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Research paper

Advancing river modelling in ungauged basins using satellite remote sensing: the case of the Ganges–Brahmaputra–Meghna basin

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ABSTRACT
River modelling is the process of simulating the water flow dynamics of a stream network against time-varying boundary conditions. Such river models are often an important component of any flood forecasting system that forecasts river levels in flood-prone regions. However, large river basins such as the Ganges, Brahmaputra, and Meghna (GBM), Indus, Irrawaddy, Salween, Mekong, and Niger in the developing world are mostly ungauged as they lack the necessary and routine *in situ* measurements of river bed depth/slope, bathymetry (river cross section), flood plain mapping, and boundary condition flows for setting up of a river model. For such basins, proxy approaches relying primarily on remote-sensing data from space platforms may be the only way to overcome the lack of *in situ* data. In this study, we share our experience in setting up the one-dimensional River Analysis System model of the Hydrologic Engineering Center over the stream network of the GBM basin. Good-quality *in situ* measurements of river hydraulics (cross section, slope, flow) were available only for the basin's downstream and flood-prone region, which comprises 7% of the total basin area. For the remaining 93% of the basin area, data from the following satellite sensors were used to build a functional river model: (a) Shuttle Radar Topography Mission to derive river network and adjust river bed profiles; (b) Landsat–MODIS for updating river network and flow direction generated by elevation data; (c) radar altimetry data to build the depth versus width relationship at river locations; and (d) satellite precipitation-based hydrologic modelling of lateral flows into major rivers. We measured the success of our approach by systematically testing how well the basin-wide river model could simulate river-level dynamics at two measured downstream low-lying locations. This paper summarizes the key hurdles faced and offers a step-by-step 'rule book' approach to setting up river models for large ungauged river basins around the world. By following these rules in a systematic way, the root mean squared error for river-level simulation was reduced from 3 to 1 m. Such a guide can be useful for setting up river hydraulic models for flood forecasting systems in ungauged basins such as the Niger, Mekong, Irrawaddy, and Indus.

Keywords: Rivers; hydrodynamic modelling; HEC-RAS; Ganges; Brahmaputra; Meghna; satellite remote sensing

1 Introduction

Modelling surface water that crosses international boundaries poses unusual challenges. There are around 260 transboundary lakes and river basins that cover more than 40% of the Earth's land surface and account for an estimated 60% of global freshwater flow (Wolf *et al.* 1999, Hossain *et al.* 2014). Among these, the Nile, Niger, Mekong, Indus, Irrawaddy, Ganges, Brahmaputra and Meghna (GBM), Salween, and Zambezi river basins host some of the world's largest population centres (Figure 1; Vörösmarty *et al.* 2009). Differences in ground network coverage (Hossain and Lettenmaier 2006), monitoring protocols, data recording and sharing, and lack of resources (Balthrop and Hossain 2010) heighten the challenge for coordinated surface water modelling in these river basins (Akanda 2012). Flood forecasting is a major application that often suffers from this lack of basin-wide coordination of surface water modelling for downstream flood-prone regions (Katiyar and Hossain 2007). The forecasting of transboundary flooding in nations downstream of these basins remains notoriously difficult, using conventional modelling approaches that rely on extensive and real-time *in situ* data (Hossain *et al.* 2014).

A perfect example of a flood-prone downstream nation that has an urgent need to enhance its flood forecasting is Bangladesh (Hopson and Webster 2010, Hirpa *et al.* 2012). This country has an extensive river network and is located in the confluence zone of the Ganges, the Brahmaputra, and the Meghna rivers. Each year, Bangladesh faces devastating floods caused primarily by

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swelling of rivers from increased runoff upstream during the monsoon season. The heavy monsoon rainfall during the months of July, August, and September over the vast catchment area, most of which (93%) lies outside the country, is one of the major causes of this transboundary flooding inside Bangladesh. A country such as Bangladesh has little control over the flows of its own transboundary rivers as most of it is generated and regulated upstream by upstream nations. Thus, Bangladesh has limited ability to predict upstream boundary conditions of river levels for a flood forecasting domain, and is unable to accurately forecast floods further downstream.

This situation is not unique to Bangladesh. The flood forecasting problem can be generalized for most of the downstream nations in humid river basins where *in situ* data network, monitoring protocols, and sharing among riparian nations are largely absent (Figure 1; Hossain and Katiyar 2006). In fact, we can conceptualize the river (surface water) modelling problem for downstream and flood-prone nations of large river basins using the schematic shown in Figure 2. In the upstream region, the sources of the river flow are typically snow-capped mountains and glaciers (or a lake). Typically, snow-capped mountains and glaciers have negligible contribution to surface water dynamics at most downstream regions. However, for the rest of the vast regions encompassing the foot of the mountains all the way to the upstream edges of the downstream flood-prone region, the flood behaviour remains ungauged. Yet this vast region needs to be modelled accurately so that the flow entering the downstream flood-prone region can be predicted.

Over the last few decades, *in situ* gauge measurements have been considered as the only available technique to understand the global surface water resources. Frequent measurement of river stage is relatively common for the developed world's river basins. However, stream gauge sites in developing countries are much sparser and less routinely available (Alsdorf *et al.* 2007). Even if we make the assumption of a dense network of gauges for stream flow (river level) measurements in the river network, it is unlikely that the flood forecasting problem for flood-prone deltas in the developing world would be resolved. First, availability of the *in situ* records in real time would likely be highly limited. Second, the *in situ* gauge measurement technique has significant limitations and drawbacks in capturing flow over flood plains and wetlands and involves installation and maintenance costs (Matthews and Fung 1987, Prigent *et al.* 2001, Alsdorf and Lettenmaier 2003).

There are now solutions to the lack of *in situ* measurements in such ungauged basins. Two such approaches have become popular: (1) satellite-based surface water estimation, and (2) use of a hydrodynamic–hydrologic modelling frame work (Siddique-E-Akbor *et al.* 2011). Space-borne estimation of surface water not only overcomes the political boundary issue, but can also introduce cost-effective methods of prediction in ungauged basins around the world. Incorporating satellite-based surface water estimation into representative hydrodynamic–hydrologic model to simulate river levels (hereafter called 'river model') can address the flood forecasting problem in transboundary river basins (Schumann *et al.* 2009). Over the last decade, significant advancement has been made in identifying flood inundation extent using various sensors to evaluate the performance of river models in sparsely gauged or ungauged basins (Brakenridge *et al.* 2007). Use of space-borne radar altimeters can measure river-level elevation (Birkett 1995, 1998, Frappart *et al.* 2006, Schumann *et al.* 2009). Another remarkable advancement of satellite-based flood extent estimation involves microwave radar (Synthetic Aperture Radar), which can penetrate cloud and vegetation and provide a useful land–water mask to validate hydraulic models (Lee *et al.* 2009, 2010, Schumann *et al.* 2009, Sikder and Hossain 2014). In particular, the planned Surface Water and Ocean Topography (SWOT) wide-swath radar interferometric altimetry mission (Pavelsky *et al.* 2014) will provide both the width (inundation or water extent) and height of river simultaneously as an elevation map for the first time. This mission, which is due for launch in 2020, will represent a fundamentally unique source of satellite-based surface water measurement considered very crucial for model calibration and assimilation.

The key to improving flood forecasting in downstream nations of transboundary basins is to set up a river (hydrodynamic) model to improve the upstream boundary conditions of the forecasting domain. Modelling of river flow and water level often involves the use of physical models that solve the fundamental laws of mass conservation, momentum and energy in a numerical scheme using finite step lengths and time steps. While most models currently available simulate essentially the longitudinal (along flow direction) dynamics (as 1D), there are many models available that also solve for the interactions with flood plains (2D). Currently, there are a wide variety of river models (alternatively called hydrodynamic models). Any interested reader should refer to Jia and Wang (1999) or Horritt and Bates (2002) among many other sources for more information on river models. In all such models, boundary conditions need to be specified upstream and downstream of the modelling domain containing the river network so that the model can solve iteratively the time- and space-varying water-level conditions along the river reach of the network. Solving a river network is analogous to solving for a pipe network using energy loss equations. However, often times it may be necessary to calibrate additional parameters such as roughness of the river bed and floodplains and expansion/contraction loss coefficients in widening or constricting rivers. River modelling also requires information on river bathymetry, which is the geometric shape of the river cross section along a river reach. Overall, there is a significant amount of data required to prepare a river model for simulation of flow dynamics inside the river network. In the conventional set up of models, such data are obtained through measurement or from field studies or inferred from proxy approaches. For example, bathymetry needs to be measured frequently using techniques such as sonar or using a simple gage. When not available, one has to often 'assume' cross section

