RESEARCH REPORT

IMPACT OF FLOODS ON EDUCATION OUTCOMES: EVIDENCE FROM BANGLADESH USING SATELLITE AND CENSUS DATA

Mohammad Mainul Hoque
Kazi Iqbal
Paritosh K. Roy

April 2024

BANGLADESH INSTITUTE OF DEVELOPMENT STUDIES

Research Report No. 200
DOI: https://doi.org/10.57138/NRUH9916

Mohammad Mainul Hoque
Research Fellow
Bangladesh Institute of Development Studies (BIDS)
Dhaka, Bangladesh

Kazi Iqbal
Research Director
Bangladesh Institute of Development Studies (BIDS)
Dhaka, Bangladesh

Paritosh K. Roy
Assistant Professor
Institute of Statistical Research and Training (ISRT)
University of Dhaka, Bangladesh

Published by
Bangladesh Institute of Development Studies
E-17, Agargaon, Sher-e-Bangla Nagar
G.P.O. Box No. 3854, Dhaka-1207, Bangladesh
Phone: 880-2-58160430-37
FAX: 880-2-58160410
Website: www.bids.org.bd
E-mail: publication@bids.org.bd

Price:	Inland	Foreign
	Tk. 200.00	US$ 10.00

Printed in Bangladesh at RK Communication, 67/1, Purana Paltan Line, Dhaka-1000.

Contents

List of Tables

List of Figures

Abbreviations

BANBEIS	Bangladesh Bureau of Educational Information and Statistics
EVI	Enhanced Vegetation Index
HIES	Household Income and Expenditure Survey
JSC	Junior School Certificate
LSMS	Living Standard Measurement Survey
LSWI	Land Surface Water Index
MIR	Mid-infrared
MODIS	Moderate Resolution Imaging Spectrometer
NDVI	Normalised Difference Vegetation Index
NIR	Near-infrared
SSC	Secondary School Certificate

Abstract

We study the impact of floods on the education outcomes of high school students in Bangladesh. We construct satellite image-based measures of flood at the union level and combine them with the census data of all high schools for the years 2011-2018. Exploiting within-union variations of the flood measures, we find that the passing rates of public exams and school-based exams of the secondary schools in a union drop significantly if greater areas of that union are flooded. In the case of public exams, for example, the passing rates decreased by 4-9 per cent if the flooded area of a union increased by 1 per cent after controlling for school and year-fixed effects. The impact is found to be more pronounced for female students - the passing rates of female students were about 2 percentage points lower than the male students in the SSC examinations. While the literature argues that the impact of natural disasters on education outcomes is indirect and long-term, we provide robust evidence suggesting that floods' direct and immediate impact on education outcomes can be substantial. Our results have a significant bearing on education policies and disaster management strategies of natural flood-prone developing countries.

CHAPTER 1
INTRODUCTION

The impact of natural disasters on education outcomes has been found to be largely indirect and long-term. These indirect impacts of natural disasters have been studied in the context of early life exposure and its subsequent impacts in later years as well as across generations (Caruso, 2017; Maccini & Yang, 2009). Micro evidence tracks the channels through which these long-term impacts work, including disaster-induced malnutrition (Alderman, Hooveven, & Rossi, 2008; Alderman & Kinsey, 2006). Since the impacts are largely conceptualised as long-term, the evidence on short-term impacts is limited to dropout and enrollment channels only (Zimmerman, 2020; Shah & Steinberg, 2017). Our study contributes to this strand of literature by examining another contemporaneous channel — results of school-based and public examinations. We use unique school-level census data and combine them with flood measures constructed from satellite data. We find that floods have significant, negative, and immediate impacts on the academic performances of high school students in Bangladesh.

Bangladesh offers an interesting context to examine the impact of floods on education outcomes. Floods have been an annual event in South Asia, particularly in Bangladesh, claiming hundreds of lives and damaging houses, physical infrastructure, and livelihood opportunities of millions of people (EM-DAT; Flood Forecasting and Warning Center, undated). Bangladesh is a low-lying country located downstream of three large river basins - the Ganges, Brahmaputra, and Meghna rivers. The discharge from these three rivers is compounded by heavy rainfall during the monsoon (June – September), causing floods almost every year, with a devastating flood every 5–8 years (Flood Forecasting and Warning Center, undated). That is, Bangladesh experiences floods almost every year, but the extent of coverage and severity varies substantially. For example, in the 2018 flood, only about 5 per cent of the country was inundated, while in 2011, 15 per cent of the land went underwater (Figure 1). We exploit this spatial variation in flooding over time using remote sensing data and pair them with education outcomes at the union level for the years 2011-2018. To the best of our knowledge, ours is the first systematic examination of the causal impact of floods on academic performance.

We use the percentage of areas flooded in a union during a year as a measure of the extent of the flood. Flood measures are constructed using the algorithm of Sakamoto, Cao, Van Nguyen, Kotera, & Yokozawa (2009), which is widely used in the economics literature (Guiteras, Jina, & Mobarak, 2015; Chen, Valerie, Yuanyuan, & Steven, 2017). NASA's Moderate Resolution Imaging Spectrometer (MODIS) data are used to construct inundation maps for the years 2011-2018. We match these measures of flood with the school census data at the union level. The Bangladesh Bureau of Educational Information and Statistics (BANBEIS), a government organisation, conducts a yearly census on secondary schools. In our study, we cover all secondary schools of the country from 2011 to 2018. Our two major variables of interest are school-based assessments and public exam passing rates, available with gender breakdowns.

While we estimate a reduced form specification, the underlying mechanisms through which flood impacts schooling outcomes are worth noting. Both school-level and household-level inputs can be affected by floods, and these might lead to a lower level of learning and poorer examination results. Not surprisingly, when a large part of the country is inundated every year, educational institutions are no exception. A country-wide school census conducted by BANBEIS in 2017 found that 11,745 (above 50 per cent) education institutions were affected by disasters such as floods, cyclones, waterlogging, river-bank erosion, earthquake, and salinity in the past 10 years, of which 22 per cent were affected by flood alone. School surveys show that floods damage school buildings, furniture, water and electricity supply, sanitation, etc. (UNESCO survey). These damages can lead to a full or partial closure of the schools. Even if the schools remain open, attendance of the students and the teachers can be very low due to household/individual specific causes. These include temporary displacement of the households, damages of the household level inputs (e.g., household income), disaster-related illness, disruption of transportation to schools, damages to school materials (e.g., textbooks, uniforms), etc. All these factors can lead to deficiencies in learning outcomes and can impact academic performance.

Our identification strategy exploits the exogenous variations of flood at the union level and exposure of different schools and student cohorts to this natural disaster. By pairing the census data of all secondary schools with the flood measures, we find that passing rates of school-based exams and public exams of the secondary schools in a union dropped significantly if greater areas of that union were flooded after controlling for school level and year fixed effects. In the case of public exams (JSC and SSC), the passing rate decreased by 4-9 per cent when the flooded area of a union increased by 1 per cent. Floods are also found to impact students' results in the right tail of the distribution - a 1 per cent increase in flooded union leads to about a 2 per cent decrease in GPA-5. We find similar results for school-based assessments. A 1 per cent increase in flooded areas results in 3-4 per cent drops in passing rates for all grades after controlling for school-grade and year-fixed effects. Students in grade 8 and above are found to be affected more. Note that the census data do not allow us to account for the dropouts and repeaters. We only observe the students who are promoted to the next grades. Hence, our results can be interpreted as a lower bound for the extent of the impact.

Our results exhibit an important gender dimension - the impact is found to be more pronounced for female students. The passing rates of the female students were about 2 percentage points lower than the male students in the SSC examinations. The share of female students receiving GPA-5 was about 0.4 percentage points lower than the male students, and this figure is very robust and statistically significant. In the case of school-based assessments, the passing rates also were lower for female students. Interestingly, the impact on female students is driven by the impact of students from classes 9 and 10 only. These results have important implications for gender equality in education in disaster-prone developing countries, particularly achieving Sustainable Development Goal (SDG) 4.

A number of features distinguish our study from the existing literature. First, literature on the impact of natural disasters on education largely studies the impact of the shocks in early life on adult outcomes. In this case, early life generally spans from utero to pre-schooling ages. While early life exposures to disasters are important channels, we show that natural disasters can impact education outcomes contemporaneously for high school students. Second, we use the universe of all secondary schools in Bangladesh. This allows us to capture the students' academic performances with more precision than the household surveys used in the current literature. We use results from the school-based examinations as well as the public examinations, which are more direct measures of academic performance than the outcome variables of the household surveys. To the best of our knowledge, ours is the first study that uses school-level administrative data to examine the impact of floods on direct education outcomes such as exam results. Third, we construct flood measures using remote sensing data. By comparing reported flood measures with satellite-based data, Guiteras et al. (2015) argued that reported measures of floods are often biased due to the nature of exposure of the respondents. On top of recall bias, self-reported data is prone to errors caused by reference dependence - differential exposure to floods can lead to different perceptions of the extent of the same floods by the respondents. Our measures of floods are thus free from such biases.

The rest of the paper is organised as follows. Chapter 2 discusses the relevant literature. Chapter 3 describes data and variables on education and flood. Chapter 4 highlights the empirical strategy, while Chapter 5 describes the regression results. Chapter 6 discusses the overall implications of the results, and Chapter 7 concludes.

CHAPTER 2
RELATED LITERATURE

Theoretically, the link between natural disasters and human capital formation can go either way: natural shocks can increase the relative returns from human capital compared to physical capital. The destruction of physical capital in the aftermath of natural disasters causes a fall in expected return from investment in physical capital and creates an incentive to invest in human capital. The empirical support for this argument from cross-country panels is mixed (Skidmore & Toya, 2002; Cuaresma, 2010). Note that such an incentive to invest in human capital may not work in the case of developing countries as credit-constrained rural people often experience a negative income shock when exposed to natural disasters, and in response, they disinvest in both physical and human capital. Importantly, human capital production can also be affected by risk due to increased chances of natural disaster-related mortality (Checchi & García Peñalosa, 2004).

