

1 **The effects of changing land use and flood hazard on poverty in coastal** 2 **Bangladesh**

3 Mohammed Sarfaraz Gani Adnan ^{a,b*}, Abu Yousuf Md Abdullah ^c, Ashraf Dewan ^d, Jim W.
4 Hall ^a

5

6 ^a Environmental Change Institute, School of Geography and the Environment, University of Oxford,
7 South Parks Road, OX13QY Oxford, United Kingdom

8 ^b Department of Urban and Regional Planning, Chittagong University of Engineering and Technology
9 (CUET), Chittagong 4349, Bangladesh

10 ^c School of Public Health and Health Systems, Faculty of Applied Health Sciences, University of
11 Waterloo, Ontario, Canada

12 ^d Spatial Sciences Discipline, School of Earth and Planetary Sciences (EPS), Curtin University, Perth,
13 Western Australia 6102, Australia

14

15 **Abstract**

16 The construction of polders in the coastal region of Bangladesh has significantly
17 modified the patterns of flooding, as well as leading to significant land use/land cover
18 (hereinafter, LULC) changes. The impact of LULC change and flooding on poverty is complex
19 and poorly understood. This study presents a spatiotemporal appraisal of poverty in relation to
20 LULC change and pluvial flood risk in the south western embanked area of Bangladesh. A
21 combination of logistic regression (LR), cellular automata (CA), and Markov Chain models
22 were utilised to predict future LULC based on historical data. Flood risk assessment was
23 performed at present and for future LULC scenarios. A spatial regression model was
24 developed, incorporating multiple parameters to estimate the wealth index (WI) for present-
25 day and future scenarios. In the study area, agricultural lands reduced from 34% in 2005 to 8%
26 in 2010, while aquaculture land cover increased from 17% to 39% during the same time. The
27 rate of LULC change was relatively low between 2010 and 2019. Based on the recent trend,
28 LULC was predicted for the year 2030. Flood risk was positively correlated with LULC and
29 the expected annual damage (EAD) was estimated at \$903 million in 2005, which is likely to
30 increase to \$2096 million by 2030, considering changes in LULC scenarios. The analysis
31 further showed that the EAD and LULC change were negatively associated with the WI.
32 Despite consistent national GDP growth in Bangladesh in recent years, the rate of increase of
33 WI is likely to be low in the future because flood risk and patterns of LULC change have a
34 negative effect on WI.

35 Key words: Land use change model; flood risk; poverty; Cellular Automata; Markov Chain

36 1. Introduction

37 It is widely recognised that poor people are disproportionately exposed to
38 environmental hazards ([Winsemius et al., 2018](#)). There are several possible reasons for this.
39 For instance, poor people tend to inhabit remote low-lying floodplains, due to the limited
40 development opportunities and relatively cheaper lands ([Dasgupta, 2007](#)). Their livelihoods
41 and assets are less protected ([Bangalore et al., 2019](#); [Hossain et al., 2012](#)), and thus, they have
42 relatively a low capacity to cope with property losses resulting from flooding ([Brouwer et al.,](#)
43 [2007](#)).

44 Bangladesh is located in the floodplain of three major rivers — the Ganges,
45 Brahmaputra, and Meghna. The combined discharge generated of these three rivers is the
46 highest in the world. The peak run-off depth is also the highest, which, combined with storm
47 surges generated from the Bay of Bengal. This makes a major portion of the country is prone
48 to flooding ([Dasgupta, 2007](#)). Flood processes in the coastal region of Bangladesh are complex,
49 as it can occur from multiple sources such as intense precipitation during the monsoon, high
50 water levels in the rivers, and cyclone induced storm surges ([Adnan et al., 2019](#)). Different
51 environmental stresses create biophysical and socioeconomic challenges in the coastal region.
52 For instance, frequent flooding and increasing soil salinity limit agricultural productivity,
53 which is the main source of livelihoods in coastal Bangladesh ([Rahman et al., 2020](#)).

54 Flood management approaches in the coastal region of Bangladesh include both
55 structural and non-structural measures ([Paul and Rashid, 2017](#); [Rahman and Salehin, 2013](#)).
56 Major surge events induced by cyclones in the 1950s forced the then government to invest in
57 the Coastal Embankment Project (CEP) in the 1960s. The CEP aimed at increasing agricultural
58 production to ensure food security, by preventing salinity intrusion in the coastal region
59 particularly during the dry season. As a part of the CEP, 139 polders (enclosed coastal
60 embankments) were created in between the 1960s and 1980s ([Islam et al., 2016](#); [Warner et al.,](#)
61 [2018](#)). The construction of the polders has brought both beneficial and harmful effects on
62 society and the environment. The protection from flooding afforded by embankments led to an
63 increase in agricultural productivity until the 1980s ([Adnan et al., 2020](#)). Embankments have
64 demonstrably protected the polder area against storm surges and fluvio-tidal floods of moderate
65 severity ([Adnan et al., 2019](#)). However, the separation of floodplains from adjacent rivers
66 caused geomorphological changes in the polder areas, exacerbating land subsidence inside
67 polders ([Auerbach et al., 2015](#)). Accelerated land subsidence and inadequate drainage are
68 accountable for frequent pluvial flooding (locally called ‘waterlogging’) ([Adnan et al., 2019](#)).

69 Generally, the construction of structural flood control measures, such as polders, shapes
70 the pattern of human settlements and land use, which in turn impacts the extent of flood risk.
71 Such flood control measures create the so-called “levee effect” ([White, 1945](#)). Whilst people
72 tend to settle in less flood-prone areas, presence of structural flood defence system encourages
73 floodplain development by engendering a sense of safety ([Di Baldassarre et al., 2013](#); [Montz
74 and Tobin, 2008](#)). Therefore, the failure of structural systems in the form of overtopping or
75 breaching of embankments may exacerbate flood damages ([Hui et al., 2016](#)).

76 The pattern of land use/land cover (LULC) in the coastal region of Bangladesh has
77 experienced major changes over the past half-century, following the construction of polders
78 ([Abdullah et al., 2019](#); [Huq et al., 2015](#); [Khan et al., 2015](#); [Parvin et al., 2017](#); [Rahman et al.,
79 2017](#)). Such changes largely occurred due to frequent and diverse natural hazards (e.g., floods)
80 and increases in inundation, soil salinity, and land erosion ([Brouwer et al., 2007](#); [Khan et al.,
81 2015](#)). For instance, about 1% of agricultural land along the south western coast was
82 transformed into non-agricultural use in each year over the past four decades due to the
83 occurrence of frequent flooding ([Rahman et al., 2017](#)). The transformation of agricultural land
84 to shrimp culture has been a common practice in the area since the 1980s as it can be more
85 profitable ([Khan et al., 2015](#)). However, such land transformation has reportedly been leading
86 to an increase in soil salinity, reducing agricultural production ([Khan et al., 2015](#); [Rahman et
87 al., 2017](#)).

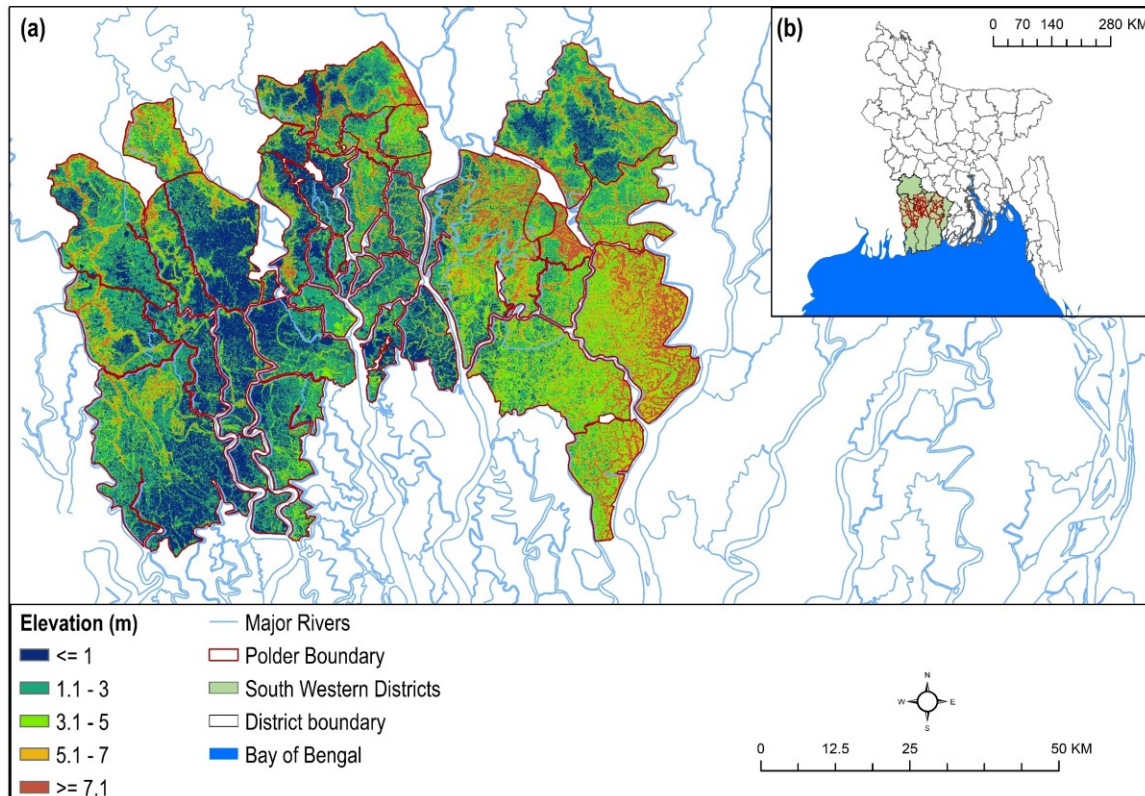
88 Whilst anthropogenic drivers profoundly change the pattern of LULC, such
89 transformation of land may affect local flooding processes ([Wheater and Evans, 2009](#)). The
90 pattern of LULC determines the amount of runoff generated during a precipitation event, thus,
91 influencing the water balance in an area. Hence, LULC may affect both the probability of
92 flooding and its consequences ([McColl and Aggett, 2007](#); [Szwagrzyk et al., 2018](#)). Flood losses
93 are not only dependent on extreme hydro-meteorological conditions of a region, unplanned
94 land use can multiply property damages ([Lee and Brody, 2018](#)). In coastal Bangladesh,
95 unplanned LULC change may lead to environmental degradation such as soil salinization,
96 disappearance of seasonal lagoons, and deterioration of water quality by increasing salinity
97 ([Islam et al., 2015](#)).

98 Generally, flooding and poverty coexist particularly within rural communities, as
99 damages caused by recurring flood events deplete assets, negatively impact agricultural
100 incomes and thus lower quality of life of communities ([Dube et al., 2018](#)). It has been

101 hypothesised that increasing flood risk and unplanned LULC change may create a poverty trap
102 in the coastal region of Bangladesh ([Ahmed, 2018](#); [Borgomeo et al., 2017](#)), inhibiting long-
103 term development prospects ([Parvin et al., 2017](#)). Marginalised farmers could not generate
104 adequate income through agricultural activities, whilst being unable to transform their
105 agricultural land into aquaculture due to high cost associated with such change ([Islam et al.,](#)
106 [2015](#)). As a result, they are unable to migrate out of such areas due to social and economic
107 constraints and related costs ([Dasgupta, 2007](#)).

