

Estimation of flood damage functions for river basin planning: a case study in Bangladesh

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Abstract Located at the low-lying deltaic floodplain of Ganges–Brahmaputra–Meghna river basin, Bangladesh suffers damages from flooding with regularity. From the perspective of long-term planning and management, a reliable flood damage function is a critical component in the estimation of flood-induced economic loss. Such functions are, however, notoriously difficult to develop. This study utilizes in-stream water level and flood-affected area (FAA) data from Flood Forecasting and Warning Center and Bangladesh Water Development Board to evaluate the best form and data input characteristics of flood damage functions for Bangladesh. The performance of various function configurations (geographic data, water level data, and function form) was tested. The Nash–Sutcliffe efficiency and residual error analysis results suggest that, in general, the logistic function performs better than the other two function forms, and the maximum of daily-maximal water level is the best suited to estimate (FAA). As expected, when information is available from all basins (the Ganges, the Brahmaputra, and the Meghna), the resulting flood damage functions provide the most accurate estimations of FAA. Furthermore, the comparison between single- and multivariable flood damage functions does not demonstrate a clear advantage of using multivariate function in our study area. When flood damage functions with finer spatial and temporal resolution can be constructed using remote sensing technology or hydrodynamic modeling, the intra-year and district-level changes to FAA can be evaluated. These findings provide a better flood management plan for Bangladesh and have potential to be generalized to other similarly flood-affected nations.

Keywords Flood-affected area · Water level · Ganges · Brahmaputra · Meghna

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1 Introduction

Bangladesh annually suffers the consequences of its location in the low-lying deltaic floodplain of the Ganges–Brahmaputra–Meghna (GBM) river basin. Heavy monsoon rainfall and a poor drainage system result in large-scale flooding and have amounted to billions of dollars in losses over the past 30 years (Yu et al. 2010). Even in “normal” years, about 20 % of Bangladesh (31,000 km²) is flooded, while up to about 80 % of the land area is considered flood prone (Mirza 2002; Biswas 2008). Situated at the mouth of the GBM rivers, Bangladesh receives an annual sediment load between 0.5 billion and 1.8 billion tons per year. This inundation of sediment gradually changes the valley geometry and floodplain topography and regularly results in a reduction in water conveyance capacity (Biswas 2008).

It has long been recognized in Bangladesh that engineering measures such as storage, marginal embankments, and improvement of water ways can play a role in the mitigation of flood damage. More recently acknowledged is the importance of non-structural measures such as river basin planning and management, flood forecasting and early warning systems, and flood plain zoning. In 1972, the Flood Forecasting and Warning Center (FFWC) was founded under the Bangladesh Water Development Board (BWDB) to work as the national focal point with respect to flood monitoring, forecasting, warning, and dissemination of information. Currently, FFWC utilizes advanced software such as “MIKE11” and “Flood Watch” to provide real-time forecasts and warning services during the monsoon season (Islam et al. 2010).

Flood management studies can be generally classified as motivated by the problems of (1) long-term planning and management or (2) emergency response. The concern of this paper is planning and management, and the problem is addressed through an evaluation of candidate flood damage functions for Bangladesh at the national level. Flood damage functions are a component of most river basin planning studies aiming at the estimation of economic losses due to floods. They can be incorporated in the model framework either as an objective (Malekmohammadi et al. 2010) or as a constraint (Karamouz et al. 2008). The reliability of calculated economic loss results (e.g., Lund 2002; Zhu and Lund 2009) is dependent on a reasonable flood damage function. However, many previous studies have concluded that the construction of “monetary-based” flood damage functions is not supported by the quantity and quality of data available, which are often plagued by errors in field surveys and in value estimation, among other scale-specific difficulties (USACE 1996; Booi 2004; Merz et al. 2004; Messner et al. 2007; Thielen et al. 2008). In this paper, we address the problem of unavailable or unreliable damage information by defining flood damage in terms of “affected area” and utilize a systematic approach to evaluate the potential utility of candidate flood damage functions for Bangladesh. We analyze information from the three contributing basins (the Ganges, the Brahmaputra, and the Meghna), using a variety of flood characteristics (e.g., water level), and with multiple functional forms (linear, exponential, and logistic). Historical water level data from the FFWC and flood-affected area (FAA) data from the BWDB are the primary data sources. Results of this study have the potential to improve flood damage functions generally, and especially for Bangladesh’s national flood management program.

2 Literature review

A number of previous studies have explored flooding issues in Bangladesh from a variety of aspects, such as the relationship between rainfall and flood severity, the construction of flood warning systems, and flood impact mitigation. A summary of these studies is

provided here. This review of the literature is specific to those studies related to the use of flood damage functions in river basin planning models and the construction of flood damage functions. The most commonly used metrics of flood magnitude and flood damage forms are identified.

2.1 Flooding in Bangladesh

Recent catastrophic floods took place in 1988, 1998, 2004, and 2007 (Islam et al. 2010), causing losses from one to over two million metric tons of rice, or 4–10 % of the annual rice production. These losses pose a significant threat to food security in Bangladesh. Dasgupta (2007) found that flood-prone districts in Bangladesh tend to have consistently greater headcount ratios of poverty and that floods cause spikes in poverty headcount ratio, especially in historically flood-prone areas.

Flooding primarily takes place during the monsoon season as the GBM Rivers dispel enormous discharge that converges in an area with low gradient and flat terrain (Dhar and Nandargi 2000). Flooding in Bangladesh is caused by a combination of flash floods from neighboring hills, inflow of water from upstream catchments, overbank spilling of rivers from in-country rainfall, and drainage congestion. The Ganges and the Brahmaputra are two of the most sediment-heavy rivers in the world. According to Islam et al. (1999), the annual combined suspended sediment load of the two rivers in Bangladesh is 1,037 million tons (approximately 300 in the Ganges and 700 in the Brahmaputra). Of the total suspended sediment load, approximately half is delivered to the coastal area of Bangladesh. Drainage congestion due to bank erosion is particularly problematic in the Brahmaputra River where there is a significant intra-annual variability in water level, as well as active changes in the course of the river (Sharma et al. 2005, 2010). There has been marked coastal erosion in the western portion of the GBM delta during the past 50 years in response to sea-level rise and a decreased sediment load (due in large part to the introduction of upstream barrages) (Rahman et al. 2011), a pronounced aggradation (accretion) in the east during the past 300 years (Allison and Kepple 2001), and a reduction in water conveyance capacity throughout (Biswas 2008).

Mirza (2002, 2003) evaluated the relationship between monsoon timing and three extreme historical floods in Bangladesh in 1987, 1988, and 1998 and suggested that the extreme floods of 1988 and 1998 were attributable to the concurrence of peak flows in the Ganges and the Brahmaputra. The author conducted a sensitivity analysis for 20 years of floods of the Ganges, Brahmaputra, and Meghna rivers under different GCM scenarios (IPCC Coupled Model Intercomparison Project phase 3, CMIP 3) and concluded that the probability of flooding in the basin will increase. Studies of the Brahmaputra River in India have found that floods on that river in recent years have already become more severe, due to an increased frequency of extreme weather events and a variety of newly emerged manmade interventions: occupation of the floodplain, destruction of wetlands, and poor management of flood control measures (Bhattachaiyya and Bora 2009; Jamir et al. 2008).