Models of human capital investment in a risky environment indicate lower investment in education. This behavioural impact is compounded by other shocks caused by the risky environment - natural disaster-induced income shocks can lead to malnutrition which may have a long-term impact on education outcomes. There is ample evidence of such indirect impacts. For example, Alderman et al. (2006) found that drought-induced stunting of children aged 12-24 months resulted in delayed school enrollment and reduced grade completion in Zimbabwe. Draught-led malnutrition (i.e. slow height growth) has also been found to delay enrollment and cause poorer academic achievement in Tanzania (Alderman et al., 2008).

Examining the Indonesian adult women who were born between 1953 and 1974, Maccini and Yang (2009) reported that women who experienced a higher rainfall than average during their infancy were found to be more educated, healthier, and wealthier in the year 2000, which is largely because of better child and maternal nutrition. Dell, Benjamin and Benjamin (2014) suggest that such weather-induced nutrition shocks seem to have long-lasting impacts. Utilising the drought and rainfall-induced variation in wages in rural India, Shah and Steinberg (2017) showed that children who were exposed to drought in early life also had lower schooling attainment. Their results indicate that the ultimate impact on schooling depends on how the opportunity costs of children’s time change in response to natural shocks. They reported that during periods of heavy rainfall and higher wages, children contemporaneously switch out of school as they substitute for their parents' work either in farm or household chores. Jacoby and Skoufias (1997) found similar results using the difference-in-difference technique - a ten per cent decline in agricultural income due to excessive rainfalls led to a fall in school attendance of about five days.

Our study also has a bearing on the recent literature that studying how high temperature impacts students' academic achievement by affecting their cognitive ability (Graff Zivin, Joshua, & Solomon, 2015; Cho, 2017; and Park, 2017). The negative effect on students' cognitive ability from high temperature is due to physiological changes that affect attention, memory, and accuracy, sleep deprivation, and heightened risk of food poisoning during high-temperature episodes. Exploiting National Longitudinal Survey of Youth (NLSY79) data in the US, Graff Zivin et al. (2015) showed that higher temperature on the test days reduced students' mathematics test scores but had no effect on reading scores. However, they did not report any long-term effects, which are probably due to parents' compensatory behaviour of allocating more resources to the affected children. In a quasi-experimental setting, Park (2017) utilised school and student-level administrative data from a public school district in New York and reported that high temperatures have a persistent effect on learning outcomes, as revealed in students' performance in high stake exams even after netting out students' ability and compensating behaviour. In contrast to Graff Zivin et al. (2015), Park (2017) presented evidence of long-run impact, reporting that cumulative temperature stress in the senior years in high school affected NYC students' cumulative learning and in-time graduation rates. A similar type of finding is reported by Cho (2017)—high summer temperature relative to a normal daily average temperature negatively affected Korean students' math and English scores, and the impact is larger in relatively cooler places where students are not used to hot days.

CHAPTER 3
DATA AND VARIABLES

3.1 Education Outcomes

Bangladesh Bureau of Education Information and Statistics (BANBEIS), under the Ministry of Education, collects information on all secondary schools every year with a structured questionnaire. This census on secondary schools includes data on infrastructure, management, students, and teachers. We consider public school exams to be the chief performance indicator for students. Since the public exams are administrated by regional education boards[1], and the results are reported by this authority, the accuracy of the data is very high. Note that the public exams are standardised across schools under an education board. The students sit for twice during their high school life: the Junior School Certificate Exam after the completion of grade 8 and the Secondary School Certificate after grade 10. The number of students passed and the number of students with the highest grade point average (GPA-5) for these two exams are available by school and gender. In addition to the public exams, the census has data on school-based assessments–the passing rate from one grade to upper grade with a gender breakdown.

Table 3.1 presents the descriptive statistics of the education variables used in the regression models. The total number of schools increased from 15,605 in 2011 to 16,623 in 2018, implying that our panel is not a balanced panel. The average number of high schools per union has also increased, which was 4.87 in 2018. About half of the students are female; this ratio has been steady over the years. Average passing rates in the SSC examination for all students vary substantially over the years – the figure varies from 77 per cent to 92 per cent. We observe similar fluctuations for the girls in the SSC examination. The passing rates of JSC vary less than the SSC over the years – it varied between 82 and 92 per cent. About 3 to 6 per cent of the students received GPA-5 in SSC in the study period, and we observed a similar pattern for the female students. Unlike the passing rates, the share of students with GPA-5 in the JSC examination varied substantially from 1 to 9 per cent and for female students this figure varies from 1 to 10 per cent. We also report average passing rates of grades 6-10 with gender breakdown. The figures show that there is substantial variation across years.

[1] There are 8 education boards that conduct SSC and JSC examinations in Bangladesh - Dhaka, Rajshahi, Cumilla, Jashore, Chattogram, Barishal, Sylhet, and Dinajpur.

Table 3.1: Descriptive Statistics of the Education Variables

Variable	2011	2012	2013	2014	2015	2016	2017	2018
Total number of high schools	15605	15899	15949	16119	16254	16359	16401	16623
Average number of high schools per union	4.64	4.69	4.69	4.73	4.75	4.78	4.80	4.87
	(2.32)	(2.34)	(2.32)	(2.35)	(2.34)	(2.36)	(2.38)	(2.43)
Average number of students per high schools	331.75	259.15	270.53	284.90	305.33	338.98	353.92	376.99
	(312.5)	(254.7)	(252.4)	(268.2)	(285.9)	(328.3)	(323.3)	(352.2)
Average percentage of girls per school	0.58	0.48	0.50	0.51	0.51	0.52	0.52	0.51
	(0.39)	(0.29)	(0.28)	(0.28)	(0.28)	(0.27)	(0.27)	(0.26)
Average passing rates in SSC per school	0.80	0.85	0.88	0.92	0.85	0.87	0.79	0.77
	(0.14)	(0.12)	(0.11)	(0.09)	(0.15)	(0.13)	(0.18)	(0.17)
Average passing rates of girls in SSC per school	0.79	0.84	0.88	0.91	0.85	0.88	0.80	0.78
	(0.16)	(0.15)	(0.13)	(0.11)	(0.17)	(0.15)	(0.19)	(0.18)
Share of students with GPA-5 in SSC per school	0.03	0.03	0.04	0.06	0.04	0.04	0.03	0.04
	(0.07)	(0.07)	(0.08)	(0.10)	(0.09)	(0.08)	(0.08)	(0.08)
Share of girls with GPA-5 in SSC per school	0.04	0.03	0.03	0.06	0.04	0.04	0.03	0.03
	(0.06)	(0.07)	(0.08)	(0.11)	(0.09)	(0.09)	(0.09)	(0.08)
Average passing rate in JSC per school	0.82	0.85	0.89	0.90	0.92	0.93	0.83	0.85
	(0.17)	(0.15)	(0.12)	(0.14)	(0.11)	(0.10)	(0.19)	(0.15)
Average passing rates of girls in JSC per school	0.81	0.85	0.89	0.90	0.93	0.93	0.84	0.86
	(0.18)	(0.17)	(0.14)	(0.15)	(0.12)	(0.11)	(0.19)	(0.16)
Share of students with GPA-5 in JSC per school	0.01	0.01	0.06	0.05	0.07	0.09	0.06	0.02
	(0.04)	(0.05)	(0.10)	(0.10)	(0.11)	(0.13)	(0.11)	(0.05)
Share of girls with GPA-5 in JSC per school	0.01	0.01	0.07	0.06	0.08	0.10	0.07	0.02
	(0.04)	(0.05)	(0.12)	(0.11)	(0.13)	(0.15)	(0.13)	(0.06)
Average passing rates in grade 6	0.75	0.88	0.90	0.91	0.90	0.91	0.91	0.92
	(0.21)	(0.17)	(0.15)	(0.15)	(0.17)	(0.17)	(0.17)	(0.17)
Average passing rates of girls in grade 6	0.74	0.69	0.76	0.78	0.78	0.80	0.81	0.85
	(0.24)	(0.39)	(0.36)	(0.35)	(0.35)	(0.34)	(0.33)	(0.32)
Average passing rates in grade 7	0.74	0.87	0.89	0.90	0.90	0.91	0.91	0.92
	(0.22)	(0.17)	(0.15)	(0.16)	(0.17)	(0.17)	(0.18)	(0.18)
Average passing rates of girls in grade 7	0.74	0.69	0.75	0.77	0.77	0.81	0.81	0.84
	(0.25)	(0.38)	(0.36)	(0.35)	(0.35)	(0.33)	(0.34)	(0.32)
Average passing rates in grade 8	0.68	0.79	0.82	0.85	0.85	0.88	0.88	0.91
	(0.24)	(0.20)	(0.18)	(0.17)	(0.19)	(0.18)	(0.18)	(0.17)
Average passing rates of girls in grade 8	0.65	0.66	0.71	0.74	0.73	0.77	0.78	0.81
	(0.28)	(0.34)	(0.32)	(0.33)	(0.34)	(0.33)	(0.33)	(0.33)
Average passing rates in grade 9	0.78	0.80	0.87	0.88	0.88	0.90	0.90	0.93
	(0.25)	(0.22)	(0.19)	(0.19)	(0.21)	(0.20)	(0.21)	(0.21)
Average passing rates of girls in grade 9	0.74	0.55	0.69	0.72	0.73	0.79	0.80	0.86
	(0.31)	(0.40)	(0.39)	(0.38)	(0.38)	(0.36)	(0.35)	(0.35)
Average passing rates in grade 10	0.78	0.77	0.84	0.86	0.84	0.86	0.84	0.87
	(0.25)	(0.21)	(0.20)	(0.18)	(0.22)	(0.21)	(0.23)	(0.23)
Average passing rates of girls in grade 10	0.72	0.55	0.67	0.69	0.67	0.73	0.73	0.78
	(0.32)	(0.37)	(0.38)	(0.38)	(0.39)	(0.37)	(0.36)	(0.37)

Note: Standard deviations are in brackets.