108 Regulating LULC change is an intervention to reduce flood risk, which has been
109 adopted in different coastal cities ([Adnan and Kreibich, 2016](#)). Therefore, it is essential to
110 understand the association between LULC and flood risk. Risk-based flood management
111 approaches have received attention globally due to recent experience of several catastrophic
112 events in many regions across the world ([Hall et al., 2015](#); [Hall et al., 2003b](#); [Poussin et al.,](#)
113 [2015](#)), as well as the projected increase in the frequency and severity of flooding due to climate
114 change-induced sea level rise ([Koks, 2018](#)). An empirical analysis of flood risk can support
115 decision-makers to appraise and sequence investments for flood management ([Dawson et al.,](#)
116 [2011](#); [Hall et al., 2003a](#); [Hall et al., 2019](#); [Hino and Hall, 2017](#); [Sayers et al., 2002](#)). The
117 methods used in research and practice for quantifying flood hazard and vulnerability range
118 from simple approaches (with numerous simplifying assumptions) to very complex
119 applications, which are both data and time-intensive and computationally expensive ([Apel et](#)
120 [al., 2009](#); [Dewan, 2013](#)).

121 In the existing literature, the association between flood risk and poverty has been
122 comprehended primarily by estimating exposure of poor people to flooding at various
123 geographical scales ([Bangalore et al., 2019](#); [Brouwer et al., 2007](#); [Qiang et al., 2017](#);
124 [Winsemius et al., 2018](#)). In the case of coastal Bangladesh, a few studies have applied
125 quantitative approaches (based on household survey data) to show how poverty exacerbates
126 flood vulnerability/risk ([Aker and Mallick, 2013](#); [Brouwer et al., 2007](#)). However, little is
127 known about (i) how the pattern of LULC change influences flood risk at present and in the
128 future; (ii) what is the association between LULC change and risk of flooding, and how they
129 impact poverty spatially. We address these questions by estimating: (i) flood risk in relation to
130 current and future LULC scenarios; and (ii) the change in poverty in relation to a change in
131 LULC and flood risk.



132

133

Figure 1 South western embanked area of Bangladesh

134

2. Materials and methods

135

136

137

138

139

140

141

This study was conducted in three stages. First, a model was established to analyse spatiotemporal patterns of LULC change and predict future LULC. Second, pluvial flood hazard was modelled to simulate the depth and extent of inundations for various return periods of monsoonal precipitation. Then flood risk was estimated at each LULC scenario (historical and future), for different flood return periods. Finally, a spatial regression model was developed to estimate poverty, incorporating geographical, environmental, and socio-economic parameters including LULC change and flood risk.

142

2.1. Description of the study area

143

144

145

146

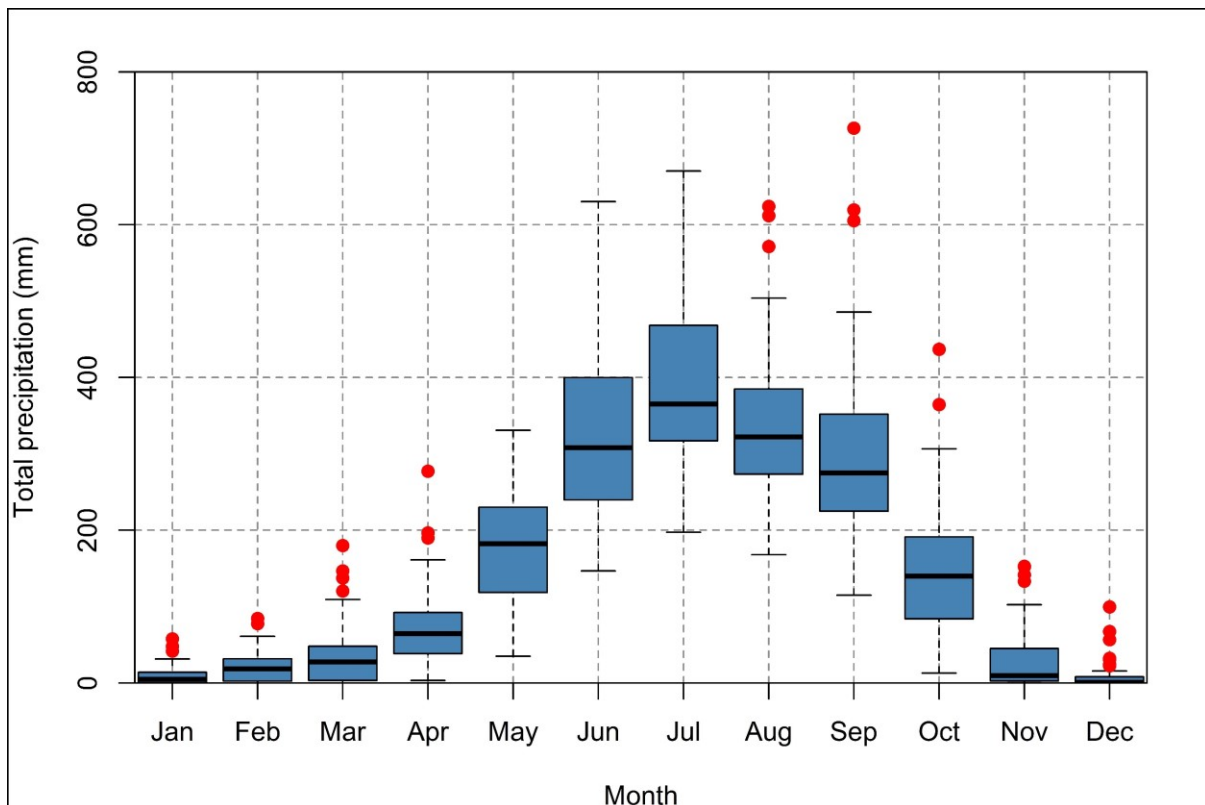
147

148

149

This study focussed on polders in the south western coast of Bangladesh. The area includes a total of 44 polders, located in five coastal districts: Bagerhat, Jessore, Khulna, Pirojpur, and Satkhira (Figure 1). These polders were constructed to protect about 5187 km² of land, where approximately 5.3 million people live ([WorldPop, 2018](#)). The area has a mean elevation of 3.5 m and is heavily intersected by tidal rivers. The area is prone to three types of flooding — pluvial, fluvio-tidal, and surge floods. Inadequate drainage channels and increasing land subsidence exacerbate frequent pluvial flooding during the monsoon months (May to

150 September) ([Adnan et al., 2019](#)), when the area receives the maximum amount of precipitation
 151 (Figure 2). A lack of sedimentation and accelerated compaction within the embanked area led
 152 to a loss of 1.0-1.5 m elevation since the construction of polders in the 1960s ([Auerbach et al.,](#)
 153 [2015](#)). Agriculture, shrimp farming, and the natural resources of the Sundarban mangrove
 154 forest (located in the south of the study area) are the major sources of livelihoods and economy
 155 of the inhabitants ([Khan et al., 2015](#)). Approximately 80% of the total shrimp ponds of
 156 Bangladesh are located in south western coast ([Ahmed, 2018](#)). However, increased soil salinity
 157 resulting from the excessive shrimp farming has negatively impacted crop yield. The situation
 158 potentially affects the livelihoods of the poorest segments of society ([Szabo et al., 2016](#)). A
 159 risk-sensitive land use policy would help to alleviate the complex problems of the south
 160 western coast ([Rahman et al., 2017](#)). Thus, this study aimed to provide spatial information on
 161 land use change and flood risk, as well as their association with poverty.



162
 163 Figure 2 Box and whisker plot of monthly rainfall (1965-2012) for south western embanked
 164 area

165 **2.2. Data**

166 This study examined the effects of LULC change and flood risk on poverty. A range of spatial
 167 and hydrometeorological data were used to model LULC change, assess flood risk, and
 168 estimate poverty. A list of data is given in Table 1. The LULC dataset used in this study is an

169 updated version of [Abdullah et al. \(2019\)](#). The dataset contains five classes: agricultural,
 170 aquaculture, bare land, built-up area (urban), vegetation with the rural settlement, and
 171 waterbody. The Advanced Land Observing Satellite (ALOS) digital elevation model (DEM)
 172 ([JAXA, 2015](#)) at 30 m resolution used to derive maps of various geomorphological parameters
 173 (e.g. elevation, slope, curvature) and establish flood hazard model. The ALOS DEM was used
 174 as it is considered to be highly reliable and freely available DEM, which has a low root mean
 175 square error (1.78m) in vertical accuracy ([Adnan et al., 2020](#)). Hydrometeorological data were
 176 collected from various organisations including Bangladesh Meteorological Department
 177 (BMD), Bangladesh Agricultural Research Council (BARC), and Water Resources Planning
 178 Organisation of Bangladesh (WARPO). This study considered the Wealth Index (WI) as an
 179 indicator of poverty. The WI data was obtained from [Steele et al. \(2017\)](#).

180 Table 1. Different data types used in this study

| Data | Description | Source |
|---------------------------------|--|--|
| 1. LULC | LULC data of 2005, 2010, and 2019 at 30 m resolution | (Abdullah et al., 2019) |
| 2. DEM | ALOS DEM of 30 m resolution | (JAXA, 2015) |
| 3. Precipitation | Gridded (5km grid points) precipitation data of 10-day temporal resolution from 1965-2012 | (www.bmd.gov.bd/) |
| 4. Climate | Monthly average temperature, monthly average daylight hour data from 1988-2012, across four weather stations | (http://www.barc.gov.bd/) |
| 5. Poverty | Gridded Demographic and Health Surveys (DHS) Wealth Index (WI) | (Steele et al., 2017) |
| 6. Soil salinity | Gridded soil salinity index | (Abdullah et al., 2018) |
| 7. Population density | Total number of people per 100 m grid-cell | (https://www.worldpop.org) |
| 8. Gross Domestic Product (GDP) | Gridded GDP data of 30 arc-sec (~900m) resolution | (Kummu et al., 2018) |
| 9. Agricultural employment | Number of people employed in the agricultural sector | (De Bono and Chatenoux, 2014) |
| 10. Spatial data | GIS vector data of road network, river channels, and growth centre | (http://www.warpo.gov.bd) |

181

182

2.3. Modelling LULC change

This study predicted LULC during 2030 using a combination of logistic regression (LR), cellular automata (CA), and Markov Chain models, following an approach by [Arsanjani et al. \(2013\)](#). A similar modelling approach has been used in several studies for detecting and simulating LULC change ([Ahmed et al., 2013](#); [Kityuttachai et al., 2013](#); [Mitsova et al., 2011](#); [Shahbazian et al., 2019](#); [Wang et al., 2019](#)). We applied this approach for following reasons: (i) it can incorporate both environmental and socio-economic variables; (ii) the model can incorporate a wide range of spatial factors; (iii) the LR model can use data at different scales; and (iv) the CA model can control spatial dynamics of LULC changes ([Arsanjani et al., 2013](#); [Shahbazian et al., 2019](#)).

The CA model uses a principle that areas tend to change to a state based on the state of their neighbouring areas ([Arsanjani et al., 2013](#)). A CA system includes four components such as cells, states, neighbourhoods, and rules ([Shahbazian et al., 2019](#)). Cells are defined as the smallest unit and the state of each cell is determined by its initial state, the conditions in the surrounding cells, and a set of transition rules ([Arsanjani et al., 2013](#); [Verburg et al., 2004](#)). The CA model in this study incorporated a LULC change map, transition potential maps created using LR models, the change rate calculated in the change analysis step, and a transition probability matrix predicted for a future year (using Markov Chain model).