2.2 Applying flood damage functions in a river basin model

Originally proposed by White (1964), flood damage functions are among the most common methods for flood damage estimation worldwide (Dutta et al. 2003). Flood damage functions define the relationship between flood severity (as measured by depth, volume, duration, etc.) and projections of resultant damage, which are usually derived using historical flood damage information and questionnaire survey data through regression and

Table 1 Example case studies of flood damage function around the world

Study	Location and scale	Dependent variable	Independent variable	Method
Apel et al. (2009)	Germany/city	% of loss	Water level	Linear/square root/quadratic
Boettje et al. (2011)	Denmark/city	Monetary loss	Water level	Discontinue functions to fit logistic shape
Booij (2004)	Vietnam/basin	Monetary loss	Water level	Exponential
Chang et al. (2008)	Taiwan/basin	Monetary loss	Flood depth	Logarithmic
Davis (1985)	USA/city	% of loss	Flood depth	Logistic shape
Dutta et al. (2003)	Japan/basin	Monetary loss	Flood depth/duration	Logarithmic/exponential
Karamouz et al. (2008)	Iran/basin	Monetary loss	Water level	Logistic shape
Mirza (2002)	Bangladesh/national	Crop damage	Volume	Linear
Pretenthaler et al. (2010)	Austria/city	Monetary loss	Flood depth/volume	Kernel fitting/linear
Smith (1994)	Australia/city	Monetary loss	Flood depth	Logarithmic
SOC (2012)	USA/basin	% of loss	Flood depth	Logistic shape
Villiers et al. (2007)	South Africa/city	Monetary loss	Flood depth	Quadratic
Yazdi and Neyshabouri (2012a)	Iran/basin	% of loss	Water level	Logistic shape

other data-driven approaches (Smith 1994). Table 1 presents the location and key characteristics of select examples of previous flood damage function studies. According to Table 1, the applicable spatial scale of approaches of this type has been as large as a country (or basin, if transnational) or as small as a city. The choice of flood damage variables throughout the studies is fairly standard. Monetary loss (absolute or percentage) is the most common dependent variable, and in-stream water level or land-based inundation flood depth is the most widely used flood characteristics (independent variables). However, the function shape varies from study to study, with logistic, exponential, and linear functions three of the most commonly used.

Detailed guidelines or handbooks for flood damage estimation are available for Australia (UNSW 1981), the USA (Davis 1985; USACE 1996), the UK (Penning-Rowsell et al. 2005), and the EU (Messner et al. 2007). These reports provide theoretical background and step-by-step guidance for the application of flood damage functions to flood impact and risk assessment. Normally, streamflow duration curves are constructed first (based on modeling results or observations), and the expected flood damage is calculated under different flow conditions using a flood damage function. When the flow pattern changes due to climate change impacts or human behavior changes, the expected flood damage will change correspondingly.

Long-term flood planning and management projects of significant scale often warrant the development of a mathematical model of the water resources system that considers both physical hydrological environments and anthropogenic influences. When such models have been built, and if flood management is among the considerations, flood damage functions as described above can be incorporated in the water resources system modeling structure. Most of these studies used monetary loss to define flood damages. Some studies use single-objective optimization, such as Karamouz et al. (2008), which minimized the total cost for flood mediation actions: sandbags, embankment, and levee construction. Zhu and Lund (2009) minimized the total cost for levee design, and Malekmohammadi et al. (2010) determined the optimal reservoir operation to minimize flood damages. Other studies evaluated the “trade-off” between flood damages and mediation cost (Yazdi and Neyshabouri 2012b; Woodward et al. 2014). Woodward et al. (2014) also suggested using multi-objective methods to consider flood risk management to avoid the drawback that single-objective optimization does not necessarily provide a comprehensive view of the solution space and can therefore potentially distort the decision-making process. In a real multi-objective modeling framework, objectives do not have to be in the same unit (e.g., monetary). For example, Yang and Cai (2011) evaluated the trade-off between the total economic loss (flood loss and recreational losses) and fish biodiversity for reservoir reoperation purpose.

In this study, to avoid the pitfalls of monetary data inadequacies, we use FAA as an alternative to the monetary-based flood damage. FAA is published annually by BWDB as an indicator of the year’s flood severity. We hypothesize that, for the purposes of planning and management modeling, the minimization of FAA is a reasonable surrogate for minimization of monetary damage. FAA can be translated into monetary terms through inclusion of land-use/land-cover data (including a number of other complicating factors related to both the value and vulnerability of land-use types) but has not been quantitatively evaluated in this study.

3 Study area and data

The BWDB has a network of monitoring stations through which daily water level and runoff have been collected throughout the nation since the 1950s. Three key stations, one

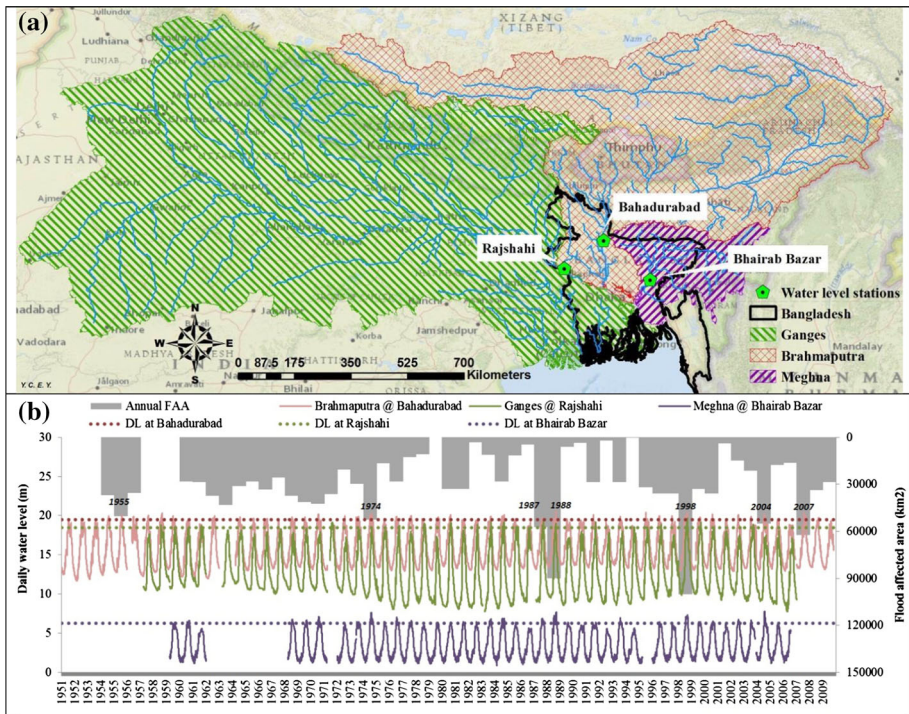


Fig. 1 a Ganges–Brahmaputra–Meghna Basin and water level stations; b daily water level data (1951–2009) for three water level stations and FAA in Bangladesh. The dashed lines represent dangerous water level for three stations

