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Satellites, Self-reports, and Submersion: Exposure to Floods in Bangladesh†

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A burgeoning "climate economy" literature (Dell, Jones, and Olken 2014) attempts to understand and project the economic impacts of anthropogenic climate change. This literature has largely focused on uncovering the effects of changes in temperature and precipitation on economic activity. Important papers have documented both short-run effects—for example, on agriculture (e.g., Schlenker and Roberts 2009), health (e.g., Deschênes and Greenstone 2011), and labor (e.g., Graff Zivin and Neidell 2013)—and long-run effects—for example, on economic growth (Dell, Jones, and Olken 2012), and education (e.g., Maccini and Yang 2009). This has been made possible by the availability of temperature and precipitation data with reasonable spatial and temporal resolution.

Global climate change is not only expected to alter temperature, it is also projected to cause more powerful cyclones, greater coastal storm surges, and increased frequency and severity of flooding (Intergovernmental Panel on Climate Change 2014). The economics literature has made less progress in modeling the socioeconomic effects of these other phenomena expected to be associated with climate change, and which may have more intense, deleterious effects in the short run. A handful of recent papers have used physical science models to create such data (e.g., Anttila-Hughes and Hsiang 2012; Hsiang and Jina 2014). However, no similar effort has been made for flooding, a class of disaster that affects more people than any other (EM-DAT 2012). We describe the progress we have made in creating a time series of flood exposure derived from a new analysis of satellite data. We focus on the lower Ganges Delta, and the nation of Bangladesh in particular, one of the countries historically most affected by floods, and predicted to experience increasing flood severity due to climate change (Mirza 2011).

This paper makes two key contributions. First, we present new, objective long-run time series measures of floods that will allow us to study human behavioral responses to changes in the distribution of disaster events. In particular, the unexpected nature of the change may itself have productivity consequences separate from the occurrence of a disaster event. The socioeconomic consequences of the disaster may therefore depend on the novelty factor, i.e., how much experience people already had in dealing with similar events in the past. This is a dimension of adaptation that is possible to study only with rich data on the variation in background frequency of exposure at the locations where those events occur. Our dataset does exactly this, giving accurate measures of both the long-term average and the short-term variation in exposure required to study adaptation.[1]

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[1] In an analogous approach, Hsiang and Jina (2014) use a physical model to examine responses to tropical cyclones in groups of countries with a range of average exposures, from

Second, we show that rainfall and self-reported exposure are weak proxies for true flood exposure. The most damaging floods are caused by rivers bursting their banks, generally caused by rainfall occurring over an entire river basin[2] and not just directly above where flooding occurs. We demonstrate that flooding in districts in Bangladesh is not directly correlated with rainfall at those specific locations. Floods are a result of complex hydrology and this lack of correlation will likely hold in many locations around the world. We also show that self-reported exposure is a weak proxy for objective exposure, and that measurement error is likely to be correlated with important determinants of socioeconomic outcomes, in particular mean exposure to floods.

I. Measuring Floods and Their Impacts

In the climate impacts literature, we wish to estimate the following equation:

$$(1) \qquad y = f(E) + \varepsilon\,,$$

where y represents an outcome of interest and E represents environmental exposure. Unbiased, precise estimation of f requires accurate data on both outcomes and exposures. For example, we could model agricultural yields, y, as a function of temperature and precipitation, $f(T,P)$. In contrast, much of the work on the impact of extreme events has relied on self-reported survey data or nationally reported disaster statistics for both the left-hand side variable y (e.g., damage, losses) and the right-hand side variable E (e.g., subject states her household was affected by flooding). This is equivalent to modeling:

$$(2) \qquad y_1 = f(y_2) + u$$

with y_1 and y_2 both being outcomes of some underlying environmental exposure, leading to compounding of errors:

$$(3) \qquad y_1 = f(E) + \varepsilon + u.$$

In agriculture, this would be similar to estimating the effect of climate on income by regressing income on agricultural yields, which clearly would provide little information about the relationship of interest. Additionally, errors in measurement, u, may be correlated with ε, which represents other determinants of outcomes. For example, poorer households might be more exposed but less able to assess damages accurately.

To estimate the impacts of floods we face a singular problem: no comprehensive database of flood exposure through time exists for Bangladesh. We derive flood extent for each union[3] in Bangladesh using remote-sensing data collected by the NASA Moderate Resolution Imaging Spectroradiometer (MODIS). MODIS is an array of satellites that scan the Earth's surface every two days, recording reflectance values over 36 bands in the visible and infrared spectra. As clouds are opaque to visible and infrared light, cloud cover will restrict the use of images for detecting surface properties. Due to this, data are processed into cloud-free composites of 16 days. Composite data are available for the period 2000–2013 at 250m $\times$ 250m resolution. This results in a total of 3,159 $\times$ 2,482 pixels for each of 253 time periods. These 1.98×10^9 pixels are used to derive flood extents for the whole period.