3.2 Construction of Flood Measures

We construct the flood indicators from remote sensing data collected by the NASA Moderate Resolution Imaging Spectroradiometer (MODIS). We follow similar procedures adopted in the recent economics literature (Guiteras et al., 2015; Chen et al., 2017). Xiao et al. (2006) proposed the original algorithm, and Sakamoto, Cao, Nguyen, Kotera, & Yokozawa (2009) made further developments. Islam, Bala and Haque (2010) followed this methodology, along with some modifications to identify flooded areas in Bangladesh. The different hydro-geological conditions in Bangladesh were the primary concern in their adjustment. They compared the results to the maps based on more data-intensive methods (RADARSAT) images, hydrological data, and digital elevation model data), and concluded that MODIS data-based flood measures performed well in Bangladesh. We use the parameters of Islam et al. (2010) to construct our flood measures as they are tailored to the hydrological conditions of Bangladesh.

We apply a few filters to exclude permanent water bodies and swamps. First, note that the shape files of large permanent water bodies of Bangladesh are available from the Survey of Bangladesh, a government agency. So, we exclude these water bodies from the maps. Second, in order to account for smaller water bodies for which shape files are not available, we treat the water-related pixels for the period mid-September to mid-March (dry season) as permanent water bodies. Third, a number of districts in the southwest, such as Khulna, Satkhira, Bagerhat, Patuakhal, Barguna, and Pirojpur, have lower land surface elevation, and a large part of the area of these districts is covered by Sundarban forest, which is a mangrove forest. We found a large number of red dots (water bodies) across these districts in the dry season. We exclude these and treat them as permanent water bodies.

In non-technical terms, the construction of flood measures involves the following steps. MODIS 16-day spectral data is used to generate vegetation indices (See Appendix A1 for details). Based on pre-specified values of these indices, the algorithm differentiates between water and non-water-related pixels. These water-related pixels capture permanent water bodies, floods, and mixtures. Note that we have already identified permanent water bodies, as stated above. Again, based on some parameter values, flood is separated from other water-related pixels. The mixture denotes the mixture of water and non-water pixels that are not floods.

3.3 Flood Maps

Using our flood construct for the period 2011-2018, we find that the coverage of the floods varies substantially from year to year (Figure 3.1). For example, in 2011, about 15 per cent of the country was flooded, while it was only about 5 per cent in 2018. In other years, the extent of flood coverage fluctuates between 6 and 12 per cent. Since 2011 experienced the most severe flood in our sample period, we illustrate the construction of the flood measures using 2011.

Figure 3.1: Yearly Variations of the Extent of Flood

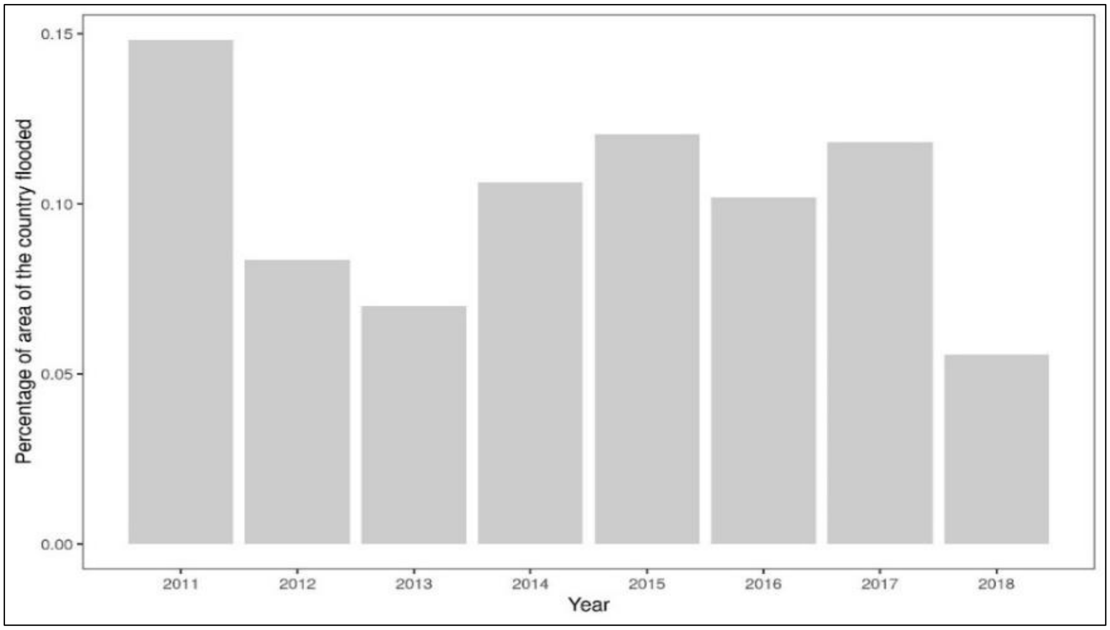


Figure 3.2 portrays 25 flood maps of Bangladesh in 2011 in 16-day intervals since the MODIS data generate vegetation indices every 16 days. The maps identify the permanent water bodies, floods, lands, and mixtures. Note that the red dots of floods started to appear in the last week of May 2011 and lasted till September 2011. We observed floods from June-August, and the extent of flood coverage reached a peak in the last week of July 2011.

Finally, we construct one map for 2011 considering flood data from 25 different points in time with 16-day intervals (Figure 3.3). By construction, if there is any water in mid-September to mid-May (dry season), we consider them permanent water bodies. To construct the flood map of the country, we will consider only four months–mid-May to mid-September. If a grid in a union is found flooded at any point in these 4 months, we label the grid as flooded.

For example, if a union has 10 grids and we find that 5 grids are flooded at any point in the four months, we record that half of the union is flooded. That is, the union-level flood is measured by the proportion of flooded grids of a union.

Figure 3.2: Flood Maps of 2011 by 16-day Intervals

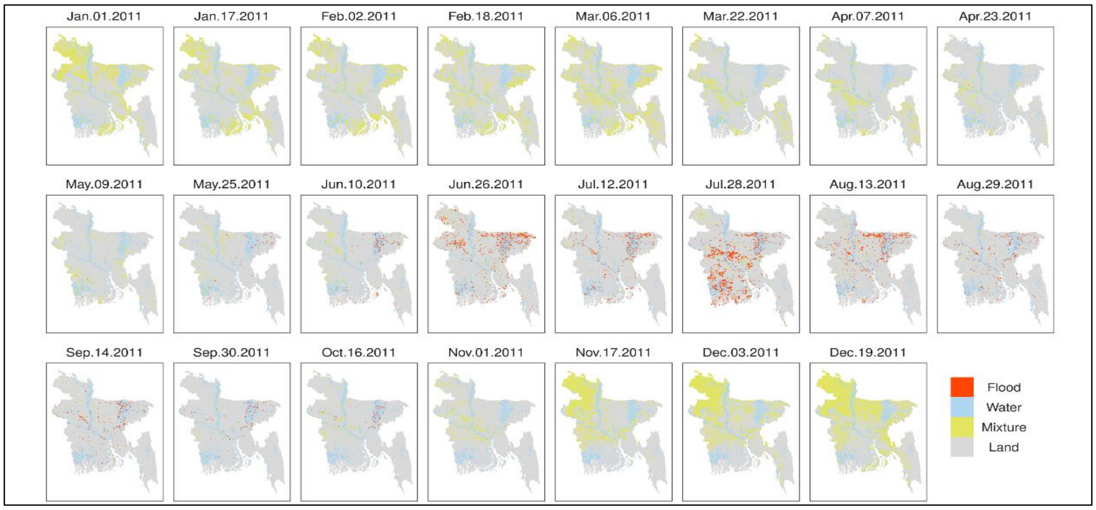
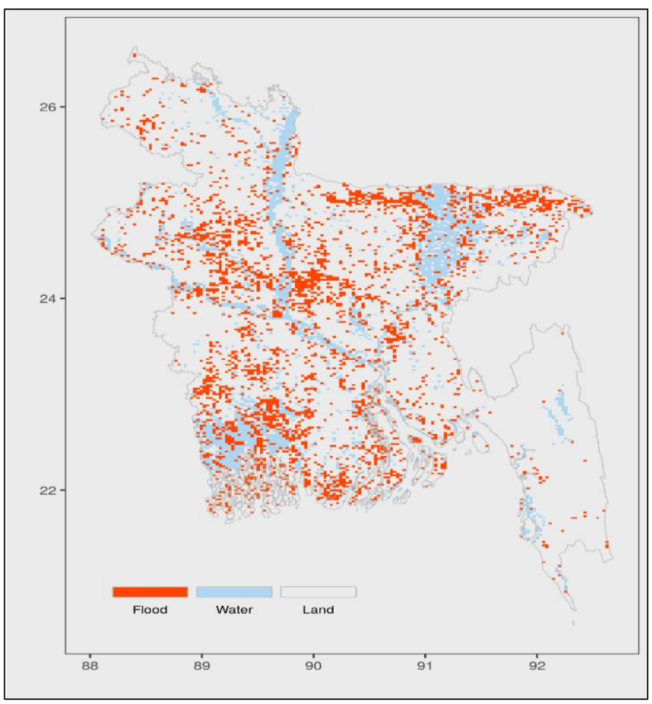


Figure 3.3: Flood Map of 2011



CHAPTER 4
EMPIRICAL STRATEGY

The underlying analytical framework of the study is a simple education production function (Todd & Wolpin, 2003; Hanushek, 2008; Glewe, Hanushek, Humpage, & Ravina, 2011). Since floods impact both school level as well as household level inputs of the education production function, we use a reduced form model to estimate the impact of floods on education outcomes. We use school, grade-cohort, and year-fixed effects to control for all confounders that can contaminate the causal inference.