2.3.1. Analysing LULC change

LULC data of 2005, 2010, and 2019 were analysed to detect spatiotemporal changes. The model initially calibrated LULC change over the period 2005-2010. While developing a LULC change map, the transition areas less than 5 km² (~0.001% of total area) were ignored, otherwise, the modelling approach would have been computationally expensive. As a result, the 2005-2010 change map included a total of 12 LULC transition categories.

2.3.2. Driving forces for detecting change

The LR models were established for all 12 transitions, to estimate the degree of influence of different factors (driving forces) on a type of LULC ([Shahbazian et al., 2019](#)). LULC changes could be governed by various combinations of geographical, environmental, and socio-economic factors ([Dewan and Yamaguchi, 2009](#)). Based on the knowledge attained from literature as well as expert knowledge on the study area, a total of 14 variables were selected (Table 2). For a LULC transition, the LR model incorporated a binary (change to a LULC class and no-change) dependent variable and different combinations of independent

215 variables (driving forces). Combinations of independent variables were selected in a way that
 216 yielded the highest relative operating characteristic (ROC) and adjusted odds ratio values,
 217 indicating performance of the models ([Arsanjani et al., 2013](#)).

218 The LR model creates probability surface maps using the following equation ([Hosmer
 219 Jr et al., 2013](#)):

$$p = 1/(1 + e^{-z}) \quad (1)$$

220 where p ranges from 0 to 1 on an S-shaped curve, explaining the probability of a cell
 221 changing to a LULC class; z is the linear combination of independent variables (driving forces),
 222 which was estimated using the following equation:

$$z = b_0 + b_1x_1 + b_2x_2 + \dots + b_nx_n \quad (2)$$

223 where b_0 is the model intercept, b_i ($i = 1, 2, \dots, n$) indicates the coefficients of
 224 independent variables, and x_i ($i = 1, 2, \dots, n$) represents the n number of independent variables.

225 **2.3.3. Simulating future LULC**

226 The CA-Markov Chain model was used to predict LULC change based on the estimated
 227 transition probabilities ([Arsanjani et al., 2013](#); [Shahbazian et al., 2019](#)). The Markov Chain
 228 model predicted the quantity of change in each LULC transition. Based on the Bayes' theorem
 229 of conditional probability, LULC was predicted using the following formula ([Sang et al.,
 230 2011](#)):

$$S(t+1) = P_{ij} \times S(t) \quad (3)$$

231 where $S(t)$ and $S(t+1)$ are the LULC status at the time t and $t+1$, respectively; the
 232 transition probability matrix P_{ij} was estimated as follow:

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1n} \\ P_{21} & P_{22} & \dots & P_{2n} \\ \dots & \dots & \dots & \dots \\ P_{n1} & P_{n2} & \dots & P_{nn} \end{bmatrix} \quad (4)$$

$$\left(0 \leq P_{ij} < 1 \text{ and } \sum_{j=1}^n P_{ij} = 1, (i, j = 1, 2, 3, \dots, n) \right)$$

233 where n is the total number of LULC classes. In this study, probability values of 2019
 234 and 2030 were predicted based on transition matrices of 2005-2010 and 2010-2019,
 235 respectively. However, the spatial distribution of LULC in a Markov Chain model is unknown.

236 Therefore, the CA model was integrated to provide a spatial dimension to the model ([Arsanjani](#)
237 [et al., 2013](#); [Corner et al., 2014](#); [Shahbazian et al., 2019](#)).

238 **2.3.4. Validating the outputs**

239 The LULC change model was validated for the year 2019. Therefore, considering
240 LULC maps of 2005 and 2010 as the initial and final state maps, the model predicted LULC
241 map of 2019. We compared predicted LULC map with observed data of 2019. Kappa statistic
242 was estimated to determine the degree of agreement between observed and modelled LULC
243 maps ([Mitsova et al., 2011](#)).

244 **2.4.Flood risk assessment**

245 Flood risk assessment was carried out for various LULC scenarios to estimate temporal
246 changes of direct economic damage due to floods of various magnitudes. The risk was defined
247 as the product of flood hazard, exposure, and vulnerability. The expected annual damages
248 (EAD) at different LULC scenarios were estimated to represent spatiotemporal pattern of flood
249 risk ([Rojas et al., 2013](#)).

250 **2.4.1. Flood frequency analysis**

251 This study primarily focused on pluvial flooding, considering increased frequency and
252 severity of this type of flooding in the study area. Although historically, three types of flooding
253 (pluvial, fluvio-tidal, and storm surge induced flooding) affect the study area, occurrence of
254 pluvial flooding is a relatively recent and frequent phenomenon. [Adnan et al. \(2019\)](#)
255 documented that monsoon precipitation caused inundation in the area every year from 1988 to
256 2012. Persistent pluvial flooding damages crops and therefore impacts the livelihoods of people
257 who inhabit the south western coast ([Alam et al., 2017](#)).

258 Flood frequency analysis was carried out to estimate return periods of monsoon
259 precipitation, which is the main source of pluvial flooding in the study area ([Adnan et al.,](#)
260 [2019](#)). Seven recurrence intervals (i.e. 1, 2, 5, 10, 20, 50, and 100 years) of floods were
261 considered here. Inundation depth was estimated at each cell within the study area. Since
262 pluvial flood hazard model takes monthly precipitation as an input, we generated raster layers
263 of monthly precipitation of seven return periods. To decide whether the climate in the near
264 future (i.e. 2030) is likely to be in a ‘changed’ or ‘unchanged’ state, a precipitation trend
265 analysis was performed. Therefore, linear regression models of monthly precipitation were
266 established ([Panda and Sahu, 2019](#)). We also applied an autocorrelation function (ACF) to
267 estimate whether monthly total precipitation was autocorrelated between years ([Feng et al.,](#)

268 [2016](#)). No significant autocorrelation was found between successive years. The linear
269 regression models confirmed the absence of a significant trend in monthly precipitation. The
270 results of precipitation trend analysis are summarised in Table S3 and Figure S1 (see
271 supplementary document). To generate monthly precipitation layers of seven return periods,
272 extreme value analysis was conducted at each grid cell by fitting a generalized extreme-value
273 (GEV) distribution using the L-moment method, following [Adnan et al. \(2019\)](#).

274 **2.4.2. Flood hazard assessment**

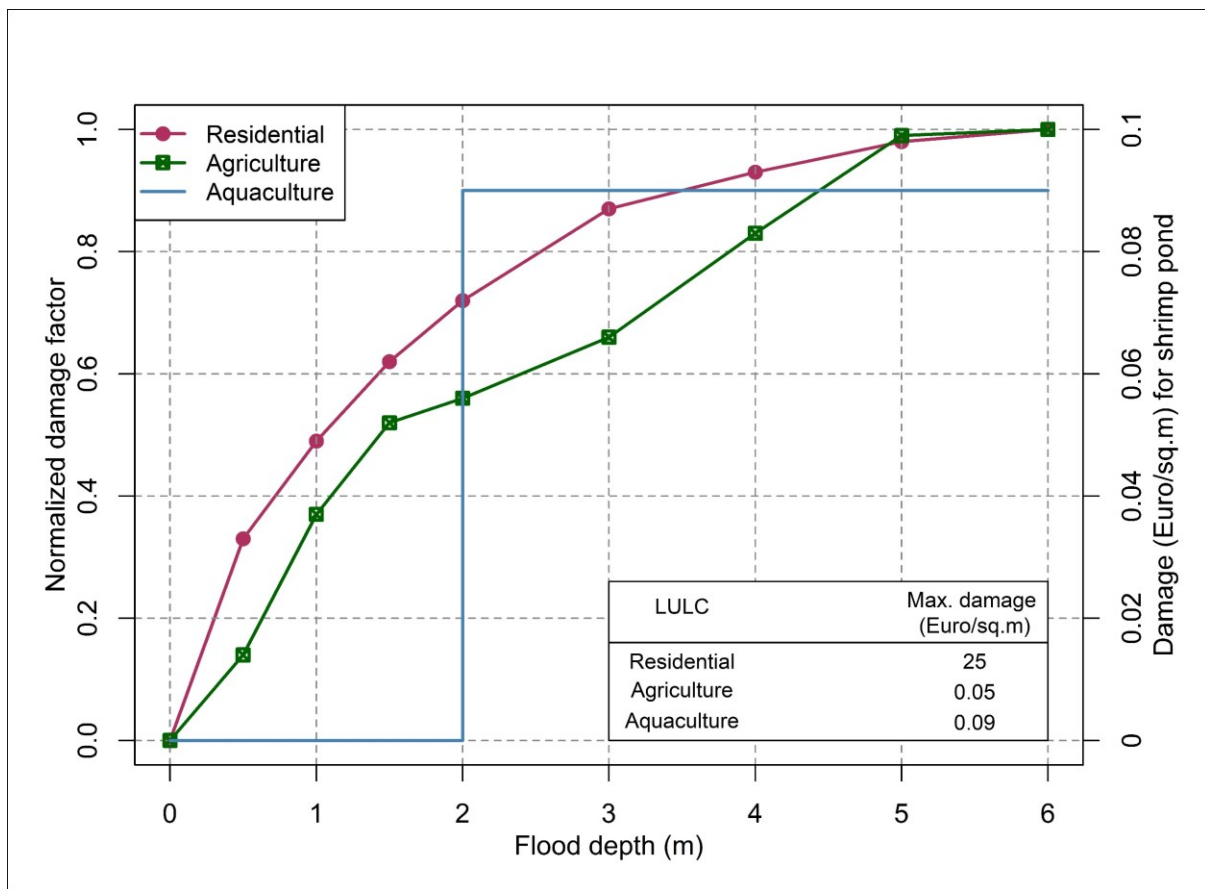
275 Flood hazard assessment included a hydrological simulation of floods of various return
276 periods ([Rojas et al., 2013](#)). Inundation maps were also derived for seven recurrence intervals
277 of monsoon precipitation — 1, 2, 5, 10, 20, 50, and 100 years — using a pluvial flood rainfall-
278 runoff and spreading model established for the study area by [Adnan et al. \(2019\)](#). The
279 modelling process started with estimating monthly water balance. A Thornthwaite and Mather
280 water balance model was accompanied by the flood model, which estimated monthly excess
281 precipitation at each grid cell, after subtracting evapotranspiration from monthly total
282 precipitation. Monthly excess precipitation layers from May to September were aggregated to
283 prepare excess precipitation layers during the monsoon. The inundation model incorporated
284 the ALOS DEM to identify depressions and their catchments. During a flood event, the
285 estimated total volume of excess precipitation was assigned to each depression according to
286 the respective catchment position to represent both flood depth and extent. Further description
287 of the model, validation process and sensitivity analysis can be found in [Adnan et al. \(2019\)](#).
288 The flood hazard mapping resulted in inundation maps of seven recurrence intervals.

