## **Flooded Cities**

Adriana Kocornik-Mina (Alterra - Wageningen UR) Thomas McDermott (University College Cork) Guy Michaels (London School of Economics) Ferdinand Rauch (University of Oxford)

### Introduction

- Examine effect of large floods on cities worldwide
  - Do flood prone areas concentrate more urban economic activity? Does flood risk change this?
  - <u>Does recovery involve moving to higher ground</u>?
- Use spatially disaggregated inundation maps from >50 <u>large</u> floods, which affected >1,800 cities in 40 countries worldwide from 2003-2008
- Measure economic impact using night lights data

## Why Study Flooding?

- Large floods are very damaging. According to Dartmouth Flood Observatory, floods worldwide from 1985-2014:
  - Killed over half a million people
  - Displaced over 600 million people
  - Caused over US\$500 billion of damage
- Involves externalities, affects human capital accumulation
- Matters for zoning & infrastructure investments (floodprevention, sewerage, transportation, etc.)
- Climate change could worsen floods if (i) sea levels rise, or (ii) extreme weather events become more frequent
- More generally, sheds light on city-wide adaptation, especially to <u>recurrent</u> shocks

## Why Study Urban Flooding?

- Urban flooding is important and understudied:
  - Earliest towns emerged on flood plains, but today's cities no longer benefit much from floods' fertile soil
  - Growing majority of world's population now is urban
  - Urbanizing areas include low-elevation coastal zones and other flood-prone areas
  - Much urban growth takes place in poor countries with little zoning/planning
  - Slums develop on cheap land with poor infrastructure, which could be particularly flood-prone

## Main findings

- About 5% of cities worldwide were flooded at least once in >50 large flood events from 2003-2008
  - For flooded cities, odds of recurrence rise to ~19%
- Low elevation urban areas (<10m above sea level):
  - Are hit by large floods ~4 times as often
  - Have denser economic activity (more night lights)
    - Even after conditioning on proximity to coast and rivers
    - Applies even in areas prone to extreme rainfall

## Main findings (continued)

• Large scale floods (and extreme rainfall) dim the lights, but the lights recover within a year

- No evidence of move to higher ground: low elevation areas recover just like other areas
  - True even away from coasts and rivers
  - The only exception are newly populated areas, where floods have some persistent impact

## **Related literature**

- Urban economics
  - Recovery of cities after shocks: wars (Davis & Weinstein 2002; Brakman et al 2004; Miguel and Roland 2011)
    - We add global perspective on recovery from shocks
  - Urban form and allocation of economic activity within cities: Glaeser and Shapiro (2002), Hornbeck (2015)
    - We contribute by looking within cities globally
  - Urbanization in developing countries: Henderson et al.
    (2013); Barrios et al. (2006); Jedwab et al (2014)
    - We study how cities in (mostly) developing countries respond
  - Economic analysis using lights data: Henderson et al. (AER, 2012); Michalopoulos and Papaioannou (QJE,2014)
    - We contribute by applying the approach at local level

## Related literature

- Economics of disasters, and especially flooding:
  - Case studies (Katrina: Glaeser 2005, Basker & Miranda 2014; Tsunami of 2004: de Mel et al. 2012; Mississippi 1927: Hornbeck & Naidu 2013)
  - Learning: Gallagher (2014) studies US counties and "communities"
  - Effect of natural disasters on national GDP (e.g. Cavallo et al 2013)
  - Effect of tropical storms on long run growth Hsiang & Jina (2014)
    - We combine detailed inundation maps with elevation data. This allows us to conduct spatially disaggregated analysis at the global level
- Costs of climate change
  - Literature concerned with estimating exposure (Hanson et al 2011) and costs in coastal cities (Hallegatte et al 2013)
  - A key question is how people adapt to potential changes
    - We suggest that responsiveness is rather limited, suggesting that cost of increases in future flooding may be higher than anticipated

### What is the Economic Problem?

- Is it "efficient" for impoverished people to live in flood-prone areas, balancing risk and reward?
  - Kydland & Prescott (1977): flood protection problem
  - Government assistance to victims: insurance problem
- So flood-prone areas are overpopulated, and this could be exacerbated by:
  - Limited information (or access to it) on flood risk
  - Historical lock-in: locations near rivers or coasts historically attractive (Michaels & Rauch 2013)