There are a few identification challenges. First, the schools located in non-flood-prone areas tend to be of better quality than the schools in flood-prone areas. Typically, the flood-prone areas are remote areas where quality teachers may not want to settle. Note that about 97 per cent of high schools are privately owned, where teachers can choose schools, unlike government schools. In the case of government schools, the government decides the placement of the teachers. Moreover, the infrastructure, management, and reputation of the schools are also better in the better-off areas, which are largely unaffected by floods. Hence, cross-sectional variations cannot produce causal inference. So, we use school-fixed effects to capture the school-level variations of students' education outcomes. Second, in some years, public exams can be harder than in other years. If these years coincide with floods, we will mistakenly pick up the effect of harder exams, not the floods. Since public exams are the same across schools, we control for year-fixed effects. Year-fixed effects also capture the year-specific changes that are common to all schools and students, such as exam policies, textbooks, syllabi, etc. Third, in the case of school-based exams, some cohorts may be worse than others, and we can wrongly attribute it to floods. Hence, we use school-grade-level fixed effects to avoid this erroneous attribution.

Fourth, we use sub-district level time trends, which are the interactions of sub-districts and years. This will remove any spurious correlation between education outcomes and floods over time. The education outcomes of schools in a sub-district may improve over time due to reasons other than floods (or, lack thereof), and the sub-districts tend to experience less flooding due to higher public investment in flood controls or hydrological changes of rivers over time. If this is the case, we may spuriously pick up correlation if we do not use sub-district specific trends. Finally, the extent of exogeneity of flood occurrence–though floods occur almost every year in Bangladesh during the monsoon period, the exact timing of the onslaught and severity are hardly predictable. Moreover, the north-eastern part of the country is vulnerable to flash floods, which are highly unpredictable in nature. It is important to take into account that households and schools take mitigation measures to minimise the impact of floods. The government also builds infrastructure to protect the lives and livelihoods of the citizens from floods. Hence, our estimated marginal effect is the impact of floods net of mitigation effects.

Regarding empirical specification, consider public examinations first. We estimate the short-term impact on education outcomes by constructing a school panel for the period 2011-2018 and exploiting within-school variations over time. The reduced form model we estimate is the following.

$$A_{st,\mathrm{g}} = \beta_0 + \beta_1 F_{st} + \mu_s + \delta_t + \eta_{st} + e_{st,\mathrm{g}} \tag{1}$$

where $A_{st,g=8\,\&10}$ is the students' achievement in junior school final (JSC) and high school final (SSC) exams in school s in time period t. In this case, g corresponds to grades 8 and 10 only. We use two types of outcome measures – passing rate and GPA 5 (highest grade point average). Since education outcome variables are available for both male and female students, this allows us to examine if the impact of flood varies with gender. F_{st} is the flood measure in year t of the union the school s is located. Since we do not have school-level GIS data, we cannot construct flood measures around the schools – the catchment area of the schools. So, we assume that the degree of exposure of a union to flood is the same for all schools in that union. Note that the average size of the union is about 20 square kilometres, including permanent water bodies; on average, a union has about 5 high schools. Given the high density of schools in a union, this is not a very implausible assumption. μ_s and δ_t are school and year-fixed effects, respectively. Since outcome variables are available only at two grade levels (8 and 10), we cannot control for school-grade-level fixed effects here. η_{st} is the sub-district specific time trends, and finally, $e_{st,\mathrm{g}}$ is the error term. As flood isexogenous to any other left-out variables in the error term, *Corr* (F_{st}, e_{sgt}) = 0 holds, and β_1 yields the causal impact of floods on education outcomes.

Now, consider the performance of school-based examinations. We exploit school-grade variations for the period 2011-2018. The reduced form specification is as follows.

$$A_{sgt} = \beta_0 + \beta_1 + \mu_{sg} + \delta_t + \eta_{st} + e_{sgt} \tag{2}$$

where A_{sgt} is students' schooling outcome in grade g in school s in time period t, and F_{st} is the flood measure in year t and at the union level as described before. μ_{sg} is school-grade-level fixed effect that would control for school-grade-specific time invariants in the schools. For example, if class-teacher quality for a particular grade is exceptionally good in a school, μ_{sg} controls for such unobservable.

Finally, we want to check if the impacts on education outcomes vary with the severity of flood measures. To this end, we categorise the extent of flood measures into four quantiles. Note again that our flood measure is the percentage of areas flooded in a union in a year. If a union is in the top quantile in terms of the area inundated in year *t*, we consider that the union is exposed to severe floods in year *t*. A union is moderately affected by the flood if it belongs to the second quantile. The bottom two quantiles represent very low to no-flooding, and this is the reference group. So, a school can belong to different flood quantiles over time since the severity of floods can vary across years. The empirical specification is similar to specification 2 above except for the measure of flood.

$$A_{st,\mathrm{g}} = \beta_0 + \beta_{\mathrm{Q}} F\mathrm{Q}_{st} + \mu_s + \delta_t + \eta_{st} + e_{st,\mathrm{g}} \tag{3}$$

where FQ_{st} are dummy variables that denote if a school *s* experienced a severe or moderate flood in year *t*. The coefficients of interest β_{Q} capture if students from severely flooded schools and moderately flooded schools performed differently than non-affected schools.

CHAPTER 5
REGRESSION RESULTS

5.1 Flood and Public Examinations

We begin our regression analysis with the public exam by estimating model 1 above. Note again that we consider two public examinations that high school students have to sit for– the secondary school certificate (SSC) after grade 10 and the junior school certificate (JSC) after grade 8. The results for SSC exams are presented in Tables 5.1 and 5.2, while those for JSC exams are presented in Tables 5.3 and 5.4. The dependent variables are the passing rates in the public exams and the proportion of students obtaining the highest grade point average, GPA5.

Table 5.1: Flood and Passing Rate in SSC Exams

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Proportion Passed the SSC Exam				
Proportion of Union flooded	**-0.033*** **	**-0.054*** **	**-0.026*** **	**-0.062*** **	**-0.030*** **
	[0.004]	[0.005]	[0.005]	[0.005]	[0.005]
No. of Students in School		-0.000***	-0.000***	-0.000***	-0.000***
		[0.000]	[0.000]	[0.000]	[0.000]
School FE		YES	YES	YES	YES
Year FE			YES		YES
Sub-district x year				YES	YES
No. of Obs.	112,233	112,124	112,124	112124	112,124
No. of Schools	14,682	14,682	14,682	14,682	14,682
adj. R^2	0.002	0.199	0.303	0.248	0.350

Note: Standard errors clustered at the union level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We start with a parsimonious specification examining the relationship between passing rates of SSC examination and the key explanatory variables–proportion of a *union* inundated (column 1) in Table 5.1. We then restrict the model gradually by adding school-fixed effects in column 2, both school-fixed effects and year-fixed effect in column 3, school-fixed effect and sub-district specific trend in column 4, and finally, school-fixed effect, year-fixed effect, and sub-district-specific trend in column 5. In all cases, standard errors are clustered at the union level. Note that the total student count within a school is included as a school-level time variant measure in all specifications. Regression results show that as the share of flooded areas increases by 1 per cent, the passing rate in SSC examination decreases by about 3-6 per cent. All the coefficients are significant at a 1 per cent level. In the full specification (column 5) when we control for school FEs, year FEs, and sub-district specific trends, the drop in passing rate is 3 per cent. Interestingly, the passing rate in the SSC examination is lower for the larger schools, captured by the larger number of students.

Now, we consider the right tail of the SSC results distribution- the highest grade point average (GPA-5). In this case, the dependent variable is the proportion of students who obtained GPA-5 in the SSC exam. The coefficients are significant when we do not control for year FEs. In other specifications with school FEs and sub-district specific trends, an increase in one per cent of flooded areas in a union leads to about a 2 per cent decrease in GPA-5.

Table 5.2: Flood and GPA-5 in SSC Exam

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Proportion Obtained GPA 5 in the SSC Exam				
Proportion of Union flooded	**-0.022*** **	**-0.015*** **	-0.001	**-0.016*** **	-0.000
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
No. of Students in School		-0.000***	-0.000**	-0.000***	-0.000***
		[0.000]	[0.000]	[0.000]	[0.000]
School FE		YES	YES	YES	YES
Year FE			YES		YES
Sub-district x year				YES	YES
No. of Observations	110,833	110,728	110,728	110,728	110,728
No. of Schools	14,676	14,685	14,685	14,685	14,685
adj. R^2	0.002	0.665	0.678	0.673	0.686

Note: Standard errors clustered at the union level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Now, we turn to the JSC examinations, and the dependent variable is the passing rate (Table 5.3). Similar to previous regression tables, we start with our variable of interest – the proportion of union flooded and gradually add all FEs. The passing rate is found to decline by about 2-5 per cent with a one per cent increase in flooded areas in a union, controlling for only school FEs and sub-district specific trends. However, when we control for year FEs, the size of the coefficient becomes very small, and the significance level drops to 10 per cent.

Table 5.3: Passing Rate in Junior School Certificate (JSC) Exam

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Proportion Passed the JSC Exam				
Proportion of Union flooded	**-0.020*** **	**-0.049*** **	**-0.015*** **	**-0.027*** **	**-0.009***
	[0.005]	[0.006]	[0.005]	[0.005]	[0.005]
No. of Students in School		-0.000***	-0.000***	-0.000***	-0.000***
		[0.000]	[0.000]	[0.000]	[0.000]
School FE	YES	YES	YES	YES	YES
Year FE			YES		YES
Sub-district x year				YES	YES
No. Observations	128,752	128,624	128,624	128,624	128,624
No. of Schools	[16,605]	[16,477]	[16,477]	[16,477]	[16,477]
adj. R^2	0.001	0.268	0.349	0.332	0.406

Note: Standard errors clustered at the union level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Now, we consider GPA-5 of the JSC examination (Table 5.4). The dependent variable is the proportion of students who obtained GPA-5 in the JSC exam. The impact of floods on GPA-5 in the JSC examination is smaller in magnitude and significant at a 10 per cent level when we include all FEs and sub-district-specific trends. A one per cent increase in flooded areas in a union lowers the GPA-5 in the JSC examination by 0.5 per cent. The coefficients for the size of schools are significant at a 1 per cent level, as before.

