Essays on the Economics of Natural Disasters

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Chapter 1

Introduction

Natural disasters have always been and probably always will be a problem for humans and their settlements. With global warming seemingly increasing the frequency and strength of the climate related disasters, and more and more people being settled in urban centers, the ability to model and predict damage is more important than ever.

The aim of this thesis has been to model and analyze a broad range of disaster types and the kind of impact that they have. By modeling damage indices for disaster types as different as hurricanes and volcanic eruptions, the thesis helps with understanding both similarities and differences between how disasters work and what impact they have on societies experiencing them. The thesis comprises four different chapters in addition to this introduction, where all of them include modeling of one or more types of natural disasters and their impact on real world metrics such as local budgets, birth rates and economic growth.

Chapter 2 is titled "Natural Disaster Damage Indices Based on Remotely Sensed Data: An Application to Indonesia". The objective was to construct damage indices through remotely sensed and freely available data. In short, the methodology exploits that one can use nightlight data as a proxy for economic activity. Then the nightlights data is matched with remote sensing data typically used for natural hazard modeling. The next step is to construct damage indices at the district level for Indonesia, for different disaster events such as floods, earthquakes, volcanic eruptions and the 2004 Christmas Tsunami. Ex ante, prior to the incidence of a disaster,

district level damage indices could be used to determine the size of the annual fiscal transfers from the central government to the subnational governments. Ex post, or after the incidence of a natural disaster, damage indices are useful for quickly assessing and estimating the damages caused and are especially useful for both central and local governments, emergency services, and aid workers so that they can respond efficiently and deploy resources where they are most needed. The chapter is published as a World Bank Policy Research Paper under Skoufias *et al.* (2017a).

Chapter 3 utilizes the indices from Chapter 2 to showcase a potential area of use for them. The title is "The Reallocation of District-Level Spending and Natural Disasters: Evidence from Indonesia" and the main focus is on Indonesian district-level budgets. The aim was to use the modeled intensity from Chapter 2 to a real world scenario that could affect policy makers. By using the natural disaster damage indices constructed from the physical events and the exposure to them, this chapter utilizes local level economic data from Indonesia to analyze whether districts redistribute their expenditures following natural disasters such as floods, earthquakes, volcanic eruptions and the 2004 tsunami. There is evidence that some disaster types cause districts to move costs away from more general line items to areas such as health and infrastructure, which are likely to experience added pressure due to disasters. Furthermore, volcanic eruptions and the tsunami led to less investment into more durable assets both for the year of the disaster and the following year. This chapter is also forthcoming as a World Bank Policy Research Paper under Skoufias *et al.* (2017b).

The fourth chapter, titled "Urban Global Impact of Earthquakes from 2004 through 2013", is a short chapter focusing on earthquake damage and economic growth. This chapter is an expansion of the index used in the previous two chapters, where we use global data instead of focusing on a single country and serves as a good example of how modern data can be used to model global impacts. Using a comprehensive remotely sensed dataset of contour maps of global earthquakes from 2004 through 2013 and utilizing global nightlights as an economic proxy we model economic impact in the year of the quakes and the year after. More specifically,

a combination of the contour maps, global housing data and local seismic codes is used to construct vulnerability curves for more than 150 countries. Overall, it is shown that earthquakes negatively impact local urban light emissions by 0.7 percent.

Chapter 5 is named "A Whirlwind Romance: The Effect of Hurricanes on Fertility in Early 20th Century Jamaica" and deviates from the prior chapters in that it is a historical chapter that looks at birth rates in the early 1900s. The goal was to use the complete and long-term birth database for Jamaica and match this with hurricane data to check fertility rates. We investigate the impact of hurricanes in the Caribbean on fertility rates in Jamaica for the period 1901 to 1929. More specifically, we create a hurricane destruction index derived from a wind speed model that we combine with data on more than 1 million births across different parishes in Jamaica. Analyzing the birth rate following damaging hurricanes, we find that there is a strong and significant negative effect of hurricane destruction on the number of births. Overall, we find that hurricanes resulted in 10,201 fewer births, or roughly 1 percent of the total. We further show that damaging hurricanes reduce births for up to, and including, 17 months after the event but find no evidence of a temporal displacement of births. In addition, we find no support for the Trivers-Willard hypothesis that one sex becomes more prevalent than another. However, there is evidence that the fall in births is due predominantly to single mothers having fewer children relative to married couples.

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Chapter 2

Natural Disaster Damage Indices Based on Remotely Sensed Data: An Application to Indonesia

Abstract

Combining nightlight data as a proxy for economic activity with remote sensing data typically used for natural hazard modeling, this chapter constructs novel damage indices at the district level for Indonesia, for different disaster events such as floods, earthquakes, volcanic eruptions and the 2004 Christmas Tsunami. Ex ante, prior to the incidence of a disaster, district-level damage indices could be used to determine the size of the annual fiscal transfers from the central government to the subnational governments. Ex post, or after the incidence of a natural disaster, damage indices are useful for quickly assessing and estimating the damages caused and are especially useful for central and local governments, emergency services, and aid workers so that they can respond efficiently and deploy resources where they are most needed.

2.1 Introduction

Quickly assessing and estimating the damage caused after the incidence of a natural disaster is important for both central and local governments, emergency services and aid workers, so that they can respond efficiently and deploy resources where they are most needed. Recently, remote sensing technologies have been used to analyze the impact of disasters, such as hurricanes (Myint *et al.*, 2008; Klemas, 2009), floods (Haq *et al.*, 2012; Wu *et al.*, 2012, 2014; Chung *et al.*, 2015), landslides (Nichol *et al.*, 2006), earthquakes (Fu *et al.*, 2005; Yamazaki & Matsuoka, 2007), wildfires (Holden *et al.*, 2005; Roy *et al.*, 2006), volcanoes (Carn *et al.*, 2009; Ferguson *et al.*, 2010) and tsunamis (Römer *et al.*, 2012). These remote sensing techniques are useful for providing quick damage estimates shortly after the disasters giving emergency services a chance to respond quickly and local governments an overview of estimated costs and necessary repairs.

In addition to their usefulness in the aftermath of a disaster, estimates of the potential damage associated with a natural disaster are also useful for policy making prior to the realization of the natural hazard event. In many cases the incidence of a natural hazard event can turn into a natural disaster simply because of inadequate preparation ex-ante. Indonesia, for example, is highly exposed to natural disasters by being situated in one of the worlds most active disaster hot spots, where several types of disasters such as earthquakes, tsunamis, volcanic eruptions, floods, landslides, droughts and forest fires frequently occur. The average annual cost of natural disasters, over the last 10 years, is estimated at 0.3 percent of Indonesian GDP, although the economic impact of such disasters is generally much higher at local or subnational levels (The Global Facility for Disaster Reduction and Recovery, 2011). The high frequency of disasters experienced has important impacts on expenditures by local governments that could be anticipated, at least in part, through upward adjustments in the annual fiscal transfers from the central government to the subnational governments.[1] Such ex-ante adjustments in the level of fiscal transfers would be more useful if they could be based on estimates of the potential dam-

[1]For example, Indonesia experienced 4,000 disasters between 2001 and 2007 alone, including floods (37%), droughts (24%), landslides (11%) and windstorms (9%) (The Global Facility for Disaster Reduction and Recovery, 2011).

ages associated with the incidence of a natural disaster as opposed to estimates of the intensity of the potential natural hazard that might occur. However, although in recent years there has been much progress towards the modeling of the main natural hazards, there continues to be a scarcity of estimates of the damages associated with the incidence of these disasters. The value of damage caused by a natural disaster is typically a complicated function of the size of population living in that area, the level and type of economic activity carried out, the value of the physical infrastructure in place, and the resilience of infrastructure and people's livelihoods to the natural hazards.

This chapter fills some of the gaps in the literature by using different remote sensing sources and data on the physical characteristics of the events to construct four damage indices for natural disasters in Indonesia. The indices cover floods, earthquakes, volcanic eruptions and a tsunami, and are all weighted by local economic activity in an area, and then aggregated up to a district level.[2] All data used in the construction of the indices are free and publicly available, making the methods used a potentially very useful alternative for both central and local governments to quickly get a rough estimate of the damages caused by a disaster (either ex-ante or ex-post).[3]

Importantly, all of the indices constructed take into account local exposure. Given limited access to highly disaggregated local economic activity data, nightlight intensity derived from satellite imagery has proved to be a good proxy; see, for instance, Henderson *et al.* (2012), Hodler & Raschky (2014) and Michalopoulos & Papaioannou (2014). By utilizing the grid cells of approximately 1 square kilometer we can break down areas in cities and districts into where they are busiest, and thus take into account not only the local physical characteristics of a natural disaster but also the local economic activity exposed to it.

The chapter is structured as follows. Section 2.2 of the chapter discusses in more detail the incidence and types of natural disasters. Section 2.3 discusses the nightlights data. Sections 2.4-

[2] A tropical cyclone index was also constructed, but no hurricanes had strong enough winds to cause any damage on land.

[3] In a separate paper, Skoufias *et al.* (2017b), we correlate the damage indices of these disasters at the district level with the ex-post allocation of district expenditures in different sectors and by economic classification.

2.7 discuss in detail the construction of the four damage indices, while section 2.8 concludes.

2.2 Natural Disasters in Indonesia

Natural disasters are prevalent events across most parts of Indonesia. According to the Indonesian National Disaster Management Authority (BNPB) there were more than 19,000 natural disasters in the period 2001 - 2015 (National Disaster Management Agency, BNPB, 2016), making Indonesia a useful country for any natural disaster analysis. The most frequent disasters are floods and landslides (52 percent), strong winds (21 percent) and fires (15 percent), while the most damaging ones are earthquakes, tsunamis and volcanic eruptions, which all cause major damage to buildings and infrastructure in addition to the human casualties. The deadliest year according to the BNPB data was 2004, where there were more than 167,000 deaths due to natural disasters and 166,671 of them stemming from the tsunami in December 2004.

2.2.1 Floods

The tropical climate of Indonesia often leads to annual floods. The BNPB data registered more than 10,000 incidents of floods or landslides leading to more than 3,500 fatalities from 2001 through 2015. During the period from 1985 to 2016, The Darthmouth Flood Observatory (DFO) registered 3,808 floods of magnitude 4 or more and 1,175 floods of magnitude 6 and up.[4] Of these floods, there were 126 large scale floods with a centroid within Indonesia in the period from 2001 to 2016 as can be seen in Figure 2.1. Of the 34 provinces, 27 experienced having a centroid of a large scale flood event during these years.[5]

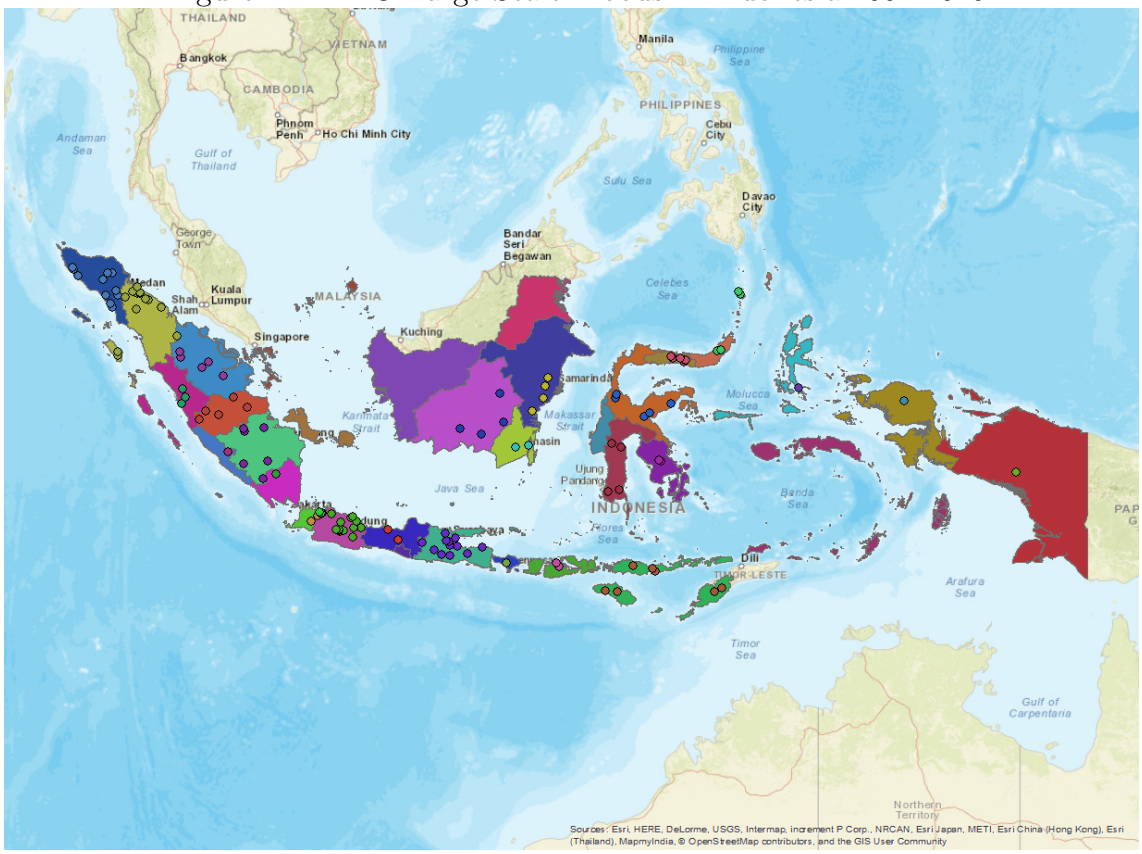
2.2.2 Earthquakes

Due to Indonesia's location inside the Pacific Ring of Fire, one of the most seismically active areas in the world, it is often struck by earthquakes. BNPB counted almost 400 earthquakes from 2001 to 2015, with the largest number of casualties coming from the tsunami created by

[4]Magnitude is defined as: $M = \log(D \cdot S \cdot AA)$, where D is the duration of the flood; S is the severity on a scale consisting of 1 (large event), 1.5 (very large event) and 2 (extreme event); and AA is the size of the affected area. Flood events registered by DFO have mainly been derived from news and governmental sources.

[5]The provinces where no large scale centroid was present were Bangka Belitung, Riau Islands, Kalimantan Barat, Yogyakarta, Sulawesi Barat, Kalimantan Utara and Maluku. Note that some of these, like Kalimantan Utara, Kalimantan Barat, Sulawesi Barat and Yogakarta, did most likely experience large scale flood during these years, but that the centroid was in another province. The remaining three provinces consist mainly of smaller islands, so the flooded area will most likely not constitute a large scale flood event.

Figure 2.1: DFO Large Scale Floods in Indonesia 2001-2016



Source: G.R.Brakenridge (2016)

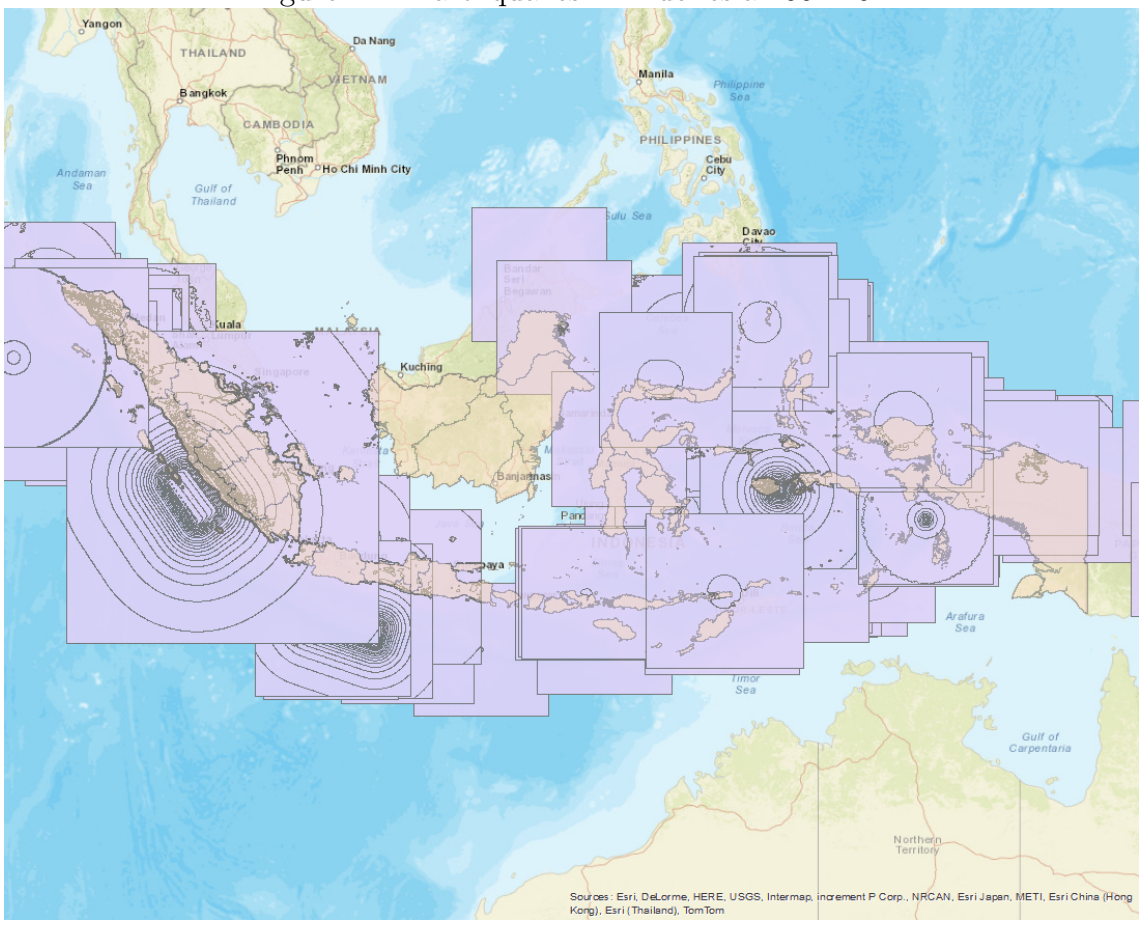
a 9.0 earthquake located off the coast of Aceh, otherwise known as the earthquake that caused the 2004 tsunami. Apart from that, there were more than 8,000 registered fatalities due to earthquakes over the same period. Overall, this makes earthquakes the deadliest of the natural disasters that strike Indonesia.

Figure 2.2 shows how common earthquakes are in Indonesia by displaying contour maps[6] of all earthquakes of magnitude 5.0 and above that struck Indonesia from 2004 through 2014. In total, the United States Geological Survey (USGS) registered 261 earthquakes.[7]

[6]These maps are also known as ShakeMaps, which are produced by USGS.

[7]There are 1,002 earthquakes registered by USGS that were of magnitude 5.0 or more that had a point with a PGA of at least 0.05 within Indonesia. Many of these points create little to no damage. The 261 earthquakes mentioned above are quakes that are mostly contained within Indonesia.

Figure 2.2: Earthquakes in Indonesia 2004-2014



Source: USGS

2.2.3 Volcanic activity

Indonesia has the highest number of active volcanoes in the world, numbering almost 150. Of these, many have had eruptions in both more historical times and after the year 2000. The most famous eruption is probably the explosion of Krakatau in August 1883, when two-thirds of the Krakatau Island erupted and disappeared, killing more than 35,000 people and causing a global mini ice age and weather disruptions for years. BNPB have registered 92 eruptions over our 15-year time period and more than 60 major volcanoes that have had eruptions since 1900. The most recent one is the 2010 Mount Merapi eruption that killed 324 people and dislocated more than 320,000.

In addition to the BNPB data, during the years 2004 through 2015 the Darwin Volcanic Ash Advisory Centre (DVAAC) had 587 days where they issued a red warning, implying an ongoing

or imminent volcanic eruption. The most active volcanoes - measured by number of days with red warnings - are shown in Table 2.1, with the top 5 volcanoes constituting almost 75 percent of the red warnings. These are also volcanoes that have been in the media, with Merapi already mentioned and Sinabung, which had several eruptions in 2010, 2013 and 2014. These two volcanoes are located close to densely populated areas, with Sinabung located in North Sumatra and Merapi in central Java.

Table 2.1: Most Active Volcanoes 2004-2015

Volcano	Number of Days with Red Warning
Sinabung	224
Merapi	92
Manam	74
Egon	36
Soputan	31

2.2.4 2004 Christmas Tsunami

The Christmas Tsunami in 2004 is the worst singular natural disaster during the modeling period, and one of the worst natural disasters in world history. As seen in the photo in Figure 2.3 the destruction was absolute in parts of Indonesia. The total death toll across Indonesia and 13 other countries was more than 230,000 people and there were many more missing. In addition, the World Bank (2005) estimated a total economic impact of 4.5 billion US dollars. The official BNPB data for Indonesia estimates 166,671 deaths due to the tsunami.

The cause of the tsunami was an earthquake of magnitude 9.0 150 miles south-south east of Banda Aceh on the morning of 26 December. This quake created a tsunami with waves more than 20 meters high at the highest. Due to the fault line of the earthquake being in a north-south direction, the greatest strength of the tsunami was in an east-west direction (Athukorala & Resosudarmo, 2005). This led to the largest damages being in the northern part of Sumatra, in the province of Aceh, where entire villages were wiped out as seen in the photo of Banda Aceh (Figure 2.3).

Figure 2.3: Destruction in Banda Aceh

Source: The Atlantic (2014)

2.3 Nightlight Data

Natural disasters are inherent local phenomena in that they either affect only parts of areas and/or affect parts within areas differently. It is thus important to take the local population/asset exposure into account when constructing more aggregate proxies. Arguably one would like to have measures of exposure as spatially disaggregated as possible. For a country like Indonesia, data are usually sparse and at a very aggregated spatial level.

