# The Economic Dynamics after a Flood: Evidence from Satellite Data

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**Abstract**

This study investigates the effect of flash floods on local economic activity in Central America and the Caribbean. I measure these rarely analyzed floods by constructing a high-resolution, physically based index of flash flood occurrence from satellite data and connect these to changes in local night light emissions. After accounting for tropical cyclone activity, flash floods have a delayed, short-term negative effect on economic activity. In countries with a low to medium human development index (HDI), the average effect can be up to $-5.7\%$ in the following months. Back-of-the-envelope calculations suggest that flash floods in these countries cause GDP growth to be 0.84 percentage points lower due to their high frequency. Countries with higher development appear more resilient and are only marginally affected. Also, flash floods exhibit a peculiar spatial spillover pattern where the effect is overall negative but less so if more nearby locations are affected. (JEL O11, Q54, R11)

# 1 Introduction

When Tropical Storm Ophelia poured extreme rainfall over New York City on September $29^{th}$ in 2023, the resulting flash floods wreaked havoc: the city shut down its subway, roads, and airport terminals, and a state of emergency had to be declared. Less than a week before, heavy rainfall in the night caused a flash flood early on the $25^{th}$ near Guatemala City when a small river broke its banks, destroying several homes and causing deaths and missing people.[1] These are not isolated incidents. According to the Emergency Events Database (EM-DAT), 0.9 Million people were affected by flash floods in 2022, the $5^{th}$ most among all natural hazard subtypes.[2] In addition, the frequency and severity of flash floods are projected to increase with climate change (IPCC, 2023). The Caribbean and Central America are especially at risk from flash floods by being already one of the world's most rainfall- and thunderstorm-heavy regions. Further aggravating the risk, urbanization is often unregulated, and soil degradation is common (Pinos and Quesada-Román, 2021). Therefore, understanding how flash floods impact economic activity in Central America and the Caribbean is crucial for its development. This study contributes to this understanding by physically modeling flash flood events from satellite rainfall data and connecting these to changes in night light activity while controlling for tropical cyclone activity and local characteristics.

While the direct physical damage from natural hazards is self-evident, the overall economic consequences are not. In many countries, natural disasters are a major channel through which climate and environmental degradation impact the economy and lower development (Felbermayr and Gröschl, 2014). A growing literature has thus started to study the economic impacts of various types of natural disasters: tropical storms (Strobl, 2012; Hsiang and Jina, 2014; Deryugina, 2017; Ishizawa and Miranda, 2019; Kunze, 2021), earthquakes (Barone and Mocetti, 2014; Fabian et al., 2019), droughts (Barrios et al., 2010; Hornbeck, 2012) and urban floods (Kocornik-Mina et al., 2020), to name a few. Many estimate the overall economic impact of the natural disaster, while others are explicitly entertaining the notion of direct (first-order) and indirect (second-order) effects. The direct impact can be viewed as the immediate destruction and rebuilding cost. The indirect impact is characterized by second-order effects such as the re-organization of the

[1] See the FloodList program news funded through the European Union's Copernicus scheme.

[2] After droughts (107 Million), tropical cyclones (15 Million), earthquakes (3.6 Million), and convective storms (1.6 Million) but before river floods (0.1 Million) and forest fires (0.03 Million).

economy. For instance, when an establishment is destroyed, this disrupts the value chain. Similarly, if a firm goes out of the market, the now laid-off workers will be subject to unemployment. These second-order effects are often considerable. Deryugina (2017) finds that US hurricanes substantially increase transfers such as unemployment benefits to affected counties, significantly exceeding direct disaster assistance in value.

The literature quantifying the impact of extreme rainfall and flood events specifically can be divided into two groups. Those concerned with extreme rainfall use aggregated weather data such as the region-specific deviation in monthly rainfall to estimate economic impacts of weather anomalies (Dell et al., 2012, 2014; Felbermayr et al., 2022; Kotz et al., 2022). These studies implicitly evade many flash flood events because a monthly measure of rainfall cannot reliably identify short (usually less than a day), extreme rainfall events. The other group uses flood report data instead to overcome this issue (Loayza et al., 2012; Fomby et al., 2013; Kocornik-Mina et al., 2020). The advantage of flood report data like EM-DAT or the Dartmouth Flood Observatory (DFO) is that it identifies the natural hazard by impact. But it also comes at a cost: relying on media reports like the EM-DAT to identify and locate flood events introduces reporting, selection, and endogeneity biases (Panwar and Sen, 2020). For example, insurance penetration and reported damages are highly correlated with a country's development (Felbermayr et al., 2022). The DFO instead relies on satellite imagery on cloud-free days to quantify the flooded area. Since flash floods have a short lifespan and occur in combination with heavy rainfall and thus cloud coverage, many go unnoticed. To the best of my knowledge, no study focuses on the economic impact of flash floods, as there is no consistent nor exhaustive database of them. It is thus necessary to develop a physically consistent index of occurrence that reliably identifies flash flood events to study their economic impacts.

Macroeconomic models of natural disasters are generally based on classical growth theory with the event as a one-time shock to the capital stock (Hallegatte et al., 2007; Strulik and Trimborn, 2019). However, it has been argued that these models cannot capture the effects of short-term shocks from natural hazards adequately to derive long-term impacts (Cavallo et al., 2013). Regardless of this debate, the economic impact has to be assessed empirically to provide estimates for model parameters (Strulik and Trimborn, 2019). This impact has to be estimated for each hazard separately since they are not necessarily comparable. Some might destroy a larger share of certain types of capital, some damage a larger share of public infrastructure, and others displace more people. It has also been recognized that with climate change making natural hazards more common in many parts of the world, jointly considering events based on their frequency and intensity is crucial when estimating the effects on growth. For instance, in a Solow-like model that allows for non-equilibrium dynamics, Hallegatte et al. (2007) show a sharp increase in GDP losses if natural hazards intensity or frequency increase above a certain threshold. The capacity of an economy to cope with a natural hazard, determining the threshold, is linked to its development (Hallegatte and Dumas, 2009). For instance, the more developed economy can cope better with severe and frequent shocks to its infrastructure as it has the necessary means for timely reconstruction.

To frame the analysis, there are four hypotheses about an economy's growth dynamics after a natural disaster: a return to the same output level after an initial decline, a decline in output level without recovery, or an increase in the level of output either immediately with creative-destruction or after some time as build-back-better (Botzen et al., 2019). The question of which hypothesis is most adequate, focusing on high-impact natural disasters, has not reached a conclusive answer (Skidmore and Toya, 2002; Crespo Cuaresma et al., 2008; Klomp, 2016). Most evidence points towards an initial decline in output that gradually recovers over time. In contrast, the no-recovery, build-back-better, and creative-destruction hypotheses have support in specific settings (Strobl, 2012; Felbermayr and Gröschl, 2014; Noy and Strobl, 2023) It is suggested that this depends mainly on the type of disaster, the time period and geographic scope of the analysis (Lazzaroni and van Bergeijk, 2014; Klomp and Valckx, 2014). Critically, the scale of analysis matters. Economic mechanisms that would cause output to increase are typically motivated on the micro- or perhaps city level. For example, local build-back-better might siphon investments into an area affected by a natural disaster at the cost of other locations. Similarly, the negative impact might be relatively short-term such that rebuilding is completed within a year. It follows that country-by-year panel data is not adequate if considering growth dynamics of a small-scale, high-frequency natural hazard such as flash floods. In particular, the impacts of flash floods might be absorbed by spatial equilibrium effects or temporal smoothing of economic choices.

A critical part of the methodology is therefore to detect extreme rainfall events that likely trigger flash floods on a high spatial and temporal resolution. I use the flash flood intensity-duration classification from Collalti et al. (2023) as a physical measure for flood incidence. This classification is based on intensity-duration-frequency (IDF) curves from conditional copula sampling and exhaustive information on all flash flood events in Jamaica from 2001 to 2018. Jamaica shares a similar topography, soil composition, and climate with the whole region of Central America and the Caribbean, so the classification is well-calibrated. I use rainfall information from the Integrated Multi-satellitE Retrievals for GPM (IMERG), which employs the Global Precipitation Measurement (GPM) constellation satellite data. Of the 64 M cell-wise rainfall events in Central America and the Caribbean in 2000 - 2021, 2.3 M or approximately 1.7% can be classified as a flash flood.

I estimate a flash flood's effect on aggregate economic activity by using satellite images of night lights at a monthly frequency. The source of night light data is NASA's Black Marble product that removes cloud-contaminated pixels and corrects for atmospheric, terrain, vegetation, snow, lunar, and stray light effects on the VIIRS Day/Night Band (DNB) radiances. Controlling for tropical storms and various fixed effects, I find that night lights decrease significantly by up to 5.7% in the following months for low and medium-development countries. Afterward, there is a quick recovery within the first year. A back-of-the-envelope calculation implies that there is, due to their high frequency, a decrease in the GDP growth rate by 0.84 percentage points for low- and medium-development countries in the region attributable to flash floods. The reaction in night lights is considerably less pronounced for high and very high-development countries.