Table 5.4: Flood and GPA-5 in Junior School Certificate Exam

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Proportion obtained GPA-5 in the JSC Exam				
Proportion of Union flooded	**-0.017*** **	**-0.011*** **	**-0.007*** **	**0.007** **	**-0.005***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
No. of Students in School		0.000***	-0.000	-0.000***	0.000**
		[0.000]	[0.000]	[0.000]	[0.000]
School FE	YES	YES	YES	YES	YES
Year FE			YES		YES
Sub-district x year				YES	YES
No. of observations	125,515	12,5384	12,5384	125,384	125,384
No. of schools	[16,599]	[16,468]	[16,468]	[16,468]	[16,468]
adj. R^2	0.001	0.524	0.617	0.549	0.629

Note: Standard errors clustered at the union level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Flood and Female Students in Public Exams

There is ample evidence, both academic and anecdotal, that suggests that women and girls are affected more than men and boys in households in the face of natural disasters, particularly floods. Hence, in this section, we examine if the education outcomes, such as passing rates and GPA-5 of the female students, are worse than those of the male students due to floods. Similar to previous tables, we keep on adding the school and year fixed effects as well as sub-district specific trends in subsequent specifications (Table 5.6). Our regression results show that a one percentage increase in flooded areas in a union leads to about 2 percentage point lower passing rate for female students compared to male students. This result is very robust across specifications and significant at a 1 per cent level.

Now, we turn to the results on GPA-5. Table 5.6 presents the regression results. The dependent variable is the share of students who obtained a GPA-5 in the SSC examination in total students. The coefficients of the interaction term are highly robust to the inclusion of FEs and sub-district-specific trends. The share of female students with a GPA-5 drops by 0.04 percentage points compared to male students if the flooded area of a union increases by one per cent. All the coefficients of the interaction term are significant at 1 per cent level.

Table 5.5: Flood and Gender Differentials in Passing Rate in SSC Exam

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Proportion of Students Passed in the SSC Exam				
Proportion of Union flooded	-0.037***	-0.077***	-0.018***	-0.083***	-0.016***
	[0.004]	[0.006]	[0.006]	[0.006]	[0.006]
Proportion of Area Flooded (PF)* Female		**-0.019*** **	**-0.019*** **	**-0.018*** **	**-0.018*** **
		[0.003]	[0.003]	[0.003]	[0.003]
Female		0.009***	0.009***	0.009***	0.009***
		[0.001]	[0.001]	[0.001]	[0.001]
Total Number of Students in School		-0.000***	-0.000***	-0.000***	-0.000***
		[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.850***	1.434***	0.905***	27.870***	-54.176***
	[0.001]	[0.023]	[0.020]	[1.197]	[9.816]
School FE		YES	YES	YES	YES
Year FE			YES		YES
Sub-district x year				YES	YES
No. of Obs.	180,765	180,602	180,602	180,602	180602
No. of Schools	14,753	14,753	14,753	14,753	14,753
adj. R^2	0.002	0.223	0.271	0.259	0.305

Table 5.6: Flood and Gender Differentials in Obtaining GPA-5 in SSC Exam

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Proportion of Students obtained GPA-5 in the SSC Exam				
Proportion of Union flooded	-0.022***	-0.016***	0.002	-0.016***	0.003**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Proportion of Area Flooded* Female		**-0.004*** **	**-0.004*** **	**-0.004*** **	**-0.004*** **
		[0.001]	[0.001]	[0.001]	[0.001]
Female		0.001***	0.002***	0.001***	0.002***
		[0.000]	[0.000]	[0.000]	[0.000]
Total Number of Students in School		-0.000***	-0.000***	-0.000***	-0.000***
		[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.040***	0.047***	0.038***	0.043***	0.040***
	[0.001]	[0.004]	[0.006]	[0.006]	[0.006]
School FE		YES	YES	YES	YES
Year FE			YES		YES
Sub-district x year				YES	YES
No. of Obs.	173,727	173,565	173,565	173,565	173,565
No. of Schools	14,780	14,740	14,740	14,740	14,740
adj. R^2	0.002	0.559	0.571	0.567	0.579

Note: Standard errors clustered at the union level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In the case of the JSC examination, we find similar results for the female students. Table 5.7 presents the results for the passing rates of the JSC exam, and Table 5.8 presents the GPA-5 results. In both cases, floods lead to greater deterioration of JSC results for the female students. Similar to the SSC examination, the difference in the passing rate between male and female students is about 2 percentage points. This difference is highly robust and statistically significant at a 1 per cent level. The difference in obtaining a GPA-5 in the JSC examination is also very robust and significant, and this difference is higher than that of the SSC examination. The share of girls obtaining a GPA-5 is about 2 percentage points lower than the boys in the JSC exam because of floods.

Table 5.7: Floods and Gender Differentials in Passing Rates in JSC Exam

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Proportion of Students Passed in the JSC Exam				
Proportion of Union flooded	-0.018***	-0.023***	-0.003	-0.005	0.004
	[0.005]	[0.006]	[0.005]	[0.005]	[0.005]
Proportion of Area Flooded* Female		**-0.025*** **	**-0.018*** **	**-0.024*** **	**-0.018*** **
		[0.003]	[0.003]	[0.003]	[0.003]
Female		0.008***	0.008***	0.008***	0.008***
		[0.001]	[0.001]	[0.001]	[0.001]
Total Number of Students in School		-0.000***	-0.000***	-0.000***	-0.000***
		[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.877***	0.906***	0.910***	-8.552***	2.986
	[0.001]	[0.002]	[0.003]	[0.488]	[6.243]
School FE		YES	YES	YES	YES
Year FE			YES		YES
Sub-district x year				YES	YES
No. of Obs.	233,294	233,263	233,263	233,263	233,263
No. of Schools	16,605	16454	16454	16454	16454
adj. R^2	0	0.251	0.314	0.302	0.361

Note: Standard errors clustered at the union level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.8: Flood and Gender Differentials in GPA-5 Rate in JSC Exam

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Proportion of Students Obtained GPA-5 in the JSC Exam				
Proportion of Union flooded	-0.015***	0.015***	-0.004	0.021***	-0.001
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Proportion of Area Flooded* Female		**-0.015*** **	**-0.011*** **	**-0.015*** **	**-0.011*** **
		[0.002]	[0.002]	[0.002]	[0.002]
Female		0.018***	0.019***	0.018***	0.019***
		[0.000]	[0.000]	[0.000]	[0.000]
Total Number of Students in School		-0.000***	0	-0.000***	0.000***
		[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.047***	-0.135***	0.036***	-10.267***	0.022
	[0.001]	[0.010]	[0.007]	[0.491]	[1.674]
School FE		YES	YES	YES	YES
Year FE			YES		YES
Sub-district x year				YES	YES
No. of Obs.	225,274	224,811	224,811	224,811	224,811
No. of Schools	16,601	16,448	16,448	16,448	16,448
adj. R^2	0.001	0.473	0.543	0.485	0.553

Note: Standard errors clustered at the union level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Floods and School-Based Assessments

Table 5.9 shows the regression results for school-based assessments for grades 6 to 10 students. The first two columns report regression results for all students, while the last two columns report results for female students only. Unlike previous models, we control for the share of female students in schools. The coefficients for the flooded area show that the grade level passing or promotion rates are also affected by floods. A 1 per cent increase in flooded areas in a union leads to about a 3-4 per cent decline in passing rates for all students. This drop is significantly higher for the female students when we control for all FEs and sub-district level trends – 3.7 per cent for the girls as opposed to 3.2 per cent for all students.

Table 5.9: Flood and Promotion Rates in School-Based Assessments

	All Students		Female Students	
	1	2	3	4
Proportion of Area Flooded	**-0.038*** **	**-0.032*** **	**-0.040*** **	**-0.037*** **
	[0.006]	[0.007]	[0.008]	[0.009]
Total Number of Students in School	0	-0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Proportion of female students in school	-0.019***	-0.021***	0.399***	0.435***
	[0.004]	[0.005]	[0.133]	[0.122]
Constant	0.853***	0.858***	0.466***	0.452***
	[0.003]	[0.004]	[0.070]	[0.064]
Number of Schools	15,814	15,814	15,814	15,814
No. of Obs.	326,271	326,271	326,271	326,271
adj. R-sq	0.236	0.292	0.241	0.273
School-Grade Fixed Effect	YES	YES	YES	YES
Year	YES	YES	YES	YES
Sub-district x year		YES		YES

Note: Standard errors clustered at the union level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Table 5.10, we lump all grades together to examine the impact on grade-level results. However, the impact might vary with grades. We report grade-specific impact in Table 5.10. Our results show that the floods affect the students of the higher grades mostly–grade 8 and above. Interestingly, female students up to grade 8 appear immune to flood. The students of higher grades might be affected more because the materials taught in the classrooms are generally harder. Hence, absenteeism may have a larger impact on the results of higher grades. Moreover, students in the higher grades may have to spend more time in household work during floods than the younger ones, and this leaves lesser time for study.

Table 5.10: Flood and Grade-specific Promotion Rate in School-Based Assessments

	All		Female	
	1	2	3	4
Grade VI *Proportion of Area Flooded	-0.014	-0.006	-0.022	-0.017
	[0.007]	[0.008]	[0.013]	[0.014]
Grade VII*Proportion of Area Flooded	-0.016**	-0.01	-0.024*	-0.021
	[0.008]	[0.008]	[0.013]	[0.014]
Grade VIII*Proportion of Area Flooded	**-0.019****	**-0.014***	0.017	0.021
	[0.007]	[0.008]	[0.012]	[0.013]
Grade IX*Proportion of Area Flooded	**-0.067*****	**-0.066*****	**-0.083*****	**-0.083*****
	[0.010]	[0.011]	[0.016]	[0.016]
Grade X*Proportion of Area Flooded	**-0.066*****	**-0.066*****	**-0.070*****	**-0.071*****
	[0.010]	[0.010]	[0.015]	[0.015]
Total Number of Students in School	-0.000**	-0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.846***	0.850***	0.681***	0.685***
	[0.002]	[0.002]	[0.006]	[0.005]
No. of Schools	15,860	15,860	15,860	15,860
No. of observations	339,120	339,120	339,120	339,120
adj. R-sq	0.228	0.281	0.194	0.223
School Grade Fixed Effect	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES
Sub-district x year		YES		YES

Note: Standard errors clustered at the union level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Grade dummies are not reported in the table.