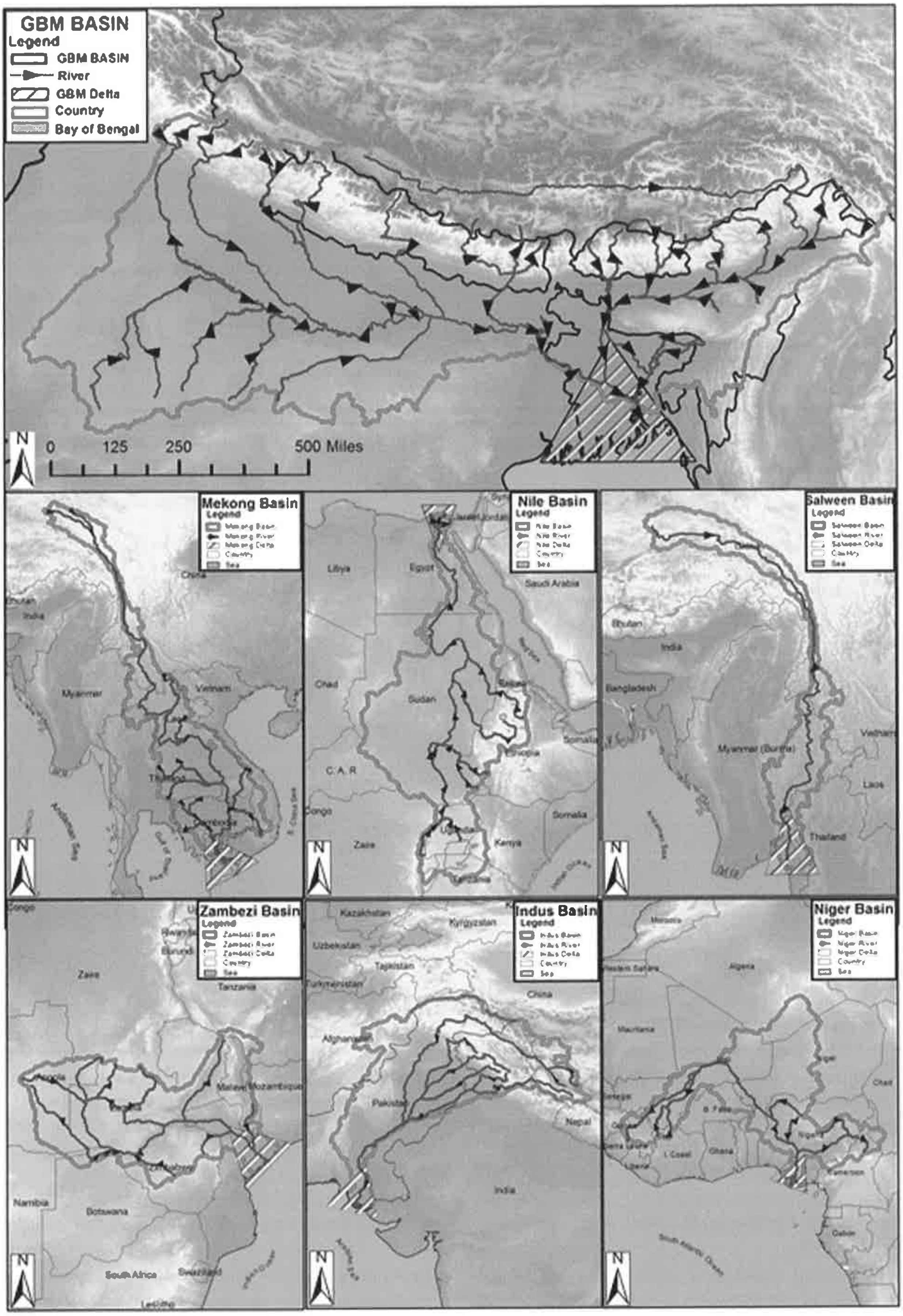

Figure 1 GBM basins and similarly ungauged river basin around the world showing the major river network, delta (flood-prone region) and flow direction.

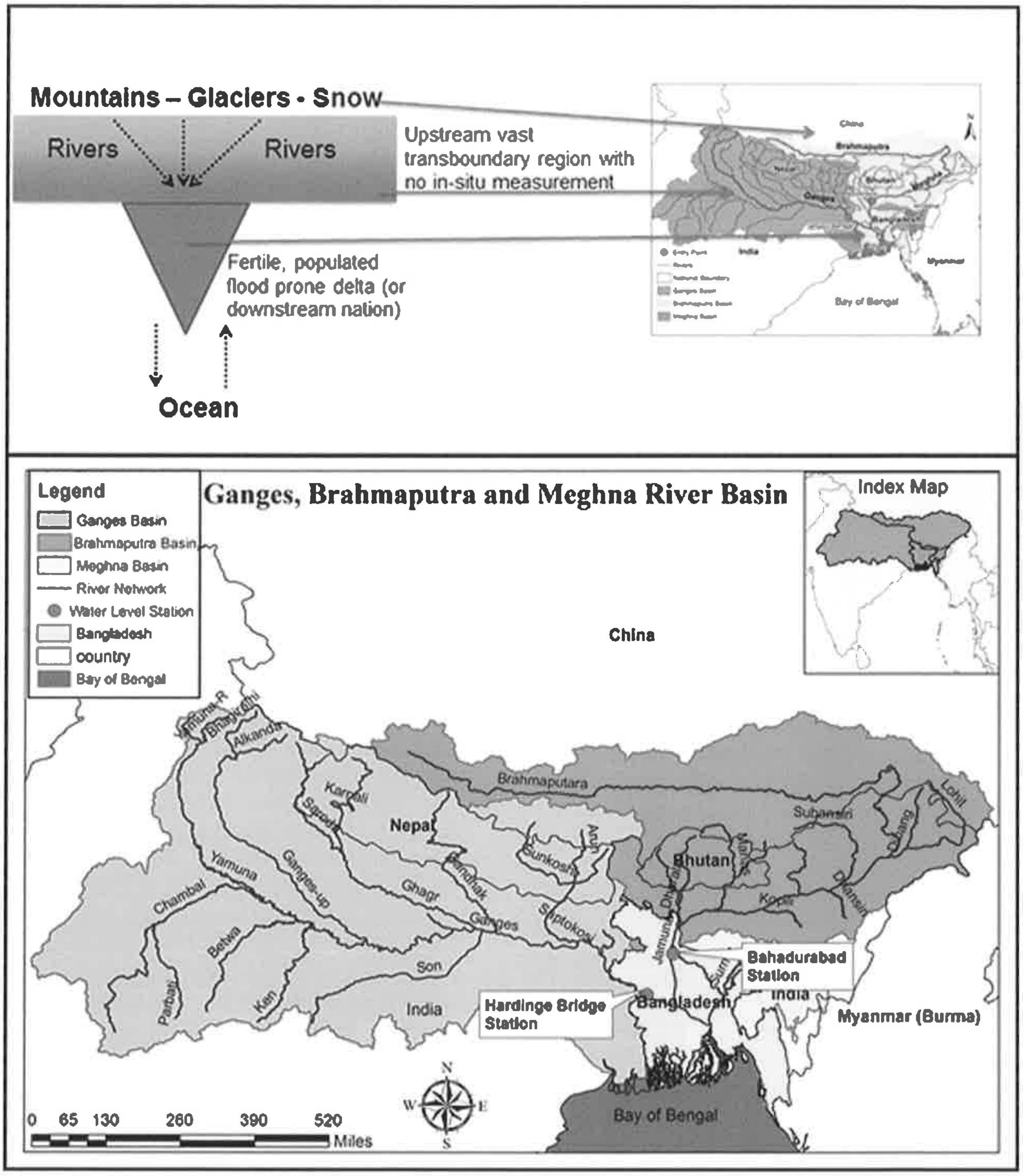

Figure 2 Upper panel shows the conceptual flood forecasting problem in flood-prone downstream nations in large and ungauged transboundary basins. The lower panel shows similar scenario for the GBM basins. The rectangular region (upper panel) of the conceptual schematic represents the vast ungauged region. The interface between the delta and the upstream region is where flow conditions are required from a river model to initialize a flood forecasting system (shown as red circles). The real-world example of GBM basins and Bangladesh is shown on the lower panel and can be conceptualized for Mekong, Irrawaddy, Salween, and Indus (see Figure 1 lower panels).

based on the available literature on the rivers, which can lead to large errors in modelling.

