Rainfall stations over GBM basins with available data from 2002 to 2010. (b) Meteorological stations with hourly weather data over GBM basin (source: NCDC).

Table 1. Model domain and resolution of the GBM basins.

Basin	Area (km^2)	Spatial resolution	No. of grid cells	Peak elevation (m)
Ganges	1 087 300	0.125°	5506	3892
Brahmaputra	552 000	0.250°	775	8848
Meghna	82 000	0.125°	467	600

can only enter a grid cell via the atmosphere; 4) grid cells are simulated independently of each other, and the entire simulation is run for each grid cell separately, one grid cell at a time, rather than for each time step, looping over all grid cells; and 5) routing of streamflow is performed separately from the land surface simulation, using a separate model [i.e., the routing model of Lohmann et al. (1998)]. As noted earlier, the model domain is the GBM basins of South Asia (Figure 3), composing a catchment area of 1.72 million km^2. Table 1 provides the area of each river basin, the gridcell size and the total number of grid cells.

3. Model calibration and validation

The model simulation period was divided into two parts: 2002–05 and 2006–10. The daily simulation period 2002–05 was used for calibration, while the period 2006–10 was used for validation (at daily time step). The GBM basin model-simulated daily streamflow data of all rivers corresponding to the gridcell outlet locations along the rivers. Figure 1 shows the locations of simulated streamflow data where rated streamflow data were available. The GBM basin model-simulated streamflow at Bahadurabad on the Brahmamputra River (known as Jamuna River inside Bangladesh) and Hardinge Bridge on the Ganges River are shown in Figures 4 and 5, respectively. It is evident from Figure 4 that the GBM basin model-simulated streamflow was underestimated at Bahadurabad on the Jamuna River. On the other hand, Figure 5 shows that the GBM basin model-simulated streamflow was overestimated during peak monsoon season at Hardinge Bridge on the Ganges River. Overall, the over- and underestimation pointed to the need for calibration and further model tweaking.

Among the VIC model parameters to be calibrated, the ones recommended are soil parameters such as variable infiltration curve parameter (b_infilt), fraction of the DSmax parameter (Ds), fraction of maximum soil moisture (Ws), Dsmax, and thickness of each soil moisture layer (depth). Based on published literature on the VIC model (see Liang et al. 1994; Cherkauer et al. 2003; Bowling and Lettenmaier 2010), these parameters are the most sensitive set requiring calibration. A set of parameters with different combinations were used for model simulation for sensitivity analysis for the years 2002–05. Based on the optimum value of streamflow [i.e., with minimum root-mean-square error (RMSE) in streamflow simulation], a corresponding set of soil parameters was set as calibrated. The calibrated soil parameters for the Brahmaputra and Ganges basins are shown in Table 2.

In addition to calibration of soil parameters (which, however, did not completely resolve the issue of over-/underestimation of streamflow simulation), model equations related to simulation of ET needed to be adjusted for bias for improvement of streamflow simulation. Results from the calibration period indicated that the GBM basin model had a tendency to simulate either unusually large or

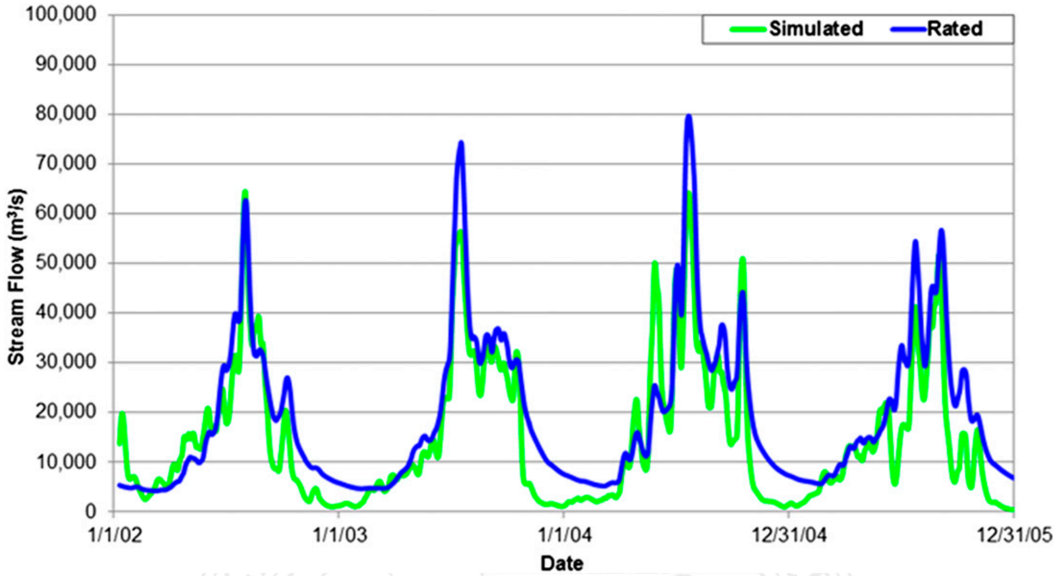

Figure 4. GBM basin calibrated model's simulation of streamflow at Bahadurabad of the Jamuna (Brahmaputra) River for the period of 2002–05.

small amounts of ET, potentially because of quality issues in the temperature, snow, and wind data and not the equation that estimates ET. This unusual ET estimation, either exceeding 80% or less than 10% of total precipitation, was found to lead to an overall underestimation or overestimation of streamflow, respectively,