These results are important for several reasons. First, the findings contribute to the literature on physically modeled natural disasters in economics (Nordhaus, 2010; Hsiang and Jina, 2014; Eichenauer et al., 2020). Second, extreme rainfall events and the associated pluvial floods are, after droughts, the extreme events most likely to increase in probability and intensity due to climate change (Seneviratne et al., 2021). For instance, the $6^{th}$ IPCC Report states that *"Projected increases in direct flood damages are higher by 1.4 to 2 times at 2°C and 2.5 to 3.9 times at 3°C compared to 1.5°C global warming without adaptation."* (IPCC, 2023). Knowledge of how a natural hazard shock propagates through the economy is necessary to inform policymakers about climate change risks adequately.

The remainder of the paper is organized as follows: Section 2 presents the study region, describes the data and provides summary statistics. In Section 3, the identification strategy is detailed, whereas Section 4 provides results which are discussed in Section 5. Finally, Section 6 concludes.

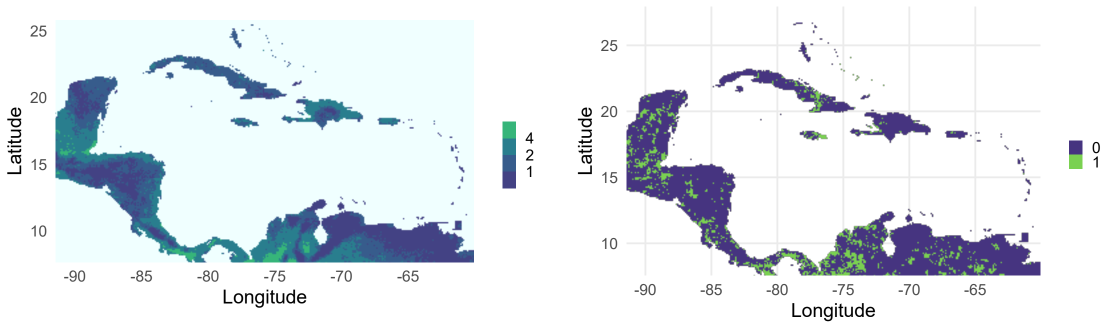
# 2 Data

Three categories of variables are employed for this study. The first is concerned with hazards. This includes a satellite-derived rainfall measure and the subsequent creation of a flash flood indicator as the variable of interest. Also, I construct an index of hurricane destructiveness. The second category is the economic variable, where I use night light data to infer changes in economic activity. Third, auxiliary data on topography and land use serve as sources for potential heterogeneity that I will explore.

Figure 1: Map of Flash Flood Distribution

(a) Average Number of Floods

(b) Floods June 2015




*Notes:* Map of the average number of flash floods per year from June 2000 to October 2021 and map of the flash flood incidents in June 2015.

## 2.1 Study Region

The study region of Central America and the Caribbean is characterized by its proximity to the sea: no location is further away from it than 200 km (Encyclopedia Britannica, 2022). The tropical climate is tempered by elevation, latitude, and local topography. Rainfall occurs in a dry and wet season pattern and is heaviest between May and November. Topography is diverse: most countries have humid lowlands along the coast, while there are pronounced hills and mountain ranges. Natural vegetation is equally varied. Tropical forests occupy lowlands, while evergreen forests clothe hills and mountains. However, much of Central America and the Caribbean's timberland has been cleared for crop cultivation.

## 2.2 Flash Floods

Floods come in various forms that determine the flood hazard and risk. Floods caused by local excess rainfall, so-called pluvial floods, can be divided into surface water floods and flash floods. Surface water floods are caused when rain falls over a prolonged period such that the drainage systems and general runoff cannot deal with the amount of water, resulting in a shallow, standing flood. Flash floods, on the other side, are characterized by shorter, more intense extreme rainfall events. Torrential rainfalls trigger these dangerous floods due to their quick onset and ravageous, debris-sweeping flow. They are an especially localized phenomenon that can occur almost everywhere and is difficult to forecast.

In this study, flash floods are measured via a binary classification that indicates whether, in a month, an episode of heavy rainfall likely triggered some flash flood at a location. The classification is from Collalti et al. (2023), who employ a hydro-statistical methodology and exhaustive data on confirmed flash flood events in Jamaica to estimate a decision rule for the optimal classification of flood incidence. Specifically, the procedure starts by first defining appropriate rainfall events that relate to weather conditions via an inter-event time definition, where 12 h without rainfall meteorologically delimits a rainfall event from another. By using remote sensing data from the Global Precipitation Measurement (GPM) Integrated Multi-satellitE Retrievals (IMERG) on a $0.1° \times 0.1°$ (approx. 11 km $\times$11 km at the equator) grid with half-hourly data, coverage is consistent for the whole study region (Huffman et al., 2015). Local extreme events are then used to estimate the dependence between the intensity (mm/h) of such an event and its duration (h) via copula functions. The common method of generating intensity-duration-frequency (IDF) curves for some frequency corresponding to a return period flexibly characterizes the dependence structure. One IDF curve assigns for every duration of an event an intensity given a certain return period. This relationship is negative and concave. Finally, the IDF curve which best predicts the data on confirmed flash floods in Jamaica serves to classify rainfall into potential flood events. As a decision rule, I require that a rainfall event must have an intensity of at least 2 mm/h above the IDF curve to be classified as a flash flood to reduce the number of false positives. If an event exceeds this threshold, I treat it as a flood-inducing rainfall event.[3]

I employ this decision rule on the same satellite-based rainfall estimate to recover flood events. The satellite precipitation algorithm combines various microwave and infrared precipitation measurements to produce precipitation estimates, adjusted with surface gauge data. The sample period is June $1^{st}$ 2000 to June $30^{th}$ 2021. For every month

[3]Results do not change qualitatively for a threshold of 5 mm/h and can be found in section 4.4 of the results.

with one rainfall event above the threshold, the corresponding GPM/IMERG grid cell area is considered treated by a flash flood.[4] In the study region, one of the most rainfall-intense regions in the world, locations experience a flash flood 1.7 times each year on average, according to the index. There is considerable spatial variation for the average occurrence probability but also spatial clustering for a given month, as Figure 1 shows. Table 1 provides summary statistics of all rainfall events.

Table 1: Flash Flood Summary Statistics

| Statistic | Mean | St. Dev. | Min | Median | Max |
|---|---|---|---|---|---|
| Flash Flood Rainfall Events (N = 1’056’508) | | | | | |
| Intensity mm/h | 6.61 | 3.31 | 3.93 | 5.50 | 113.18 |
| Duration h | 16.60 | 11.14 | 1.00 | 13.50 | 214.50 |
| Year | 2009.44 | 5.79 | 2000 | 2009 | 2021 |
| Month | 7.02 | 2.99 | 1 | 7 | 12 |
| Longitude | −80.15 | 8.28 | −91.95 | −81.55 | −58.05 |
| Latitude | 16.07 | 8.07 | 7.05 | 14.25 | 31.95 |
| Non Flash Flood Rainfall Events (N = 63’049’303) | | | | | |
| Intensity mm/h | 1.21 | 1.36 | 0.10 | 0.77 | 190.22 |
| Duration h | 6.65 | 10.84 | 0.50 | 3.50 | 3’875.00 |
| Year | 2010.49 | 6.12 | 2000 | 2011 | 2021 |
| Month | 6.83 | 3.05 | 1 | 7 | 12 |
| Longitude | −78.00 | 9.22 | −91.95 | −79.65 | −58.05 |
| Latitude | 15.73 | 7.54 | 7.05 | 13.95 | 31.95 |

*Notes:* Characteristics of flash flood and non-flash flood rainfall events.

