GIS-based SWMM model for simulating the catchment response to flood events

Pawan Kumar Rai, B. R. Chahar and C. T. Dhanya

ABSTRACT

The Storm Water Management Model (SWMM) has been an effective tool for simulating floods in urban areas, but has been seldom applied for river systems. In this study, a geographic information system (GIS)-based SWMM model was developed to authenticate the model's viability as a streamflow simulator for modeling floods in the Brahmani river delta. The model was set up using a Shuttle Radar Topography Mission-Digital Elevation Model (SRTM-DEM), National Remote Sensing Centre Landuse/Land Cover (NRSC LU/LC), soil from National Bureau of Soil Survey (NBSS), Indian Meteorological Department (IMD) meteorological forcings, and tuned using India-Water Resource Information System (India-WRIS) streamflow data. The calibration and validation of the model was carried out on a monthly time scale from 1980 to 2012, using a Monte Carlo based auto-calibration technique. In addition, a daily basis calibration-validation was carried out. The Nash–Sutcliffe efficiency and Percent Bias values were found to lie between 0.616–0.899 and 0.09–14.1%, respectively. Moreover, the root mean square error-observations standard deviation ratio (RSR) values were almost close to zero indicating reasonably good model performance. Subsequently, the model reasonably predicted the maximum flow that should be regulated to prevent any possible inundation in the downstream areas. The developed model can thus be employed as an effective flood modeling tool.

Key words | flood, GIS, Monte Carlo based auto-calibration, SWMM

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INTRODUCTION

River flooding has caused extensive socio-economic loss globally. In India, the eastern states of Orissa, Andhra Pradesh and West Bengal have witnessed high magnitude monsoonal floods annually. These natural disasters are a result of severe meteorological and hydrological conditions aggravated by anthropogenic activities. El Alfy (2016) reported that rapid urbanization reduces infiltration and increases runoff as a consequence of which flood peaks and flood volume increase even if rainfall intensity is low. Although flooding cannot be completely avoided, its ill-effects can be minimized conventionally by two approaches: firstly, through flood protection works by designing and constructing river banks, dams and flood storage to guard the inundation susceptible areas apart from regulating the reservoir discharge and secondly, by developing a flood warning system which can assist in the evacuation of people, property and livestock.

In recent times, there has been an ever-increasing emphasis on the development of flood warning systems as they offer a relatively cheaper option as compared to the costlier flood protection works. Various models such as HEC-1 developed by the US Army Corps of Engineers, TR-55 developed by the Soil Conservation Service (SCS), MOUSE developed by the Danish Hydraulic Institute (DHI), and Storm Water Management Model 5 (SWMM5) developed by the US Environmental Protection Agency,

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are available for predicting runoff from the watershed (US Army Corps of Engineers 1985; SCS 1986; DHI 1995; Rossman 2010).

Among the above-mentioned models, SWMM is one of the most widely used open-source models available for research and practical applications in urban as well as non-urban drainage systems (Kim et al. 2015). The major advantage of SWMM is that it incorporates the capabilities of both hydrological and hydraulic models. Moreover, a calibrated and validated SWMM model is much easier to use for accurate flood prediction as it requires only minimal meteorological data like temperature and rainfall. Although an SWMM model was developed for urban applications, researchers across the world have successfully used it to model rural areas wherein it was concluded that the model is equally applicable for natural watersheds (Jang et al. 2007; Jun et al. 2010; Chung et al. 2011).

Nowadays, geographic information system (GIS) has emerged as a vital part in hydraulic and hydrologic studies due to the spatial nature of the parameters governing the hydrological processes (Ji & Qiuwen 2015). It plays a crucial role in parameterizing the distributed hydrological models wherein the abstraction of hydrologic information, such as catchment discretization, stream network, basin boundary, can be done via GIS packages. Use of GIS in catchment discretization is evolving as a latest trend which is yielding better flood predictions as compared to the conventional approaches (Dongquan et al. 2009). El Alfy (2016) coupled GIS and remote sensing with HEC-HMS to analyze the maximum flood in urbanized arid areas.

In past decades, various studies emphasized on calibrating SWMM model to bring an agreement in simulated and observed values (Choi & Ball 2002). In recent times, auto-optimization of model parameters has gained popularity over manual calibration as it is efficient and time saving (Boyle et al. 2000). Barco et al. (2008) used a pattern search optimization method for auto-tuning four SWMM parameters, namely: width, imperviousness, Manning's coefficient and depression storage. Auto-calibration methods such as Monte Carlo optimization are useful in evaluating the model results on statistical criteria and have been effectively used in small catchments of Australia (Loveridge & Rahman 2012). This technique can be employed to check the impact of numerous sets of input parameters on the model outputs, with great computational efficiency.

In view of the above, a GIS-based auto-calibrated SWMM model was used to model the flood prone Brahmani river watershed of India. Hence, Brahmani basin was simulated in SWMM5 model using inputs from GIS to validate the applicability of SWMM in large natural catchments. The model was then integrated with a Monte Carlo algorithm for calibration and then evaluated for its applicability in flood applications on natural catchments. This modeling study can facilitate water resource managers in efficient planning and management of natural disasters such as floods.