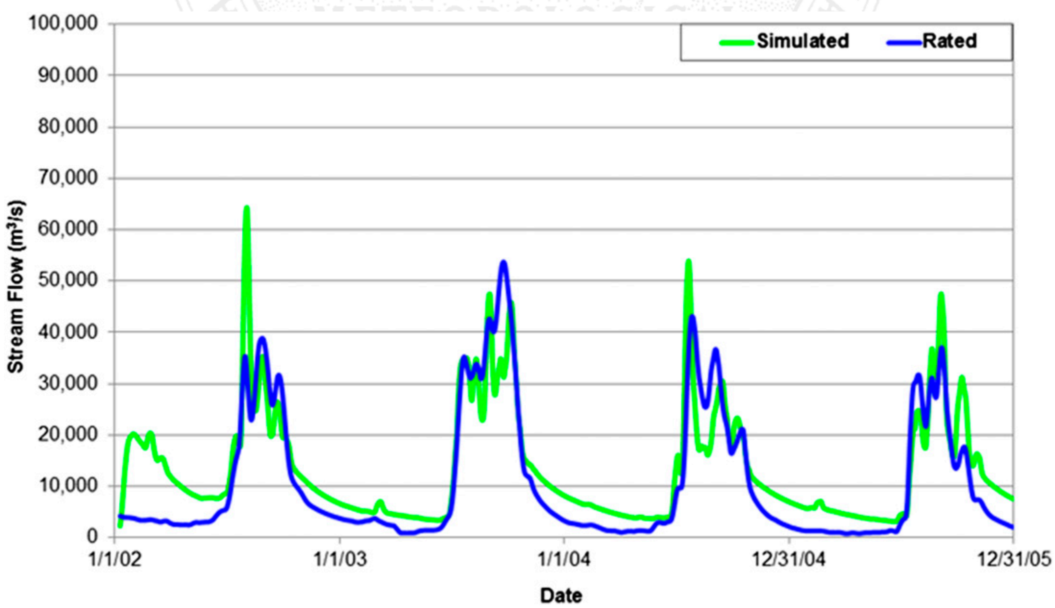

Figure 5. GBM basin calibrated model's simulation of streamflow at Hardinge Bridge of Ganges River for the period of 2002–05.

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Table 2. Calibrated soil parameters for the Brahmaputra and Ganges basins.

Soil parameter	Range used for sensitivity studies (manual optimization)	Calibrated value	
		Brahmaputra basin	Ganges basin
b_infilt	0.000 01–0.4	0.2	0.001 00
Ds (fraction)	0.001 to <1	0.001	0.123 45
Dsmax (mm day^{-1})	>0–30	11.51	1.790 10
Ws (fraction)	>0.5–0.9	0.90	0.123 45

because of the model's tendency for water balance. Thus, by applying a multiplicative correction factor to the ET equation, a significant amount of bias in ET estimation could be removed. It should be clarified here that such an adjustment of bias in ET (through the ET equation) is an "ad hoc" procedure to overcome the fundamentally intractable quality of input forcing data that we have no control of. Furthermore, and for the same reasons of input forcing data quality, we explored the impact of gridcell size on the simulation of accuracy of streamflow. The goal was to identify if a more representative gridcell size existed that would be more appropriate given the quality and scale of the input forcing data. We explored two gridcell sizes: 0.25° (25 km) and 0.125° (12.5 km). By exploring two different gridcell resolutions, more accurate simulation of streamflow was possible by assigning an appropriate gridcell size for each basin. Thus, ET applied a correction factor while each basin was investigated for the gridcell size that improved AU2 streamflow simulation accuracy [Equation (2)]. The model efficiency was used as a key performance criterion and was evaluated using the following equation:

$$\text{Efficiency} = 1 - (\sigma^2_{\text{error}}/\sigma^2_{\text{rated}}), \qquad (1)$$

where, Q_{sim} is model-simulated streamflow, Q_{rated} is rated streamflow, and σ is the standard deviation.

In the VIC model, the ET was calculated using the following equation with correction factor:

$$E = \text{ET Correction Factor} \times \sum_{n=1}^{N} C_n \times (E_{c,n} + E_{t,n}) + c_{N+1} \times E_1, \qquad (2)$$

Where E is the total evapotranspiration;

ET correction factor is the multiplication factor for adjusting ET;
C_n is the vegetation fractional coverage for the nth vegetation tile;
C_{N+1} is the bare soil fraction $\sum_{n=1}^{N} C_n = 1$;
$E_{c,n}$ is the evaporation from the canopy layer;
$E_{t,n}$ is evaporation from the vegetation tiles; and
E_1 is evaporation from the bare soil.

For reducing runoff over Brahmaputra basin of GBM basin model, a factor of less than 1.0 was used [because this basin produced an unusually high ET; see Equation (2)]. Sensitivity analysis of ET correction factor for Brahmaputra basin is T3 shown in Table 3. Based on model performance of GBM basin over Brahmaputra basin, an ET correction factor of 0.30 was found to minimize the RSME values for

Table 3. Quantitative analysis of GBM basin model during calibration for 2002–05.

Basin	RMSE ($m^3 s^{-1}$)	Correlation	Efficiency	Remarks
Brahmaputra	13 486	0.87	0.66	Without calibration
Brahmaputra	7606	0.91	0.84	Calibration, ET correction factor, and representative grid size
Ganges	7031	0.92	0.75	Without calibration
Ganges	6523	0.89	0.78	Calibration, ET correction factor, and representative grid size

simulation of streamflow. On the other hand, the GBM basin model overestimated streamflow at the Ganges basin. For the Ganges basin, the ET correction factor was therefore set to greater than 1.0 to increase runoff. Through sensitivity, it was found that an ET correction factor of 1.20 yielded minimum RMSE in streamflow simulation (Table 3). Using the calibrated soil parameters, representative gridcell size, and ET correction factor, the GBM basin model was validated for the period of 2006–10. The validation of the GBM basin model was made both qualitatively and quantitatively.