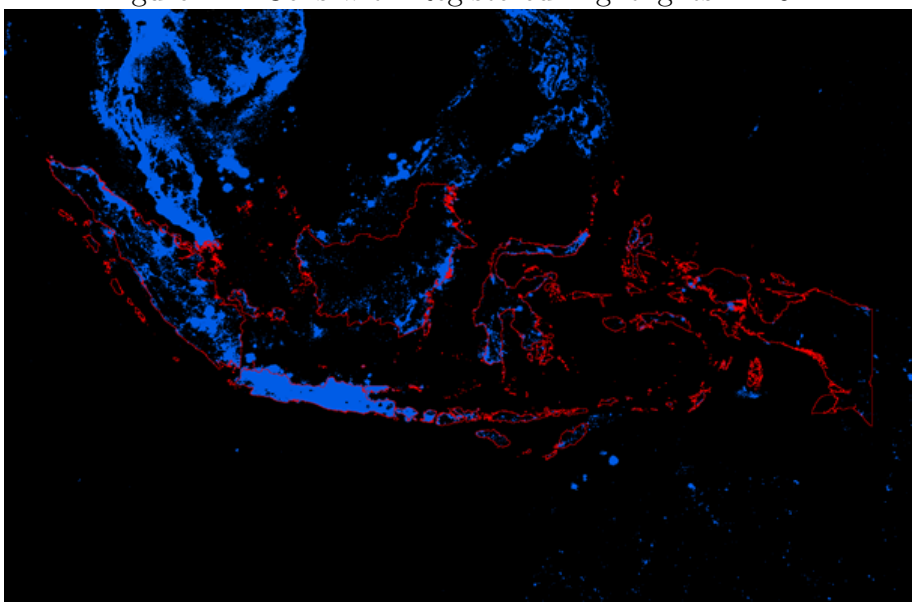
An alternative approach is thus to use nightlights as a proxy for local economic activity. As a matter of fact, nightlights have found widespread use where no other measures are available; see, for instance, Henderson *et al.* (2012), Hodler & Raschky (2014) and Michalopoulos & Papaioannou (2014). In Henderson *et al.* (2012), Indonesia is used as an example of using nightlights to capture an economic downturn following the Asian financial crisis in the late 1990s. Their results show that swings in GDP change can generally be captured. Nevertheless one has to account for factors such as cultural differences in light usage, latitude and gas flares. In our case this is unlikely to affect our results since we use nightlights to capture exposure within a country rather than across countries.

The nightlight imagery we employ is provided by the Defense Meteorological Satellite Program (DMSP) satellites. In terms of coverage each DMSP satellite has a 101 minute near-polar orbit at an altitude of about 800km above the surface of the earth, providing global coverage twice per day, at the same local time each day, with a spatial resolution of about 1km near the equator. The resulting images provide the percentage of nightlight occurrences for each pixel per year normalized across satellites to a scale ranging from 0 (no light) to 63 (maximum light). Yearly values were then constructed as simple averages across daily values of grids, and are available from 1992.[8] We use the stable, cloud-free series; see Elvidge *et al.* (1997).

[8]For the years where satellites were replaced, DMSP provides an average from both the new and old satellite. In this chapter we use the imagery from the most recent satellite but as part of our sensitivity analysis we also re-estimated our results using an average of the two satellites and the older satellite only. The results of these latter two options were almost quantitatively and qualitatively identical.

The data revealed 414,644 cells which had a nightlight value greater than 0 in them at least once during the period 2001-2013. Figure 2.4 - containing all cells with nightlights in 2012 - shows that the large cities and densely populated areas on Java, Sunda Islands, coastal Kalimantan and Sumatra are fully covered in lights. Inner parts of Kalimantan and most parts of New Guinea are more sparsely lit.

Figure 2.4: Cells with Registered Nightlights in 2012



2.4 Flood Damage Index

The modeling of floods can be done by remote sensing (Brakenridge & Anderson, 2006; Wu *et al.*, 2012; Haq *et al.*, 2012) or through a combination of weather data and GIS systems as for example in Knebl *et al.* (2005); Asante *et al.* (2007); Dessu *et al.* (2016). We utilize the latter, as remote sensing is useful for assessing whether an area is flooded or not, but it is weaker on modeling the intensity of the flood. Moreover, cloud cover generally limits the accurate detection of floods from remote sensing sources.

To model floods we have decided to use the Geospatial Stream Flow Model (GeoSFM) which is a software that is "designed to use remotely sensed meteorological data in data sparse parts of the world"(Artan *et al.*, 2008). GeoSFM was developed by USGS and USAID and is a hydrological modeling tool used to model stream flows across large areas, in particular areas where highly localized data are lacking. It has been used in regions such as the Great Horn of Africa (Asante *et al.*, 2007; Mati *et al.*, 2008; Dessu *et al.*, 2016) and Nepal (Shrestha *et al.*, 2011), with Dessu *et al.* (2016) finding that the model captures 76% of the monthly average variability, making it useful for flood simulation.

The inputs needed to model stream flow for basins are soil- and terrain-based - such as digital elevations models (DEM) and land cover and soil data - and weather-based, such as precipitation and potential evapotranspiration (PET) data. The HYDRO1K data set from USGS, which is a DEM made for hydrological modeling based on the USGS' 30 arc-second DEM of the world, is used as elevation input. The land cover data are the Global Land Cover Characterization (GLCC) data set also from USGS, while the soil data are from the FAO Digital Soil Map of the World.

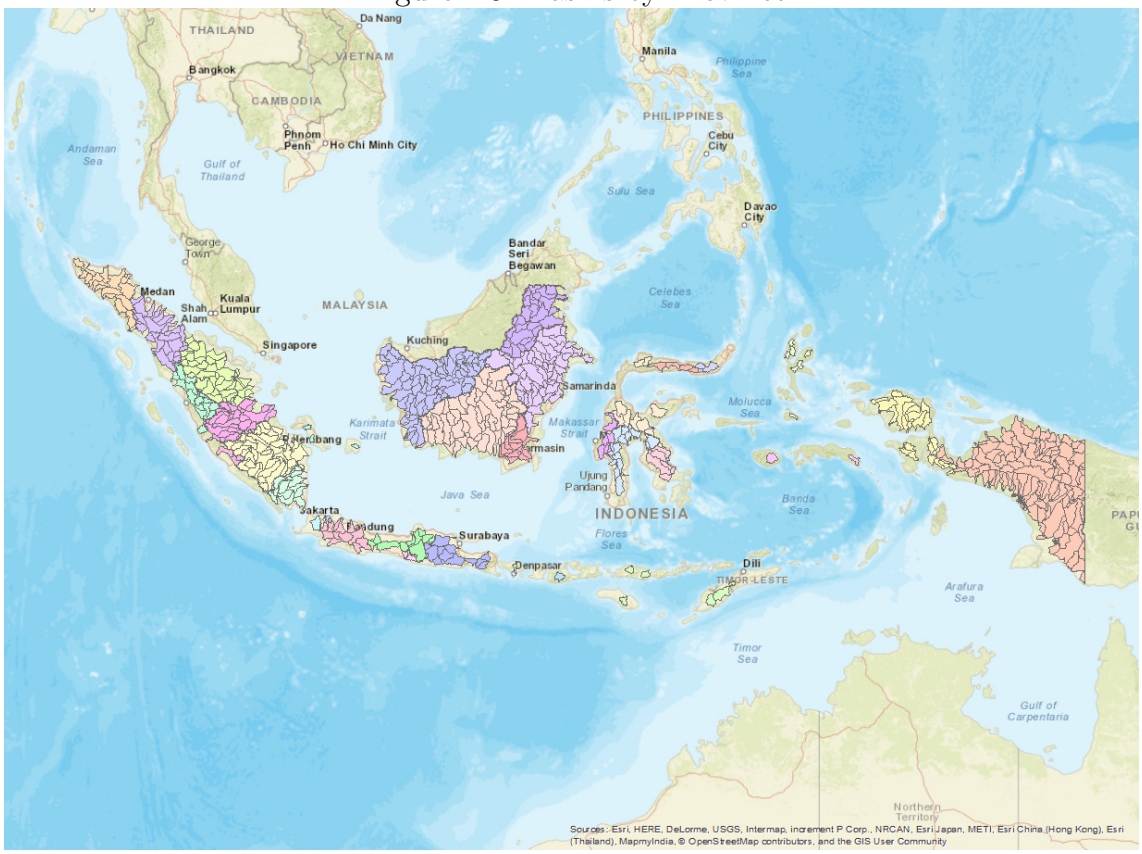
The daily precipitation data are from the 3-hourly data set from the Tropical Rainfall Measurement Mission Project (TRMM) and the PET data are 6-hourly data from the Global Data Assimilation System (GDAS), both data sets are aggregated up to daily data. The PET data are available from February 2001 and onwards, while the precipitation data are available for

the period 1998-2014. Given that we only have nightlight data through 2013, we will focus on floods for the period 2001-2014.

GeoSFM uses the inputs to construct basins based on the terrain and then uses a linear soil moisture accounting routine to model surface runoff and soil moisture based on precipitation and PET. It is worth noting that although a more complex and better non-linear routine is also supported, it does not work well for our more generalized macro-modeling with fairly low resolution data. Finally, GeoSFM models the stream flow for each basin for each day of our time period.

Note that GeoSFM does not model coastal floods, nor does it model flash floods in areas where there are no rivers or streams of a certain length. Figure 2.5 shows that there are parts of Indonesia and even one province - Riau Islands - which have no basins. Another weakness is that it does not take into consideration the specific terrain within each basin. Floods are generally very localized events and the low resolution of our data makes it impossible to model the intensity of the stream flow within a basin and also causes some river outlets to be slightly inland instead of running all the way to the ocean.

Figure 2.5: Basins by Province



2.4.1 Construction of Index and Results

The first part of constructing the index involves defining when a flood event is happening. In Wu *et al.* (2012) they propose four runoff based methods to define a flood threshold, and in addition Wu *et al.* (2014) propose a slightly modified flood threshold definition with a point being flooded when:

$$R > P_{95} + \sigma \qquad and \qquad Q > 10m^3/s \tag{2.1}$$

where R is the routed runoff in millimeters, P_{95} is the 95th percentile value and σ is the standard deviation of the routed runoff. Q is the discharge in cubic meters.

We found that with the GeoSFM modeled data, runoff was not a good proxy for flooding, due to it only capturing a limited number of floods. Discharge, Q, was a better proxy, leading to a new - but very similar - equation:

$$Q > P_{95} + \sigma \qquad and \qquad Q > 10m^3/s \tag{2.2}$$

By manually checking against the DFO floods, we find that our data do hit several of the large scale events in Figure 2.1.

Damage Index

Due to floods being very localized, the modeling of damage is difficult, and no standard exists in the literature. Penning-Rowsell *et al.* (2005) base destruction on value of housing stock and the Standards of Protection and then uses an estimate of number of properties affected by different return period floods. Scawthorn *et al.* (2006) use a combination of building stock and velocity of the stream flow, whereas Kreibich *et al.* (2009) look at different parameters such as velocity, depth, energy head, stream flow and intensity. They find velocity to be a poor parameter for assessing damage, while water depth and energy head show the best results. Stream flow and intensity are also weak as parameters. Finally, Merz *et al.* (2010) assess different damage influencing parameters and point to the fact that most "damage influencing factors are neglected in damage modeling, since they are very heterogeneous in space and time, difficult to predict, and there is limited information on their (quantitative) effects". Overall, there is limited support in the literature for a strong correlation between these parameters and damages on anything but a very localized scale.

As for assessing the damage itself, Merz *et al.* (2010) discuss damage functions and the two main approaches, which involve one empirical approach where damage data are collected after the flood and one synthetic approach where they construct potential what if-scenarios. Once again the assessments rest on very localized data, which we do not have for Indonesia. Overall, it means that we cannot expect anything more than rough estimates. A common denominator for the papers mentioned above is that there is some measurement of intensity. Given that stream flow is an intensity proxy, we have used that to construct a simple measurement for intensity. The equation is:

$$I_{b,t} \equiv \begin{cases} 0, & \text{if } Flood = 0 \\ \frac{Q_{b,t} - \bar{Q}_b}{\sigma_b}, & \text{otherwise} \end{cases} \tag{2.3}$$

where $I_{b,t}$ is the intensity of the flood in basin b at date t, $Q_{b,t}$ is the stream flow in the same basin at the same time and $\bar{Q}_b$ and σ_b are mean and standard deviation of stream flow in b. The intensity is set to zero if the flood threshold - 95th percentile plus 1 standard deviation above the average - has not been exceeded. By normalizing, we obtain a measure that is comparable across all regions and that is independent of the absolute river flows. The assumption is that people living close to rivers will be prepared for variations in water levels, and that people living close to rivers with highly variable stream flows are more prepared for these events than people living close to more stable rivers.

To aggregate the flood impact each basin is weighted based on the nightlights in it. The weights per basin, b, in province p, $W_{b,p,t-1}$, are defined as:

$$W_{b,p,t-1} \equiv \frac{\sum_i^I L_{b,i,t-1}}{\sum_j^J L_{p,j,t-1}}, \qquad b = 1, \ldots, B, \qquad p = 1, \ldots, P \tag{2.4}$$

where $\sum_i^I L_{b,i,t-1}$ is the sum of lights, i, in basin b one year, $t-1$, before the flood year and $\sum_j^J L_{p,j,t-1}$ is the same at a province or district level.

Finally, the weights from (2.4) are multiplied with the intensity from (2.3) to get the overall flood impact, $FI_{b,p,t}$ in basin b on the province p at time t:

$$FI_{b,p,t} \equiv W_{b,p,t-1} \cdot I_{b,t}, \qquad b = 1, \ldots, B \qquad p = 1, \ldots, P \tag{2.5}$$

One thing to note here is that for basins that span several provinces or districts, we have assumed the same intensity, but the weight is based on nightlights within each individual province.

Results

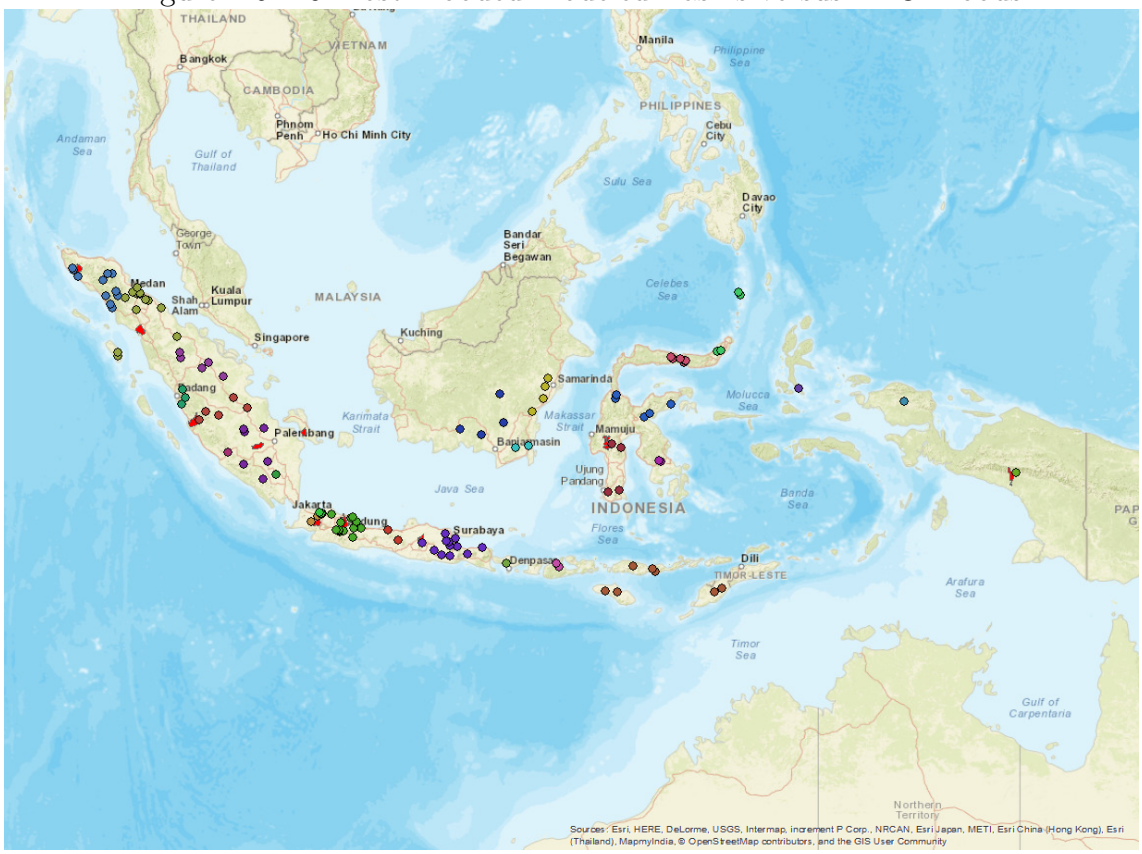
The stream flow was simulated for 5,082 consecutive days, from 1 February 2001 to 31 December 2014.[9] Table 2.2 shows that the top 10 basins with most flood days had close to 200 days of flooding over the 14-year period. As expected, these basins do overlap with some of the busiest

[9]For Bali we did it for 5,080 days due to problems with 30 and 31 December 2014.

flood areas according to the DFO, as shown in Figure 2.6. The lower part of Table 2.2 reveals that the driest basin had a mere 12 days of flooding. All 33 provinces with a basin had days that went above our flood threshold set in Equation (2.2).

All months in our model have flood events, but there are big differences. The range goes from 527 events every March and down to 154 events every August, with the traditional rainy season (November-March) producing the highest number of flood events, whereas the dry season months (June-October) are the driest. Aggregating the numbers for the rainy season, there are 2,215 events every year across the basins, while there are only 995 events every year during the dry season.

Figure 2.6: 10 Most Flooded Modeled Basins versus DFO Floods



Total number of basins that are partly or fully inside Indonesia is 495, and these basins have a total of 55,605 flood events or slightly more than 112 per basin. In other words, the average basin has been flooded for a total of 8 days a year over the 14-year period in question. This is not entirely unexpected given the climate in Indonesia and the way our threshold is made. Also, if we compare with the DFO data where they have 3,808 floods of magnitude 4 or higher

Table 2.2: Basins with Most and Least Flood Events

Basin Number	Affected Provinces	Number of flood events
2	Bangka-Belitung	192
705	Sumatera Selatan	190
133	Aceh	189
632	Jambi, Sumatera Barat	189
282	Sumatera Utara	187
872	Jawa Barat	186
868	Jawa Barat, Banten	183
916	Jawa Tengah, Jawa Timur	183
558	Sulawesi Barat, Sulawesi Selatan	180
709	Papua	177
256	Kalimantan Barat, Kalimantan Tengah	12
444	Riau	17
197	Sulawesi Tengah	21
316	Kalimantan Barat	24
314	Kalimantan Barat	27

through their period from 1985-2016, which converts to almost 123 fairly large scale flood events per year, our model provides a reasonable proxy for events.

Even though the results seem logical on a per basin basis, the time steps in the model are 1 day at a time, which is too slow for the unfolding of a flood event, implying that downstream basins that would normally fill up very quickly will now only be filled up the day after, and then the next basin will be filled two days later and so forth. This means that the amount of days with floods are inflated. We believe that this does not affect our results much, though, as the number of events per province will not affect the end results, since we weigh by affected nightlight and not by number of days of floods.

Despite the numerous floods in Indonesia, they generally do not affect a large percentage of the population, as per Table 2.3. The mean of nightlights when excluding areas with 0 nightlight is 3.39 percent. If we assume that 3.39 percent of the approximately 250 million people of Indonesia are affected, the floods would impact 8.5 million people.

Table 2.3: Descriptives of Weights and Intensity for Modeled Flood Events

Statistic	N	Mean	St. Dev.	Min	Max
Weights	45,005	0.034	0.060	0.00003	0.557
Intensity	45,005	4.516	2.608	0.989	50.944
Damage Index	45,005	0.155	0.351	0.0001	12.780

Excluding zero damage observations

Comparison of Model versus DFO Floods

The DFO flood database is mostly based on news sources, providing an overview of the big floods in Indonesia. To check the database against the GeoSFM model, the focus will be on the largest events of magnitude 6 and above. Given how the DFO data do not give any intensity estimates and focus primarily on displacement numbers and area, while our model is driven by intensity the comparison will only focus on whether GeoSFM results do overlap in time and/or province with the centroid of the DFO floods.

Table 2.4 shows the DFO data on the left side, first column being the start month of the flood, followed by duration, magnitude, the province where the centroid of the flood is, dead and displaced. The right side shows the modeling results where the focus is on duration. The first column under model results shows the number of days for the centroid province, then overall number of days with floods anywhere in Indonesia during the period, then looking at the same island - using that as a proxy for neighboring regions - where one examines total days the island provinces were flooded during the flood and finally how many of the days of the flood duration that a province on the same island was flooded.

Generally, the model performs well, in particular on Sumatra and Kalimantan (Borneo), with the example where the 2008 flood was captured for all 25 days in the centroid province. Overall, it shows at least one flooded basin on Kalimantan and Sumatra for 85% of the days the major floods happened. The results are somewhat worse on Java, where only 37% of the days have a flood. A primary reason for this might be that Java is very narrow and hence the streams are short and might not be captured in our model. Java also has larger percentage of land not covered by a basin, ref Figure 2.5, also due to its narrowness which makes the low resolution

landcover data underestimate the size of the basins.

Aggregated numbers

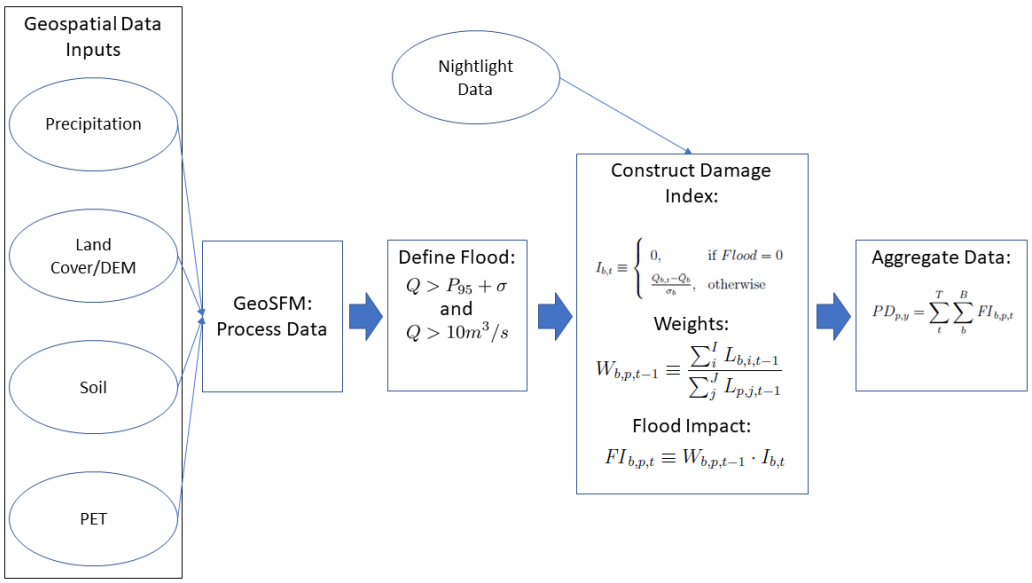
Finally, to aggregate up to a district or province level, we have used a simple method for the total damage experienced per year:

$$PD_{p,y} = \sum_{t}^{T} \sum_{b}^{B} FI_{b,p,t}, \qquad p = 1, \ldots, P, \qquad y = 2001, \ldots, 2014 \tag{2.6}$$

where p is the province or district, sum of t is all the days in year y, sum of b are all the basins in the province or district and $FI_{b,p,t}$ is the flood impact from Equation 2.5 for province or district p. Normally one might use an average flood impact across the year, but by doing this, we capture repeated flood events and areas that experience generally high flooding.