in each basin, are used in this study. The Rajshahi station on the Ganges River, the Bahadurabad station on the Brahmaputra River and the Bhairab Bazar station on the Meghna River were chosen after a preliminary check of the length of the data record (at least 40 years). The locations and historical daily water level for these stations are given in Fig. 1. Bahadurabad station has the most complete dataset (least missing data) from 1949 to 2009. Rajshahi station has the longest dataset (from 1922 to 2006) but with sparse data prior to 1957. Bhairab Bazar station has coverage only from 1959 to 2006. In Fig. 1, we show the time series from 1951 to 2009 during which time water level data are available from all three stations. Each station has its own “dangerous water level,” defined by the BWDB. They are as follows: 18.5 meter above sea level (masl) for Rajshahi (Ganges River); 19.5 masl for Bahadurabad (Brahmaputra River); and 6.5 masl for Bhairab Bazar (Meghna River). Dashed lines in Fig. 1 show dangerous water levels for these stations, specifically. These dangerous water levels are used as a critical water level in each warning system. The annual flood reports published by BWDB (2012) provide time series of annual FAA (km^2), beginning in 1954. The bars in Fig. 1 present the data graphically. Forty-eight years from 1954 to 2009 were selected in which the FAA data and water level data from all three basins are mostly overlapped, making possible the construction of flood damage functions. This period included several years of exceptional (1987, 1988, 1998, and 2007) and catastrophic (1955, 1974, and 2004) floods (labeled on Fig. 1), as defined by Mirza (2002). Thirty-six years of data were used for model development, and 12 years were used for evaluation.

4 Methodology

The goal of this work is to evaluate candidate flood damage functions in Bangladesh as one element in a basin-wide water resources planning model for the Brahmaputra. The primary purpose of the water resources planning model is to evaluate water allocation in terms of basin-wide economic profits resulting from hydropower development, irrigation network improvement, flood mitigation, and other investment options. A reliable flood damage function is a required component of an analysis for this purpose. In order to satisfy this requirement, it was necessary to first identify the explanatory factors. Based on the limitations posed by the available data, and in keeping with standard methods presented in the literature, we attempted to model the FAA using information from all of the following: (1) an understanding that the best predictive river flow source might be one of the three rivers (Ganges, Brahmaputra, or Meghna) or some combinations of the three; (2) the expectation that the predictive flow characteristic might be the water level or the flood duration; and (3) the shape of the function might be exponential, logistic, or linear. We will explain the contribution of each factor in this section. One limitation of using daily water level data alone (not in coordination with daily streamflow measurements) is that we are forced to assume that the rating curve (water level-flow volume) is not significantly nonlinear. This might not be a good approximation for such sediment-heavy rivers for which the cross-section might be altered annually, as suggested by Hopson and Webster (2010). Future studies are recommended to explore this question further.

4.1 Individual basin information

Streamflow data from three stations Rajshahi, Bahadurabad, and Bhairab Bazar can be used individually to represent the Ganges, Brahmaputra, and Meghna river basins, respectively, or collectively to indicate the state of the delta area for the entire GBM. Forty-six thousand km² of the drainage area of the Ganges basin is located inside Bangladesh (Ahmad and Ahmed 2003), and the long-term average annual total runoff is 355 billion cubic meters (BCM) into Bangladesh (Mirza et al. 2003). The Brahmaputra has a similarly sized drainage area located inside Bangladesh (47,000 km²). The average annual total runoff is 642 BCM, almost double that of the Ganges. The Meghna River has the smallest drainage area (36,000 km²) located in Bangladesh, but still contributes average annual total runoff of 149 BCM to Bangladesh.

The Brahmaputra and Meghna river basins experience slightly earlier water level rises than does the Ganges due to the progression of the summer monsoon air mass from the southeast to the northwest (Mirza 2003). In general, the water levels start to rise between mid-April and early-May in the Brahmaputra and Meghna and reach their peaks between July and August. The water level in the Ganges begins to rise between mid-May and early-June and reaches its peak in August or September. Islam et al. (2010) explained that, in addition to the predictable seasonality of the monsoon rainfall, sea surface temperature and the El Niño-southern oscillation (ENSO) also likely affect flow and water level in these three basins. During years in which the flood peak of the Ganges and Brahmaputra coincided (potentially attributable to the effects of ENSO), extreme floods (e.g., 1988 and 1998) have occurred in Bangladesh (Mirza 2003).

4.2 Flood characteristics

Table 1 summarizes the river flow characteristics used as independent variables for damage estimation in previous studies. Water level, or more descriptively, the river stage, is one of the most commonly used flood descriptors. According to daily water level data obtained from the BWDB, the long-term average daily water levels are 12.89, 15.58, and 3.52 masl at Rajshahi, Bahadurabad, and Bhairab Bazar stations, respectively. In this study, since FAA data were available only on an annual basis, only one value of water level could be correlated to FAA each year. We therefore tested the predictive power of two related versions of water level: (1) the maximum of the monthly average water level (MML) for each year and (2) the maximum daily water level (MDL) for each year. In the case of the MML, average monthly values were first calculated by averaging the daily water levels for each month, and the maximum of the 12 monthly averages was then used in the correlation with annual FFA. In the case of the MDL, the maximum of the 365 (or 366) daily water levels was correlated directly with annual FFA.

In addition to the water level, flood duration is another commonly used flood characteristic in flood damage function construction. Duration is important especially for extreme flood events. Ahmad and Ahmed (2003) concluded that one reason that the 1998 flood event in Bangladesh was especially destructive was its long duration (65 vs 20 days in 1988). To address this, we calculate the total number of days when daily water level in each river is above its respective dangerous water level line (DAL) and use this number as an indicator for flood duration. Finally, we define a “Flood Index” (FI) as the product of the MDL and the DAL and used it as the fourth tested flood characteristic. This approach is similar to that of Ahmed and Mirza (2000) who presented a flood intensity index as the product of flood duration (number of days) and the depth of the flood above the flood danger level for a given area.

4.3 Function format

We tested three forms of flood damage functions in this study: linear, exponential, and logistic. Equation (1) is the linear flood damage function.

$$\text{Flood Affected Area} = \alpha \times \text{FC} + \beta \quad (1)$$

where α and β are model parameters and FC is the chosen flood characteristic such as MDL or DAL described in the previous section. A linear model is the most straightforward modeling format, where α represents the marginal change of FAA per unit changes of FC (slope).

