Routine Disasters: Floods, Human Capital and Adaptation in Bangladesh ∗

Raymond Guiteras‡ Amir S. Jina‡ A. Mushfiq Mobarak§
University of Maryland University of Chicago Yale University

Abstract

Flooding is one of the costliest and deadliest natural disasters on the planet, affecting more people each year than any other disaster. We aim to understand what medium- and long-term impacts are associated with exposure to flooding in early life in a flood-prone region. We create a measure of flood extent using satellite observations for all of Bangladesh in the period 2000-2013 and match this to outcomes on physical development of infants. We find that exposure to abnormal floods at the time of birth or in utero leads to an increase in stunting by approximately 2% and an overall decline in standard measures of height-for-age among children under 5 years of age. We find evidence of adaptation—households that are routinely exposed to larger or more frequent floods experience smaller impacts in the event of an abnormal flood than those who are exposed less often. By examining impacts on first-born versus other children, we see that investments may partially compensate for this effect. Lower height-for-age ratios and stunting are associated with high infant mortality and illness, as well as negative educational and labor market outcomes in later life. This could represent a significant extra cost associated with environmental impacts in flood-prone developing countries, which will be exacerbated as climate change increases the frequency and severity of flooding in many parts of the world.

∗We would like to thank Jesse Anttila-Hughes, Ram Fishman, Jan von der Goltz, Michael Greenstone, Rema Hanna, Mary Heskel, Rick Hornbeck, Solomon Haiong, Meha Jain, Supreet Kaur, Kyle Meng, Chris Small, Anja Tolonen, Anna Tompsett, and seminar participants at Columbia University, George Washington University, University of California, Berkeley, and University of San Francisco for discussions and suggestions. We would like to particularly thank Anik Ashraf, Juan-Diego Bonilla, Ravid Chowdhury, Mahnaz Islam, Kristian López, Giordano Palloni, Enrique Traveria, and Claudia Vargas for excellent research assistance throughout this project. This work is funded by a grant from the International Growth Centre. This version: April 1, 2015

†Email: guiteras@econ.umd.edu
‡Email: amirjina@uchicago.edu
§Email: ahmed.mobarak@yale.edu
1 Introduction

Floods are one of the most devastating of all natural disasters experienced by society. For example, in 2011 there were over 6,000 people killed, 140 million affected, and $70 billion in estimated damages caused by floods globally (EM-DAT, 2012). South Asia is particularly susceptible to flooding (Mirza, 2010), and Bangladesh, a deltaic country situated at the outflow of the Ganges-Brahmaputra-Meghna (GBM) basin, is among the most affected countries (Ali, 1999). Most of Bangladesh lies at or slightly above sea-level and is at the outlet of a river system which drains an area ten times as large as its own surface area (see figure 1). Due to the projected changes from climate change, Bangladesh will likely be further impacted (Mirza, 2002). In addition to these projected changes, rainfall and flooding in Bangladesh are subject to large interannual variability, influenced by ENSO (Chowdhury, 2003) and remote hydro-meteorological conditions in the larger GBM basin (Chowdhury and Ward, 2004; Shaman et al., 2005) which currently often lead to devastating disasters.

Large floods draw international attention and support which to a great degree can decrease the immediate impacts of the disaster. Del Ninno et al. (2001) details the losses in crops, arable land, household assets, and lives as a result of the 1998 floods which inundated 80% of the country. Del Ninno states that the worst immediate impacts were averted due to policy interventions on a large scale that saw food and other necessities distributed to affected areas. However, the long-term effects of an environmental shock of this size have rarely been studied. Hsiang and Jina (2014) find evidence that, for tropical cyclones, national incomes decline and do not recover after nearly two decades, which suggests that response to immediate impacts of a disaster does not preclude potentially large longer-term negative impacts. In addition to large events, Bangladesh experiences many smaller floods every year which receive little or no attention from the government or international community, but can lead to substantial losses for affected households. From self-reported damage assessments Gray and Mueller (2012) report that, on average, floods can cause damage to rural households that are as much as 20% of annual income, but few received assistance. This is a common trait among smaller disasters in developing countries (Besley and Burgess, 2002). These “small disasters”, with more common levels of exposure, are suspected to be responsible for large costs once the full impacts are quantified (UNISDR, 2013) and could be responsible for longer-term impacts, which may affect the development possibilities in Bangladesh. This leads to two key questions:

1. Are there prolonged negative outcomes resulting from flooding or similar disasters and environmental conditions? This dynamic has been observed for rainfall (Maccini and Yang, 2009)

2. What indirect impacts (e.g., market access interruption or health effects) may increase the total costs of floods beyond the direct damages? Previous research suggests that the indirect effects may be substantial in comparison to directly measured damages (Anttila-Hughes and Hsiang, 2012).

We develop a novel measure of flood exposure over the entirety of Bangladesh from 2000-2013 using spectral data from a set of NASA satellites. The frequency of observation is once every 16 days. In other work, we show that this measure of flooding is uncorrelated with rainfall directly over the flooded districts (Guiteras et al., 2015) due to the complex hydrology that leads to flooding. In Bangladesh,
as in many areas of the world, it is often distant rainfall that leads to flooding in a given location. This suggests that studies using rainfall to capture flood impacts are actually estimating the response to a distinct phenomenon and missing the true flood impacts.

An important contribution of this paper, and a unique advantage of our data, is to examine the impacts from average levels of exposure rather than purely looking at low-probability, high-impact events. In this way, we can think of the detected impacts as the “environmental burden” that needs to be accommodated into the development process. An objective measure of exposure is of particular importance, as people in areas of different average flood exposure experience seemingly similar shocks in very different ways (Guiteras et al., 2015). We specifically examine the medium- and long-term impacts on human capital associated with exposure to flooding in early life (Almond and Currie, 2011). Early life shocks have been exploited in many different studies, and yet few of them have been able to demonstrate the extent to which subsequent investments may mitigate the early impacts. By looking at higher order births, we find suggestive evidence that household investments can undo the worst impacts of early life exposure, though they do not entirely erase them.