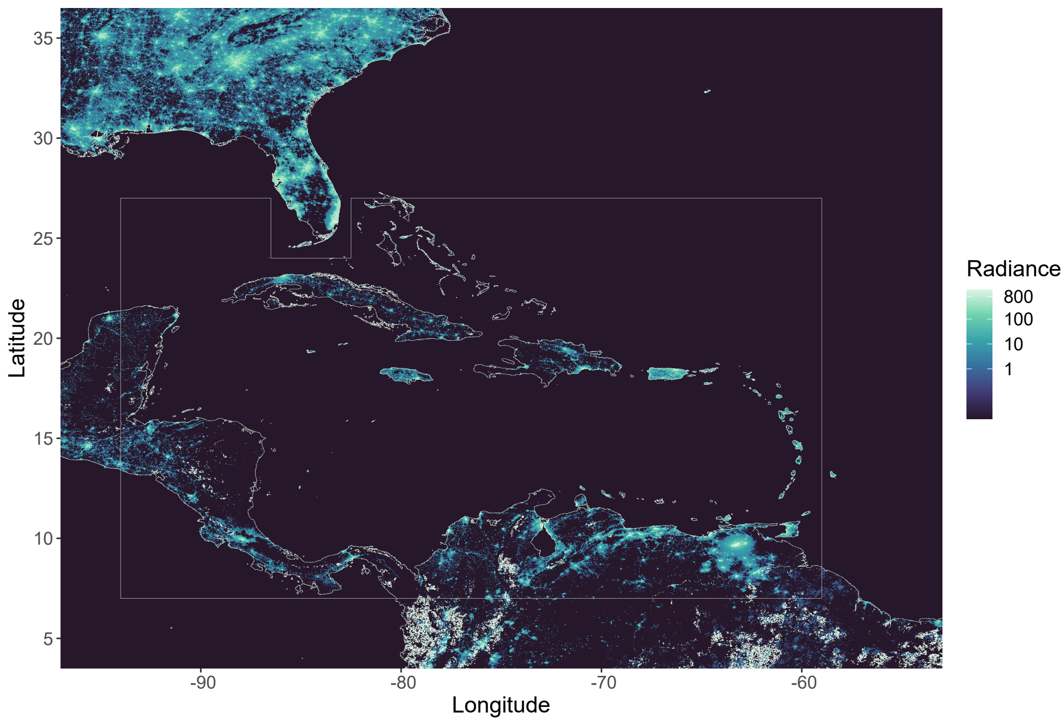
## 2.3 Night Lights

The source of night light data is NASA’s Black Marble product. Black Marble processing of the Visible Infrared Imaging Radiometer Suite (VIIRS) Day-Night Band (DNB) removes cloud-contaminated pixels and corrects for atmospheric and other light effects such as gas flares, is calibrated across time, and validated against ground measurements (Román et al., 2018). The VIIRS DNB provides global daily measurements of nocturnal visible and near-infrared light. The VIIRS DNB is said to be ultra-sensitive in low light conditions, making it suitable for monitoring remote areas as well as highly urbanized locations.

[4] Flash floods that start in one month and end in the next are only assigned to the month when the rainfall event started.

I use version VNP46A3, which provides monthly composites generated from daily observations. Monthly composites remove much of the noise in daily observations and also ensure continuous measurements even when there is cloud coverage for several days in a row, which is not uncommon in the tropics. Black Marble has been available globally since January 2012 on a 15 arc-second (approx. 500 m) linear latitude-by-longitude grid. Figure 2 shows lights at night in January 2012, where radiance was top-coded at 800 $W/(cm^2 - sr)$ to shrink the color scale and make differences at lowly lit places visible. For the analysis, all cells not on land are removed - both ocean and lakes.[5]

Figure 2: Map of Night Lights




*Notes:* Night light map in January 2012 where the grey polygon indicates the study region.

## 2.4 Tropical Storms

In analyzing the effect of floods, which are due to extreme rainfall in the Caribbean and Central America, it is necessary to separate the flood effect from the effect of tropical storms' wind destruction. I follow Strobl (2011) in calculating the local wind exposure during a storm with the Boose et al. (2004) version of the Holland (1980) wind field

[5] Due to ships, some cells do have night light activity even if not on land.

model. The model estimates the location-specific wind speed by taking into account the maximum sustained wind velocity anywhere in the storm, the forward path of the storm, the transition speed of the storm, the radius of maximum winds, and the radial distance to the storm's eye. The model further adjusts for gust factor, surface friction, asymmetry due to the storm's forward motion, and the shape of the wind profile curve. The source of storm data used is the HURDAT Best Track Data (Landsea and Franklin, 2013). These 6-hourly track data are linearly interpolated to hourly observations. $WIND_{cst}$, the wind experienced at any point $i$, during storm $j$ at time $t$ is given by:

$$V_{ijt} = GD\left[V_{mjt} - S\left(1 - \sin(T_{ijt})\right)\frac{V_{hjt}}{2}\right] \times \left[\left(\frac{R_{mjt}}{R_{ijt}}\right)^{B_{jt}} \exp\left\{1 - \left[\frac{R_{mjt}}{R_{ijt}}\right]^{B_{jt}}\right\}\right]^{1/2} \tag{1}$$

where $V_{mst}$ is the maximum sustained wind velocity anywhere in the storm, $T_{ijt}$ is the clockwise angle between the forward path of the storm and a radial line from the storm center to the $i$-th cell of interest, $V_{hjt}$ is the forward velocity of the TC, $R_{mjt}$ is the radius of maximum winds, and $R_{ijt}$ is the radial distance from the center of the storm to point $i$. The remaining ingredients in Equation (1) consist of the gust factor $G$ and the scaling parameters $D$ for surface friction, $S$ for the asymmetry due to the forward motion of the storm, and $B$, for the shape of the wind profile curve. Appendix A.1 provides additional information on the model parameters.

The wind speed is then translated to an index of economic impact via the non-linear damage function by Emanuel (2011):

$$wn_{it} = \frac{v_{ijt}^3}{1 + v_{ijt}^3} \times 100 \tag{2}$$

with

$$v_{ijt} = \frac{\max(V_{ijt} - V_{thresh}, 0)}{V_{half} - V_{thresh}} \tag{3}$$

where $V_{ijt}$ corresponds to the maximum wind speed of hurricane $j$ in location $i$ at time $t$. Then, $V_{thresh} = 92$ km/h is the lower threshold below which no damages occur, whereas $V_{half} = 203$ km/h is where 50% destruction is expected. Conveniently, a one-unit increase can be interpreted as a 1% increase in damages. The maximum $v_{ijt}$ in a given month represents the tropical cyclone impact in subsequent analysis.

## 2.5 Topography

Data on topography are from Amatulli et al. (2018). They provide a suite of global topographic variables at 1 km to 100 km resolution, namely elevation and terrain ruggedness. The terrain ruggedness index (TRI) is the mean of the absolute differences in elevation between a focal cell and its 8 surrounding cells. Elevation and TRI were gathered on the highest resolution of 1 km $\times$ 1 km, and then the average for each GPM/IMERG rainfall cell was calculated.

Table 2: Summary Statistics

| Flash Flood Cell $\times$ Month Observations (N = 205'784) | | | | | |
|---|---|---|---|---|---|
| Statistic | Mean | St. Dev. | Min | Median | Max |
| Night Light | 4.15 | 32.72 | 0.001 | 0.69 | 5'355.50 |
| Wind Index | 0.02 | 1.20 | 0.00 | 0.00 | 319.76 |
| # Historical Floods | 30.47 | 14.41 | 0 | 29 | 79 |
| Longitude | −78.89 | 8.41 | −91.95 | −77.65 | −60.05 |
| Latitude | 12.77 | 4.90 | 7.05 | 10.75 | 26.75 |
| Year | 2015.82 | 2.80 | 2012 | 2016 | 2021 |
| Month | 7.29 | 2.82 | 1 | 7 | 12 |
| Elevation m | 247.52 | 350.47 | −0.52 | 113.54 | 4'145.80 |
| Terrain Ruggedness | 14.28 | 16.28 | 0.00 | 6.37 | 98.53 |
| Non Flash Flood Cell $\times$ Month Observations (N = 1'356'244) | | | | | |
| Statistic | Mean | St. Dev. | Min | Median | Max |
| Night Light | 7.08 | 65.92 | 0.001 | 0.66 | 7'010.11 |
| Wind Index | 0.01 | 0.78 | 0.00 | 0.00 | 327.47 |
| # Historical Floods | 21.54 | 13.18 | 0 | 20 | 79 |
| Longitude | −77.08 | 9.42 | −91.95 | −76.05 | −60.05 |
| Latitude | 12.98 | 4.78 | 7.05 | 11.15 | 26.75 |
| Year | 2016.33 | 2.74 | 2012 | 2'016 | 2'021 |
| Month | 6.20 | 3.51 | 1 | 6 | 12 |
| Elevation m | 344.08 | 510.79 | −0.52 | 132.98 | 4'196.78 |
| Terrain Ruggedness | 16.44 | 18.97 | 0.00 | 6.93 | 110.82 |

*Notes:* Summary statistics grouped by treatment status.

## 2.6 Land Cover

Data on the land cover are from the Copernicus Global Land Cover Layers - Collection 2 (Buchhorn et al., 2020). They provide global maps at a resolution of 100 m $\times$ 100 m for

23 land cover classes (discrete classification) or alternative ten base classes for fractional classification. Classification accuracy is 80% for the discrete case. The base classes include built-up, permanent water, tree, and cropland cover, which is sufficiently detailed for this analysis. Consolidated maps are available for the years 2015 - 2018. The map from 2018 is used for all the analysis as the most recent consolidate.[6] I use the fractional classification on the highest resolution before aggregating the fractions to the panel data cell level. That way, the fractional interpretation conserves its meaning.

### 2.7 Summary Statistics

Table 2 displays summary statistics. There are 13'702 cells with 114 monthly observations starting in January 2012 and ending in June 2021 for a panel of 1.56 Million observations.[7] Out of these 1.56 Million observations, 205'784 or 15% are hit by a flash flood. Observations that are hit emit less light at night on average (4.15 vs. 7.08 $W/(cm^2 - sr)$), have, on average, been hit more frequently in the period 2000 - 2010 (30.5 vs. 21.5 times), have a lower average elevation (247.5 m vs. 344.08 m) and have a slightly less rugged terrain (14.28 vs. 16.44 TRI). In summary, the two groups of observations are not equal; local characteristics and seasonality likely affect whether a flash flood occurs. The subsequent empirical analysis has to consider these differences.