Equation (2) is the exponential flood damage function. Like the linear function, two parameters γ and δ are needed to determine the shape of the exponential curve. Generally speaking, the function is usually more sensitive to δ than to γ .

$$\text{Flood Affected Area} = \gamma \times e^{\delta \times \text{FC}} \quad (2)$$

Stedinger and Grygier (1985) suggested a logistic flood damage function following the general logistic format (Richards 1959), and this is included here as Eq. (3). Four parameters minimal flood characteristic (MinFC), critical flood characteristic (CFC), G and ε are used to determine the shape of the logistic function (S-curve), and the “Max Flooded Area” can be estimated based on the historical record.

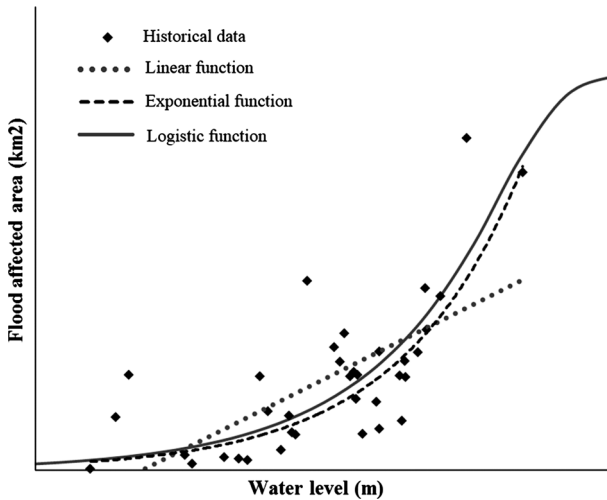


Fig. 2 Conceptual diagram of flood damage functions with observed flooded area

$$\text{Flood Affected Area} = \frac{\text{Max Flooded Area}}{(1 + \text{MinFC} \times e^{-G(\text{FC}-\text{CFC})})^{1/\varepsilon}} \tag{3}$$

Values of parameters in these equations are determined by statistical parameter estimation methods: ordinary least squares (OLS) estimates. Figure 2 demonstrates the shape of these three formats. The dotted line is an example of (1), the dashed line is an example of (2), and the solid line is an example of (3).

5 Results

Nash–Sutcliffe efficiency (NSE) was used to evaluate the performance of each function configuration. A specific function configuration is composed of the selected: (1) basin data; (2) flood characteristic; and (3) function format. The maximal positive and negative residuals were used to evaluate the error.

5.1 Nash–Sutcliffe efficiency of function configurations

Table 2 summarizes NSE values for different function configurations. We first evaluated the average NSE across basins, flood characteristics, and the three function formats. Based on the NSEs shown in Table 2, of the three basins, the Meghna River water level is the best predictor of FAA in Bangladesh. The overall average NSEs for the Meghna, Brahmaputra, and Ganges are 0.506, 0.321, and 0.12, respectively. If water level information from all three basins is used, the average NSE increases to 0.522. The flood characteristic with the best predictive power is the MDL, with an average NSE across all basins of 0.467. DAL (NSE = 0.322) and FI (NSE = 0.321) are the least effective predictors. Of the flood model forms, the logistic function has the highest average NSE value (0.476) across all basins. The linear function has a similar NSE value (0.435), and the exponential function has the lowest average NSE value (0.191).

According to Table 2, the best model (the highest NSE value) is a logistic function using the MDL mean from all three basins. We designate this function configuration “Fit 1,” which identified as “a” in Table 2. However, in some cases, water level data might not be available simultaneously for all three basins. Using data only from the Brahmaputra River (which has the longest period of water level data), the best flood damage function is a logistic curve based on MDL. The Brahmaputra-MDL-to-Bangladesh-FAA flood damage function is termed “Fit 2” and so labeled as “b” in Table 2. Likewise, the best fit using only Meghna River data fits a logistic curve to MML data. The Meghna-MML-to-Bangladesh-FAA relationship is labeled as “c” (termed “Fit 3”) in Table 2. No reasonable estimation can be made of FAA in Bangladesh using water level data only from the Ganges River.

5.2 Residual error analysis and model uncertainty

The NSE efficiency is an indicator of the general performance of a function, but does not provide information regarding maximal bias, which provides an upper end to the distribution of possible flooded area. In order to evaluate function bias, we calculated the maximum positive and negative residual errors for each function configuration and summarized these findings in Fig. 3. Figure 3 shows that the max-negative residuals are larger than max-positive residuals, meaning that the function underestimates larger FAAs more severely than it overestimates smaller FAAs. However, when an exponential function is fit to DAL and FI, the Meghna and the Brahmaputra show much larger positive residual error. Interestingly, in terms of basin selection, data from Ganges show the smallest positive residual, meaning that if we estimate FAA using only Ganges water level data, the overestimation will be the smallest. On the other hand, when data from all basins are used, the negative residual will be the lowest, which means that the underestimation of FAA will be smallest. Of the flood characteristics, use of MDL results in the smallest positive residual, while use of MDL, DAL, and FI all results in similar negative residuals. Of the three function shapes, the logistic function shows the lowest positive and negative residuals.

As in the results of the NSE analysis, individual combinations of predictive factors show different results. Fitting an exponential function to the Ganges’ FI gives the smallest positive residual, but also the greatest negative residual. Similarly, fitting a logistic function to the Meghna-MML resulted in a small negative residual. However, the positive residual is not as good. Figure 3 suggests that in order to reduce both positive and negative residuals, use of water level data from all basins is preferable. We plotted results (calculated FAA) from all model runs in time series and superimposed them with observations to show the model uncertainty range. Some models (most of them with exponential format) significantly overestimate FAA in 1974 and 1998, and most models underestimate FAA in 1988. The uncertainty (band width) is much larger for extreme flood years compare to normal flood years.

We can combine the analysis of NSE, residual bias, and model uncertainty and identify the function configuration that results in higher NSE and smaller residual bias. In general, the logistic function provides better performance than the other two function types, and of the flood characteristics, MDL is the best predictor. Taking these findings into account, we identified the top three function configurations of factors (Fit 1, Fit 2, and Fit 3 indicated as “a”, “b”, and “c” in Table 2) from Fig. 4 and plotted them against historical observations in Fig. 5. Fit 1 captures the FAA in year 1988 and 1998 (exceptional floods) and year 1974 (catastrophic floods) relatively well. The highest residual error is $7,267 \text{ km}^2$ in 1998. Fit 2 misses the FAA in year 1987 (exceptional flood) by $39,000 \text{ km}^2$. That is because,

Table 2 NSE of different flood damage function configurations

Nash–Sutcliffe efficiency	Max of monthly daily-mean WL	Max of daily-max WL	Days above DWL	Flood index
Ganges				
Linear	0.117	0.143	0.186	0.187
Exponential	-0.036	-0.019	0.056	0.055
Logistic	0.141	0.210	0.198	0.200
Brahmaputra				
Linear	0.320	0.447	0.504	0.502
Exponential	0.316	0.616	-0.413	-0.374
Logistic	0.360	0.630 ^b	0.472	0.469
Meghna				
Linear	0.518	0.528	0.563	0.582
Exponential	0.455	0.478	0.356	0.280
Logistic	0.627 ^c	0.595	0.546	0.545
All				
Linear	0.438	0.544	0.688	0.689
Exponential	0.455	0.706	0.069	0.053
Logistic	0.593	0.727 ^a	0.640	0.661