Qualitative analyses of GBM basin model-simulated and streamflow data were first made based on the visual inspection of the hydrographs at a particular location of the river. Figures 6 and 7 show the streamflow hydrographs for the Jamuna (Brahmaputra) at Bahadurabad station and the Ganges River at Hardinge Bridge, respectively. For the Jamuna River, the GBM basin model-simulated streamflow was in close agreement with rated (observed) streamflow data, with underestimation of the peaks. On the Ganges River, the model-simulated stream was overestimated during peak flows during the monsoon season (Figure 7). Overall, there was an agreement between simulated and rated streamflow data. Table 4 provides a summary the quantitative analyses of the calibrated GBM basin model during validation period using measures of efficiency, RMSE, and correlation.

4. Assessment of skill of satellite precipitation forcing data

4.1. General assessment of skill

Satellite rainfall data were used to run some specific model scenarios, since rainfall data are the key input for hydrological modeling. The hydrological model scenario run is referred to essentially as a hydrologic model being successively executed several times for the same period using a specific input dataset or a perturbation of a key variable state for each model run. In this study, two different rainfall data products were used to prepare meteorological forcing files as an input for GBM basin model scenario runs for the period of 2002–10. Furthermore, GBM basin hydrological model-simulated streamflow data using different rainfall data were analyzed with respect to rated streamflow data.

Scenario runs were performed using two different satellite rainfall data such as CMORPH (Joyce et al. 2004; Joyce and Xie 2011), and 3B42RT (Huffman et al. 2007). These scenarios are as follows:

(i) Scenario 1: GBM basins model is run using CMORPH rainfall data.

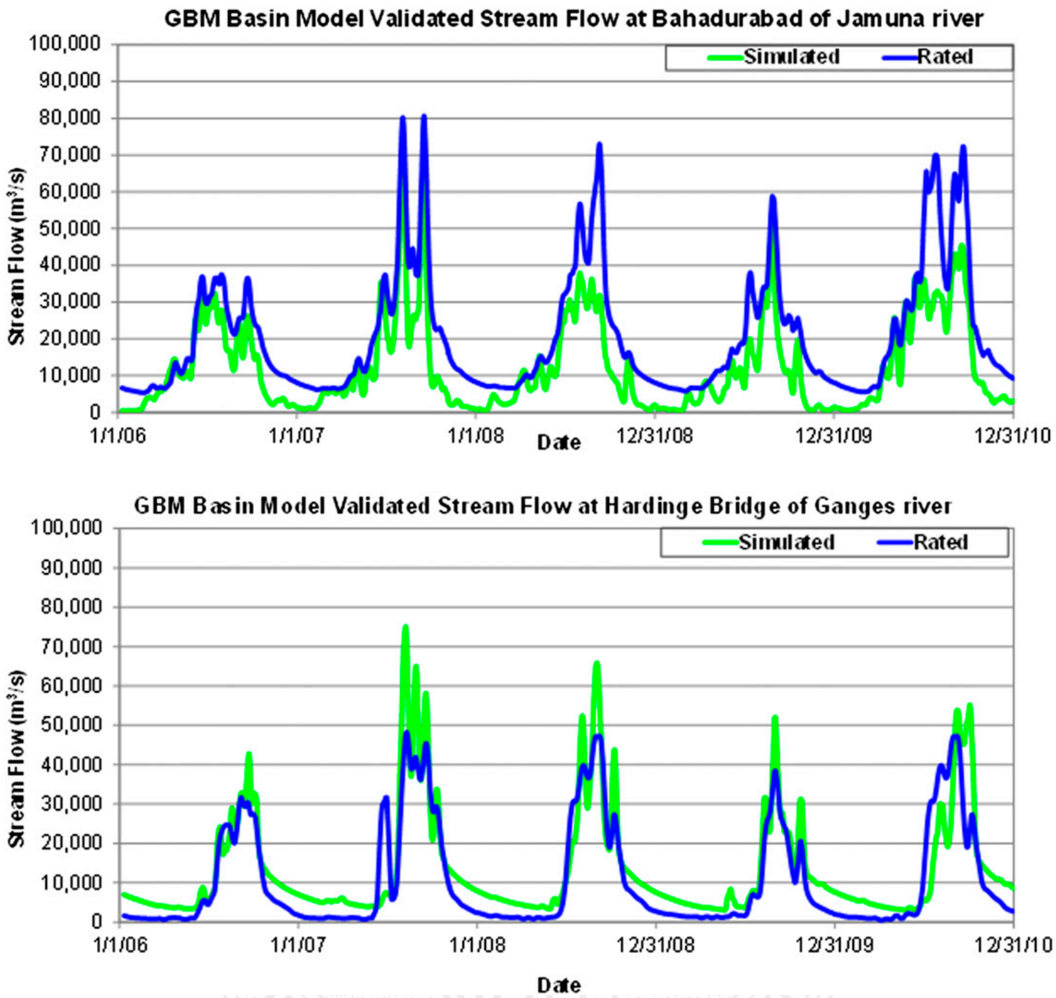

Figure 6. (top) Model-simulated (validated) streamflow at Bahadurabad of the Jamuna River for the period of 2006–10 and (bottom) model-simulated (validated) streamflow at Hardinge Bridge of the Ganges River for the period of 2006–10.

(ii) Scenario 2: GBM basins model is run using 3B42RT rainfall data.