# Simple Bayesian updating model of location choice

- Location choices: Risky or Safe
- So why do some choose risky location?
  - Some people may get more utility from R
  - Moving costs
  - Public subsidy
  - Lack of information (floods reveal extent of risk)

## What do we take from the model?

- 1. Examine probability of large flood risk
- 2. Measure the extent to which urban economic activity concentrates in risky vs. safe areas
- 3. Test whether in areas with climatic risk economic activity avoids risky areas
- 4. Study whether floods move people to safer areas (updating or reduced moving costs)
- Examine whether there is more updating (and movement) in newly populated areas

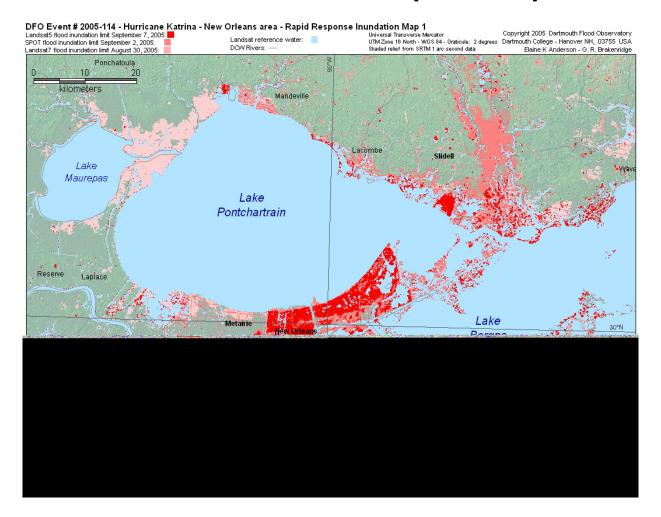
## Additional considerations

- Floods may reduce prices in flood prone areas, encouraging newcomers to move in
  - Extreme case: if housing supply is inelastic → no shift to safer locations
- Rising sea levels increase overall flood risk, and probably more so in low elevation areas
- Flooding can affect children's human capital accumulation (health & schooling disruptions)
- It can also affect other investment decisions

## Data on flooding

- <u>Data on flooding events</u>: location, timing, duration, damage, etc. from Dartmouth Flood Observatory, which covers 1,000s of floods worldwide from 1985-2014
- Use detailed inundation maps for 2003-2008 showing which locations were flooded in given points in time (based on satellite images)