We exploit the stochastic temporal variation in exposure to flooding to identify the effect upon physical development of infants. As no comprehensive, national-scale database of flooding exists for Bangladesh, we create an exogenous, physically-derived measure of flood extents using remote sensing. This ensures that our measure is not subject to reporting bias. Following the development of this remote sensing product, effect sizes are estimated by matching to data on infant health.

We find that exposure to abnormal floods at the time of birth or while in utero leads to an increase in stunting on the order of 2% and an overall decline in standard measures of height-for-age among children under 5 years of age. Flooding exposure appears to affect boys more than girls, and larger floods have larger effects upon physical development. We also find evidence of adaptation across locations, and see that households that are routinely exposed to larger or more frequent floods experience smaller impacts in the event of an abnormal flood than those who are exposed less often.

These results on physical development are important because lower height-for-age ratios and stunting are associated with high infant mortality and illness (Black et al., 2008) and more broadly with negative educational and labor market outcomes in later life (Black et al., 2007; Glewwe and Miguel, 2007). This could represent a significant extra cost associated with this extreme environment than is traditionally accounted for in Bangladesh and other flood-prone developing countries. These measures are also important indicators of child health in themselves and are often used as a metric of the success of health interventions (for example, Gertler (2004)).

The rest of the paper proceeds as follows: in section 4.2 there is a background discussion of flooding and flood impacts, as well as a summary of some of the relevant findings dealing with early life exposure to environmental shocks. Section 4.3 discusses the data used in this analysis. Section 4.4 details the remote sensing and econometric methods used herein. Section 4.5 presents results from this early analysis. The final section draws some conclusions for development and climate policy.
Figure 1: Map of the Indo-gangetic plain showing the location and size of Bangladesh relative to the Ganges-Brahmaputra-Meghna basin. Bangladesh drains water from an area about 10 times greater than itself.
2 Background

2.1 Hydrology of Bangladesh

Bangladesh is a deltaic country lying at the confluence of three major world rivers - the Ganges, the Brahmaputra, and the Meghna. This river basin is known as the Ganges-Brahmaputra-Meghna (GBM) basin. Bangladesh has a monsoonal climate, with the South Asian Monsoon providing much of the direct rainfall to Bangladesh and the GBM basin between the months of May and September. The entire area of the GBM basin is 10 times larger than the land area of Bangladesh (see fig. 1). With roughly 46% of the country lying below 10 metres elevation\(^1\), it is extremely flood-prone, with major floods having historically inundated up to 70% of total land area (Del Ninno et al., 2001). There are a number of distinct types of floods, each of which is caused by a different set of geophysical phenomena, and each of which may lead to different outcomes. Mirza et al. (2003) identify the four main types of floods affecting Bangladesh, which can be defined as follows:

1. **Flash Floods** have the shortest lead-time of prediction and often lead to the highest loss of life. They typically occur in mountainous areas or areas bordered by mountains. Land degradation and deforestation all contribute to the formation of flash floods. They often occur with little or no notice, and the high velocities involved lead to much damage and loss of life.

2. **Riverine Floods** are caused by rising water levels in a river due to precipitation that falls over the entire river basin. This hazard is slow onset and typically lasts from weeks to months. These large floods contribute most to the economic costs of flooding globally, either directly through damages to property or indirectly through interruptions to supply chains and averted economic activity.

3. **Monsoonal/Rain Floods** are floods caused by direct precipitation overhead. While this type of flood can cause much damage, it is typically more predictable than flash flooding.

4. **Storm Surge** is caused by tropical cyclones or depressions and affect coastal areas only. A storm surge occurs when a combination of low pressure and high winds lead to higher levels of sea water arriving at a coast. These floods can have major consequences due to the suddenness of onset and the associated cyclone hazard, but high waters typically do not remain for more than a few days.

The time resolution of the data that we use in the present study is periods of 16-days, with each year containing twenty three of these periods. This suggests that the measure of flood extent that we derive in this analysis is possibly too coarse to capture all but the largest of flash floods, so typically we will be discussing the impacts of riverine flooding. As noted, this is longer in duration than other types of flooding, and the timing of onset can lead to widespread damages to crops as well as loss of income if crops cannot be replanted.

It is important to note that flooding is a natural part of the ecology in many places. Flood plains are typically areas with high agricultural productivity due to the high nutrient loads and replenishment

\(^1\)Bangladesh low elevation coastal zones estimated by Center for International Earth Science Information Network (CIESIN).
of soil moisture resulting from inundation. Thus, we must draw the distinction between “normal” and “abnormal” floods. Paul (1984) details coping mechanisms for floods in Bangladesh, including liquidation of assets and informal risk-sharing mechanisms, that confer a level of adaptive capacity to households to deal with flooding. Paul (1984) defines an abnormal flood as one that is larger in extent than the climatological average flood or uncharacteristically early or late in a season. In the case of a shock that affects a large part of the risk-sharing network, or one severe enough to damage productive assets, the floods are seen to exceed the capacity of a household and negative effects will be felt. In these cases, a sizable proportion of household income could be lost: self-reported damage assessments indicate that, on average, floods can cause damage to rural households of around 20% of annual income (Gray and Mueller, 2012).

2.2 Natural disaster shocks
Floods, like all natural disasters, can have both direct and indirect effects. Additionally, effects can be short- or long-term. Research on natural disasters has typically been characterized by three different characteristics, with few if any looking comprehensively within all three:

1. Direct versus indirect impacts.

2. Long-term versus short-term impacts.

3. Self-reported versus physical measures of exposure.

Much of the disaster literature focuses on the short-term, direct effects, though recent work has shown that indirect effects may eclipse the direct ones in scope and cost. For example, Deryugina (2011), looking at the United States, finds that payments for unemployment insurance in counties affected by hurricanes increases and remains elevated for a decade after a hurricane, leading to costs greater than the hurricane damages. In a developing country setting, Anttila-Hughes and Hsiang (2012) find that the loss of life indirectly associated with typhoons is an order of magnitude higher than immediate death tolls. Many other studies dealing with natural disasters, however, have suffered from potentially large bias due to endogeneity of their measure of natural hazards - typically self-reported measures. The bias of self-reported flood damage is shown in the current context in Guiteras et al. (2015), which demonstrates that while households in areas of greater average flood exposure are more likely to report being affected by a flood episode, they tend to report the effects of it differently than those who are less frequently exposed. Without observing the objective exposure, it is impossible to identify the true impacts of floods on households. Beyond this, there are few other examples of researchers using exogenous, physically-derived measures of natural hazards in order to identify socioeconomic effects. Notable among them are Hsiang (2010) and Strobl (2012), who examine tropical cyclone impacts in the Caribbean, and Hsiang and Jina (2014), who use a physical model to examine the growth effects of tropical cyclones globally.