STUDY SITE AND METHODOLOGY

Study area

Brahmani river watershed is the largest watershed in Orissa, India after the Mahanadi basin. It is located between longitude 83°52′ to 87°30′ E and latitude 20°28′ to 23°35′ N, and covers an area of 39,269 km^2. There are two basins on either side of the Brahmani basin, namely, Baitarani on the left and Mahanadi on the right. Figure 1 depicts the location of the Brahmani river.

In Figure 1, three stations are shown: Gomlai, Jenapur and Indupur. The discharge and gauge data are available for Gomlai and Jenapur stations whereas only water level data are available at Indupur, therefore Indupur has not been considered for tuning the model. However, Indupur has been labelled in Figure 1 to show the location of the control station near the flood prone area.

The major portion of the lower part of the Brahmani delta is occupied by the densely populated Jajapur district. Both rabi (winter season) and kharif (monsoon season) crops are grown in this highly fertile delta region. Jajapur district is prone to flood during events of high rainfall intensity, resulting in great damage to lives and properties. Surface elevation in this area ranges from 3 to 24 m above mean sea level. Because of this relatively flat topography, severe flow accumulation occurs during heavy rain.

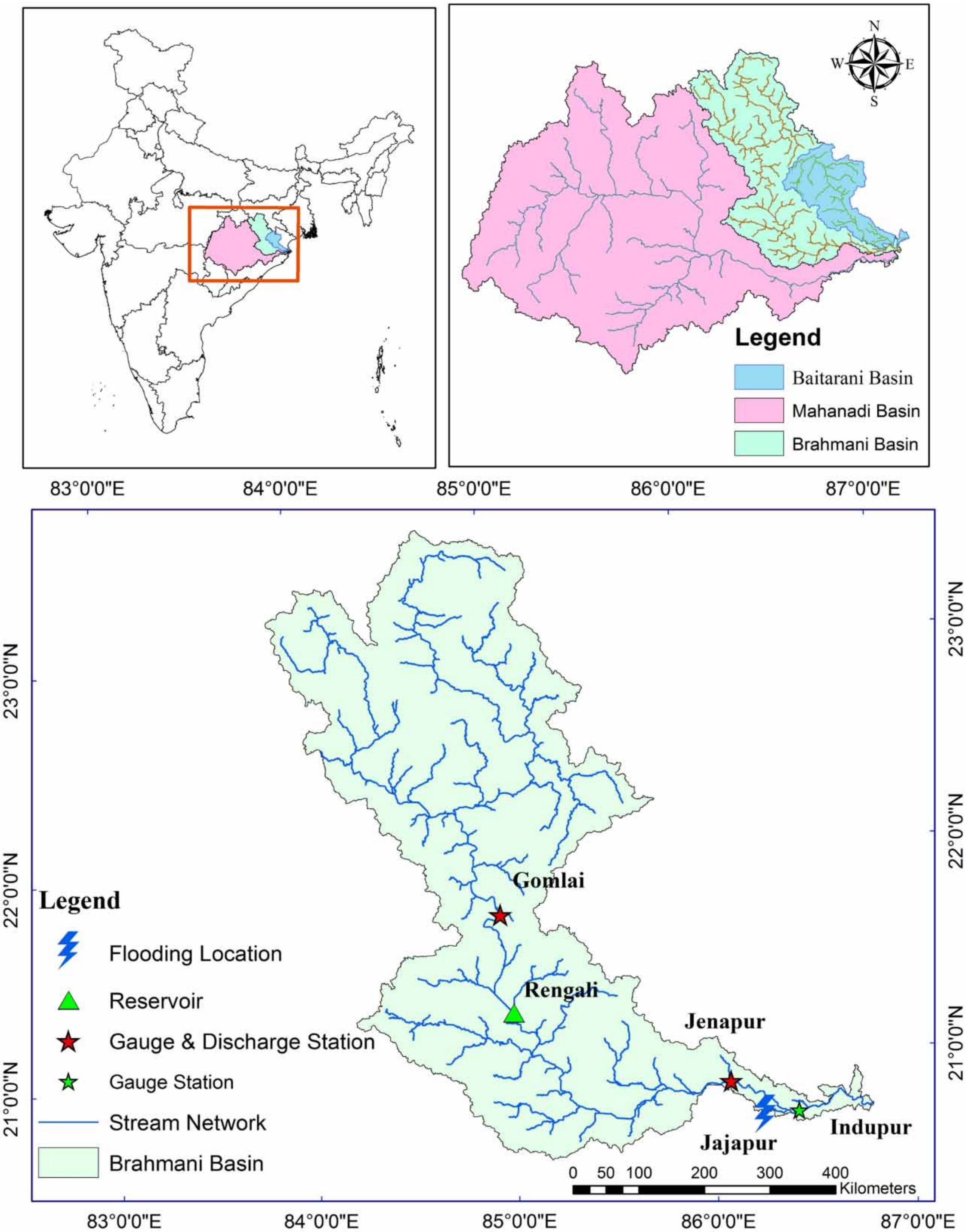

Figure 1 | Map of the Brahmani basin.

