Integrated flood risk assessment of the Arial Khan River under changing climate using IPCC AR5 risk framework

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ABSTRACT

Bangladesh is situated at the confluence of GBM basins, with 90\% of the basin area locating outside the country. Future climate change will lead to intense, prolonged, and frequent floods in Bangladesh. An integrated flood risk assessment that transforms risks from transboundary river basins to the local administrative level is necessary. A 1D-2D hydrodynamic model is developed for flood vulnerable Arial Khan River feed by basin-scale hydrologic model for low (RCP2.6) and high (RCP8.5) climate scenarios. An increasing trend in flood depth, duration, and the area is observed from the early (2020s) to the end (2080s) of the century for both scenarios. The difference between both RCPs is minimal from the 2020s to 2050s but becomes very pronounced in the 2080s. The depth-duration area with equal weightage provides better hazard results for the area. Flood risk is assessed using the IPCC AR5 framework incorporating vulnerability and exposure. Some medium-hazard zones fall into high-risk zones due to high exposure and vulnerability to flooding. The areas along the left reach are found more hazard-prone, while the areas on the right side are more risk-prone in the 2080s of RCP8.5. The hazard/risk maps will help policymakers identify priority areas for planning a sustainable flood management strategy.

Key words: AR5 risk framework: exposure, integrated flood risk, principal component analysis, vulnerability

HIGHLIGHTS

- High-resolution bias-corrected GCM climate data for RCP2.6 and RCP8.5 scenarios are considered.
- A multi-model hydrological-hydrodynamic modelling system is developed.
- IPCC AR5 climate scenarios and risk framework are considered.
- Future flood hazard and risks are assessed for Arial Khan River Floodplain for the 2020s, 2050s, and 2080s.
- Medium hazard zones might have high flood risk in the future.
1. INTRODUCTION

Bangladesh is highly susceptible to floods due to its location at the confluence of the world’s three major basins – Ganges-Brahmaputra-Meghna (GBM) and hydro-meteorological and topographical characteristics of the basins (Shaw et al. 2013). About 92.5% of the combined basin lies outside of Bangladesh in the neighbouring countries: India, China, Nepal, and Bhutan (Mirza et al. 2003). Furthermore, about 80% of the annual rainfall occurs in the monsoon (June to September) across these river basins. Therefore, Bangladesh drains out huge cross-border runoff and internal runoff through a network of rivers moving towards the final destination – the Bay of Bengal. The volume of generated runoff exceeds the natural drainage capacity most of the time and causes frequent floods in Bangladesh.

On average, annual floods inundate 20% of the country, reaching as high as about 70% during extreme flood events (Mirza 2002). Increasing GHG emissions, global warming, and climate change will undoubtedly worsen the situation manifold. IPCC (International Panel on Climate Change) fifth assessment report (AR5) projects an increase in global temperature in between 0.3 and 4.8 °C for low (RCP – Representative Concentration Pathway 2.6) to high (RCP8.5) emission scenario by the end of 21st century (IPCC 2013). At the same time, the equatorial Pacific is likely to experience an increase in mean precipitation under the RCP8.5 scenario (IPCC 2013). Climate variability is also a factor in understanding the hydrologic cycle response due to global warming. Though changes in mean precipitation and temperature have been studied intensively in recent years, precipitation variability has gained less attention. However, the detection of spatial and temporal patterns of climate variability is a challenging issue. One of the most critical factors in choosing the time resolution which can result in different spatial and temporal patterns (Amiri & Mesgari 2017, 2019; Amiri et al. 2017). Higher inter-annual climate variability is reported to be increased in the future due to global warming (Pendergrass et al. 2017). Specifically, precipitation variability will increase 3–4% K$^{-1}$ globally, and 4–5% K$^{-1}$ over land and 2–4% K$^{-1}$ over the ocean by the end of the 21st century under RCP8.5 (Pendergrass et al. 2017). All these projections indicate a significant change in the hydrological cycle of the GBM basins. Particularly, glaciers melting in the upper HKH (Hindu-Kush Himalayan) region will increase the flow in the GBM rivers, enhancing the risk of monsoon floods in Bangladesh. Simultaneously, the monsoon regime will increase precipitation in some of the places in Bangladesh. As a result, the frequency, intensity, and longevity of
floods will increase significantly in the future decades (Mohammed et al. 2018). Hence, a sustainable flood management plan considering climate change impact is necessary for Bangladesh.

At present, flood risk assessment is recognized as an essential input for formulating flood management plans and policies at the national, regional, and local levels (ISRBC 2014). Flood hazard and risk studies help planners and policymakers in identifying the priority areas for planning any future flood management strategies. Basin-scale assessment of climate change impact plays a vital role in this regard. It’s crucial for Bangladesh since more than 90% of the upstream catchment area of the river systems of Bangladesh is located outside the country (Mirza et al. 2003). Ignoring the impact of the huge flow from upstream basins might result in inaccurate flood assessment. Hence, the transformation of floods from the basin scale to the local scale is inevitable and challenging. Regional-scale hydrologic modelling coupled with local-scale hydrodynamic modelling is a novel approach for incorporating the upstream basin flow inputs in local-scale flood hazard and risk assessment. Worldwide many such studies have been conducted so far. Dankers & Feyen (2008) studied the climate change impact in future floods in Europe using regional climate model HIRHAM and flood model LISFLOOD under IPCC Special Report on Emission Scenarios (SRES) - A2 (high) and B2 (low) emissions scenario. Ahmadisharaf et al. (2017) incorporated an integrated framework of a hydrologic model, a two-dimensional hydraulic model simulation, and a GIS-based technique for future flood hazard mapping of the Swannanoa River watershed in the U.S. If we focus on Asian countries, Shrestha & Lohpaisankrit (2017) assessed the flood hazard of the Yang River of Thailand for RCP 4.5 and RCP8.5. Gusain et al. (2020) recently studied the impacts of climate change on flood hazards of the Mahanadi River Basin of India under the RCP8.5 scenario. Though the world’s research on future flood hazard and risk assessment is quite advanced, it has hardly been investigated in Bangladesh. Recently, Nishat (2017) developed the flood inundation map of the Brahmaputra River floodplain of Bangladesh for the warmest projection (RCP 8.5) considering the upstream basin-scale flood input from the Brahmaputra basin. However, it should be investigated for other flood-vulnerable rivers of the country as well.

Additionally, considering the flood threat of Bangladesh, an integrated flood risk assessment that connects the physical flood hazard with socio-economic aspects is necessary too. Previously, Das et al. (2018) quantified the future flood hazard of the Surma-Kushia river system of Bangladesh, overlooking upstream basin runoff from the Meghna Basin. Brouwer et al. (2007) studied the socio-economic vulnerability and adaptation aspects of flooding in Bangladesh under climate change. However, all these studies either account for the hydrological characteristics of flood hazard or socio-economic context. Though few combined hazard and risk studies (Tingsanchali & Karim 2005; Ali et al. 2019) are conducted in the past, these studies are based on historic hydrologic data assuming stationarity of the climate, i.e., no shift in climate over time. Such risk assessment might underestimate the long-term impact of climate change (Milly et al. 2008). Hence, an integrated flood risk assessment for the flood-vulnerable rivers of Bangladesh under future climate emission scenarios is essential.

In this study, the climate change impact of two large upstream basins – Ganges and Brahmaputra (Figure 1(a)) with a combined area of approximately 1.6 million sq. km. has been incorporated in the local river Arial Khan through employing multiple numerical models to estimate the future flood scenarios at Arial Khan River and its floodplain. It is a river of the southwest zone of Bangladesh (shown in Figure 1(c)), the upper reach of which is subjected to riverine floods (Tingsanchali & Karim 2005). The river’s water level was above the danger level (Figure 1(d)) during the big flood events - 1987, 1988, 1998, 2004, 2007, 2010, 2011, etc. of Bangladesh and caused tremendous sufferings to the people dwelling on its floodplain (FFWC 2018). The previous studies on the Arial Khan are centred on either morphological process or river erosion contexts (Winkley et al. 1994; Mamun 2008; Akter et al. 2013). No study focusing on either flood hazard or risk of the Arial Khan River is conducted yet. Considering these facts, the current study is designed to assess the flood risk of the Arial Khan River using the IPCC AR5 risk framework. To achieve the scope, three specific objectives are fixed as – (i) to develop a multi-model hydrology-hydrodynamic modelling framework is developed to estimate the future flooding scenarios in the Arial Khan River (ii) to prepare flood hazard maps for the low (RCP 2.6) and high (RCP 8.5) emission scenarios, and (iii) to prepare integrated flood risk maps of Arial Khan River floodplain using IPCC AR5 risk framework.