5.4 Severity of Flood and Education Outcomes

We discussed in Chapter 4 that the extent of flood measures has been categorised into four quantiles based on the percentage of areas flooded in a union in a year. The top quantile is termed severe flood, while the second is moderate flood. We use dummies for moderate and severe floods, and low and no flood is the base category. The regression results are reported in Table 5.11. The results show that compared to the low and no-flood groups (lowest two quantiles), only severe floods have a significant impact on the passing rates of the SSC exams for both boys and girls.

In short, we have found that floods do impact educational outcomes–they reduce passing rates and GPA-5 in both SSC and JSC examinations. Floods also adversely impact smarter students, as we have found that GPA-5 also drops due to floods. Similar to public examinations, we have found a significant impact on school-based exams. The impact of the flood is more pronounced for higher grade exams (SSC) than lower grade exams (JSC). More importantly, the female students are affected more than the male students. This is true for both public and school-based examinations.

Table 5.11: Severity of Floods and SSC Exam Results

	1	2	3	4	5	6
	Passing Rate in SSC Exam			Female Passing Rate in SSC Exam		
Moderate Flood	-0.002	0	-0.001	-0.003	-0.001	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Severe Flood	**-0.006*** **	**-0.006*** **	**-0.006*** **	**-0.007*** **	**-0.007*** **	**-0.007*** **
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]
No. of Students in School	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.873***	8.305***	-28.34***	0.873***	22.349***	-54.68***
	[0.003]	[0.495]	[7.256]	[0.003]	[0.584]	[9.571]
School FE	YES	YES	YES	YES	YES	YES
YEAR FE	YES		YES	YES		YES
Sub-district x year		YES	YES		YES	YES
N	112,124	112,124	112,124	97,529	97,529	97,529
adj. R^2	0.303	0.246	0.349	0.24	0.226	0.275

Note: Standard errors clustered at the union level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

CHAPTER 6
DISCUSSIONS

6.1 Channels of Impact

Since our analysis relies on estimating reduced form models, we cannot shed light on the channels through which the flood impacts education outcomes. The census data on education institutions do not allow us to observe the channels through which the impacts work. However, the literature on education production function helps us shed some light on the possible paths. In such production function, the common inputs are school resources, teachers' quality, peer composition, family or household attributes, including parental schooling, family size, and parental investment in child education. We briefly discuss how the school and household level inputs are affected by floods, which, in turn, can impact educational outcomes such as academic achievements.

6.1.1 School-level Inputs

Floods can affect schooling inputs such as teacher-student meeting hours due to the closure of schools and teachers' and students' absenteeism, school infrastructure including approach roads to schools, and household-specific inputs such as expenditure on education (e.g., study materials, private tuitions), nutrition, study hours, etc. There is anecdotal evidence that shows that a large number of households had to take shelter somewhere else during the flood, and the education of the children was the least priority of such households.[2] In order to provide some robust evidence on the channels through which floods impact schooling inputs, we use a dataset from a survey conducted by the Bangladesh Bureau of Education Information and Statistics (BANBEIS) of the Ministry of Education and UNICEF.[3] While only secondary schools are our subject of interest in this study, we include all four types of institutions to shed light on the fact that they are not different from other institutions as far as the impact of floods on education is concerned.

---

[2] For example, reports such as "many schools have had to be shut down due to the dwindling attendance of students who had taken refuge in flood shelters along with their family members. Books and other instruments have been lost or damaged while mid-term exams have been postponed (Dhaka Tribune, 2017)" become regular news in every monsoon in Bangladesh.

[3] This survey was designed to assess the impact of natural disasters on education. It covers 7 types of natural disasters and 1,800 educational institutions, including primary schools, secondary schools, madrasas, and colleges. The survey was conducted in 18 districts of Bangladesh in 2014. https://unesdoc.unesco.org/ark:/48223/pf0000246779/PDF/246779eng.pdf.multi

Table 6.1: Channels of Impacts of Floods on Education Outcomes

	Primary schools (N=843)	Secondary schools (N=550)	Madrasa (N=328)	Colleges (N=77)	Total (N=1798)
Floods cause damage to institutions almost every year (%)	57.96	57.45	66.16	56.41	59.23
Water supply and sanitation become ineffective due to floods (%)	52.02	52.55	51.52	50.00	52.00
Students experience difficulties coming to schools due to floods (%)	60.10	60.36	58.54	57.69	59.79
Number of days the institutions remained closed due to floods in the last flood	19.37 (21.85)	18.26 (22.44)	15.98 (16.74)	22.04 (24.03)	18.47 (21.32)
Value of damages in the last flood (BDT)	224,530 (590714)	314,459 (1173784)	312,811 (605776)	512,046 (874080)	279,231 (821297)

Note: The figures in the parentheses in the last two rows are the standard deviations. 2 observations are dropped due to missing values.

Data source: Bangladesh Bureau of Education Information and Statistics (BANBEIS), 2015.

Table 6.1 shows that about 59 per cent of the sample institutions reported that they were affected badly by floods almost every year, and this share was the highest for the madrasa (66 per cent). In the case of secondary schools, the share of damaged schools was about 57 per cent. Classes are less likely to take place when the infrastructure of schools is damaged, which leads to a reduced number of teacher-student meeting hours. The survey finds that 52 per cent of the institutions reported that their water supply and sanitation became ineffective. This percentage is about 53 per cent for secondary schools. This is an important cause of absenteeism among teachers and students, particularly among females. The percentage of institutions experiencing difficulties in coming to schools is very similar to the share of schools that experienced damage to the infrastructure. About 60 percent of institutions reported that students faced problems in coming to school due to floods, and the percentage is the same for secondary schools. This indicates that travelling to the schools becomes difficult during floods, which is likely to aggravate absenteeism problems.

The survey also reports the number of days the institutions were closed as well as the costs of damages due to the last flood. In the sample schools, students missed about 18 days due to the closure of the institutions. This is 22 days for the colleges and 18 days for the secondary schools. The institutions also reported the extent of damage due to the last flood in monetary terms. The average value of the damage was BDT 0.28 million per institution, with the highest damages for colleges – about half a million BDT. In short, the survey indicates that the infrastructure of the institutions, water and sanitation, and travel to the institutions are badly impacted by floods, and this can result in poorer academic performance for the students.

6.1.2 Household-level Inputs

Floods can directly impact the study time and study materials of the students of the affected households. Moreover, floods can lead to severe income and health-related shocks such as reduced agricultural yield and wages, unemployment, child labour (Eskander & Dendir, 2011), disease outbreaks, etc., affecting household-level inputs for education.

Table 6.2: Household-level Inputs Affected by Floods (Reported Causes of Irregular Attendance of Students in Schools by Institutions)

	Primary schools (N=843)	Secondary schools (N=550)	Madrasa (N=326)	Colleges (N=75)	Total (N=1794)
The family was displaced (%)	27.68	28.91	34.04	19.48	28.87
Education materials damaged (%)	30.31	31.82	41.03	27.27	32.60
Could not pay school fees (%)	9.07	10.00	9.42	5.19	9.25
Helped parents at home with household chores (%)	64.44	61.64	72.95	48.05	64.43
Engaged in income-earning activities (%)	53.22	47.27	52.58	38.96	50.67

Note: Six observations are dropped due to missing values.
Data source: Bangladesh Bureau of Education Information and Statistics (BANBEIS), 2015.

In order to shed some light on the extent of the impact on household-level inputs, we again resort to the BANBEIS-UNESCO survey, as discussed above. Table 6.2 reports the major causes of the irregular presence of students in schools by institutions, as stated by the institutions. Time demanded in household chores in the post-flood periods has been reported as a major cause of irregular attendance in institutions. About 64 per cent of the institutions reported this as a major cause for the full sample. This percentage was the highest for madrasas, which was about 73 per cent. In the case of secondary schools, this figure was about 62 per cent. The next major cause reported was involvement in income-earning activities. Evidence suggests that floods exacerbate the child labour situation in rural areas. About 51 per cent of the full sample and 47 per cent of the secondary schools reported that greater engagement in income-earning activities has led to lower class attendance.

Apart from these two causes, displacement of the family and damage to education materials are also reported to have impacted irregular attendance. The percentages of the institutions that reported these two causes were 29 and 33, respectively. We observe a similar magnitude for secondary schools. While literature finds income shock as an important channel, this channel seems to work less through parents' ability to pay school fees. Only about 9 per cent of institutions reported that students' irregular attendance was caused by their inability to pay fees.

6.2 Floods and Gender Inequality in Education

Our results on the impact of floods on female students are very strong and robust. We find that female students systematically perform worse than male students both in public examinations and school-based assessments when the union is flooded more. This has adverse consequences on achieving higher gender parity in education and promoting female labour participation and intergenerational transmission of human capital. Hence, our study also contributes to the literature on gender bias in human capital accumulation (Zimmermann, 2020; Maccini & Yang, 2009).

It is generally argued that women's low bargaining power and lower socioeconomic status give them disproportionately higher risk exposure to natural disasters than men (Neumayer & Plumper, 2007). The gender disparities in disaster and climate change vulnerability not only reflect preexisting gender inequalities but also reinforce them (Eastin, 2018). Our results suggest one additional reinforcing factor: the affected students' academic performance.

There are several reasons that can be argued to be responsible for poorer results by female students due to floods. Girls' household chores become more difficult to perform during a flood—cooking, cleaning, caring for siblings and the elderly, fetching drinking water[4], etc. become more cumbersome and time-consuming, leaving little time for study. Moreover, inundation and damage to roads to schools impact the attendance of female students more adversely than male students in schools. The hygiene of the toilets in schools is also compromised during floods, which may discourage girls from attending schools more than boys. Poor performance in schools due to floods may lead to dropouts, which may result in

[4] In 2017 flood 54,345 tube-wells were damaged in 19 districts, and this led to additional pressure on girls, who are traditionally responsible for collecting drinking water (UNICEF, 2017).

early marriages of girls.[5] This loss of human capital may adversely impact their labor market potential, bargaining power in the households as well as the health and education of the next generations[6].