#### Inundation map for Hurricane Katrina, New Orleans (2005)

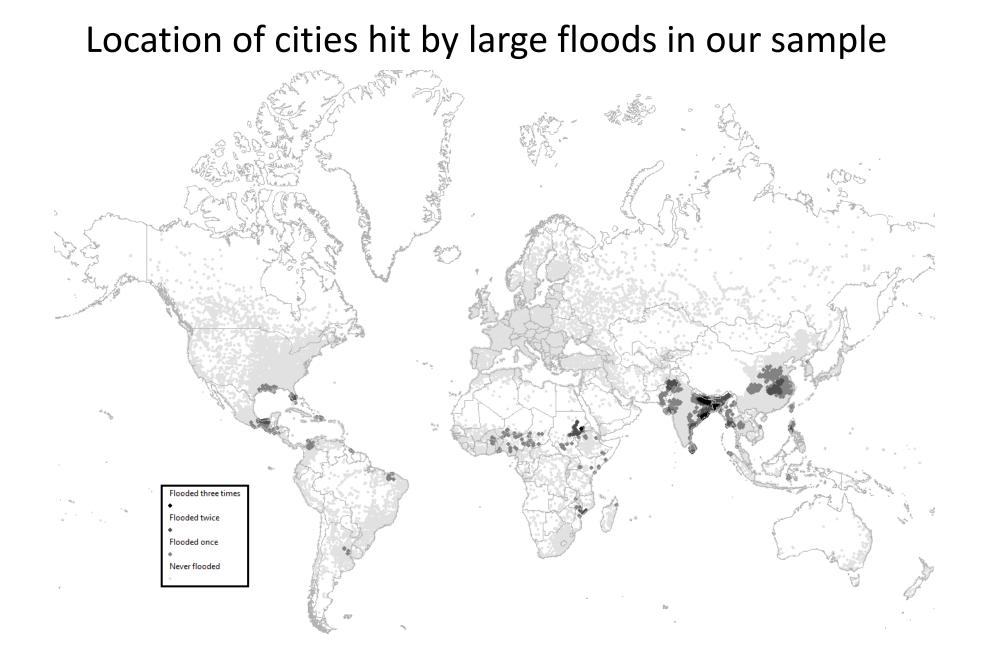


### Flood events recorded by Dartmouth Flood Observatory (U of Colorado)

		Millions displaced in				Millions displaced	
	# floods	floods			# floods	in floods	
	displacing	displacing	Millions		displacing	displacing	Millions
	≥ 100k	≥ 100k	displaced		≥ 100k	≥ 100k	displaced
Year	people	people	in all floods	Year	people	people	in all floods
1988	22	19.1	20.3	2002	16	19.0	20.3
1989	20	8.0	8.6	2003	16	20.6	21.7
1990	18	14.2	14.9	2004	19	50.0	51.0
1991	21	16.9	17.8	2005	30	18.2	19.4
1992	12	12.6	13.1	2006	25	16.7	18.7
1993	16	34.2	35.1	2007	30	33.2	35.6
1994	15	7.8	8.6	2008	24	20.7	22.3
1995	24	47.4	48.6	2009	17	7.8	8.5
1996	18	12.1	12.8	2010	17	19.8	21.2
1997	21	5.6	6.5	2011	14	6.9	7.9
1998	23	41.7	42.9	2012	12	5.1	6.1
1999	22	56.4	57.1	2013	14	6.2	7.0
2000	20	49.3	50.3	2014	9	3.1	4.0
2001	13	36.4	38.0	Total	508	589.0	618.2

# Large scale flood events with detailed inundation maps (2003-2008)

		splacing ≥ 100k ople	Floods displacing ≥ 100k people with detailed inundation maps		
		Millions		Millions	
Year	# floods	displaced	# floods	displaced	
2003	16	20.6	13	19.9	
2004	19	50.0	15	49.1	
2005	30	18.2	8	5.8	
2006	25	16.7	7	5.2	
2007	30	33.2	9	8.2	
2008	24	20.7	1	1.5	
Total	144	159.4	53	89.7	



### Inundation maps cover over 1,800 urban areas flooded in 40 countries:

Argentina	Dominican Republic	Kenya	Pakistan
Bangladesh	El Salvador	Madagascar	Philippines
Benin	Ethiopia	Malawi	Somalia
Bhutan	Ghana	Mexico	South Sudan
Brazil	Guatemala	Mozambique	Sri Lanka
Burkina Faso	Guyana	Myanmar	Sudan
Cameroon	Haiti	Nepal	Thailand
Chad	Honduras	Niger	Togo
China	India	Nigeria	United States
Colombia	Indonesia	North Korea	Vietnam

Hardest hit: India, China, and Bangladesh. Other highlighted countries also hit hard

Data on night-time lights (NTL) as measure of economic activity

- <u>Night-Time Light</u> (NTL) data for 1992-2012:
  - Collected by satellites from the US Air Force
    Defense Meteorological Satellite Program (DMSP)
  - Satellites circle earth 14 times per day recording the intensity of Earth-based lights
  - NOAA's (National Oceanic and Atmospheric Administration) National Geophysical Data Center (NGDC) processes data
  - An average 39.2 (s.d. 22.0) nights are used for each satellite-year dataset

Data on night-time lights (NTL) as measure of economic activity

- <u>Night-Time Light</u> (NTL) data for 1992-2012:
  - The digital measure is an integer between 0-63 (this does create an issue with top-coding)
  - Lights observed from space can be mapped on approximately one-kilometre squares
  - Annual data: higher frequency than other measures of local economic activity with global coverage
  - Well-suited for analyzing economic activity (Henderson et al. 2012)