As this concludes the construction of our index, a summary of the process and data used is shown in Figure 2.7.

Figure 2.7: Overview of Methodology used to Construct Flood Index



Using the above method, Table 2.5 provides the aggregated data for all provinces across all years. The impact is fairly even for the most impacted ones, with the impact numbers for

the top 10 ranging from 44 to 55. Furthermore, Sumatera Selatan, Lampung and Yogyakarta make up 8 of the top 10 impacted provinces. The overall picture fits with the DFO floods in Figure 2.1, with the populous provinces in Java, Sumatra and Sulawesi being impacted, whereas the smaller island provinces and parts of Kalimantan are not affected much. For some of the island provinces the numbers are probably underestimated, no basins will have been constructed and modeled there due to the many small islands.

Finally, Table 2.6 shows the most impacted districts over the years 2001 through 2014. The impact is much larger than for the provinces as one would expect due to the more localized data and impact. The districts are also more geographically spread out than the provinces.

Table 2.4: DFO Floods Compared with GeoSFM Results

	DFO Data					Model Results			
Date	Duration	Magnitude DFO	Centroid Province	Dead	Displaced	Flooded days in Province	Total Flood Days Sum All Provinces	Total Flood Days Sum on Island	Days Flooded on Island During Period
Jan 2002	17	6.1	Jawa Timur	147	380,000	5	17	8	7
Dec 2003	45	6.9	Jambi	148	350,000	18	45	180	41
Jan 2005	31	6.4	Sumatera Selatan	9	0	16	30	105	30
Jan 2006	20	6.2	Jawa Barat	19	10,000	6	20	13	9
May 2007	25	6.0	Kalimantan Tengah	0	3,000	23	25	79	25
Mar 2008	25	6.3	Riau	0	60,000	25	25	149	25
Apr 2010	17	6.2	Kalimantan Tengah	0	0	14	17	38	17
Feb 2012	8	6.2	Sumatera Selatan	0	1,200	6	8	27	8
Jan 2014	31	6.2	Jawa Barat	23	20,000	9	31	31	13

Table 2.5: Aggregated Flood Intensity Data by Province

Province	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Aceh	12.674	7.400	14.712	11.213	18.127	15.643	23.155	20.799	17.918	20.076	17.665	10.116	14.864	10.571
Bali	3.614	11.780	13.083	11.676	10.359	10.783	8.080	5.786	9.042	7.851	7.882	7.609	8.580	
Bangka-Belitung	1.380	1.756	1.194	1.525	1.973	0.803	0.794	0.306	0.456	0.745	1.165	0.606	0.623	0.691
Banten	7.118	7.632	13.076	14.360	11.899	9.668	27.980	19.316	14.921	21.456	12.783	15.288	7.630	4.890
Bengkulu	6.394	6.756	25.205	13.606	14.273	10.266	11.683	16.207	13.145	17.983	17.417	6.351	21.045	7.279
Gorontalo	54.770	16.760	37.260	25.281	35.026	37.234	27.620	21.607	31.719	5.607	10.702	3.680	20.092	15.921
Irian Jaya Barat	1.368	0.647	1.242	0.565	1.167	0.921	0.985	0.508	1.107	0.356	0.343	1.837	1.710	1.307
Jakarta Raya	15.099	7.370	12.681	3.931	18.294	9.950	22.154	40.751	23.394	22.670	24.347	25.294	21.573	9.362
Jambi	44.338	11.141	10.589	11.677	19.131	13.241	16.989	34.894	31.627	32.430	15.023	21.463	32.401	30.362
Jawa Barat	16.616	17.697	29.439	18.629	30.536	23.842	36.484	28.958	27.030	35.907	25.600	27.714	29.462	11.156
Jawa Tengah	29.271	41.395	42.206	35.024	26.358	24.512	28.825	27.113	31.001	22.795	20.560	20.117	25.344	14.672
Jawa Timur	13.567	17.287	25.731	21.652	22.093	19.205	28.864	19.975	24.997	28.016	12.384	16.611	28.322	11.372
Kalimantan Barat	3.833	6.570	7.145	6.320	13.792	5.801	8.921	9.740	8.574	6.321	4.663	6.273	13.122	17.092
Kalimantan Selatan	26.550	10.917	19.599	21.410	15.397	12.302	21.088	29.202	21.391	16.995	10.598	29.563	32.648	21.549
Kalimantan Tengah	11.208	16.090	38.512	37.649	27.149	20.731	32.001	29.097	26.581	8.915	17.965	18.792	31.707	23.723
Kalimantan Timur	7.603	3.046	11.437	7.066	9.124	9.208	15.114	14.168	24.098	15.236	15.408	11.198	16.020	10.496
Kalimantan Utara	1.098	3.949	8.894	1.245	5.471	6.455	12.065	24.721	16.620	6.085	4.615	5.597	7.374	10.416
Lampung	25.228	20.499	30.012	32.566	31.452	21.910	23.642	37.172	39.414	49.285	25.333	22.493	43.979	47.995
Maluku	0.000	0.000	0.216	0.000	0.000	0.014	0.000	0.000	0.000	0.000	0.358	0.000	0.278	0.705
Maluku Utara	0.904	0.959	0.241	0.510	1.006	2.406	1.574	1.873	0.353	1.230	1.749	2.629	0.913	0.796
Nusa Tenggara Barat	0.014	0.083	0.035	0.021	0.080	0.034	0.059	0.093	0.036	0.038	0.064	0.068	0.048	0.009
Nusa Tenggara Timur	6.168	9.770	15.109	15.209	15.937	7.311	10.590	10.489	6.032	9.166	9.506	8.517	12.688	5.676
Papua	17.567	5.837	18.616	15.338	18.461	11.763	30.377	31.351	24.332	31.378	25.779	24.328	35.261	28.788
Riau	7.063	20.727	17.103	11.778	20.699	17.433	35.765	26.883	23.667	29.925	25.391	15.855	20.114	41.465
Sulawesi Barat	6.880	9.094	2.650	3.918	4.512	4.888	5.244	14.403	4.637	5.044	5.727	3.625	3.596	14.663
Sulawesi Selatan	14.729	9.733	14.866	12.397	8.112	15.667	11.431	14.619	12.996	9.001	10.157	7.805	11.202	12.707
Sulawesi Tengah	2.798	2.603	10.433	24.693	10.258	14.202	2.255	12.771	8.280	0.427	9.320	4.415	7.999	5.688
Sulawesi Tenggara	2.861	2.092	6.197	2.396	13.335	5.188	14.381	11.368	3.927	4.990	4.428	2.474	4.780	1.015
Sulawesi Utara	4.253	2.709	8.590	6.575	5.250	6.360	6.551	7.062	3.813	8.950	4.976	5.710	4.719	6.018
Sumatera Barat	8.944	16.785	26.946	21.787	28.464	18.737	35.011	24.624	24.595	18.317	9.770	10.559	17.472	18.169
Sumatera Selatan	27.938	17.191	47.852	33.865	34.345	23.193	39.282	55.345	34.210	34.032	24.159	23.462	51.858	27.107
Sumatera Utara	13.788	11.627	17.135	11.155	19.981	14.664	15.477	19.144	16.001	18.513	15.272	15.037	21.185	20.517
Yogyakarta	37.598	27.613	42.810	24.707	25.250	37.895	20.736	49.592	44.909	29.360	35.296	41.184	41.429	30.332

Aggregate Results found by using equation 2.6

Table 2.6: 10 Most Impacted Districts

District	Province	Year	Flood Impact
Seruyan	Kalimantan Tengah	2010	175.080
Aceh Tengah	Aceh	2010	165.381
Bener Meriah	Aceh	2010	139.742
Pasaman	Sumatera Barat	2010	125.854
Sarolangun	Jambi	2010	118.244
Lubuk Linggau	Sumatera Selatan	2003	114.790
Keerom	Papua	2009	114.289
Tana Toraja	Sulawesi Selatan	2013	106.886
Klaten	Jawa Tengah	2002	106.488
Sukoharjo	Jawa Tengah	2002	106.488

2.5 Earthquake Damage Index

The measurement of earthquake detection and intensity has improved with remote sensing techniques. There are different methods to assess intensity and damage, ranging from satellite images (Dell'Acqua & Gamba, 2012; Tralli *et al.*, 2005; Gillespie *et al.*, 2007) to contour maps generated by seismological ground stations (De Groeve *et al.*, 2008; GeoHazards International and United Nations Centre for Regional Development, 2001; Federal Emergency Management Agency, 2006).

This chapter uses the latter method, by utilizing ShakeMaps from USGS, which are automatically generated maps providing several key parameters following an earthquake, such as peak ground acceleration (PGA), peak ground velocity (PGV) and modified Mercalli intensity (MMI). More specifically, the ShakeMaps use data from seismic stations that is interpolated using an algorithm which is similar to kriging. To model the intensity in a given coordinate, the model also takes into account ground conditions and the depth of earthquake. Wald *et al.* (2005) point to the magnitude and epicenter location - which are parameters common for the entire earthquake - that have historically been used to determine how severe earthquakes were, but that the damage pattern is not just dependent on those two parameters, but also on other, more localized parameters that the ShakeMaps use to generate intensity measures.

This is exemplified by several earthquakes such as magnitude 6.7 and 6.9 earthquakes in California in 1994 and 1989, respectively, where some areas further away from the epicenters got more damaged than closer areas. The reason why the more localized ShakeMaps with their ground shaking parameters are a better gauge than magnitude and epicenter distance is explained on page 13 of Wald *et al.* (2005) which states that: "..., although an earthquake has one magnitude and one epicenter, it produces a range of ground shaking levels at sites throughout the region depending on distance from the earthquake, the rock and soil conditions at sites, and variations in the propagation of seismic waves from the earthquake due to complexities in the structure of the Earth's crust." The ShakeMaps are interpolated grids with point coordinates spaced approximately 1.5 kilometers apart (0.0167 degrees). Figure 2.2 shows contoured maps of these points.

The PGA is a measure of the maximum horizontal ground acceleration as a percentage of gravity, PGV is the maximum horizontal ground speed in centimeters per second and MMI is the perceived intensity of the earthquake, a subjective measure. Figure 2.8 - which is originally found in Wald *et al.* (1999) - explains the relationship between the different parameters and the potential damage from different values. The assumption is that damage starts at an MMI level of V and a PGA of 3.9 percent of g. These levels are found for California in Wald *et al.* (1999), but the relationship has been found for other areas in the US in Atkinson & Kaka (2006) and Atkinson & Kaka (2007) and for places such as Costa Rica (Linkimer, 2007) and Japan, Southern Europe and Western US (Murphy & O'Brien, 1977). It should be noted that the numerical relationship differs from region to region. There are no known papers estimating these values specifically for Indonesia.

Figure 2.8: ShakeMap Instrumental Intensity Scale Legend

PERCEIVED SHAKING	Not felt	Weak	Light	Moderate	Strong	Very strong	Severe	Violent	Extreme
POTENTIAL DAMAGE	none	none	none	Very light	Light	Moderate	Moderate/Heavy	Heavy	Very Heavy
PEAK ACC.(%g)	<.17	.17-1.4	1.4-3.9	3.9-9.2	9.2-18	18-34	34-65	65-124	>124
PEAK VEL.(cm/s)	<0.1	0.1-1.1	1.1-3.4	3.4-8.1	8.1-16	16-31	31-60	60-116	>116
INSTRUMENTAL INTENSITY	I	II-III	IV	V	VI	VII	VIII	IX	X+

Source: Wald *et al.* (1999)

The different measures are largely interchangeable, and in GeoHazards International and United Nations Centre for Regional Development (2001) report, they use PGA to measure damage, pointing to the fact that PGA, unlike MMI is an objective measure, implying that MMI is not easy to obtain reliably across the globe. Also, for large scale modeling, where it is unfeasible for one to model local conditions precisely, PGA serves as a good proxy for intensity of earthquakes.

2.5.1 Construction of Damage Index and Results

Damage Index

To construct the damage index, two types of data will be used; the intensity data - expressed as PGA - and building inventory data, to assess what damage one could expect for different

intensities.

To take into account the building types in Indonesia, we use information from the USGS building inventory for earthquake assessment, which provides estimates of the proportions of building types observed by country; see Jaiswal & Wald (2008). The data provide the share of 99 different building types within a country separately for urban and rural areas. For Indonesia the building type information was compiled from a World Housing Encyclopedia survey, while the split between urban and rural is from the urban extent map of Center for International Earth Science Information Network - CIESIN - Columbia University *et al.* (2011). Without any other information available, we use this as an indication of the distribution of building types in Indonesia, but, necessarily, assume that the distribution is homogenous within urban and rural areas.

Fragility curves by building type are derived from the curves constructed by Global Earthquake Safety Initiative project; see GeoHazards International and United Nations Centre for Regional Development (2001). More specifically, buildings are first divided into 9 different types.[10] Each building type itself is then rated according to the quality of the design, the quality of construction, and the quality of materials. Total quality is measured on a scale of zero to seven, depending on the total accumulated points from all three categories. According to the type of building and the total points acquired through the quality classification, each building is then assigned one of nine vulnerability curves which provides estimates of the percentage of building damage for a set of 28 peak ground acceleration intervals.

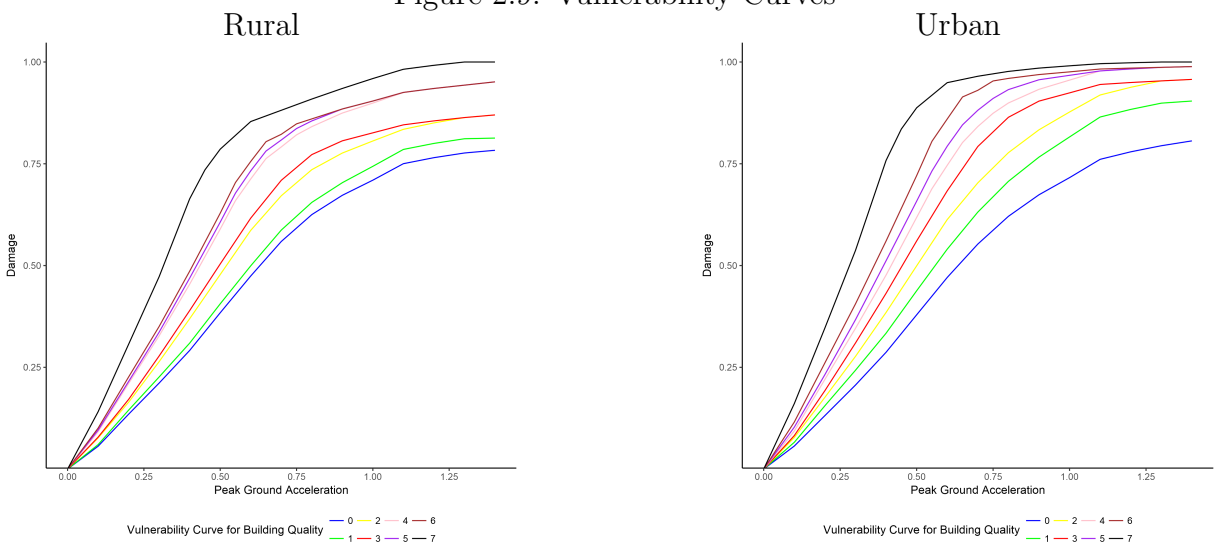
In order to use these vulnerability curves for Indonesia we first allocated each of the 99 building types given in the USGS building inventory to one of the 9 more aggregate categories of the GESI building classification. However, to assign a building type its quality-specific vulnerability curve we would further need to determine its quality in terms of design, construction,

[10] Wood, steel, reinforced concrete, reinforced concrete or steel with unreinforced masonry infill walls, reinforced masonry, unreinforced masonry, adobe and adobe brick, stone rubble, and lightweight shack or lightweight traditional.

and materials, an aspect for which we unfortunately have no further information. We instead assume that building quality is homogenous across building type in Indonesia and experiment with seven different sets of vulnerability curves, each set under a different quality ratings scenarios (ranging from 0 to 7).

Figure 2.9 depicts the building share weighted vulnerability curves of Indonesia for urban and rural areas.

Figure 2.9: Vulnerability Curves



To model estimated damage due to a particular earthquake event the data from the ShakeMaps and GESI are used. Then, one identifies the value of peak ground acceleration that each nightlight cell in Indonesia experiences by matching each earthquake point with its nearest nightlight cell. If the cell is further away than 1.5 kilometers or if it experiences shaking (PGA) of less than 0.05 the value is set to 0. In order to derive a cell i specific earthquake damage index, ED, the following equation is applied:

$$ED_{i,q,p,t} = W_{i,p,t-1} \cdot DR_{i,p,k,t,pga_{k,q}}, \qquad p = 1, \ldots, P, \qquad k = U, R, \qquad q = 0, \ldots, 7 \tag{2.7}$$

where DR is the damage ratio according to the peak ground acceleration, pga, and the urban (U) or rural (R) qualification, k, of cell i, defined for a set of 8 different building quality q

categories. t is the year of the event and p is the province or district.[11] The weight $W_{i,p,t-1}$ is similar to before, being defined as:

$$W_{i,p,t-1} \equiv \frac{L_{i,p,t-1}}{\sum_j^J L_{j,p,t-1}}, \qquad i = 1, \ldots, I, \qquad p = 1, \ldots, P \tag{2.8}$$

which translates to the weight of the light from nightlight cell i in year $t-1$ over the total amount of nightlight cell light, $\sum_j^J L_{p,j,t-1}$, in province p in year $t-1$.

Results

With the above method, we find that 27 of the 34 provinces were damaged by earthquakes at some point in time.[12] Table 2.7 shows that the big islands Java and Sumatra have the most affected nightlight cells, given how densely populated they are and how much seismic activity is experienced there this is expected.

Table 2.7: Times a Lit Nightlight Cell is Damaged by Earthquake by Province

Province	Times Nightlight Cell Damaged	Percentage of Total
Aceh	1,170	22.28
Sumatera Utara	722	13.75
Sumatera Barat	511	9.73
Sulawesi Tengah	354	6.74
Jawa Barat	353	6.72
Sumatera Selatan	283	5.39
Jawa Tengah	259	4.93
Jawa Timur	242	4.61
Bengkulu	165	3.14

Finally, there were 5,251 cases where the instance hit a nightlight cell that was lit. Table 2.8 shows that the individual nightlight cell weights are small, as expected, but the impact of having buildings of quality 4 is that within a cell that is hit, on average a bit more than 6 percent of the buildings are destroyed.[13]

[11] In our case the value of p in DR is irrelevant as all provinces have the same fragility curves. However, if one looks at different countries or have local data, it would affect the results

[12] The seven not affected were Bangka Belitung, Kalimantan Barat, Kalimantan Selatan, Kalimantan Tengah, Kalimantan Timur, Kalimantan Utara and Kepualauan Riau.

[13] We did the same for buildings of quality 0 (the best) and 7 (the worst), something which led to maximum

Table 2.8: Descriptives of Weights and Intensity for Building Quality 4

Statistic	N	Mean	St. Dev.	Min	Max
Weights	5,251	0.226	0.407	0.009	9.328
Damage	5,251	0.062	0.043	0.046	0.547
Intensity	5,251	0.016	0.035	0.0004	0.859

Weights and Intensity multiplied by 1,000 and excluding weights of zero

Aggregated data

When aggregating, a similar method as in section 2.4 is used, but now the aggregation is done directly by nightlight cells instead of by basin. The equation is:

$$ED_{p,q,y} = \sum_{i}^{I} \sum_{t}^{T} ED_{i,q,p,t}, \qquad p = 1, \ldots, P, \qquad q = 0, \ldots, 7 \qquad y = 2004, \ldots, 2014 \tag{2.9}$$

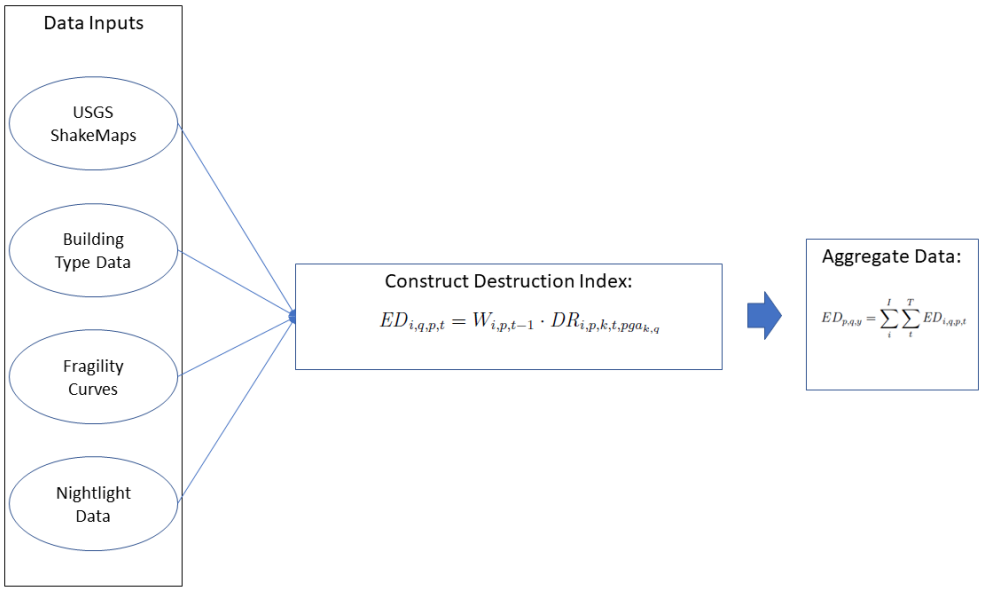
where sum of t is the sum of all days in the year y, i is all nightlight cells in the province or district p and ED is the damage from equation 2.7.

Figure 2.10 gives an overview of the full process used to construct our index.

Table 2.9 provides the full overview of damage by province, showing the large differences between the provinces and how they vary from year to year, as one can expect with highly randomized events such as earthquakes. Using Yogyakarta - which was only impacted by earthquakes in 2006 - as an example, there was a loss of 0.4 percent of the total building mass, causing damages estimated to be approximately 3.1 billion US dollars in addition to more than 5,000 deaths and tens of thousands of injured and displaced people. Apart from that, provinces on Sumatra make up 6 of the top 10 most damaging years. Even though Indonesia is often hit by severe earthquakes, even in the worst of years they only destroy about 1 percent of the buildings in a province. That being said, 1 percent of total building mass and infrastructure

damage values of 33% for the best buildings and 84% for the worst versus 55% for our base case, showing how the overall damage is highly dependent on building quality information.