We follow the framework of Sakamoto et al. (2009) and adapt it based on extensive fieldwork and observation in Bangladesh in 2012. 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 that for greenness then we can say that there is overlying surface water. In practice, the algorithm for classifying floods is more complex, though the intuition remains the same.

The land surface at each point in time is classified into three categories: (i) *Non-flood*: pixels which show no evidence of standing surface water; (ii) *Mixed*: pixels which show a mixture of standing water and vegetation; and (iii) *Flood*: pixels which are unambiguously flooded over their whole extent. We then use the time

low to high. They find significantly larger marginal effects in the "naïve," or less frequently exposed, countries.

[2] See online Appendix Figure 1 for a map of the entire scale of the river system of which Bangladesh is part.

[3] Administrative units have the following hierarchy: Division $\supset$ District (Zila) $\supset$ Sub-district (Upazila) $\supset$ Union. Unions have an average size of approximately 10–20 km^2.

dimension to distinguish between temporary flooding and permanent water.

II. Other Data

Survey Data.—We use the nationally representative Child and Mother Nutrition Survey (CMNS) of Bangladesh 2005 (BBS/UNICEF 2007), which focuses on children aged 0–59 months and their mothers. Data were collected throughout 2005. Importantly for the current analysis, questions were asked about the impact of floods during the monsoon season in 2004, regarded as a particularly bad flood year. Fifty-seven percent of households report being affected by the 2004 floods.

Rainfall Data.—Rainfall data for each district in Bangladesh is derived from the Tropical Rainfall Measuring Mission satellite at daily frequency from 1998 to 2013. This is summed to give monthly totals.

Merging Data.—Pixel-level floods data are projected onto union boundaries, obtained from the Government of Bangladesh's Local Government Engineering Division (LGED) and averaged at the union level. Unions are matched to the CMNS via Bangladesh Bureau of Statistics (BBS) geocodes. We exclude urban locations, resulting in 1,792 households.

III. Results

A. *Rainfall versus Flooding*

Flooding in Bangladesh results from rainfall accumulating over the entire river basin. Flooding in a particular place may be less influenced by nearby rainfall than by a complex and broad set of hydrological conditions in an area approximately ten times its size. We estimate the correlation between monthly rainfall and monthly flood extent measured at the Zila (district) level over the period 2002–2011 (Figure 1). The overall correlation is positive but modest (0.09), and far from uniform throughout time. In fact, correlation is negative for approximately 40 percent of the months between 2002 and 2011, and the tenth to ninetieth percentiles span −0.27 to 0.42. We conclude that rainfall is a poor proxy for floods. This will be especially true when the exact timing of a flood is important—for example, a flood that occurs during a sensitive growing period for crops or during a vulnerable stage of human development may have disproportionately large impacts.

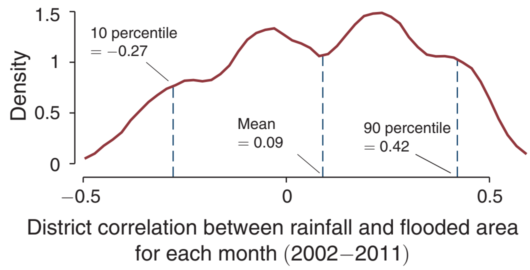

Figure 1. Distribution of Correlation Coefficients, ρ_t ($flood_i$, $rain_i$) for All Districts, i, in Bangladesh for Each Month, t, in Our Dataset

B. *Self-reports versus Satellites*

Self-reported data are not only subject to recall error, but also to other forms of cognitive bias like reference dependence. A flood which has a larger effect might have greater pertinence and so be more likely to be reported. Of particular concern for analysis of flooding is that people may adapt to the average exposure conditions, viewing them as a reference point to judge deviations from that average. This would imply that a household frequently exposed to larger floods and one not frequently exposed may view a flood of the same magnitude in different ways. We must also be concerned that this difference will result from adaptation. This could be positive (a household invests in protecting vulnerable productive assets and property when flood impacts are understood) or negative (a household ceases to invest in vulnerable assets, accepting some decrease in productivity in the process).