There are a number of ways that effects of floods might persist in a population. For example, the shock to household income due to a flood can threaten food security through loss of earnings. Banerjee (2007) finds that, in flood affected districts of Bangladesh, while wages do seem to rebound in the long-term, in the aftermath of a flood there is a notable decline. Deryugina (2011) finds that short-run
output in the construction industry may rise after disaster because demand rises, and this may lead to migration into disaster affected regions which provides some measure of compensation for lost revenue streams. Similarly, Strömberg (2007), Yang (2008) and Deryugina (2011) observe that natural disasters tend to cause transfers of wealth into the affected region. This is because the marginal product of capital will rise when capital and labor become relatively scarce after disaster, causing individuals and wealth to migrate into devastated locations (Miguel and Roland, 2010; World Bank, 2010). Many of these results, however, were derived in developed countries (notably the United States) or countries affected by one-time shocks like wars, and it is not immediately clear that the inflows of wealth will occur in poorer agricultural lands that are persistently affected by an environmental hazard, like flooding.

Additionally, the health consequences, like immediate loss of life (Jonkman, 2005) as well as disease (due to contaminated water, for example) and injury (Ahern et al., 2005; Du et al., 2010), can place an extra burden on household incomes. In the case of large floods, government and international attention can ameliorate the worst effects of this shock to incomes. Del Ninno et al. (2003) find that, after the 1998 floods in Bangladesh, a government food distribution program reduced the worst effects of the disaster and vulnerable groups were able to maintain an adequate calorie intake, thus avoiding many negative health effects. The authors note that this is not always the case for smaller disasters.

It is unclear, then, if these results and successful interventions, like those after the 1998 floods noted in the previous paragraph, can be generalized to the case of all flooding in Bangladesh, where floods often damage many of the poorest regions and migration or transfers into those regions may be low or non-existent. Many of the long-term impacts on health, education, and labor could be as a result of disinvestment in capital after a loss of income. It has been argued that the loss of physical capital encourages households to invest relatively more heavily in human capital since it is more durable, which would improve prospects for long-run growth (Skidmore and Toya, 2002), however recent evidence suggests that disinvestment in durable physical or human capital following a disaster may be an irreversible consequence that will lead to persistent effects throughout the economy (Anttila-Hughes and Hsiang, 2012; Banerjee and Watts, 2010; Duflo, 2000; Jacoby and Skoufias, 1997; Maccini and Yang, 2009; Udry, 1994).

A potential source of uncertainty in this paper is the extent to which population movements might compensate for the worst effects of natural disasters. In the analysis presented here, we exclude observations in which a household is recorded as having moved. Large population movements in Bangladesh due to natural hazards would result in the worst affected households being absent from the sample, which will bias our results downward. Gray and Mueller (2012) discuss the extent to which climate-related hazards lead to internal migration in Bangladesh and find that flooding itself has a small impact on mobility, though larger for women and the poor. Penning-Rowsell et al. (2013) find that there is little permanent movement away from hazard prone areas despite the dangers. Both of these findings provide some support for not considering migration as a major source of bias in flood-related impacts.

\footnote{A brief summary of historical floods in Bangladesh can be found in Mirza (2002).}
2.3 Methods for detecting floods

Flood detection using remote sensing has a long history (Sanyal and Lu, 2004; Tralli et al., 2005). Multiple instruments have been used to try to capture the extents of floods\(^3\). Flood mapping has typically been done for the purposes of disaster relief or for infrastructure planning. Creating a credible flood risk map is essential to insurance, zoning, and construction in many places around the world. For the purpose of disaster relief, flood mapping needs to be extremely accurate, so that areas of need can be identified. This often requires a combination of remote sensing, GIS, and hydrological modeling that can be data- and computationally-intensive. Hazard mapping tends to not require perfect delineation of floods, but just express a level of risk of flooding in a given area. For the current purpose, both approaches are inappropriate. We follow Sakamoto et al. (2009) and develop a measure of flood extent using solely remote sensing. This allows for the creation of a dataset which can be matched to specific periods, exploiting the stochastic timing and extent of floods to identify their effects.

2.4 Climate change and flooding in South Asia

The main driver of floods in South Asia is the South Asian Monsoon. This is an extremely complex regional realization of a global climatological feature that affects most of the tropics. It varies on intra-seasonal, inter-annual, and decadal timescales (Wang, 2006). In addition, there is a long-term change to the climate in the region due to anthropogenic climate change (IPCC, 2007), though it remains unclear what the exact direction of the precipitation changes will be. The existing vulnerability and the future changes have become a major policy concern in the region (Field et al., 2012; World Bank, 2010). Mirza (2010) notes that most of the changes to flood extent and depth will occur in Bangladesh between 0 and 2°C warming, causing increasing damage to crops and affecting public health, particularly of poorer women and children. With most climate scientists agreeing that 2°C warming is inevitable, the consequences for Bangladesh will be severe. Flooding in Bangladesh is governed in a large part by events outside its boundaries in the larger GBM basin (Chowdhury and Ward, 2004; Shaman et al., 2005) and is also subject to influence by ENSO (Chowdhury, 2003). Recent projections have suggested that a warming world would contain more positive ENSO-like events, and this change will further exacerbate flooding in the region.