Calibrated and validated soil parameters, gridcell size, and ET correction factors were used to run the model. For scenario runs, daily time series model simulations were performed for the period of 1 January 2002–31 December 2010. The performance of the GBM basin models was evaluated qualitatively and quantitatively. The GBM basin model-simulated streamflows along with rated streamflows at Bahadurabad of the Jamuna River and at Hardinge Bridge of the Ganges River are
F8 shown in Figures 7 and 8, respectively. Quantitative comparison was made based on RMSE, correlation, and efficiency of GBM basin models. These metrics are
T5 summarized in Table 5. For the Jamuna River, the GBM basin model-simulated

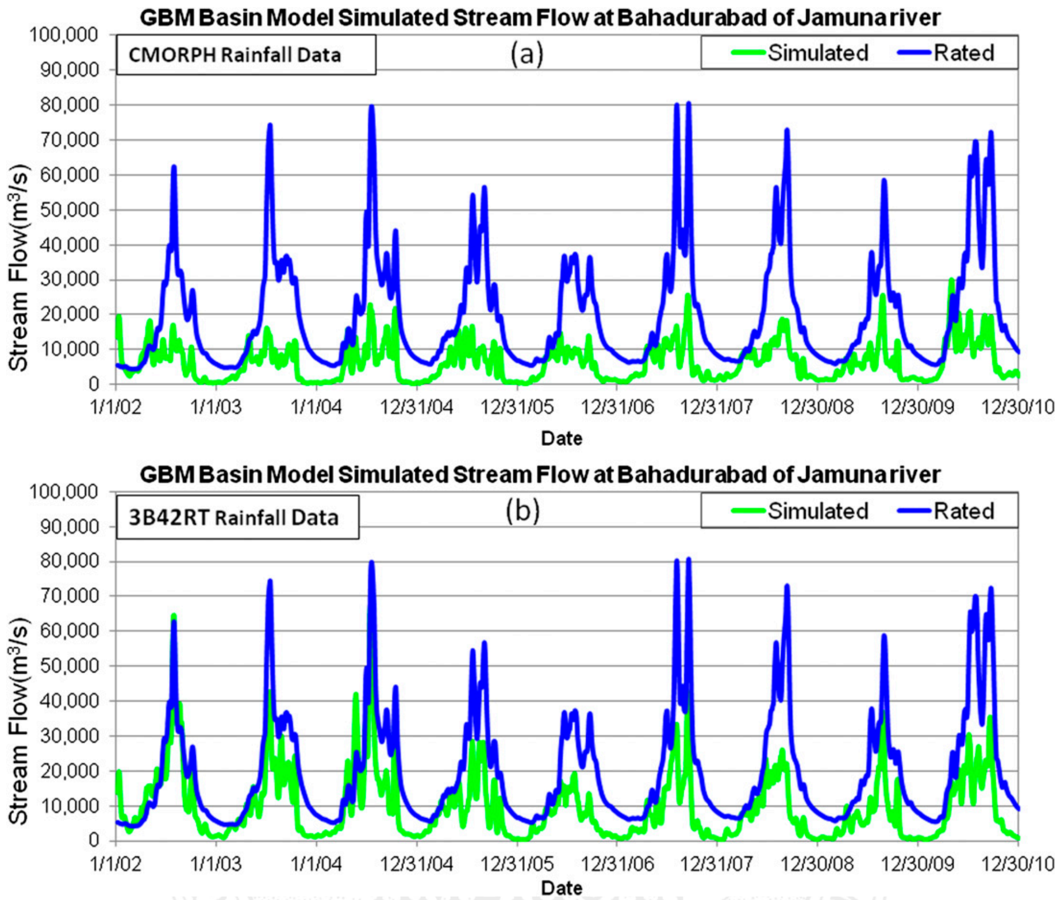

Figure 7. Simulated streamflow using (a) CMORPH satellite precipitation data and (b) 3B42RT satellite precipitation data at Bahadurabad station of the Jamuna River for 2002–10.

streamflow was in close agreement with rated streamflow data, with slight underestimation of the peaks (Figure 7). Although agreement was observed in the Ganges River, the model overestimated the peaks (Figure 8). The agreement between simulated and rated streamflow data using 3B42RT rainfall data was found for most part to be almost similar to that using gridded in situ data.

In the Brahmaputra and Ganges basins, a good correlation ranging from 0.65 to 0.80 was found between simulated and rated streamflow data for both satellite

Table 4. Independent validation of VIC model during the period of 2006–10. "Calibrated" is also inclusive of ET correction factor and representative grid size selection.

Basin	RMSE ($m^3 s^{-1}$)	Correlation	Efficiency
Brahmaputra (calibrated)	10 918	0.92	0.82
Ganges (calibrated)	7081	0.89	0.77