Figure 2.10: Overview of Methodology used to Construct Earthquake Index



being damaged does constitute a significant portion of local budgets. As another example, the September 2009 earthquake in West Sumatra inflicted damages for an estimated 2.3 billion US dollars, with repair costs and losses of 64 million US dollars on government buildings (Raschky, 2013).

The numbers per district are shown in Table 2.10, and they suffer much more damage than the provinces, with the most impacted district losing 5 percent of building mass.

Table 2.9: Aggregated Earthquake Damage Data by Province

Province	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Aceh	0.040	0.728	0.160	0.152	0.044	0.010	0.269	0.345	4.597	3.869	0.000
Bali	0.557					0.014		0.184			
Banten		0.003	0.268			0.032			0.142	0.022	
Bengkulu	0.447	0.623		8.905	0.380	0.270	0.378	0.154	1.224	0.176	
Gorontalo			0.021		0.929	0.000			0.404	0.000	
Irian Jaya Barat	0.030				0.178	0.410	0.000		0.000		1.217
Jakarta Raya						0.060					
Jambi				1.071	0.033	0.070	0.000				
Jawa Barat			0.018	0.047		0.171	0.007		0.047	0.000	
Jawa Tengah			0.404								
Jawa Timur			0.012							0.190	
Lampung			0.019	0.040		0.000					
Maluku	0.000	0.253	0.378	0.176	0.000	0.000	0.049		5.202	0.105	
Maluku Utara			0.095	0.769	0.644	0.000	0.000	0.147	0.238	4.216	0.918
Nusa Tenggara Barat		0.006	0.248	0.771	0.038	0.187	0.031				
Nusa Tenggara Timur	0.215	0.000		0.048	0.070	0.274		0.026	0.804		1.056
Papua	1.070		0.000	0.000	0.056	0.021	0.235	0.272	0.687	0.392	0.048
Riau		0.003		0.056		0.360					
Sulawesi Barat		0.000				0.123		1.431			
Sulawesi Selatan								0.261	0.000		
Sulawesi Tengah	0.000	0.654	0.185		0.180	0.659	0.050	1.513	5.346	0.000	
Sulawesi Tenggara		0.110	0.052		0.060			0.464			
Sulawesi Utara		0.069	0.050	0.651	0.011	0.263					0.111
Sumatera Barat	0.032	0.175	0.000	9.094	0.173	3.072	0.008	0.000	0.000	0.316	
Sumatera Selatan		0.000		0.816	0.000						
Sumatera Utara	0.002	0.208	0.072	0.010	0.041	0.022	0.175	2.175	0.048		0.000
Yogyakarta			4.318								

Note: Multiplied by 1,000 and results found by using equation 2.9

Table 2.10: 10 Most Impacted Districts

District	Province	Year	Intensity
Alor	Nusa Tenggara Timur	2014	53.184
Waropen	Papua	2010	45.070
Mukomuko	Bengkulu	2007	44.215
Aceh Tengah	Aceh	2013	41.736
Nabire	Papua	2004	39.864
Bener Meriah	Aceh	2013	37.750
Sangihe Talaud	Sulawesi Utara	2009	32.947
Lembata	Nusa Tenggara Timur	2012	31.692
Halmahera Selatan	Maluku Utara	2013	31.511
Aceh Barat	Aceh	2012	22.141

Note: Multiplied by 1,000

2.6 Volcano Damage Index

A volcanic eruption consists of ash clouds, pyroclastic flows and lava flows, the latter two which are very difficult to model without extensive local data. Unfortunately, there is little to no academic research that has looked into large scale volcanic modeling for all aspects of eruptions. For modeling ash clouds, Joyce *et al.* (2009) points to remote sensing through satellite images that detect SO_2 emissions as a potential method.

To construct a damage index for eruptions, we use a two-fold process. First, volcanic ash advisory data are used from Volcanic Ash Advisory Centers (VAAC) to detect eruptions; second, satellite images containing sulphur dioxide data from the OMI/AURA satellite are used to model the intensity of the eruptions. The OMI/AURA images have been utilized by Carn *et al.* (2009) and Ferguson *et al.* (2010) to model eruption intensity.

2.6.1 Volcano Modeling

There are at least two types of software that are used to model eruptions. Voris (Felpeto *et al.*, 2007), which models ash clouds, lava flows and energy cones, and HYSPLIT from Air Resources Laboratory, which models air pollution dispersion. Voris relies on highly localized data due to the lava flow and energy cone modeling, which one will not have in most cases and that does not fit well for large scale modeling across time and space. HYSPLIT does have batch inputs, but still requires several inputs per eruption, some which are not easily obtainable.

The third solution, which is related to the ash clouds mentioned by Joyce *et al.* (2009), is based off ash advisory data to determine whether an eruption happened and OMI/AURA satellite data to determine the scale of the eruption. This will not help with modeling lava flows and energy cones, but due to the very localized nature of the flows, there are no good sources or methods to model it for several eruptions from different volcanoes, leaving the ash clouds as a good proxy for all damages.

Ash advisory data

Ash advisories from the Darwin VAAC (DVAAC), which are ash cloud warnings for airplanes, are used to determine whether an eruption is happening. The warnings show relevant data such as volcano name, position, summit height, height of clouds and a color code that reflects the condition of the air/volcano. There are 4 different codes ranking from the normal state, green, to imminent danger of or ongoing volcanic eruption, red. Over the period from 2004 until 2015, the DVAAC issued 12,962 warnings and of these more than 90 percent were either of code red or orange. Data on advisories from code orange or below were not used, due to eruptions of this scale not being large enough to be properly captured by the SO_2-data. By limiting the data to code red events, there are 1,785 events spread across 587 dates.[14]

OMI/AURA Satellite images

To measure the intensity of an eruption, data from the Sulphur Dioxide images of the OMI/Aura project (Krotkov & Li, 2006) are used. These consist of satellite images from October 2004 and onwards. The data have been used to model ash cloud intensity and movement in several articles such as Carn *et al.* (2009) and Ferguson *et al.* (2010).

The satellite images have a spatial resolution of $13 \cdot 24$km and are taken from 80km above ground. The spectral imaging shows the SO_2 vertical column density in Dobson Units and there are 14 or 15 orbits per day, where one orbit covers an area approximately 2,600km wide. A dobson unit is a measure of density, and at sea level the typical concentration in clean air is less than 0.2DU. The images contain 4 values for column density based on the center of mass altitude (CMA), which is a measure of the altitude one assumes the center of the distribution is at. There are 4 different estimates for the vertical column density, ranging from 0.9km above ground to 18km above ground.

For volcanic activities one normally uses a CMA of either 8km or 18km (OMI team, 2012), where the former is a middle tropospheric column (TRM) and is for use in medium eruptions,

[14]There were 571 different dates, but some of these dates issued red warnings to 2 or more volcanoes.

while the latter is an upper tropospheric and stratospheric column (STL) and is for explosive eruptions. Despite this difference, the data are interchangeable in the sense that one can interpolate from one CMA to the others.

OMI is more sensitive above clouds, which both measures mentioned will normally be. The standard deviation for both measures is as low as 0.1DU over Indonesia. The data for both STL and TRM are very similar and this chapter uses the STL-data as that are most useful for the biggest events.

2.6.2 Construction of Damage Index and Results

Damage Index

When constructing a damage index based on SO_2 values from ash clouds, one has to set thresholds for distance from the event and from the centroid of the nightlight cell and also a lower sulphur dioxide-value. There are no papers or literature that have estimated any parameter values and there are no usable local data, so the thresholds have been set somewhat arbitrarily.

First off, one wants to set a distance threshold estimating how far away the eruption could cause damage. Note that one wants ground results and not for the aviation industry, since planes can be affected very far away as evidenced by the total stand still of planes across Europe during the 2010 Eyjafjallajökull eruption. We decided to set a very relaxed condition with any point closer than 10 degrees of latitude and longitude included. Figure 2.11 portrays the plume approximately 7 hours after one of the biggest Merapi eruptions on 4 November 2010, where the plume moved relatively slowly and after 1000km it dissipated at the lower altitudes, which shows that our 10 degree threshold works well.

Secondly, to match the nightlight data with the OMI/Aura data, a maximum distance between a nightlight point and the nearest SO_2 point is set at 50km. The SO_2 points are fairly scattered due to cloud covers, hence to get a more consistent grid of nightlight and SO_2 values we have chosen a distance that is approximately two times the longest side of an OMI cell.

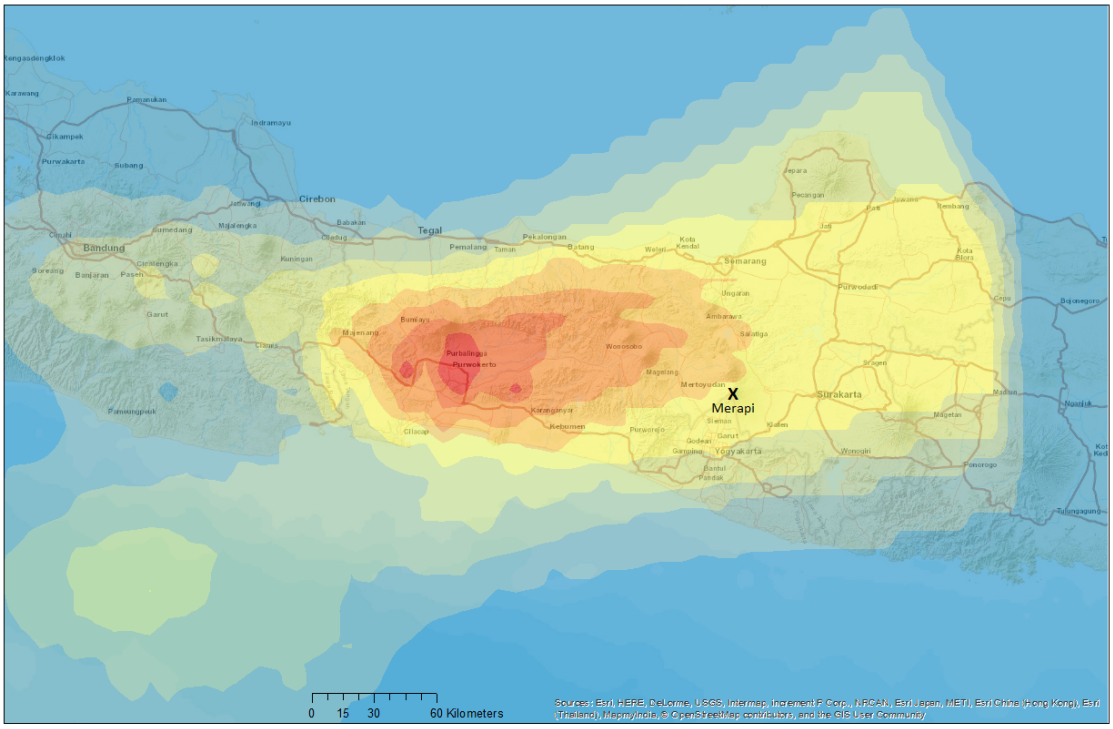
Finally, a minimum SO_2 value in Dobson Units is chosen. According to the Belgian Institute for Space Aeronomy, a typical normal level in air is 0.1DU and a strong eruption is above 10, which is the threshold value chosen.

Once the thresholds have been set, the same nightlight weighting method as for our other indices is applied and then the weights are multiplied with the SO_2 value to get an intensity value. The equation is:

$$VD_{i,t} \equiv \begin{cases} 0, & \text{if } VSO2_t < 10 \\ W_{i,p,t-1} \cdot VSO2_t, & \text{otherwise} \end{cases} \tag{2.10}$$

where i is the nightlight cell on date t, and $W_{i,p,t-1}$ is the previously used weight where i is the nightlight cell, $t-1$ is the nightlight strength from the prior year and it is divided by the sum of total nightlights in the province or district. Finally, $VSO2_t$ is the SO_2 value on date t.

Figure 2.11: Merapi Ash-Cloud 4 November 2010 at 05.33UTC (7h post-eruption)



Results

Applying our constraints, the 587 dates with a red warning have been reduced to 16 days. Of these, 7 are from the 2010 eruption on Merapi, the biggest event during the time period.

Table 2.11 provides the affected nightlight cells by year and volcano and the results are closely correlated with the events of the period. The main one is the Merapi eruption in 2010, Soputan with volcanic explosivity index events of level 2 and 3 in 2004, 2005, 2007 and 2008 (Global Volcanism Program, 2013) and Sinabung with several eruptions in 2014, which all fit the model well.

Table 2.11: Nightlight Cells by Year and Volcano

Volcano	2004	2005	2007	2008	2010	2014	Total
Kelut						2,311	2,311
Manam		62					62
Merapi					129,352		129,352
Sangeang Api						1,156	1,156
Sinabung						3,566	3,566
Soputan	6,164	586	4,672	3,704			15,126
Total	6,164	648	4,672	3,704	129,352	7,033	151,573

Table 2.12: Affected Nightlight Cells by Province and Year

Province	2004	2005	2007	2008	2010	2014	Total
Aceh						2,078	2,078
Banten					940		940
Jawa Barat					52,034		52,034
Jawa Tengah					71,356		71,356
Jawa Timur					2,320	2,311	4,631
Nusa Tenggara Timur						1,156	1,156
Papua		62					62
Sulawesi Utara	6,164	586	4,672	3,704			15,126
Sumatera Utara						1,488	1,488
Yogyakarta					2,702		2,702
Total	6,164	648	4,672	3,704	129,352	7,033	151,573

Table 2.12 refer to province impacts, and the eruptions affected numerous provinces on Java and Sumatra, with Jawa Barat and Jawa Tengah being the most affected with more than 120,000 cells with an SO_2-value above 10 at some point. This is further underlined by nine of the ten most affected districts in Table 2.13 being in these two provinces, which are linked to

the Merapi eruption in 2010. Apart from that, Sulawesi Utara were affected all the years from 2004 through 2008 by the eruptions on Soputan.

Table 2.13: Top 10 Districts with Most Affected Nightlight Cells

District	Province	Affected Cells
Cilacap	Jawa Tengah	16,114
Sukabumi	Jawa Barat	10,724
Kebumen	Jawa Tengah	10,080
Ciamis	Jawa Barat	9,612
Banyumas	Jawa Tengah	9,384
Cianjur	Jawa Barat	8,260
Brebes	Jawa Tengah	6,112
Minahasa Selatan	Sulawesi Utara	5,960
Garut	Jawa Barat	5,622
Bandung	Jawa Barat	5,342

The final table in this section, Table 2.14, provide descriptives of the SO_2 variable and the nightlight weights, as well as the product of the two. Overall, the mean SO_2 value during these events is almost 20, with a max close to 60, which is 600 times the normal level of 0.1DU SO_2.

Table 2.14: Descriptives of Weights and Intensity

Statistic	N	Mean	St. Dev.	Min	Max
Weights	114,587	0.046	0.084	0.007	2.354
SO2 level	114,587	19.748	10.556	10.083	57.231
Intensity	114,587	0.855	1.707	0.075	42.857

Weights and Intensity multiplied by 1,000 and excluding weights of zero

Aggregated data

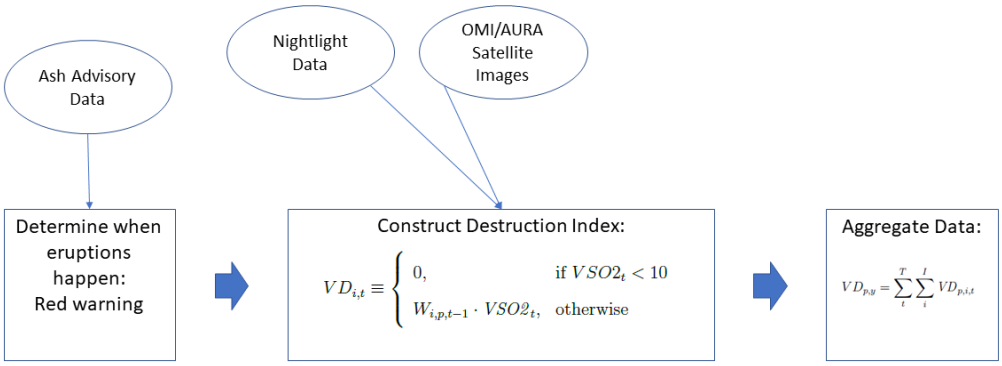
To aggregate the data, the same method as before is applied, with:

$$VD_{p,y} = \sum_{t}^{T} \sum_{i}^{I} VD_{p,i,t}, \qquad p = 1, \ldots, P, \qquad y = 2004, \ldots, 2014 \tag{2.11}$$

where all days t of a year and all nightlight cells i in province or district p are aggregated.

Figure 2.12 shows the steps in the construction of the index.

Figure 2.12: Overview of Methodology used to Construct Volcano Index



The province overview, shown in Table 2.16, is caused by the Merapi eruption, with 3 of the top 4 being due to that eruption. Jawa Tengah and Yogyakarta are the two most affected provinces, given their immediate proximity to Merapi. One thing to note is that Jawa Timur, which is east of Merapi, was hardly affected at all.

For districts, the Merapi results are even more pronounced, with all districts in the top 10 being from the 2010 eruption. All the Jawa Tengah districts are west of the volcano. It is somewhat surprising to find that some of the districts in the immediate vicinity of Merapi are not on the list, but this can be due to the timing and quality of the satellite images. Given the time interval between images, the SO_2 clouds could have traveled past the closest districts by the time an image was taken. Regardless, the results are uniform in that all affected districts are neighbors. Overall, the model seems to give a fair picture of when and where the eruptions were at their most intense, although the ground level intensity can be hard to specify.

Table 2.15: 10 Most Impacted Provinces

Province	Year	Intensity
Jawa Tengah	2010	34.641
Yogyakarta	2010	18.607
Sulawesi Utara	2004	16.224
Jawa Barat	2010	10.271
Sulawesi Utara	2007	6.387
Sulawesi Utara	2008	4.861
Nusa Tenggara Timur	2014	2.356
Aceh	2014	2.134
Sulawesi Utara	2005	0.684
Jawa Timur	2010	0.660

Note: Multiplied by 1,000

Table 2.16: Aggregated Volcano Intensity Data by Province and Year

Province	2004	2005	2007	2008	2010	2014
Aceh						2.134
Banten					0.163	
Jawa Barat					10.271	
Jawa Tengah					34.641	
Jawa Timur					0.660	0.432
Nusa Tenggara Timur						2.356
Papua		0.061				
Sulawesi Utara	16.224	0.684	6.387	4.861		
Sumatera Utara						0.487
Yogyakarta					18.607	

Results found by using equation 2.11

Table 2.17: 10 Most Impacted Districts

District	Province	Year	Intensity
Purwokerto	Jawa Tengah	2010	184.673
Banyumas	Jawa Tengah	2010	168.916
Cilacap	Jawa Tengah	2010	149.878
Kebumen	Jawa Tengah	2010	141.635
Banjarnegara	Jawa Tengah	2010	106.472
Purbalingga	Jawa Tengah	2010	98.697
Purworejo	Jawa Tengah	2010	92.593
Kulon Progo	Yogyakarta	2010	72.177
Wonosobo	Jawa Tengah	2010	69.568
Banjar	Jawa Barat	2010	60.208

Note: Multiplied by 1,000

2.7 Tsunami Damage Index

The final disaster damage index constructed is for the 2004 Christmas tsunami. There is little local district level damage data available, so it was decided to use the methodology from Heger (2016), whereby inundation maps are used to construct a district level damage index assuming a uniform damage across all flooded areas.

2.7.1 Construction of Damage Index and Results

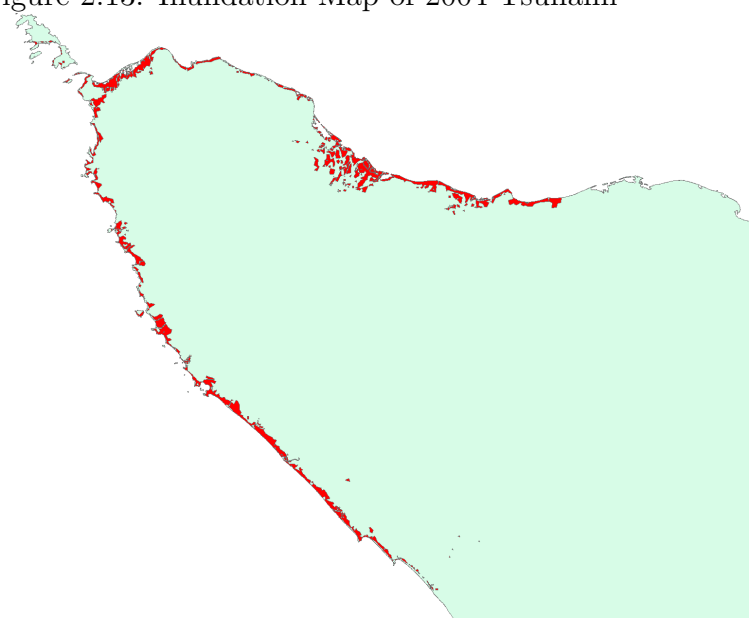
Damage Index

Despite all the media coverage and attention the 2004 tsunami had, there is not much detailed spatial information readily available for research. Heger (2016) has done some research on the causal effects of the tsunami in his PhD thesis, and we will follow his method closely to model flood impact.

To construct an inundation map of the affected areas, a map based on MODIS satellite pictures from Anderson *et al.* (2004) is used. The map itself is fairly low resolution, but it provides a good overview of the inundated areas. In terms of the intensity of the flood, there are no existing data on that, but a uniform flood intensity across all flooded areas is assumed, just as in Heger (2016). The resulting map is shown in Figure 2.13, which shows that a large proportion of the Aceh coastline was struck by the tsunami.

To make this map, the inundation map from DFO was used as a base. Spatial algorithms were then applied to detect the difference in color between inundated and non-inundated areas. This process started with overlaying the base map on a regular shapefile of Indonesia, then detecting the specific color of inundated areas, before constructing a new shapefile where all inundated areas (areas with the same color) have value 1 and all other areas have value 0.