Rengali dam is a multi-purpose reservoir located around 160 km upstream of the Brahmani delta. It was commissioned in 1984 for irrigation, hydro-power generation and flood mitigation purposes. The dam has a storage capacity of about 5,150 million m^3 and an area of around 378.4 km^2.

METHODS

Model description

In the current study, the Brahmani river was modelled using an open source Storm Water Management Model 5 (SWMM5) to assess the model's applicability in natural watershed conditions. SWMM was first developed in 1971 and, since then, has been updated a number of times. Unlike its predecessors, Version 5 is a GUI model developed by United States Environment Protection Agency (USEPA) and CDM Inc. (Rossman 2010). SWMM can model flow through the channel as well as through overland flow for both single and multiple precipitation events. Quality and quantity of runoff can also be tracked at every time step. SWMM is categorized in four compartments: (i) precipitation and air pollutants contribute to the atmosphere compartment, (ii) runoff due to rainfall comes under the land surface compartment, (iii) watershed generated runoff flowing through the channel network comes under the transport compartment, and (iv) the land surface provides infiltration to the ground-water compartment, which then feeds the transport compartment.

A continuity equation (Equation (1)) and Manning's equation (Equation (2)) are used by SWMM on each sub-catchment by treating every catchment as a nonlinear reservoir (Huber & Dickinson 1992). Rossman (2010) defined a sub-catchment as a land which drains into a pour point, which can either be a storm drain or another sub-catchment.

$$\frac{dV}{dt} = A\frac{dd}{dt} = A*\mathrm{i} - \mathrm{Q} \tag{1}$$

where $V =$ volume of water in a sub-catchment; $dt =$ time step; $A =$ area of the sub-catchment; $i =$ effective rainfall; and $Q =$ outflow from the sub-catchment;

$$Q = W\frac{1}{n}(d - d_p)^{\frac{5}{3}}.S^{\frac{1}{2}} \tag{2}$$

where $W =$ width of the sub-catchment; $n =$ Manning's roughness coefficient; $d_p =$ storage in surface depression; and $S =$ slope of the sub-catchment.

This model is used worldwide by researchers and engineers for studying urban as well as non-urban drainage areas (Kim et al. 2015). Chung et al. (2011) reported that the SWMM model fits well for studying water quality in the pre-development scenario for urban areas. Jang et al. (2007) reported that in addition to the urban catchments, SWMM is equally applicable for modelling natural watersheds.

The significance of surface water–ground water interactions and the need of considering both in a hydrosystem was highlighted by Bourgault et al. (2014). Cai et al. (2016) investigated river-aquifer interactions in three diverse regions of Heihe river basin during different seasons and concluded that these interactions are largely affected by hydro-meteorology, topography and anthropogenic activities. The SWMM model is also capable of handling these surface water–ground water interactions. Jun et al. (2010) studied the Gapcheon watershed of Korea having 12% urbanized area and concluded that SWMM can be used for studies pertaining to groundwater change and long term channel discharge.

Data used

The data required for modelling purposes were collected from various government and online sources (Table 1).

There are six stations in the basin where discharge data are available, but they have either data gaps or limited record length. Therefore, two stations have been considered for calibration-validation purposes, one in the upstream of Rengali reservoir (Gomlai) and the other on the downstream (Jenapur). Daily discharge data are available at both these stations from 1980 to 2012.

Parameter estimation

Depth-area curves using DEM

A Shuttle Radar Topography Mission-Digital Elevation Model (SRTM-DEM) was used to develop the depth-area relationship for the Rengali reservoir in the Brahmani basin. The reservoir extent was digitized on the basis of its topography using Google Earth and ArcGIS. Then, the DEM was clipped according to the obtained reservoir shapefile. Number of cells and their corresponding cell depth were then obtained from the attribute table of the clipped DEM. The area (A_c) contributing to each depth was calculated from the following equation:

$$A_c = n*\mathrm{D}^2 \tag{3}$$

Table 1 | Description of the data used

S. no.	Spatial data	Resolution	Source
1	Digital Elevation Model (DEM)	90 m × 90 m	Shuttle Radar Topography Mission (SRTM) of USGS
2	Landuse/Land Cover (LU/LC) of 2010	1:2,50,000	National Remote Sensing Centre, ISRO
3	Soil	1:2,50,000	National Bureau of Soil Survey & Landuse Planning (NBSS-LUP)
4	Meteorological data	Precipitation (1901–2013): 0.25 × 0.25 gridded data Temperature (1951–2013): 1.0 × 1.0 gridded data	Indian Meteorological Department (IMD), Pune, India
5	Hydrological data	Daily streamflow data (1980–2012)	India-WRIS Web Portal

where n is the number of cells with the same elevation and D is the cell size. Since the DEM is of 90 × 90 m resolution, the area of each cell will be 8,100 m^2. Finally, the depth versus number of cells histogram was developed and given as input to SWMM.