While most of the studies in the past focus on either flood hazard or risk assessment, the novelty of the current study lie in assessing local-scale flood hazard incorporating upstream basin flows using RCP low and high emissions scenarios and then connecting the physical flood hazard with socio-economic contexts in terms of vulnerability and exposure indices to assess integrated flood risk, and finally assessing flood risk analysis using the most recent emission scenarios and integrative climate risk framework proposed by the IPCC in AR5. Among all the RCP scenarios of Coupled Model Intercomparison Project 5 (CMIP5), the RCP2.6 and RCP8.5 are selected as being optimistic (low concentration) and pessimistic (high concentration)
scenarios of the future. The concept and associated definitions of hazard, exposure, vulnerability, and risk used in the present study are annexed in Supp. Table 1.

2. STUDY AREA

Bangladesh is the greatest deltaic plain at the confluence of the GBM rivers and their tributaries, covering an area of 1.7 million sq. km (Figure 1(a)). Being originated from the Himalayas of China, the Ganges and the Brahmaputra rivers flow through China and India and enter Bangladesh. Flowing some distance in Bangladesh, both the rivers join to form the Padma River (Figure 1(b)). Bifurcating from the Padma at Goalundo (Figure 1(c)), the Arial Khan River flows through Faridpur and Madaripur districts before falling into the Tentulia River (BWDB 2011).

The Arial Khan River maintains a meandering channel through its course and is navigable throughout the year. The total length of this river is 160 km, with an average width of 300 m and a bed slope of 0.00003 (BWDB 2011). The river has two parts: the Arial Khan Upper (AKU), and the other is called the Arial Khan Lower (AKL). The Arial Khan Upper and its adjacent floodplains are selected due to its existing problems with monsoon flood inundation (Tingsanchali & Karim 2005) [Figure 1(c)]. The reach length chosen considered in this study is 70 km. The floodplains of this portion of the river consist of eight Upazilas–Madaripur, Shibchar, Rajoir, Janjira, Shariatpur, Bhang, Sadarpur, and Maksudpur of four districts – Madaripur, Shariatpur, Faridpur, and Gopalgonj. The floodplains of this portion of the river consist of eight Upazilas – Madaripur, Shibchar and Rajoir of Madaripur district, Janjira, and Shariatpur of Shariatpur district, Bhang, and Sadarpur of Faridpur district, and Maksudpur of Gopalgonj district. District and Upazila are served as the first and second-level administrative units, respectively. For detailed

Figure 1 | Study area (a) Ganges-Brahmaputra-Meghna (GBM) Basins with their in Bangladesh, (b) Brahmaputra-Ganges-Padma River system connected with the Arial Khan River, (c) Arial Khan River and floodplain and (d) Water level time series of Arial Khan River at d/s hydrological station (Madaripur SW 5) wrt flood danger level.
analysis, Upazila is considered as the land unit in this study. The total study area is nearly 1,825 km². The selected reach of the Arial Khan River is not protected by any flood embankment or coastal polder.

3. MATERIALS AND METHODS

3.1. Data

To develop the hydrodynamic models, the measured discharge, river cross-section, and water level data are collected from the BWDB. For the flood modelling, the 90 m SRTM DEM is used in the model. On the other hand, the river cross-sections’ elevations and water level are measured in Public Work Datum (PWD). Hence, the DEM has vertically translated from MSL (mean sea level) to PWD datum by adding an elevation of 0.46 m. The Landsat-5 TM image is downloaded from the USGS website (Supp. Table 2). Exposure and vulnerability statistics are collected from the Population Census 2011 and Agriculture Census 2008 of the Bangladesh Bureau of Statistics (BBS 2020). These are the most recent demographic and socio-economic data currently available in Bangladesh. The different datasets used in this study are tabulated in Table 1.

3.2. Climate data

Climate studies are highly dependent on the climatic projections simulated by different Global Climate Models (GCMs) and Regional Climate Models (RCMs). The coarse resolution (100–200 km) of the GCMs of CMIP5 poses different limitations to simulate regional-scale climate impact. Though downscaled high-resolution RCMs with detailed spatial information address this gap, such dynamic downsampling requires another step of computation at a different regional modelling grid with boundary conditions set from lower resolution global scale GCM. Hence, it is computationally expensive and introduces additional uncertainties from physical parameterizations, boundary conditions, regional model setups, and bias corrections (Koutroulis et al. 2018). Hence, several studies are suggested for climate models (GCM) with higher resolution that are able to simulate the observed energy spectrum of the climate system (Koutroulis et al. 2016; Zhang et al. 2016). To address these gaps, some improved and higher resolution Atmosphere Global Climate Models (AGCMs) is driven by a subset of CMIP5 GCMs and forced with Sea Surface Temperature (SST) and Sea Ice Concentration (SIC). ‘EC-EARTH3-HR’ (Hazeleger et al. 2011) is such an AGCM simulated under the HELIX project. It is bias-corrected data with a high spatial resolution of 0.5° (~50 km). Mohammed et al. (2018) checked the quality of the climate data and used it to model future flow scenarios of Brahmaputra and Ganges Basins in SWAT and found satisfactory results for both basins. Hence, this high-resolution and bias-corrected climate data is used in this study. However, since EC-Earth-HR is performed under the HELIX project for low (RCP2.6) and high (RCP8.5) emission scenarios only, it’s not possible to explore this research for other RCP scenarios.

3.3. Model selection

A multi-model hydrology-hydrodynamic modelling framework is developed here to estimate future flooding scenarios in this study. There are many recognized hydrologic models such as HEC-HMS, SWAT, VIC, TOPMODEL, MIKE SHE, etc. The SWAT model is chosen here as it is an open-source model widely recognized at regional scales hydrological modelling due to its accuracy and flexibility (Mohammed et al. 2017). Many regional basin-scale hydrological studies have been
conducted using SWAT since 2007 to date and have appreciated satisfactory results (Abbaspour et al. 2007; Solaymani & Gosain 2015; Rajib et al. 2020).

Among the hydrodynamic models, HEC-RAS, Delft3D, MIKE 11, LISFLOOD-FP, TU-Flow, etc., are some widely used numerical models. The hydrodynamic models are selected based on their application, spatial-temporal dimension, time-space-resource availability, etc. (Betancur-Pérez et al. 2016). 3D models are typically applied in small-scale coastal (Fossati & Piedra-Cueva 2013) or river modelling (Nicholas & McLelland 2004), fish pass (Gisen et al. 2017; Stamou et al. 2018), hydraulic structures (Nagata et al. 2005; Yang 2007), vortex analysis (Zhong et al. 1998), salinity (Larson et al. 2005), etc. Flood inundation mapping is a simple 2D overflow phenomenon. The vertical component is not crucial here. Application of a 3D model in such cases might cause complexities in the model setup and increase computational time, cost and space. Hence, large-scale flood inundation analysis is conducted with a 2D (Sutter 2019) or 1D-2D coupling (Rangari et al. 2019; Costabile et al. 2020). The open-source hydrodynamic model HEC-RAS is a widely recognized flood model for its accuracy in analyzing river systems and recently added feature of 1D-2D river-floodplain coupling (HEC-RAS 2016). The ability of HEC-RAS to perform combined 1D and 2D modelling within the same model allows 1D modelling in the main channel and 2D modelling in the floodplains (Brunner et al. 2015). As high-resolution river bathymetry data is practically non-existent in Bangladesh, the 1D-2D coupling provides a convenient trade-off between spatial accuracy and data requirements. Recently, many flood studies were conducted using HEC-RAS 1D/2D coupled model (Patel et al. 2017; Vozinaki et al. 2017; Das et al. 2018) and found better results.

3.4. Methodology
The primary objective of this study is to prepare flood hazard and risk maps for the Arial Khan River floodplain using a multi-model hydrology-hydrodynamic modelling framework under future climate change scenarios. A complete research methodology is illustrated in Figure 2 and described in the subsequent sections.

3.4.1. Regional hydrological modelling in SWAT
For a robust estimate of the future discharge scenarios, a SWAT model of Ganges and Brahmaputra basins developed by Mohammed et al. (2018) has been used here (Figure 1(a)). SWAT model follows the basic water balance equation, as shown in Equation (1).

\[
SW_t = SW_0 + \sum_{i=1}^{t} R_i - Q_i - ET_i - P_i - QR_i
\]

where, \(SW_t\) is the final soil water content, \(t\) is time, \(SW_0\) is the initial soil water content on day \(i\), \(R_i\) is the amount of precipitation on day \(i\), \(Q_i\) is the amount of the surface runoff on day \(i\), \(ET_i\) is the amount of the evapotranspiration on day \(i\), \(P_i\) is the amount of the percolation on day \(i\), and \(QR_i\) is the amount of return flow on the day \(i\).
The SWAT model has been developed using 90 m DEM from HydroSHEDS, GlobCover land-use map from ESA, digital soil-map from FAO, and meteorological data from Princeton Global Forcing. The performance of the model is graphically shown in Supp. Figure 4 and statistically quantified in Supp. Table 3. More details on the SWAT model development, sensitivity analysis, calibration, and validation are found in Mohammed et al. (2018).