Figure 2.13: Inundation Map of 2004 Tsunami

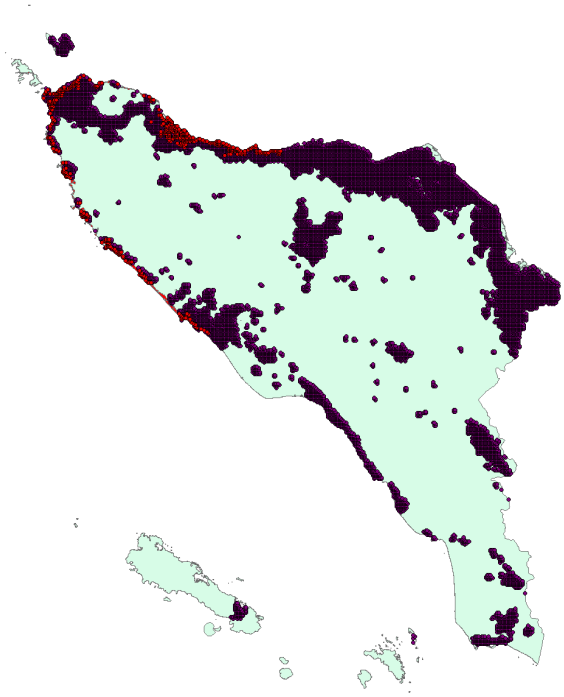


Results

Figure 2.14 shows the inundated area nightlight cells, combined with the nightlight cells in all of Aceh. The tsunami did not strike the most densely populated areas, 460 nightlight cells were hit, out of a total of 13,456 cells in all of Aceh. Given that the tsunami happened 26 December 2004, it is more appropriate to link the incident with the 2004 nighlights, instead of 2003, as is done for the other disaster types. Using the 2004 numbers, there were 364 lit inundated cells out of 7,607 total lit cells in Aceh. Interestingly, in 2005, the year after the disaster, there is a strong decline, with 306 and 6,352 lit cells for the inundated areas and Aceh, respectively. The average light intensity has gone down, from 7.39 per cell to 6.33 in the inundated areas and from 6.37 to 5.18 in the province as a whole.

Finally, Table 2.18 shows the weights which are - again - defined as nightlight in the cell over total nightlight in the province. Although the numbers look very small, by multiplying the means by number of cells, one gets approximately 5.5 percent. Knowing that the census numbers for Aceh in 2000 gave a population of just under 4 million and in 2010 of just under 4.5 million and if one multiplies the population numbers with the affected cells number of 5.5 percent of the total, one gets 221,894 and 249,631, respectively. Given the official numbers of 166,671 dead due to the tsunami, an assumption of total destruction in all inundated areas

Figure 2.14: Aceh Nightlights and Tsunami Affected Nightlights



seem a bit high, given that 166,671 of 230,000 is 72.47 percent. A damage of 75 percent in the inundated cells is chosen, giving a final damage index formula:

$$TD_i = W_{i,p,t-1} \cdot D, \qquad i = 1, \ldots, I \tag{2.12}$$

where TD_i is the province weighted damage from nightlight cell i, $W_{i,p,t-1}$ is the same weight as for earthquakes[15] and D is the flat damage number of 0.75.

Table 2.18: Descriptives of Weights by Year

	All Cells		Only Lit Cells	
Year	Cells	Mean[a] (st.dev[a])	Total Cells	Mean[a] (st.dev[a])
2003	460	0.0965 (0.1356)	295	0.1505 (0.1433)
2004	460	0.1206 (0.1369)	364	0.1524 (0.1373)
2005	460	0.1281 (0.1656)	306	0.1925 (0.1698)

a. Multiplied by 1000

[15]The only affected province is Aceh

Aggregated data

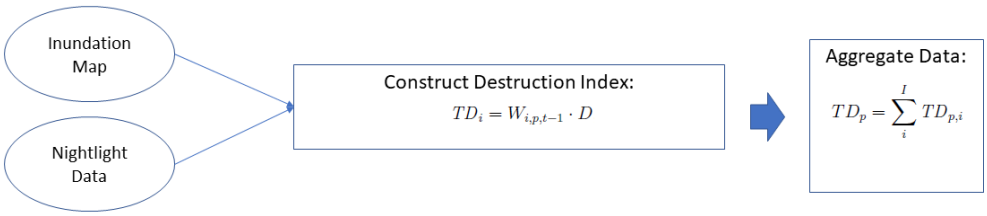
Aggregating the data is done using the same method as in all previous sections, where the nightlight cell impacts across the province or district is summed up:

$$TD_p = \sum_{i}^{I} TD_{p,i} \tag{2.13}$$

where all nightlight cells i in province or district p are aggregated.

The process used to construct the tsunami index is very similar to the other indices as outlined in Figure 2.15.

Figure 2.15: Overview of Methodology used to Construct Tsunami Index



Since the tsunami only affected one province, it is easy to see the total damage done by it on Aceh. With our assumptions, the tsunami destroyed about 4 percent of the buildings in Aceh. This is clearer once broken down into district level damage. There were 6 districts affected by the tsunami, with Aceh Jaya, Banda Aceh and Pidie all experiencing damage of more than 20 percent. The other 3 affected districts - Aceh Barat, Aceh Besar and Bireuen - experienced damage between 5 and 10 percent due to the tsunami.

Table 2.19: Aggregated Tsunami Damage by District and Province

District	Province	Intensity
Aceh Barat	Aceh	0.071
Aceh Besar	Aceh	0.078
Aceh Jaya	Aceh	0.221
Banda Aceh	Aceh	0.229
Bireuen	Aceh	0.055
Pidie	Aceh	0.210
Aggregated	Aceh	0.042

2.8 Conclusion

With the continuous increase in remote sourcing data, it has gotten much easier and cheaper to monitor and assess the damages from natural disasters. Joyce *et al.* (2009) and Gillespie *et al.* (2007) have done an extensive review of how satellite images can be used to map natural disasters, while this chapter has contributed with providing new techniques that utilize other remote sourced data such as ShakeMaps and ash advisory data.

Throughout, techniques based on freely available data have been used to construct damage indices for different disaster types. Generally the indices can be used in any area of the world, and if calibrated with local data, they could provide an excellent tool for local governments or stakeholders in early disaster assessments.

The indices can be used to get quick damage estimates and inform where to provide relief, as well as in research such as what the authors have done in Skoufias *et al.* (2017b), where the indices are used to analyze district budget redistributions following natural disasters.

The main caveat is the indices have not been validated against local level damage data. If one had access to high resolution monetary or intensity data, the estimates would be much more precise.

Table 2.20 gives an overview of the different data sources and software used. All disasters have used the DMSP global nightlights data to weight the indices based on economic activity. Recently, the VIIRS nightlight data provide an alternative for assessing economic activity or events, as showcased for GDP in China (Li *et al.*, 2013; Shi *et al.*, 2014) and Africa (Chen & Nordhaus, 2015) and for storms and floods in the US (Cao *et al.*, 2013; Sun *et al.*, 2015). If one is interested in events after 2012, the VIIRS data provide higher spatial resolution and track changes by month instead of yearly.

Alternatives do exist for choice of software if one wants everything to be open source and free.

Instead of ArcGIS, packages such as QGIS and RGDAL for R are potential alternatives. R and Python are used more and more for spatial data and can often provide the necessary tools to do the modeling. Instead of statistical software such as Matlab and Stata, R and Python once more provide excellent alternatives.

Table 2.20: Disasters and the Data Sources and Softwares used

Disaster Type	Data Sources	Software Used
Flood	Hydro1K GLCC FAO Digital Soil Map TRMM GDAS	GeoSFM (ArcView 3.3) Python Stata ArcGIS
Earthquake	USGS ShakeMaps USGS Building Inventory World Housing Encyclopedia Urban Extent Map (CIESIN) GESI	Python Stata ArcGIS
Volcanic Eruption	Ash Advisory Data OMI/AURA Satellite Images	Python Matlab Stata ArcGIS
Tsunami	DFO Inundation Map	Python ArcGIS Stata

Chapter 3

The Reallocation of District-Level Spending and Natural Disasters: Evidence from Indonesia

Abstract

District-level government spending data from Indonesia and natural disaster damage indices are combined together to analyze the extent to which districts are forced to reallocate their expenditures across categories after the incidence of floods, earthquakes, and volcanic eruptions. The results reveal that district government spending is quite sensitive to the incidence of natural disasters at the local level. In the case of floods, districts reallocate spending away from the category of general administration to sectors such as health and infrastructure. Moreover, volcanic eruptions seem to lead to less investment in durable assets both in the year of the disaster as well as in the following year. Overall, these results highlight the potentially useful role of a national disaster risk financing insurance program towards maintaining a relatively stable level of district-level spending in different sectors.

3.1 Introduction

During the period 2003 through 2013 natural disasters have been estimated to have caused damages of up to USD 1.5 trillion (Food And Agriculture Organization of the United Nations, 2015), arguably leading to stagnating GDP growth and funding issues for impacted countries. These disasters affect public finances through losses in revenues from lower tax income from less production output and increased spending for aid and rebuilding (Hofman *et al.*, 2006). In Indonesia, specifically, it was estimated that the annual impact of natural disasters is around 0.3 percent of GDP, potentially rising to up to 3 percent (The Global Facility for Disaster Reduction and Recovery, 2011). There are a number of studies that have examined how natural disasters have impacted the fiscal sector of affected countries. For a large set of countries and different natural disaster events grouped together, Lis & Nickel (2010), for example, estimate that the negative budgetary impact of extreme weather events can be up to 1.1 per cent of GDP. Melecky & Raddatz (2014) analysis shows that government expenditure increases, whereas revenue does not respond to climate shocks. Looking at tropical storms in the Caribbean, Ouattara & Strobl (2013) demonstrate that hurricane strikes cause an increase in government spending and short term deficit financing. Lastly, Noy & Nualsri (2011) also note that the fiscal impact of natural disasters depends on the country-specific macroeconomic dynamics occurring in the aftermath of natural disaster shocks.

The funding of these financial shortfalls could be done through both ex-ante strategies, such as insurance as well as ex-post financing, for example through loans. However, for developing countries, it can often be difficult to get access to external loans through private markets, leaving only insurance, external aid, tax increases or internal redistribution of finances as potential sources of funding (Bevan *et al.*, 2016; Mahul & Ghesquiere, 2010). With insurance still uncommon in most developing countries[1], foreign aid usually available only after large disasters, and tax increases politically unpalatable, redistribution of spending across different budget categories is perhaps the only remaining or default alternative for post-disaster financing for many

[1]Rauch & Neuthor (2013), for example, claim that for the years 1980-2012, low income countries constituted 10 percent of disaster losses, but only 1 percent of the insured losses.

governments.

Budget reallocation as a response to post-disaster financing has received only scarce attention in the literature. For example, papers such as Bevan *et al.* (2016) focus on the redistribution at a sovereign level, and only as a theoretical exercise. In this chapter we will use detailed budget expenditure data for Indonesian districts for the period 2005 through 2012, and combine these with spatially disaggregated damage indices for floods, earthquakes, volcanic eruptions and the 2004 tsunami to construct a unique spatial panel data set. This will allow us to obtain a first empirical estimate of how local governments change their spending following natural disasters.

The district level budget data contains revenues and expenditures provided every year to the Regional Financial Information (SIKD) and is broken down across 12 different economic sectors such as health, education, agriculture and infrastructure. In addition to the sectoral breakdown, local government spending is also classified into four categories; namely, capital expenditure, goods and services, personnel and other, providing an alternative for analyzing any changes among these categories.

The natural disaster damage indices are constructed by modeling the local strength of each disaster using its physical characteristics and taking account of local exposure to these aspects using nightlight intensity derived from satellite imagery, following Skoufias *et al.* (2017a). The disasters examined are floods, earthquakes, volcanic eruptions and the 2004 tsunami, all of which are modeled using different remote sensing data that are aggregated up to district level.

The remainder of this chapter consists of four parts. First, there is a brief section on the construction of the damage indices. Then a part presenting the budget data, followed by the main part with the methodology and results, before finishing with a conclusion.

3.2 Natural Disaster Damage Indices

The methodology and data sources used to make damage indices for natural disasters is extensively covered in Skoufias *et al.* (2017a), which is equivalent to Chapter 2 in this thesis. Generally, the paper uses remote sensing data for the different disaster types - floods, earthquakes, volcanic eruptions and the 2004 tsunami - that is combined with nightlight data - used as a proxy for economic activity - to construct an index that estimates the impact on districts and provinces.

More specifically, the nightlight data used provides a normalized annual light value ranging from 0 (no light) to 63 (maximum light) and is from the Defense Meteorological Satellite Program (DMSP) satellites. Using this data as a proxy for economic activity - when no other data exists - has been employed in papers such as Henderson *et al.* (2012), Hodler & Raschky (2014) and Michalopoulos & Papaioannou (2014). In our case, the nightlight data has been employed as a weight for the economic impact of disasters.

Floods are modeled through a combination of remote sensing images and GIS-modeling using the Geospatial Stream Flow Model (GeoSFM). The remote sensing inputs comprise weather data, such as rain and temperature, as well as soil and terrain data. These sources are then used by GeoSFM to model basins across Indonesia and the stream flow in each of these. The final steps consist of setting a threshold for when a stream flow is strong enough to flood the basin and then weight this with the nightlight data and aggregate up to a district level.

The earthquake index is constructed from computer generated contour maps by the US Geological Survey (USGS) of earthquake intensity data, commonly used as potential damage proxy (De Groeve *et al.*, 2008; GeoHazards International and United Nations Centre for Regional Development, 2001; Federal Emergency Management Agency, 2006). Utilizing the contour maps as a base for damage infliction, we combine them with the nightlight and building type data from the USGS building inventory for earthquake assessment to create fragility curves by building type; see Jaiswal & Wald (2008) and GeoHazards International and United Nations Centre

for Regional Development (2001). Finally, the data is aggregated up to a district level set.

To model volcanic eruption intensity, we utilized a two-fold process. First, volcanic ash advisory data from Volcanic Ash Advisory Centers (VAAC) is used to detect eruptions. The advisories are produced for the airline industry to warn airplanes about impending or ongoing eruptions through color coded messages. We use only the highest warning level of ongoing eruption as a threshold of when to include an eruption in the data set or not. Second, images containing sulphur dioxide data from the OMI/AURA satellite are used to model the intensity of the eruptions. These images provide SO_2 density data and have been utilized by Carn *et al.* (2009) and Ferguson *et al.* (2010) to model eruption intensity before. The data is then combined with the nightlight data and aggregated up to district level.

Finally, the 2004 Christmas tsunami has been modeled following a method where Heger (2016) uses inundation maps to construct a district level damage index assuming a uniform damage across all flooded areas. To construct an inundation map of the affected areas, a map based on MODIS satellite pictures from Anderson *et al.* (2004) is used with spatial algorithms to detect the difference in color between inundated and non-inundated areas. Once the map is constructed, it is weighted and aggregated just like the other indices.

As for the indices themselves, the actual coefficients for floods and volcanic eruptions are simple intensity measures that do not convey anything on their own apart from an intensity weighted by nightlights. For earthquakes and the tsunami, the numbers show the overall damage to buildings in the district.

Table 3.1 shows the descriptives of the damage indices, with floods striking districts 2,417 times over the 8 year time period, meaning that approximately 300 districts are affected by floods annually. The earthquakes struck 435 times, while the volcanic eruptions and the tsunami affected a limited number of districts, due to the limited number of big events. The strongest earthquake damage almost 5 percent of the buildings in a district, while the district that was

worst hit by the tsunami experienced damage to 23 percent of the building mass.

Table 3.1: Descriptives Damage Indices - 2005 - 2012

Disaster	N	Mean	SD	Min	Max
Flood	2417	27.94	22.25	0.01	175.08
Earthquake	435	2.54	4.94	0.01	45.07
Volcanic Eruption	61	32.25	42.58	0.03	184.67
Tsunami	6	0.14	0.08	0.06	0.23

Note: Earthquake mean, SD, min and max multiplied by 1,000

3.3 District Expenditure Data

The financial data used is the District budget data for the years from 2001 to 2012 (Fiscal Year of January-December every year). It was derived from the Regional Financial Information System (Sistem Informasi Keuangan Daerah, SIKD) of the Ministry of Finance. The district expenditures are available for 12 different sectors/functions (such as agriculture, health, education, etc.) and for four economic classifications (personnel, goods and services, capital, and other).

The 12 sectors are presented in the top panel of Table 3.2, where nominal numbers are converted into yearly ratios, which eliminate inflationary issues as well as spending differences due to district size and wealth.[2] The three largest sectors are General Administration (GA), Education and Infrastructure. Most of the sectors have between 4,000 and 4,500 observations, but public law and order, housing and - in particular - religious affairs have much fewer observations, implying that the overall ratios might be skewed a bit by districts that report these sectors compared to districts that do not. However, on average the under-reported sectors constitute less than 5 percent of the total expenditures, making their overall impact small. The reason for the fewer observations[3] and the lack of completeness are unknown, but we will be treating

[2]Nominal data is shown in appendix A.1

[3]Religious affairs are only reported for Aceh, implying that it is a province specific category

missing data as missing and make ratios based on a total of reported sectors.

Table 3.2: Descriptives of ratios of Expenditure data by Economic Sectors and Categories

Sector	N	Mean	St. Dev.	Min	Max
General Administration	4,505	0.333	0.146	0.013	1.000
Public Law and Order	3,201	0.010	0.008	0.000	0.213
Economy	4,422	0.024	0.017	0.000	0.210
Environment	4,119	0.017	0.021	0.000	0.341
Housing and Public Facilities	3,401	0.023	0.041	0.000	0.345
Health	4,433	0.086	0.033	0.000	0.444
Tourism and Culture	3,997	0.006	0.012	0.000	0.372
Religious Affairs	717	0.006	0.008	0.0001	0.112
Education	4,440	0.328	0.125	0.000	1.000
Social Protection	3,972	0.009	0.008	0.000	0.127
Infrastructure	4,432	0.151	0.082	0.000	0.602
Agriculture	4,422	0.042	0.023	0.000	0.353

Category	N	Mean	St. Dev.	Min	Max
Capital Expenditures	4,770	0.236	0.112	0.000	0.976
Goods and Services	4,775	0.190	0.060	0.000	0.578
Other expenditures	4,747	0.085	0.058	0.000	1.000
Personnel Expenditures	4,790	0.493	0.138	0.000	1.000

The economic classifications ratios are in the bottom panel of Table 3.2.[4] The four categories are split partly by durability and partly by other criteria. Capital Expenditure is defined as expenditures on assets with durability of more than 12 months, whereas Goods and Services are on assets with a durability of less than 12 months. The former typically comprises purchase of land, buildings and large equipment, while the latter includes items such as work clothes, small repairs, stationaries and short term rental. Personnel Expenditures is mainly salaries to public servants, but also includes some other costs related to employees such as accident/death expenditures and expenditures related to tax income. Finally, the Other Expenditures include financial costs such as interests and subsidies as well as unforeseen costs related to for example natural disasters.

Table 3.2 shows that Personnel Expenditures are the highest cost classification, with 49.3 percent of the costs being allocated to personnel. Overall the reporting seems to be more

[4]Nominal data is shown in Appendix A.1

consistent for the four classifications since the number of observations is very similar for all four areas. That being said, some of the districts report that 100 percent of their costs for a year have been allocated to cover other or personnel, which seems unlikely.

3.4 Impact of Natural Disasters on District Spending

Despite the potentially large impact natural disasters can have on local finances, the literature analyzing the economic effects is practically non-existent. Our analysis will provide a simple framework that can be used for any natural disaster type and any type of local financial data.

For Indonesia, the local level that will be analyzed are districts. A caveat with that level, is that the number of districts has increased during the period due to administrative splitting. Out of 511 districts 167 of them have been part of a split, implying that the budget numbers would change sometime during our period. Any split districts will have to be disregarded as the nominal and relative size of the expenditures will change following a split.

Furthermore, not all of the 344 non-split districts have been affected by a disaster. The modeled damage indices have registered that 304 of the 344 districts have experienced at least one natural disaster large enough to be included.[5]

Finally, there are 488 districts that have reported at least one sector or classification for at least one year. Of these 488 there are 299 districts that are non-split and have experienced a natural disaster.

3.4.1 Methodology

Given that the data is structured as spatiotemporal panel data it lends itself to a fixed-effect regression methodology with the expenditure ratios as the dependent variable and the damage indices as independent variables. That being said, the different ratios are necessarily related. We have therefore chosen to use the method for seemingly unrelated regression (SUR) as explained in Blackwell III *et al.* (2005).

Their methodology is based upon Baltagi (2001), Judge *et al.* (1988) and Wooldridge (2002).

[5] 397 of the 511 total districts have been impacted by a natural disaster.

In short, they use a system of SUR with error components. It is assumed that all coefficients of constant terms are the same across the system and that all independent variables are quantitative and require restriction across the panels in their equations, while fixed-effect dummies vary by panel.

In our case this translates into a set of equations. The basis is:

$$\begin{aligned} B_{j,i,t} = \beta_{j0} + \beta_{j1} \cdot PD_{i,t} + \beta_{j2} \cdot ED_{i,t} + \beta_{j3} \cdot VD_{i,t} + \beta_{j4} \cdot TD_{j,t}, \qquad j = 1, \ldots, J \\ + \sum_{k=1}^{K} \left(\beta_{j,4+k} \cdot PD_{i,t-k} + \beta_{j,5+k} \cdot ED_{i,t-k} + \beta_{j,6+k} \cdot VD_{i,t-k} \right) + \alpha_{j,i} + \mu_t + \lambda_{j,i,t} + \epsilon_{j,i,t} \end{aligned} \tag{3.1}$$

where the left hand side is defined as the ratio:

$$B_{j,i,t} \equiv \frac{C_{j,i,t}}{\sum_{k=1}^{J} C_{k,i,t}}, \qquad j = 1, \ldots, J \tag{3.2}$$

where j are different economic sectors or classifications, i is the district, t is the year and C is the expenditure. On the right hand side of Equation 3.1 we find the different damage indices by year and district. These are identical across the different economic sectors. Finally, there is a fixed effect term, $\alpha_{j,i}$, a yearly dummy term μ_t, a time trend term per district term $\lambda_{j,i,t}$ and an error term, $\epsilon_{j,i,t}$. Note that the above model has included a lag operator, i.e. allowed for disasters the prior years.[6] The model can be used both with and without the lag terms.

3.4.2 Creating Panel Data

Equation 3.1 yields the best results if the input data is balanced. However, there are several years and sectors missing for many of the districts in our data set. Table 3.3 shows how the number of districts change with how strict a criteria one sets for the data. Balanced means that a district has reported the specific sector for all years, whereas unbalanced means all observations regardless of how many years a district has reported. More precisely, unbalanced 1yr

[6] Due to the limited time period, we only lagged for one period. Hence why the tsunami index is not included in the lag operator

and 2yr means that a district has not reported for 1 or 2 years in a sector.

Comparing the results with the optimal case of all 299 districts having reported for all 8 years, we see that the number of districts reporting data for a sector across all years is very low. There is actually no district that has reported for all sectors in all years. Allowing for the expenditure data to be unbalanced adds many more districts. However, leaving the sectors fully unbalanced, i.e. a district would be included even if a sector is only reported once, would potentially skew the data. By including districts that did not report a sector expenditure one or two of the years, we increase the number of observations and avoid the districts that rarely report a sector. The assumption is that districts that regularly file their expenditures are more likely to report correct numbers. The difference between allowing 1 and 2 years of missing reporting is fairly significant, most likely due to some years generally having fewer reports. For example, the years 2007 and 2011 had less than 200 districts reporting across all sectors[7], reasons for which are unknown.