## 3 Empirical Strategy

To develop an empirical strategy, we first need to consider the nature of the phenomenon studied, our variable of interest, and its relation with the outcome. The variable of interest is a binary indicator of whether, within a given month and a certain location, a rainfall episode was so extreme that the area can be classified as flash flooded. For identification, a Difference-in-Difference (DiD) setup with a two-way fixed effects model (TWFE) is suggested. The panel structure of the data readily allows for the estimation of such a model with ordinary least squares (OLS). Three assumptions must be fulfilled for a causal

[6] Arguably, land cover and flash flood severity are simultaneously and dynamically influencing each other, to some degree. Since no data is available for the whole study period, especially not on a monthly scale, the land cover data is static compared to rainfall or night light data. Note that the land cover data is only used for an exercise concerning heterogeneous effects for which the static picture of 2018 is likely a close enough approximation.

[7] The rainfall data has been available since 2000. Thus, lags of flood events before 2012 have been supplemented to the panel.

interpretation of the effects: no anticipation effect, parallel trends, and linear additive effects. In the case of an extreme weather event, these can be satisfied. Weather, especially extreme rainfall, is nigh impossible to forecast for horizons longer than two weeks. There is seasonality in the likelihood of an extreme event, with seasons that are heavy in rain and seasons that are dry. Further, not all places bear the same risk: some areas close to mountains or in the path of persistent, high-moisture wind systems are more likely than others to experience extreme rainfall. Even then, knowing the underlying probability of extreme events in a location or during a specific time of the year does not allow us to predict the occurrence of a single event with sufficient confidence in weather forecasts. Reversing that argument means that, given location and season, no further observable characteristics would lead to selection bias. Thus, there is a quasi-randomness in the occurrence of a flood that can be exploited to estimate a causal effect when controlling for observed differences in flash flood risk. This can be done in a fixed effects regression with both individual and time fixed effects:

$$log(ntl_{it}) = \sum_{j=0}^{m} \beta_j f_{itj} + \gamma_i + \delta_t + \varepsilon_{it}. \tag{4}$$

where $log(ntl_{it})$ is the natural logarithm of night light at cell $i$ at time $t$, $f_{itj}$ are lagged binary flash flood indicators up to a length of $m$ months and $\sum_{j=0}^{m} \beta_j$ are the corresponding constant coefficients. The $\gamma_i$ are unobserved cell fixed effects, $\delta_t$ are the unobserved time fixed effects, and $\varepsilon_{it}$ is the error term. Note that this and all subsequent regressions are estimated with ordinary least squares (OLS). This specification removes location and time-specific averages, reducing the remaining variation to estimate the coefficients of interest and potentially allowing for a causal interpretation. Cell-specific $\gamma_i$ control for time-invariant effects that might spuriously correlate flood impact with economic activity. For instance, if a region experiences frequent flood events but enjoys prosperous economic development due to natural resources, then one should control for such region-specific effects. Similarly, $\delta_t$ controls for time fixed effects that are location invariant and might be correlated with flood risk and economic activity that is uncorrelated with the occurrence of a flood. For instance, floods are more common during the rainy season when fewer tourists arrive.

Some extreme rainfall episodes are likely attributable to tropical cyclones (TCs). To separate the effect of TC wind damage from extreme rainfall, I include lags of the wind index derived in Section 2.4. Also, there might be a spatial spillover of flood events across cells, for which I also include lags:

$$log(ntl_{it}) = \sum_{j=0}^{m} \beta_j f_{itj} + \sum_{j=0}^{m} \alpha_j wn_{itj} + \sum_{j=0}^{m} \nu_j nfl_{itj} + \gamma_i + \delta_t + \varepsilon_{it}. \tag{5}$$

where $\alpha_j$ gives us the effect of a 1% increase in economic damages due to TC winds $j$ periods ago and $\nu_j$ the local effect for a flood event in a neighboring cell.[8]

The dependent night light variable requires some further discussion and modeling choices. Monthly emissions at night are the average of all daily measurements without cloud coverage. For approximately 6.3% of observations, there is no cloud-free night in a month. Therefore, I fill in missing night light values as the average between the preceding and succeeding non-missing observations. This might be problematic because cloudy periods are correlated with high rainfall episodes. In the data, the linear correlation between a flood occurrence and no night light measurement for that cell is 0.056, relatively modest but statistically significant due to the large sample size. Even after this processing, the underlying night light data remains noisy, especially for lower-level night light cells. I account for this in several specifications by first calculating a three-monthly moving average of night light.[9] Both the filling of missing observations and the moving average induce some bias toward zero for coefficient estimates of the flood impact on night lights. This is due to the combination of a positive correlation between the occurrence of a flood and missing observations in night lights and the smoothing from filling missing values and the moving average. Since the positive correlation is modest, this bias should not be problematic and behave similarly to attenuation bias in that the estimated coefficients are shrunk toward zero.

In addition, there are two other issues with regard to causal identification. For one, it might be that some countries have higher growth rates and structural changes in the likelihood of flood events during the study period, for instance, caused by climatic variation. These potential common country-specific trends in flash flood exposure and economic activity could bias the results in both directions. I thus include country-specific linear time trends. Second, it might be that the rainy season and yearly cycles of economic

[8]Neighbors are defined by queen-type, one field away. Each cell, therefore, has eight neighboring cells directly adjacent by moving one cell in either direction. Taking into account elevation by only considering higher elevation neighbors has no impact on results (not reported).

[9]A similar strategy has been employed by Naguib et al. (2022) to estimate the dynamic impacts after a Hurricane in India via night lights.

activity (e.g., due to tourism) are not aligned the same across all countries. Then, the time-fixed effect does not remove all confounding variation. I thus include the month of the year by province fixed effects. The province is the level one administrative sub-unit for all countries but small island states, where the province is considered equal to the country.[10] This gives the following model specification:

$$log(MA_3(ntl_{it})) = \sum_{j=0}^{m} \beta_j f_{itj} + \sum_{j=0}^{m} \alpha_j wn_{itj} + \sum_{j=0}^{m} \nu_j nfl_{itj} + \\ \gamma_i + \delta_t + \pi_c time_t + \omega_{pt}(month_t \times province_i) + \varepsilon_{it}. \quad (6)$$

with $\pi_c$ being the country $c$ specific linear time trend and $\omega_{pt}$ the month of the year by province $p$ fixed effect. The dependent variable $log(MA_3(ntl_{it}))$ is the natural logarithm of the three-monthly moving average transformed night light.

So far, little attention has been given to the error term. Neighboring cells likely affect the error term of the focal cell. With the current assumptions, such dependence is ruled out and potentially biases the estimation. Also, given the panel structure of the data, there is likely autocorrelation in the error term. To account for both, I use Driscoll and Kraay (1998) standard errors. The treatment of missing values in night light and the moving average specification suggest an autocorrelation length of three months.

## 4 Results

Regression results estimated with ordinary least squares (OLS), restricted to a maximum lag length $m = 3$ for conciseness, are displayed in Table 3. Results in column (1) are from the simplest model in Equation 4. It suggests a positive contemporaneous effect of 4% in the month of the flash flood that then reverses to −3% three months after. The same can be found in column (2) with the model from Equation 5, which adds controls for tropical storm wind speed and neighboring cells' flood incidents. An increase of the tropical storm wind destruction index by one percentage point decreases light emissions by 0.8% contemporaneously, an effect that weakens but persists over the following months. Floods in neighboring cells do not appear to impact the focal cell in this specification. When

[10]This yields a total of 282 provinces. Examples where the country equals the province include Saint Lucia and Martinique.

using the same specification but the $MA_3$ transformed series of night lights in column (3), the contemporary positive effect of a flash flood disappears. When further including the additional controls as in Equation 6, there is a positive contemporaneous effect for flash floods that turns negative after some months. While not providing an estimate that should be taken literally due to the arbitrary cut-off at $m = 3$, this comparison is still informative, and a few points can be noted. First, introducing both wind speed and neighboring cells flood does not change the coefficients of the flood indicators. Second, transforming the dependent variable via moving average affects the result and should be considered when including a longer time horizon. Lastly, controlling for province-specific seasonality, the coefficients of flood incidents become less negative, indicating a correlation between flood incidents and location-specific seasonality.[11]

## 4.1 Dynamics

Figure 3 shows dynamic effects for longer time horizons and added leads. The full model in use is shown in Equation 6. Results are once with moving average smoothing and once with the unaltered night lights. Leads show no clear pre-trends before an event, be it a flash flood or a tropical storm. The effect upon impact starkly differs between the two hazards: for flash floods, we have a contemporaneous *increase* in the level of night light emissions, while for a tropical storm, there is a contemporaneous *decrease*. In the case of a tropical storm, this decrease in the level is then recovered in subsequent months. For flash floods, the dynamics are different. After the initial increase in emissions, the effect on the level becomes $-1\%$ to $-2\%$ three to six months after the event. Then, there is a quick recovery, and no effect is discernible eight months after the flash flood. The main difference in comparing $MA_3$ with direct night light measures is that the $MA_3$ dynamics are smoother and shrunk towards zero, as expected. No systematic bias is discernible such that the night light measure without moving average smoothing is preferred in subsequent analysis for more straightforward interpretation.