Catchment delineation

El Alfy (2016) used Arc-Hydro tool for deriving the morphometric characteristics of the catchment. In the present study, an ArcGIS hydrological analysis toolbox was used for delineation of catchment with the help of DEM and flow direction. The steepest descent from each cell is taken to calculate the flow direction. In the post-processing stage, the derived basin layers were converted into vector form from the raster dataset obtained and then given to the SWMM model.

Other parameters

In the case of hydrodynamic models, parameters are classified into two types: measured parameters and inferred parameters. While measured parameters include geometric characteristics of the system such as surface elevation, node depth, channel geometry and catchment area, the inferred parameters are measured directly from the model (Yu *et al.* 2001; Choi & Ball 2002).

Choi & Ball (2002) reported that during the calibration process, the measured parameters are considered error free, whereas some adjustments are required in the inferred parameters. Therefore, inferred parameters such as infiltration parameters, depression storage, percentage of impervious and pervious area, and roughness coefficient of channel and catchment, were adjusted during the calibration process.

The catchment area was calculated through field calculator functionality of ArcGIS, to give it as an input to the SWMM model. Furthermore, width, percentage imperviousness and slope of the sub-catchment were calculated with the help of DEM, land use and sub-catchments area in ArcGIS environment. Channel and node parameters of the river network were extracted from DEM using an ArcGIS 3D analyst toolbox.

Calibration

Calibration is done to match the model output with the field observed data. Automatic optimization techniques such as Monte Carlo optimization can be used for such iterative processes. The developed SWMM model was calibrated and validated on a monthly as well as daily basis using Monte Carlo based optimization. The Latin-hypercube sampling method was employed to generate 2000 samples for each parameter. The Latin Hypercube Sampling (LHS) is an efficient and time saving approach that involves stratified sampling. Hardyanto & Merkel (2007) developed a 3-D FEM groundwater model to demonstrate the employability of LHS for uncertainty and sensitivity analysis.

During calibration, twelve inferred parameters were used. Parameters, such as width, % impervious and slope, have different values for different catchments. Hence, these were given an initial value and then varied within the pre-defined calibration interval. The range of these parameters as well as their initial values are shown in Table 2. The calibration

Table 2 | Initial values and calibration range of major parameters

Parameter	Initial value	Calibration interval	References
N-perv	0.1	0.02–0.8	Huber & Dickinson (1992), Temprano *et al.* (2007), Rossman (2010)
N-imperv	0.012	0.011–0.033	Huber & Dickinson (1992), Rossman (2010)
Imperv, width and slope		± 25%	Temprano *et al.* (2007)
Des-imperv (mm)	0.4	0.3–2.5	Huber & Dickinson (1992), Rossman (2010)
Des-perv (mm)	3	2.0–5.1	Huber & Dickinson (1992), Rossman (2010)
Zero-imperv (%)	15	5–20	Huber & Dickinson (1992), Rossman (2010)
Max. infilt (mm/h)		25–110	Huber & Dickinson (1992), Rossman (2010)
Min. infilt (mm/h)		0–10	Huber & Dickinson (1992), Rossman (2010)
Decay constant (1/h)	4	2–7	Huber & Dickinson (1992), Rossman (2010)
Drying time (days)	7	2–14	Huber & Dickinson (1992), Rossman (2010)

intervals were defined as per existing literature (Huber & Dickinson 1992; Temprano *et al.* 2007; Rossman 2010).

For calibration, SWMM was run for each set of the above-mentioned parameters and the obtained simulated results were compared with the observed data at Gomlai and Jenapur gauging stations.

During calibration-validation, the agreement between the monitoring data and the SWMM outputs was evaluated based on three statistical criteria such as Nash–Sutcliffe Efficiency (NSE) (Nash & Sutcliffe 1970), Percent Bias (PBIAS) (Gupta *et al.* 1999) and root mean square error-observations standard deviation ratio (RSR) (Singh *et al.* 2004; Moriasi *et al.* 2007).

NSE indicates the fit of observed versus simulated data on 1:1 line. It varies between $-\infty$ and 1.0, with $NSE = 1$ being the optimal value. PBIAS is a measure of mean tendency of simulations to be greater or lesser than the corresponding observations. Positive values of PBIAS indicate model underestimation bias, whereas negative values indicate overestimation bias. RSR is based on root mean square error and standard deviation of observations. $RSR = 0$ indicates flawless model simulation.

RESULTS AND DISCUSSION

Depth-area curve of Rengali reservoir

On the basis of depth versus number of cells histogram, the depth vs. cumulative area relationship was defined as shown in Figure 2. It can be observed from Figure 2 that the maximum area of the Rengali reservoir is contributed by the DEM cells which have an elevation of about 122 m.