Table 3.3: Comparison of Data depending on Balanced vs Unbalanced

	Balanced		Unbalanced		Unbalanced 1yr		Unbalanced 2yr	
Sector	Mean	Total	Mean	Total	Mean	Total	Mean	Total
Agriculture	90	720	228	1,827	168	1,343	205	1,643
Economy	92	736	230	1,838	170	1,359	207	1,653
Education	92	736	230	1,841	171	1,366	207	1,654
Environment	71	568	212	1,694	129	1,030	171	1,366
General Administration	107	856	234	1,873	176	1,409	213	1,703
Health	92	736	230	1,840	171	1,366	207	1,654
Housing and Public Facilities	10	80	105	841	38	304	71	568
Infrastructure	91	728	230	1,836	168	1,344	206	1,650
Social Protection	53	424	203	1,622	119	949	158	1,267
Tourism and Culture	59	472	190	1,518	115	920	157	1,256
Public Law and Order[a]			231	1,386			123	738
Total		6,056		18,116		11,390		15,152

Given how the expenditure data is distributed, the unbalanced panel that allows for 2 missing years of reporting is the best compromise between a balanced panel and retaining enough observations across the sectors. To make sure that this does not affect our damage indices too much, we have shown how the disaster descriptives change in Table 3.4.

[7] General Administration had 202 reports in 2011

Compared with the full set of disasters shown in Table 3.1, the mean and standard deviation for floods and earthquakes fall. The main reason for the earthquake coefficients to move down is that some big earthquakes hit districts that has later been split. One of the more active earthquake areas is the province of Aceh, which has experienced many district splits. This is also why the number of tsunami districts is just 1 or 2 instead of the 6, which is all affected districts. Volcanic eruptions see a slight increase in mean, whereas the standard deviations are close to what they are for the full sample.

Some sectors with fewer observations, such as Public Law and Order, Housing and Social Protection deviate more from the norm than the more robust sectors with more observations. However, importantly, most sectors stay within a fairly tight band both for mean and standard deviation, implying that the sectors experience similar disaster impact. Overall, we believe the number of observations for floods and earthquakes is high enough to provide fairly robust results, and even volcanic eruptions can be useful as a guidance. The tsunami index however is suffering from having only one or two districts in our sample.

Table 3.4: Damage Indice Descriptives when Unbalanced 2 years

	Flood			Earthquake[a]			Volcanic Eruption			Tsunami		
Sector	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
General Administration	1,691	25.86	22.01	222	1.66	3.34	44	34.87	42.58	1	0.23	
Agriculture	1,631	25.99	22.12	220	1.81	3.54	43	35.13	43.05	2	0.15	0.11
Public Law and Order	738	27.41	22.80	81	2.12	3.59	33	40.10	46.52			
Economy	1,641	26.01	22.09	220	1.81	3.54	44	34.87	42.58	2	0.15	0.11
Environment	1,360	25.74	21.34	183	1.87	3.63	41	36.51	43.56	2	0.15	0.11
Housing and Public Facilities	568	26.54	20.97	66	2.04	4.10	16	35.07	42.57	1	0.23	
Health	1,642	26.03	22.09	220	1.81	3.54	44	34.87	42.58	2	0.15	0.11
Tourism and Culture	1,244	26.59	22.49	176	1.87	3.55	39	34.08	43.78	2	0.15	0.11
Education	1,642	26.03	22.09	220	1.81	3.54	44	34.87	42.58	2	0.15	0.11
Social Protection	1,255	25.15	21.66	172	2.01	3.81	30	28.72	38.29	2	0.15	0.11
Infrastructure	1,638	26.01	22.10	219	1.80	3.55	44	34.87	42.58	2	0.15	0.11
Category	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
Capital Expenditures	1,740	27.28	21.89	207	2.15	3.73	47	33.41	41.67	2	0.15	0.11
Goods and Services	1,739	27.27	21.90	207	2.14	3.74	47	33.41	41.67	2	0.15	0.11
Other Expenditures	1,733	27.24	21.85	210	2.16	3.71	47	33.41	41.67	2	0.15	0.11
Personnel Expenditures	1,752	27.22	21.87	210	2.11	3.72	47	33.41	41.67	2	0.15	0.11

[a] Mean and standard deviation numbers multiplied by 1,000

For the economic categories, the overall data looks better, as seen in the lower panel of Table 3.4.

The flood and earthquake districts are well covered, and for volcanic eruptions it is the same districts that have reported for all categories. Finally, the tsunami data is covered through two districts. Overall, the data is more complete than for sectors.

3.4.3 Results

Having decided on the methodology and datasets we ran the regressions based on Equation 3.1, both with and without lags. There were two different sets of regressions, one with the 12 sectors as dependent variables and another one with the four categories being the dependent variables. In both cases, the damage indices were independent variables. In addition we controlled for the fixed effects, potential time trends and potential regional time trends. The datasets used were the panels missing no more than 2 years of reporting.[8]

Note that lags have not been included for the tsunami data. The reason for this being that the tsunami data is already lagged. The tsunami happened on 26 December 2004, hence a lot of the expenses incurred and any shifts in spending are likely to not be realized until the fiscal year of 2005. As mentioned in the report by The Global Facility for Disaster Reduction and Recovery (2011) the budget allocation for 2005 had already been approved, so major changes were needed during the mid-year budget revision of 2005. Furthermore, the earthquake data does not start until 2005, so to be able to control for all disasters at the same time, the starting year is 2005. As for the other lags, they are added to check whether any spending patterns or redistribution of expenses occur the year after the disaster has struck.

To better understand the results and the timing, it is worth noting how disasters are financed in Indonesia. In short, from the report by The Global Facility for Disaster Reduction and Recovery (2011), Law 24/2007 provides the framework for how disasters are handled and the responsibilities of central and local governments. In general, minor disasters are handled by local governments through their budgets, whereas any disaster deemed a national disaster or a disaster of national importance will be financed by the central government. The disaster

[8] We also ran the regressions based on balanced data and 1 year of reporting missing. Overall the results were quite similar, but for some of the lesser reported sectors they differed more.

funding is split into three phases: the response phase immediately after the disaster, then the recovery phase typically being the period three to six months post-disaster and finally the recovery phase. The central government assists all three phases when a disaster is deemed a national disaster or when the costs go higher than what the local governments can afford. It is noted that what constitutes a national disaster and not is not clearly defined. For example the Merapi eruption in 2010 was not declared a national disaster, but the central government did support local governments in both response and recovery phases.

Sector Results

The first sector results are presented in the left panel of Table 3.5, which shows the coefficients for the sector regressions.[9] Each column presents the coefficient for each disaster by sector. Since SUR has been used, the table shows the result for one regression, i.e. all coefficients are part of the same regression.

For floods, several of the districts have changed their sector expenditures. The four large sectors - Education, GA, Health and Infrastructure - all have changes that are significant, with GA and Infrastructure being so at a 1 percent level, while Health and Education are significant at 5 and 10 percent levels, respectively. Also Agriculture shows a 1 percent significance, while Economy, Public Law and Order and Tourism and Culture also show significance. Overall, we find that the key variables show a strong significance.

There is a strong negative effect on GA and Education, whereas Health and Infrastructure expenditure goes up. For a disaster type such as flooding it makes sense that health and infrastructure spending goes up since there will be an increased need for medical attention and roads and other infrastructure might be swept away.

Regarding the other sectors, Agriculture is highly significant and spending goes up, potentially due to fields and other arable land being washed away or flooded. Agriculture is a sector that

[9] Only main sectors are shown. For full results, see Appendix A.2

is often close to water sources and hence might be more prone to be hit by floods. The rather general sector of Economy also experiences a statistically significant increase in spending, a pattern it shares with Tourism and Culture. It has to be mentioned that these are rather small sectors with Tourism and Culture constituting 0.6 percent of the total budget on average.

In terms of what this translates into, the left panel of Table 3.6 shows percentage point changes for the four largest sectors for the different disaster types given a mean and max disaster. GA would decrease almost 1 percentage point from 33.3 to 32.4. Assuming a mean budget of 441,703RP million[10] that translates into 4,036 RP million (300,000USD) less being spent on GA. For Education the decrease is 0.7 percentage points from 32.8 percent to 32.1 percent. Health goes up 0.3 percentage points to just about 9 percent and Infrastructure goes up 0.9 percentage point to 16 percent a change of almost 6.5 percent. Overall, we do find significant shifts in the districts spending patterns once a flood hits. Given that floods are usually relatively small in scale, it is plausible that they have an immediate effect on the local districts' budgets since they are expected to be able to cover these minor events on their own.

If the worst flood hits the mean district, GA will constitute 5.7 percent less of the total, and Education 4.4 percent less. Health and Infrastructure will see an increase of 2.2 percent and 5.8 percent respectively. Any 5 percent shift in the mean budget equals 22,000 RP million (USD1,650,000), showing that the shifts here are very large. Only the four key sectors make up a larger share of the budget than 5 percent.

Continuing with the earthquake results in the next column in Table 3.5, there is no significance apart from for Tourism and Culture and Public Law and Order, which are significant at a 10 and 5 percent level, respectively. The reason for the lack of significance might be down to earthquakes being more likely to be declared national disasters and/or recovery costs exceeding what local governments are capable of covering, one might expect to find a limited effect during the year of the disaster.

[10] As found in the nominal tables in Appendix A.1

For volcanic eruptions, the results show the same strong negative effect as floods for GA and positive effect for Health. At the same time it shows a strongly significant and decreased spending for Infrastructure and increased spending for Education. The latter two are somewhat counterintuitive, but one could expect limited damage on infrastructure due to volcanic eruptions, given that many of the districts are not in the immediate proximity of the volcano and that the SO_2-proxy will not capture lava and pyroclastic flows that are more likely to cause damage on infrastructure. The increase in Education is harder to explain, but it could be due to the somewhat limited amount of observations for the volcanic events. Another reason can be that response and recovery financing after the (by far) biggest event - the Merapi Eruption in 2010 - came from the Central Government, meaning that any effect on local spending might be skewed or incorrect.

The key sectors' change for volcanic eruptions show that a mean eruption would lead to Education spending taking up 1.9 percent more of the total, GA 0.4 less, Health 0.5 more and Infrastructure 1.2 less. The worst eruption would lead to increases of 10.7 and 2.8 percent for Education and Health and decreases of 2.5 and 7 percent for GA and Infrastructure. This seems to be too high, and these changes could be due to some other transfers to the districts.

The fourth column shows the tsunami results. Agriculture and Economy expenditure are strongly negative. In addition, Education spending is strongly significant and positive. Finally there is a decrease in GA, which is 10 percent significant. The changes translate into a 10.1 increase in Education spending and a 7.4 percent decrease in GA. However, these results might not be very robust, given the very limited number of districts in our dataset and the fact that funding for response, recovery and reconstruction came from a plethora of sources including international donors and governments as well as the Indonesian Government.

Continuing with columns 5 through 9 in Table 3.5 - the same model with the addition of variables lagged a year - the same pattern shows itself across the sectors for flood. With the addition of the lags, the significance decreases for some of the sectors. For instance, the Health

Table 3.5: Regression results for Unbalanced 2 year Sector Data with lags

	Without Lag				With Lag			
Sector	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami
Agriculture	0.094***	0.092	-0.038	-0.285***	0.108***	0.083	-0.049	-0.173***
	(0.033)	(0.170)	(0.047)	(0.051)	(0.030)	(0.193)	(0.041)	(0.027)
Education	-0.253*	0.514	0.581***	0.726***	-0.307**	0.154	0.671***	0.607*
	(0.136)	(1.423)	(0.178)	(0.280)	(0.131)	(1.543)	(0.156)	(0.312)
General Administration	-0.327***	1.624	-0.134**	-0.529*	-0.381***	2.400*	-0.186**	-0.555**
	(0.117)	(1.418)	(0.064)	(0.290)	(0.105)	(1.411)	(0.090)	(0.273)
Health	0.124**	0.208	0.151***	-0.045	0.127**	0.245	0.144***	-0.025
	(0.060)	(0.221)	(0.033)	(0.074)	(0.059)	(0.220)	(0.027)	(0.076)
Infrastructure	0.331***	-0.033	-0.380**	-0.119	0.374***	0.010	-0.404**	-0.037
	(0.093)	(0.869)	(0.179)	(0.154)	(0.095)	(0.911)	(0.162)	(0.157)
Agriculture Lag					0.104***	0.546**	-0.032	
					(0.038)	(0.254)	(0.036)	
Education Lag					-0.426**	-4.006**	0.529***	
					(0.206)	(1.832)	(0.196)	
General Administration Lag					-0.316**	5.058**	-0.180*	
					(0.154)	(2.003)	(0.100)	
Health Lag					0.048	0.473***	-0.030	
					(0.042)	(0.198)	(0.034)	
Infrastructure Lag					0.270	1.810*	-0.141	
					(0.171)	(0.998)	(0.175)	
Observations	15,152	15,152	15,152	15,152	15,152	15,152	15,152	15,152

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
[a] Coefficients and standard errors multiplied by 1,000.

Table 3.6: Percentage change of Total Budget by Key Sectors

	Without Lag				With Lag			
Sector	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami
Mean disaster								
Education	-0.71*	0.13	1.87***	10.16***	-0.86**	0.04	2.16***	8.50*
General Administration	-0.91***	0.41	-0.43**	-7.41*	-1.06***	0.61*	-0.60**	-7.77**
Health	0.35**	0.05	0.49***	-0.63	0.35**	0.06	0.46***	-0.35
Infrastructure	0.92***	-0.01	-1.23**	-1.67	1.04***	0.00	-1.30**	-0.52
Education Lag					-1.19**	-1.02**	1.71***	
General Administration Lag					-0.88**	1.28**	-0.58*	
Health Lag					0.13	0.12***	-0.10	
Infrastructure Lag					0.75	0.46*	-0.45	
Max Disasters								
Education	-4.43*	2.32	10.73***	16.7***	-5.37**	0.69	12.39***	13.96*
General Administration	-5.73***	7.32	-2.47**	-12.17*	-6.67***	10.82*	-3.43**	-12.77**
Health	2.17**	0.94	2.79***	-1.04	2.22**	1.10	2.66***	-0.58
Infrastructure	5.80***	-0.15	-7.02**	-2.74	6.55***	0.05	-7.46**	-0.85
Education Lag					-7.46**	-18.06**	9.77***	
General Administration Lag					-5.53**	22.80**	-3.32*	
Health Lag					0.84	2.13***	-0.55	
Infrastructure Lag					4.73	8.16*	-2.60	

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

sectors shows no effect the year after a flood has hit. However, there is still a decrease in GA and Education. Agriculture still experiences an increase in spending the year after, while Infrastructure is not significant. Potential reasons for the other shifts can be that Health spending consists of an increase in short term spending, while the medium term health effects after a flood are not as pronounced. The same can be said for infrastructure, i.e., washed out roads and railroads are fixed as soon as possible and hence the sector is not as affected the next year. It should be noted that there is an overall effect on the budget the year after, though, although it is less than for the year the disaster strikes. For agriculture it might be harder to fully assess the damage and some of the repair costs will come in the form of help the year after. Any shortcomings seem to be taken from General Administration and Education. The changes for Law and Order are hard to explain, but that sector is very small in general.

The final four columns of Table 3.6 show the percentage changes for the four key sectors with the lagged variables. GA and Education decreases by 1.1 and 0.9 percent, while Health and Infrastructure increases by 0.4 and 1 percent. These changes are in line with the results without the lags, potentially showing that the effects of floods can affect next year's budget as well. For the year after the disaster, GA and Education still show significant decreases, with spending 0.9 and 1.2 percent lower. The total effect on GA and Education on the budget for the year after the disaster is negative 1.9 and 2 percent. If one assumes that the max flood strikes a district, the changes are in excess of minus 5 percent for GA and Education and plus 5 percent for Infrastructure. Overall, there is some evidence that districts tend to redistribute costs not just for the year of the disaster, but also for the year after.

For earthquakes, most of the sectors are significant the year after the disaster. As mentioned, earthquakes are more likely to be declared national disasters and/or recovery costs exceeding what local governments are capable of covering, which might limit the local costs during the year of the disaster, while one might see a stronger effect the year after, once the true reconstruction phase starts. For the year after the disaster, Education is strongly negatively affected. In terms of Health and GA there is a strong positive effect, and Health is 1 percent

significant. For two sectors that one might expect a large change in, Infrastructure is just 10 percent significant and Housing not significant at all. It is not clear why this would be the case, but potentially it is easier to get central government funding for infrastructure and housing reconstruction. One sees a strong significant increase in most other sectors, with Agriculture, Economy, Environment, Public Law and Order, Social Protection and Tourism all being positive and significant the year after. A potential reason for this can be transfer from Central Governments somehow being included in the local budgets.

In terms of actual change, the year after the earthquake one would see a decrease of 1 percentage points for Education and a 1.3 percentage point increase in GA, whereas the other sectors will see minor changes. However, assuming that the worst earthquake struck a district, the changes would be negative 18 percent for Education and positive 22.8 percent for GA. As for the floods, earthquakes show some evidence of redistribution happening in the year after the disasters.

The volcanic eruptions' coefficients are very similar as the model with no lags, with GA, Education, Health, Infrastructure and Environment being significant in the disaster year. For the year after the disaster, GA, Education and Environment stay significant, while Economy and Public Law and Order become significant. The largest effect is seen on Education, which changes 2.2 percent with the disaster year and 1.7 percent the year after, for a total effect of 3.9 percent. At the same time, GA decreases 1.2 percent in total.

Finally, there are no lag variables for the tsunami, as the original coefficients have already been lagged one year. However, the regular variables are included in the SUR with the other indices and their lagged variables. The results stay the same as for the model with no lags both in terms of significance and the coefficient sizes, with just minor changes.

Overall, our models seems to have performed well with fairly consistent results across both models. Generally speaking, these types of disasters do seem to lead to a reallocation of

resources, both for budgets in the disaster year as well as for the budget the year after a disaster.

Category Results

Table 3.7 shows the results for the four economic categories, with columns 2-5 presenting the results for the model without lag. Floods cause a 1 percent significant decrease in spending on Goods and Services, which is partly offset by a 10 percent significant gain in Other Expenditures. This seems plausible, Other Expenditures have been known to be used to fund natural disaster repairs and short term goods and services consists of many small and flexible line items where purchase can be postponed or canceled.

The percentage changes to the expenditures are shown in Table 3.8, with four panels where the top one shows the changes for a mean disaster and the bottom one shows for a maximum damage disaster. Furthermore, each panel is split into two with the model without lag being on the left side and the model with lag is on the right side. The changes are relatively speaking fairly small compared to what was found for the sectors. Goods and Services is down 0.9 percent, while Other Expenditures increase by 0.3 percent for a mean disaster. With the strongest possible flood, Goods see a decrease of 5.7 percent, while Other increases by 2.1 percent. This might be due to each of the categories including a wide variety of costs from different sectors, leading to a smoothing effect. Potentially it can also be that the more balanced number of observations lead to better estimates and that changes overall are less pronounced than what it could seem like for the sectors.

Earthquakes see no immediate expenditure effects across the categories, similar to the sectors. Volcanic eruptions experience strongly significant changes in Capital and Personnel Expenditures, with the former being negative and the latter being positive. The same coefficient change holds for the tsunami. The reason for this might be that investment into durable long term items is not a priority shortly after big disasters as the eruptions and tsunami were. Another possibility is that repairs and investment for the larger items are being covered by the central

government or other sources when the disasters are big and that the districts prefer to change costs to personnel that can be of immediate assistance. For Volcanic Eruptions the changes after a mean disaster is positive 2.7 percent into Personnel and negative 2.2 for Capital, while the tsunami saw a close to 12 percent increase for Personnel and a similar decrease for Capital.

The results for the lagged model are very similar for the disaster year, as seen in Table 3.7. The main difference is for the earthquake coefficients, that see 5 percent and 1 percent significance for Capital and Personnel expenses for the year following the disaster. The capital being positive and the personnel change being negative. This can possibly be due to the recovery phase having started and the local districts taking on more of the disaster costs, with preference being given to the repairs of long term assets over hiring people. However, for volcanic eruptions the picture is the opposite, with Capital being negatively affected and Personnel being positive. This can - as mentioned earlier - be due to our SO_2 model not being a good proxy for damage to durable assets.

The changes for the different disaster types are summarized in the rightmost columns of Table 3.8, with the main difference compared to the lag free budgets are that earthquakes now cause a 0.8 percent increase to Capital costs in the year after the disaster combined with a 1.1 percent decrease in Personnel Expenditures. Furthermore, Volcanic Eruptions lead to a total decrease of 4.3 percent to Capital Expenditures across the disaster year and the lag year, while at the same time Personnel increases by 4 percent. However, for the year after the disaster, the coefficients are only 10 percent significant.

The overall results for the four categories show - like the sector results - that some redistribution seem to occur in the districts following disasters. The level of change depends on the strength of the disaster, but there might be an issue arising from some disasters being large enough to cause the central government or other sources to come in and provide funding.

Table 3.7: Regression results for Unbalanced 2 year Category Data

	Without Lag				With Lag			
Category	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami
Capital Expenditure	0.191	0.416	-0.696***	-0.846***	0.241	0.910	-0.794***	-0.675***
	(0.172)	(1.086)	(0.266)	(0.157)	(0.194)	(0.974)	(0.253)	(0.172)
Goods and Services	-0.323***	-0.110	-0.186	-0.003	-0.345***	-0.006	-0.105	-0.027
	(0.097)	(0.682)	(0.184)	(0.326)	(0.102)	(0.733)	(0.182)	(0.310)
Other Expenditures	0.119*	-0.490	0.024	-0.010	0.125**	-0.426	0.000	0.001
	(0.068)	(0.880)	(0.196)	(0.101)	(0.062)	(0.837)	(0.187)	(0.077)
Personnel Expenditures	-0.144	-0.666	0.842***	0.856***	-0.183	-1.122	0.902***	0.721***
	(0.134)	(0.706)	(0.149)	(0.195)	(0.135)	(0.702)	(0.153)	(0.186)
Capital Expenditure Lag					0.375	3.262**	-0.539*	
					(0.284)	(1.430)	(0.284)	
Goods and Services Lag					-0.145	0.660	0.338	
					(0.142)	(0.924)	(0.209)	
Other Expenditures Lag					0.085	1.169	-0.148	
					(0.102)	(1.290)	(0.206)	
Personnel Expenditures Lag					-0.353*	-4.158***	0.332*	
					(0.201)	(1.257)	(0.172)	
Observations	7,540	7,540	7,540	7,540	7,540	7,540	7,540	7,540

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
[a] Coefficients and standard errors multiplied by 1,000.