289 **2.4.3. Flood vulnerability analysis**

290 Flood vulnerability assessment generally includes the estimation of direct or indirect
291 damages due to floods. Direct damages, which primarily occurred because of physical contact
292 of houses, building, and public infrastructures with floodwater, are estimated as a function of
293 flood depth in different cells, the relationship between flood depth and LULC (or structural
294 use), and total cell area ([Apel et al., 2009](#)). Indirect damages can be an outcome of the failures
295 of critical infrastructure systems, such as transportation, production, and energy ([Koks et al.,
296 2019](#)). The scope of the study was however limited to estimating direct flood damages. It was
297 estimated for three types of LULC (i.e. agriculture, aquaculture, and residential) using the
298 following equation ([Islam et al., 2019](#)):

$$D_j = \left(\sum_{i=1}^n x_i \times f(x_i) \right) \times A \quad (5)$$

299 where D_j is the total damage (in million USD (\$)) during a flood return period of j , x_i is
 300 the flood depth (m) in cell i , $f(x_i)$ is the damage function for the flood depth level x in cell i ,
 301 and A is the area of a cell. Global depth-damage curves, adopted from [Huizinga et al. \(2017\)](#),
 302 were used to estimate direct tangible flood damage to residential and agricultural LULC. The
 303 depth-damage curve for aquaculture lands was obtained from [Islam et al. \(2019\)](#) (Figure 3).
 304 The maximum damage values in depth-damage functions were given in Euro, which we
 305 converted into USD using a currency conversion rate of 1 Euro = 1.11 USD.



306
 307 Figure 3 Depth-damage curves (adopted from [Huizinga et al. \(2017\)](#) and [Islam et al. \(2019\)](#))

308 Pixel-scale (30 m resolution) flood damage was estimated in a GIS for seven flood
 309 return periods (1, 2, 5, 10, 20, 50, and 100-year) at four LULC scenarios of 2005, 2010, 2019,
 310 and 2030. Inundation maps (see section 2.4.2) were overlaid on LULC maps to record flood
 311 depth and LULC according to each pixel. This dataset was imported in an R package and
 312 integrated with equation 5 to estimate pixel-scale flood damage, as well as total damage of the
 313 study area.

314 2.4.4. Estimating flood risk

315 Following flood hazard and vulnerability assessments, risks were estimated in the form
316 of expected annual damage (EAD) for four LULC scenarios (2005, 2010, 2019, and 2030). The
317 EAD can be estimated using the following equation ([Olsen et al., 2015](#)):

$$EAD = \iint_{A p} D(p) dp dA \quad (6)$$

318 where $D(p)$ is the damage occurred during an event with the annual probability of
319 exceedance p (approximated by the inverse of the flood return period (T)), A is the total area
320 of the region under study. Since the choice of return periods influences flood risk estimates, a
321 consideration of all return periods between the low and high probability floods enables an
322 accurate estimation of risk ([Ward et al., 2011](#)). The probability space of flood risk for each
323 integer year flood return period between 1 and 100 is discretised into 100 equal intervals, by
324 interpolating flood damages estimated between seven recurrence intervals ([Rojas et al., 2013](#)).
325 An exceedance probability curve was developed by plotting flood damages against
326 corresponding exceedance probabilities. The exceedance probabilities of 0.01 (100-year) and
327 1 (1-year) were considered correspondingly as the lower and upper limits of the probability
328 curve. The EAD was estimated as the area under the curve (AUC), applying the trapezoidal
329 rule given in equation 7 ([Olsen et al., 2015](#)).

$$EAD = \frac{1}{2} \sum_{i=1}^n \left(\frac{1}{T_i} - \frac{1}{T_{i+1}} \right) (D_i + D_{i+1}) \quad (7)$$

330 where n is the total number of return periods which is 100; T_i is the return period of
331 the i^{th} event; D_i is the estimated flood damage during the i^{th} event.

332 2.5. Downscaling poverty data

333 Flood damage may exacerbate the degree of poverty in a region, whilst poor people
334 may be compelled to live in riskier locations ([Dube et al., 2018](#)). This study aimed at
335 investigating the spatiotemporal distribution of poverty, diagnosing its association with flood
336 risk and LULC change. [Steele et al. \(2017\)](#) developed a gridded poverty dataset for Bangladesh,
337 combining data from multiple sources such as mobile phone, satellite, and traditional survey.
338 The spatial scale of the database was determined by developing the service area coverage of a
339 cellular network using the Voronoi polygons. The spatial resolution of the data varies from 60
340 m to 5 km, where poverty was represented as asset, consumption, and income-based measures

341 of wellbeing. In this study, we considered the asset-based measure, i.e., Demographic and
342 Health Surveys (DHS) Wealth Index (WI), because the WI yielded the highest accuracy of
343 predictions than other poverty metrics ([Steele et al., 2017](#)). The WI is a measure of household's
344 living standard that is calculated using survey data on household characteristics (e.g. material
345 used for housing construction), ownership of selected assets (e.g., television, bicycles), and
346 access to different facilities such as water supply and sanitation
347 (<https://www.dhsprogram.com>). The values of the WI can be either positive or negative, where
348 a higher value implies higher socioeconomic status ([Steele et al., 2017](#)).

349 We downscaled the gridded WI data obtained from [Steele et al. \(2017\)](#), establishing a
350 GIS-based ordinary least square (OLS) model (equation 8) based on ten spatial parameters
351 (Table 4). The south western embanked area is comprised of 303 Voronoi polygons. The
352 polygons were used to extract the values of all parameters.

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon \quad (8)$$

353 where y is the WI, X_n is the value n^{th} parameter, β is the regression coefficient, and ε is
354 the random error in prediction or residuals.

355 Spatial parameters included soil salinity, elevation, EAD, relative flood frequency,
356 distance from northing and easting coordinates, LULC change, population density, GDP, and
357 the number of people employed in the agricultural sector. The selection of parameters was
358 based on their (i) role in influencing poverty (ii) availability as gridded data. Soil salinity
359 impacts poverty as increasing salinity in the coastal region hinders agricultural activity ([Szabo
360 et al., 2016](#)). A map of relative flood frequency was collected from [Adnan et al. \(2020\)](#). To
361 represent ground elevation, ALOS DEM was used. The EAD map developed in this study (see
362 section 2.4.4) was included in the regression model. A binary (change or no-change) LULC
363 change map from each previous time step was incorporated. Two layers, representing the
364 Euclidean distance from northing and easting lines were produced, to understand the spatial
365 distribution of WI. GDP indicates the extent of human and economic development of a country,
366 may influence WI. Gridded GDP data was extracted for the study area from a global dataset
367 developed by [Kummu et al. \(2018\)](#). The dataset has a spatial resolution of 30 arc-sec (~900m)
368 and generated for years 1990, 2000, and 2015. Using the GDP data of 2015, we projected the
369 GDP of 2010, 2019, and 2030, incorporating existing and projected GDP growth rates provided
370 by the World Bank and the International Monetary Fund (IMF), respectively. Sources of

371 gridded soil salinity, population density, and agricultural employment data are given in Table
372 1.

373 The year 2010 was considered as a base year for this analysis, as WI data was developed
374 based on 2011 DHS and 2010 Household Income and Expenditure (HIES) survey data.
375 Performance of the model was determined by estimating the coefficient of determination (R^2).
376 The generated OLS regression equation was used to predict WI for the year 2019 and 2030.
377 Therefore, four independent variables were adjusted accordingly: The EAD, LULC change,
378 population density, and GDP, while other variables were assumed to be constant.

379 **3. Results**

380 **3.1. LULC change modelling**

381 *3.1.1. Temporal change of LULC*

382 Figure 4 (a) shows temporal changes of observed LULC from 2005 to 2019 and their
383 spatial variations are presented in Figure S2 (see supplementary document). From 2005-2010,
384 a significant decrease in agricultural land was observed, while the proportion of aquaculture
385 category increased substantially. More than 50% of agricultural lands transformed into
386 aquaculture use, with another 25% into rural settlements. Contrarily, LULC change from 2010-
387 2019 was relatively stable, when the main transformation took place in bare land; about 23%
388 bare land area transformed into rural settlements. Stable growth in rural and urban settlements
389 was observed between the years 2005 and 2019.

390 *3.1.2. Driving factors*

391 Various combinations of geographical, environmental, and social factors account for
392 different types of LULC transition. Table 2 shows regression coefficients of different factors
393 influencing the transformation of agricultural lands into aquaculture, rural, and urban use
394 within 2005-2010. The probability of LULC change from agricultural to aquaculture use is
395 higher in areas characterised by low elevation, concave curvature, frequently affected by
396 flooding, located in proximity to existing aquaculture lands, roads, and drainage channels, high
397 level of soil salinity, and located in the northern portion of the study area. Notably, we found a
398 positive correlation of flood frequency with LULC change from agriculture to rural and urban
399 settlements. About 57% of the study area was inundated by at least two historical flood events
400 from 1988 to 2012 ([Adnan et al., 2020](#)). Therefore, substantial development of the residential
401 area took place in the flood-prone zones. A summary of LR models of the remaining nine
402 LULC transitions is given in Table S1 of the supplementary document.

403 Table 2. Driving factors of LULC change from 2005 to 2010

| Factors | Regression coefficient | | |
|------------------------------------|----------------------------|---------------------------------|--------------------------------------|
| | Agriculture to aquaculture | Agriculture to rural settlement | Agriculture to built-up area (urban) |
| Intercept | 1.41 | 1.25 | 9.53 |
| Elevation | -0.02 | 0.11 | -0.37 |
| Slope | -1e ⁻⁰⁴ | 2e ⁻⁰⁵ | -2e ⁻⁰⁴ |
| Curvature | 0.05 | | |
| Flood frequency | 0.69 | 0.19 | 0.43 |
| Distance from aquaculture land | -0.34 | | |
| Distance from existing road | -0.04 | -0.05 | -0.06 |
| Distance from residential area | | -0.07 | -2.42 |
| Distance from adjacent river | -0.11 | | |
| Distance from drainage channel | -0.35 | | |
| Distance from growth centre | | 0.07 | 0.11 |
| Soil salinity | 0.39 | 0.25 | |
| Distance from northing coordinates | -0.19 | -0.31 | -0.09 |
| Distance from easting coordinates | | -0.003 | 0.10 |
| Population density | -0.21 | 0.05 | 0.18 |

404

405 The performance of each LR model is indicated by the estimated ROC and odds ratio
 406 (Table 3). A ROC value 1 indicates a perfect fit and ROC value 0.5 represents a random fit.
 407 Also, a higher adjusted odds ratio indicates a better performance of a model ([Arsanjani et al.,](#)
 408 [2013](#)). In this study, the LR model for LULC transformation from agriculture to aquaculture
 409 cover obtained highest estimates of these performance indicators.