2.5 Early-life exposure to environmental shocks

This paper also engages with the flourishing literature in economics on early life impacts of shock and their long-term consequences, often known as the Barker Hypothesis. Almond and Currie (2011) provide a good summary of the literature in this field. The current paper is distinct for several reasons, but perhaps most notable is the focus on frequent, “mild” environmental exposure rather than a low-frequency, catastrophic shock. Research on early-life exposures has often focused on large, distinct, and unique shocks; for example, a rapid decline in air pollution due to a recession and its effect upon infant mortality (Chay, 2003), exposure to radioactive fallout from Chernobyl (Almond et al., 2007), or a catastrophic famine (Chen and Zhou, 2007). There is a concern that some of the effects observed in these papers with unique or distinctive shocks may not be possible to generalize to

---

\(^3\)among them MODIS, AVHRR, and Landsat
more common environmental exposures. As flooding is a relatively common and natural part of rural life in Bangladesh, we seek to find the negative effects from exposure to this mundane environmental phenomenon, as it will be more likely to be generalizable across the region and into the future.

3 Data

**Flood Data** Flood data are calculated from satellite observations of surface reflectance taken from the Moderate-Resolution Imaging Spectroradiometer (MODIS) instruments operated by NASA. MODIS is an array of two satellites that scan the Earth’s surface every two days, recording reflectance values over 36 bands in the visible and infra-red spectra at various spatial resolutions. As clouds are opaque to visible and infra-red light, cloud cover will restrict the use of images for detecting surface properties. Due to this, data are processed into cloud-free composites of 8 or 16 days, of which we use the latter. Composite data are available for the period between 2000-2013 at 250m×250m resolution. This results in a total of 3,159×2,482 pixels for each of 253 time periods for four separate reflectance bands (resulting in approximately $1.98 \times 10^9$ observations). In addition, a preprocessed index for vegetation is also obtained (Huete et al., 1997). Details of the construction of our flood index is given in section 4.

**Other climate data** Recent evidence suggests that precipitation influences health and economic outcomes in early life (Maccini and Yang (2009)). Since Bangladesh drains an area many times greater than its own size (as in figure 1), it can be expected that flooding will be driven by rainfall in the wider basin, and that it is possible that precipitation may be correlated with flooded extents. For this reason, we include precipitation as a control in some models. Daily precipitation is obtained from the Tropical Rainfall Measuring Mission (TRMM) for 1998-2013. This is a 0.25°×0.25° gridded rainfall product measured by a network of satellites. As this resolution translates to roughly 25×25 km resolution at the latitude of Bangladesh, it is considerably larger than the resolution on our flood measure.

Due to potential error introduced by boundary effects of using single pixels, we take spatially-weighted averages of precipitation over each district of the Bangladesh and match these precipitation measures to clusters based upon a cluster’s presence within that district. Bangladesh has 64 districts with an average surface area of 2305 km². For robustness, we use individual TRMM pixels matched to DHS clusters and an average of the overlying pixel and the 8 adjacent pixels. The daily TRMM data are then temporally aggregated to match the 16-day periods at which the MODIS data are available and standardized for each district. Following Maccini and Yang (2009), we also look at rainfall totals throughout the agricultural season prior to birth.

**Socioeconomic Data** For the current analysis, the 2004, 2007, and 2011 rounds of the Bangladesh Demographic and Health Surveys (DHS, 2005, 2009, 2013) are used. The DHS is a nationally representative sample survey which contains information on health and socioeconomic indicators. Standardized World Health Organization (WHO) measures of physical development of children under the age of 5 years old are calculated from weight, height, and age variables (de Onis, 2006). The resulting anthropometric measures of height-for-age, weight-for-age, and weight-for-height are unitless Z-scores that
Figure 2: Map of Bangladesh showing the flooded regions in 2007 with the locations of DHS 2007 survey clusters overlaid. Pixels in which there were floods detected for at least one of the twenty-three observations periods of the satellite through the year are shown as colored pixels. Orange or red pixels will usually signify permanent water (i.e., rivers or lakes).
Table 1: Summary statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>(Std. Dev.)</th>
<th>Min.</th>
<th>Max.</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Birth trimester flood proportion</td>
<td>0.04</td>
<td>(0.06)</td>
<td>0</td>
<td>0.49</td>
<td>15286</td>
</tr>
<tr>
<td>Birth trimester rainfall (Z)</td>
<td>0.02</td>
<td>(0.38)</td>
<td>-0.91</td>
<td>1.39</td>
<td>14401</td>
</tr>
<tr>
<td>Gender</td>
<td>0.51</td>
<td>(0.5)</td>
<td>0</td>
<td>1</td>
<td>18586</td>
</tr>
<tr>
<td>Age (days)</td>
<td>891.27</td>
<td>(524.24)</td>
<td>1</td>
<td>1823</td>
<td>18586</td>
</tr>
<tr>
<td>Stunting</td>
<td>0.44</td>
<td>(0.5)</td>
<td>0</td>
<td>1</td>
<td>18541</td>
</tr>
<tr>
<td>Urban</td>
<td>0.32</td>
<td>(0.47)</td>
<td>0</td>
<td>1</td>
<td>18586</td>
</tr>
<tr>
<td>HH education (years completed by HH head)</td>
<td>4.89</td>
<td>(4.05)</td>
<td>0</td>
<td>17</td>
<td>18567</td>
</tr>
</tbody>
</table>

are derived from comparison to internationally measured cohorts of children\(^4\). The DHS also contains limited information on household socioeconomic characteristics that we use as controls in the analysis. In particular these are highest education level of household and an asset index of wealth following Filmer and Pritchett (2001). The locations of the DHS survey clusters from 2007 are shown along with flooded extents from the same year in figure 2.

4 Methods

4.1 Constructing an exogenous measure of flood extent

Remote sensing of flood extents has received much attention from the remote sensing and natural hazards communities, though many of the methods have been expensive and data-intensive, often requiring extensive hydrological modeling. However, the intention of many of these efforts is to perfectly delineate flood-zones in near-realtime for disaster relief efforts or to categorize areas of higher long-term flood risk for disaster or infrastructure planning. For the latter purposes, the specific timing of events are not important. The former methodology creates a snapshot of great spatial detail, while the latter looks over long time horizons to produce the average flood-risk of an area. Exact timing of floods is not a main priority of either method.