### 3.4.2. Hydrodynamic modelling in HEC-RAS

The hydrodynamic modelling framework used here is HEC-RAS 5.0.1, developed by the US Army Corps. For 1D unsteady analysis, HEC-RAS solves 1-D Saint Venant Equation derived from Navier-Stokes Equations for shallow water flow conditions using an Implicit Finite Difference method. For 2D analysis, HEC-RAS uses the Implicit Finite Volume algorithm and solves either the full 2D Saint Venant equations or the 2D Diffusion Wave equations as defined in Equations (2)–(4) depending on the requirement and preference (Brunner 2016; Quiroga et al. 2016).

\[
\frac{\delta \xi}{\delta t} + \frac{\delta p}{\delta x} + \frac{\delta q}{\delta y} = 0
\]

\[
\frac{\delta p}{\delta x} + \frac{\delta \left( \frac{p^2}{h} \right)}{\delta x} + \frac{\delta \left( \frac{pq}{h} \right)}{\delta y} = -\frac{n^2 p g \sqrt{\left( \frac{p^2 + q^2}{h^2} \right)}}{\delta x} - g h \frac{\delta \xi}{\delta x} + pf + \frac{\delta}{\rho \delta x} \left( h \tau_{xx} \right) + \frac{\delta}{\rho \delta y} \left( h \tau_{xy} \right)
\]

\[
\frac{\delta q}{\delta t} + \frac{\delta \left( \frac{q^2}{h} \right)}{\delta x} + \frac{\delta \left( \frac{pq}{h} \right)}{\delta y} = -\frac{n^2 q g \sqrt{\left( \frac{p^2 + q^2}{h^2} \right)}}{\delta x} - g h \frac{\delta \xi}{\delta y} + qf + \frac{\delta}{\rho \delta x} \left( h \tau_{yx} \right) + \frac{\delta}{\rho \delta y} \left( h \tau_{yy} \right)
\]

where \( h \) is the water depth (m), \( p \) and \( q \) are the specific flow in the \( x \) and \( y \)-direction (m\(^2\)s\(^{-1}\)), \( \xi \) is the surface elevation (m), \( g \) is the acceleration due to gravity (ms\(^{-2}\)), \( n \) is the Manning resistance, \( \rho \) is the water density (kg m\(^{-3}\)), \( \tau_{xx}, \tau_{yx} \) and \( \tau_{yy} \) are the components of the effective shear stress and \( f \) is the Coriolis (s\(^{-1}\)).

### 3.4.2.1. HEC-RAS 1D Model.

An HEC-RAS 1D model is developed to simulate the upstream boundary flow to the HEC-RAS 1D-2D flood model (Supp. Figure 1). This 1D model has been set up for the Ganges, Brahmaputra, and Padma River system using Bahadurabad Transit and Hardinge Bridge as upstream boundaries and Sureswar as a downstream boundary. The u/s discharge boundaries and d/s water level boundary used for model calibration and validation are shown in Supp. Figure 2(a) and 2(b).

### 3.4.2.2. Statistical Modelling.

The Padma is the parent river (only contributor as well) of the Arial Khan. The hydrology of the Arial Khan River follows almost the same pattern as the Padma River (FFWC 2018). A statistical regression model is developed between the discharge at Mawa of the Padma River to that of Chowdhury Char of the Arial Khan River. Mawa station of the Padma River is the closest station (10 km) to the Chowdhury Char of the Arial Khan River. The other closest station is nearly 40 km away at Bauria Transit which is also the confluence of two mighty rivers Brahmaputra and Ganges, making its flow disturbed. Hence, it is not appropriate for this purpose.

### 3.4.2.3. HEC-RAS 1D/2D coupled Flood Model.

For the 1D river modelling, the bathymetry is set up using HEC-GeoRAS and HEC-RAS (Supp. Figure 3 (a), (b)). Later, the daily discharge and water level of Chowdhury Char and Madaripur are used as model boundaries (Supp. Figure 2c and 2d). For the 2D floodplain, a square gridded – mesh is prepared in HEC-RAS Geometry Editor. Though a smaller mesh size increases the flood accuracy, it increases the manifold’s computational time and space requirement. After several trials and errors, a square mesh of 150 m is used for this study. Among six peripheral boundaries (Supp. Figure 3 (c)), two boundaries are added to the left edge to incorporate the flood impact of the neighbouring Padma River. The rest of the boundaries are added (with a normal depth of 0.1 m) to the lower periphery to remove the stagnant floodwater during the recession period. Lateral structures are set up along the river banks to create connections between the 1D river and the 2D floodplain.

After the model simulation, three flood parameters – flood depth (m), duration (days), and flood extent (m\(^2\)) are drawn out from the model. Flood depth (m) and area (m\(^2\)) are extracted for their maximum value. The duration is computed when water depth exceeds a specified threshold flood depth of 0.6 m. The result of the flood modelling is then used as the input in flood hazard assessment described in section 3.6.
3.5. Model performance evaluation

The performance of the hydrodynamic and statistical models is evaluated using statistical indicators – Nash Sutcliffe Efficiency (NSE), Coefficient of Determination ($R^2$), and Normalized Root Mean Square Error (NRMSE). These are the most widely accepted indices used for evaluating the performance of hydrodynamic models. Threshold values of the statistical indicators are taken from Moriasi et al. (2007).

NSE is a normalized statistic that determines the relative magnitude of the residual variance compared to the observed data variance. It ranges from 1 to $\infty$ with 1 as the optimum value. It is defined as:

$$NSE = 1 - \frac{\sum_{i=1}^{n} (y_{i}^{\text{obs}} - y_{i}^{\text{sim}})^2}{\sum_{i=1}^{n} (y_{i}^{\text{obs}} - y_{\text{mean}}^{\text{obs}})^2}$$

(5)

$R^2$ determines the proportion of the variance in the dependent variable that is predicted from the independent variables. It ranges from 0 to 1, with 1 as the optimum value. It is defined as:

$$R^2 = \left[ \frac{\sum_{i=1}^{n} (y_{i}^{\text{obs}} - y_{\text{mean}}^{\text{obs}})(y_{i}^{\text{sim}} - y_{\text{mean}}^{\text{sim}})}{\left( \sum_{i=1}^{n} (y_{i}^{\text{obs}} - y_{\text{mean}}^{\text{obs}})^2 \right)^{1/2} \left( \sum_{i=1}^{n} (y_{i}^{\text{sim}} - y_{\text{mean}}^{\text{sim}})^2 \right)^{1/2}} \right]^{2}$$

(6)

Normalized Root Mean Square Error (NRMSE) is used in this study to quantify the error between the observed values and model computed/simulated values using the following equation [Equation (7)]:

$$\text{NRMSE} = \left[ \frac{1}{n} \sum_{i=1}^{n} \left( \frac{y_{i}^{\text{obs}} - y_{i}^{\text{sim}}}{y_{i}^{\text{obs}}} \right)^2 \right]^{1/2}$$

(7)

where, $y_{i}^{\text{obs}}$ is the $i^{\text{th}}$ observed value for the constituent, $y_{i}^{\text{sim}}$ is the $i^{\text{th}}$ simulated value for the constituent, $y_{\text{mean}}^{\text{obs}}$ is the mean of the observed data, $y_{\text{mean}}^{\text{sim}}$ is the mean of the simulated data, and $n$ is the total number of observations.

3.6. Hazard assessment

One or more parameters, such as flood depth, duration, inundation area, wave velocity, and rate of rising of water level (i.e., tide), are usually used to estimate flood hazards (Tingsanchali & Karim 2005). The hazard parameters are selected based on the characteristics of the area (UN 1991). Arial Khan floodplain is a part of the southwestern river system of Bangladesh. This region is a large floodplain with flat topography with an average percent (%) rise of 1.128 (Supp. Figure 6), showing that the impact of velocity is very low here. Analyzing the historical observed water level data, the average tidal range is found less than 0.1 m at the model downstream boundary (Madaripur station) during the flood season. Hence, the flood flow velocity, wave velocity, and tide level are not dominating factors over the study area. Considering these study area characteristics, three hazard parameters, (a) flood depth, (b) duration, and (c) area, are preliminarily selected for the hazard assessment. A sensitivity analysis is also conducted, showing how the parameters are influencing the resulting hazard maps.

3.6.1. Hazard index (HI)

The hazard index is the intensity of flood hazards. Each hazard category of different indicators is given a linear index from 1 to 5. A larger index means higher hazard, while a smaller hazard index means lower hazard. Among the available flood depth classifications, Agro-ecological zone land classification by FAO and Flood classification by National Water Management Plan (NWMP) are widely used in Bangladesh. Agro-ecological zone land classes are used for agricultural purposes. NWMP classification is used by the FFWC (Flood Forecasting and Warning Center) of BWDB, which is the officially mandated government organization of Bangladesh for all kinds of food-related studies. Considering the purpose of this study, the flood depths are classified following the NWMP guidelines. The hazard classification for the duration of flooding used
here has been followed by Tu & Tingsanchali (2010). The area inundated is computed as a percentage of the Upazila flooded out of the total area. The hazard index classification followed in this study is given in Table 2.