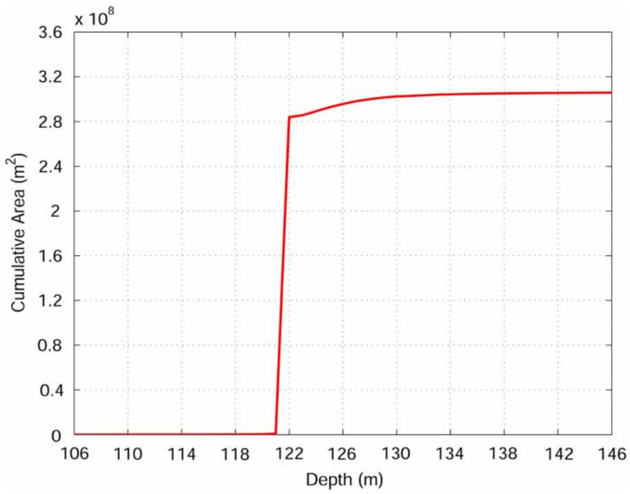

Figure 2 | Depth-area relationship for Rengali reservoir.

Model results

Saleh *et al.* (2000) and Santhi *et al.* (2001) categorized the performance of SWAT model based on the NSE values as: very good ($NSE > 0.65$), good ($0.54 < NSE < 0.65$) and satisfactory ($0.5 < NSE < 0.54$). Donigian *et al.* (1983) and Van Liew *et al.* (2007) defined the range of PBIAS to be very good ($PBIAS < \pm 10$), good ($\pm 10 < PBIAS < \pm 15$) and satisfactory ($\pm 15 < PBIAS < \pm 25$). Similarly, Singh *et al.* (2005) and Moriasi *et al.* (2007) ranked the SWAT, HSPF model

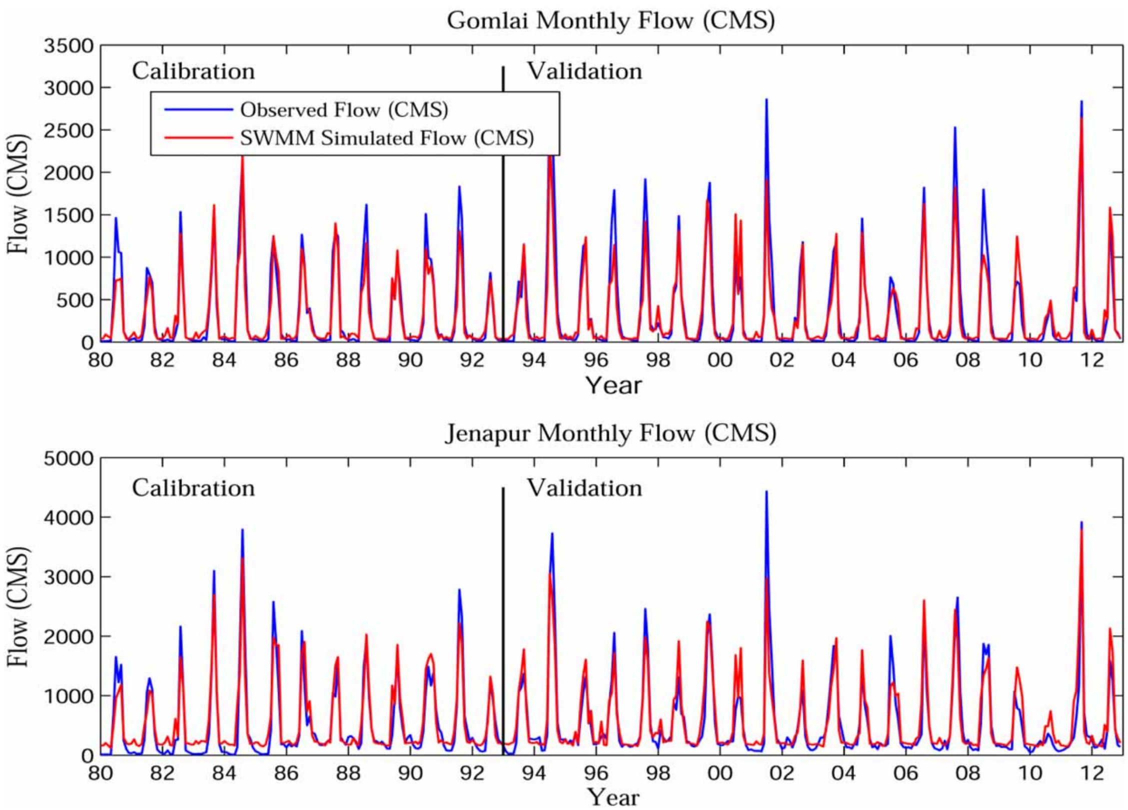

Figure 3 | SWMM model performance on a monthly basis.

simulations on the basis of RSR statistic as very good (0.00 < RSR < 0.50), good (0.50 < RSR < 0.60) and satisfactory (0.60 < RSR < 0.70).