### Additional Data

- <u>Urban extent</u>: cities defined according to 1995 urban extent grids (CIESIN's Global Rural-Urban Mapping Project - GRUMP) using lights
- <u>Population density</u>: GRUMP website
- <u>Topography</u>: The US Geological Survey (USGS) data determine elevation in meters above sea level for 1 square kilometres grid
- <u>Coastlines, rivers, soil types and land cover</u>: USGS
- <u>Rainfall data</u>: Climatic Research Unit at East Anglia

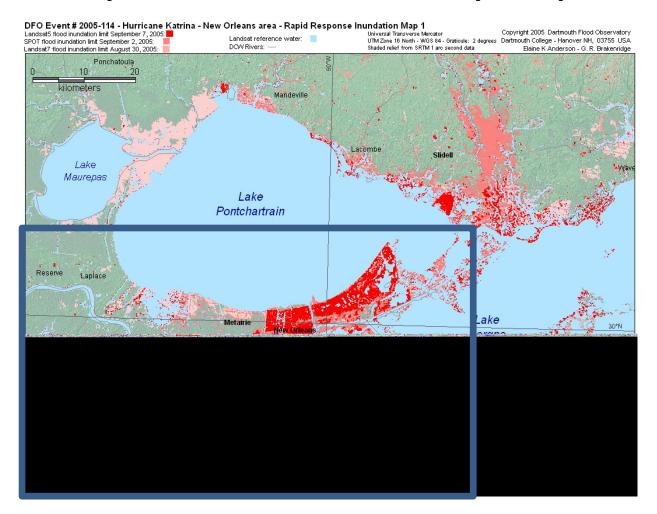
### Constructing dataset

- Map all the data onto an equal area 1km<sup>2</sup> grid covering the entire world
- We restrict data GRUMP-defined urban areas
  - Rural areas typically have little light to begin with, so little prospect of detecting local impact

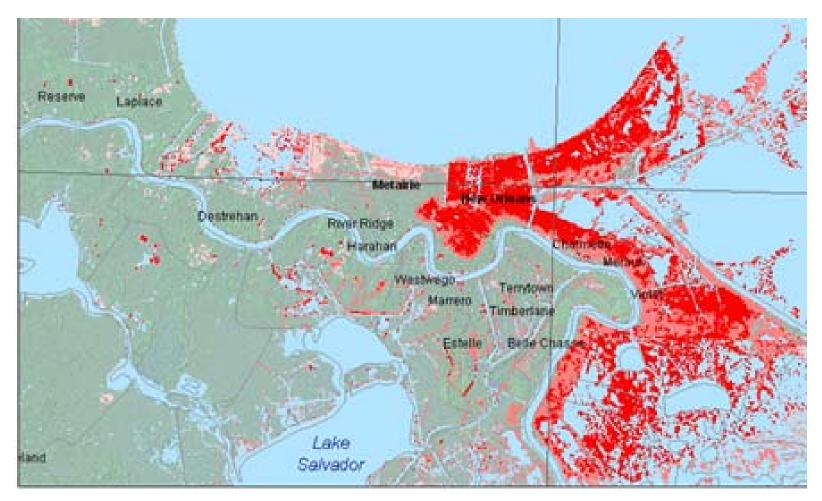
## Constructing dataset (continued)

- Use Inundation maps from Dartmouth Flood Observatory to pinpoint whether a given city is flooded in a given year
  - We focus on events, which according to DFO (media-based) information displaced at least 100,000 people
  - We define a city as flooded if at least one gridpoint in the city is flooded
- We restrict most of our analysis to cities that are flooded at least once