[11] The change in coefficients moving from column 3) to column 4) is mainly driven by the month $\times$ province interaction, not by the country-specific (time) slopes. Coefficients becoming less negative thus indicates that there is a negative correlation between local seasonality in the probability of heavy rainfall episodes and economic activity in the following months that is not due to a flood event.

Table 3: Regressions: $m = 3$

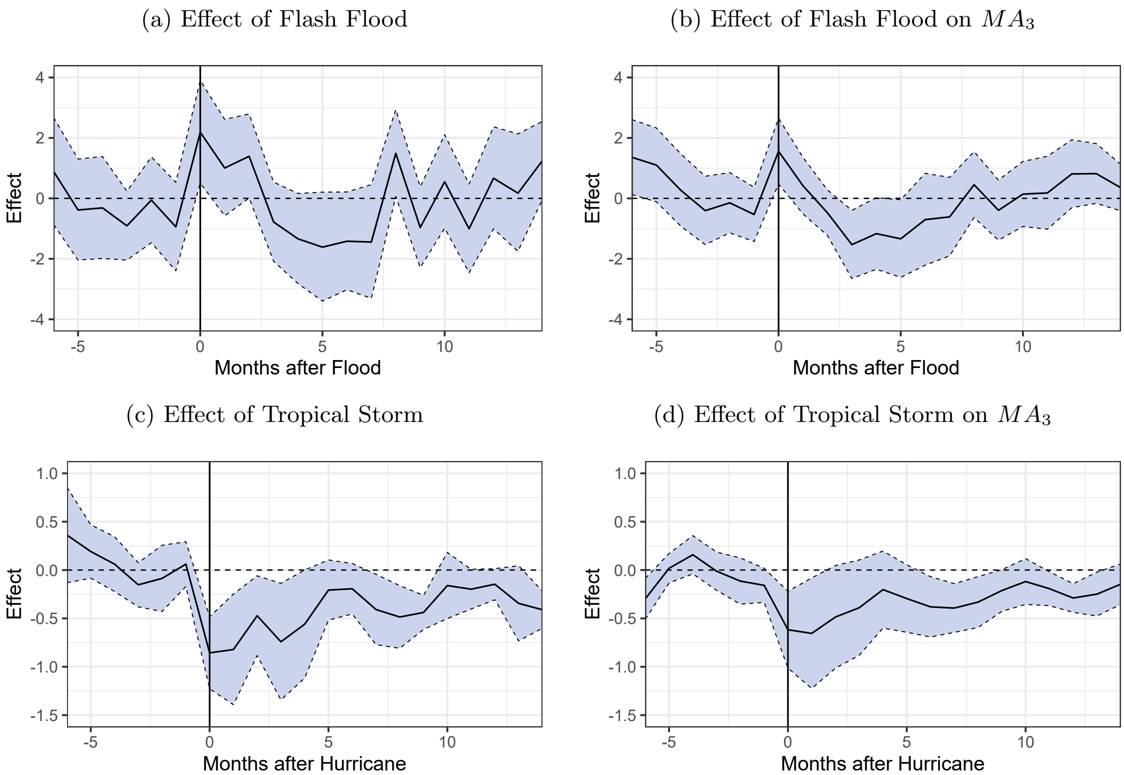
| | $log(ntl_{it})$ | | $log(MA_3(ntl_{it}))$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $fl_0$ | 0.04*** (0.02) | 0.04*** (0.01) | 0.005 (0.01) | 0.02*** (0.005) |
| $fl_1$ | -0.002 (0.01) | -0.002 (0.01) | -0.02** (0.01) | 0.004 (0.005) |
| $fl_2$ | -0.01 (0.01) | -0.02 (0.01) | -0.03*** (0.01) | -0.005 (0.004) |
| $fl_3$ | -0.03** (0.01) | -0.04*** (0.01) | -0.04*** (0.01) | -0.01** (0.006) |
| $wn_0$ | | -0.008*** (0.002) | -0.005*** (0.002) | -0.006*** (0.002) |
| $wn_1$ | | -0.006** (0.003) | -0.004* (0.002) | -0.006** (0.003) |
| $wn_2$ | | -0.001 (0.002) | -0.002*** (0.0007) | -0.004 (0.003) |
| $wn_3$ | | -0.004*** (0.0006) | -0.003*** (0.0006) | -0.004 (0.002) |
| $nfl_0$ | | 0.001 (0.009) | 0.007 (0.005) | 0.01*** (0.004) |
| $nfl_1$ | | 0.0004 (0.007) | 0.006 (0.005) | 0.006 (0.004) |
| $nfl_2$ | | 0.002 (0.006) | 0.005 (0.005) | 0.0006 (0.003) |
| $nfl_3$ | | 0.007 (0.007) | 0.004 (0.005) | -0.003 (0.003) |
| Observations | 1,466,766 | 1,466,766 | 1,394,986 | 1,394,986 |
| $R^2$ | 0.82 | 0.82 | 0.87 | 0.89 |
| Fixed Effects | | | | |
| Date | ✓ | ✓ | ✓ | ✓ |
| Location | ✓ | ✓ | ✓ | ✓ |
| Country | | | | ✓ |
| Month × province | | | | ✓ |
| Varying Slopes | | | | |
| Country | | | | ✓ |

*Notes:* Table of regression results for a maximum lag length of $m = 3$ showing coefficients for flash floods, tropical storm wind speed, and neighboring floods. The regression in column (1) follows Equation 4, column (2) follows Equation 5, column (3) also follows Equation 5 but with a moving average dependent variable and column (4) follows Equation 6. *p<0.1; **p<0.05; ***p<0.01

### 4.1.1 Spillovers

A flood in a neighboring location could have opposing effects on economic activity. For one, economic activity might be displaced from the flood-affected area to nearby unaffected areas. Then, coefficients $\nu_j$ in Equations 5 and 6 would be positive, especially for the first months after an event. Conversely, a flood could impede industry linkages in the affected area and nearby locations by, for instance, impassable roads, resulting in negative $\nu_j$. A third option is that there are no spillovers where all effects are contained within the cells of size 11 km × 11 km. Figure 4 sheds some light on this question. There is a contemporary positive effect similar to a flood in the focal cell but of a smaller size. Then, the effect becomes smaller until it becomes only significantly negative by $-1\%$ nine months after

Figure 3: Dynamic Effects of Flash Floods an Tropical Storms




(a) Effect of Flash Flood

(b) Effect of Flash Flood on $MA_3$

(c) Effect of Tropical Storm

(d) Effect of Tropical Storm on $MA_3$

*Notes:* Dynamic effects of flash floods and tropical storms on night lights in percentage points. The black line plots the log-transformed coefficients with two-sided 90% confidence bands in blue. The regression model is as in Equation 6 with $log(ntl_{it})$ as the dependent variable in (a) and (c), and $log(MA_3(ntl_{it}))$ in (b) and (d).

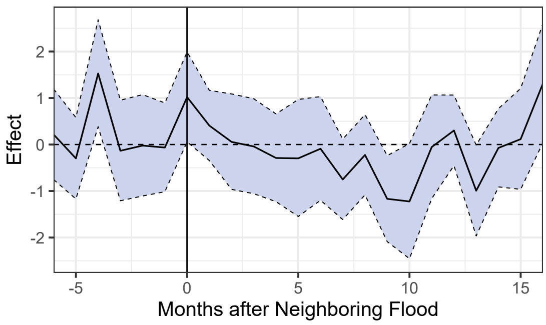
the event. Interestingly, this negative effect of a flood in a neighboring cell occurs later than in the case of a flood in the focal cell. This raises the question of the spillovers' nature. Arguably, the contemporary effect could be due to a similar mechanism for both neighboring and focal cells. On the other side, the following dynamics suggest some sort of hierarchy where negative impacts slowly spread out from the focal.