For the current statistical purpose we require a measure of flooding that is comprehensive both throughout time and across a large spatial area. This allows us to assign historical flood conditions to individuals based on location at certain critical periods (i.e., while they are infants). Additionally, in contrast to the two approaches discussed above, we wish to look historically at the precise timing of floods for a large number of individuals, so we can accept some error in our detected flood zones. We follow the method of Xiao et al. (2006), taking further developments of that method as detailed in Sakamoto et al. (2009). This method was developed to identify paddy agriculture in the Mekong Delta, Vietnam. Paddy agriculture is conducted by inundating fields, which leaves a spectral signature of standing surface water mixed with vegetation. This also identifies flooded zones and performs well when compared to more data intensive methods of flood delineation in Bangladesh (Islam et al. 2010).

The intuition behind the method is to construct two measures, one of which is sensitive to surface water and the other to surface vegetation (or greenness). If the value of the index for water surpasses $\ldots$

\(^4\)The anthropometric measures are calculated using the WHO STATA code available here: http://www.who.int/childgrowth/software/en/
Figure 3: Classification algorithm for detecting floods using MODIS data, adapted from Sakamoto et al. (2009).
that for greenness then we can say that there is overlying surface water. In practice we relax this simple assumption and use a buffer threshold value (given by the difference between surface water and greenness) to ensure accuracy.

We begin by calculating the Land Surface Water Index (LSWI) for all MODIS data over Bangladesh

\[
LSWI = \frac{\rho_{\text{NIR}} - \rho_{\text{MIR}}}{\rho_{\text{NIR}} + \rho_{\text{MIR}}} \tag{4.1}
\]

where \(\rho\) refers to the intensity of light at a particular wavelength indicated by the subscript. Here, \(\text{NIR}\) is near infra-red, \(\text{MIR}\) is middle infra-red\(^5\). Equation 4.1 gives an approximate measure of “blueness” at the surface and is analogous to the Normalized Difference Vegetation Index\(^6\). However, it cannot accurately determine surface water when used in isolation, and so we exploit the difference between LSWI and a vegetation index, in this case the Enhanced Vegetation Index (EVI):

\[
\text{EVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} + 6 \times \rho_{\text{RED}} - 7.5 \times \rho_{\text{BLUE}} + 1} \tag{4.2}
\]

where, as above, \(\rho\) refers to the intensity of light at a particular wavelength, with \(\text{BLUE}\) and \(\text{RED}\) being light in the blue and red regions of the spectrum, respectively.

The difference between LSWI and EVI is referred to as DVEL. An algorithm is then applied that assigns one of three values to each pixel based upon the values of each of these three indices:

- **Non-flood**: Pixels which show no evidence of standing surface water
- **Mixed**: Pixels which show a mixture of standing water and vegetation
- **Flood**: Pixels which are unambiguously flooded over their whole extent

The temporal dimension of the data is then exploited to assign “permanent water” status to pixels which are flooded for more than 180 days in a year. The exact threshold values were modified and validated with extensive ground-truthing in Bangladesh during the monsoon season in 2012, though some concerns are noted below. This classification procedure is visualized in figure 11. Figure 5 displays the results of this classification for 2004, a notably bad flood year.

Flood extents are then calculated for each survey cluster in the DHS by calculating the percent of land that is classified as flooded in a circle of radius 5km around each cluster. This distance is chosen for several reasons. Firstly, to preserve anonymity the DHS geolocations are randomly jittered by 5 km, so we wish to capture the actual location within our measure. Secondly, the average extent of a flood that can be considered damaging would have to be greater than the pixel size available, so 10 kilometers is chosen as an appropriate magnitude. Figure 4 shows the flooded percentage of an example survey location. The high level of “mixed” pixels in the winter months in both figures 5 and 4 is likely due to winter rice cultivation. We then standardize the flood magnitudes for every 10

---

\(^5\)The wavelengths observed in each of the spectral bands is as follows: \(\text{BLUE}: 459 - 479\ \text{nm}; \ \text{RED}: 621 - 670\ \text{nm}; \ \text{NIR}: 841 - 875\ \text{nm}; \ \text{MIR}: 2105 - 2155\ \text{nm}.
\(^6\)\(\text{NDVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} + \rho_{\text{RED}}}\)
Figure 4: Flood histories for each DHS location over the three rounds (2004, 2007, 2011) are obtained by calculating the percentage of each land water class within a 10km diameter bounding area. Example for a single time period for a single DHS location. Single period landcover classification is amended in the time series to contain permanent water bodies as those that are classed as flooded for greater than 50% of a year.
kilometer area surrounding the survey clusters. This is achieved by taking the mean of each satellite observation period (of 16-days) and averaging over all years, after which Z-scores of flooding extent are calculated\(^7\). Standardized flood extents are matched to each observation in the DHS by cluster number and birth-date for the 9 month periods before and after birth, and aggregated to trimesters.

**Some concerns with flood extent measure** It should be noted that the flood measure as presented is subject to a number of limitations that will be addressed as the research proceeds. Chief among these concerns is the effect of cloud cover on the ability to detect floods. Inspecting figure 5, we see that for periods in the middle of the year, during the monsoon season, there are large areas of missing values due to clouds. It is highly likely that these areas are subject to significant flooding in the monsoon season, and so the absence of these pixels will lead to a downward bias on our estimates. We address this by employing a number of interpolation methods, including simple nearest neighbor completion of missing pixels, and more complex methods, for example spline smoothing interpolation as employed by Jain et al. (2013). This will allow for the calculation of the flood extent during periods with missing values due to cloud cover by interpolating between observed surface data points. Results presented below use exposure interpolated with nearest neighbor matches.

### 4.2 Econometric analysis of the impact of flooding

We model physical development of children under the age of five as a linear function of flood exposure at birth, including *in utero* and *post partum* exposure in some model extensions. We estimate the following model:

\[
Y_{i,T} = \sum_{L=-k}^{k} [\beta_L \times FLOOD_{i,t-L}] + \gamma \times X_i + \delta_i + \mu_i + \nu_i + \epsilon_{i,t}
\]  

(4.3)

where \(Y_{i,T}\) is the outcome of interest at time \(T\), when the observation is taken; \(X_i\) is a vector of controls; and \(\delta, \mu, \) and \(\nu\) are birth-order\(^8\), birth-month, and location fixed effects, respectively. The coefficient of interest is \(\beta_L\) for time \(t = 0\) and periods of observation both before and after birth. Equation 4.3 is estimated using ordinary least squares (OLS). Throughout, standard errors are clustered by DHS survey cluster. Because we are exploiting the exact timing of floods for identification, and because this timing and extent is largely stochastic and cannot be predicted long in advance, we assume our measure of flooding, \(FLOOD\), is exogenous.