The model was calibrated and validated on a monthly time scale for 13 years (1980–1992) and 20 years (1993–2012) respectively, using Monte Carlo based auto-calibration technique. Figure 3 shows the calibration-validation plots on a monthly basis for two gauging stations, namely: Gomlai and Jenapur. It can be seen from Table 3 that the model performed in very good range (Donigian *et al.* 1983; Saleh *et al.* 2000; Santhi *et al.* 2001; Singh *et al.* 2005; Moriasi *et al.* 2007; Van Liew *et al.* 2007) when tested on monthly time scale on statistical criteria such as NSE, PBIAS and RSR.

It was also calibrated on a daily basis from 2004 to 2006 (3 years) and validated on the same time scale from 2007 to 2012 (6 years). Figure 4 depicts the performance of model on daily basis. As can be seen from Table 4, the model performance on a daily basis lies in the very good category at Gomlai station (Donigian *et al.* 1983; Saleh *et al.* 2000; Santhi *et al.* 2001; Singh *et al.* 2005; Moriasi *et al.* 2007; Van Liew *et al.* 2007). During the calibration of Jenapur station, though model performance was very good on RSR criterion, it marginally dropped to the good category when evaluated on NSE and PBIAS criteria. Similarly, for the validation phase, the performance of the model on NSE and RSR was in the very good range and its PBIAS value was

Table 3 | SWMM model performance based on a monthly basis

	NSE		**RSR**		**PBIAS**	
	Calibration	**Validation**	**Calibration**	**Validation**	**Calibration**	**Validation**
Gomlai	0.899	0.87	4.2705e – 06	2.6467e – 06	7.66	7.80
Jenapur	0.884	0.851	3.1945e – 06	2.3026e – 06	– 9.04	– 6.85

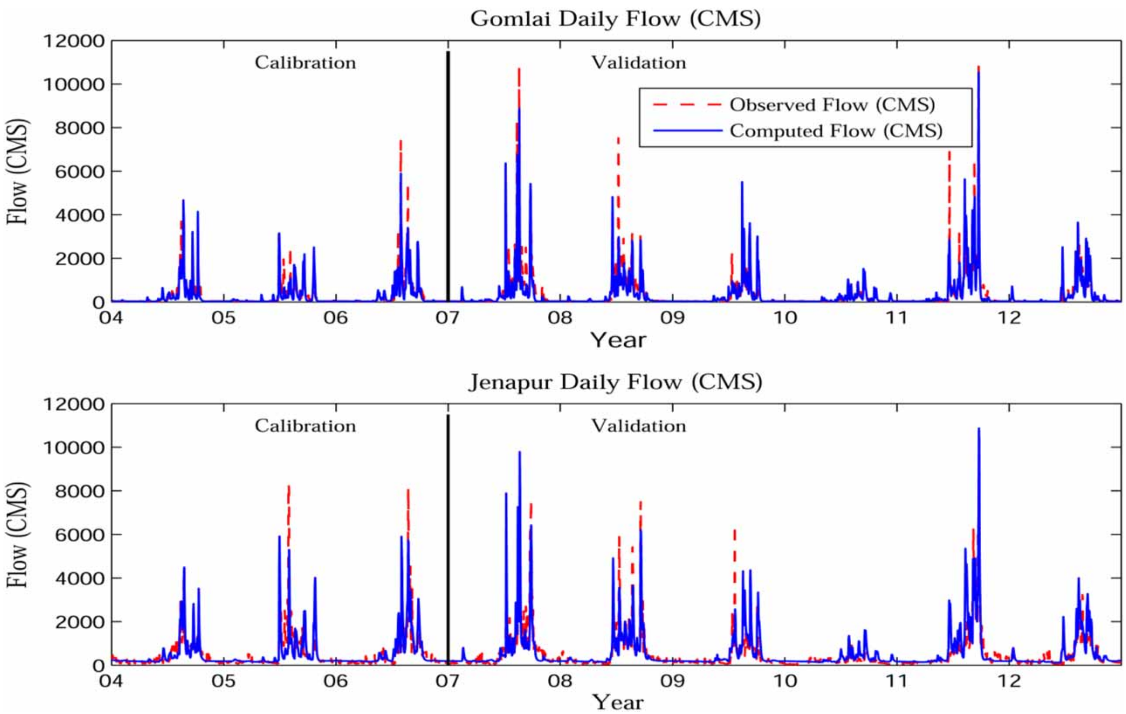

Figure 4 | SWMM simulated results on a daily basis.

Table 4 | SWMM model performance based on a daily basis

	NSE		RSR		PBIAS	
	Calibration	**Validation**	**Calibration**	**Validation**	**Calibration**	**Validation**
Gomlai	0.725	0.711	7.9773e − 07	3.0724e − 07	0.41	0.09
Jenapur	0.616	0.664	8.3523e − 07	3.3065e − 07	−10.63	−14.13

found to be in the good range. It may be noted that the model performance declined marginally on daily time scale probably because a detailed operation policy for Rengali reservoir located upstream of Jenapur was not applied to the model for paucity of data.