### 3.6.2. Mean hazard index (MHI)

The MHI has been calculated for depth and duration, considering the percentage of land area under each category as given by Equation (8):

$$\text{MHI} = \frac{\sum_{i=1}^{n} \text{HI}_i \cdot F_i}{\sum_{i=1}^{n} F_i}$$  \hspace{1cm} (8)

where, $\text{HI}_i$ is hazard index, $F_i$ is flood hazard, and $n$ is the total land units.

### 3.6.3. Hazard factor (HF)

The HF represents the combined flood effect due to flooding depth, duration, and area, as shown in Equation (9).

$$\text{HF} = a \cdot \text{WHI}_d + b \cdot \text{WHI}_t + c \cdot \text{WHI}_i$$  \hspace{1cm} (9)

where $\text{WHI}_d$ and $\text{WHI}_t$ are the weighted average hazard index for flooding depth and duration, respectively, and $\text{WHI}_i$ is the arithmetic average for the area. $a$, $b$, and $c$ are the weightage factors of the hazard indicators.

### 3.7. Exposure and vulnerability assessment

#### 3.7.1. Indicator selection

The Exposure and Vulnerability indices are selected following the concept of IPCC AR5. The selection is based on hazard type, data availability, expert opinions, local communities, livelihoods, etc. Later, this list has been improved by looking into recent literature (Kabir et al. 2017; Jahan 2018; Uddin et al. 2019). In total, 3 exposure and 12 vulnerability indicators are selected. The exposure indicators are – 1. Population Density, 2. No. of Household, and 3. Cropped Land. Among the vulnerability indicators, there are 4 Sensitivity indicators (1. Disable Population, 2. Dependent Population Ratio, 3. Female to Male Ratio, and 4. Poverty Rate), and 8 Adaptive Capacity indicators (1. Pucca and Semi-Pucca House, 2. Communication Infrastructure, 3. Crop Productivity, 4. Literacy Rate, 5. Health Centre, 6. Flood Shelter, 7. Growth Centre, and 8. Flood Forecasting & Warning System). The Sensitivity indicators give positive (+)\(^2\) dependency on estimating vulnerability, while Adaptive capacity provides the negative (−)\(^2\) dependency. This approach of quantifying vulnerability in terms of positive and negative dependence is introduced by Cutter et al. (2003) and later used by Allen et al. (2016) and Jahan (2018) for vulnerability assessment.

\(^1\) A pucca house is one that has walls and roof made of pucca material such as bricks, stones, cement concrete, timber, etc and Semi-Pucca house: A house that has fixed walls made up of pucca material but roof is made up of the material other than those used for pucca house

\(^2\) A positive (+) dependency means that an increase in the variable indicates an increase in vulnerability, whereas a negative (−) dependency means that an increase in the measured variable indicates a decrease in vulnerability.

### Table 2 | Hazard index for the selected hazard indicators

| Depth of Flooding (m) | Category   | HI | Depth of Flooding (day) | Category | HI | Area Inundated (%) | Category | HI |
|----------------------|------------|----|-------------------------|----------|----|-------------------|----------|----|
| D ≤ 0.3              | Very Low   | 1  | T ≤ 5                   | Short    | 1  | 0 ≤ A ≤ 20        | Very Low | 1  |
| 0.3 < D ≤ 0.9        | Low        | 2  | 3 < T ≤ 7               | Medium   | 2  | 20 ≤ A ≤ 40       | Low      | 2  |
| 0.9 < D ≤ 1.8        | Medium     | 3  | 7 < T ≤ 25              | Long     | 3  | 40 ≤ A ≤ 60       | Medium   | 3  |
| 1.8 < D ≤ 3.6        | High       | 4  | 25 < T                  | Very Long| 4  | 60 ≤ A ≤ 80       | High     | 4  |
| D > 3.6              | Very High  | 5  |                         |          |    | 80 ≤ A ≤ 100      | Very High| 5  |
3.7.2. Normalization of the indicators

Normalization ensures comparability among the indicators regardless of their units of measurement (Kabir et al. 2017). A normalized index is established with dimensionless values ranging from 1 (indicating low value) to 100 (indicating high value) for each indicator of exposure and vulnerability. For each indicator \( I \), Upazila values \( I_t \) are normalized \( I_{nor} \) to values in a common range of 1 to 100 using Equations (10) and (11) as used by (Jahan 2018).

\[
I_{nor} = 1 + \frac{(I_t - I_{min})(100 - 1)}{(I_{max} - I_{min})} \quad (10)
\]

In the case of high values indicating higher vulnerability (positive dependency) or:

\[
I_{nor} = 1 + \frac{(I_{max} - I_t)(100 - 1)}{(I_{max} - I_{min})} \quad (11)
\]

In the case of high values indicating reduced vulnerability (negative dependency).

3.7.3. Weightage of the indicators

The weightage of indicators is provided to ensure that the most significant indicators are given more importance than the others (Kabir et al. 2017). Equal Weighting (Sarkar, 2019), Expert Weighting (Ahsan & Warner 2014), PRA (Youhunus 2017), AHP (Lappas & Kallioras 2019), PCA (Uddin et al. 2019) are widely used weightage methods for socio-economic vulnerability assessment in Bangladesh. Expert weighting, PRA, AHP provide better results for the small-scale weightage selection process (Jahan 2018). However, none of these approaches satisfactorily quantifies large-scale weight assessment as they highly depend on human judgment, sample size, and techniques and are computationally expensive. In these particular cases, Statistical methods are considered to be more scientifically defensible, unbiased towards expert opinion and local perception, and less resource-intensive. PCA is such a statistical method that extracts a smaller and more coherent set of uncorrelated (orthogonal) factors from a large number of variables, where the first component accounts for the largest possible amount of variation in the original variables, and each succeeding component accounts for as much of the remaining variability as possible (Gbetibouo et al. 2010). Hence, PCA is used to provide Upazila-wise weightage to the indicators. After assigning weights using PCA, the Exposure and Vulnerability of each of the Upazilas are calculated by using Equations (12) and (13).

\[
\text{Exposure} = W_1 I_{EX1} + W_2 I_{EX2} + W_3 I_{EX3} + \ldots + W_n I_{EXn} \quad (12)
\]

\[
\text{Vulnerability} = W_1 I_{v1} + W_2 I_{v2} + W_3 I_{v3} + \ldots + W_n I_{vn} \quad (13)
\]

where \( W \) is the weight of the indicator, \( I_{EX} \) is the normalized indicator of exposure, and \( I \) is the normalized indicator of vulnerability. Suffix 1,2,...,n are used to represent each item, and \( n \) is the total number of items.

3.8. Integrated risk assessment

Finally, flood risk (R) is calculated as the consequence of the physical hazard (H), intersecting with vulnerable (V) and exposed people (E) following the IPCC AR5 risk framework as shown in Equation (14) (IPCC 2014; Allen et al. 2016).

\[
R = H \times E \times V \quad (14)
\]

3.9. Post-Processing in ArcGIS

Hazard, exposure, vulnerability, and risk indices are normalized and classified into five categories maintaining an equal interval for each case, 0–20, 20.01–40, 40.01–60, 60.01–80, and 80.01–100 for Very Low, Low, Medium, High and Very High respectively. Finally, the Upazilla-wise hazard, exposure, vulnerability, and risk maps are prepared in ArcGIS.
4. RESULTS AND DISCUSSION

4.1. Calibration and validation of developed models

4.1.1. Calibration & validation of HEC-RAS 1D model

The 1D HEC-RAS model for the Ganges-Brahmaputra-Padma (GBP) River has been calibrated and validated using the BWDB observed flow at the Mawa station for four months from July to October for the year 2016 and 2017, respectively. Flow at Mawa station is chosen since these are later used for developing statistical regression equations between Arial Khan Offtake and Padma. Here, the model’s sensitivity has been tested by changing Manning’s roughness coefficient $n$ value for the model and comparing the change in maximum discharge at Mawa station. The relation between Manning’s $n$ value and corresponding maximum discharge at Mawa shows discharge decreases for a higher Manning’s $n$ value (Figure 3(c)). An increase in Manning’s $n$ value of 0.005 of the HEC-RAS 1D model for the GBP River System results on average 1,074.31 m$^3$/s decreases in maximum discharge. After checking that the model is sensitive to Manning’s $n$, various sets of Manning’s $n$ as (0.015–0.02), (0.02–0.025), (0.025–0.03), and (0.03–0.035) for the main channel and floodplains are adopted for calibrating the model. The comparison of observed and simulated flow at Mawa (SW 93.5 L) station for various Manning’s $n$ and corresponding statistical performance is presented in Table 3a. The simulated discharge hydrographs for $n = 0.015–0.02$ and $n = 0.02–0.025$ do not match the observed stage in the beginning and end-stage, and there are some outliers in the simulated values. The trend and shape of the simulated and observed hydrograph are almost similar for $n$ as 0.025–0.03 and $n$ as 0.03–0.035. Finally, $n$ as 0.025 for the main channel and $n$ as 0.03 for the floodplains have been fixed as it gives the most acceptable values of $R^2$ and NSE. The values of $R^2$ and NSE have been found in the values of 0.9168 and 0.9138, respectively, indicating that the simulated value is very close to the observed value and within the acceptable range. Using the calibrated Manning’s $n$, validation has been performed for the year 2017. Figure 3(f) shows the simulated flow hydrograph is in close agreement with the observed hydrograph. In this case, the coefficient of determination $R^2$ and NSE have been found 0.8212 and 0.7424, respectively, which indicates that the validated value is closer to the observed value (Table 3a).