### 5 Results

In this section, the main result is presented. Robustness checks are then performed to understand the timing of flood impacts on physical development, the effect of precipitation on outcomes, comparisons between the various anthropometric measures, and the differences between the two survey periods.

---

\(^7\)This is done to account for adaptation to flood hydrology. A community more adapted to larger floods will only see the abnormally large floods as threatening livelihoods, and similarly for regions that suffer less extensive floods.

\(^8\)Birth-order is of noted importance for human capital investments (e.g. Black et al., 2005). This is particularly relevant for South Asia, which is home to the largest concentration of stunted children in the world, thought to largely be related to birth-order effects (Jayachandran and Pande, 2013).
Figure 5: Progression of flooding through 2004. Each time period corresponds to a 16-day interval during the year, with $t=1$ beginning on January 1st and ending on January 16th and so on. As indicated in the text, missing pixels due to monsoonal clouds will downwardly bias results for the flooding season. The high proportion of mixed pixels during the winter months are likely due to winter (boro) rice cultivation.
We also look for evidence of adaptation to flooding, and examine whether there is non-linearity in the response to flood extent.

Main result

The main results are shown in tables 2 and 4. In table 2 the dependent variable is stunting. Stunting is classified as having a height-for-age Z-score greater than two standard deviations below the mean. In table 4 results for height-for-age are presented. Table 2 present our main findings. The model with birth month and birth year fixed effects (column 3) is our preferred specification. We see that exposure to flooding in the second and third trimesters in utero increases the likelihood of stunting. A one standard deviation shock in the third trimester would increase the likelihood of stunting by about 2%. Columns (4) and (5) divide the sample by gender and we see that the effect sizes reported for boys is large and significant while the effect size for girls is not significantly different from zero. This is consistent with findings in the literature that male fetuses are weaker (for example, Almond and Currie, 2011), and supports the idea that the effect here is at least in part a physiological effect due to some harm in utero rather than an economic one resulting from conscious choices in the household.

Table 2: Main results: Stunting

<table>
<thead>
<tr>
<th>Sample restrictions</th>
<th>All</th>
<th>Boys</th>
<th>Girls</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable</td>
<td>Stunted</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion of area flooded during trimester</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st trimester</td>
<td>0.458***</td>
<td>0.237</td>
<td>0.209</td>
</tr>
<tr>
<td></td>
<td>(0.149)</td>
<td>(0.146)</td>
<td>(0.146)</td>
</tr>
<tr>
<td>2nd trimester</td>
<td>0.502***</td>
<td>0.259*</td>
<td>0.267*</td>
</tr>
<tr>
<td></td>
<td>(0.159)</td>
<td>(0.150)</td>
<td>(0.147)</td>
</tr>
<tr>
<td>3rd trimester</td>
<td>0.604***</td>
<td>0.312**</td>
<td>0.302**</td>
</tr>
<tr>
<td></td>
<td>(0.148)</td>
<td>(0.146)</td>
<td>(0.145)</td>
</tr>
<tr>
<td>4th trimester</td>
<td>0.505***</td>
<td>0.210</td>
<td>0.182</td>
</tr>
<tr>
<td></td>
<td>(0.139)</td>
<td>(0.136)</td>
<td>(0.136)</td>
</tr>
<tr>
<td>Birth month FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Birth year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Education &amp; wealth controls</td>
<td>Y</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>15112</td>
<td>15112</td>
<td>15093</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.062</td>
<td>0.104</td>
<td>0.125</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Robustness

Precipitation controls  The inclusion of precipitation controls is presented in table 3. Precipitation lag lengths match those of flood exposure and are included as averages over trimesters. We see that the inclusion of precipitation controls has little effect upon the estimated effects sizes. This is consistent with the idea discussed in the introduction, that flooding in Bangladesh is often less about immediate rainfall overhead as it is about rainfall across the entire GBM basin. The coefficients on the rainfall variables is interesting, showing similarity to Maccini and Yang (2009). Above average rainfall in the months of birth lead to positive outcomes, as it potentially signifies a good agricultural season.

Agricultural season restriction  We restrict the sample to only those children who are in utero during the flood season, beginning with the completion of a full trimester of flood season. If flood season begins in May, one full trimester of flood season exposure will begin in August. While we still see an effect of in utero exposure, it has shifted towards the second trimester and the third trimester coefficient has decreased. This suggests that it is flood earlier in the year (at abnormal times) that may have more of an impact, since an April flood for example, will only appear in this stratification in the second or first trimester variables.

Other anthropometric measures  We choose height-for-age as a measure of physical development that can be affected by early life exposure, and in particular, long-term malnutrition. Other anthropometric measures may respond differently to exposure to flooding at birth. The relationship between stunting (measured with height-for-age) and wasting (measured with weight-for-age/height) has been a subject of long discussion in the nutritional literature (e.g. Bhutta et al., 2008; Victora, 1992. Victora (1992) notes that stunting can be considered as a longer term response to malnutrition whereas wasting is considered a short-term or “acute” response, while also noting that stunting may be caused by other limiting factors like micronutrient deficiency. In many parts of the world there is a surprising lack of correlation between indicators of stunting and indicators of wasting in children. As weight is more more variable and dependent upon recent nutritional status, we would expect that weight-for-age and weight-for-height Z-scores would not respond to early life exposure to environmental shocks. Columns (1)-(3) of table 4 tests this hypothesis and finds that neither weight-for-height (2) nor weight-for-age respond to flooding exposure in the third trimester significantly.