Given that the set-up of such a river model using conventional data sources (from *in situ* networks) is virtually impossible in Mekong, GBM, Indus, Irrawaddy, Salween, Niger, and Zambezi basins, there is a need to explore 'proxy' approaches involving indirect estimates. In this study, we attempted to find out: *To what extent can we advance river modelling in these basins using alternate data sources such as models and satellite platforms over the ungauged regions?* We summarize our findings as a modelling exercise and as a step-by-step rule book (or guide) for modellers and forecasters of other river basins to adopt. We document our experience in setting up the one-dimensional River Analysis System (RAS) model of the Hydrologic Engineering Center (HEC; http://www.hec.usace.army.mil/software/hec-ras/documents/hydref/) over the stream network of the GBM basin. Good-quality *in situ* measurements of river hydraulics (cross section, slope, flow) were available for the downstream and flood-prone region, which comprises only 7% of the total basin area. For the remaining 93% of the basin area, we used data from satellite sensors. We measured the success of our approach by systematically testing how well the basin-wide river model could improve the simulation of river-level dynamics at two measured downstream locations inside Bangladesh. In the next sections we describe the study region, data (*in situ* and satellite), and river model. Then we present the methodology and findings of each step for implementing a satellite-based solution. Finally, the last section summarizes the findings and provides conclusions.

2 Study area

The GBM basin constitutes the study region. The annual average flow of the Ganges, Brahmaputra, and Meghna rivers is about 12,120, 19,200 and 3510 m^3/s, respectively (Parua 2003). During the monsoon season, the combined flow of the Ganges and the Brahmaputra exceeds a combined discharge of 100,000 m^3/s and consequently inundates up to 80% area of the country. With a view to minimizing the damage caused by such floods, Bangladeshi authorities have developed a deterministic forecast technique using river discharge data collected at the India–Bangladesh border at Hardinge Bridge on the Ganges and Bahadurabad on the Brahmaputra and other staging stations within Bangladesh (Webster *et al.* 2010).

3 Data

Data used in this study can be divided into two categories – *in situ* (ground-based) and satellite-based. *In situ* data comprised river-level monitoring (and rated discharge) at two upstream boundary points – Bahadurabad and Hardinge Bridge – of the Brahmaputra and Ganges Rivers, respectively (Figure 2). In this study, the river model developed and verified by Siddique-E-Akbor *et al.* (2011) for the major rivers of Bangladesh was used as the starting point (i.e. base model) for scaling up to the entire GBM basin. What we mean by 'scaling up' is that the upstream components of the river network necessary for setting up the model were also constructed using proxy information and then combined with the downstream part comprising the base model. This resulted in a more complete river model for the entire river system. The base model consisted of Ganges, Jamuna, Old Brahmaputra, Surma, Padma, and Meghna (estuary), for which the HEC-RAS model had already been set up. A total of 226 river cross sections were incorporated in this base model. The Public Works Datum of Bangladesh, which is 0.46 m below the Mean Sea Level, has been used to reference the river bed-level bathymetry (Siddique-E-Akbor *et al.* 2011). This base model was extended to the entire GBM basin area, which was the key target of this study.

The main satellite data comprised the following: (a) Shuttle Radar Topography Mission (SRTM) for deriving river network and flow direction; (b) Landsat–MODIS (Visible) for updating river network and flow direction generated by elevation data (note: resolution of Landsat and MODIS images are 30 and 500 m, respectively); (c) radar altimetry data to build depth versus width relationship at river locations in ungauged regions and to test modelled derived river heights; (d) satellite precipitation data for hydrologic modelling of lateral flows into the major rivers of the river model. SRTM was an 11-day mission in the year 2000 that captured elevation data on a near global scale to generate the most complete high-resolution digital topographic database of Earth to date (http://srtm.usgs.gov/mission.php). In our study, the 90 m × 90 m (3 arc seconds) resolution Digital Elevation Model (DEM) images produced by SRTM were mosaicked together for the GBM basin area. Landsat (name indicating LAND + SATellite) is one of the longest running enterprises for the acquisition of high-resolution satellite imagery of the Earth surface in the visible and near infrared wavelengths. Landsat images can be converted to land–water masks, which can then facilitate the accurate delineation of multiple streams, braided bars, and flood plains. Consequently, the data are useful for estimating various hydraulic parameters (Woldemichael *et al.* 2010). In this study, Landsat-7 images have been processed to generate a land–water classification mask for the entire GBM basin.

With the advancement of satellite technology, radar altimetry now provides a promising technique to directly measure stage variations in large rivers (Birkett 1998). In our study, Envisat-satellite-based water-stage data were processed for selected locations of the GBM basin. Envisat data were collected at 15 locations for 2002–2010. For hydrologic modelling of rainfall runoff transformation, National Climatic Data Center of USA's Global Summary of the Day precipitation data and satellite precipitation data were used as key forcing variables. Precipitation data ranging from 2002 to 2010 were collected for the entire GBM basin for modelling of rainfall–runoff transformation and lateral flow contribution to the river network.

4 Model

Two types of models have been applied in this study. One is hydrodynamic for river modelling, while the other is hydrologic for lateral flow simulation from rainfall–runoff processes in the ungauged regions. The river model used was HEC-RAS (version 4.1.0) because a comprehensive version already existed as the starting base for the downstream region of Bangladesh (Siddique-E-Akbor *et al.* 2011). HEC-RAS, which stands for

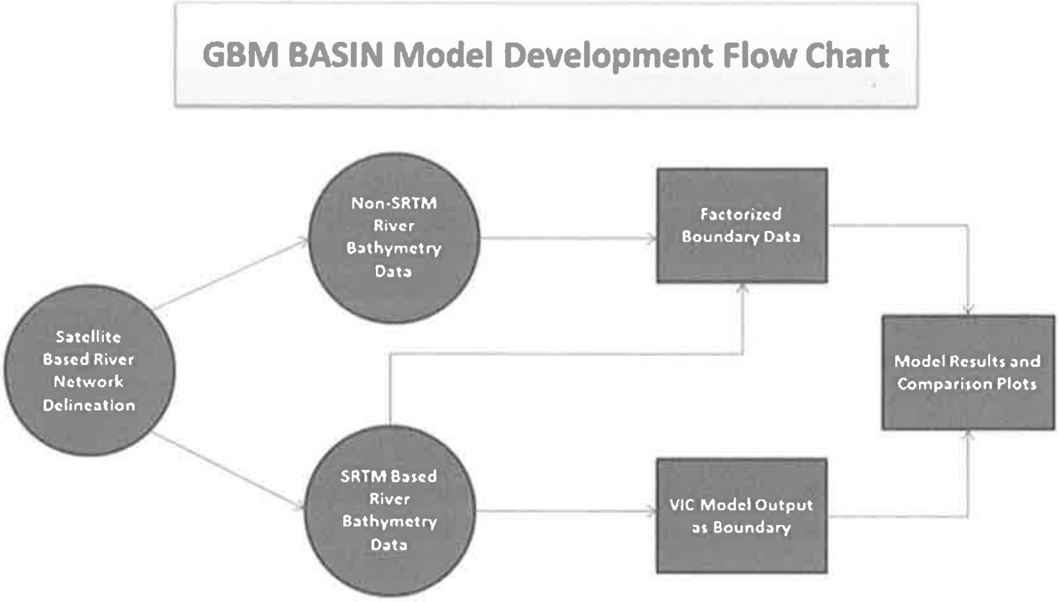

Figure 3 The flow chart showing the GBM basins river model development work.

Hydrologic Engineering Center River Analysis Software, was developed by U.S. Army Corps of Engineers. This software allows hydraulic calculation of rivers' flow for one-dimensional steady and unsteady conditions (Siddique-E-Akbor *et al.* 2011). It consists of four modules: steady flow water surface profile, unsteady flow simulation, sediment transport/movable boundary computation, and water quality analysis. The goal was to 'expand' this RAS set-up to the rest of the basin so that the water levels at the boundary conditions of Bahadurabad and Hardinge Bridge (Figure 2) could be better predicted from upstream conditions. The model computational strategy is based on the solution of a one-dimensional energy equation.