While the success of many developing countries like Bangladesh in achieving the gender parity target in education in the Millennium Development Goals (MDGs) is noteworthy, the measurement of gender parity in terms of enrollment only has been under question. Xu, Shonchoy and Fujii (2019) showed that household-level inputs such as education expenditure, private tutoring, etc., are much lower for girls than boys in Bangladesh, indicating lower academic performance of the girls in the schools. Our results indicate that floods may compound the problem of resource (time and money) allocation between boys and girls, resulting in poorer results in schools and, thus, aggravating gender inequality in education.

[5] "Why climate change is creating a new generation of child brides" (The Guardian, 2017).
[6] Ahmed and Iqbal (2016) found that if mothers' education does not exceed secondary level, it cannot produce any significant impact on their children's health.

CHAPTER 7
CONCLUSION

In this study, we combine the flood measures created from satellite images with the census data of high schools for the period 2011-2018 at the lowest administrative level of Bangladesh. Exploiting within-school variations of passing rates and GPA-5 in both public exams and school-based assessments, we find that the adverse impact of floods on students' academic performance is significant. Importantly, the impact is significantly higher for female students. This is the first robust evidence on the impact of floods on academic performance, which has a strong bearing on both the education and disaster management policies of flood-prone developing countries.

The results of our study have important policy implications for both disaster/climate change and education sectors in flood-prone developing countries. Estimation of the cost of disasters such as floods often ignores its impact on human capital. While these costs are both direct and indirect in nature and very complex to estimate, it is important to appreciate the existence of such costs and their extent. Considering its impact on human capital and thus the long-term growth, the results shed light on the importance of protecting the school infrastructure as well as the complementary inputs such as connecting roads from natural disasters. The education policies and strategies of the disaster-prone countries are require to recognise the implications of the impact of disasters on education outcomes.

Our estimated impact of floods is the net effect, accounting for the household responses. It is obvious that household responses are not enough to mitigate the impact of floods on education outcomes. The government can intervene with specific programs such as extra hours of teaching in the post-disaster periods with special allowances for the teachers. Evidence suggests that standard conditional cash transfer programs in Mexico, where the transfer depends on school attendance, were effective in keeping children in the schools in the face of shocks (Janvry et al., 2006). There is also evidence that in the aftermath of floods, the incidence of child labour increases (Eskander & Dendir, 2011). However, this incidence is found to be lower in households with greater access to credit. Hence, the provision of special credit to the affected households can also prevent flood-induced dropouts and child labour.

In short, the academic achievements of the students in the flood-prone areas are found to be systematically lower than those of the other regions. This can create regional poverty traps through lower human capital. Hence, targeted programs are required for flood-prone educational institutions to better manage the impact of disasters.

REFERENCES

Ahmed, M., & Iqbal, K. (2016). Is there any threshold in the relationship between mother's education and child health? Evidence from Nigeria. *The Developing Economies*, *54*(3), 243-256.

Alderman, H., Hoddinott, J., & Kinsey, B. (2006). Long-term consequences of early childhood malnutrition. *Oxford Economic Papers*, *58*(3), 450-474.

Alderman, H., Hoogeven, H., Rossi, M. (2008). Preschool nutrition and subsequent school attainment: Longitudinal evidence from Tanzania. *Economic Development and Cultural Change.*

Alvi, E., & Dendir, S. (2011). Weathering the storms: Credit receipt and child labor in the aftermath of the great floods (1998) in Bangladesh. *World Development*, *39*(8), 1398-1409.

Banerjee, L. (2007). Effect of flood on agricultural wages in Bangladesh: An empirical analysis. *World Development*, *35*(11), 1989-2009.

Bangladesh Bureau of Education Information and Statistics (BANBEIS), 2015. Climate change, education for sustainable development in Bangladesh. Ministry of Education, Government of Bangladesh.

Caruso, G. D. (2017). The legacy of natural disasters: The intergenerational impact of 100 years of disasters in Latin America. *Journal of Development Economics*, *127*, 209-233.

Checchi, D., & García-Peñalosa, C. (2004). Risk and the distribution of human capital. *Economics Letters*, *82*(1), 53-61.

Chen, J. J., Mueller, V., Jia, Y., & Tseng, S. K. H. (2017). Validating migration responses to flooding using satellite and vital registration data. *American Economic Review*, *107*(5), 441-445.

Cho, H. (2017). Effect of summer heat on test scores: A cohort analysis. *Journal of Environmental Economics and Management*, *83*, 185-196.

Cuaresma, J. C. (2010). Natural disasters and human capital accumulation. *The World Bank Economic Review*, *24*(2), 280-302.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature*, *52*(3), 740-798.

Eastin, J. (2018). Climate change and gender equality in developing states. *World Development*, *107*, 289-305.

EM-DAT (undated). The OFDA/CRED International disaster database, Université catholique de Louvain, Brussels, Belgium http://www.emdat.be/

Flood Forecasting and Warning Center (undatd), Bangladesh Water Development Board, Government of Bangladesh.

NBER Working Papers. (2011). *School resources and educational outcomes in developing countries: A review of the literature from 1990 to 2010* (17554). Cambridge, Massachusetts: Glewwe, W., Hanushek, E. A., Humpage, S. D., and Ravina, R.

NBER Working Paper (2015). *Temperature and human capital in the short- and long-run (*21157*).* Cambridge, Massachusetts: Graff Zivin, J., Hsiang, S. M., & Neidell, M.

Guiteras, R., Jina, A., & Mobarak, A.M. (2015). Satellites, self-reports, and submersion: Exposure to floods in Bangladesh. *American Economic Review: Papers and Proceedings*. *105*(5), 232-236.

Hanushek, E. A. (2008). Education production functions. *The New Palgrave Dictionary of Economics*. Basingstoke.

Islam, A. S., Bala, S. K., & Haque, M. A. (2010). Flood inundation map of Bangladesh using MODIS time-series images. *Journal of Flood Risk Management*, *3*(3), 210-222.

Jacoby, Hanan G. and Emmanuel Skoufias. (1997). Risk, financial markets, and human capital in a developing country. *The Review of Economic Studies*, *64*(3), 311-335

Janvry, Alain, Frederico Finan, Elisabeth Sadoulet and Renos Vakis. (2006). Can conditional cash transfer programs serve as safety nets in keeping children at school and from working when exposed to shocks? *Journal of Development Economics*, 79(2), 349-373.

Maccini, S., & Yang, D. (2009). Under the weather: Health, schooling, and economic consequences of early-life rainfall. *American Economic Review*, *99*(3), 1006-1026.

Neumayer, E., & Plümper, T. (2007). The gendered nature of natural disasters: The impact of catastrophic events on the gender gap in life expectancy, 1981–2002. *Annals of the Association of American Geographers*, *97*(3), 551-566.

Department of Economics, Harvard University Working Paper (2017). *Hot Temperature, Human Capital and Adaptation to Climate Change.* Cambridge: Park, J.

Sakamoto, T., Van Cao, P., Van Nguyen, N., Kotera, A., & Yokozawa, M. (2009). Agro-ecological interpretation of rice cropping systems in flood-prone areas using MODIS imagery. *Photogrammetric Engineering & Remote Sensing*, *75*(4), 413-424.

Sakamoto, T., Van Nguyen, N., Kotera, A., Ohno, H., Ishitsuka, N., & Yokozawa, M. (2007). Detecting temporal changes in the extent of annual flooding within the Cambodia and the Vietnamese Mekong Delta from MODIS time-series imagery. *Remote Sensing of Environment*, *109*(3), 295-313.

Shah, M., & Steinberg, B. M. (2017). Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital. *Journal of Political Economy*, *125*(2), 527-561.

Skidmore, M. and Toya, H. (2002). Do natural disasters promote long-run growth? *Economic Inquiry, 40*(4), 664–687.

Todd, P. E., & Wolpin, K. I. (2003). On the specification and estimation of the production function for cognitive achievement. *The Economic Journal*, *113*(485), F3-F33.

UNICEF (2017). *Bangladesh Humanitarian Situation Report (Monsoon Floods).* Dhaka, Bangladesh.

Xiao, X., Boles, S., Frolking, S., Li, C., Babu, J. Y., Salas, W., & Moore III, B. (2006). Mapping paddy rice agriculture in South and Southeast Asia using multi-temporal MODIS images. *Remote Sensing of Environment*, *100*(1), 95-113.

Xiao, X., Boles, S., Liu, J., Zhuang, D., Frolking, S., Li, C., & Moore III, B. (2005). Mapping paddy rice agriculture in southern China using multi-temporal MODIS images. *Remote Sensing of Environment*, *95*(4), 480-492.

SMU Economics & Statistics Working Paper. (2019, September). *Illusion of gender parity in education: Intrahousehold resource allocation in Bangladesh.* Singapore: Xu, S., Shonchoy, A., & Fujii, T.

Zimmermann, L. (2020). Remember when it rained–Schooling responses to shocks in India. *World Development*, *126*, 104705.

Appendix

A.1 Construction of Flood Measures

In particular, we use the Terra MODIS vegetation indices version 6 (MOD13Q1 V6) data generated every 16 days at 250m spatial resolution as a level 3 product for the spatial extent of Bangladesh. This dataset is available for the year 2000 to the present. The MOD13Q1 V6 product provides two primary preprocessed Vegetation Index (VI) values on a per-pixel basis. The first is the Normalised Difference Vegetation Index (NDVI) and the second vegetation index is the Enhanced Vegetation Index (EVI). The NDVI and EVI indices are generated from atmospherically corrected bi-directional surface reflectance that has been masked for water, clouds, heavy aerosols, and cloud shadows. MODIS images are collected daily; however, the vegetation products are composites of the best pixels from 16 consecutive days. The algorithm chooses the best available pixel value from all the acquisitions from the 16 days. The criterion used is low clouds, low view angle, and the highest VI value. Compared with other space and airborne sensors and radiometric field measurements, the accuracy of the MOD13Q1 V6 is now within ±0.025, which indicates that the MODIS VI product has achieved the validation stage 3. The MOD13Q1 product provides pixel value for reflectance bands 1: Red, 2: NIR (near-infrared), 3: Blue, and 7: MIR (mid-infrared).