Extended exposure window  To ensure that the effects we observe are due to floods at the time of birth, we extend the exposure window to increase the number of “trimesters” of exposure under consideration. Fig. 6 shows the results from a model with lags and leads covering 18 months before birth until 12 months after. We see that the effect on stunting is largely contained in the in utero period. Point estimates differ from our main specification due to constriction of the sample size. We note that the first three month period before the in utero period also seems to display increased stunting. However we conclude that this is due to a necessary coarseness in the matching of exposure to birthdates (which is accurate only to within a 16 day window) and so this may overlap with the in utero period.
Table 3: Precipitation and agricultural season

<table>
<thead>
<tr>
<th>Sample restrictions</th>
<th>Stunting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion of area flooded during trimester</td>
<td></td>
</tr>
<tr>
<td>1st trimester</td>
<td>0.237</td>
</tr>
<tr>
<td></td>
<td>(0.146)</td>
</tr>
<tr>
<td>2nd trimester</td>
<td>0.259*</td>
</tr>
<tr>
<td></td>
<td>(0.150)</td>
</tr>
<tr>
<td>3rd trimester</td>
<td>0.312**</td>
</tr>
<tr>
<td></td>
<td>(0.146)</td>
</tr>
<tr>
<td>4th trimester</td>
<td>0.210</td>
</tr>
<tr>
<td></td>
<td>(0.136)</td>
</tr>
<tr>
<td>Rainfall average during trimester</td>
<td></td>
</tr>
<tr>
<td>1st trimester</td>
<td>0.0291**</td>
</tr>
<tr>
<td></td>
<td>(0.0138)</td>
</tr>
<tr>
<td>2nd trimester</td>
<td>-0.00373</td>
</tr>
<tr>
<td></td>
<td>(0.0154)</td>
</tr>
<tr>
<td>3rd trimester</td>
<td>-0.0397***</td>
</tr>
<tr>
<td></td>
<td>(0.0138)</td>
</tr>
<tr>
<td>4th trimester</td>
<td>0.0171</td>
</tr>
<tr>
<td></td>
<td>(0.0136)</td>
</tr>
<tr>
<td>Observations</td>
<td>15112</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.104</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Table 4: Other anthropometric measures

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HAZ</td>
<td>WHZ</td>
<td>WAZ</td>
<td>Stunting</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sample restrictions</td>
<td>All</td>
<td>2004</td>
<td>2007</td>
<td>2011</td>
<td>Birth order&gt;1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion of area flooded during trimester</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st trimester</td>
<td>-0.586</td>
<td>-0.785**</td>
<td>-0.816**</td>
<td>0.828**</td>
<td>0.284</td>
<td>-0.101</td>
<td>0.275</td>
</tr>
<tr>
<td></td>
<td>(0.398)</td>
<td>(0.363)</td>
<td>(0.326)</td>
<td>(0.365)</td>
<td>(0.226)</td>
<td>(0.222)</td>
<td>(0.175)</td>
</tr>
<tr>
<td>2nd trimester</td>
<td>-0.639</td>
<td>-0.335</td>
<td>-0.449</td>
<td>-0.0704</td>
<td>0.454**</td>
<td>0.0339</td>
<td>0.439**</td>
</tr>
<tr>
<td></td>
<td>(0.411)</td>
<td>(0.366)</td>
<td>(0.326)</td>
<td>(0.415)</td>
<td>(0.229)</td>
<td>(0.220)</td>
<td>(0.181)</td>
</tr>
<tr>
<td>3rd trimester</td>
<td>-0.656*</td>
<td>-0.316</td>
<td>-0.341</td>
<td>0.184</td>
<td>0.339</td>
<td>0.155</td>
<td>0.379**</td>
</tr>
<tr>
<td></td>
<td>(0.387)</td>
<td>(0.355)</td>
<td>(0.332)</td>
<td>(0.404)</td>
<td>(0.213)</td>
<td>(0.227)</td>
<td>(0.180)</td>
</tr>
<tr>
<td>4th trimester</td>
<td>-0.404</td>
<td>-0.265</td>
<td>-0.243</td>
<td>-0.057</td>
<td>0.251</td>
<td>0.0399</td>
<td>0.432**</td>
</tr>
<tr>
<td></td>
<td>(0.397)</td>
<td>(0.329)</td>
<td>(0.323)</td>
<td>(0.396)</td>
<td>(0.174)</td>
<td>(0.228)</td>
<td>(0.168)</td>
</tr>
<tr>
<td>Observations</td>
<td>15112</td>
<td>15598</td>
<td>15246</td>
<td>2891</td>
<td>5054</td>
<td>7167</td>
<td>10024</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.137</td>
<td>0.068</td>
<td>0.133</td>
<td>0.155</td>
<td>0.122</td>
<td>0.090</td>
<td>0.114</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Figure 6: Increasing the number of lags and leads of flood exposure demonstrates that the effects of exposure are predominantly contained to the in utero period.

**Variation by survey period**  Within the birth years in our sample, 2004 is noted as the worst flood year. This could lead to a difference in outcomes between surveys as each round has a different number of children born in high flood years. Figure 7 shows a kernel density estimation for the standardized distribution of flooding at birth for all children in the 2004, 2007 and 2011 rounds, and confirms the higher flood exposure of children measured in the earlier samples (with more mass at the higher end of the distribution). To see if this measurement period affects our results, we run the model for each survey year separately. Results are displayed in columns (4) - (7) of table 4. While we do see some differences between years in many coefficients, the third trimester coefficient remains quite stable, with 2007 seeming to have a larger marginal effect on stunting.

**Birth-order effects**  If there is an economic component to the impacts that we see upon human capital (i.e., households disinvest in infants in times when household incomes contract), we might also expect to see a different effect for children with older siblings. This is because, when viewed purely as an investment, an earlier child is more valuable (Black et al., 2005). For this reason, we would expect to see an increase in the effect of floods on younger siblings. Figure 8 plots the values of the birth order fixed effects - essentially the birth order group specific intercepts. Compared to the child born first, we see that higher order births have worse anthropometric measures compared to the first born child. This implies a comparative lack of investments in higher order children. To understand the role birth order plays, we restrict the sample to only higher order births (from the second child upwards) in column (7) of 4. We see that the marginal effect of flood exposure is magnified for all periods, with significant increases of stunting due to exposure in the second and third trimesters. The coefficient on
the third trimester is about 25% larger than in the case with the full sample. This could result from two, potentially simultaneous, explanations. First, in the event of a shock, a family may differentially spend on their infant children. A first-born child may suffer less of a loss of well-being in the case of a contraction of household income, or a mother pregnant with a first-born child may be better provided for. A second explanation is that, after the effects of early life exposure become apparent, a family may invest differently in a first-born versus a later born child. This would imply that, while the initial impact of the shock might be equal for all children, compensatory behavior \textit{ex post} may partially decrease the impact. If there is a difference in this compensatory behavior across a number of children, this would account for these results. This finding agrees with previous findings on birth order and physical development in South Asia (Jayachandran and Pande, 2013), but the addition of the compensatory behavior with regards to environmental shocks changes the interpretation to one of both development and environmental factors. Results for higher birth order for the other WHO anthropometrics are shown in appendix table 5.