In Table 1 we divide households into those that reported they were affected in a variety of ways by the 2004 floods, and those who reported no such effects. We present the number of households answering "Yes" and "No" in each case. We then estimate the average flood exposure across all households in each category. We see that households reporting "Affected by July '04 floods" did experience a higher objective flood exposure (11.8 percent inundation compared to 6.5 percent for those answering

TABLE 1—COMPARISON OF SELF-REPORTED FLOOD EFFECTS AND OBJECTIVELY MEASURED FLOODED AREA

	Answered "YES" to survey question		Answered "NO" to survey question	
	No. of HH answered YES	Satellite-derived flood proportion average	No. of HH answered NO	Satellite-derived flood proportion average
Survey question				
Affected by July '04 floods	900	0.118	892	0.065
House damaged/lost	534	0.155	366	0.063
Latrine damaged/lost	307	0.152	593	0.100
Water source damaged/lost	142	0.169	758	0.108
Food stocks damaged/lost	64	0.248	836	0.108
Crops damaged/lost	667	0.114	233	0.130
Farm destroyed	197	0.076	703	0.129
Livestock died	67	0.169	833	0.114
HH members sick	49	0.239	851	0.111
HH members died	3	0.094	897	0.118
Lost employment/inc. source	102	0.096	798	0.121

Notes: Values in the YES and NO columns represent the objectively measured flood extent in July 2004 as a proportion of total sub-district area, averaged over the number of households who reported either an effect or no effect. Each row is a separate question asking about self-reported damages from flooding in July 2004.

"No"). However, if we look at the exposure of those who lost their farms, we see the opposite pattern. Households in riskier areas could have changed farming practices, and so those who reported losing their farms may have been affected by a smaller, but unexpected flood.

We then examine the response of households at low average exposure levels to the deviation of the 2004 flood from their local average, and compare this to the response of households at higher average levels. We run a logit regression to determine the probability of reporting being "affected" as a function of average exposure, the deviation from average in July 2004, and their interaction.[4] Figure 2 shows that low exposure households are more likely to report being affected if they experience a larger flood (dashed line). In contrast, high exposure households reporting is comparatively inelastic to flood size in 2004. Households in each category appear to perceive exposure relative to their average environment. This renders self-reports of little value, and points to the need for objective measures of exposure.

[4]Full results shown in online Appendix Table 1.

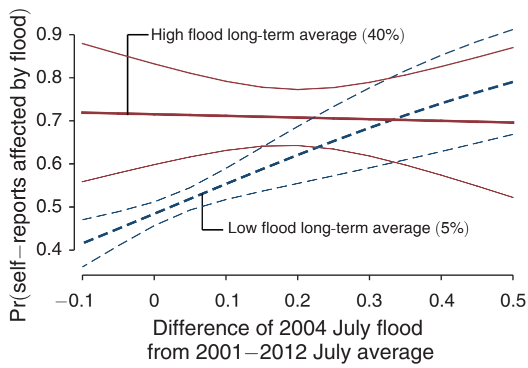

FIGURE 2. INTERACTION BETWEEN AVERAGE FLOOD EXPOSURE AND FLOOD EXPOSURE IN 2004
(*95 percent confidence interval shown*)

IV. Conclusions and Future Directions

People appear to be adapted to their average environment, and to experience seemingly similar shocks differently. This limits the usefulness of self-reported data in understanding the impacts of an extreme event like flooding. Moreover, without knowledge of average levels of exposure, we are unable to understand what this adaptation might entail. This is crucial when trying to understand the impacts of climate change, as people will not only experience new exposures, but also experience them differently. Future work will aim to identify these differential responses, and to characterize adaptive investments and behaviors.

REFERENCES

Anttila-Hughes, Jesse K., and Solomon M. Hsiang. 2011. "Destruction, Disinvestment, and Death: Economic and Human Losses Following Environmental Disaster." Unpublished.

Bangladesh Bureau of Statistics (BBS), and UNICEF. 2007. *Child and Mother Nutrition Survey of Bangladesh 2005*. Dhaka: Bangladesh Bureau of Statistics and UNICEF.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics* 4 (3): 66–95.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2014. "What Do We Learn from the Weather? The New Climate-Economy Literature." *Journal of Economic Literature* 52 (3): 740–98.

Deschênes, Olivier, and Michael Greenstone. 2011. "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US." *American Economic Journal: Applied Economics* 3 (4): 152–85.

EM-DAT. 2012. The OFDA/CRED International Disaster Database. Brussels: Université Catholique de Louvain.

Graff Zivin, Joshua, and Matthew Neidell. 2013. "Environment, Health, and Human Capital." *Journal of Economic Literature* 51 (3): 689–730.

Hsiang, Solomon M., and Amir S. Jina. 2014. "The Causal Effect of Environmental Catastrophe on Long-run Economic Growth: Evidence from 6,700 Cyclones." National Bureau of Economic Research Working Paper 20352.

Intergovernmental Panel on Climate Change (IPCC). 2014. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects.* Cambridge: Cambridge University Press.

Maccini, Sharon, and Dean Yang. 2009. "Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall." *American Economic Review* 99 (3): 1006–1026.