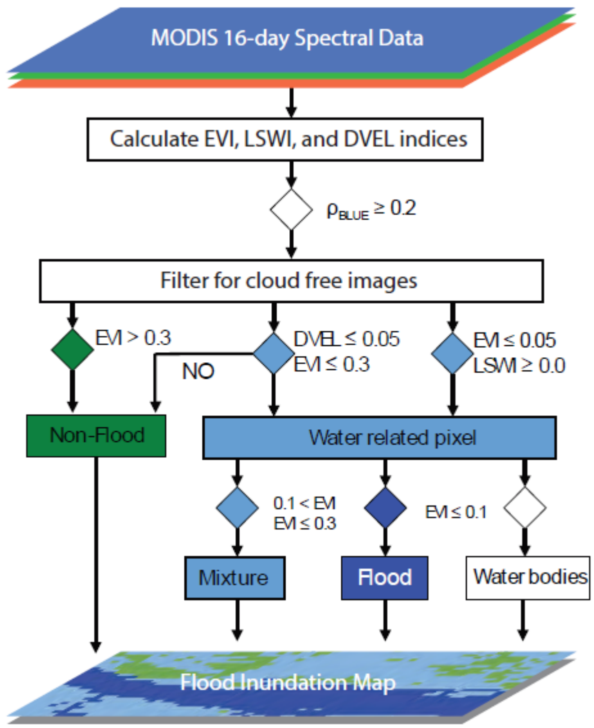
The inundation measures are constructed based on geo-location-specific comparisons of pixel values derived from satellite images during the dry season and flood season (mainly during the monsoon season). The algorithm described in the following diagram (Figure A1) indicates whether a grid-level pixel is associated with one of the following categories: the flood, mixed, non-flood, and water-related pixel.

The steps of the algorithm are as follows:

- Step 1: Detect cloud cover pixels from the image. If blue reflectance (band 3) is equal to or greater than 0.2, it is a cloudy pixel, and the band 2 (NIR) and band 7 (MIR) pixels for the corresponding locations are treated as missing. Then, the concept of a moving window filter is used to calculate a moving window mean for such a grid from a specified neighbourhood around that grid.
- Step 2: Compute the Land Surface Water Index (LSWI) defined as LSWI = (NIR - MIR)/ (NIR + MIR), and a difference value between EVI and LSWI (DVEL) describes as DVEL = LSWI - EVI.

➢ Step 3: Identify the water-related and the non-flood pixels according to the original method developed by Xiao et al. (2005, 2006). Based on the EVI, LSWI, and DVEL, we classify the grid as flood, mixed, non-flood, and water-bodies by following the classification criteria in Figure A1.

Figure A1: Construction of Flood from Remote Sensing Data



A.2 Validation of Flood Maps

i. With HIES data

The Household Income and Expenditure Survey (HIES) is similar to the Living Standard Measurement Survey (LSMS) – a survey that is almost universally used to measure the socioeconomic status of citizens. We use the latest HIES to validate our measures of flood constructed by remote sensing data. While the self-reported incidence of natural disasters can be subject to reporting errors stemming from cognitive bias, such as reference dependence (Guiteras et al. 2015), this can still be a useful benchmark. The section on shocks and coping (6B) of the questionnaire includes a question "did you experience shock in the past 12 months?" and the options include flood. Out of 46,026 households, 2,673 (5.81%) households reported that they experienced a flood in the past 12 months. We then collapse these households at the union level to create a union-level measure of flood. This yields 2204 unions, and the average flood measure is 0.0589.

Now, we compare this union-level self-reported flood measure with the measure created from satellite data. Note that since the survey of HIES was conducted in 2016, we consider satellite dates to be 2015 and 2016 only. We consider 2016 because it is likely that a part of the sample was surveyed after the wet season of 2016.

We regress the satellite measures of flood on the survey measures of flood at the union level, controlling for district dummies. The results are reported in Table A below. The coefficients of flood measures based on satellite show a strong correlation between these two measures, and they are highly significant. This is in the order of 0.25 for both years. The strong correlations persist even after controlling for district dummies.

Table A1: Survey-based vs. Satellite-based Flood Measures

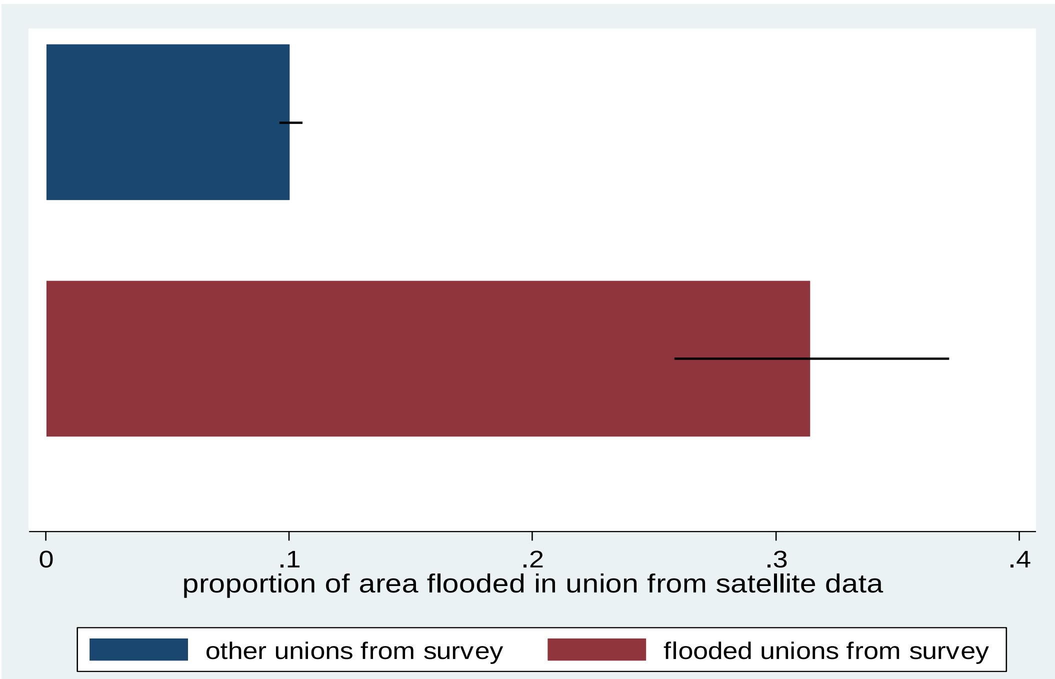
	Satellite measure 2015		Satellite measure 2016	
	(1)	(2)	(1)	(2)
Flood measures based on satellite	0.252***	0.177***	0.254***	0.159***
	(0.037)	(0.033)	(0.040)	(0.035)
Constant	0.035***	-0.001***	0.038***	-0.005***
	(0.005)	(0.000)	(0.005)	(0.001)
District dummy	No	Yes	No	Yes
Observations	1,752	1,752	1,750	1,750
R-squared	0.067	0.346	0.055	0.340

Note: Robust standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Dependent variable: Percentage of households in a union mentioned that they experienced a flood in the past 12 months.

ii. With BANBEIS data

In order to examine the quality of satellite data, we rely on two sets of observational data– i) a census of high schools conducted by BANBIES, and ii) a survey of educational institutions in the disaster-prone areas by BANBEIS in 2014, sponsored by UNESCO. The census of high schools is conducted every year, which contains information on about 18 thousand schools across the country. Each school has a unique identifier - EIIN number. On the other hand, the UNESCO survey, conducted in 2014 only in the disaster prone districts, covers 1800 educational institutions. However, this survey includes primary schools, secondary schools, colleges, madrasa, and vocational institutions. So, we select only secondary schools from this sample and the number of secondary schools is 550 with a unique EIIN number. This allows us to merge this sub-sample with the census data using the EIIN number of each school.

Figure A2: Extent of Flood at the Union Level: Satellite Data vs. Survey Data



A key advantage of the UNESCO survey is that it has a detailed module on different types of disasters and, in particular, whether the locality of the school experienced floods or not. There are three frequencies of incidence of flood in the survey – every year, once in 2-5 years and once in more than 5 years. In this case, we combine all three options and create a dummy variable if the locality of the school is a flood-prone area or not. Note that out of 550 schools, 93 schools reported that they didn't experience a flood at all. So, we consider that 457 schools are in flood-prone areas. If our satellite-based flood measures are a good proxy for actual flood, we expect to find a high flood measure in the unions of these 457 schools. Since the UNESCO survey was conducted in 2014, we examine the satellite flood measures for 2013.

We use all other secondary schools as our comparison group, and this data comes from the school census. In short, we compare the satellite-based flood measures of the flood-prone areas with those of the rest of the country at the union/ward level. Since each union can have multiple schools, we collapse the data at the union level. If there are three schools in a union, for example, and two of them are in flood-prone areas, the value of the survey-based flood indicator of the union is 0.66.

Figure A2 shows the satellite-based measures of flood for both flood-prone unions and other unions/wards of the country. It shows that in the flood-prone unions, about 34.17 per cent of the area was flooded in 2013, whereas this figure is only about 10.07 per cent for other unions/wards. In order to probe more, we regress the percentage of areas flooded in a union in 2013 constructed by satellite data on the union-level indicator of flood from school survey data, controlling for district dummies. The regression results reported in Table A2 show that the coefficient of the survey-based flood indicator is statistically significant at a 1 per cent level, indicating high predicting power. Moreover, the R-sq is also high (0.25).

Table A2: Regression Results: Correlation between Satellite and Survey Measures of Flood

Variables	
Indicator for flood-prone area from survey [0,1]	0.167***
	(0.028)
Constant	0.119***
	(0.012)
District dummy	Yes
Observations	5,084
R-squared	0.248

Note: Robust standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Dependent variable: Percentage of areas flooded (constructed from satellite data) in a union in 2013.