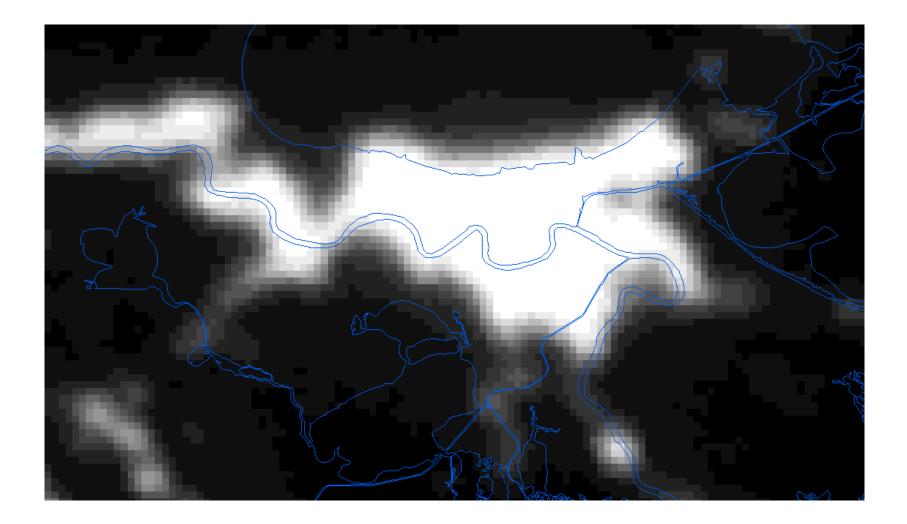
#### Hurricane Katrina, New Orleans (2005) Displaced ~500,000 people



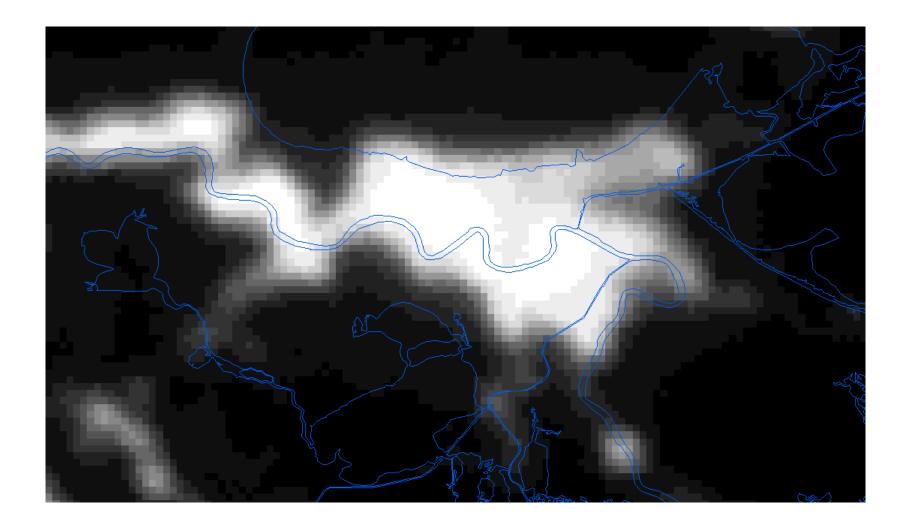
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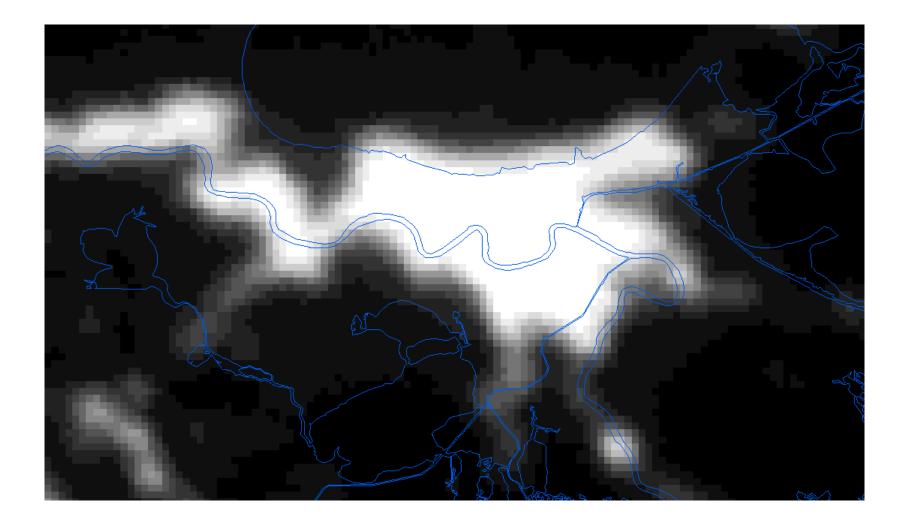
## New Orleans – lights in 2004