## 4.2 Heterogeneity

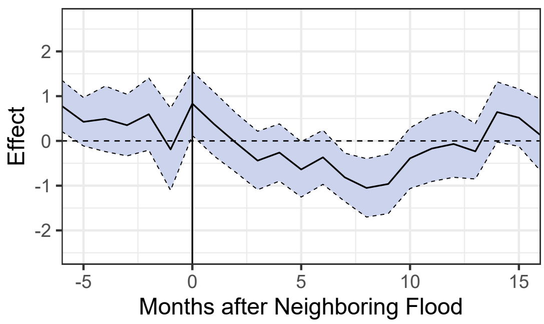
The economic impact of a flash flood likely depends on local characteristics. These can include the history of previous floods, the share of built-up area, terrain ruggedness, elevation, or agricultural activity. A steeper, more rugged topography might be associated with more detrimental impacts in case of a flood. Previous exposure to floods could make households and firms more resilient or, conversely, scar their ability to recover from further

Figure 4: Dynamic Effects of Neighboring Flash Floods

(a) Effect of Neighboring Flash Flood




(b) Effect of Neighboring Flash Flood on $MA_3$




*Notes:* Dynamic effects of neighboring flash floods on night lights in percentage points. The black line plots the log-transformed coefficients with two-sided 90% confidence bands in blue. The regression model is as in Equation 6 with $log(ntl_{it})$ as the dependent variable in (a) and $log(MA_3(ntl_{it}))$ in (b).

shocks. Table 4 displays results of regressions that include interactions of the binary flood indicator with these local characteristics. Since we expect from the results that the effect is largest around four months post-flood, I only use the indicator $fl_4$ of a flood four months ago for the regression with interactions to keep the number of terms tractable for interpretation. The coefficient of $fl_4$ here thus gives the cumulative effect a flood has four months after the event. In contrast, the interaction provides the change in cumulative effect per one unit change in the variable for heterogeneity. The local characteristics have been normalized to a mean of zero for interpretation. This will not change the direct effect of $fl_4$ mechanically. The coefficient of $fl_4$ is $-2\%$ in all but one specification. The number of floods between June 2000 and 2010 (# Hist. Floods) has no additional effect (model column 1). The same applies to the terrain ruggedness index (TRI) and elevation above sea level (models columns 2 and 3). The higher the share of built-up area, the weaker the effect of a flood (model column 4). The effect is not only statistically significant: the estimated coefficient of 0.5% lowers the flash flood effect per 1% of the built-up area, indicating that highly developed locations do not experience a reduction in night lights (the $75^{th}$ percentile of the area built is 0.74%).[12] Arguably, the built-up area is a measure of human settlement and economic activity. A higher development might be associated with higher quality infrastructure (paved roads vs. dirt roads, adequate drainage systems,

[12]Data on land cover is from 2018. Thus, the cell fixed effects purge it from any direct impact, as it does so for elevation and TRI, and we have only the interaction for interpretation.

and a more resilient electric grid). An alternative explanation is that emergency relief efforts for more built-up areas are better endowed by local decision-makers such that flash floods have less of a negative impact there. In contrast, the percentage of area covered by agricultural crops does not influence the effect of a flash flood (model column 5). The same holds for land coverage in forests, grassland, or shrubs (results not reported).

Floods in neighboring cells do not directly affect the night light level four months afterward, though their interaction with a flash flood in the focal cell is positive and statistically significant (model column 6). This implies that a flood does not harm economic activity if there are floods in neighboring areas. Conversely, floods in neighboring areas are only negatively impacted if the focal cell is not hit by a flood. One explanation for this phenomenon might be that if a larger geographical area is subject to a hazard, there is a more pronounced relief effort by a central state, explaining both the positive interaction effect and the insignificant effect of a flood in a neighboring cell.

### 4.3 Heterogeneity by Development

Besides heterogeneity concerning the focal cell, we can also consider heterogeneity with respect to the country's development. Evidence shows that flood events mainly affect low- and medium-developed countries (Loayza et al., 2012). The human development index (HDI) is a summary measure of average achievement in key dimensions of human development and classifies countries into low, medium, high, and very high development.[13] The HDI is calculated on the country level and available for virtually all states worldwide. Some Caribbean islands are overseas territories of larger countries, such as the USA (Virgin Islands, Puerto Rico), France (Guadeloupe, Martinique), or the Netherlands (ABC Islands), for which the HDI predominantly represents mainland development. Nevertheless, these Islands boast comparatively high development and are expected to be similarly impacted to other very high-development states in the region, such as the Bahamas or Panama. Regressing an interaction between the HDI category as of 2021 and flash flood incidence onto log night light models potential heterogeneity in effect by country development. Again, I use the indicator of a flood four months ago $fl_4$ for interaction.

[13] The HDI itself is often the subject of critique. For instance, it does not consider inequality directly. Still, it is a measure that, compared to GDP, is more resourceful in comparing development.

Table 4: Regressions: Heterogeneity

| | $log(ntl_{it})$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $fl_4$ | -0.01 (0.009) | -0.02$^*$ (0.009) | -0.02$^*$ (0.010) | -0.02$^*$ (0.009) | -0.02$^*$ (0.009) | -0.02$^{**}$ (0.009) |
| $fl_4$ × # Hist. Floods | -0.0006 (0.0005) | | | | | |
| $fl_4$ × TRI | | -0.0007 (0.0004) | | | | |
| $fl_4$ × Elevation | | | $-1.6 \times 10^{-5}$ $(1.6 \times 10^{-5})$ | | | |
| $fl_4$ × Built % | | | | 0.005$^{***}$ (0.002) | | |
| $fl_4$ × Agriculture % | | | | | $-3 \times 10^{-5}$ (0.0005) | |
| $nfl_4$ | | | | | | -0.008 (0.005) |
| $fl_4$ ×$nfl_4$ | | | | | | 0.01$^{**}$ (0.005) |
| Observations | 1,466,766 | 1,466,766 | 1,466,766 | 1,466,766 | 1,466,766 | 1,466,766 |
| $R^2$ | 0.84 | 0.84 | 0.84 | 0.84 | 0.84 | 0.84 |
| Fixed Effects | | | | | | |
| Date | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Location | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Country | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month × province | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Varying Slopes | | | | | | |
| Country | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Notes:* Table of regression results with only $fl_4$ as the indicator for the interaction with various sources of potential effect heterogeneity. Variables for interaction are normalized such that the coefficient for $fl_4$ gives the estimate when the interacted variable is at its mean. Standard errors are in parentheses. $^*$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

Table 5: Regressions: HDI

| | $log(ntl_{it})$ | |
|---|---|---|
| | (1) | (2) |
| $fl_4$ | | -0.02* (0.009) |
| $fl_4$ × HDI = low | -0.07* (0.04) | |
| $fl_4$ × HDI = medium | -0.04** (0.02) | |
| $fl_4$ × HDI = high | 0.01 (0.01) | |
| $fl_4$ × HDI = very high | -0.01 (0.02) | |
| $fl_4$ × HDI = Territory | -0.005 (0.04) | |
| Observations | 1,466,766 | 1,466,766 |
| $R^2$ | 0.84 | 0.84 |
| Fixed Effects | | |
| Date | ✓ | ✓ |
| Location | ✓ | ✓ |
| Country | ✓ | ✓ |
| Month × province | ✓ | ✓ |
| Varying Slopes | | |
| Country | ✓ | ✓ |

*Notes:* Table of regression results with only $fl_4$ as the indicator for the interaction with the five levels of HDI. Column (1) shows heterogeneous effects from a regression with the interaction terms, and column (2) the unconditional average effect from a regression without interaction. Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 5 shows results that point towards the importance of economic development in absorbing natural hazards. Results in column (1) suggest that cells that lie in low (medium) developed countries emit 7% (4%) less light at night four months after a flood, whereas cells in higher developed countries appear to not react locally to a flood. On average, for the study region, the level of night light decreases by 2% six months after a flash flood (column 2). Albeit small, this effect can still be economically significant given the high frequency of such heavy rainfall episodes. Assessing the dynamic response heterogeneity concerning the countries' development while controlling for the dynamics due to tropical storms and spillovers would ask for a fixed effects model with many interactions where the serial correlation of the indicators might become problematic. Instead, I use local projections introduced by Jordà (2005) and recently employed in the context of natural hazards by Naguib et al. (2022) to study dynamic changes in night light due to tropical storms in India. Local projections are performed as a set of sequential regressions, where the dependent variable is shifted $m$ steps ahead instead of introducing $m$ lags of the flood indicator. An additional benefit of the local projection method is that it directly yields impulse-response functions with correctly specified confidence bands. The specification I use is

$$\begin{aligned}\Delta ntl_{it+m} =&\beta_1 f_{it} + \alpha_1 wn_{it} + \nu_1 nfl_{it} + \\ &\gamma_i + \delta_t + \pi_c time_t + \omega_{pt}(month_t \times province_i) + \varepsilon_{it+m}\end{aligned} \tag{7}$$