^a the best fitted function using data from all three basins

^b the best fitted function using data from Brahmaputra only

^c the best fitted function using data from Meghna only

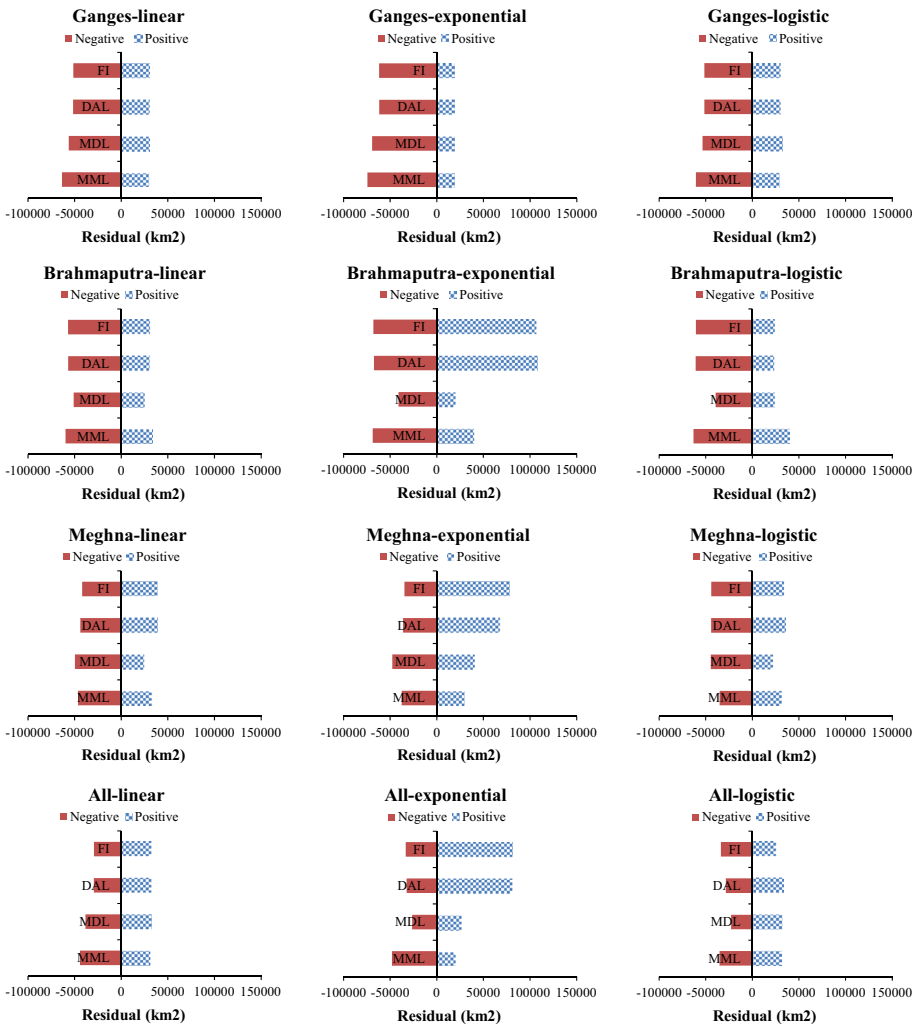


Fig. 3 Maximum positive and negative residual errors of different function configurations

according to the water level data from BWDB, the monsoon flood in that year was largely attributable to high water level and longer duration in the Meghna, specifically. This is also the reason why Fit 3 captures the FAA in that year. Both single-basin functions (Fits 2 and 3) underestimate the FAA in year 1998 (exceptional flood) due to missing information from the Ganges. As discussed earlier, the 1998 flood was exceptional largely because of the occurrence of flood peaks in the three rivers simultaneously (without the typical delay in the Ganges peak resulting from east–west monsoon movement).

5.3 Function validation

Due to limitations in the available data, we were only able to validate the flood damage functions using water level data from the Brahmaputra alone. Twelve years were used,

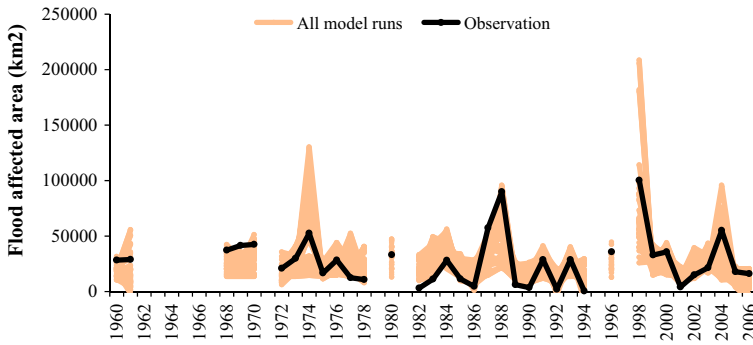


Fig. 4 Results of 36 models superimposed with observations to demonstrate the model uncertainty range

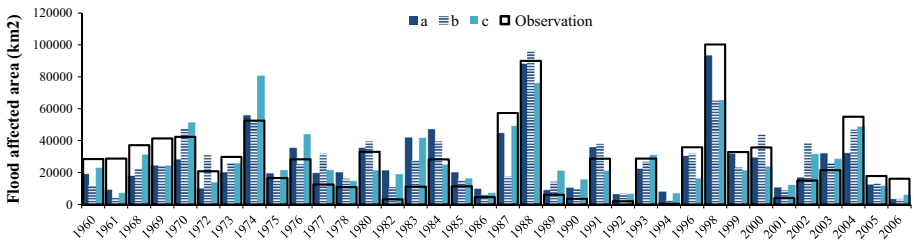


Fig. 5 Observed and modeled flood-affected area under three best function configurations

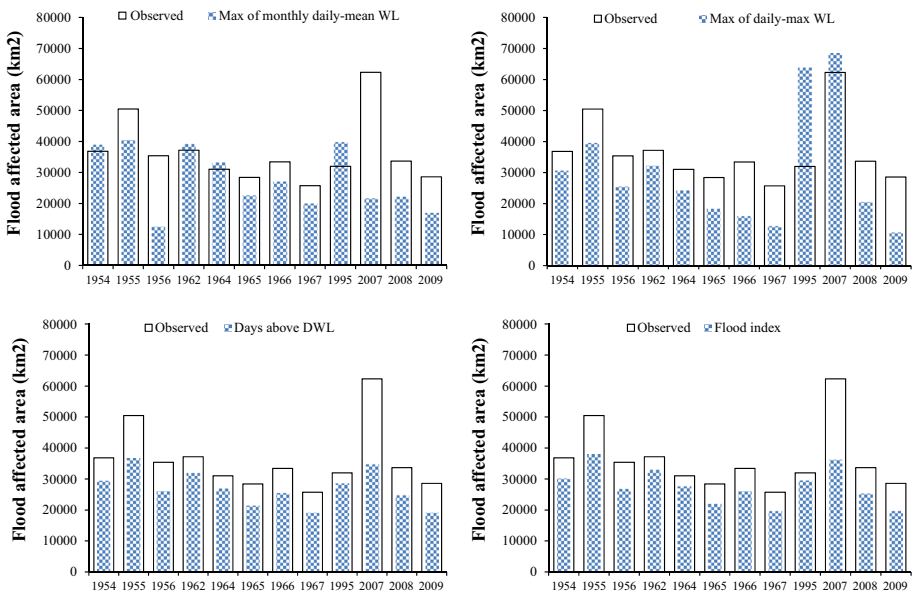


Fig. 6 Example flood damage function validation using Brahmaputra water level data only and logistic function