410

Table 3. ROC and adjusted odds ratio values of LR models

| *Transitions | ROC | Adjusted odds ratio |
|--------------------|------|---------------------|
| LULC -1 to LULC -2 | 0.93 | 81.27 |
| LULC -1 to LULC -3 | 0.71 | 5.23 |
| LULC -1 to LULC -4 | 0.91 | 24.67 |
| LULC -1 to LULC -5 | 0.73 | 4.60 |
| LULC -1 to LULC -6 | 0.89 | 17.82 |
| LULC -2 to LULC -3 | 0.74 | 8.10 |
| LULC -3 to LULC -1 | 0.67 | 4.28 |
| LULC -3 to LULC -2 | 0.89 | 14.38 |
| LULC -3 to LULC -5 | 0.68 | 2.96 |
| LULC -5 to LULC -1 | 0.63 | 2.07 |
| LULC -5 to LULC -2 | 0.93 | 35.74 |
| LULC -5 to LULC -3 | 0.82 | 9.81 |

* LULC -1= Agriculture; LULC -2 = Aquaculture; LULC -3 = Bare land; LULC -4 = Built-up area (urban); LULC -5 = Vegetation with rural settlement; LULC -6 = Waterbody

411

412

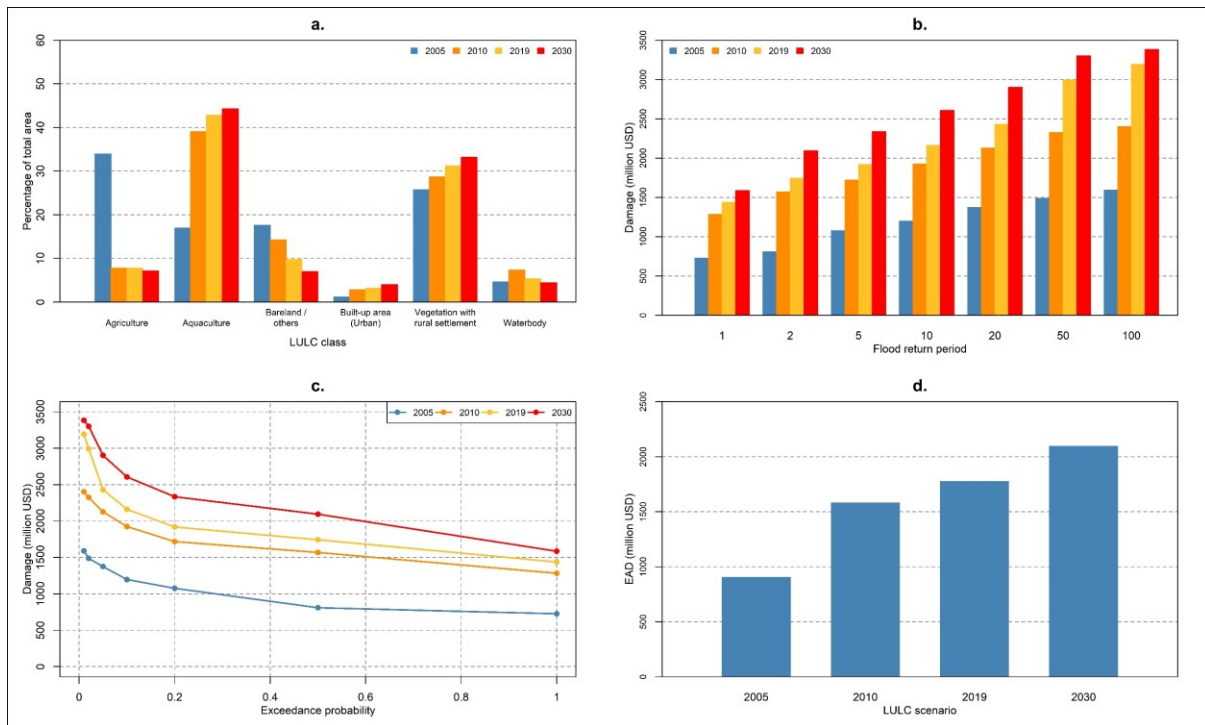
413 **3.1.3. Predicting LULC**

414 The combination of LR and CA-Markov chain model determined LULC quantitatively,
415 where the LR model generated probability surfaces of different transitions, the Markov chain
416 model predicted the quantity of change in each LULC transition, and the CA model controlled
417 the spatial dynamics the projected LULC. The Markov chain model estimated the transition
418 probability of 2030 based on the transition matrix 2010-2019 (Table S2, supplementary
419 document). The simulation suggests that the proportion of agricultural land, bare land, and
420 general waterbody is likely to decrease, while aquaculture lands, as well as rural and urban
421 settlement areas, would increase (Figure 4a). In the case of the spatial distribution of different
422 categories of LULC, aquaculture is likely to remain as the dominant type of LULC in northern
423 and western segments of the study area given its economic return. Agricultural activities would
424 mostly take place in the eastern segment, where “vegetation with rural settlement” is likely to
425 be the dominant LULC category (Figure S2, supplementary document). The validation process
426 yielded a kappa coefficient of 0.87, which indicates an acceptable degree of accuracy.
427 However, the choice of driving forces affects the accuracy of the model ([Wang et al., 2019](#)).
428 Although different environmental and socio-economic factors were considered in this study, a
429 limited number of driving forces may have resulted in some errors in the predicted LULC.

430 **3.2. Association between LULC change and flood risk**

431 **3.2.1. Flood damage**

432 Flood damages are associated with the type of LULC in the study area. Figure 4 (b)
433 shows estimated damages during floods of different recurrence intervals, under four LULC
434 scenarios. An increasing trend of flood damages was estimated, with changes in recurrence
435 intervals and LULC scenarios. The estimated average damage (across all recurrence intervals)
436 of \$1180 million in 2005 is likely to increase by the year 2030 to \$2601 million. From 2005-
437 2010, the highest increase of flood damage was estimated at \$839 million for a flood event
438 with a 50-year return period. Within this period, a significant transformation of LULC was
439 observed, which resulted in a decrease in agriculture lands and an increase in aquaculture land
440 (Figure 4 (a)).



441

442

443

444

445

446

447

448

449

450

451

452

453

454

455

456

457

458

459

460

Figure 4 (a) Trend of LULC change from 2005 – 2030; (b) Estimated damages during floods of different return periods under four LULC scenarios; (c) Exceedance probability distribution curve; (d) Comparison of EAD among four LULC scenarios

3.2.2. Flood risk for various LULC scenarios

An exceedance probability curve in Figure 4 (c) and estimated EAD in Figure 4 (d) indicates contribution of LULC change to flood risk. Notably, in Figure 4 (c), the difference of flood losses between the highest and the lowest exceedance probabilities does not vary greatly. In 2005, damage of \$809 million was estimated for the median annual maximum flood event (an event with a 2-year return period). The damage increased to \$1591 million when the exceedance probability reduced to 0.01. In 2030, damages may range from \$1586 million to \$3384 million for floods with annual exceedance probabilities from 1 to 0.01, respectively. A relatively small difference in estimated damages between the low and high probability floods is because even frequent floods (e.g. the median annual maximum) cause a substantial extent of inundation, and thus, significant damages (Figure 4 (b)). With an increase in the magnitude of precipitation, depths in the inundated areas tend to increase substantially, rather than the extent of inundations. We estimate that the extent of inundation may range from 5% area (for the 2-year return period flood) to 15% area (for the 100-year flood).

LULC change has resulted in increased exposure primarily of residential (rural and urban) and aquaculture lands, which may result higher flood risk in the future. The EAD of the

461 year 2005 was estimated to be approximately \$903 million, which may be more than twice
 462 (\$2096 million) by the year 2030 (Figure 4 (d)), assuming persistent LULC change in the
 463 future.

464 3.3. Association among LULC change, flood risk, and poverty

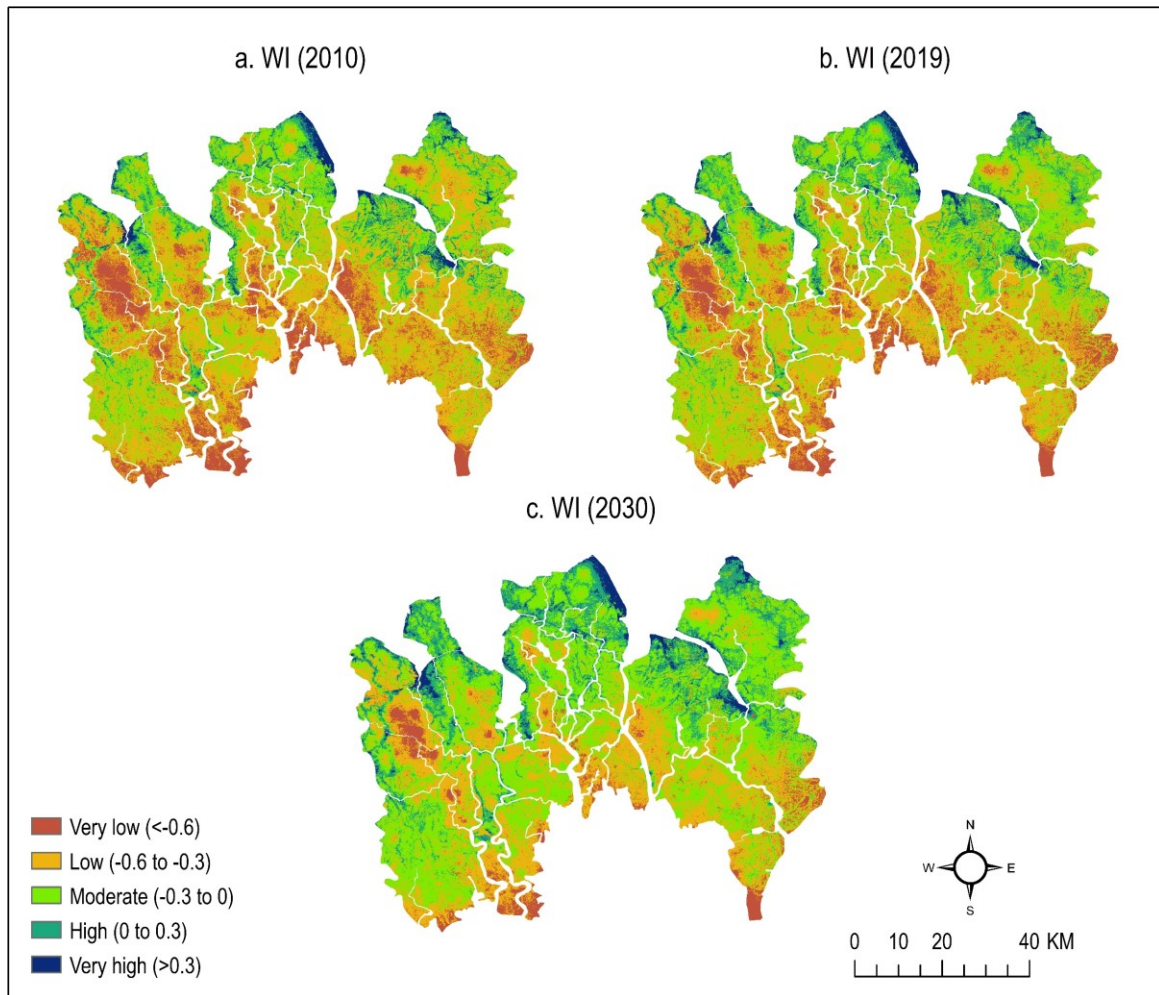
465 Table 4 summarises the results of the OLS regression model, developed to explain the
 466 degree of influence of different parameters on WI in the study area. Among the ten factors
 467 included, nine were found to be statistically significant. The estimated regression coefficients
 468 indicate that the WI was relatively higher in areas where land elevation, population density,
 469 and GDP are high, as well as a larger number of people employed in agriculture. Conversely,
 470 higher soil salinity, EAD, flood frequency, and LULC change negatively affected the WI. The
 471 regression coefficients were incorporated in Equation 8 in a GIS to estimate WI at each pixel,
 472 encompassing the study area. The estimated R² in Figure 6 (c) exhibits the performance of the
 473 model. The R² value of 0.81 indicates an acceptable level of agreement between observed
 474 versus modelled WI values for 2010.