4.1.2. Performance of regression model

A statistical regression model is developed between the discharge at Mawa of the Padma River to that of Chowdhury Char of the Arial Khan River. Five different regression models: Linear, Exponential, Logarithm, Polynomial, and Power, are tried using the observed discharge data for the monsoon period of the year from 1965 to 2017 (Figure 3(a) & Table 4). A two-tailed Student T-test is conducted at a 5% significance level to check the quality of the data obtained from differential equations. For T-test,

- The null hypothesis (H0) assumes that the difference between the true (observed) mean ($\mu$) and the comparison (model) value (m0) is equal to zero (H0: $\mu = m0$), i.e., no significant difference in the observed mean and model mean.
- The alternative hypothesis (H1) assumes that the difference between the true mean ($\mu$) and the comparison value (m0) is not equal to zero (H1: $\mu \neq m0$), i.e., a significant difference exists between the observed mean and model mean.

If the $p$-value is less than significance level alpha = 0.05, we reject the null hypothesis. On the other hand, if the $p$-value is greater than alpha = 0.05, we support the null hypothesis. The $p$-values of Exponential (7.1044E-190), Polynomial (0.01008314), and Power (1.08119E-06) are less than alpha. Hence, we reject the null hypothesis, i.e., the population means are different. On the other hand, the $p$-values of Linear (0.945843311) and Logarithmic (0.986220415) are greater than alpha 0.05. Hence, we can support the null hypothesis, i.e., that the population means are the same. The linear Equation (Equation (15)) is selected for further investigation based on the $R^2$ and NSE values among the Linear and Logarithmic equations.

$$Q_{Arial\ Khan} = 0.0358 + Q_{Padma} - 281.03$$

where $Q_{Arial\ Khan}$ and $Q_{Padma}$ are the discharge of Chowdhury Char and Mawa.

The 95% Confidence and Prediction Interval are estimated for the selected Linear Regression Equation (Figure 3(b)) to quantify the uncertainty. Here, the confidence interval shows the uncertainty involved in predicting means response at 95% confidence interval that means it is 95% confident that the mean discharge of Arial Khan will fall in this range. On
Figure 3 | Performance evaluation of the developed models (a) Different Statistical Regression Models between Arial Khan River and Padma River, (b) Confidence and Prediction Interval for the selected Linear Regression Model (c) Change in Discharge due to change in Manning’s $n$ value of Ganges-Brahmaputra-Padma River HEC-RAS model at the Padma River (d) Change in Water level due to change in Manning’s $n$ value of Arial Khan HEC-RAS model (e) Calibration & (f) Validation of GBP model; (g) Calibration and (h) validation of the flood model.
the other hand, the prediction interval shows the range of uncertainty in predicting a single response at a 95% confidence interval that means it is 95% confident that any discharge of Arial Khan will fall in this range.

### 4.1.3. Calibration & validation of HEC-RAS flood model

The 1D model of the Arial Khan flood model has been calibrated using the observed daily water level data at Chowdhury Char station for twelve months from January - December of 2015. The model's sensitivity has been tested by changing the Manning's $n$ value for the Arial Khan River and comparing the change in maximum water level at Chowdhury Char. The relation between Manning's $n$ and corresponding maximum water level at Chowdhury Char shows water level increases for a higher Manning's $n$ value (Figure 3(d)). An increase in Manning's $n$ value of 0.005 results on average 0.38 mPWD increase in maximum water level. After the sensitivity checking, various Manning's $n$ as (0.010 – 0.015), (0.015 – 0.02), (0.02 – 0.025), (0.025 – 0.03), (0.03 – 0.035) are adopted for various calibration simulations. Comparing observed and simulated stage hydrographs at Chowdhury Char station for different sets of Manning's ‘$n$’ shows that the trend and shape of the

| Model | Period | Calibration Location | Trials | Main Channel | Floodplains | Performance Evaluation |
|-------|--------|----------------------|--------|--------------|-------------|------------------------|
| (a) Ganges-Brahmaputra-Padma River System | Calibration (2016) | Padma River (Mawa-SW 93.5 L) | 1 | 0.015 | 0.020 | 0.7327 | 0.7501 |
| | Validation (2017) | Padma River (Mawa-SW 93.5 L) | 3 | 0.025 | 0.030 | 0.9138 | very good |
| | | | 4 | 0.030 | 0.035 | 0.9136 | 0.9166 |
| (b) Arial Khan River | Calibration (2015) | Arial Khan River (Chowdhury Char – SW 4A) | 1 | 0.010 | 0.015 | 0.943 | 0.9974 |
| | Validation (2017) | Arial Khan River (Chowdhury Char – SW 4A) | 3 | 0.020 | 0.025 | 0.775 | 0.9929 |
| | | | 4 | 0.025 | 0.030 | 0.630 | 0.9908 |
| | | | 5 | 0.030 | 0.035 | 0.471 | 0.9974 |

### Table 4 | Performance of different statistical relationship between Padma and Arial Khan

| No. | Regression Equation | Equation | T test (P value) | Two-tailed T test at 5% Significance Level | R² | NSE |
|-----|---------------------|----------|-----------------|-------------------------------------------|----|-----|
| 1   | Linear              | $Y = 0.0358x - 281.03$ | 0.94584 |Reject Alternate Hypothesis, Mean Is Same, Acceptable | 0.592 | 0.592 |
| 2   | Exponential         | $y = 343.78e^{3E-05x}$ | 7.10E-190 |Reject Null Hypothesis, Mean Is Not Same, Not Acceptable | 0.619 | –0.569 |
| 3   | Log                 | $Y = 1663.4ln(x) - 16,326$ | 0.98622 |Reject Alternate Hypothesis, Mean Is Same, Acceptable | 0.555 | 0.555 |
| 4   | Polynomial          | $Y = 7E-09x^2 + 0.035x - 261.32$ | 1.01E-02 |Reject Null Hypothesis, Mean Is Not Same, Not Acceptable | 0.592 | 0.5983 |
| 5   | Power               | $y = 0.0014x^{1.2779}$ | 1.08E-06 |Reject Null Hypothesis, Mean Is Not Same, Not Acceptable | 0.674 | 0.5942 |
observed and hydrograph are almost similar (Figure 3(g)). The simulated hydrograph of \( n = 0.015 \) for the main channel and \( n = 0.02 \) for the floodplain matches more accurately with the observed hydrograph. The simulated water level and observed water level almost matches in monsoon from June to September. The model overestimates during the dry season from October to May. However, as the main focus of this study is monsoon flood hazard assessment, this discrepancy does not affect the final results.

Among different sets of roughness values, the \( R^2 \) and NSE values of \( n = 0.01–0.015 \) have been found 0.9974 and 0.943, and the \( R^2 \) and NSE values of \( n = 0.015–0.02 \) have been found 0.9974 and 0.892. The visual observation shows that \( n = 0.015–0.02 \) more accurately captures the monsoon season flow than \( n = 0.01–0.015 \). Hence, \( n = 0.015–0.02 \) has been fixed as Manning’s ‘\( n \)’ for all the cross-sections of the Arial Khan River. Using the calibrated Manning’s \( n \), validation for the model has been performed for the year 2017. The validation has also shown satisfactory results. Figure 3(h) shows that the simulated stage hydrograph is in close agreement with the observed hydrograph. There were slight differences in simulated water level and observed water level in the dry season like calibration. In the validation, the coefficient of determination \( R^2 \) and NSE have been found 0.989 and 0.882, respectively, which indicates a good correlation between the observed and simulated data and indicates the model’s accuracy for further analysis.