Mirza, M. Monirul Qader. 2011. "Climate Change, Flooding in South Asia and Implications." *Regional Environmental Change* 11 (S1): 95–107.

Sakamoto, Toshihiro, Van Cao Phung, Van Nguyen Nhan, Akihiko Kotera, and Masayuki Yokozawa. 2009. "Agro-Ecological Interpretation of Rice Cropping systems in Flood-Prone Areas Using MODIS Imagery." *Photogrammatic Engineering and Remote Sensing* 75 (4): 413–24.

Schlenker, Wolfram, and Michael J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to US Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences of the United States of America* 106 (37): 15594–98.

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1. Azreen Karim, Ilan Noy. 2020. Risk, poverty or politics? The determinants of subnational public spending allocation for adaptive disaster risk reduction in Bangladesh. *World Development* **129**, 104901. [Crossref]
2. Thi Ngoc Tu Le. 2020. Floods and Household Welfare: Evidence from Southeast Asia. *Economics of Disasters and Climate Change* **4**:1, 145-170. [Crossref]
3. Giang Nguyen, Trung Thanh Nguyen. 2020. Exposure to weather shocks: A comparison between self-reported record and extreme weather data. *Economic Analysis and Policy* **65**, 117-138. [Crossref]
4. Meha Jain. 2020. The Benefits and Pitfalls of Using Satellite Data for Causal Inference. *Review of Environmental Economics and Policy* **14**:1, 157-169. [Crossref]
5. Joyce Chen, Valerie Mueller. 2019. Climate-induced cross-border migration and change in demographic structure. *Population and Environment* **41**:2, 98-125. [Crossref]
6. Diana De Alwis, Ilan Noy. 2019. The Cost of Being Under the Weather: Droughts, Floods, and Health-Care Costs in Sri Lanka. *Asian Development Review* **36**:2, 185-214. [Crossref]
7. Maike Hamann, Kevin Berry, Tomas Chaigneau, Tracie Curry, Robert Heilmayr, Patrik J.G. Henriksson, Jonas Hentati-Sundberg, Amir Jina, Emilie Lindkvist, Yolanda Lopez-Maldonado, Emmi Nieminen, Matías Piaggio, Jiangxiao Qiu, Juan C. Rocha, Caroline Schill, Alon Shepon, Andrew R. Tilman, Inge van den Bijgaart, Tong Wu. 2018. Inequality and the Biosphere. *Annual Review of Environment and Resources* **43**:1, 61-83. [Crossref]
8. André Albuquerque Sant'Anna. 2018. Not So Natural: Unequal Effects of Public Policies on the Occurrence of Disasters. *Ecological Economics* **152**, 273-281. [Crossref]
9. Florence Crick, Shaikh M.S.U. Eskander, Sam Fankhauser, Mamadou Diop. 2018. How do African SMEs respond to climate risks? Evidence from Kenya and Senegal. *World Development* **108**, 157-168. [Crossref]
10. Azreen Karim. 2018. The Household Response to Persistent Natural Disasters: Evidence from Bangladesh. *World Development* **103**, 40-59. [Crossref]
11. Md Tanvir Pavel, Syed Hasan, Nafisa Halim, Pallab Mozumder. 2018. Natural Hazards and Internal Migration: The Role of Transient Versus Permanent Shocks. *SSRN Electronic Journal* . [Crossref]
12. Ingrid Dallmann, Katrin Millock. 2017. Climate Variability and Inter-State Migration in India. *CESifo Economic Studies* **63**:4, 560-594. [Crossref]
13. Yashodhan Ghorpade. 2017. Extending a Lifeline or Cutting Losses? The Effects of Conflict on Household Receipts of Remittances in Pakistan. *World Development* **99**, 230-252. [Crossref]
14. Joyce J. Chen, Valerie Mueller, Yuanyuan Jia, Steven Kuo-Hsin Tseng. 2017. Validating Migration Responses to Flooding Using Satellite and Vital Registration Data. *American Economic Review* **107**:5, 441-445. [Abstract] [View PDF article] [PDF with links]
15. Daniel Osberghaus. 2017. The effect of flood experience on household mitigation—Evidence from longitudinal and insurance data. *Global Environmental Change* **43**, 126-136. [Crossref]
16. Dave Donaldson, Adam Storeygard. 2016. The View from Above: Applications of Satellite Data in Economics. *Journal of Economic Perspectives* **30**:4, 171-198. [Abstract] [View PDF article] [PDF with links]
17. Solomon Hsiang. 2016. Climate Econometrics. *Annual Review of Resource Economics* **8**:1, 43-75. [Crossref]
18. Bimal Kanti Paul, Sharif Mahmood. 2016. Selected physical parameters as determinants of flood fatalities in Bangladesh, 1972–2013. *Natural Hazards* **67**. . [Crossref]