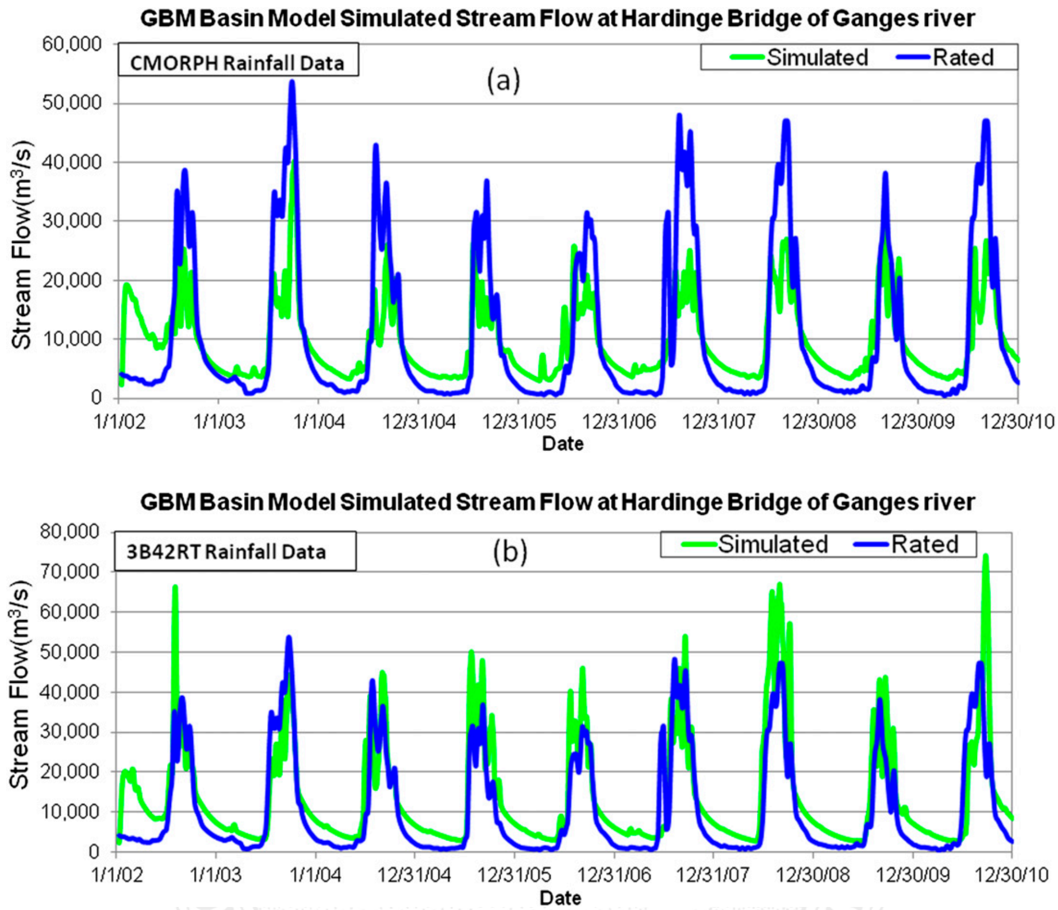

Figure 8. Simulated streamflow using (a) CMORPH satellite precipitation data and (b) 3B42RT satellite precipitation data at Hardinge Bridge of the Ganges River for 2002–10.

precipitation scenarios (3B42RT and CMORPH). This indicated that the satellite products have sufficient skill to follow the expected interseasonal hydrological trends. On the other hand, the GBM basin model yielded an efficiency [see Equation (1)] of 57% (for 3B42RT) in estimating the streamflow in the Brahmaputra basin while the efficiency was 61% (for 3B42RT) for the Ganges basin (Table 5). For CMORPH, the GBM basin model efficiency was 34% and 59% in the Brahmaputra and Ganges basins, respectively (Table 5). This less than satisfactory

Table 5. Quantitative analyses of GBM basin models for different scenarios.

Rainfall data	Basin	Gridcell size	RMSE ($m^3 s^{-1}$)	Correlation	Efficiency
CMORPH	Brahmaputra	0.25	18 675	0.70	0.36
CMORPH	Ganges	0.125	8167	0.85	0.61
3B42RT	Brahmaputra	0.25	14 399	0.80	0.61
3B42RT	Ganges	0.125	7976	0.85	0.69

efficiency for CMORPH could be attributed to the estimation uncertainty of satellite rainfall data over the Brahmaputra and Ganges basins. For both satellite precipitation scenarios, the overall efficiency was found lower in the Brahmaputra basin than the Ganges basin potentially because of errors in the high-elevation precipitation (snow) that dominate the surface runoff generation mechanism.

4.2. Skill assessment as a function of elevation

Skill assessment was made based on the monthly average rainfall for the satellite precipitation products from 2002 to 2010. The in situ rainfall data from National Climate Data Center (NCDC) or APHRODITE were used as a reference rainfall. Error analyses of satellite rainfall data were made spatially. In this study, the total error was defined as satellite rainfall minus reference rainfall (i.e., in situ for most part, except for 2008–10, when 3B42 V7 was used to fill missing values in station data). The rainfall error was broken down spatially for the Ganges and Brahmaputra basins in two elevation categories: (i) 0–1000 m and (ii) more than 1000 m. This was done to assess the effect of elevation for estimating rainfall products using satellite data (Gebregiorgis et al. 2012). The elevation categories were chosen to also assess the impact of orographic effect on satellite rainfall estimation. The average elevation of the Brahmaputra basin is relatively high (much greater than 1000 m). On the other hand, the average elevation of the Ganges basin is relatively low (less than 1000 m). A sample spatial rainfall error map (monthly error of F9 3B42RT rainfall data with respect to elevation at GBM basin) is shown in Figure 9.

Spatial rainfall error maps were generated for the two different satellite precipitation products from 2002 to 2010. For these two satellite rainfall products, high and low rainfall error was observed during the monsoon season (July–October) and the dry season (November–June), respectively. In general, during the monsoon season, both CMORPH and 3B42RT products underestimated the rainfall in the Brahmaputra basin, most likely because of the orographic effect in the eastern regions of the Brahmaputra basin. Another reason could potentially be the compounding effect due to extensive snow cover at higher elevations (Kamal-Heikman et al. 2007). Gebregiorgis et al. (2012) had earlier reported that most satellite precipitation products typically "miss" precipitation over regions with snow cover. Less runoff is therefore likely to be simulated for the two satellite products. Large positive rainfall errors are also seen in the Brahmaputra basin, which indicates the occurrence of false precipitation (i.e., satellite estimating a nonzero rain value for a nonprecipitating event). It is likely that this error (as false precipitation) first propagates to a soil moisture component until the soil column reaches its maximum holding capacity, after which the remainder of the positive error portion transfers to the runoff process as false runoff. The Ganges basin, however, yields relatively low rainfall error, which could be attributed to the lower elevation of the basin.