4.1.3.1. Comparison of 2D Flood Inundation. The 2D flood inundation is validated comparing with the available satellite images. The simulated flood inundation map on 25 August 2004 is validated by comparing the flood area derived from the Landsat-5 TM satellite image taken on the same day, as shown in Figure 4. The model flood map shows a significant flood around the Arial Khan River, which agrees with the Landsat map of that day. Additionally, a quantitative comparison of the flood inundation area has been made between Landsat and Simulated flood map based on NDWI (Normalized Difference Water Index). The flood area found from the satellite image, and the simulated model is 550.76 km\(^2\) (26% of the study area) and 510.11 km\(^2\) (24% of the study area). Upazila-wise, the floods in Janjira, Shibchar, Madaripur, and Bhanga highly coincide with the satellite image. However, the flood in Sadarpur is slightly overestimated, and the floods in Shariatpur and Madaripur are somewhat underestimated. The flooding along the main channel was accurately simulated as the upstream discharge was accurately estimated through the above-mentioned hydrological and hydrodynamic models. However, since the local rainfall is not dynamically incorporated in the 2D modelling, the model couldn’t appropriately capture the flood in the peripheral depressions filled by the local rain. Hence, the periphery of the study area (especially the southwest and southeast zone) was slightly underestimated.

4.2. Climate change projections

The calibrated and validated Ganges-Brahmaputra SWAT model is simulated with the EC-EARTH3-HR data from 1976 to 2100 for RCP2.6 and RCP8.5 scenarios and daily flow hydrographs are extracted. The hydrographs show that the future flow for RCP2.6 and 8.5 is similar from 1976 to 2040 (Supp. Figure 5). After that, the future flow for the RCP8.5 scenario is significantly higher than that of RCP2.6 for both of the basins.

Figure 4 | Qualitative comparison of inundation map prepared using (a) Landsat-S satellite images and (b) model simulation.
From SWAT simulations, three thirty-year long time slices are considered for each of the RCP scenarios – the early (2020s: 2006–2035), the mid (2050s: 2036–2065), and the end (2080s: 2066–2095) of the 21st century. The climate data typically contains a lot of outliers. So, extreme flood scenarios are assessed by the 90th percentile rather than the mean or maximum of the dataset (Bonsal et al. 2001). This concept has been used in many climate studies for generating future climate scenarios (Beniston et al. 2007; Braun et al. 2014). Hence, the 90th percentile daily flow hydrographs for each of the mentioned time slices of RCP 2.6 and 8.5 scenarios have been extracted, as shown in Figure 5. Later on, these hydrographs have been used as the future u/s discharge boundaries of the HEC-RAS 1D model.

### 4.3. Projected changes in floods

The projected flood parameters are extracted, and flood maps for different time periods under RCP2.6 and RCP8.5 are prepared in ArcGIS (Figure 6). An increasing trend in the flood area, depth, and duration are observed from the 2020s to the 2080s for RCP2.6 and RCP8.5 scenarios. The difference between RCP2.6 and RCP8.5 is not significant from the 2020 to 2050s. However, the difference becomes very prominent after the 2050s. At the end of the 21st century, the total inundated area is nearly 523 km² (29% of the total area) under RCP2.6, while it is almost 800 km² (44% of the total area) under RCP8.5.

![Figure 5](http://iwaponline.com/jwcc/article-pdf/doi/10.2166/wcc.2021.341/918158/jwc2021341.pdf)

**Figure 5** | 90th Percentile daily flow hydrograph for the 2020s, 2050s, 2080s (a) the Brahmaputra and (b) Ganges for RCP2.6 (c) the Brahmaputra and (d) Ganges for RCP8.5.
Figure 6 | Flood depth in (a) 2020s (b) 2050s (c) 2080s under RCP2.6 and in (d) 2020s (e) 2050s (f) 2080s under RCP8.5; Flood duration in (a) 2020s (b) 2050s (c) 2080s under RCP2.6 and in (d) 2020s (e) 2050s (f) 2080s under RCP8.5; Flood extent in (a) 2020s (b) 2050s (c) 2080s under RCP2.6 and in (d) 2020s (e) 2050s (f) 2080s under RCP8.5.
In total, 6 Upazila (Sadarpur, Madaripur, Rajoir, Shibchar, Shariatpur, and Zanjira) out of 8 Upazilas is flooded in the 2020s of RCP2.6 and RCP8.5 (Table 5). The flood in Shariatpur is very insignificant. No flood is found in Bhanga and Maksudpur Upazilas. However, the flooding scenario changes with time, especially it significantly exacerbates after the 2050s. At the end of the 21st century, the flood-affected areas are 5, 76, 17, 113, 55, 73, 45, and 138 km² under RCP2.6 and 100, 81, 109, 131, 84, 94, 60 and 139 km² under RCP8.5. Therefore, it can be inferred that the flood-affected area will increase significantly in both RCP8.5 due to climate change.

4.4. Sensitivity of flood hazard parameters

The sensitivity analysis of the hazard parameters is important to assess (a) the sensitivity of each of the hazard parameters in the resulting hazard maps and (b) also their relative importance in the results. To answer these, different combinations of hazard maps are developed based on individual parameters (depth, duration, and area) as well as a combined parameter (Figure 7). These figures explain how the different hazard parameters will influence the resulting hazard maps individually and combinedly. The sensitivity analysis further shows that the combined hazard map might better represent the actual flood scenario for the study area than the ones prepared on the individual parameter. For example, if only depth or duration is considered, the Maksudpur is found in a high and very high hazard zone in the 2080s of RCP8.5. But if the flood maps are critically observed (Figure 6), it is evident that it (Maksudpur) is far from the Arial Khan and Padma River. So, it is usually flooded only in high floods. However, as it is a low-lying area (Supp. Figure 7), the flood water remains there for a long duration. So, depth and duration are found high there, even though the inundation area is minimal. Since the site is not accounted for in individual cases, Maksudpur falls into the High Hazard zone. The inclusion of inundation areas in hazard estimation represents the real flood scenario of Maksudpur. So, all three parameters seem sensitive for the hazard assessment of the Arial Khan floodplain. So, the combined hazard maps are used for the rest of the paper.

The next question is the relative importance of each of the three selected parameters in the final hazard maps. For this, the corresponding weightage factors of depth (a of Equation (9)), duration (b of Equation (9)), and area (c of Equation (9)) are tested by the trial-and-error method. Five trials are given as 1st Trial : (0.333, 0.333, 0.333), 2nd trial: (0.4, 0.3, 0.3), 3rd Trial: (0.3, 0.4, 0.3), 4th Trial: (0.3, 0.3,0.4) and 5th Trial: (0.35, 0.35, 0.25) (Table 6). No difference between the first and second trials is found. A very insignificant difference is found in the rest of the trials (marked by yellow). Among the total 48 sets, three sets are found different in the 3rd and 4th Trials, and seven sets are found different in the 5th Trial (marked by yellow). Since the difference is not very significant, an equal weightage of 0.333 is adopted for each hazard indicator. However, these sensitivity results might be useful for planners and policymakers to capture the future hazard characteristics of the Upazillas under a given set of parameter/weightage conditions. For example, Madaripur might be in either High, or Very High, or Low or Medium Hazard in the 2020s of RCP 2.6 and RCP 8.5 if higher weightage is given to either depth (2nd Trial) or duration (3rd Trial). The same happens to Rajoir in the 2020s of RCP 2.6. Given higher weightage

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**Table 5 | Upazila-wise flood inundated area (km²) under RCP 2.6 and RCP 8.5**

| Upazila    | Flood Affected Area (km²) | RCP 2.6 |     | RCP 8.5 |     |
|------------|---------------------------|---------|-----|---------|-----|
|            |                           | 2020s   | 2050s | 2080s   | 2020s | 2050s | 2080s |
| Bhanga     |                          | 0       | 2    | 5       | 0    | 2     | 100   |
| Sadarpur   |                          | 51      | 72   | 76      | 52   | 75    | 81    |
| Maksudpur  |                          | 0       | 7    | 17      | 0    | 7     | 109   |
| Madaripur  |                          | 65      | 94   | 113     | 70   | 104   | 131   |
| Rajoir     |                          | 24      | 38   | 55      | 30   | 48    | 84    |
| Shibchar   |                          | 50      | 64   | 73      | 50   | 69    | 94    |
| Shariatpur |                          | 11      | 26   | 45      | 14   | 33    | 60    |
| Zanjira    |                          | 114     | 135  | 138     | 114  | 137   | 139   |
| Total      |                          | 316     | 437  | 523     | 330  | 473   | 798   |
to either depth (2nd trial) or area (4th Trial), Maksudpur may fall in either Medium or High Hazard zone in the 2080s of RCP 2.6, Rajoir may fall in either Medium or High Hazard zone in 2050s of RCP 2.6 and 2020s of RCP 8.5 and Shariatpur might fall in either Medium or High range in the 2020s, 2050s of RCP 2.6 and 2020s, 2050s of RCP 8.5.