The Variable Infiltration Capacity (VIC) Model was used as the hydrologic model for rainfall–runoff modelling transformation and simulation of lateral flows in the RAS river model. VIC is an open-source macro-scale semi-distributed

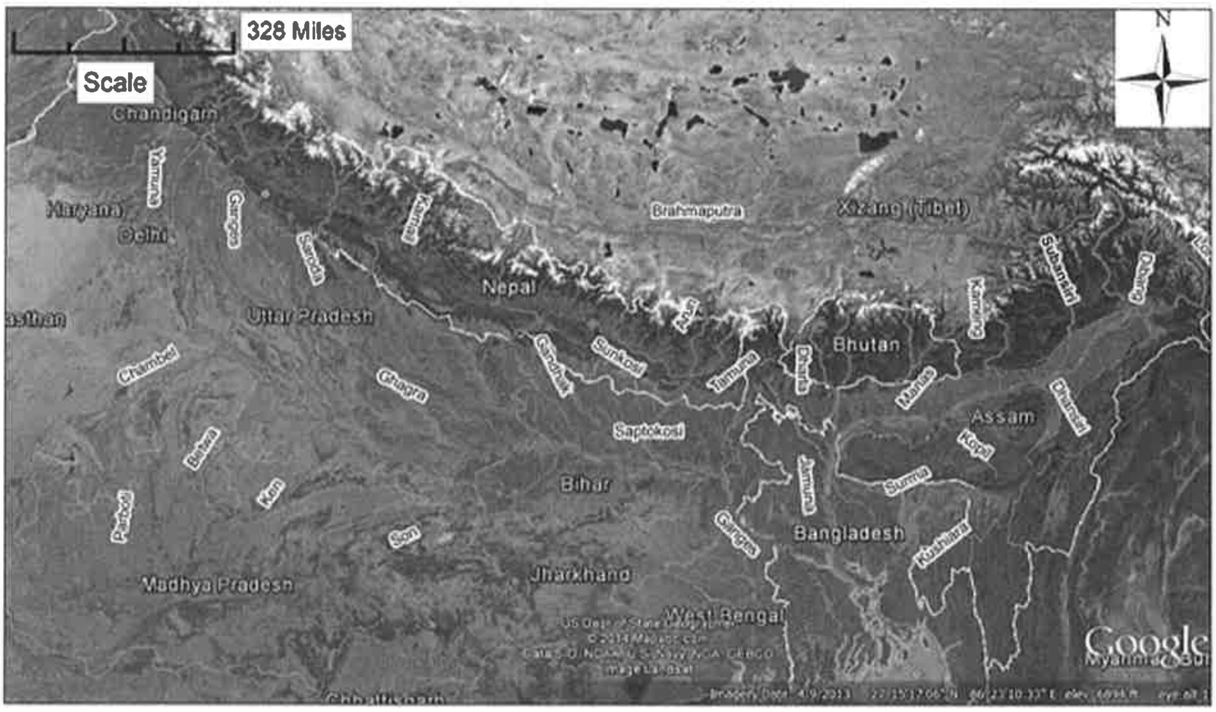

Figure 4 Digitized river network for the entire GBM basins used in HEC-RAS river model.

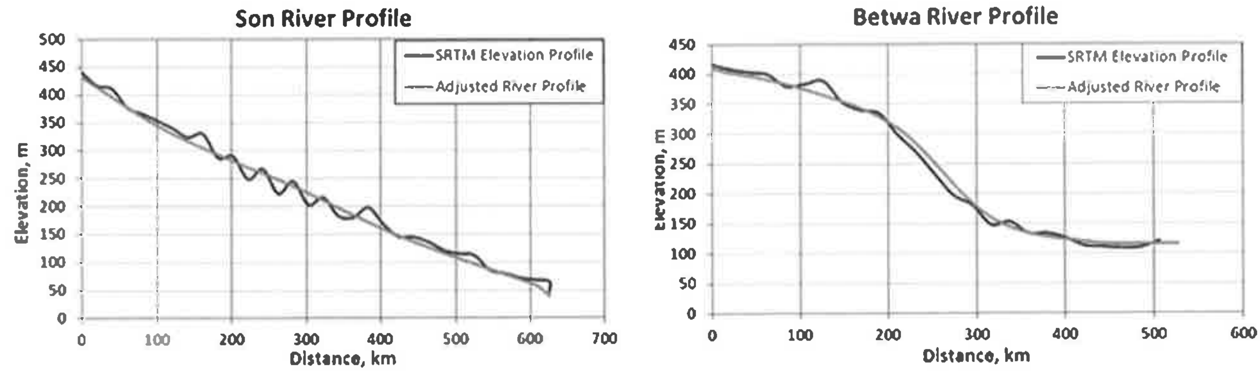

Figure 5 Example of SRTM-DEM-extracted river bed profile calculation and its adjustment for Son and Betwa Rivers of the Ganges river system. The black line is showing the extracted river profile from the SRTM DEM and the red line representing the profile that has been considered as the slope along the rivers. This profile has been adjusted with river bed profile computed by the 'backward' extension of river bed slopes measured inside Bangladesh.

hydrological model first developed by Liang *et al.* (1994). Capable of solving water and energy balances, it requires a minimum set of input forcing data such as precipitation, temperature (minimum and maximum), and wind speed. The model represents the land as a lumped grid of large (>1 km) flat, uniform cells, and inputs are time series of daily or sub-daily meteorological drivers (e.g. precipitation, air temperature, wind speed) (Sheffield *et al.* 2006). The grid cells are simulated independently of each other. Routing of stream flow is performed separately from the land surface simulation, using a separate model (typically the routing model of Lohmann *et al.* 1998). In this study, we used the VIC model set-up over the GBM basin reported by Siddique-E-Akbor *et al.* (2014). A recent example of the use of the VIC model for flow forecasting has been reported for the Indus basin by Shrestha *et al.* (2014).

5 Methodology

The study has been conducted with a view to develop a satellite-based hydrodynamic river model that can simulate the river flow dynamics of the entire GBM basin, and generate water level and discharge along rivers up to the upstream points of the forecasting domain. The flowchart in Figure 3 shows the various steps

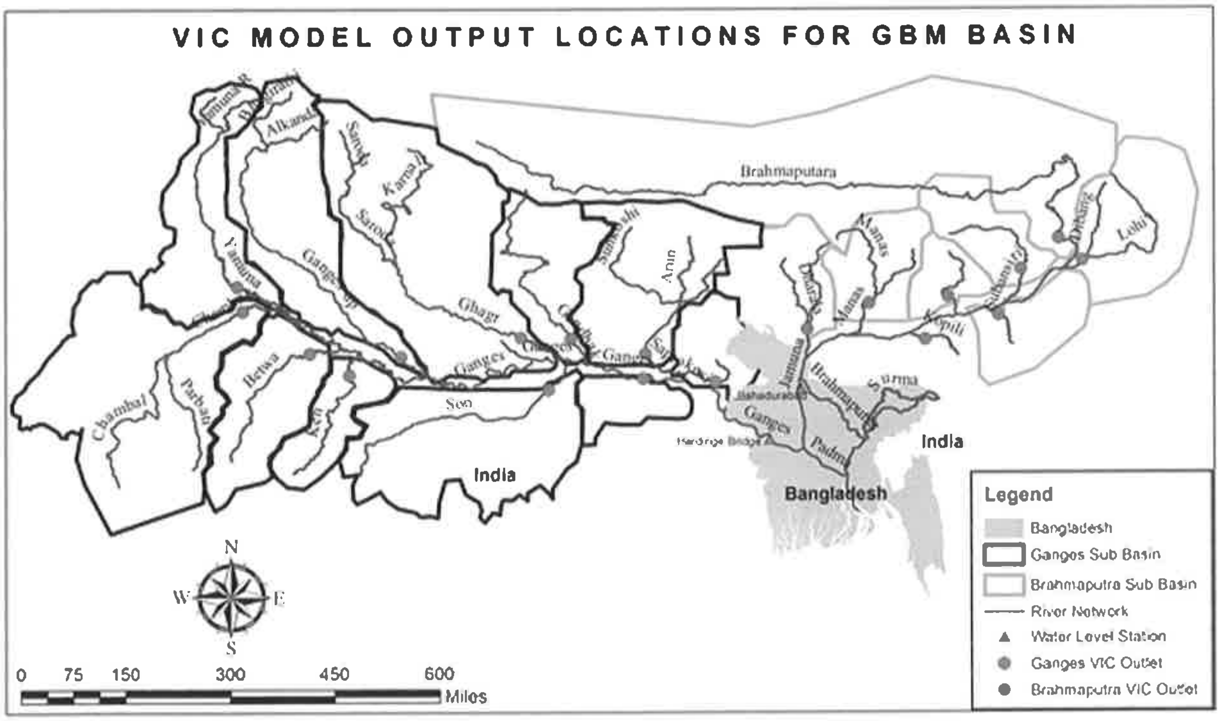

Figure 6 VIC model generated stream flow for each sub-basin. VIC model result for the GBM basins were subdivided into sub-basins to capture lateral (tributary) flow contribution to the river system at the downstream confluence point. The areas bounded by solid black boundary line represent the sub-basins. Red and pink circular points show the locations of each sub-basin outlet points for Ganges and Brahmaputra basins, respectively.
Note: River 'Jamuna' is the local name for Brahmaputra inside Bangladesh.