**Spatial lags** A concern for the analysis is that negative effects of flooding could be due to selection, as wealthier or more healthy households move small distances away from more flood prone areas. this would cause the more marginal households to remain in flood prone areas, and negative effects would result, while areas at greater distances from floods would experience positive effects. We test this explicitly with a spatial lag model. We estimate a model like our main specification, but specifically including flood exposure from annuli that incorporate the area around each DHS cluster in 5km increments. Fig. 9 present both a graphical depiction of the distances used in the analysis and the results from the spatial lag model itself. We see that for areas within the 5km buffer around the community, effects on stunting are larger than at greater distances, though none of the coefficients
is significant. This may indicate that spatial displacement is not a concern to identification, but it cannot be rigorously excluded as a possibility.

**Evidence of adaptation** Households that are more frequently exposed to larger floods may display greater adaptation to flooding. This can be achieved either through investments in protective measures, or disinvestments in susceptible capital. To examine whether this is the case, the sample is divided into quintiles of average exposure to flooding over the whole period (2000-2013). The model is run with interaction terms between flood quintiles and trimesters of flood exposure. The results are displayed in figure 10. For every trimester, households that are less frequently exposed experience a larger marginal response to flooding. This declines as exposure increases for each of the in utero periods. For households in the middle quintile, effects look to be close to zero, but importantly they remain statistically indistinguishable from our main effect (shown in gray). Impacts increase slightly as we look at more exposed regions. This is consistent with costly adaptation.

## 6 Discussion

This paper presents results of the effects of flooding on physical development outcomes in Bangladesh. The main innovation is the creation and use of an exogenous measure of flood exposure derived from remote sensing and its combination with pre-collected survey data. This allows us to identify an effect of early life exposure to flooding. We see negative effects on physical development of infants, with the effect being larger in boys than girls, and also find evidence of adaptation to this natural hazard.

However, the exact mechanism of these impacts is unclear. As previously noted, flooding is a complex hazard which has both positive and negative effects. For example, a flood can cause some
Figure 9: Upper panel shows radii used for flood extent calculation, centered on a riverside community. Inner radius of 5 kilometers is used in the main specification. The annuli from 5-10, 10-15, and 15-20 kilometers, are used in the spatial lag model. Lower panel shows results for second and third trimester exposure on stunting in each buffer.
damage to crops in a given year, but lead to improvements in soil moisture and fertility in subsequent seasons, leaving the net effect unclear. This is why the timing of both floods and of births that we exploit to identify our effects are so critical—a flood early in the season may destroy crops, while later in the season it may only reduce the yield slightly. Given that we see significant impacts while a child is \textit{in utero}, it can be surmised that the effect is a physiological one channeled through the mother. This may be due to nutrition, maternal stress, maternal effort levels, or some other factor. However, the results on birth order would suggest that some behavioral response is at play, though the exact details are unclear from the data.

It is also unclear the extent to which infant mortality may be biasing these results. If there is significant “harvesting” of fetuses or young children due to exposure to flooding, then we might be missing some of the worst effects in our analysis. This would cause downward bias of our effect sizes as only the stronger children would survive. Despite this, we still see an effect of “scarring” in our results, and so this may be a lower bound on the effects of flooding exposure.

We find these results on physical development to be interesting because lower height-for-age ratios and stunting are associated with negative educational and labor market incomes in later life. This could represent a significant extra cost associated with environmental impacts in Bangladesh and other flood-prone developing countries. We explicitly aim to understand the effects of more mild environmental exposure rather than large shocks, as the latter might lead to a lack of generality of the results. This paper, and further work related to these results, aim to quantify the burden of a common exposure rather than an uncommon one.
### Appendix

#### 7 Supplementary Tables and Figures

Table 5: Other anthropometric measures with higher birth order

<table>
<thead>
<tr>
<th>Trimester</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>haz</td>
<td>whz</td>
<td>waz</td>
</tr>
<tr>
<td>Trimester 1</td>
<td>-0.391</td>
<td>-0.509</td>
<td>-0.555</td>
</tr>
<tr>
<td></td>
<td>(0.480)</td>
<td>(0.438)</td>
<td>(0.417)</td>
</tr>
<tr>
<td>Trimester 2</td>
<td>-0.910*</td>
<td>0.299</td>
<td>-0.245</td>
</tr>
<tr>
<td></td>
<td>(0.496)</td>
<td>(0.423)</td>
<td>(0.388)</td>
</tr>
<tr>
<td>Trimester 3</td>
<td>-0.722</td>
<td>0.00569</td>
<td>-0.0757</td>
</tr>
<tr>
<td></td>
<td>(0.493)</td>
<td>(0.430)</td>
<td>(0.414)</td>
</tr>
<tr>
<td>Trimester 4</td>
<td>-0.897*</td>
<td>-0.0298</td>
<td>-0.368</td>
</tr>
<tr>
<td></td>
<td>(0.461)</td>
<td>(0.391)</td>
<td>(0.385)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Observations</th>
<th>10024</th>
<th>10436</th>
<th>10113</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjusted $R^2$</td>
<td>0.147</td>
<td>0.071</td>
<td>0.133</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Figure 11: An illustration of flood susceptibility in Bangladesh, drawn from flood extent of the 1998 floods. Adapted from Del Ninno et al. (2001).
References


World Bank (2010). *Natural hazards, unnatural disasters: the economics of effective prevention*.