4.5. Future flood hazard assessment

The Spatio-temporal change of hazard zones for RCP2.6 and RCP8.5 are shown in Figure 7 (s, t, u, v, w, and x). The 2020s of RCP8.5 is similar to that of RCP2.6 except for Rajoir, which falls in the high hazard zone. Maksudpur, Sadarpur, Bhanga, Madaripur, and Shibchar have become more hazardous from the 2020s to the 2080s under the RCP8.5 climate scenario. The percentage area under different hazard zones for both RCP2.6 and 8.5 are summarized in Table 7a. In the 2020s of RCP2.6, 18%, 24, 47, and 11% are found in the very low, medium, high, and very high hazard zones. On the other side, during the 2020s of RCP8.5, 18%, 11, 60, and 11% are found in the very low, medium, high, and very high hazard zones. In the 2020s, there is only one area under a very high hazard zone. However, it has changed to 11% in the medium, 68% in the high, and 21% in the very high hazard zone in the 2080s of RCP2.6. In the 2080s, under RCP8.5, the scenario is more alarming. While no area falls in the very low, low, and medium hazard zone, 41 and 59% of the area fall under the high hazard and very high hazard zone, respectively. So, low and very low hazard zone will be diminishing at the end of the century. On the contrary, high and very high hazard zone will increase due to climate change impact.

4.6. Exposure and vulnerability assessment

The relative contribution of the indicators of exposure and vulnerability for each of the Upazilas is shown in Figure 8(a)–8(c). The weightage of the selected indicators was calculated individually in SPSS statistics both for exposure and vulnerability using PCA, as shown in Table 7. The exposure and vulnerability map of the Arial Khan River floodplain is shown in Figure 9(a) and 9(b).

Figure 9(a) shows that 28%, 27%, 0, 21, and 24% are under Very Low, Low, Medium, High, and Very High exposure zones, respectively. It further shows that the exposure is least in Zanjira and Sadarpur. The reason behind this is the low population density, household, and cropped land in these two Upazilas (Figure 8(a)). As there are few populations and croplands in these areas, they are less exposed to floods. On the other hand, the population and cropland are high in Shibchar and Madaripur (Figure 8(a)). Hence, they are more exposed to flood hazards.

The Upazila-wise vulnerability zones are shown in Figure 9(b). The percentage areas are 11, 22, 0, 37, and 29 under Very Low, Low, Medium, High, and Very High vulnerability zones. Madaripur is found the least vulnerable among all the Upazilas...
due to its low Disable population, Dependent population ratio, Female to male ratio, and Poverty rate (Figure 8(b)). Contrary, adaptive capacities such as pucca and semi-pucca houses, communication infrastructure, crop productivity, literacy, health centre, flood shelter, and growth centre are high (Figure 8(c)). Madaripur is highly developed as a district town, i.e., less flood sensitive and highly adaptive compared to other Upazilas. It is the only Upazila that has a flood forecasting and warning station. Hence, Madaripur falls in the very low-vulnerable zone. Again, though Zanjira falls into the very low exposed zone, it has the highest vulnerability. Because the percentage of dependable people and the poverty rate are the highest here. At the same time, pucca and semi-pucca houses, communication infrastructure, and growth centre numbers are very low.

4.7. Future flood risk assessment

When vulnerability and exposure are combined with hazard, flood risk zones are identified across the floodplains of the Arial Khan River. Figure 10(a)–10(f) shows the Spatio-temporal change of flood risk zones for each of the Upazilas of the study area.
under RCP2.6 and RCP8.5. The percentage of areas under different risk zones under RCP2.6 and RCP8.5 are shown in Table 8(b). In the 2020s under RCP2.6 scenarios, 55, 33, and 11% are under the very low, low, and medium risk zones. It becomes 37% in the very low-risk zone, 21% in the low-risk zone, 24% in the medium-risk zone, and 18% in the very high-risk zone in the 2080s under RCP2.6. On the other hand, it is 37%, 10%, 24, 11, and 18% in the very low, low, medium, high, and very high hazard zone, respectively, under RCP8.5. So, it is observed that future climate change will decrease very low and low-risk zone and increase high and very high-risk zone in the 2080s under RCP8.5.
The integrated risk analysis further shows that the incorporation of vulnerability and exposure along with hazard provides a wide horizon to the overall assessment. For example, in the 2080s, Zanjira falls in the high hazard zone. However, when the associated exposure and vulnerability indices are considered, it falls in a low-risk area. Though this Upazila is profoundly affected by the flood, the exposure and vulnerability are low. Hence, overall flood risk has been decreased. Therefore, despite its high hazardous categorization, it becomes a very low-risk zone in the 2080s. The opposite happens for Madaripur. If only the flood hazard factor is considered, it falls in a low hazard zone. However, it falls under the very high-risk area, when vulnerability and exposure factors are considered hazard factors. Because both exposure and vulnerability factors are high for Madaripur. Likewise, the hazard maps change patterns when they are converted to risk maps.

Some medium hazard zones fall into high-risk zones due to their high exposure and vulnerability to flooding. In contrast, some high hazard zone falls into the low-risk area because of its low exposure and vulnerability. Hence, allocation of resources or flood management plans should be made based on hazard and risk analysis. For example, a high hazardous
area might be protected with structural measures such as embankment, dredging, river training works, etc. On the other hand, a highly exposed site to floods might be restricted for cultivating lands and building houses or infrastructures. Besides, a medium or low exposed area can be protected by incorporating and improving early forecasting and warning system and proper evacuation system during the flood. In such cases, allocation of resources such as flood shelters, health centres cannot eliminate its flood damage and loss.

On the other hand, a low hazardous area with a high socio-economic vulnerable community needs more Pucca and Semi-pucca houses, communication infrastructures, flood shelters, health centres, growth centres, flood forecasting and warning system, and employment opportunity. So, hazard-risk maps make it easier to plan which plan or strategy should be taken for a certain Upazila and that too staying within a limited budget. Thus, it is very important to consider each of the risk components, i.e., hazard, exposure, and vulnerability, and their integrated results for a sustainable flood management plan.

5. DISCUSSION

The observed flood pattern shows that since the riverine flood is caused due to water flowing over the river banks, the Upazilas (Shibchar, Bhanga, and Madaripur) along the river are found with higher flood depth, duration, and area (Figure 6). Hazard is entirely dependent on these three parameters, so the same pattern has been observed in hazard maps as well (Figure 9). Janjira and Sadarpur are found in the high hazardous category due to the flood impact of the Padma River. In brief, the Upazilas along the left reach of the Arial Khan River is found more hazard-prone at the end of the 21st century. Flood risk is associated with the hazard, exposure, and vulnerability. Hence, the risk zones do not follow the same spatial distribution/pattern as flood or hazard maps. Instead, the Upazilas on the right side (Bhanga, Maksudpur, and Rajoir) of the Arial Khan River are found more risk-prone (Figure 10). These three Upazillas are low to medium exposed to flood (Figure 9(a)). Bhanga is very high hazard-prone (Figure 7(x)), and Maksudpur and Rajoir are high flood vulnerable (Figure 9(b)). Hence, combining all three components, these are found in high-risk-prone zones.

The temporal pattern of the flood maps shows consonance with the IPCC AR5 report. According to this report, CO₂ concentration, global temperature, northern sea-ice extent, sea-level rise remain almost similar from baseline to 2020s for both RCP2.6 and RCP8.5 scenario (IPCC 2014). Then the differences between the RCP2.6 and RCP8.5 scenario becomes very rapid and high after the 2050s. Similar trends are found in the current study. The difference between RCP2.6 and RCP8.5 is found minimal from the 2020 to 2050s but becomes very pronounced in the 2080s (Figure 6).

Furthermore, according to IPCC AR5, the global surface temperature is likely to exceed 1.5 °C at the end of the 21st-century relatives to the base period (1850 to 1900) for all RCP scenarios except RCP2.6. It is likely to exceed 2 °C under RCP 6.0 and RCP8.5 and more likely not to exceed 2 °C under RCP 4.5. Furthermore, it is also stated that warming will continue below 2100 under all RCP scenarios except under RCP2.6 (IPCC 2014). Hence, inundation depth, duration, and area are found much higher in RCP8.5 than RCP2.6, and they are the highest in the 2080s of RCP8.5. The results of this study harmonize with the recent flood studies conducted in the nearby countries considering RCP emission scenarios as well. Shrestha &
Lohpaisankrit (2017) reported that flood depth and area would be the maximum by the end of the 21st century under the RCP8.5 projection in the Yang Basin of Thailand. The recent studies by Nishat (2017) and Rahman (2019) on the Brahmaputra and Old Brahmaputra River of Bangladesh also show a significant increase of high to very high hazard and risk zone by the end of 2100 under RCP8.5.