From Figure 5, it can be seen that there is a good agreement between the observed and simulated flood peaks for maximum yearly and maximum monthly flood from year 2003 to 2012. Thus, the developed SWMM model can be said to be an effective tool for operational flood warning.

Furthermore, it was found that the model was able to provide the critical location having high flooding probability. The model was run for the year 2011 and it reported flooding near a place called Jajapur downstream of Jenapur. This result is in line with the observed records which also reported inundation at this location in 2011. The Jajapur region experiences frequent floods in spite of having sufficient channel cross-section, as the area does not receive sufficient flow velocity due to its flat terrain.

The channel capacity value of 1 signifies full channel, whereas 0 value stands for completely empty channel. It can be observed from Figure 6 that the channel capacity reaches its maximum limit near Jajapur. It can also be seen that the flow velocity is relatively higher at Jenapur and its channel capacity is adequate enough to route any flood.

Figure 7 indicates that even though Jenapur receives discharge as high as 10,579 m^3/s, there is no inundation in the area. However, downstream of Jenapur (near Jajapur), it was found that the maximum flow should not be more than

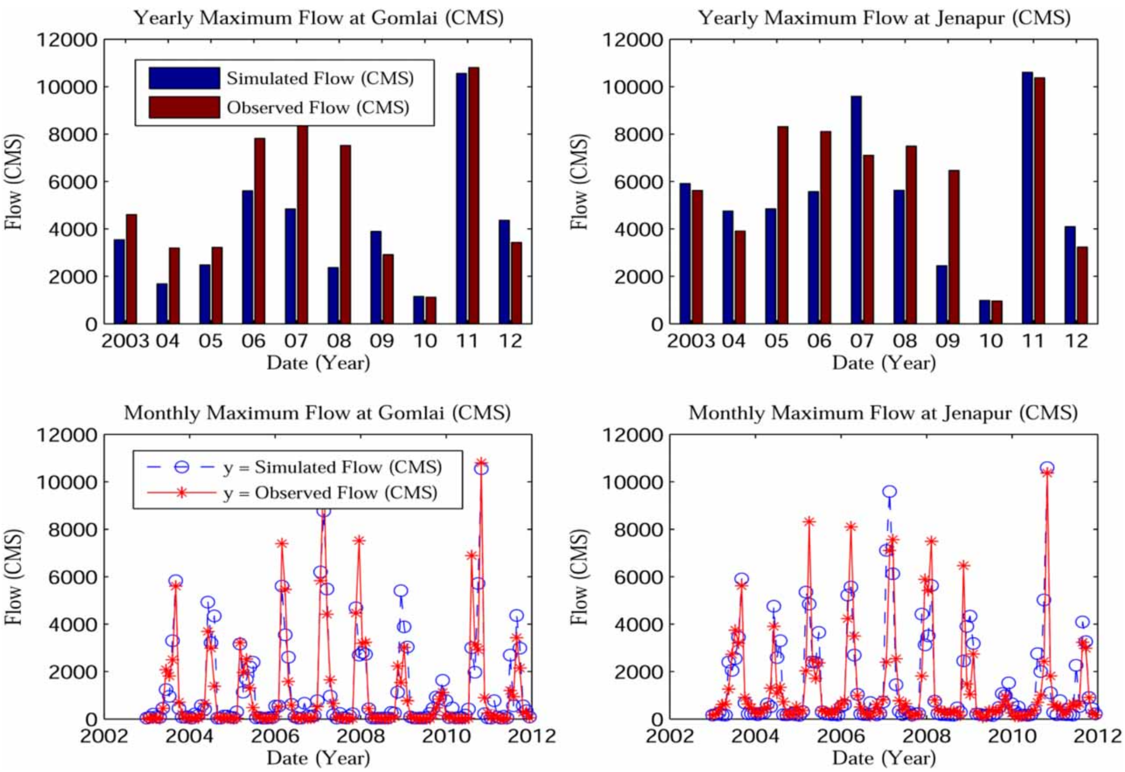

Figure 5 | Comparison of simulated and observed maximum yearly and monthly discharge.