including year 2007, which was classified as an exceptional flood year, and year 1955, which was classified as a catastrophic flood year. Figure 6 presents results using four flood characteristics and with the logistic function as an example. According to Fig. 6, all four flood characteristics capture the 1955 FAA relatively well, although small underestimation occurs in all functions. However, only the function using MDL captures the 2007 FAA. This is also the major reason why this function configuration outperforms all but one (“Fit 1”) of the function configurations tested. However, this function configuration is also the only one (among the four validated) that overestimates the 1995 FAA. This is because the max daily water level in 1995 is high at Bahadurabad (20.36 meters compared to the dangerous water level of 19.5 meters), but with relatively fewer days above the dangerous water level in that year (14 days, compared to year 2007, which has 21 days). Therefore, the FAA calculation is biased upward by this water level information.

6 Discussion

This section discusses the comparison between single- (shown in the result section) and multivariable flood damage functions and points to potential improvements for future studies.

6.1 Multivariate nonlinear flood damage function

Schroter et al. (2014) tested the complexity of flood damage models and concluded that for their case study area (Germany), models with additional independent variables outperform models using only water depth as independent variables. We have conducted a similar evaluation in our case study area, Bangladesh, to check whether the same conclusion can be drawn.

In the previous section, all functions use a single predictor. Here, we use a data mining approach, genetic programming (GP), to construct multivariate flood damage functions. GP is a heuristic algorithm which has been shown to be an efficient method by which to construct an equation with multiple independent variables (e.g., Savic et al. 1999; Dorado et al. 2002; Yang et al. 2008). Following the rules of natural selection, GP is a symbolic learning technique that determines the best format and coefficients for the regression function. To evaluate results from different data sources, we use GP to construct flood damage functions: (1) using data from all three basins and (2) using data from the Brahmaputra only. The best GP relationship resulting (among 100 trails) from the use of data from all three basins is given in Eq. (4).

$$\text{Flood Affected Area} = (\text{MDL}_B + \text{DAL}_G + \text{DAL}_B + \text{DAL}_M) \times (\text{MDL}_M - 0.7) \quad (4)$$

where MDL_B is the maximum daily water level from Brahmaputra, and DAL_G , DAL_B , and DAL_M are number of days above dangerous water level from Ganges, Brahmaputra, and Meghna, respectively. The best GP results using data only from the Brahmaputra are given in Eq. (5).

$$\text{Flood Affected Area} = 4(\text{MDL}_B + \text{DAL}_B) \times (\text{MDL}_B - 0.895) \quad (5)$$

Note that all MDL and DAL values in Eqs. (4) and (5) are standardized. Actual FAA results are compared with their single-variable counterparts (“Fit 1” and “Fit 2”) in Fig. 7. No significant improvement is observed. The NSE is 0.721 for Eq. (4) and 0.727 for “Fit

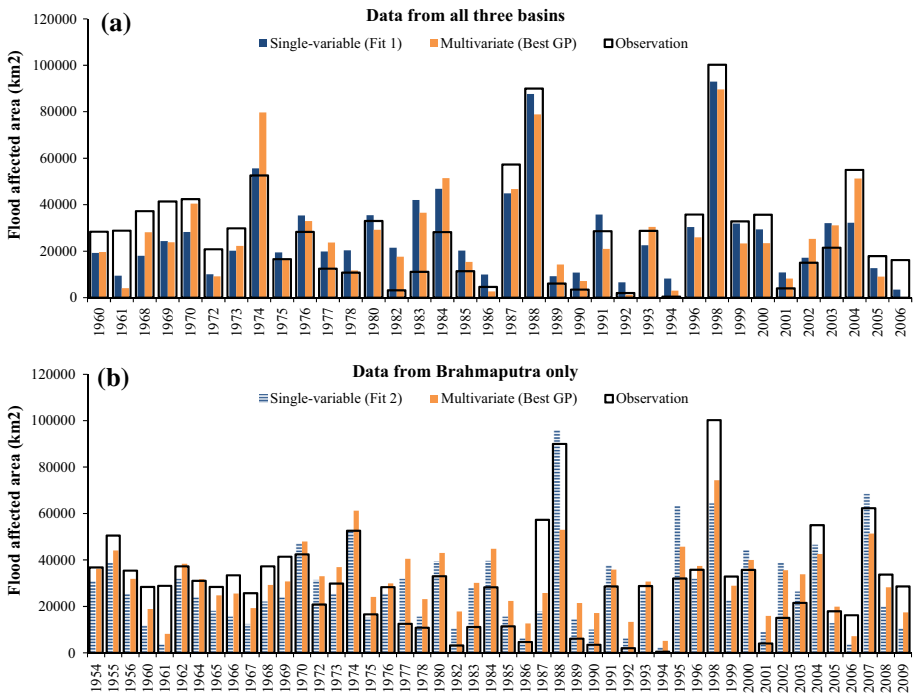


Fig. 7 Observed and modeled flood-affected area for single and multivariate flood damage functions

1”; the NSE is 0.565 for Eq. (5) and 0.630 for “Fit 2.” Figure 7a shows that Eq. (4) and “Fit 1” both capture extreme floods in year 1998 and 1988. Although Eq. (4) outperforms “Fit 1” in year 2004, it significantly overestimates the year 1974. Similar results can be seen in Fig. 7b. Equation (5) slightly improves the result in year 1998 but underestimates the year 1988. The overestimation in year 1995 is less in Eq. (5), but it results in overestimates in years 1977–1986.

These results suggest that switching from a single-variable flood damage function to a multivariate flood damage function does not necessarily improve the model performance in Bangladesh; this is contrary to the conclusion from Schroter et al. (2014) for Germany. Geographic differences, observation uncertainty, and different definition of flood damages all likely to contribute to this contrary result.

6.2 Finer resolution extensions

Because FAA data were only available at the scale of the entirety of Bangladesh, flood damage functions evaluated in this study were limited to their effect on all of Bangladesh. Data did not support basin-specific explorations. Therefore, these functions are sufficient for the long-term planning purpose as discussed above, but cannot be used to evaluate intra-year or district-level FAA effects. Data with finer temporal and spatial resolution would be necessary for that task.