F10 F11 Figures 10 and 11 show observed and simulated hydrograph and hyetographs (accumulated) for the Jamuna and Ganges River stations (or basins), respectively, to infer the nature of error propagation. Streamflow is dependent on precipitation amount. In these figures, the yearly accumulated rainfall was plotted against rated and simulated streamflow to get the relationship between rainfall and streamflow. Figure 10 indicates that yearly average accumulated rainfall was found to be around

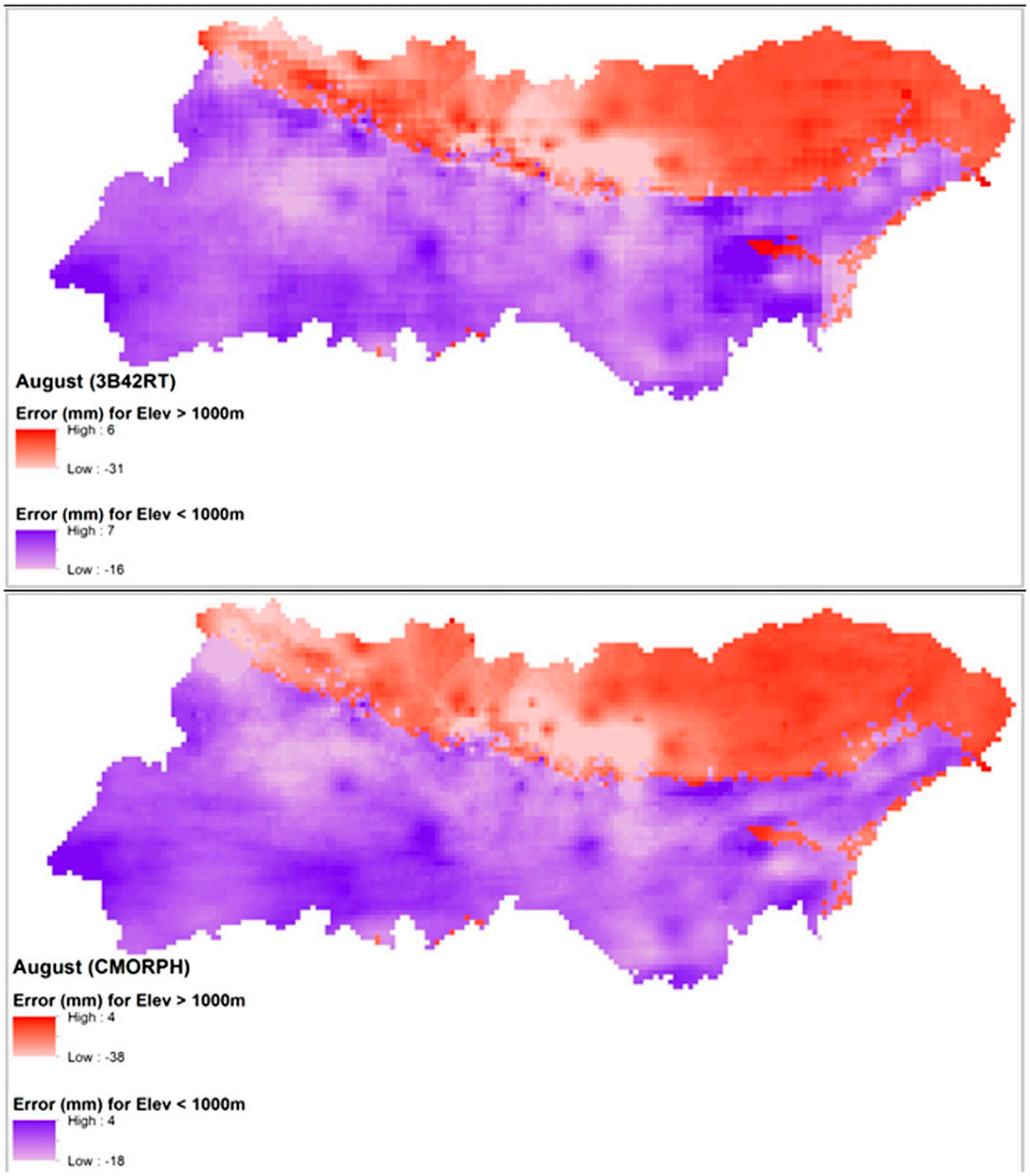

Figure 9. Climatologic precipitation error map for (top) 3B42RT and (bottom) CMORPH with respect to elevation divide (1000 m) at the Ganges, Brahmaputra, and Meghna basins for the month of August (averaged over 9 years).

1400 (CMORPH) and 1850 mm (3B42RT) for the Brahmaputra basin. On the other hand, the average daily simulated streamflow was found to be 6500 (CMORPH) and 9500 $m^3 s^{-1}$ (3B42RT) for this basin. For the Ganges basin (Figure 10), yearly average accumulated rainfall was 1450 (CMORPH) and 2000 mm (3B42RT). The average daily simulated streamflow was found to be 9700 (CMORPH) and 14 000 $m^3 s^{-1}$ (3B42RT) for this basin. For the Brahmaputra and Ganges basins,