475 Table 4. Estimated regression coefficients for downscaling wealth index (WI) data

| Variables | Coefficient | Standard error | t-value | VIF | p-value |
|---------------------------------------|--|----------------|---------|------|-----------------------|
| Intercept | -2.984 | 0.536 | -5.572 | | 0.000*** |
| Soil salinity | -0.125 | 0.136 | -0.925 | 2.70 | 0.317 |
| Land elevation | 0.042 | 0.009 | 4.472 | 3.08 | 7e ⁻⁰⁶ *** |
| EAD | -0.016 | 0.007 | -2.153 | 1.14 | 0.0373* |
| Relative flood frequency | -0.324 | 0.181 | -1.791 | 1.81 | 0.059• |
| Distance from northing coordinates | -0.132 | 0.018 | -7.481 | 1.59 | 0.000*** |
| Distance from easting coordinates | 0.151 | 0.028 | 5.345 | 3.07 | 0.000*** |
| LULC change | -0.213 | 0.091 | -2.336 | 1.40 | 0.003** |
| Population density | 0.182 | 0.012 | 14.754 | 1.68 | 0.000*** |
| GDP | 0.012 | 0.005 | 2.520 | 1.31 | 0.013* |
| Agricultural employment | 0.298 | 0.039 | 7.342 | 1.40 | 0.000*** |
| R²: 0.81 | Significance level: 0 '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1 ' ' 1 | | | | |

476
 477 The WI of the study area was classified according to five categories using the Jenks
 478 scheme (Figure 5). During the base year of 2010, most of the south western zone (about 58%)
 479 was classified as areas with 'low' and 'very low' level of WI. Relatively, a higher WI was
 480 observed in the northern and western segments of the study area (Figure 5 (a)). The simulation

481 showed a potential increase in WI in the year 2019 and 2030 (Figure 5 (b and c)). Figure S3 in
482 the supplementary document compares the spatial distribution of WI in 2010 between the
483 disaggregated data created in this study and the WI grid developed by [Steele et al. \(2017\)](#).

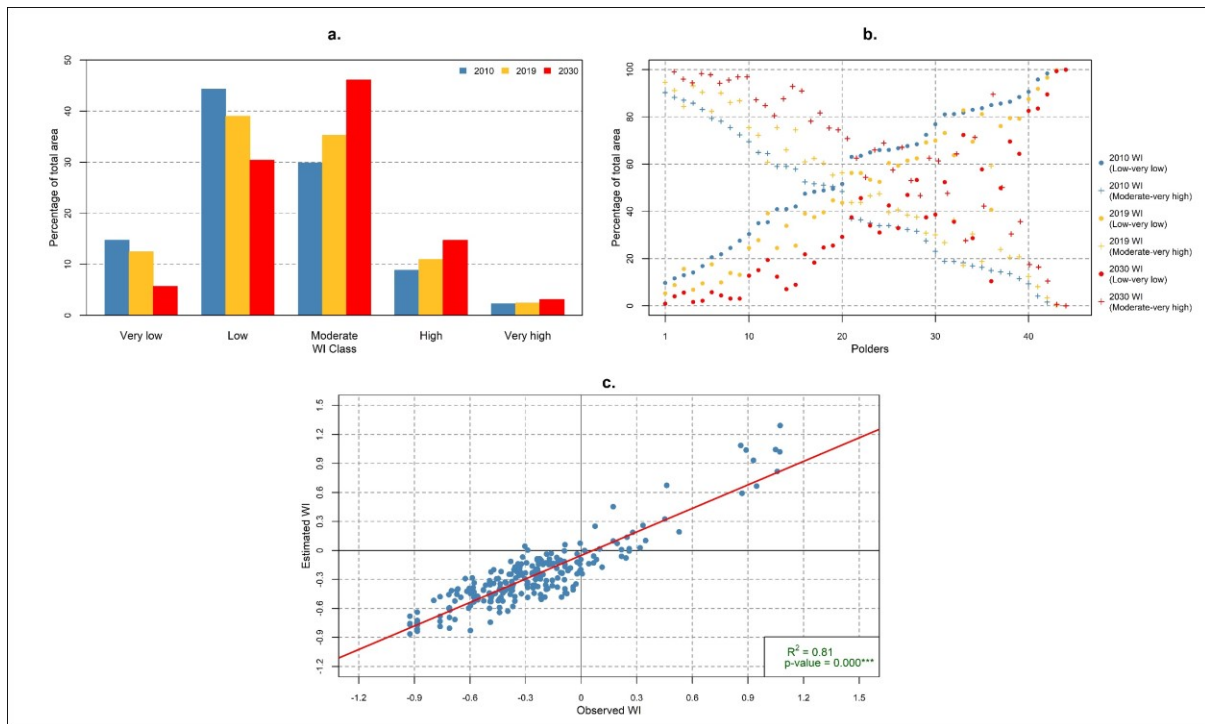


484

485 Figure 5 Spatiotemporal change of wealth index (WI) in the study area

486 Areas classified as ‘very low’ WI would potentially decrease from 15% area in 2010 to
487 about 6% area in 2030, while the proportion of areas with ‘moderate’ WI may increase from
488 30% to 46%, respectively. However, the rate of increase in the proportion of areas classified as
489 ‘high’ and ‘very high’ WI was estimated to be insignificant (Figure 6 (a)). The proportion of
490 total area with positive WI (‘high’ and ‘very high’ categories) is likely to increase from 11%
491 in 2010 to 18% in 2030. Bangladesh has an increasing GDP per capita growth, which was about
492 6.9% annually, on average, from 2010-2019. Population density has also been projected to
493 increase in the future. Although these two variables exhibited a positive correlation with WI,
494 LULC change and increasing EAD may hinder the growth of the WI in 2030. The estimated
495 WI of 2010, 2019, and 2030 were disaggregated at the polder scale to identify marginalised

496 polders at present and in future (Figure 6 (b)). In general, more than 50% of the total area in
 497 most of the polders were classified as zones with ‘low’ and ‘very low’ WI. In 2010, there were
 498 19 polders where more than 50% area was classified as ‘moderate’ to ‘very high’. Nonetheless,
 499 the numbers increased in 2019 and 2030 for which correspondingly 21 and 34 polders were
 500 identified, with the majority of the area (>50%) classified as ‘moderate’ to ‘very high’ WI.



501
 502 Figure 6 Temporal change of wealth index in: (a) South western embanked area and (b)
 503 Polders; (c) Association between observed and estimated WI in 2010

504 4. Discussion

505 Monitoring and managing LULC changes have been recognised as an essential
 506 geographic phenomenon for guiding socio-economic development ([Corner et al., 2014](#);
 507 [Shahbazian et al., 2019](#)). This study analysed and simulated LULC changes in the south
 508 western embanked area of Bangladesh to understand their association with flood risk and
 509 poverty. The study results indicated that the proportion of agricultural lands decreased
 510 significantly between 2005 and 2019. This result is similar to a few other studies that focused
 511 on LULC changes in south western Bangladesh ([Islam et al., 2015](#); [Khan et al., 2015](#); [Rahman](#)
 512 [et al., 2017](#)). A significant reduction of agricultural lands is reportedly associated with growing
 513 prevalence of shrimp farming, which reflects a socio-economic trend whereby land-owners
 514 near existing shrimp farms are more likely to convert to shrimp, together with the effect of
 515 salinity intrusion, in particular following surge flood events, which forced farmers to transform

516 their agricultural lands into aquaculture use ([Islam et al., 2015](#); [Khan et al., 2015](#)). The
517 projection of future LULC indicated a potential increase in settlement areas, while bare lands
518 are likely to decrease. Such LULC transformation may follow a pattern which was observed
519 from 2010-2019. [Rahman et al. \(2017\)](#) also predicted a similar pattern of LULC change by
520 2028 in a small administrative unit (*'upazila'*) of the south western coast. They explained that
521 the natural increase of settlement and vegetation may lead to such changes in LULC.

522 Simulating future LULC is subject to uncertainty ([Szwagrzyk et al., 2018](#)). Although
523 combined LR and CA-Markov Chain model considers a wide range of driving forces, it does
524 not incorporate exogenous covariates such as personal preferences and government regulations
525 ([Arsanjani et al., 2013](#)). For instance, lower market price, higher production cost, and increased
526 frequency of diseases caused a decline in benefits in brackish water shrimp farming in the last
527 decade ([Akber et al., 2017](#)). Although aquaculture was perceived as one of the few options for
528 economic development ([Akber et al., 2017](#)), intensive aquaculture and subsequent salinity
529 intrusion may result in poverty, promoting rural unemployment, social unrest, conflicts and
530 forced migration ([Johnson et al., 2016](#)). Despite a reduction in brackish water shrimp
531 cultivation in recent years, mixed cultivation of sweet water shrimp and fish has proved to be
532 beneficial, which may persist in future. Therefore, in the current study, we considered the trend
533 of LULC change in the last decade to predict future LULC. An alternative to the current LULC
534 change model, an Agent Based Model (ABM) can incorporate individual-related factors, an
535 approach which has been followed in recent studies to model LULC change ([Arsanjani et al.,](#)
536 [2013](#)). However, the main limitation of the ABM is that it requires a large sample of empirical
537 data to parameterise the model ([Valbuena et al., 2010](#)). In summary, LULC change modelling
538 is a complex process and therefore, results should be used with caution ([Wang et al., 2019](#)).
539 For example, areas predicted to be transformed into settlements by the LULC model should be
540 interpreted as areas most suitable for future settlement development, rather than the precise
541 locations of future change ([Szwagrzyk et al., 2018](#)).

542 Notably, this study found a positive association between LULC change and losses
543 caused by floods for various recurrence intervals. A lack of risk-oriented residential
544 development might be associated with increased flood risk. The majority of rural houses are
545 temporary or semi-permanent structures ([Akter and Mallick, 2013](#)). Exposure of those areas to
546 floods results in significant damages. Similar evidence of residential development in wetlands
547 in recent years can be found in the existing literature ([Akber et al., 2018](#)). Aquaculture lands,
548 comprised of shrimp or freshwater ponds, can withstand a certain depth of floodwater (i.e. < 2

549 m). However, when the depth increases, shrimp or fish may escape and cause financial losses
550 ([Islam et al., 2019](#)).

551 We found that pluvial floods that occur each year cause substantial damage in the south
552 western embanked region. This more or less inevitable flood damage is attributed to
553 geomorphological characteristics of the study area. Land subsidence in the embanked region
554 created depressions, which are prone to frequent pluvial flooding. Therefore, annual monsoon
555 precipitation causes a substantial extent of inundation. For instance, a monsoon precipitation
556 event of 2.1-year return period in 1990 inundated about 9.3% of the total area ([Adnan et al.,
557 2019](#)). From 2009-2014, pluvial flooding in Khulna Division (where the study area located)
558 caused greater damage than any other natural hazards ([BBS, 2015](#)). Frequent pluvial flooding
559 in the south western embanked region causes both damages to crops and delay to winter crop
560 cultivation ([Alam et al., 2017](#)).

561 This study further presented a spatially explicit regression model to estimate poverty in
562 terms of the WI. The results indicated a positive correlation of GDP and population density
563 with the WI. A similar pattern of association of these parameters with poverty was reported
564 elsewhere ([Dasgupta, 2007](#)). The results of poverty modelling in this work highlighted that the
565 rate of increase of WI is likely to be low in the future because of the pattern of LULC change
566 and associated increase in flood risk. Few other studies have quantified the association between
567 poverty indicators and flood risk/vulnerability ([Akter and Mallick, 2013](#); [Brouwer et al., 2007](#)).
568 Those studies were based on household-level survey data, where poverty was considered as an
569 indicator of flood risk.