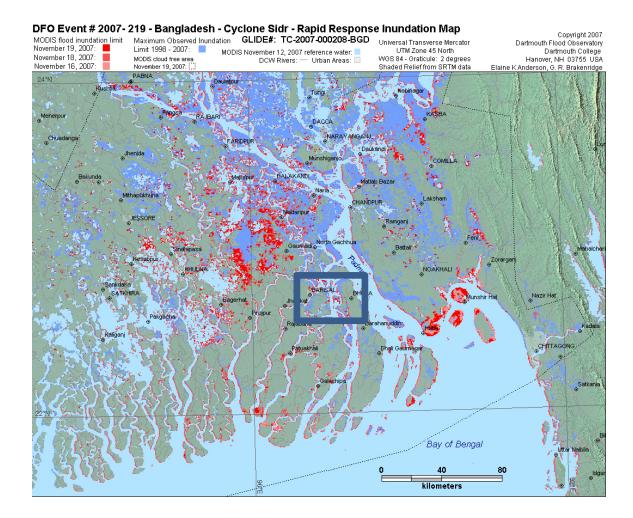
#### New Orleans – lights in 2005



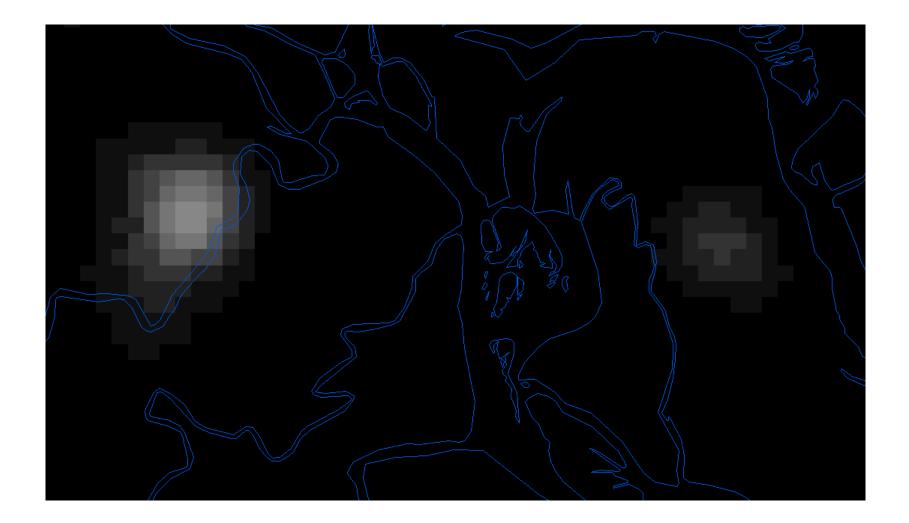
## New Orleans – lights in 2006



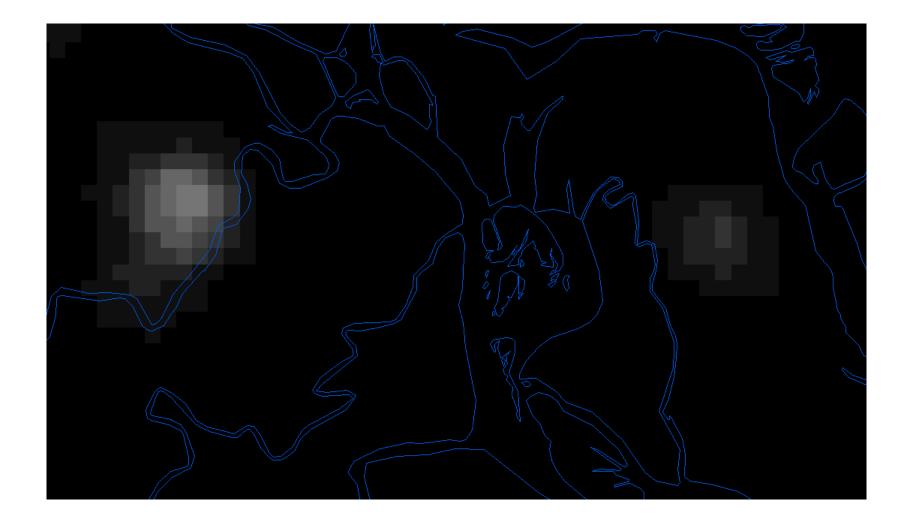
#### Tropical Cyclone Sidr in Bangladesh (2007) Displaced ~3,000,000 people