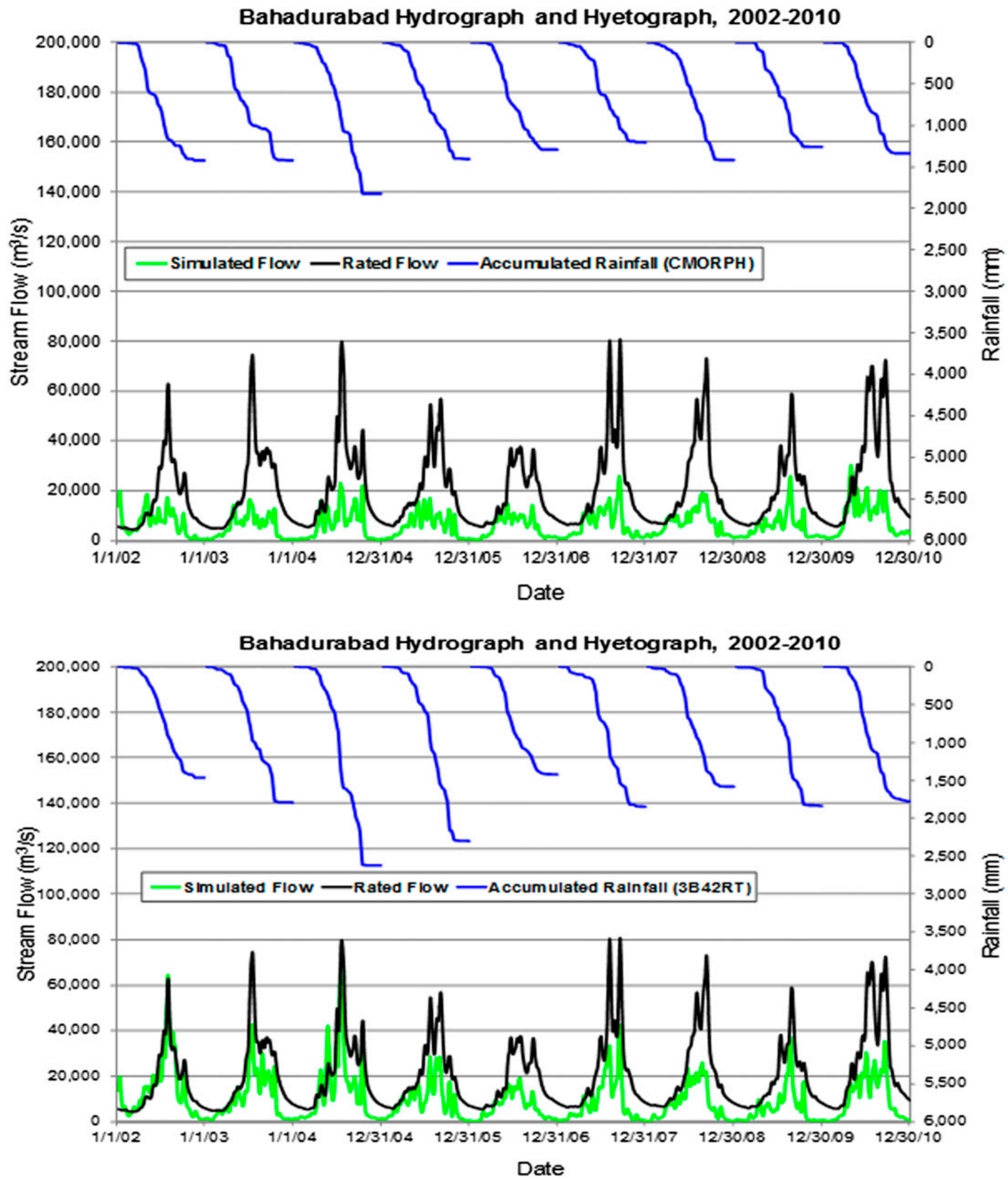

Figure 10. Bahadurabad (Jamuna River) rated (observed) and simulated hydrograph and hyetographs for (a) CMORPH satellite precipitation data and (b) 3B42RT satellite precipitation data during 2002–10.

the average daily rated (observed) streamflow at the Hardinge Bridge and Bahadurabad stations was observed to be 20 000 and 10 500 $m^3 s^{-1}$, respectively, which indicates that the climatologic mismatch in the satellite-simulated and observed flows ranges from 50% to 100%. The mismatch is considerably higher for the Brahmaputra basin.

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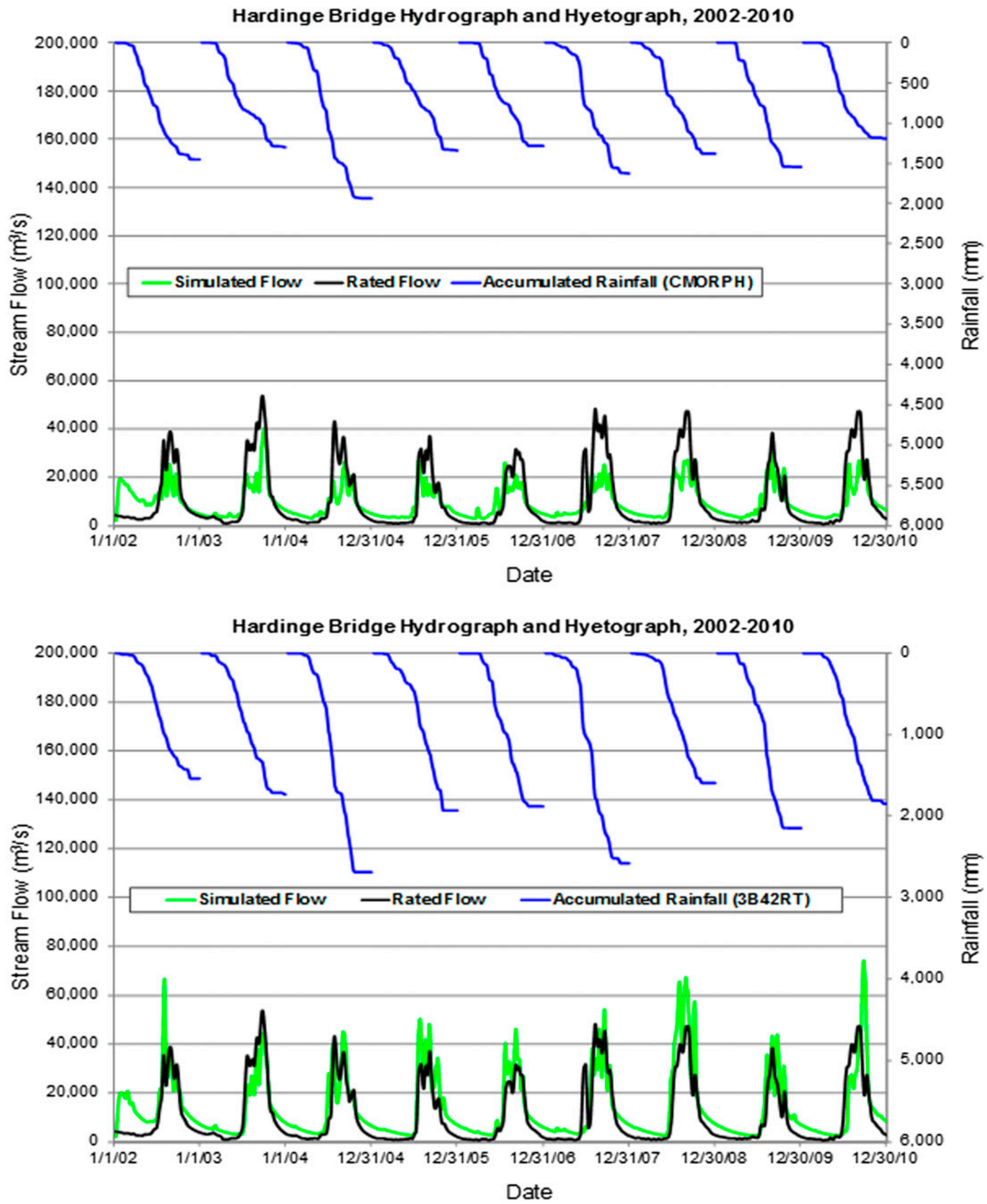