570 **5. Conclusion**

571 This study quantified the degree of influence of LULC change and flood risk on poverty
572 in the south western embanked area of Bangladesh. Poverty was estimated, in terms of WI, for
573 the present-day and for future LULC and flood risk scenarios. The analysis indicated that the
574 region has been experiencing a rapid LULC change, resulting in a significant decrease in
575 agricultural lands, while the proportion of aquaculture lands increased consequently. Based on
576 the recent pattern of changes, LULC was predicted for the year 2030. The study further
577 demonstrated that losses due to floods of various recurrence intervals have increased with
578 LULC change. The exposure of residential areas (rural and urban) was predicted to increase in
579 future. A lack of attention to flood is risk in land development decisions may explain the
580 increased flood loss. Likewise, the expected annual flood damage (EAD) was also estimated

581 to increase in the future LULC scenario. Moreover, we further estimated that LULC change
582 and EAD negatively influence WI, which may restrict the growth of the WI in the future. The
583 area with negative WI is predicted to decrease from 89% area in 2010 to 82% area in 2030,
584 which is slower than one might expect given Bangladesh's predicted GDP growth. This is
585 because flood risk and patterns of LULC change have a negative effect on WI. Among 44
586 polders analysed, more than 50% area in 11 polders would potentially have 'low' and 'very
587 low' WI.

588 When interpreting the findings of this study, uncertainty related to flood damage
589 functions and values of input parameters for poverty estimation should be considered. We
590 considered global flood depth-damage functions for different LULC, due to the unavailability
591 of micro (local)-level functions. We estimated flood losses for different categories of LULC,
592 as building-level land use data are not available for all of the study area. While describing
593 uncertainty in flood depth-damage function, [Huizinga et al. \(2017\)](#) highlighted that materials
594 of structures primarily determine the maximum damage that may occur during a flood. In this
595 study, the accuracy of the projected WI depends on the accuracy of input parameters.
596 Parameters value (e.g. soil salinity and flood frequency) which were assumed to remain
597 constant in may change in the future. The dynamics in soil salinity may also change in future
598 climate change scenarios. Although few studies focused on modelling soil salinity in coastal
599 Bangladesh under future climate change scenario ([Dasgupta et al., 2015](#); [Payo et al., 2017](#)), the
600 coarser resolution of their results restricted this study to incorporate such data in estimating
601 WI. However, the statistical significance of salinity remains low. Also, GDP and population
602 density were projected for the future year considering national-level growth rates, which may
603 vary at the local scale such as polder level.

604 This study highlights that the absence of risk-oriented land use planning is potentially
605 increasing flood risk in the coastal region. Various national and regional level policies of
606 Bangladesh have addressed this issue and express the need to formulate land use plans
607 following a risk-based approach. For instance, the Coastal Development Strategy focused on
608 developing a coastal land use plan. More recently, the Bangladesh Delta Plan (BDP) 2100
609 emphasised the adoption of measures to mitigate flood risk, to achieve a long-term goal of
610 reducing poverty and ensuring sustainable livelihoods ([Khan, 2018](#)). Spatial information on
611 flood risk and land use changes provided in this study should inform stakeholders such as the
612 Ministry of Land in identifying areas required land use policy intervention. Also, the proposed
613 methodology to assess the implications of changing land use and flood risk for poverty should

614 be of interest to land use planners. The results can help target policies in areas with greater
615 poverty at present and in future scenarios. To the best of our knowledge, this study is the first
616 attempt to model spatiotemporal change of poverty with changes in land use and flood risk.
617 Although many studies focused on land use change modelling and/or flood risk assessment,
618 there is a dearth of studies that quantify their combined influence on local level poverty.

619 **Acknowledgement**

620 This work is an output from the REACH programme (www.reachwater.org.uk) funded
621 by UK Aid from the UK Department for International Development (DFID) for the benefit of
622 developing countries (Aries Code 201880). However, the views expressed, and information
623 contained in it are not necessarily those of or endorsed by DFID, which can accept no
624 responsibility for such views or information, or reliance placed on them.

625 **6. Reference**

- 626 Abdullah, A.Y.M., Biswas, R.K., Chowdhury, A.I., Billah, S.M., 2018. Modeling soil salinity
627 using direct and indirect measurement techniques: A comparative analysis.
628 *Environmental Development* 29, 67-80.
- 629 Abdullah, A.Y.M., Masrur, A., Adnan, M.S.G., Baky, M.A.A., Hassan, Q.K., Dewan, A., 2019.
630 Spatio-Temporal Patterns of Land Use/Land Cover Change in the Heterogeneous
631 Coastal Region of Bangladesh between 1990 and 2017. *Remote Sensing* 11, 790.
- 632 Adnan, M.S.G., Haque, A., Hall, J.W., 2019. Have coastal embankments reduced flooding in
633 Bangladesh? *Science of the Total Environment* 682, 405-416.
- 634 Adnan, M.S.G., Talchabhadel, R., Nakagawa, H., Hall, J.W., 2020. The potential of Tidal River
635 Management for flood alleviation in South Western Bangladesh. *Science of The Total*
636 *Environment* 731, 138747.
- 637 Adnan, S.G., Kreibich, H., 2016. An evaluation of disaster risk reduction (DRR) approaches
638 for coastal delta cities: a comparative analysis. *Natural Hazards* 83, 1257-1278.
- 639 Ahmed, B., Kamruzzaman, M., Zhu, X., Rahman, M., Choi, K., 2013. Simulating land cover
640 changes and their impacts on land surface temperature in Dhaka, Bangladesh. *Remote*
641 *Sensing* 5, 5969-5998.
- 642 Ahmed, S., 2018. Shrimp farming at the interface of land use change and marginalization of
643 local farmers: critical insights from southwest coastal Bangladesh. *Journal of land use*
644 *science* 13, 251-258.
- 645 Akber, M.A., Islam, M.A., Ahmed, M., Rahman, M.M., Rahman, M.R., 2017. Changes of
646 shrimp farming in southwest coastal Bangladesh. *Aquaculture International* 25, 1883-
647 1899.
- 648 Akber, M.A., Khan, M.W.R., Islam, M.A., Rahman, M.M., Rahman, M.R., 2018. Impact of
649 land use change on ecosystem services of southwest coastal Bangladesh. *Journal of*
650 *Land Use Science* 13, 238-250.
- 651 Akter, S., Mallick, B., 2013. The poverty–vulnerability–resilience nexus: Evidence from
652 Bangladesh. *Ecological Economics* 96, 114-124.
- 653 Alam, M.S., Sasaki, N., Datta, A., 2017. Waterlogging, crop damage and adaptation
654 interventions in the coastal region of Bangladesh: A perception analysis of local people.
655 *Environmental Development* 23, 22-32.

656 Apel, H., Aronica, G.T., Kreibich, H., Thielen, A.H., 2009. Flood risk analyses - How detailed
657 do we need to be? *Natural Hazards* 49, 79-98.

658 Arsanjani, J.J., Helbich, M., Kainz, W., Boloorani, A.D., 2013. Integration of logistic
659 regression, Markov chain and cellular automata models to simulate urban expansion.
660 *International Journal of Applied Earth Observation and Geoinformation* 21, 265-275.

661 Auerbach, L.W., Goodbred, S.L., Jr., Mondal, D.R., Wilson, C.A., Ahmed, K.R., Roy, K.,
662 Steckler, M.S., Small, C., Gilligan, J.M., Ackerly, B.A., 2015. Flood risk of natural and
663 embanked landscapes on the Ganges-Brahmaputra tidal delta plain. *Nature Climate*
664 *Change* 5, 153-157.

665 Bangalore, M., Smith, A., Veldkamp, T., 2019. Exposure to Floods, Climate Change, and
666 Poverty in Vietnam. *Economics of Disasters and Climate Change* 3, 79-99.

667 BBS, 2015. Bangladesh Disaster-related Statistics 2015. *Climate Change and Natural Disaster*
668 *Perspectives Bangladesh Bureau of Statistics (BBS), Ministry of Planning, Dhaka,*
669 *Bangladesh.*

670 Borgomeo, E., Hall, J.W., Salehin, M., 2017. Avoiding the water-poverty trap: insights from a
671 conceptual human-water dynamical model for coastal Bangladesh. *International*
672 *Journal of Water Resources Development*, 1-23.

673 Brouwer, R., Akter, S., Brander, L., Haque, E., 2007. Socioeconomic Vulnerability and
674 Adaptation to Environmental Risk: A Case Study of Climate Change and Flooding in
675 Bangladesh. *Risk Analysis* 27, 313-326.

676 Corner, R.J., Dewan, A.M., Chakma, S., 2014. Monitoring and prediction of land-use and land-
677 cover (LULC) change, Dhaka megacity. Springer, pp. 75-97.

678 Dasgupta, A., 2007. Floods and poverty traps: Evidence from Bangladesh. *Economic and*
679 *Political Weekly*, 3166-3171.

680 Dasgupta, S., Hossain, M.M., Huq, M., Wheeler, D., 2015. Climate change and soil salinity:
681 The case of coastal Bangladesh. *Ambio* 44, 815-826.

682 Dawson, R.J., Ball, T., Werritty, J., Werritty, A., Hall, J.W., Roche, N., 2011. Assessing the
683 effectiveness of non-structural flood management measures in the Thames Estuary
684 under conditions of socio-economic and environmental change. *Global Environmental*
685 *Change* 21, 628-646.

686 De Bono, A., Chatenoux, B., 2014. A global exposure model for GAR 2015, *The Global*
687 *Assessment Report on Disaster Risk Reduction 2015.* United Nations Office for
688 *Disaster Risk Reduction (UNISDR), Geneva.*

689 Dewan, A., 2013. *Floods in a megacity: geospatial techniques in assessing hazards, risk and*
690 *vulnerability.* Springer.

691 Dewan, A.M., Yamaguchi, Y., 2009. Land use and land cover change in Greater Dhaka,
692 Bangladesh: Using remote sensing to promote sustainable urbanization. *Applied*
693 *geography* 29, 390-401.

694 Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Salinas, J.L., Blöschl, G., 2013. Socio-
695 hydrology: conceptualising human-flood interactions. *Hydrol. Earth Syst. Sci.* 17,
696 3295-3303.

697 Dube, E., Mtapuri, O., Matunhu, J., 2018. Flooding and poverty: Two interrelated social
698 problems impacting rural development in Tsholotsho district of Matabeleland North
699 province in Zimbabwe. *Jamba: Journal of Disaster Risk Studies* 10, 1-7.

700 Feng, G., Cobb, S., Abdo, Z., Fisher, D.K., Ouyang, Y., Adeli, A., Jenkins, J.N., 2016. Trend
701 analysis and forecast of precipitation, reference evapotranspiration, and rainfall deficit
702 in the Blackland Prairie of Eastern Mississippi. *Journal of Applied Meteorology and*
703 *Climatology* 55, 1425-1439.

704 Hall, J.W., Berkhout, F., Douglas, R., 2015. Responding to adaptation emergencies. *Nature*
705 *Climate Change* 5, 6-7.