There are two ways in which better data could be generated to improve studies of this type: (1) processing remote sensing data for inundation (flood-affected) area and (2) using a hydrodynamic model to calculate inundation area. Satellites and airborne instruments

provide remotely sensed information that can be used to estimate the extent and dynamics of flood inundation for large areas. For example, Amarnath (2013) developed an algorithm to map flood inundation area from satellite images using the original optical data from moderate resolution imaging spectroradiometer (MODIS) to calculate 8-day, pixel level (250–500 m) flood inundation area for South Asia. By superimposing population or land-cover (crop type) data, the inundation area can be further processed for real flood damages. Islam et al. (2009) also used MODIS data with different methods to map flood inundation in Bangladesh. A comprehensive review of this method specific for Monsoon Asia is provided by Sanyal and Lu (2004). Neal et al. (2012) and Wu et al. (2012) used global satellite rainfall data and hydrodynamic models to compute 1-km-resolution flood inundation area globally. Usually, a 2D flood model will be incorporated with the hydrodynamic model using the continuity equation to link flow (volume) fluxes with water depth changes in each cell. Furthermore, a momentum equation can be used to track the water balance between cells (e.g., Bates et al. 2010). A number of recent papers document the ability of macro-scale hydrological models to forecast streamflow when coupled with large-scale weather/climate forecasting models, which have demonstrated utility on a number of different timescales, especially for large basins in South Asia (e.g., Indus Basin by Shrestha et al. 2014). Combining these macro-scale hydrological models with the functions developed in this work, water management officials could obtain real-time projections of FAAs. This has the potential to address the “timing” issue that has so far been neglected. Advances in probabilistic forecasting could then enable risk-based decision-support frameworks, as proposed by Dale et al. (2014).

After careful validation with observed data, the conclusion is that both methods could provide reliable flood inundation area data at a finer resolution, which would help to construct flood damage functions at the sub-national and sub-annual level.

7 Conclusion

From the perspective of river basin planning and management, a reliable flood damage function is critical for estimating economic loss due to floods. This is especially true for countries such as Bangladesh that suffer flood damages every year. Heavy monsoon rainfall and a poor drainage system result in annual flooding and have inflicted billions of dollars in damages on the country in the past 30 years (Yu et al. 2010). The FFWC was founded under the BWDB as the national agency responsible for flood monitoring, forecasting, warning, and dissemination of information. Using the FFWC water level data from stations located in the Ganges, Brahmaputra, and Meghna basins, and FAA data from BWDB, we tested flood damage functions developed using information from: the water level of the three contributing river systems; with different flood characteristics (the maximum of the monthly average water level “MML,” the maximal daily water level “MDL,” days when daily water level is above the dangerous water level “DAL” and Flood Index “FI”); and with different function forms (linear, exponential and logistic).

Using the NSE and residual error analysis, we found the logistic function to outperform the other two function forms (linear and exponential) and MDL to be the most suitable flood characteristics (following by the MML). However, using the linear function with DAL and FI information from all basins also provided reasonable results. As expected, when information is available from all three basins, the resulting food damage functions provide the most accurate FAA estimation. If, however, information were not available for

all three basins, using the water level data from Brahmaputra and Meghna could still provide a reasonable estimate of FAA in Bangladesh.

The comparison between single and multivariate flood damage function does not demonstrate a clear advantage of using multivariate function in Bangladesh. Flood damage functions with finer spatial and temporal resolution could be constructed with the help from remote sensing technology or hydrodynamic modeling. These enhanced flood damage functions can be used to evaluate intra-year or district-level FAA changes for Bangladesh.

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References

- Ahmad QK, Ahmed AU (2003) Regional cooperation in flood management in the Ganges–Brahmaputra–Meghna region Bangladesh perspective. *Nat Hazards* 28:181–198
- Ahmed AU, Mirza MMQ (2000) Review of causes and dimensions of floods with particular reference to flood'98: national perspectives. In: Ahmad QK, Chowdhury AKA, Imam SH, Sarker M (eds) *Perspectives on flood 1998*. University Press Ltd., Dhaka
- Allison MA, Kepple EB (2001) Modern sediment supply to the lower delta plain of the Ganges–Brahmaputra River in Bangladesh. *Geo-Mar Lett* 21:66–74
- Amarnath G (2013) An algorithm for rapid flood inundation mapping from optical data using a reflectance differencing technique. *J Flood Risk Manag* 12. doi:10.1111/jfr3.12045
- Apel H, Aronica GT, Kreibich H, Thielen AH (2009) Flood risk analyses—how detailed do we need to be? *Nat Hazards* 49:79–98
- Bangladesh Water Development Board (BWDB) (2012) Annual flood report 2012, Dhaka, Bangladesh
- Bates PD, Horritt MS, Fewtrell TJ (2010) A simple inertial formulation of the shallow water equations for efficient two dimensional flood inundation modelling. *J Hydrol* 387:33–45
- Bhattachaiyya NN, Bora AK (2009) Floods of the Brahmaputra River in India. *Water Int* 22(4):222–229
- Biswas AK (2008) Management of Ganges–Brahmaputra–Meghna system: way forward. In: Varis O, Tortajada C, Biswas AK (eds) *Management of transboundary rivers and lakes*. Springer, Berlin Heidelberg
- Boettle M, Kropp JP, Reiber L, Roithmeier O, Rybski D, Walther C (2011) About the influence of elevation model quality and small-scale damage functions on flood damage estimation. *Nat Hazards Earth Syst Sci* 11:3327–3334
- Booij MJ (2004) Flood damage assessment and modelling in the red river basin in Vietnam. International workshop on flood controls decision support system. 10–12 Feb 2004, Hanoi, Vietnam
- Chang LF, Lin CH, Su MD (2008) Application of geographic weighted regression to establish flood-damage functions reflecting spatial variation. *Water SA* 34(2):209–216
- Dale M, Wicks J, Mylne K, Pappenberger F, Laeger S, Taylor S (2014) Probabilistic flood forecasting and decision-making: an innovative risk-based approach. *Nat Hazards* 70:159–172
- Dasgupta A (2007) Floods and poverty traps: evidence from Bangladesh. *Econ Polit Wkly* 42(30):3166–3171
- Davis SA (1985) Business depth-damage analysis procedures, research report 85-R-5. Institute for Water Resources, Water Resources Support Center, U. S. Army Corps of Engineers, Ft. Belvoir, Virginia, USA
- Dhar ON, Nandargi S (2000) A study of floods in the Brahmaputra basin in India. *Int J Climatol* 20:771–781
- Dorado J, Rabunal JR, Puertas J, Santos A, Rivero D (2002) Prediction and modelling of the flow of a typical urban basin through genetic programming: applications of evolutionary computing. *Lect Notes Comput Sci* 2279:190–201
- Dutta D, Herath S, Musiake K (2003) A mathematical model for flood loss estimation. *J Hydrol* 277:24–49
- Hopson TM, Webster PJ (2010) A 1–10 day ensemble forecasting scheme for the major basins of Bangladesh: forecasting severe floods of 2003–07. *J Hydrometeorol* 11:618–641