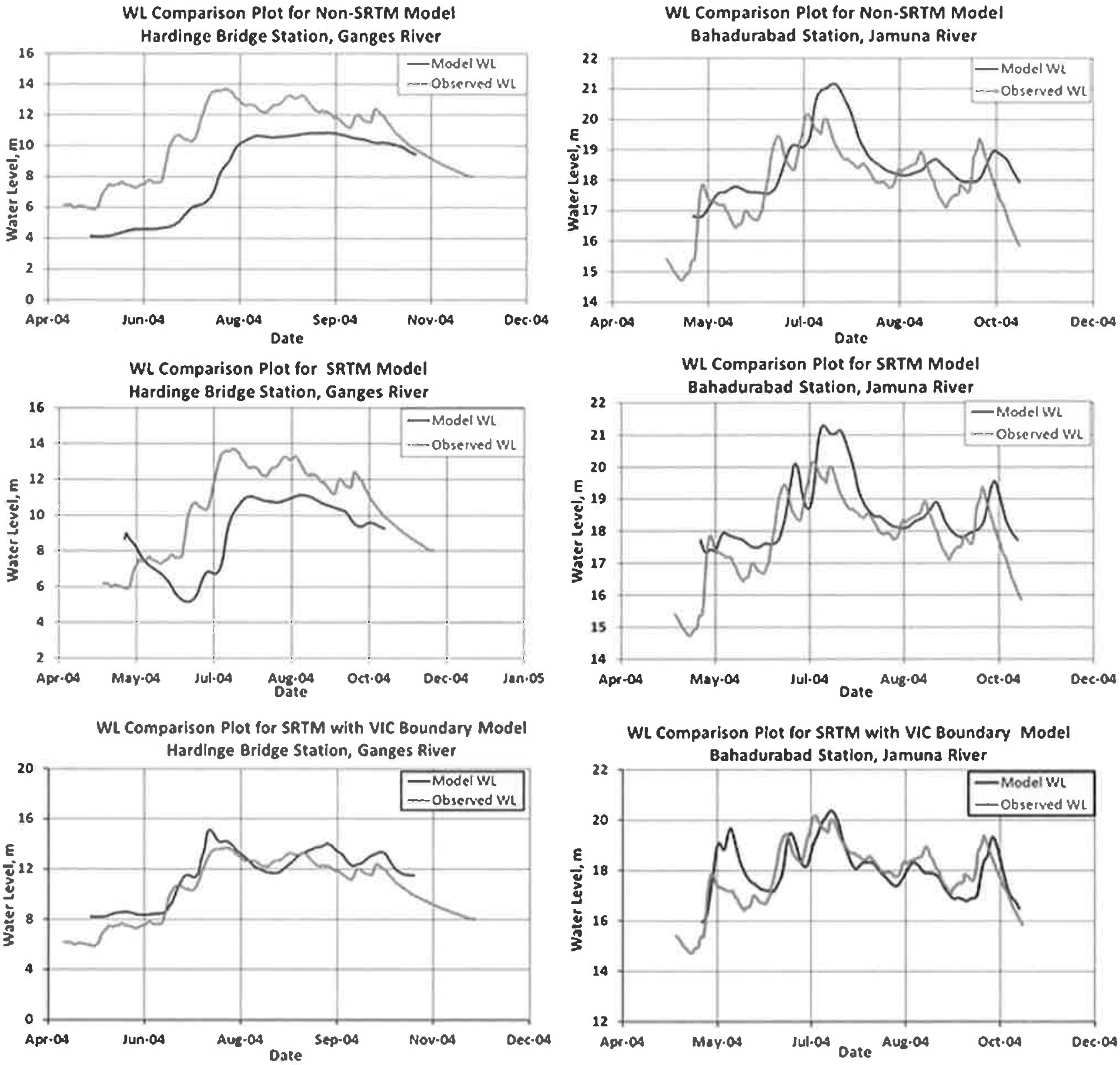

Figure 7 Comparison of HEC-RAS simulated and observed river levels for various model scenarios. Uppermost panel: model scenario (a) Non-SRTM RAS model with Factorized Boundary Flow data. (Note: River 'Jamuna' is the local name for Brahmaputra inside Bangladesh); middle panel – model scenario (b) – SRTM RAS model with Factorized Boundary Flow data that use more realistic river bed slopes. Lowermost panel – model scenario (c) – SRTM RAS Model with Hydrologic Model Derived Boundary.

that were applied for the study objectives. To capture the most recent river network distribution, satellite data (from SRTM elevation) and aerial imagery based on a geo-browser known as Google Earth were used.

Figure 3 summarizes the overall approach used. Two procedures were followed to develop a river bathymetry dataset to incorporate in the HEC-RAS model. The first one was based on the surveyed (*in situ*) river bathymetry data collected for the major rivers inside Bangladesh (the forecasting domain). Another dataset was SRTM-DEM-extracted river bathymetry data. Use of these two separate bathymetry datasets generated two separate RAS river model set-ups. As a first cut, the upstream boundary data of GBM rivers were generated by a 'factorizing' procedure using the measured downstream flow data (explained later). Next, the VIC hydrologic model that generated flow data (from rainfall–runoff transformation) for the GBM basin was used as upstream boundary data. Simulated model results were compared against the observed river-level data measured at Hardinge Bridge and Bahadurabad station inside Bangladesh.

The rivers located within the GBM basin are morphologically very active and frequently change their courses at decadal timescales. As a result, to develop the most up-to-date GBM model set-up, it is essential to acquire the latest and most accurate river network distribution over the entire basin. The virtual globe Google Earth is an excellent source of information for

Table 1 RMSE and correlation between model output and gauging station data for model scenarios (a) and (b)

Case	Model	Station	RMSE (m)	Correlation
Before (model a)	Non-SRTM RAS model with factorized boundary	Hardinge Bridge	3.12	0.806
		Bahadurabad	1.002	0.639
After (model b)	SRTM RAS model with factorized boundary	Hardinge Bridge	2.621	0.660
		Bahadurabad	0.944	0.703
After (model c)	SRTM RAS model with hydrologic Model derived Boundary	Hardinge Bridge	1.066	0.934
		Bahadurabad	0.817	0.646

this purpose and has been used to digitize the whole GBM river network (shown in Figure 4).

As mentioned earlier, two different river bathymetry set-ups were developed for the hydrodynamic river model, and they were eventually merged. One set-up was created by extending the existing surveyed river bathymetry data within Bangladesh for the whole GBM basin. Initially, river slope or river bed profile was calculated from rivers located within the Bangladesh. These rivers slope were gradually extended 'backwards' (interpolated) to upstream rivers in India and included in the RAS model. Another hydrodynamic model set-up was developed by extracting river slope from the SRTM DEM. Elevation data from SRTM DEM were extracted along the entire digitized river network. The assumption made here is that the ground surface slope along the river is parallel to the river bed slope and thus should be a good proxy for adjusting river cross-section profiles. Elevation differences at the upstream (transboundary) regions along the river were calculated to derive the slope at 100 km increments. The slope resulting from SRTM-derived profiles (an example shown in Figure 5) was then used to adjust the river bed profile computed by the earlier 'backward' extension of river bed slopes measured inside Bangladesh. In this way, river bed slopes for upstream (ungauged) regions were made physically more consistent to the surrounding reality. Similar to the adjustment of river bed slopes, two sets of boundary flow data were applied to the GBM basin model. The initial set was generated from the base RAS model for Bangladesh at the locations of Hardinge and Bahadurabad. The boundary (discharge) data were then distributed 'backwards' (we call it 'factorized') for the upstream-most boundary locations (according to the sub-basin area drained) of all the upstream rivers in the ungauged region.

The second set of boundary flow data were generated from the VIC model simulation of the rainfall–runoff transformation. For a simulation period longer than a few weeks, it is reasonable to assume that the GBM basin, given the vast size, experiences rainfall and its consequential transformation as runoff (and eventually stream flow) somewhere within its domain. Thus, the river model's simulation of water levels can be dynamically updated if this hydrologic contribution is also considered. The VIC hydrological model was therefore simulated for the entire GBM basin to produce daily fluxes (runoff and stream flow) at spatial scales ranging from 12.5 km to 25 km (Siddique-E-

Figure 8 Location of Envisat data points on the river Ganges in upstream (transboundary) region of India where *in situ* data are unavailable.