Figure 11. Hardinge Bridge (Ganges River) rated (observed) and simulated hydrograph and hyetographs for (a) CMORPH satellite precipitation data and (b) 3B42RT satellite precipitation data during 2002–10.

A more physical and detailed understanding of the uncertainty of satellite precipitation data (and its implication in hydrologic simulation of streamflow) is afforded by breaking down the error components into hit bias, false precipitation, and missed bias. These three error components are independent and add up

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to total bias of a precipitation product (Tian et al. 2009). Recently, Gebregiorgis and Hossain (2014b) performed a comprehensive assessment of precipitation products of APHRODITE and satellite platforms (3B42V7 and PERSIANN), where total bias and hit bias were found to be higher at regions of higher elevation. Future studies should look into such in greater detail to identify more ways of using precipitation data from various sources in a manner that yields more robust simulation of streamflow.

5. Conclusions

The VIC-3L distributed (grid based) hydrologic model for the Ganges, Brahmaputra, and Meghna (GBM) basins satisfactorily captured the streamflow dynamics in the lower reaches of rivers in Bangladesh. This model provided a platform for conducting various future studies, such as satellite rainfall error propagation, developing tools to improve precipitation estimation and to assess the skill of climate model forecast precipitation data.

The hydrologic modeling tool (VIC4.0.6) used for the simulation of streamflow is essentially a grid-based macroscale hydrologic model that solves full water and energy balances. The model requires a fairly good representation of the basins of study area. We hypothesize that some if not all of the errors in streamflow simulation are due to the fact that the model considers only grids of the basins that grossly approximate the natural terrestrial variability within a grid. In this study, only two gridcell sizes (0.125° and 0.250°) were considered for the GBM basin model. Therefore, these coarse gridcell sizes may have some negative influence on the fidelity of model forecasting. The following two issues are therefore recommended for future studies:

- GBM basin hydrologic model was calibrated and validated only at the downstream locations of the basin where rated streamflow data were available. Internal calibration (or nested calibration) at locations midstream and upstream of the rivers (in India) should be carried out to improve the model's predictability and achieve a better representation of the physical parameters.
- The effect of gridcell size needs to be addressed more accurately in the hydrologic model through a sensitivity analysis to identify a truly optimal and representative size that is compatible with the skill of the forcing data. In this study, only two scales were considered: 0.25° and 0.125°.

In conclusion, it is important at this stage to remind ourselves of the challenges of water management in the social and hydropolitical context of the GBM basins. There are three key issues that make the understanding of water availability and vulnerability very important for this region. First, around the year cropping to support the "green revolution" and food demand means that the fertile regions of GBM are never left fallow with three major growing seasons (e.g., spring–summer, summer–fall, and winter–spring). Consequently, this means that GBM basin crop production not only depends on the monsoon rains during summer–fall growing season but also is heavily dependent on the glacier melt and snow-fed groundwater (deep and shallow) during the nonmonsoon growing seasons (Byerlee 1992). Second, GBM regions, such as the low lying delta of Bangladesh, are most vulnerable to uncoordinated human activity in the upstream (higher elevation) regions, such as extraction, diversion, and dam impoundment of river waters (Mirza 2004; Mazumder 2004). Finally, frequent cyclones, accelerated sea level rise, and Himalayan glacier retreat currently undermine the water availability and food production in the GBM basins. Recent disasters highlighting this third point are the storm surge damages resulting from Cyclones Sidr (2007) and Aila (2009) over the Ganges basin.

For all the above reasons, the hydrological modeling effort presented herein using the spatially distributed VIC-3L hydrological model over the GBM basin is a first step toward a practical means to perhaps overcoming the fundamentally intractable issues of hydropolitics. The modeling technique should have a significant impact on the economics and well-being for the 630 million inhabitants in the region. Continuing improvement of hydrologic modeling and forecasting efforts in the region is therefore necessary.

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