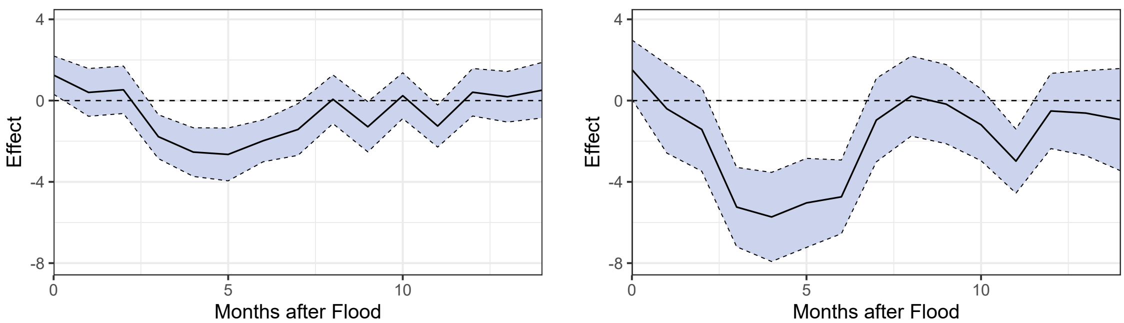
where I run a series of $m$ regressions with the coefficient $\beta_1$ associated with regression $m$ gives the effect of a flash flood on $\Delta ntl_{it+m}$, the cumulative growth between $t-1$ and $t+m$. I also estimate a variation of 7 with an interaction $fl_{it} \times HDI_{low,med.}$ which separates the effect a flood has on countries with low and medium HDI from those with at least high HDI:[14]

$$\begin{aligned}\Delta ntl_{it+m} =& \boldsymbol{\beta} fl_{it} \times HDI_{low,med.} + \alpha_1 wn_{it} + \nu_1 nfl_{it} + \\ &\gamma_i + \delta_t + \pi_c time_t + \omega_{pt}(month_t \times province_i) + \varepsilon_{it+m}.\end{aligned} \tag{8}$$

Figure 5: Dynamic Effects of Flash Floods from Local Projections

(a) Average Effect

(b) Effect for low and medium HDI




*Notes:* Dynamic effects of flash floods on night lights in percentage points. The black line plots the growth rate $m$ months after a flood with two-sided 90% confidence bands in blue. (a) plots the average effects as in Equation 7 and (b) the effects for low and medium HDI countries as in Equation 8.

Figure 5 shows the dynamic effect of a flash flood on night light from local projections. As hinted by the results four months after a flood in Table 5, the aggregate effect is driven

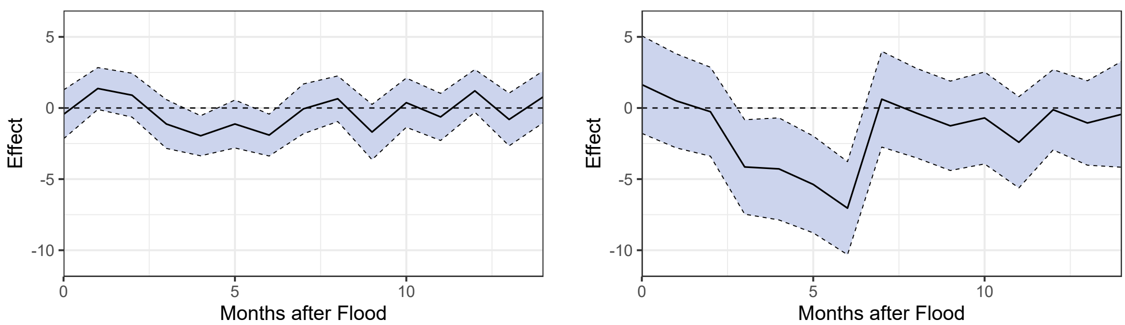
[14] The only country with a low HDI is Haiti. Thus, I group it with countries with a medium HDI: Guatemala, El Salvador, Honduras, Nicaragua and Venezuela.

by those cells in low- to medium-developed countries. In both cases, an initial increase in night lights of 1% quickly reverses and reaches a low of −2.6% on average and −5.7% in low- and medium-development countries. Note that in comparison to the dynamics in Figure 3 or 4, where the effect size can not be interpreted as direct impulse-response-function,[15] they can be interpreted that way with local projections. The IRFs from local projections confirm that there is indeed a 1) positive contemporaneous impact, 2) negative growth in the following months, reaching its low four to five months after the event, and 3) recovery in the months following. Not only that, but the results from local projections suggest more substantial and more pronounced reductions in night light emissions due to a flash flood than the results from the model in Equation 6 suggests.

Figure 6: Dynamic Effects of Flash Floods with Alternative Event Definition

(a) Average Effect

(b) Effect for low and medium HDI




*Notes:* Dynamic effects of flash floods on night lights in percentage points with the definition of 5 mm/h above the classification threshold. The black line plots the growth rate $m$ months after a flood with two-sided 90% confidence bands in blue. (a) plots the average effects as in Equation 7 and (b) the effects for low and medium HDI countries as in Equation 8.

## 4.4 Alternative Event Definition

The main analysis already provides considerable robustness to the results. In this section, I provide further evidence that the event definition, when rainfall events are causing floods, is robust. In the main analysis, I require a rainfall event to have an excess intensity of 2 mm/h above the threshold. Out of the total 63 Million rainfall events, where most are minor showers, 1.06 Million or 1.7% are above this threshold. When focusing on the

[15]The issue with the FE model with many lags in a dynamic setting is that the flood indicators $fl_0$, $fl_1$, etc. are serially correlated. To avoid issues with respect to growth, I chose to model night light in levels as in Brei et al. (2019).

period where night light data is available and aggregating these to the monthly level, around 15% of cell-by-month observations are treated by a potential flood. One might be concerned with the frequency of treatment, especially with regard to back-of-the-envelope calculations that rely on the estimated effect and the frequency of the natural hazard. Thus, I use a much more restrictive definition of 5 mm/h above the threshold calibrated with the universe of flash flood events for Jamaica since 2000. Then, only 2.9% of cell-by-month observations experience a rainfall event that likely triggers flash floods. The average return period is almost three years. Results of the local projections as in Equation 7 and 8 are shown in Figure 6. Confidence bands are wider, and the dynamics are the same as with the 2 mm/h classification. The effect size is, as expected, larger for low- and medium-development countries; for instance, after six months, the estimate suggests a reduction in night light activity of $-7\%$ instead of $-5.7\%$ in the main analysis. This suggests that the excess threshold of 2 mm/h is appropriate, and by choosing a threshold of 5 mm/h, one conditions on the more extreme extreme events.

## 5 Discussion

The analysis has four critical implications. First, episodes of extreme rainfall that likely trigger flash flooding have a sizeable negative effect on economic activity as measured by night light emissions. Second, the dynamics after the flood differ from a tropical storm, the arguably closest natural disaster commonly analyzed in economics. In the case of a flood, there is a brief contemporary positive effect that becomes negative in months four and five before recovering in month ten. A tropical storm, in contrast, has a negative effect upon impact from where recovery is comparatively slower. This result indicates the different mechanisms through which either of the hazards influences economic activity. The third key implication is about spatial spillovers. There is a spatial spillover from floods in neighboring areas onto the local economy, but to a more minor degree. Also, there is a longer lag between event and effect than if the area had been hit directly. If several neighboring areas are hit simultaneously, then there is a *positive* spillover, reducing the negative effect of being hit. The fourth key implication is that the estimated negative effect of a flash flood is driven by locations in low- and medium-developed countries.

A natural next point is to assess how detrimental floods are in economic terms. Taking the estimates from the local projections, the total effect[16] in the year after an event is a

[16]Here, total effect relates conceptually to the integral of the IRF, which is, in the case of month-wise

$-0.9\%$ reduction in night lights for the study region and $-2.2\%$ for low and medium developed countries. In recent years, more attention has been given to the question of translating changes in night light emissions into economic variables such as GDP.[17] In their seminal paper, Henderson et al. (2012) lay foundations on using night light data to augment income growth measures. They find that the elasticity between the growth of lights and GDP growth is around 0.3. For low- and middle-income countries, there is an average of 1.27 flash floods in a cell per year, and assuming that they are evenly distributed concerning economic activity,[18] a back-of-the-envelope calculation implies a decrease in the GDP growth rate by $-2.2\% \times 0.3 \times 1.27 = -0.84\%$. Note here that while each shock is transitory and can thus be thought of as a level change, the series of shocks are on such a high frequency that a change in the growth rate best represents their cumulative impact. To put this into perspective, the average GDP growth rate from the World Bank annual national accounts data for the countries in the low to medium category in the 10-year period 2012 to 2021 were: Haiti (0.82%), Guatemala (3.46%), El Salvador (2.09%), Honduras (3.26%), Nicaragua (3.16%), and Venezuela (1.02%). Flash floods do not explain the differences between these countries' growth rates and likely do not account for the current development. However, these countries would especially suffer if extreme rainfall events' severity or frequency increases.

To put the impacts of flash floods into perspective, it is informative to compare them to other natural hazards such as hurricanes and urban floods. Ishizawa et al. (2019) investigate the impacts of hurricanes on monthly economic activity in a similar setup as this study via night lights for the Dominican Republic. Their estimated effect is highly dependent on storm intensity but is said to peak 9 months after impact and go to zero after 15 months. For the average storm, the effect peaks at about -7.5%, more than 3×

growth effects in the LP framework, equal to the mean effect for the first 12 months after an event.