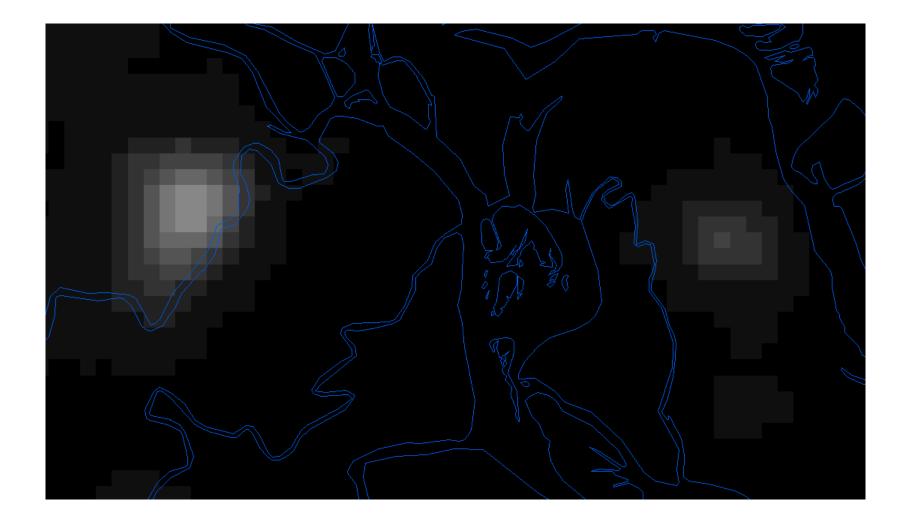
#### Barisal and Bhola, Bangladesh, 2006



#### Barisal and Bhola, Bangladesh, 2007



#### Barisal and Bhola, Bangladesh, 2008



# Annual frequency of large urban floods ~4 times higher in low elevation areas

Elevation <10m	0.036	0.041	0.034
	(0.017)	(0.018)	(0.019)
River 0-9km		0.009	0.009
		(0.006)	(0.006)
Coast 0-9km		-0.010	-0.001
		(0.003)	(0.001)
Constant	0.013	0.012	
	(0.005)	(0.004)	
Country f.e.	No	No	Yes

Note: 3,807,799 observations. Robust standard errors are clustered by country.

FloodFreq<sub>ik</sub> =  $\beta_{11} + \beta_{12}$  (Elev<10m)<sub>i</sub> +  $\beta_{13}$  River<sub>i</sub> +  $\beta_{14}$  Coast<sub>i</sub> + Country<sub>k</sub> +  $\varepsilon_{ik}$ 

### Low elevation urban areas more lit, even in areas with extreme rainfall

Elevation<10m	0.182 (0.037)	0.184 (0.037)	0.137 (0.032)	0.157 (0.033)	0.110 (0.028)
Elevation<10m x Precip>1000mm		-0.034 (0.075)	-0.032 (0.075)		
Precip>1000mm (in single month)		-0.063 (0.079)	-0.081 (0.074)		
Elevation<10m x Precip>500mm				0.113 (0.044)	0.112 (0.048)
Precip>500mm (in single month)				-0.043 (0.064)	-0.054 (0.062)
Country f.e.	No	No	Yes	No	Yes

3,642,083 observations. Robust standard errors are clustered by country.

 $ln(Y_{ilk}) = \beta_{21} + \beta_{22} (Elev<10m)_i + \beta_{23} Precip_i + \beta_{24} Precip_i x (Elev<10m)_i + Country_k + \varepsilon_{ilk}$ 

#### Effect of large floods on night lights

Estimate using panel of urban gridpoints from 2003-2008:

 $ln(Y_{ilk}) = \beta_{31} + \beta_{32} Flood_{jt+s} + Gridpoint_i + Year_t + Country_k x Trend_t + \varepsilon_{it}$ 