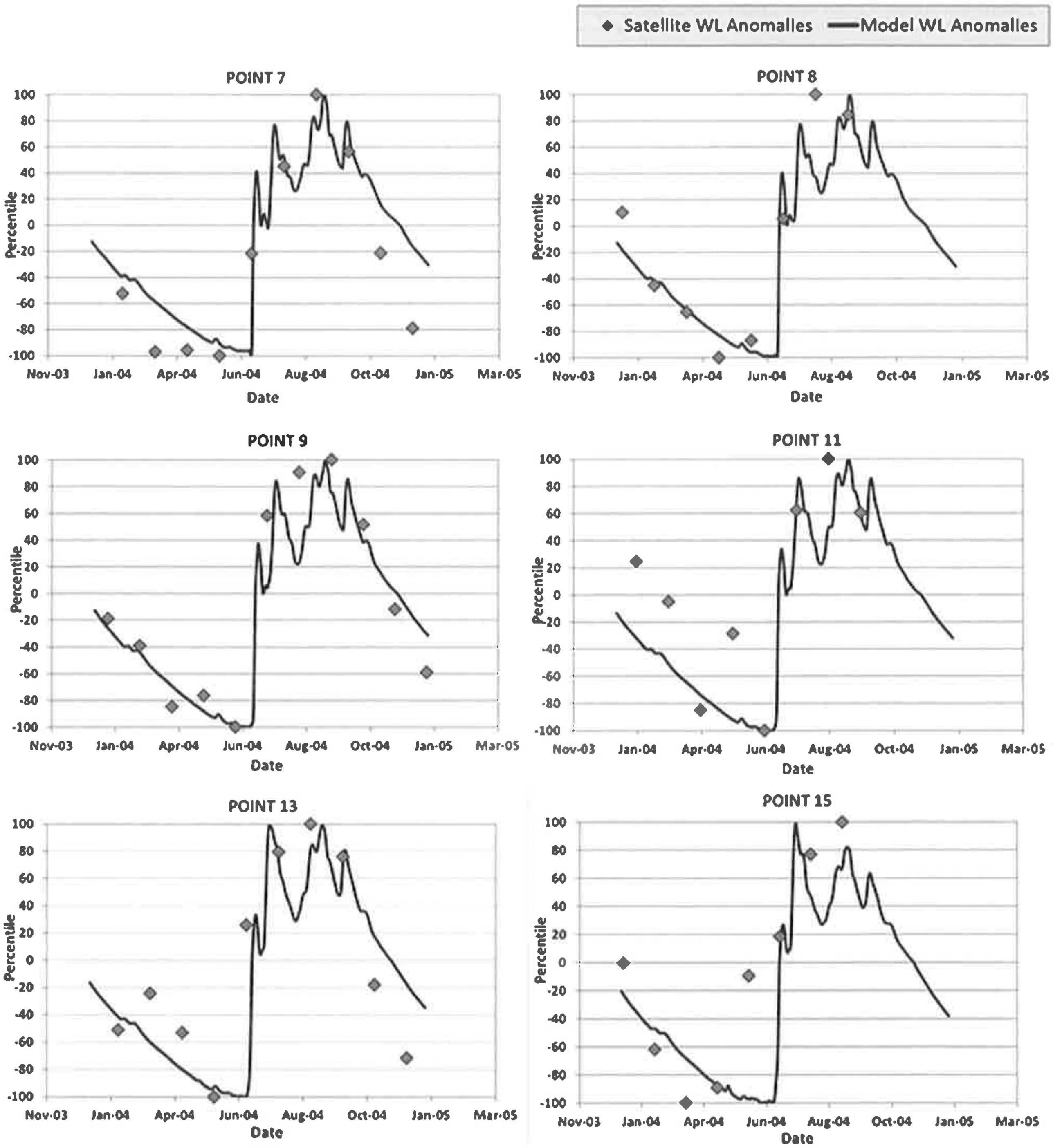

Figure 9 Anomalies between Envisat (satellite)-based water level and RAS-model-generated water level (scenario c).

Akbor *et al.* 2014). This VIC model output was then used to generate sub-basin-wise flow estimations for lateral flows (Figure 6). This sub-basin-wise flow data was then applied as the boundary data for the GBM RAS model.

6 Results and discussion

Three different model set-ups have been systematically developed to progressively evaluate the performance of the GBM HEC-RAS modelling. The HEC-RAS modelling was simulated for the mixed flow regime (subcritical, supercritical, critical, drawdown). The hydrological year of 2004–2005 was simulated to analysed performance of the model set-ups. The major parameter for the calibration of the RAS model set-ups was the Manning's roughness coefficient. In this study, Manning's roughness value ranged from 0.018 to 0.035. Hereafter, we describe the performance of each of the RAS model set-ups that were systematically 'upgraded' for improvement.

The three types of RAS model (or model scenarios) set-ups progressively developed and upgraded were: (a) Non-SRTM

RAS Model with Factorized Boundary Flow Data; (b) SRTM RAS Model with Factorized Boundary Flow Data; and (c) SRTM RAS Model with Hydrologic Model-based Boundary Flow Data. Here model set-up 'a' represents the HEC-RAS set-up that has bathymetry data for the entire GBM basin derived from the 'backward' extension of river bed slopes measured inside Bangladesh. The boundary flow data have been generated by multiplying factors of the known boundary data for major rivers within Bangladesh. Model set-up b consists of the same boundary flow data, but its bathymetry data have been extracted from the SRTM DEM and later adjusted for greater realism. Finally, the set-up for model set-up 'c' has been developed by incorporating the same bathymetry data of model set-up 'b' with VIC model generated lateral flow (rainfall–runoff transformation) data for the GBM basin applied to the river model.

6.1 *Non-SRTM RAS model with factorized boundary flow data*

Simulated model results have been compared with river levels observed at gauging stations of Hardinge Bridge and Bahadurabad located within the Bangladesh (Figure 7 uppermost panel). Ganges basin simulated water level from HEC-RAS could not satisfactorily capture the dynamics of the actual measured water-level data. On the other hand, Brahmaputra basin simulated model results captured the dynamics in river level albeit with some systematic errors such as errors in time delays. At Hardinge Bridge, model output showed underestimation as compared with the observed water-level data. Bahadurabad station showed overestimation of the measured water-level data. The root mean squared error (RMSE) values of river-level simulation for Hardinge and Bahadurabad locations were 3.12 and 1.002 m, respectively. The corresponding correlation values were 0.806 and 0.639.

6.2 *SRTM RAS model with factorized boundary flow data*

More reliable bathymetry (river bed slope) data (from SRTM) were incorporated in this set-up to investigate the HEC-RAS model performance. The model was simulated using the same boundary flow data (i.e. factorized). Figure 7 (middle panel) shows the comparison plot between observed water-level data and simulated model results. For Hardinge Bridge and Bahadurabad stations, RAS model results indicated modest improvements in that the river water levels match slightly better with observations. For the Hardinge Bridge station, calculated RMSE was 2.621 m, whereas for Bahadurabad station the RMSE was 0.944 m. Table 1 shows the calculated RMSE and correlation value at the river locations for the model set-ups 'a' and 'b'.

6.3 *SRTM RAS model with hydrologic model derived boundary flow data*

Sub-basin-based hydrologic model extracted stream flow data from VIC hydrologic model was applied as upstream boundary (lateral) data for the SRTM-based RAS model. With the dynamic nature of lateral flow consideration, we observed the greatest improvement for this model set up. Figure 7 (lowermost panel) shows comparison plots of simulated and observed river levels for the model scenario 'c'. Model results show almost similar patterns for the Hardinge Bridge and Bahadurabad station, where the water levels closely resemble the observed data. Munier *et al.* (2015) have reported similar value in using a hydrologic model for lateral flow estimation to improve reservoir-level estimation and low flow river levels. In this case, a peak is overestimated at Bahadurabad station during May 2004, which is likely indicative of the propagation of VIC model uncertainty in flow simulation for that time period. Interested readers may refer to Siddique-E-Akbor *et al.* (2014) for a detailed assessment of the VIC model uncertainty of flow simulation for the rivers. Table 1 shows the calculated value of RMSE and correlation.