[17] Chen and Nordhaus (2019) compare DMSP/OLS and VIIRS for predicting cross-sectional and time-series GDP data for the US. They find that VIIRS performs well at predicting metropolitan area night light growth. Gibson et al. (2021) compare the ability of the DMSP/OLS and VIIRS to predict local GDP for Indonesia and finds that the DMSP/OLS is twice as noisy as the VIIRS. They find elasticities around $0.17 - 0.19$ when using VIIRS night light to predict Indonesia's second-level sub-national GDP and elasticity of 0.5 for provincial-level GDP.

[18] Flood incidents are negatively correlated with the percentage of built area with a correlation coefficient of -0.02. There is thus more built-up area and economic activity in locations that experience fewer floods. However, the strength of the correlation is low enough that it can be ignored for this back-of-the-envelope calculation.

the effect of the average flash flood as estimated in this study. Kocornik-Mina et al. (2020) studies floods in the context of cities and displacement due to flood risk. Conceptually, their focus on large-scale urban floods should lead to more substantial impacts than the narrow notion of flash floods used here.[19] They find that large floods *"... reduce a city's economic activity, as measured by nighttime lights, by between 2 and 8 percent in the year of the flood"*. The estimated average effect for the year of the flood in this study is smaller with $-0.9\%$.

Besides the effect size, we can also distinguish between the dynamic response after a flash flood, tropical storm, and other natural hazards. There is a contemporary increase in night light emissions for floods which does not appear for tropical storms. Several factors can lead to this phenomenon. It is well-known that buildings and structures that have been flooded are prone to catching fire due to corrosion and damage to electrical circuits. Even a single fire in a relatively large region would lead to a significant increase in night lights. Gas flares, for instance, are a major source of night light emission in remote areas, and data on night lights have been used successfully to estimate their emissions (Elvidge et al., 2009). The second factor that leads to the phenomenon of a positive contemporaneous effect is disaster aid. While it is hard to quantify, it is easy to see that aid flowing into an area will increase light emissions for the duration of the endeavor. Still, this cannot explain why it would be different for different natural hazards. For this, we need to consider the type of destruction each hazard brings. Strong winds from hurricanes directly destroy buildings and damage overland power lines.[20] This destruction is immediately reflected in a lower night light emission. This contrasts with the destruction brought by flash floods. While also destroying buildings, flash floods directly destroy roads and other transportation structures that are only indirectly affected by hurricanes (Diakakis et al., 2020). Since most roads are unlit in Central America and the Caribbean, their destruction or deterioration does not directly cause night light emissions to fall. However, they hamper economic activity by increasing the cost of transporting goods and commuting to work (Hallegatte et al., 2016). While in the short term of one to two months, this cost might be absorbed by firms and households, they cannot do so for a

[19] Flash floods constructed via the IDF-curve approach likely generate more small-scale events than the subset of floods with at least 100'000 people displaced and detailed inundation maps in the DFO data as in Kocornik-Mina et al. (2020).

[20] See the Saffir-Simpson Hurricane Wind Scale, which directly describes the damage to houses and the electricity infrastructure in its classification.

more extended period. Repair and reconstruction occur but are done only six to eight months after an event. This story fits the results that 1) more developed countries with a higher quality infrastructure are less affected, 2) areas with a higher percentage of built area, including paved roads, are less affected, and 3) negative and positive spatial spillover effects from floods exist in certain configurations. While 1) and 2) follow straightforwardly from this analysis, 3) concerning spatial spillovers requires further research to substantiate this line of argument. For one, work has to be done to understand how firms are affected when there is a flood in their vicinity. A fruitful route might be to separately consider specific industries, such as construction or manufacturing. Also, a better understanding of how gaps in the transportation network in developing countries affect economic activity is necessary.

The main strength of the paper, the construction of a flash flood indicator based on physical characteristics, is its main weakness. On one side, it allows me to flexibly and consistently define a hazard across multiple countries. This is the first study in economics to rigorously define localized flood events from rainfall data directly. Others, such as Cavallo et al. (2013) and Kocornik-Mina et al. (2020), rely on event databases that are not necessarily consistent across time or countries. At the same time, by not directly observing the hazardous event but rather inferring it from a decision rule related to rainfall characteristics, I can not be certain to cover all events adequately. Strictly speaking, the results must be understood in terms of a rainfall event that likely causes some flooding in the area. Since the classification method has been calibrated on high-quality, exhaustive data for all flood events in Jamaica since 2000, it should perform well for the study region. However, extending the methodology to other regions or doing a global analysis requires appropriate calibration in each region (Hirpa et al., 2018).

Through empirical studies focusing on a specific type of natural disaster, we obtain a clearer picture of how various types can be discerned. The flash floods investigated here are characterized by their frequency, local occurrence, and the lagged dynamic reaction with a quick recovery. Other hazards do have different signatures on economic activity. With hurricanes, it has been suggested that their imprint on the economy is significant even several years afterward (Hsiang and Jina, 2014), while droughts trigger specific migratory reactions (Kaczan and Orgill-Meyer, 2020). These findings could be assessed more formally and more thoroughly in a general equilibrium growth model that considers different natural disasters and their potential trajectories concerning climate change. There is a great need for such an undertaking: most integrated assessment models assume climate change impacts to be a single, non-linear scalar of all outputs in all sectors in all locations. This omits practically all insights gained in the economic natural disasters literature. In conjunction with this neglect, it has to be noted that the uncertainty for climate change projections from economic growth is magnitudes larger than the uncertainty from the natural sciences. Thus, it is paramount for economists in the field to find precise, causal estimates for various channels through which climate change will impact the economy, natural disasters being one of them.

## 6 Conclusion

I study the dynamic effect of extreme rainfall events that lead to flash floods on local economic activity measured by night light emission in Central America and the Caribbean. One such event decreases local emissions by up to $-5.7\%$ in low and medium-development countries, while there is little effect in higher-development countries. My results further suggest that floods cause a different dynamic reaction to hurricanes and other natural hazards. The impulse-response function shows that, after a contemporary increase in night lights by 1.3%, the effect of a flood becomes $-5.7\%$ after three months and stays in that range until reversing back to zero after seven months. In the 12 months following a flash flood, the average effect is $-2.2\%$ in low and medium-development countries. Back-of-the-envelope calculations indicate that for those countries, the total impact is equal to a reduction in the GDP growth rate of 0.84% due to the high frequency of flash floods.

Flash floods further appear to cause spatial spillovers. The effect on night light emissions when there is an event in a neighboring area is more minor and with a longer delay than if the area had been hit directly. This indicates that a flood disrupts economic processes beyond directly impacted areas. If several neighboring areas are hit simultaneously, then there is positive spillover, reducing the negative direct effect. Such negation of the negative effect of floods is consistent with the notion that relative differences across space matter and no adjustments take place if all locations are affected at the same time.

My findings have two main implications for policy. First, extreme rainfall episodes have a distinctly negative effect on economic activity in low and medium-developed countries. Before, the effect of extreme rainfall has often been masked by spatial or temporal aggregation. Since there appears to be little effect for higher-development countries, development in key areas could be a way out. Future research has to be conducted to investigate what those key areas are and how one can induce resilience in lower-development countries. Second, because flash floods are such a high-frequency natural hazard with return periods of less than one year in many parts of the study region, they can have direct effects on a country's growth rate. In a warming and humid climate, extreme rainfall events are projected to increase in frequency and severity. I show that such an increase will likely impact the growth of developing countries in Central America and the Caribbean. Consequentially, the cost of future emissions should take this into account.

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## Availability of data

The primary data used or analyzed in this study are freely available at the indicated source. Data that result through the application of the methodology in this work are available from the corresponding author upon reasonable request.

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# A Appendix

## A.1 Wind Field Model

In terms of implementing Equation 1 one should note that the maximum sustained wind velocity anywhere in the storm $V_{mst}$ is given by the storm track data, the forward velocity of the storm $V_{hst}$ can be directly calculated by following the storm's movements between successive locations along its track, the radial distance $R_{cst}$ and the clockwise angle $T_{cst}$ which are calculated relative to the point of interest $c$. All other parameters have to be estimated or values assumed. For instance, we have no information on the gust wind factor $G$, but a number of studies (see e.g. Paulsen and Schroeder, 2005) have measured $G$ to be around 1.5, and I also use this value. For $S$, I follow Boose, Serrano and Foster (2004) and assume it to be 1. While we also do not know the surface friction to determine $D$ directly, Vickery, Masters, Powell and Wadhera (2009) note that in open water, the reduction factor is about 0.7 and reduces by 14% on the coast and 28% further 50 km inland. I thus adopt a reduction factor that decreases linearly within this range as we consider points $c$ further inland from the coast. Finally, to determine the shape of the wind profile curve $B$, I employ the approximation method of Holland (1980) where $B$ is negatively correlated with central pressure and falls in the range of $1.5 - 2.5$ (Xiao et al., 2011). I use the parametric non-basin-specific model estimated by Vickery and Wadhera (2008) to calculate the radius of maximum winds $R_{mst}$.