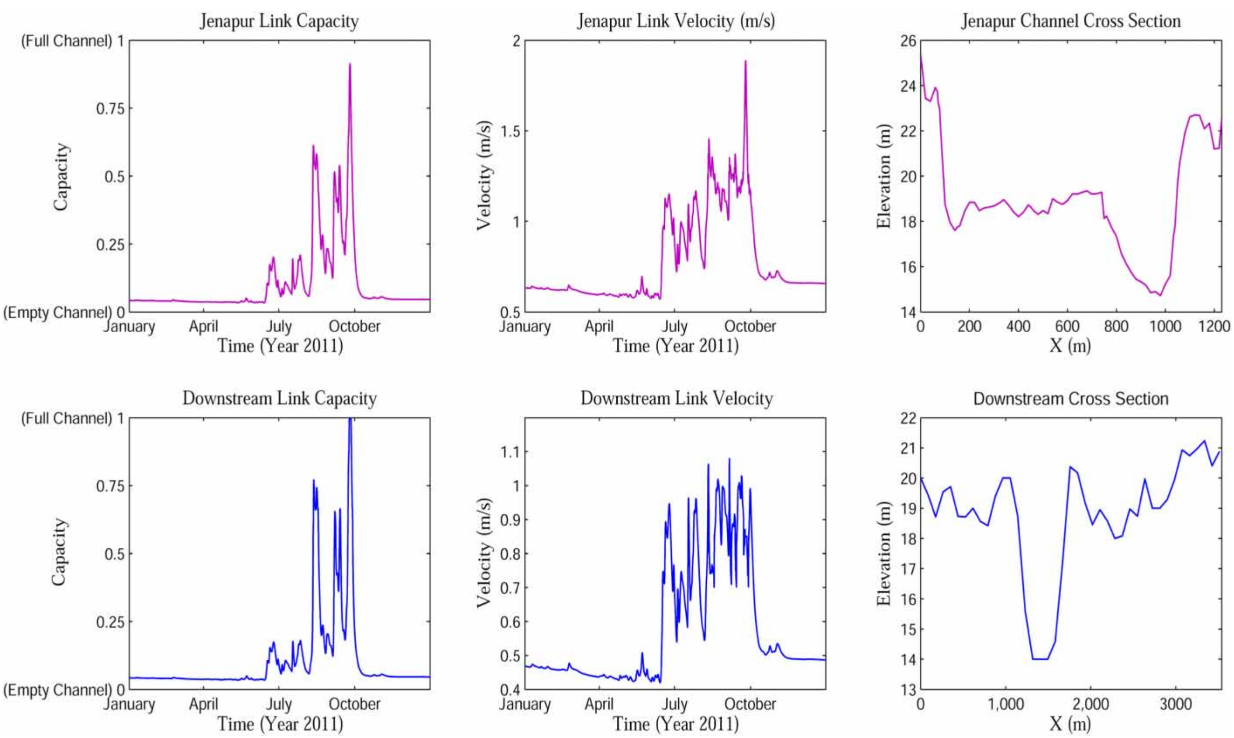

Figure 6 | Capacity, velocity and cross-section at Jenapur and downstream.

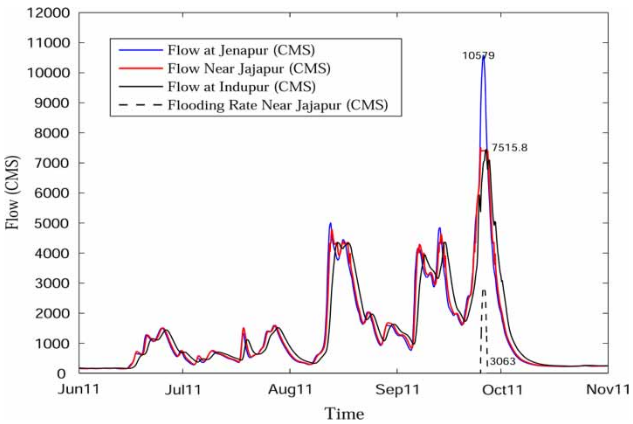

Figure 7 | Flow in the deltaic region of Brahmani basin.

7515.8 m^3/s so as to avoid any possible flooding in the region. As the channel capacity at Jajapur is insufficient to accommodate a maximum flow of 10,579 m^3/s coming from Jenapur, the region experiences flood. The model reports the maximum flood rate of 3,063 m^3/s at this location. It may be noted that this flood rate and maximum non-flooding flow is based on the river cross-sections and width obtained from the DEM and may vary with another DEM or surveyed cross-section data.

CONCLUSION

In this study, GIS-based SWMM5 model was developed to assess the feasibility of SWMM as a river flood simulator in the Brahmani delta which experiences large-scale damage due to frequent flooding. The performance of Monte Carlo optimization was quite good in auto-calibrating SWMM on a monthly and daily basis. Reasonably well NSE, PBIAS and RSR values indicate that the developed model performed quite well in calibration and validation stages on both daily as well as monthly time scales. Subsequently, the model was able to identify the exact flooding location and predicted that the maximum flow should be regulated below 7515.8 m^3/s in order to avoid any possible inundation in the downstream deltaic areas. Thus, on the basis of SWMM's performance in the present study, it can be concluded that in addition to SWMM's application in urban catchments, it can also be effectively used for simulating the catchment response to flood events in natural systems such as rivers. Therefore, instead of setting up flood monitoring stations that involve great cost, SWMM can be employed as an early warning flood prediction tool at a relatively small price. SWMM does not contain a transpiration model and considers the same temperature in the entire watershed for the purpose of calculating evaporation. Due to exorbitantly expensive station-wise meteorological data, a gridded daily dataset was used in the study. If station-wise hourly rainfall data are fed into the model, an improvement in the results could be expected. Also, the model performance might improve substantially on a daily basis if daily basis reservoir operating policies are made available to the model.

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