The present flood hazard and risk maps are compared with the hazard and risk maps of Tingsanchali & Karim (2005) that were developed focusing the whole south-west river system of Bangladesh based on stationary hydrologic data and without considering the upstream basin flow from the Ganges and Brahmaputra rivers. The previous study found higher hazard-prone areas along with the Arial Khan and Padma River for a 100-year historic flood as found in the present study by the end of the 21st century under RCP 8.5. On the other hand, a significant difference is found in the risk maps. The reasons might be – a) the current study uses the most recent Population Census 2011 while Tingsanchali & Karim (2005) used past Population Census, b) the current study considers fifteen important vulnerability and exposure indicators and their relative weights while Tingsanchali & Karim (2005) considered only one vulnerability input, i.e., the population density, and c) the current study computes integrated flood risk as to the product of the hazard, exposure, and vulnerability using IPCC risk framework while Tingsanchali & Karim (2005) computed flood risk as to the product of hazard and vulnerability. Most importantly, hazard and risk maps are qualitative studies focusing on qualitative comparisons of flood threats among the considered study areas. As the areal extent between the previous study and the current study is not the same and the input parameters and approaches are significantly different, it’s not possible to precisely compare the findings of these two studies. The present study is focused on the Arial Khan River and considered many important factors which were completely ignored in the past study. Hence, this study will provide more reliable flood risk results for the Arial Khan River under future climate change scenarios.

Overall, flood hazard and risk maps prepared in this study give a qualitative view of the potential flood scenarios for the eight Upazillas of the Arial Khan River. The hazard and risk maps will be useful in identifying the priority areas for allocating flood reliefs and planning a long-lasting future flood management strategy along the Arial Khan River. For example, the hazard and risk maps of the 2020s or 2050s can be incorporated into the short-term or mid-term plans. Additionally, the maps of the 2080s can be incorporated into any long-term plan, such as a 100-year plan. The recently approved ‘Bangladesh Delta Plan 2100’ implementation would also benefit from these flood risk maps (BDP 2017). Additionally, different hazard combinations (Depth, Duration, Area, and Depth ÷ Area) and weightage trials (0.33,0.33,0.33; 0.4,0.3,0.3; 0.35,0.35,0.25) are also provided. So, hazard prediction that any Upazilla may face in the near (the 2020s), mid (2050s), or end (2080s) future under a given set of parameterizations can be made. The planners and policymakers can take any of these combinations and make a tentative recommendation to decision-makers.

In this study, physics-based traditional numerical models – SWAT and HEC-RAS are used for computing the future flood hazard of the Arial Khan River floodplain using EC-Earth-HR projected climate data. Such a multi-model hydrology-hydrodynamic modelling system is an appropriate way to incorporate the climate change impact of large basins (Ganges and Brahmaputra) into a local river (Arial Khan). However, various uncertainties may find in the predictions made by the numerical models. For example, the SWAT has several parameters and model simplifications that introduce uncertainty in the basin model. Besides, generated SWAT flow is used as input for the hydrodynamic HEC-RAS models. These numerical models have been calibrated and validated with satisfactory results and demonstrated adequacy to represent the hydrologic and hydraulic behaviour of the study area.

Nevertheless, applying such models for transforming regional flows into local scale flood prediction might introduce few uncertainties in the result. The major uncertainties resulting from the Hydrologic models, Hydraulic models, and Regression models are quantified using Normalized Root Mean Square Error (NRMSE) (Table 9). These uncertainties might impact the resulting hazard maps. However, the uncertainties are found much smaller in the flood season, proving the models’ efficiency in flood hazard analysis and solidifying the acceptance of this study. Considering the total percentage, nearly 48% of uncertainty might come from the hydrologic models, 23% from the hydraulic models, and 28% from the Statistical regression model. The models’ uncertainties could be estimated using some advanced tools such as variance-based methods (Saltelli et al. 2008; Tate et al. 2015), Sobol’s method (Saisana et al. 2005), Fourier amplitude sensitivity test (FAST) (Saltelli et al. 1999), etc. in the future study.

The d/s boundary of the flood model is defined by the sea-level-rise (SLR) of 55–82 cm for the RCP2.6 and 8.5 scenarios provided by the IPCC AR5 report (IPCC 2014) without taking the actual SLR projections at that location. According to Mondal et al. (2018), an increase of peak water level is 72 cm at Chandpur station of the Meghna river for RCP 8.5,
which is nearest to our downstream model boundaries (Sureswar – SW95 and Madaripur – SW5). Here, the % of error is nearly \((82–72) \times \frac{100}{82} = 12\%\). However, as our downstream model boundary in the Arial Khan River is further downstream of the Chandpur, the increase of peak stage will be higher than 72 cm due to SLR. Thus, comparing with Mondal et al. (2018), the % of the error would be less than \(<10\%\), which can be neglected considering the uncertainties of climate model projections.

In this study, the vulnerability and exposure data are kept constant throughout the end of the century. The incorporation of Shared Socioeconomic Pathways (SSPs) could be a way to estimate future vulnerability and exposure data and thereby assess the actual risk scenarios in the future. The climate change research community recently adopted the SSPs framework to facilitate integrated analysis on future climate change, vulnerabilities, adaptation, and mitigation (O’Neill et al. 2014; Van Vuuren et al. 2014). In SSPs, population, GDP, and urbanization data are provided on a global scale. Later, the country scale, or subnational scale, or multi-scale, or participatory scenario approach is quantified applying the global RCP–SSP–SPA scenario framework (Kebede et al. 2018). However, it is hard to get the future projections of each of the fifteen exposure and vulnerability indicators used in this study. Hence, SSPs are kept beyond the scope of this study. Nevertheless, it could be an exciting topic for future studies.

### 6. CONCLUSION

Climate change impact on potential flood hazard and risk of the Arial Khan River floodplain are evaluated incorporating the recent RCP climate scenarios and AR5 risk framework. An increasing trend in flood depth, duration, and the area is observed from the early (2020s) to the end (2080s) of the century for both RCP2.6 and 8.5 scenarios. The situation is far worsening for RCP8.5, as expected. The increase in flood level, duration, and extent must be considered while designing any hydraulic/stormwater structures or flood measures along the flood plain. The sensitivity analysis of the hazard parameters shows that the combined parameters (Depth + Duration + Area) with equal weightage (0.33,0.33,0.33) represent the flood scenario better for the study area. The Upazilas along the left reach of the Arial Khan River is found more hazard-prone, while the Upazilas on the right side of the Arial Khan River is found more risk-prone in the 2080s of RCP8.5. The Upazila-wise hazard maps reveal that the high and very high hazard zone will significantly expand in the 2080s of RCP8.5. Similarly, risk assessment shows that the very low and low-risk zone will decrease, and the high and very high-risk areas will increase by the end of the 21st century for RCP8.5. The hazard-risk maps further make it easier to plan which plan or strategy should be taken for a certain Upazila and stay within a limited budget. Thus, it is very important to consider each of the risk components, i.e., hazard, exposure, and vulnerability, and their integrated results for a sustainable flood management plan. The results found in this study are found quite acceptable, comparing the IPCC climate studies and other relevant studies conducted in this region. Future studies can be extended by introducing the RCP–SSP–SPA scenario framework.

The flood hazard and risk maps provide useful information to policymakers regarding emergency preparedness and relief operations for high-risk and very high-risk zones in future flood events of Arial Khan. Besides, compared to the wide range of research conducted in other flood-prone countries, research work in Bangladesh on future flood situations considering recent climate change scenarios is very limited. This study presents a methodology to incorporate the climate impact of large transboundary basins to a small local river using combined hydrological, hydrodynamic, and statistical models and how to check their regional adequacy for the study area. Hence, it will be helpful for other researchers to work on the future flood scenarios of Bangladesh considering climate change impact.

#### Table 9 | Estimation of standard error using NRMSE method for each of the developed model components

| Models          | Model Flood Season | NRMSE | % Error | Flood Season | NRMSE | % Error |
|-----------------|--------------------|-------|---------|--------------|-------|---------|
| Hydrologic Models | SWAT model (Brahmaputra) | 0.33  | 10.76   | 0.27         | 13.64 |
|                 | SWAT model (Ganges)    | 1.39  | 45.69   | 0.66         | 34.14 |
| Statistical Model | Linear Regression model | 0.56  | 18.20   | 0.56         | 28.59 |
| Hydraulic Models | 1D HEC-RAS model      | 0.12  | 4.07    | 0.12         | 6.39  |
|                 | 1D2D HEC-RAS model (1D model) | 0.58  | 18.87   | 0.26         | 13.44 |
|                 | 1D2D HEC-RAS model (Flood Inundation) | 0.07  | 2.42    | 0.07         | 3.80  |
ACKNOWLEDGEMENTS

This study has been carried out in the Dept. of Water Resources Engineering (WRE), Bangladesh University of Engineering and Technology (BUET). The authors are thankful to the ‘High-End Climate Impact and eXtremes (HELIX)’ project (Funded by the European Union Seventh Framework Programme FP7/2007-2013 under grant agreement no 603864) of the Institute of Water and Flood Management (IWFM), BUET for providing the climate data for RCP scenarios. Besides, the authors show gratitude to Mrs Afeefa Rahman, Ms Purnima Das, and Dr Mashfiqus Salehin of BUET, and Dr Anne Zimmermann of Univ. of Bern for their valuable advice and support.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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First received 10 December 2020; accepted in revised form 14 July 2021. Available online 9 August 2021