- Y<sub>ijkt</sub>: mean annual light intensity in gridpoint i (located in city j, in country k) in year t
- Flood<sub>it+s</sub>: flood dummy for city j in year t+s
- Gridpoint<sub>i</sub>: gridpoint i fixed effects
- Year<sub>t</sub>: year t effects
- Country<sub>k</sub>: country k fixed effects
- Trend<sub>t</sub>: time trend
- $\varepsilon_{it}$  is error term (clustered by country)

# Lights dim when urban areas are hit by large scale flood or extreme rainfall

Flood	-0.021			-0.023		
	(0.010)			(0.010)		
Precipitation>500mm (in 1 month)		-0.025	1		-0.027	7
		(0.008	)		(0.008	)
Precipitation>1000mm (in 1 month)			-0.080			-0.083
			(0.018)	)		(0.018)
Arellano-Bond	No	No	No	Yes	Yes	Yes

Sample: only urban areas ever hit by floods. Obs.: 1,422,018. Robust standard errors are clustered by country

# Urban lights recover within 1 year of flood or extreme precipitation

Flood this year	-0.021
	(0.009)
Flood last year	-0.003
	(0.012)
Precipitation>500mm (in 1 month)	-0.025
	(0.008)
Precipitation>500mm in 1mth last year	0.004
	(0.012)
Precipitation>1000mm (in 1 month)	-0.080
	(0.018)
Precipitation>1000mm in 1mth last year	0.054
	(0.033)
Sample: only urban areas ever hit by flo	ods. Obs.: 1,422,018. Results with

Arellano-Bond are similar. Robust standard errors are clustered by country

#### Differential effect of large floods by elevation

Estimate using panel of city gridpoints from 2003-2008:

 $In(Y_{ijkht}) = \beta_1 + \Sigma_h \beta_{52h} Flood_{jt+s} \times Elevation_h + Gridpoint_i + Year_t + Country_k \times Trend_t + \varepsilon_{it}$ 

- Y<sub>ijkht</sub>: mean light intensity in gridpoint i (located in city j, in country k, and in elevation band h) in year t
- Flood<sub>jt+s</sub>: dummy for flood in city j in year t+s
- Elevation<sub>h</sub>: dummy for elevation band h
- Gridpoint<sub>i</sub>: gridpoint i fixed effects
- Year<sub>t</sub>: year t effects
- Country<sub>k</sub>: country k fixed effects
- Trend<sub>t</sub>: year effect
- $\varepsilon_{it}$  is error term (we cluster by country)

# Low elevation urban areas dimmed by floods, but recover within a year

Flood x Elevation<10m	-0.027	
	(0.006)	
Flood x Elevation≥10m	-0.019	
	(0.012)	
Flood last year x Elevation<10m		0.009
		(0.009)
Flood last year x Elevation≥10m		-0.007
		(0.023)

Sample: only urban areas ever hit by floods. Obs.: 1,422,018. Results with Arellano-Bond are similar. Robust standard errors are clustered by country

## Main findings

- Low elevation areas (<10m above sea level) hit by large urban floods about 4 times as often
- Those areas concentrate more economic activity, as reflected by night lights
- Even in areas prone to intense rainfall
  (≥500mm or even ≥1,000mm in one month)
  the low elevation areas are more lit

## Main findings (continued)

- Large scale floods or extreme rainfall dim the lights, but the lights recover within a year
- There is little evidence of adaptation: low elevation areas recovery similar to other areas
  - This applies even away from coasts and rivers
  - The only exception is in newly populated areas, where floods have some persistent effects
  - But barring this exception, even devastating and costly floods do not shift people to safer areas

## Conclusions

- Large urban floods are common and costly:
  - Globally they displace >20 million people/year
  - Large costs to the victims themselves and also:
    - Flood protection
    - Aid (domestic/international, government/NGO)
    - Rebuilding infrastructure
    - Human capital accumulation of children (lost years of schooling, damage to health/physical development)
- So living on flood plains is socially costly

## Conclusions

- We find no evidence that cities adapt to large floods by moving to higher ground
- Our findings suggest costs of lock-in of urban locations that are prone to flooding
- With rising sea levels and a changing climate, future costs may be higher than thought
- Policy implications:
  - Reconstruction could target resettlement away from riskiest parts of towns
  - New construction should avoid the flood plains