Table 3.8: Percentage change of Total Budget by Category

	Without Lag				With Lag			
Category	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami
Mean disaster								
Capital Expenditures	0.53	0.11	-2.24***	-11.84***	0.67	0.23	-2.56***	-9.45***
Goods and Services	-0.90***	-0.03	-0.60	-0.04	-0.96***	0.00	-0.34	-0.38
Other Expenditures	0.33*	-0.12	0.08	-0.14	0.35**	-0.11	0.00	0.01
Personnel Expenditures	-0.40	-0.17	2.72***	11.98***	-0.51	-0.28	2.91***	10.09***
Capital Expenditures Lag					1.05	0.83**	-1.74*	
Goods and Services Lag					-0.41	0.17	1.09	
Other Expenditures Lag					0.24	0.30	-0.48	
Personnel Expenditures Lag					-0.99*	-1.06***	1.07*	
Max Disasters								
Capital Expenditures	3.34	1.87	-12.85***	-19.46***	4.22	4.10	-14.66***	-15.53***
Goods and Services	-5.66***	-0.50	-3.43	-0.07	-6.04***	-0.03	-1.94	-0.62
Other Expenditures	2.08*	-2.21	0.44	-0.23	2.19**	-1.92	0.00	0.02
Personnel Expenditures	-2.52	-3.00	15.55***	19.69***	-3.20	-5.06	16.66***	16.58***
Capital Expenditures Lag					6.57	14.69**	-9.95*	
Goods and Services Lag					-2.54	2.97	6.24	
Other Expenditures Lag					1.49	5.27	-2.73	
Personnel Expenditures Lag					-6.18*	-18.74***	6.13*	

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

3.5 Conclusion

Using damage indices from Skoufias *et al.* (2017a) for floods, earthquakes, volcanic eruptions and the 2004 tsunami, this paper combines these indices with district-level expenditure data to investigate how districts might redistribute their spending depending on the type of disaster that strikes. The analysis yields evidence that redistribution is taking place across economic sectors and by category, irrespective of the disaster type, with the direction and the size of the redistribution differing with the type and strength of disaster. For example, floods show a strong decrease in spending on General Administration both in the year of the disaster as well as in the spending of the following year. At the same time, there is a sizeable increase in spending on infrastructure and health for the same period.

These results demonstrate how remotely sensed and freely available data can be used to analyze local economic data. Unless one has access to more complete data and local level damage data that allow better calibration of the damage indices, the methodology presented here can be used to get an overview of damages shortly after the incidence of an actual disaster. Moreover, with data available on the budget of last year, one can quickly assess which budget categories at the district-level might need extra funding. Overall this is an area that has received little attention in literature, and future research can shed more light on how local level authorities deal with disasters by comparing the results of this study in Indonesia with other emerging countries or middle income countries.

Chapter 4

Urban Global Impact of Earthquakes from 2004 through 2013

Abstract

Using a comprehensive remotely sensed dataset of contour maps of global earthquakes from 2004 through 2013 and utilizing global nightlights as an economic proxy. The damage caused by the earthquakes is modeled through a combination of the contour maps, global housing data and local seismic codes to construct vulnerability curves for more than 150 countries. Overall, it is shown that earthquakes negatively impact local urban light emissions by 0.7 percent.

Keywords: Earthquakes, Remote Sensing

4.1 Introduction

Earthquakes are some of the most devastating natural disasters there are, both in terms of economic damages and human casualties. In the last decade alone, there have been two events causing more than 200,000 casualties, the 2004 Christmas earthquake and ensuing tsunami and the Haiti earthquake in 2010. These shocks caused losses of 90%-120% of nominal GDP (Daniell *et al.*, 2011). With losses of such magnitude, it is important to not only know the ex post damages, but also to identify risk zones where ex ante policies can mitigate some of the risks. Typical exposed areas are densely populated urban areas that are also economic hubs. In this chapter, we use highly localized remotely sensed data to develop a method that can globally assess impact of earthquakes at areas of 1 square kilometer.

With improvements in remotely sensed data - from satellite images, radars and base stations monitoring weather and earth movement - it has become easier to model and estimate impact of natural disasters both at a local and global level. Substantial research has been done using remotely sensed data on disasters such as hurricanes (Myint *et al.*, 2008; Klemas, 2009), floods (Haq *et al.*, 2012; Wu *et al.*, 2012, 2014; Chung *et al.*, 2015), landslides (Nichol *et al.*, 2006), earthquakes (Fu *et al.*, 2005; Yamazaki & Matsuoka, 2007), wildfires (Holden *et al.*, 2005; Roy *et al.*, 2006), volcanoes (Carn *et al.*, 2009; Ferguson *et al.*, 2010) and tsunamis (Römer *et al.*, 2012). There are some papers exploring global effects of earthquakes Cha (1998) and Jaiswal & Wald (2008, 2011, 2013), but most articles focus either on country level GDP changes (Chen *et al.*, 1997; Dunbar *et al.*, 2003) or singular events (Selcuk & Yeldan, 2001; Cavallo *et al.*, 2010; Parker *et al.*, 2012; Potter *et al.*, 2015). This chapter aims to contribute to the literature by using highly localized economic data combined with country level vulnerability curves to estimate the global losses due to earthquakes. To do so, we utilize remotely sensed and freely available nightlights data as an economic proxy and earthquake contour maps for intensity measurement to construct a global damage index.

To account for local economic activity, and due to limited access to highly disaggregated local economic data across the globe, nightlight intensity derived from satellite imagery has proved

to be a good economic proxy; see, for instance, Henderson *et al.* (2012), Hodler & Raschky (2014) and Michalopoulos & Papaioannou (2014). Another advantage of this method is that any inflationary or purchasing parity issues will not affect the estimates. The data consists of grid cells of approximately 1 square kilometer, showing the level of light emitted from each, and hence is a useful measure of activity and how high the level is locally following an earthquake. In this chapter, only urban nightlight cells have been used, as rural nightlight cells are more likely to capture non-human factors such as forest fires, volcanoes and gas flares. To distinguish rural from urban nightlight cells, we have utilized the urban extents map from Center for International Earth Science Information Network - CIESIN - Columbia University *et al.* (2011). The focus is put on urban areas, as these normally experience higher economic losses and because a larger share of the global population now live in cities than in rural areas.[1]

Recently, Blum & Krause (2016) has argued that due to the nightlight levels being saturated, i.e. cells with the highest level cannot continue growth, the nightlights do not capture economic activity in urban areas as well as they should. A problem which is particularly prevalent in developed countries and might explain why there is stronger correlation between nightlight levels and growth in developing than in developed countries (Nordhaus & Chen, 2015; Pinkovskiy & Sala-i Martin, 2016). To check if this has affected our results, we have performed robustness checks with a subsample containing non-saturated nightlights.

The measurement of earthquake detection and intensity has improved with remote sensing techniques. There are different methods to assess intensity and damage, ranging from satellite images (Dell'Acqua & Gamba, 2012; Tralli *et al.*, 2005; Gillespie *et al.*, 2007) to contour maps generated by seismological ground stations (De Groeve *et al.*, 2008; GeoHazards International and United Nations Centre for Regional Development, 2001; Federal Emergency Management Agency, 2006). In this chapter, the earthquake damage index is constructed from computer generated contour maps from the US Geological Survey (USGS) of earthquake intensity data, commonly used as a potential damage proxy (De Groeve *et al.*, 2008; GeoHazards International

[1]The World Bank has estimated that 54% of the global population lived in urban areas in 2016

and United Nations Centre for Regional Development, 2001; Federal Emergency Management Agency, 2006). Utilizing the contour maps as a base for the damage inflicted, we combine them with the nightlight and building type data from the USGS building inventory for earthquake assessment to create fragility curves by building type; see Jaiswal & Wald (2008) and GeoHazards International and United Nations Centre for Regional Development (2001). These curves are then used as damage proxies on the individual cells.

Another factor impacting the likelihood of changes in nightlights is the quality of local buildings. To control for this, we assign a building quality by country using a combined index from Daniell *et al.* (2014), which combines a country's seismic code and local conditions such as corruption and education level to model the local building quality.

Our main hypothesis, based on the damage earthquakes cause to local infrastructure, is that one would expect to observe a decrease in nightlights for the year of the disaster. Even though many countries provide excellent disaster relief and recovery and some areas see better than expected growth in the long term, we believe that in the short to medium time span a shock such as an earthquake leads to a drop in output.

The remainder of the chapter is structured as follows. Section 2 describes the data, section 3 presents our methodology and explains how the damage index is constructed and outlines our regression model. Section 4 presents the results and section 5 concludes.

4.2 Data

4.2.1 Nightlight Data

Earthquakes are an inherently local phenomenon in that they either only affect parts of areas and/or affect parts within areas differently. It is thus important to take the local population/asset exposure into account when constructing more aggregate proxies. As a matter of fact, arguably one would like to have measures of exposure as spatially disaggregated as pos-

sible. When looking at global data, there are several issues with local economic data. Firstly, many countries provide little to no local level information. Secondly, comparing data across countries is difficult due to differences in methods, currencies and reporting standards.

An alternative approach is to use nightlights as a proxy for local economic activity. Nightlights have found widespread use where no other measures are available; see, for instance, Henderson *et al.* (2012), Hodler & Raschky (2014) and Michalopoulos & Papaioannou (2014). For example, Henderson *et al.* (2012) study Indonesia by using nightlights to capture an economic downturn following the Asian financial crisis in the late 1990s. Their results show that swings in GDP change can generally be captured. Nevertheless, if possible, one has to account for factors such as cultural differences in light usage, latitude and gas flares. The latter is unlikely to be an issue, as most flares are off the coast or away from urban areas. Fortunately, most earthquakes, and also most of the human population, are at latitudes that are captured well by the satellites. As for the cultural differences, i.e. some countries have people who use more light at night than other countries regardless of similar GDP levels, by using fixed effects regressions, any such individual differences will be controlled for.

The nightlight imagery we employ is provided by the Defense Meteorological Satellite Program (DMSP) satellites. In terms of coverage, each DMSP satellite has a 101 minute near-polar orbit at an altitude of about 800km above the surface of the earth, providing global coverage twice per day, at the same local time each day, with a spatial resolution of about 1km near the equator. The resulting images provide the percentage of nightlight occurrences for each pixel per year normalized across satellites to a scale ranging from 0 (no light) to 63 (maximum light). Yearly values were then constructed as simple averages across daily values of grids, and are available from 1992.[2] We use the stable, cloud-free series; see Elvidge *et al.* (1997).

The dataset used in this chapter includes the years 2004 through 2013 and it only includes

[2]For the years when satellites were replaced with the average from both the new and old satellite. In this chapter we use the imagery from the most recent satellite but as part of our sensitivity analysis we also re-estimated our results using an average of the two satellites and the older satellite only. The results of these latter two options were almost quantitatively and qualitatively identical.

nightlight cells that are classified as urban. The rural cells are excluded because they are more likely to capture non-human activity such as forest fires. They are also more likely to capture activity that is not easily linked to general economic activity such as the above-mentioned gas flares. The top two rows of Table 4.1 show the descriptives for the cells affected by earthquake. Our full dataset consists of more than 60 million nightlight cell observations, and of these there are 72,883 that have been hit by earthquakes during our period. The mean value of 30.47 is close to the halfway point between min and max nightlight of 0 and 63. In the second row we remove cells with zero nightlight at the time of the earthquake, but that does not materially change our descriptives.

4.2.2 Earthquake Data

To model damage and measure earthquakes, we utilize ShakeMaps from USGS, which are automatically generated maps providing several key parameters following an earthquake, such as peak ground acceleration (PGA), peak ground velocity (PGV) and modified Mercalli intensity (MMI). More specifically, the ShakeMaps use data from seismic stations that is interpolated using an algorithm which is similar to kriging.[3] To model the intensity at a given coordinate, the model also takes into account ground conditions and the depth of the earthquake. Wald *et al.* (2005) point to the damage pattern not only being dependent upon magnitude and epicenter location, which have historically been used and that are common parameters for the entire earthquake, but also on other, more localized parameters that the ShakeMaps use to generate intensity measures.

This is exemplified by several earthquakes such as magnitude 6.7 and 6.9 earthquakes in California in 1994 and 1989, respectively, where some areas further away from the epicenters were more damaged than closer areas. The reason why the more localized ShakeMaps with their ground shaking parameters are a better gauge than magnitude and epicenter distance is explained on page 13 of Wald *et al.* (2005) which states that: "..., although an earthquake has one

[3]Worden & Wald (2016) compares the algorithm used to kriging with a trend without going into further details

magnitude and one epicenter, it produces a range of ground shaking levels at sites throughout the region depending on distance from the earthquake, the rock and soil conditions at sites, and variations in the propagation of seismic waves from the earthquake due to complexities in the structure of the Earth's crust." The ShakeMaps are interpolated grids with point coordinates spaced approximately 1.5 kilometers apart (0.0167 degrees).

The PGA is a measure of the maximum horizontal ground acceleration as a percentage of gravity, PGV is the maximum horizontal ground speed in centimeters per second and MMI is the perceived intensity of the earthquake, a subjective measure. Figure 2.8 once more explains the relationship between the different parameters and the potential damage from different values. The assumption is that damage starts at an MMI level of V and a PGA of 3.9 percent of g. These levels are found for California in Wald *et al.* (1999), but the relationship has been found for other areas in the US in Atkinson & Kaka (2006) and Atkinson & Kaka (2007) and for places such as Costa Rica (Linkimer, 2007) and Japan, Southern Europe and Western US (Murphy & O'Brien, 1977). It should be noted that the numerical relationship differs from region to region. The optimal scenario would be to have damage data for all countries and regions, but lacking that, we will use building quality data to control for damages depending on the region.

The different measures are largely interchangeable, and in GeoHazards International and United Nations Centre for Regional Development (2001) report, they use PGA to measure damage, pointing to the fact that PGA, unlike MMI is an objective measure, implying that MMI is not easy to obtain reliably across the globe. Also, for large scale modeling, where it is unfeasible that one will be able to model local conditions precisely, PGA serves as a good proxy for the intensity of the earthquakes.

4.2.3 Seismic Codes and Building Practices Data

The overall damages are not only linked to the intensity of the earthquakes, but also to the quality of buildings through construction methods, local seismic codes and societal conditions

such as corruption which affects the quality of the buildings (Ambraseys & Bilham, 2011; Bilham, 2013). Daniell *et al.* (2014) constructed a world-wide seismic code index and a building practice and socioeconomic factor index.

The latter index consists of a weighting of different government and socioeconomic factors, such as corruptions perception index, education level, rule of law, corruption control, regulatory quality and government efficiency. These indicators are then weighted and normalized to a scale between 0 and 100. Corruption has been shown to impact earthquake losses negatively (Ambraseys & Bilham, 2011; Bilham, 2013) and by including Transparency International's corruption perception index and the World Bank Governance Indicators for related governance issues such as rule of law, government efficiency, control of corruption and regulatory quality, the adverse effects of corruption is accounted for. The education level is used as a proxy for how well people understand building methods and the overall knowledge about construction. Overall, the indicators are included to check how well or poorly a country implements policies that reduce earthquake risk.

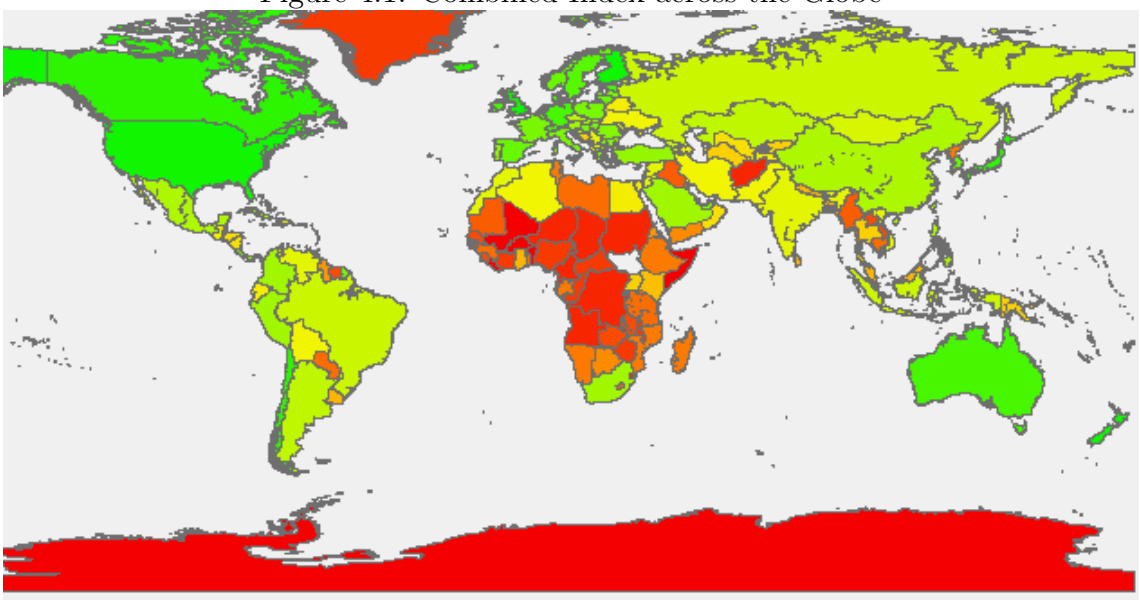
The seismic code index is focused on building design, materials and type of buildings as well as more exogenous factors such as if it is near a fault line and the type of soil. The main component in the index is the structural design method, based on the basic design principles as denoted by the building code in the country. The value of this code was subjectively based on how stringent the code was, based on the sources available, primarily the World List initiative by IAEE and the Practice of Earthquake Hazard Assessment (M. McGuire *et al.*, 1993). Other factors included in the index take into consideration the age and type of building stock. These factors are based on a multitude of sources ranging from national censuses to UN and NGO data. The reason why the composition matters is due to residential houses not being subject to seismic codes, and the age is included to establish how many buildings were built under different seismic codes. Finally, a wide variety of seismic actions are included and weighted. The factors include type of soil, proximity to fault line, interaction between soil and foundation and other indicators related to how the buildings are designed to cope with the effect of

earthquakes. This index is also weighted and normalized to a scale between 0 and 100.

In addition to the prior indices, Daniell *et al.* (2014) combine the two indices to get a combined building index for the countries. The construction of the index is made by multiplying the relative weight of the seismic code and building practice indices to obtain an overall value that accounts for both the theoretical building quality as well as practical measures of how well it is implemented. The correlation between the seismic code and the combined index is over 90% and it is almost 75% correlated with the building practice.

In this chapter, the focus will be on the combined code index, due to it being the best proxy for actual quality in the countries, as well as it being closely correlated to the other indices. The second panel of Table 4.1 shows the descriptives of the different indices, with the combined mean being much lower than the other two due to the way it is constructed.

Figure 4.1: Combined Index across the Globe



4.3 Methodology

4.3.1 Constructing Damage Index

To construct the damage index, two types of data will be used; the intensity data, expressed as PGA, and building inventory data, to assess what damage one could expect for different intensities. More specifically, when modeling earthquake damages, there will be primary damages due to the shaking and secondary damages such as fires and landslides due to the damage caused by the shaking. Bird & Bommer (2004) showed that 88% of the damage was caused by the shaking. With such a high number, and the difficulty of modeling the secondary impact, we will only focus on the intensity. Assimaki *et al.* (2005) and Wald *et al.* (2005) point to local factors such as soil and slopes also being important determinants for damage. These are already controlled for in the ShakeMaps and no further assessment will be taken. The next step in damage modeling is to match the intensity with the building stock or exposed economic assets. Yong *et al.* (2001) and Jaiswal & Wald (2008) use damage factors, which are defined as loss over replacement value, to assess damage. The loss is derived based on building types and inventory. The factor is then extrapolated to create a vulnerability curve. In this chapter we will use a similar methodology where we construct vulnerability curves from damage ratio based on building stock.

Given that the intensity data was extensively covered in the previous section, we will start with the building type data here. To account for the building types we use information from the USGS building inventory for earthquake assessment, which provides estimates of the fractions of building types observed by country; see Jaiswal & Wald (2008). The data provides the share of 99 different building types within a country, separated for urban and rural areas. The building type information was compiled from a World Housing Encyclopedia survey, while the split between urban and rural is from the urban extent map of Center for International Earth Science Information Network - CIESIN - Columbia University *et al.* (2011). Without any other information available, we use this as an indication of the distribution of building types, but, necessarily, assume that the distribution is homogenous within urban and rural areas.

The urban map from Center for International Earth Science Information Network - CIESIN - Columbia University *et al.* (2011) is shown in Figure 4.2. The map itself was constructed through a process outlined in Balk *et al.* (2006). In short, the underlying map is the gridded population population of the world, which is based on non-spatial population estimates[4] and spatially explicit administrative boundary data. The urban map uses the underlying data and adds collected population estimates, point location and the approximate footprint for urban centers. An urban center is a place with more than 1,000 inhabitants. The population estimates are published city inhabitant numbers, which is then matched with the urban footprint. To determine the urban area, the authors used the same nightlight data as we have utilized in this chapter. For areas which this was not possible, other sources were used to find the extent.

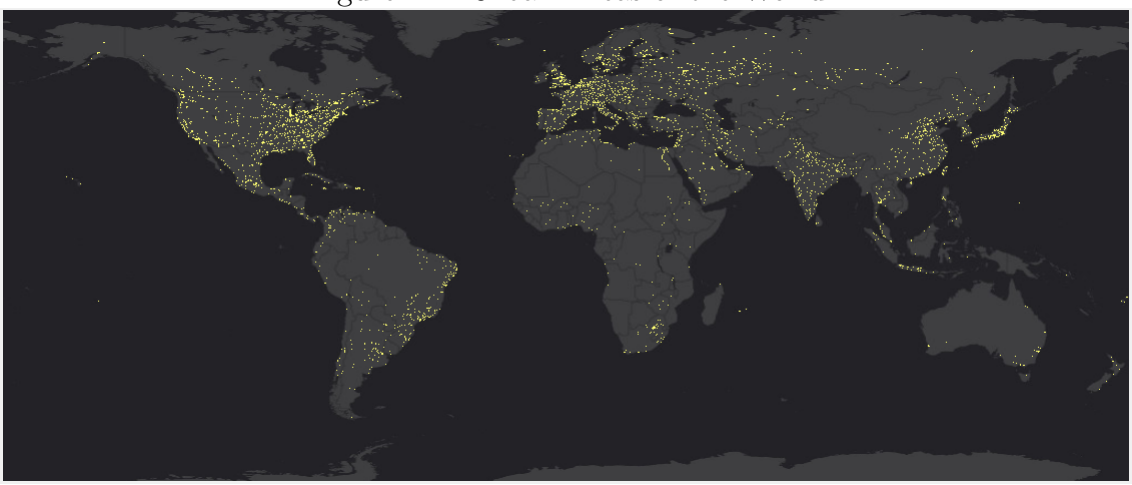
A potential problem with the urban map is that it is based on nightlights data from 1995, as this year's nightlight data has been cleaned for oil and gas flares and any non-human light source. Over the period from 1995 to 2016, the share of the world's population living in urban areas has gone from 45% to 54% according to World Bank data. This is an issue that is difficult to correct for, as the growth differs from country to country and even within countries one does not have uniform growth across cities. For example, Detroit had 1 million inhabitants in the 1990 census and only 700,000 in the 2010 one. During the same period, Houston went from 1.6 million people to 2 million people and the whole of United States' population changed from 249 million to 309 million, with the urban share changing from 75% to 80%. Due to these asymmetric changes and the lack of more recent data, we have decided to not try to control for it, and use the urban map as our base.