- 706 Hall, J.W., Dawson, R.J., Sayers, P.B., Rosu, C., Chatterton, J.B., Deakin, R., 2003a. A
707 methodology for national-scale flood risk assessment. *Proceedings of the Institution of*
708 *Civil Engineers: Water and Maritime Engineering* 156, 235-247.
- 709 Hall, J.W., Harvey, H., Manning, L.J., 2019. Adaptation thresholds and pathways for tidal flood
710 risk management in London. *Climate Risk Management* 24, 42-58.
- 711 Hall, J.W., Meadowcroft, I.C., Sayers, P.B., Bramley, M.E., 2003b. Integrated Flood Risk
712 Management in England and Wales. *Natural Hazards Review* 4, 126-135.
- 713 Hino, M., Hall, J.W., 2017. Real options analysis of adaptation to changing flood risk:
714 Structural and nonstructural measures. *ASCE-ASME Journal of Risk and Uncertainty*
715 *in Engineering Systems, Part A: Civil Engineering* 3, 04017005.
- 716 Hosmer Jr, D.W., Lemeshow, S., Sturdivant, R.X., 2013. *Applied logistic regression*. John
717 Wiley & Sons.
- 718 Hossain, M.A., Reza, M.I., Rahman, S., Kayes, I., 2012. Climate Change and its Impacts on
719 the Livelihoods of the Vulnerable People in the Southwestern Coastal Zone in
720 Bangladesh, in: Leal Filho, W. (Ed.), *Climate Change and the Sustainable Use of Water*
721 *Resources*. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 237-259.
- 722 Hui, R., Jachens, E., Lund, J., 2016. Risk-based planning analysis for a single levee. *Water*
723 *Resources Research* 52, 2513-2528.
- 724 Huizinga, J., de Moel, H., Szewczyk, W., 2017. Global flood depth-damage functions:
725 Methodology and the database with guidelines. Joint Research Centre (Seville site).
- 726 Huq, N., Hugé, J., Boon, E., Gain, A., 2015. Climate change impacts in agricultural
727 communities in rural areas of coastal Bangladesh: a tale of many stories. *Sustainability*
728 7, 8437-8460.
- 729 Islam, G.M.T., Islam, A.K.M.S., Shopan, A.A., Rahman, M.M., Lázár, A.N., Mukhopadhyay,
730 A., 2015. Implications of agricultural land use change to ecosystem services in the
731 Ganges delta. *Journal of Environmental Management* 161, 443-452.
- 732 Islam, M.A., Mitra, D., Dewan, A., Akhter, S.H., 2016. Coastal multi-hazard vulnerability
733 assessment along the Ganges deltaic coast of Bangladesh—A geospatial approach.
734 *Ocean & Coastal Management* 127, 1-15.
- 735 Islam, M.F., Bhattacharya, B., Popescu, I., 2019. Flood risk assessment due to cyclone-induced
736 dike breaching in coastal areas of Bangladesh. *Natural Hazards and Earth System*
737 *Sciences* 19, 353-368.
- 738 JAXA, 2015. ALOS global digital surface model “ALOS world 3D-30m (AW3D30)”. Japan
739 Aerospace Exploration Agency (JAXA).
- 740 Johnson, F.A., Hutton, C.W., Hornby, D., Lázár, A.N., Mukhopadhyay, A., 2016. Is shrimp
741 farming a successful adaptation to salinity intrusion? A geospatial associative analysis
742 of poverty in the populous Ganges–Brahmaputra–Meghna Delta of Bangladesh.
743 *Sustainability Science* 11, 423-439.
- 744 Khan, M.M.H., Bryceson, I., Kolivras, K.N., Faruque, F., Rahman, M.M., Haque, U., 2015.
745 Natural disasters and land-use/land-cover change in the southwest coastal areas of
746 Bangladesh. *Regional Environmental Change* 15, 241-250.
- 747 Khan, Z.H., 2018. Bangladesh Delta Plan 2100 - Baseline Studies on Water Resources
748 Management (Coast and Polder Issues), in: Alam, S., Heer, J.d., Choudhury, G. (Eds.).
749 General Economics Division (GED), Bangladesh Planning Commission, Dhaka,
750 Bangladesh.
- 751 Kityuttachai, K., Tripathi, N., Tipdecho, T., Shrestha, R., 2013. CA-Markov analysis of
752 constrained coastal urban growth modeling: Hua Hin seaside city, Thailand.
753 *Sustainability* 5, 1480-1500.
- 754 Koks, E., 2018. Moving flood risk modelling forwards. *Nature Climate Change* 8, 561-562.

755 Koks, E., Pant, R., Thacker, S., Hall, J.W., 2019. Understanding Business Disruption and
756 Economic Losses Due to Electricity Failures and Flooding. *International Journal of*
757 *Disaster Risk Science*.

758 Kumm, M., Taka, M., Guillaume, J.H., 2018. Gridded global datasets for gross domestic
759 product and Human Development Index over 1990–2015. *Scientific data* 5, 180004.

760 Lee, Y., Brody, S.D., 2018. Examining the impact of land use on flood losses in Seoul, Korea.
761 *Land use policy* 70, 500-509.

762 McColl, C., Aggett, G., 2007. Land-use forecasting and hydrologic model integration for
763 improved land-use decision support. *Journal of Environmental Management* 84, 494-
764 512.

765 Mitsova, D., Shuster, W., Wang, X., 2011. A cellular automata model of land cover change to
766 integrate urban growth with open space conservation. *Landscape and Urban Planning*
767 99, 141-153.

768 Montz, B.E., Tobin, G.A., 2008. Livin'large with levees: Lessons learned and lost. *Natural*
769 *Hazards Review* 9, 150-157.

770 Olsen, A., Zhou, Q., Linde, J., Arnbjerg-Nielsen, K., 2015. Comparing methods of calculating
771 expected annual damage in urban pluvial flood risk assessments. *Water* 7, 255-270.

772 Panda, A., Sahu, N., 2019. Trend analysis of seasonal rainfall and temperature pattern in
773 Kalahandi, Bolangir and Koraput districts of Odisha, India. *Atmospheric Science*
774 *Letters* 20, e932.

775 Parvin, G.A., Ali, M.H., Fujita, K., Abedin, M.A., Habiba, U., Shaw, R., 2017. Land use change
776 in southwestern coastal Bangladesh: Consequence to food and water supply, Land use
777 management in disaster risk reduction. Springer, pp. 381-401.

778 Paul, B.K., Rashid, H., 2017. *Climatic Hazards In Coastal Bangladesh - Non-Structural and*
779 *Structural Solutions*, I ed. Elsevier, Cambridge, United States, 342 pp.

780 Payo, A., Lázár, A.N., Clarke, D., Nicholls, R.J., Bricheno, L., Mashfiqu, S., Haque, A., 2017.
781 Modeling daily soil salinity dynamics in response to agricultural and environmental
782 changes in coastal Bangladesh. *Earth's Future* 5, 495-514.

783 Poussin, J.K., Botzen, W.W., Aerts, J.C., 2015. Effectiveness of flood damage mitigation
784 measures: Empirical evidence from French flood disasters. *Global Environmental*
785 *Change* 31, 74-84.

786 Qiang, Y., Lam, N.S.N., Cai, H., Zou, L., 2017. Changes in Exposure to Flood Hazards in the
787 United States. *Annals of the American Association of Geographers* 107, 1332-1350.

788 Rahman, M.M., Ghosh, T., Salehin, M., Ghosh, A., Haque, A., Hossain, M.A., Das, S., Hazra,
789 S., Islam, N., Sarker, M.H., 2020. Ganges-Brahmaputra-Meghna Delta, Bangladesh and
790 India: A Transnational Mega-Delta, Deltas in the Anthropocene. Springer, pp. 23-51.

791 Rahman, M.T.U., Tabassum, F., Rasheduzzaman, M., Saba, H., Sarkar, L., Ferdous, J., Uddin,
792 S.Z., Zahedul Islam, A.Z.M., 2017. Temporal dynamics of land use/land cover change
793 and its prediction using CA-ANN model for southwestern coastal Bangladesh.
794 *Environmental Monitoring and Assessment* 189, 565.

795 Rahman, R., Salehin, M., 2013. Flood Risks and Reduction Approaches in Bangladesh, in:
796 Shaw, R., Mallick, F., Islam, A. (Eds.), *Disaster Risk Reduction Approaches in*
797 *Bangladesh*. Springer, Tokyo, pp. 65-90.

798 Rojas, R., Feyen, L., Watkiss, P., 2013. Climate change and river floods in the European Union:
799 Socio-economic consequences and the costs and benefits of adaptation. *Global*
800 *Environmental Change* 23, 1737-1751.

801 Sang, L., Zhang, C., Yang, J., Zhu, D., Yun, W., 2011. Simulation of land use spatial pattern
802 of towns and villages based on CA–Markov model. *Mathematical and Computer*
803 *Modelling* 54, 938-943.

804 Sayers, P.B., Hall, J.W., Meadowcroft, I.C., 2002. Towards risk-based flood hazard
805 management in the UK. *Proceedings of the Institution of Civil Engineers: Civil*
806 *Engineering* 150, 36-42.

807 Shahbazian, Z., Faramarzi, M., Rostami, N., Mahdizadeh, H., 2019. Integrating logistic
808 regression and cellular automata–Markov models with the experts’ perceptions for
809 detecting and simulating land use changes and their driving forces. *Environmental*
810 *monitoring and assessment* 191, 422.

811 Steele, J.E., Sundsøy, P.R., Pezzulo, C., Alegana, V.A., Bird, T.J., Blumenstock, J., Bjelland,
812 J., Engø-Monsen, K., de Montjoye, Y.-A., Iqbal, A.M., 2017. Mapping poverty using
813 mobile phone and satellite data. *Journal of The Royal Society Interface* 14, 20160690.

814 Szabo, S., Hossain, M.S., Adger, W.N., Matthews, Z., Ahmed, S., Lázár, A.N., Ahmad, S.,
815 2016. Soil salinity, household wealth and food insecurity in tropical deltas: evidence
816 from south-west coast of Bangladesh. *Sustainability Science* 11, 411-421.

817 Szwagrzyk, M., Kaim, D., Price, B., Wypych, A., Grabska, E., Kozak, J., 2018. Impact of
818 forecasted land use changes on flood risk in the Polish Carpathians. *Natural Hazards*
819 94, 227-240.

820 Valbuena, D., Verburg, P.H., Bregt, A.K., Ligtenberg, A., 2010. An agent-based approach to
821 model land-use change at a regional scale. *Landscape ecology* 25, 185-199.

822 Verburg, P.H., Schot, P.P., Dijst, M.J., Veldkamp, A., 2004. Land use change modelling:
823 current practice and research priorities. *GeoJournal* 61, 309-324.

824 Wang, M., Cai, L., Xu, H., Zhao, S., 2019. Predicting land use changes in northern China using
825 logistic regression, cellular automata, and a Markov model. *Arabian Journal of*
826 *Geosciences* 12, 790.

827 Ward, P.J., De Moel, H., Aerts, J., Glade, T., 2011. How are flood risk estimates affected by
828 the choice of return-periods? *Natural Hazards & Earth System Sciences* 11.

829 Warner, J.F., van Staveren, M.F., van Tatenhove, J., 2018. Cutting dikes, cutting ties?
830 Reintroducing flood dynamics in coastal polders in Bangladesh and the netherlands.
831 *International Journal of Disaster Risk Reduction* 32, 106-112.

832 Wheeler, H., Evans, E., 2009. Land use, water management and future flood risk. *Land use*
833 *policy* 26, S251-S264.

834 White, G.F., 1945. *Human adjustment to floods*, Department of Geography The University of
835 Chicago, Chicago.

836 Winsemius, H.C., Jongman, B., Veldkamp, T.I.E., Hallegatte, S., Bangalore, M., Ward, P.J.,
837 2018. Disaster risk, climate change, and poverty: assessing the global exposure of poor
838 people to floods and droughts. *Environment and Development Economics* 23, 328-348.

839 WorldPop, 2018. Bangladesh 100m Population, Version 2, in: Southampton, U.o. (Ed.), UK.

840