- Islam MR, Begum SF, Yamaguchi Y, Ogawa K (1999) The Ganges and Brahmaputra Rivers in Bangladesh: basin denudation and sedimentation. *Hydrol Process* 12:2907–2923
- Islam AS, Bala SK, Haque A (2009) Flood inundation map of Bangladesh using MODIS surface reference data. In: 2nd international conference on water & flood management. Dhaka, Bangladesh
- Islam AS, Haque A, Bala SK (2010) Hydrologic characteristics of floods in Ganges–Brahmaputra–Meghna (GBM) delta. *Nat Hazards* 54:797–811
- Jamir T, Gadgil AS, De US (2008) Recent floods related natural hazards over west coast and Northeast India. *J Indian Geophys Union* 12(4):179–182
- Karamouz M, Abesi O, Moridi A, Ahmadi A (2008) Development of optimization schemes for floodplain management; a case study. *Water Resour Manage* 23:1743–1761
- Lund JR (2002) Floodplain planning with risk-based optimization. *J Water Resour Plan Manag* 127(3):202–207
- Malekmohammadi B, Zahraie B, Kerachian R (2010) A real-time operation optimization model for flood management in river-reservoir systems. *Nat Hazards* 53:459–482
- Merz B, Kreibich H, Thielen A, Schmidtke R (2004) Estimation uncertainty of direct monetary flood damage to buildings. *Nat Hazards Earth Syst Sci* 4:153–163
- Messner F, Penning-Rowsell E, Green C, Meyer V, Tunstall S, van der Veen A (2007) Evaluating flood damages: guidance and recommendations on principles and methods, UFZ, European Community's Sixth Framework Programme. Leipzig, Germany
- Mirza MMQ (2002) Global warming and changes in the probability of occurrence of floods in Bangladesh and implications. *Glob Environ Change* 12:127–138
- Mirza MMQ (2003) Three recent extreme floods in Bangladesh: a hydro-meteorological analysis. *Nat Hazards* 28:35–64
- Mirza MMQ, Warrick RA, Ericksen NJ (2003) The implications of climate change on floods of the Ganges, Brahmaputra and Meghna Rivers in Bangladesh. *Clim Change* 57:287–318
- Neal J, Schumann GJ-P, Bates PD (2012) A simple model for simulating river hydraulics and floodplain inundation over large and data sparse areas. *Water Resour Res* 48, Paper no. W11506
- Penning-Rowsell E, Johnson C, Tunstall S, Tapsell S, Morris J, Chatterton J, Green C (2005) The benefits of flood and coastal risk management: a handbook of assessment techniques. Middlesex University Press, London
- Pretenthaler F, Amrusch P, Habsburg-Lothringen C (2010) Estimation of an absolute flood damage curve based on an Austrian case study under a dam breach scenario. *Nat Hazards Earth Syst Sci* 10:881–894
- Rahman AF, Dragoni D, El-Masri B (2011) Response of the Sundarbans coastline to sea level rise and decreased sediment flow: a remote sensing assessment. *Remote Sens Environ* 115(12):3121–3128
- Richards FJ (1959) A flexible growth function for empirical use. *J Exp Bot* 10:290–300
- Sanyal J, Lu XX (2004) application of remote sensing in flood management with special reference to monsoon Asia a review. *Nat Hazards* 33:283–301
- Savic DA, Walters GA, Davidson JW (1999) A genetic programming approach to rainfall-runoff modeling. *Water Resour Manage* 13:219–231
- Schroter K, Kreibich H, Vogel K, Riggelsen C, Scherbaum F, Merz B (2014) How useful are complex flood damage models? *Water Resour Res* 50. doi:10.1002/2013WR014396
- Sharma N, Sankhua RN, Pandey AD (2005) Spatio-temporal modeling of hydrological variability for the river Brahmaputra using artificial neural network. In: Proceedings of the international symposium on 'role of water sciences in transboundary river basin management. Ubon Ratchathani, Thailand
- Sharma N, Johnson F, Hutton C, Clark M (2010) Hazard, vulnerability and risk on the Brahmaputra basin: a case study of river bank erosion. *Open Hydrol J* 4:211–226
- Shrestha KY, Webster PJ, Toma VE (2014) An atmospheric–hydrologic forecasting scheme for the Indus River basin. *J Hydrometeorol* 15:861–890
- Smith DI (1994) Flood damage estimation—a review of urban stage-damage curves and loss functions. *Water SA* 20:231–238
- State of California (SOC) (2012) Central Valley flood protection plan attachment 8F: flood damage analysis, the natural resources agency. Department of Water Resource, Sacramento, CA, USA
- Stedinger JR, Grygier J (1985) Risk-cost analysis and spillway design. *Comput Appl Water Resour* 1208–1217
- Thielen AH et al (2008) Methods for the evaluation of direct and indirect flood losses. In: 4th international symposium on flood defence: managing flood risk, reliability and vulnerability, Toronto, Ontario, Canada, 6–8 May 2008
- U. S. Army Corps of Engineers (USACE) (1996) Risk-based analysis for flood damage reduction studies: engineering manual. Washington, DC, USA

- UNSW (1981) Evaluation methodology of flood damage in Australia, technical project report. University of New South Wales, Australia
- Villiers GT, Viljoen MF, Booysen HJ (2007) Standard residential flood damage functions for South African conditions. *Suid-Afrikaanse Tydskrif vir Natuurwetenskap en Tegnologie* 26(1):26–36
- White GF (1964) Choice of adjustment to floods. Research Paper No. 93, Department of Geography, University of Chicago. Chicago, IL, USA
- Woodward M, Gouldgy B, Kapelan Z, Hames D (2014) Multiobjective optimization for improved management of flood risk. *J Water Resour Plan Manag* 140(2):201–215
- Wu H, Adler RF, Hong Y, Tian Y, Policelli F (2012) Evaluation of global flood detection using satellite-based rainfall and a hydrologic model. *J Hydrometeorol* 13:1268–1284
- Yang YCE, Cai X (2011) Reservoir reoperation for fish ecosystem restoration using daily inflows—A case study of Lake Shelbyville. *J Water Resour Plan Manag ASCE* 136(6):470–480
- Yang YCE, Cai X, Herricks EE (2008) Identification of hydrologic indicators related to fish diversity and abundance—a data mining approach for fish community analysis. *Water Resour Res* 44:W04412. doi:[10.1029/2006WR005764](https://doi.org/10.1029/2006WR005764)
- Yazdi J, Neyshabouri SAAS (2012a) Optimal design of flood-control multi-reservoir system on a watershed scale. *Nat Hazards* 63:629–646
- Yazdi J, Neyshabouri SAAS (2012b) A simulation-based optimization model for flood management on a watershed scale. *Water Resour Manage* 26:4569–4586
- Yu W et al (2010) Climate change risks and food security in Bangladesh. Earthcan, Washington
- Zhu T, Lund JR (2009) Up or out—economic-engineering theory of flood levee height and setback. *J Water Resour Plan Manag* 135(2):90–95