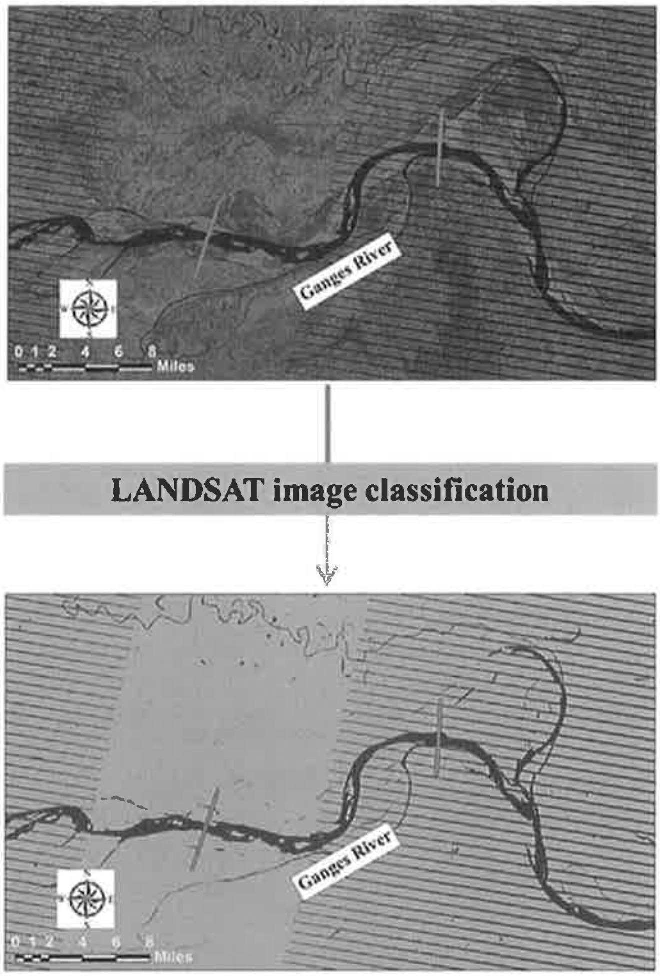

Figure 10 Classification of Landsat image on the basis of land–water classification mask. The upper panel shows the Landsat image in TIFF format. And the lower panel shows the classified image where the thick blue curve line represents the Ganges River. Red lines indicate the location where the cross sections have been extracted. Parallel blue lines are satellite-sensor-generated disturbance, which causes some difficulties to measure the width of the river.

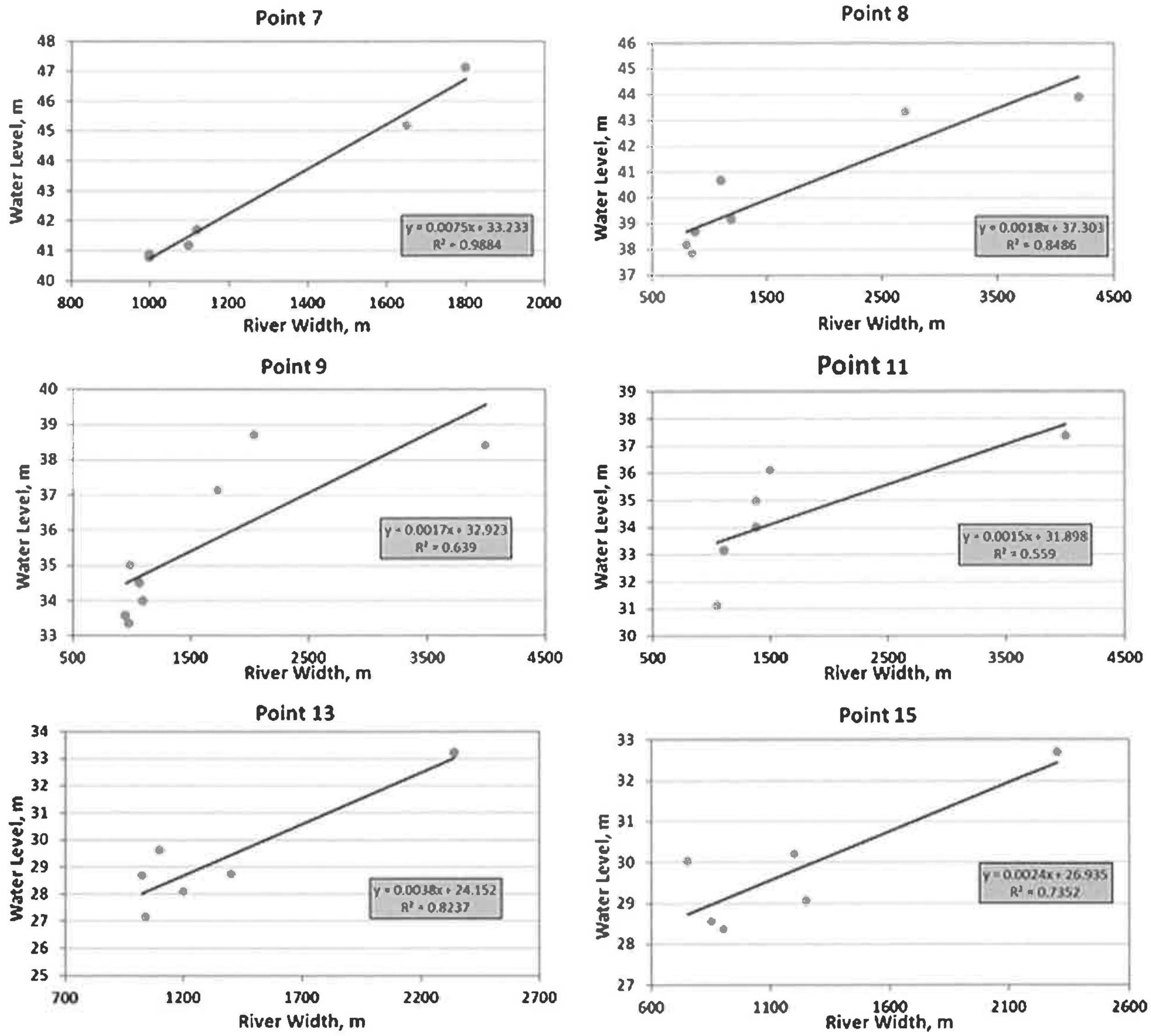

Figure 11 Relation between Landsat river width (x-axis) and Envisat water-level (y-axis) estimation. Height is relative to the local geoid (EGM08).

6.4 *Independent comparisons at ungauged river locations with satellite observations*

Although the RAS model set-ups have been assessed against the known gauged location within the Bangladesh (gauged) region, the performance over upstream and ungauged rivers remained unknown up to this point. The only tangible way to assess how the RAS model performs at upstream transboundary locations is to compare the RAS river-level simulations with that from independent radar altimetry-based river-level measurements. With that in mind, one set of Envisat (a nadir looking radar altimeter) satellite data on river heights have been collected for the 2002–2010 period (Figure 8).

Envisat-estimated water-level data (locations showed in Figure 8) were compared with the RAS-model (model set-up 'c')-generated water-level data. To ensure that any differences observed were not results of data differences between the satellite altimeter and the RAS model, the comparison was done in terms of anomalies. Anomalies of river heights were calculated from annual average river levels and expressed in the form of percentage change relative to the maximum anomaly observed in the time series (positive indicating higher than average; negative indicating lower than average). Figure 9 shows that anomalies agree reasonably consistently for most ungauged locations for RAS and Envisat measurements. The rising and receding trends of water levels appear to be picked up consistently, although some systematic bias exists for some locations. Overall, the anomalies tell us that a data assimilation framework that assimilates satellite altimeter height in the RAS model should achieve more accurate estimates of river height estimates at ungauged locations.

Envisat-satellite-based water-level data were also used for establishing the relationship between water level and river width. First, Landsat satellite images were processed to generate land–water classified images (Figure 10) using supervised classification according to the Moller-Jensen (1990) rule. Under cloudy conditions, the average classification accuracy exceeded 77% over the entire domain. A line shape file was used at the target river cross-section location to extract river width from Landsat. The calculated river width was then plotted against coincident water-level estimates from Envisat (here 'coincident' is defined as 'closest in time'). The goal was to see whether a consistent relationship between height and river width could be derived from the synergistic use of Landsat and Envisat data. A consistent relationship that is physically meaningful would indicate that two sensors with different (complementary) orbit and sampling patterns could be used as a 'team' to derive one hydraulic parameter, such as height (width), from the other, such as width (height), and thereby enhance the RAS models further at ungauged locations. A point to note herein is that the proposed SWOT mission with its wide-swath altimetry will provide both height and width simultaneously. Thus, the joint assessment of Landsat and altimeter (Envisat) may be considered as a pre-SWOT validation of wide-swath altimetry for river modelling. Figure 11 shows the relationship obtained between Landsat width vs. Envisat depth curve. Most of the plots show a very consistent relationship with many locations, some exhibiting a very linear relationship (e.g. point 7) while others showing a non-linear relationship (point 11). While the relationship does not allow us to establish a causal pattern on the cross section, it allows us to observe how the width varies in relation to the depth. We can then infer the nature of the flood plain and river type (shallow and wide in point 11, single channel and deep in point 7). Such relationships may also point to a probable trapezoidal section or one with a wide floodplain, which can then be used as an initial proxy in the river model as a more superior input than what can be inferred from the literature. Nevertheless, this consistent relationship and the agreement with observed in height anomalies between Envisat and RAS model indicate that satellite-based height and width information from a visible and microwave constellation of sensors can be assimilated routinely in a river modelling system.

7 Conclusions

Traditional ground-based surface-water measurements for the complex river deltas do not overcome the large spatial and temporal sampling gap, particularly for transboundary river basins in the developing world (e.g. in the Mekong, GBM, Indus, Niger, Irrawaddy, and Salween basins). This study explored the possibility of developing a river model using satellite remote-sensing data to overcome some of these intractable hurdles associated with the lack of data from *in situ* networks and real-time coordination of data sharing.

Our model results showed that it is possible to model the river systems of a large river basin to a satisfactory level to generate water-level dynamics if a systematic procedure is followed. Our study reports on the relative improvement of using various satellite data techniques and hydrologic models. Three different HEC-RAS river model set-ups were developed. We observe that the use of SRTM elevation data to adjust river bed slope and hydrologic model for rainfall runoff transformation to model lateral flow can significantly improve simulation of river levels downstream. The RMSE went from 3.12 to 1.066 m for the Ganges river location of Hardinge Bridge, whereas for the Bahadurabad station, the RMSE reduced from 1.002 to 0.817 m.

For readers wishing to embark on a similar journey to set up a river model over other large but ungauged river basins, we recommend the following four rules as a guide to a successful start:

RULE ONE – Use extensive historical facts, river morphology, and local knowledge of rivers to factorize upstream flows at boundary conditions. Distribute (factorize) flow according to drainage area of tributary sub-basins.

RULE TWO – Use extensive observed data or Landsat images (or any other platform, such as IKONOS/QuickBird, in the visible wavelength) to verify and correct the river network, which can change course and fail to match DEM-derived river networks.

RULE THREE – Leverage SRTM (or any satellite) based ground-level slope assessment (along the river) to adjust river bed elevation and correct river cross section profiles in the model set-up.

RULE FOUR – Use 'coincident' height and width estimates from different satellites (radar/visible and later SWOT) to infer the river cross section at ungauged locations. This can be a useful proxy for inferring river cross section shape and data assimilation of multiple satellites in river models.

RULE FIVE – Use hydrologic model driven flows from tributaries for lateral flow for large basins and a longer (>1 month) simulation period to address the rainfall–runoff transformation issues.

With the advancement of satellite data acquisition technique and precision, a more reliable and accurate way of measuring river discharge and water levels should be continued. As a further study, the level of accuracy achieved could be further enhanced by incorporating future satellite missions that will provide estimates of river height (altimeters; e.g. JASON-3, IceSat-2, Sentinels 3A and 3B), width (Landsat, MODIS), or both (SWOT Mission, Alsdorf *et al.* 2007, Pavelsky *et al.* 2014). Another area of improvement for river models for ungauged river basins is data assimilation of satellite-derived heights and widths in the hydrodynamic–hydrologic modelling system for routine 'updating' of river levels. We believe that if we strive to explore simple and robust techniques that flood forecasting agencies can independently adopt, our research will experience real transition as technology transfer and impact the developing world.

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References

Akanda, A.S., 2012. South Asia's water conundrum: hydro-climatic and geopolitical asymmetry, and brewing conflicts in the Eastern Himalayas. *International Journal of River Basin Management*, 10 (4), 307–315. doi:10.1080/15715124.2012.727824.

Alsdorf, D.E. and Lettenmaier, D.P., 2003. Geophysics: tracking fresh water from space. *Science*, 301 (5639), 1491–1494. doi:10.1126/science.1089802.

Alsdorf, D.E., Rodriguez, E., and Lettenmaier, D.P., 2007. Measuring surface water from space. *Reviews of Geophysics*, 45 (2), 1–24. doi:10.1029/20 06RG00 0197.

Balthrop, C. and Hossain, F., 2010. A review of state of the art on treaties in relation to management of transboundary flooding in international river basins and the global precipitation measurement mission. *Water Policy.* doi:10.2166/wp.2009.117.

Birkett, C.M., 1995. The contribution of Topex/Poseidon to the global monitoring of climatically sensitive lakes. *Journal of Geophysical Research*, 100 (C12), 25179–25204. doi:10.1029/95JC02125.

Birkett, C.M., 1998. Contribution of the TOPEX NASA radar altimeter to the global monitoring of large rivers and wetlands. *Water Resources Research*, 34 (5), 1223–1239. doi:10.1029/98WR00124.

Brakenridge, G.R., *et al.*, 2007. Orbital microwave measurement of river discharge and ice status. *Water Resources Research*, 430 (4). doi:10.1029/2006WR005238.

Frappart, F., *et al.*, 2006. Preliminary results of ENVISAT RA-2-derived water levels validation over the Amazon basin. *Remote Sensing of Environment*, 100, 252–264. doi:10.1016/j.rse.2005.10.027

Hirpa, F.A., *et al.*, 2012. Upstream satellite remote sensing for river discharge prediction: application to major rivers in South Asia. *Remote Sensing of the Environment.* doi:10.1016/j.rse.2012.11.013.

Hopson, T.M. and Webster, P.J., 2010. A 1-10 day ensemble forecasting scheme for the major river basins of Bangladesh: forecasting severe floods of 2003-2007. *Journal of Hydrometeorology*, 11, 618–641. doi:10.1175/2009JHM10061.

Horritt, M.S. and Bates, P.D., 2002. Evaluation of 1D and 2D numerical models for predicting river flood inundation. *Journal of Hydrology*, 268 (1), 87–99.

Hossain, F. and Katiyar, N., 2006. Improving flood forecasting in international river basins. *EOS (AGU)*, 87 (5), 49–50.

Hossain, F. and Lettenmaier, D.P., 2006. Flood prediction in the future: recognizing hydrologic issues in anticipation of the global precipitation measurement mission. *Water Resources Research*, 42, W11301. doi:10.1029/2006WR005202.

Hossain, F., *et al.*, 2013. Proof of concept of altimeter-based forecasting system for transboundary flooding. *IEEE Journal of Selected Topics in Applied Earth Observation and Remote Sensing*, 7 (2), 587–601. doi:10.1109/JSTARS.2013.2283402.

Hossain, F., *et al.*, 2014. A guide for crossing the valley of death: lessons learned from making a satellite based flood forecasting system operational and independently owned by a stakeholder agency. *Bulletin of American Meteorological Society (BAMS)*, 95 (8), 1201–1207. doi:10.1175/BAMS-D-13-00176.1.

Katiyar, N. and Hossain, F., 2007. An open-book watershed model for prototyping space-borne flood monitoring systems in international river basins. *Environmental Modeling and Software*, 22 (12), 1720–1731. doi:10.1016/j.envsoft.2006.12.005.

Jia, Y. and Wang, S., 1999. Numerical model for channel flow and morphological change studies. *Journal of Hydraulic Engineering*, 125 (9), 924–933.

Lee, H., *et al.*, 2009. Louisiana wetland water level monitoring using retracked TOPEX/POSEIDON altimetry. *Marine Geodesy*, 32 (3), 284–302.

Lee, H., *et al.*, 2010. Characterization of surface water storage change in Arctic lakes using simulated SWOT measurements. *International Journal of Remote Sensing*, 31 (3), 931–3953.

Liang, X., *et al.*, 1994. A simple hydrologically based model of land surface water and energy fluxes for GSMs. *Journal of Geophysical Research*, 99 (D7), 14415–14428. doi:10.1029/94JD00483.

Lohmann, D., *et al.*, 1998. Regional scale hydrology: I. formulation of the VIC-2L model coupled to a routing model. *Hydrological Sciences Journal*, 43 (1), 131–141. doi:10.1080/02626669809492107.

Matthews, E. and Fung, I., 1987. Methane emission from natural wetlands: global distribution, area, and environmental characteristics of sources. *Global Biogeochemical Cycles*, 1 (1), 61–86. doi:10.1029/GB001i001p00061.

Moller-Jensen, L., 1990. Knowledge-based classification of an urban area using texture and context information in Landsat-TM imagery. *Photogrammetric Engineering and Remote Sensing*, 56 (6), 899–904.

Munier, S., *et al.*, 2015. SWOT data assimilation for reservoir operations in the upper Niger River basin. *Water Resources Research*, 51, 554–575. doi:10.1002/2014WR016157.