Following the building type distribution and urban split, vulnerability curves by country are derived from curves constructed by Global Earthquake Safety Initiative (GESI) project; see GeoHazards International and United Nations Centre for Regional Development (2001). More specifically, GESI divide buildings into 9 different types[5], with each building then rated accord-

[4]Population counts by administrative area names

[5]Wood, steel, reinforced concrete, reinforced concrete or steel with unreinforced masonry infill walls, rein-

Figure 4.2: Urban Areas of the World



ing to the quality of the design, the quality of construction, and the quality of materials. Total quality is measured on a scale of zero to seven, depending on the total accumulated points from all three categories. According to the type of building and the total points acquired through the quality classification, each building is then assigned one of eight vulnerability curves which provides estimates of the percentage of building damage for a set of 28 peak ground acceleration intervals.

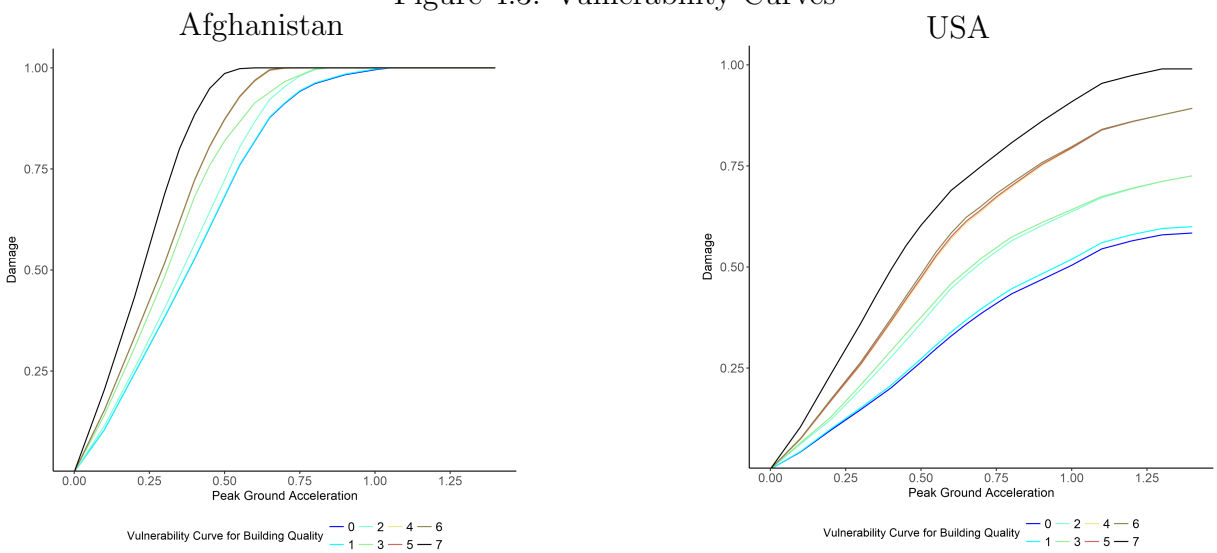
In order to use these vulnerability curves, we first allocated each of the 99 building types given in the USGS building inventory to one of the 9 aggregate categories of the GESI building classification. However, in order to assign a building type its quality specific vulnerability curve we need to determine its quality in terms of design, construction, and materials, an aspect for which we have no further information. We instead assume that building quality is homogenous across building types and experiment with seven different sets of vulnerability curves, each set under a different quality ratings scenarios (ranging from 0 to 7).

Figure 4.3 depict the building share weighted vulnerability curves of urban areas for Afghanistan and USA. Due to the difference in building quality and materials used, one can see how it takes an earthquake with PGA in excess of 1.3 before damage levels reach 100% in the US, and only for the worst quality assumption of 7, whereas in Afghanistan a PGA over 1 destroys everything

forced masonry, unreinforced masonry, adobe and adobe brick, stone rubble, and lightweight shack or lightweight traditional.

across all building quality assumptions.

Figure 4.3: Vulnerability Curves



To model estimated damage due to a particular earthquake event the data from the ShakeMaps is matched with the vulnerability curves derived from GESI. To do this, one connects each ShakeMap earthquake point with its nearest nightlight. If the cell is further away than 1.5 kilometers or if it experiences shaking (PGA) of less than 0.05 the value is set to 0. The earthquake damage index for cell i in country j at time t assuming building quality q, $ED_{i,j,q,t}$, is defined as:

$$ED_{i,j,q,t} \equiv DR_{i,j,k,t,pga_{k,q}} \qquad i = 1, \ldots, I, \qquad j = 1, \ldots, J, \qquad q = 0, \ldots, 7 \tag{4.1}$$

where DR is the damage ratio according to the peak ground acceleration, pga, and the urban-rural qualification[6], k, of cell i, defined for a set of 8 different building quality q categories.

The second last panel of Table 4.1 depict the descriptives assuming building quality 0, 4 and 7. All qualities have cells that have been hit by earthquakes strong enough to damage 100 percent of the buildings in it. Based on the building quality assumptions, we find that the mean damage in a cell differs from 4 percent in the best category, quality of 0, to 12 percent mean damage in the worst category, quality 7. The fairly significant difference in mean (and also standard

[6]In our case, the cell is always classified as urban

deviation) implies that the regression analysis done on the data will need to include robustness checks to exclude any issues related to our quality assumptions.

Finally, to account for building quality differences between countries, each country is assigned a quality based on their combined index rating. The allocation is done through constructing 8 clusters, due to there being 8 qualities, based on the combined index value of the full nightlights sample of more than 60 million cells. The clustering method is k-means, leading to each nightlight cell belonging to the cluster with the nearest mean.

Figure 4.4 depicts the fragility curves assigned to countries that have been hit by earthquakes based on the clustering method. Furthermore, the left side graph shows the assignment for clustered countries based solely on the seismic code index, whereas the right side graph is the clustering based on the combined index. Interestingly, some countries that have a strong seismic code, perform worse due to societal factors, namely Chile and Italy, while New Zealand is strengthened due to their low level of corruption and strong rule of law.

The last panel in Table 4.1 shows the impact on the data caused by the combined index clustering. The mean quality assumed is 2, which is plausible given that many of the lit urban areas of the world are in wealthy countries. In our dataset, USA has the highest number of urban nightlight cells. The classification also leads to the overall damage being between quality level 0 and 4, at 6% on average across our 72,883 affected cells.

4.3.2 Regression Model

To check for a relationship between nightlight levels and the strength of earthquakes we use a fixed effect model, correcting for time and spatial effects, given by:

$$L_{i,t} = \beta_0 + \beta_1 ED_{i,j,q,t} + \beta_2 ED_{i,j,q,t-1} + \lambda_t + \theta_i + e_{i,t}, \qquad i = 1, \ldots, I \tag{4.2}$$

where $L_{i,t}$ is the light level in cell i at year t and $ED_{i,j,q,t}$ represents the vulnerability curve value

Figure 4.4: Vulnerability Curves for Affected Countries

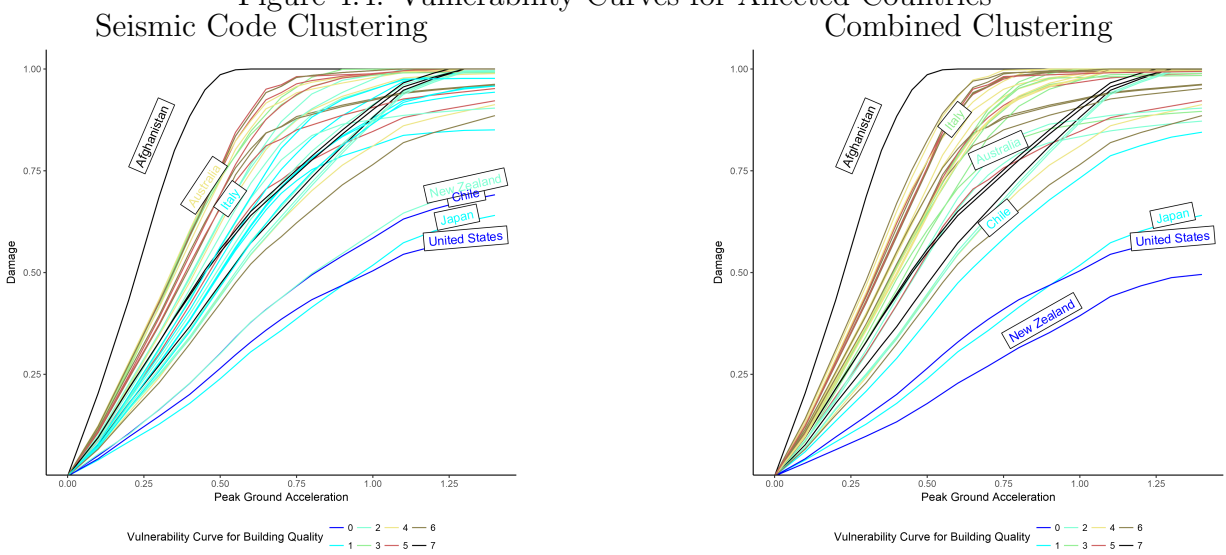


Table 4.1: Descriptives of Data

Statistic	N	Mean	St. Dev.	Min	Max
Nightlights	72,883	30.47	20.26	0.00	63.00
Nightlights - Positive Values Only	71,253	31.17	19.95	3.00	63.00
Building Practices	72,883	77.03	17.01	23.90	97.40
Seismic Code	72,883	89.61	9.52	7.00	98.10
Building and Seismic Code Combined	72,883	70.15	19.31	1.90	87.90
Vulnerability Curve Quality 0	72,883	0.04	0.05	0.01	1.00
Vulnerability Curve Quality 4	72,883	0.08	0.09	0.03	1.00
Vulnerability Curve Quality 7	72,883	0.12	0.12	0.04	1.00
Clustered Quality	72,883	2.00	1.84	0	7
Damage from Earthquakes	72,883	0.06	0.07	0.02	1.00

assuming quality q in the same cell and at the same time. To allow for lags, β_2 is the coefficient for the damage from year $t-1$, which is the vulnerability curve value from the year prior to year t. β_0 is the intercept, λ_i is a matrix of year dummies and θ_i are the cell fixed effects and $e_{i,t}$ is the error term. To correct for potential heteroskedasticity we use Driscoll-Kraay covariances from Driscoll & Kraay (1998).

4.4 Results & Discussion

Employing our model on the data for different building qualities yields the results seen in Table 4.2. The table shows the results when assuming all buildings, globally, are of quality 0, 4 and 7 with and without lags in the upper panel, revealing that nightlight cells that have been struck by earthquakes have a statistically significant lower value than cells that have not been affected. The overall impact depends - as expected - on the building quality assumption. Regressions (4)-(6) show the results with lag, and there is no evidence suggesting that the nightlight values are further affected the year after an earthquake hits.

The lower panel with regressions (7)-(12) shows the regression results with and without lag depending on how building qualities are assigned. The first assignment method is clustering in (7) and (10). Regressions (8) and (11) are the results when building quality is based on 8 ranges equally split across the full range of the index from 0 to 100, while regressions (9) and (12) are based on a rank from highest to lowest split across the 8 qualities. The results stay significant and negative across all regressions.

In terms of the overall effect, if one assumes that a mean nightlight cell containing is hit (value of 30.47 from Table 4.1) by a mean earthquake based on the clustering that damages 6 percent of the buildings, the light emission drops by 0.22 to 30.25, this is about 0.7% of the total light emitted. Assuming all buildings are quality 0, meaning that countries globally were of the best standard, yields the same result of 0.7%.[7] If one instead assumes that all buildings are of quality 7, which is the worst case, the nightlight levels drop by 1.2%. To illustrate with an example how quality improvements would lessen the impact, one can use a city such as Jakarta, with an approximate GDP of USD145 billion, if hit by a mean earthquake, the damages would be approximately USD600 million less if the buildings were 0 instead of 7.[8] Furthermore, if Jakarta was hit by an earthquake 2 standard deviations higher than the mean, roughly 23% would be damaged and the GDP would decrease by 2.8% or USD4.1 billion

[7]The difference is less that a tenth of a percent. This is due to a majority of the earthquakes affecting high quality countries

[8]Jakarta is currently quality 5

Table 4.2: Regression Results

	Without Lag			With Lag		
Qualities						
Variable	Quality 0	Quality 4	Quality 7	Quality 0	Quality 4	Quality 7
	(1)	(2)	(3)	(4)	(5)	(6)
Vuln Curve	-5.53***	-3.76***	-2.93***	-4.59**	-3.26***	-2.59***
	(1.63)	(0.95)	(0.71)	(1.50)	(0.84)	(0.63)
1 year lag				0.94	-0.11	-0.20
				(1.89)	(1.10)	(0.81)
Observations	60,730,730	60,730,730	60,730,730	54,657,657	54,657,657	54,657,657
Quality Split						
Variable	Clustering	Range	Rank	Clustering	Range	Rank
	(7)	(8)	(9)	(10)	(11)	(12)
Vuln Curve	-3.72**	-3.79***	-3.32**	-3.00**	-3.07**	-2.60**
	(1.16)	(1.12)	(1.14)	(1.06)	(1.00)	(1.09)
1 year lag				1.11	1.02	1.22
				(1.39)	(1.82)	(1.32)
Observations	60,730,730	60,730,730	60,730,730	54,657,657	54,657,657	54,657,657

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.

Recently, in academic discussions (Blum & Krause, 2016) it has been noted that the nightlight distribution is skewed towards the top end, questioning how accurately the nightlight cells capture very large and densely populated areas. This can potentially lead to an underestimation of the difference between urban and rural areas as well as between cities themselves. Furthermore, the problem is more pronounced in developed than in developing countries, due to nightlights being more saturated there. Literature has shown that nightlights are more strongly correlated with economic activity in developing than developed countries (Nordhaus & Chen, 2015; Pinkovskiy & Sala-i Martin, 2016). A simple way to check if this might have affected our results have been to exclude any cells with a max intensity higher than 55. As seen from the regressions in Table 4.3, this does not seem to affect our results much. There are only minor changes to our coefficients and no change in significance.

Overall, there is strong evidence in support of earthquakes leading to lower light levels. For a city such as Tokyo, with a GDP of more than USD1.5 trillion, a decrease of 0.7% would lead to a drop of USD10.5 billion, or if hit by an earthquake two standard deviations stronger than the mean, leading to a drop in GDP of USD42 billion.

Table 4.3: Robustness Check - Nightlight Level Below 55

	Without Lag			With Lag		
Qualities						
Variable	Quality 0	Quality 4	Quality 7	Quality 0	Quality 4	Quality 7
	(1)	(2)	(3)	(4)	(5)	(6)
Vuln Curve	-4.99***	-3.53***	-2.73***	-4.19**	-3.12***	-2.44***
	(1.48)	(0.84)	(0.61)	(1.53)	(0.85)	(0.62)
1 year lag				0.98	0.03	-0.11
				(1.61)	(0.95)	(0.71)
Observations	47,339,790	47,339,790	47,339,790	42,605,811	42,605,811	42,605,811
Quality Split						
Variable	Clustering	Range	Rank	Clustering	Range	Rank
	(7)	(8)	(9)	(10)	(11)	(12)
Vuln Curve	-3.25**	-3.35***	-2.84**	-2.61**	-2.71**	-2.17
	(1.04)	(0.98)	(1.07)	(1.05)	(0.98)	(1.09)
1 year lag				1.08	1.02	1.24
				(1.29)	(1.28)	(1.23)
Observations	47,339,790	47,339,790	47,339,790	42,605,811	42,605,811	42,605,811

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.

4.5 Conclusion

Using a comprehensive dataset of earthquakes and nightlights for the period 2004 through 2013, this chapter has shown that earthquakes lower nightlight emissions by 0.7 percent, implying

the significant impact earthquakes can have on local economies. Our hypothesis of a negative impact on nightlights from earthquakes is well supported also when accounting for a potential top ended distribution.

Further expansions of this chapter can take on different focus points. One way of improving the global measurements is through an expansion of the time period looked at, with a focus only on major earthquakes. Another avenue of exploration is to validate the damage estimates through locally obtained damage data. Instead of focusing on global impacts, one can study local effects in countries or at a parish/state-level. It would be easier to obtain local damage and building quality data if the study area is narrowed to specific countries.

Chapter 5

A Whirlwind Romance: The Effect of Hurricanes on Fertility in Early 20th Century Jamaica

Abstract

In this chapter we investigate the impact of hurricanes in the Caribbean on fertility rates in Jamaica for the period 1901 to 1929. More specifically, we create a hurricane destruction index derived from a wind speed model that we combine with data on more than 1 million births across different parishes in Jamaica. Analyzing the birth rate following damaging hurricanes, we find that there is a strong and significant negative effect of hurricane destruction on the number of births. Overall, we find that hurricanes resulted in 10,201 fewer births, or roughly 1 percent of the total. We further show that damaging hurricanes reduce births for up to, and including, 17 months after the event but find no evidence of a temporal displacement of births. In addition, we find no support for the Trivers-Willard hypothesis that one sex becomes more prevalent than another. However, there is evidence that the fall in births is due predominantly to single mothers having fewer children relative to married couples.

Keywords: Birth-rate, sex-ratio, Jamaica, Hurricanes

5.1 Introduction

Reproductive health and fertility decisions following natural disasters are widely believed to affect both short and long-term population growth and family size. However, the nature of the relationship between births and disasters is not yet fully understood. In an extensive review of the reproductive health literature Zotti *et al.* (2012) show that the effect of natural disasters on birth outcomes has not been consistently demonstrated while the economics literature has tended to focus on estimating the number of dead and wounded and quantifying the economic damages (see for example, Kahn (2005); Noy (2009); Strobl (2012)).

Studies that examine the indirect effect of disasters on the birth rates are limited and those that have been published tend to provide mixed results. For example, using only simple exposure incidence for the case of hurricanes Cohan & Cole (2002) find an increase in births after hurricane Hugo, while Hamilton *et al.* (2009) discover a decrease in births after hurricane Katrina. Pörtner (2008) also shows a negative effect on births for a long term study of Guatamala. More recently, Grabich *et al.* (2015) find no significant effects following hurricanes Charley and Ivan in Florida in 2004. Importantly, however, is that one of the difficulties with capturing outcome measures at the aggregate level is exposure misclassification and the proper control of confounders (Grabich *et al.*, 2015).[1]

The purpose of this chapter is to examine the impact of hurricane strikes on birth outcomes using historical data for the turn of the 20th century. More specifically, we consider the impact of hurricanes on births on the Caribbean island of Jamaica between 1901 and 1929. Crucially, for our analysis, and in contrast to studies of more recent hurricanes, during this period hurricanes would strike with little or no warning. Our empirical strategy is first, to construct a measure

[1]Other shocks such as terrorist attacks (Rodgers *et al.*, 2005) and blackouts (Udry, 1970; Burlando, 2014) have been shown to increase births while for earthquakes, Lin (2010) find a decrease in fertility, whereas Tan *et al.* (2009) find an insignificant decrease in births but a significant increase in birth defects. Other studies in the epidemiology literature look at the health outcomes of pregnant women (Harville *et al.* (2010) and Xu Xiong *et al.* (2010)). Finally, Caruso (2017) examines the intergenerational transmission of exposure in childhood to natural disasters in Latin America in the last 100 years. His main finding is that young children and children in utero experience worse long-term education and employment outcomes with the future fertility of an individual only negatively affected by a disaster in the case of a flood.

of exposure to hurricanes in Jamaica using a wind field model (Boose *et al.* (2004)) which we combine with a comprehensive database of parish-level births and population. In addition, we control for other weather variables at the time of the hurricane and the time of birth. Second, we estimate the short and long term fertility effects of hurricane exposure at the local parish level over a 28 year period using parish fixed effects regressions.

The contribution of this chapter is to use our wind field model and births data to test four related hypotheses. These are: (1) do hurricanes cause a temporal displacement of births such that conception is brought forward or delayed to avoid a predicted hurricane of hurricane season; (2) is there a permanent reduction in births as a result of a hurricane (as a result of reconstruction efforts, lack of basic goods and sometimes death); (3) does hurricane exposure alter the gender bias of new births to the extent that more girls are born following a hurricane (a test of the Trivers-Willard hypothesis); (4) is the impact of hurricanes on the short and long term fertility rates influenced by the marital status of mothers.

We now discuss these hypotheses in more detail. Temporal displacement (hypothesis 1) occurs when people who would have had a child at a given time bring forward or delay the date of conception due to an upcoming hurricane or hurricane season. Such a conception decision will not have a long term fertility effect since there will still be the same number of children born. If a temporal displacement effect exists then one would expect to see a positive birth rate effect in the months before and after a hurricane. However, the existing literature has suggested that the fertility effect of hurricanes can be positive or negative. Cohan & Cole (2002) looked at county level data for South Carolina after hurricane Hugo hit in 1990 and found a significant increase in births (and marriages and divorces as part of a study on life transitions) in the affected counties in the year following a hurricane. Hamilton *et al.* (2009) found a 19 percent decrease in births following hurricane Katrina although they were unable to take into account migration into or out of the affected areas in Louisiana, Alabama and Mississippi. In a more recent paper using a difference-in-differences approach Grabich *et al.* (2015) finds no significant impact on births in Florida following hurricanes Charley and Ivan in 2004 and argue that pre-

vious significant findings may be due to biases inherent in county-level regressions.

Other studies that find a positive increase in births include Nobles *et al.* (2015) who find a strong positive link between mortality and fertility after the 2004 Indian Ocean tsunami and for earthquakes by Finlay (2009). Pörtner (2008) also uses hurricane and household data from Guatemala over the period 1880 to 1997 to assess how hurricane risk affects the fertility and education of households and distinguishes between households that own and do not own land and finds that fertility increases with hurricane risk for landowners, but decreases for households that do not own land.

A different approach is taken by Evans *et al.* (2010) who investigate the effect of hurricane advisory announcements on fertility. They define the shock not as the hurricane striking, but as the warning of a storm or hurricane approaching, that may or may not eventually strike at a level that is higher or lower than the warning level given in the initial advisories. Using county level data on hurricane advisories and births for the period 1995 to 2001 they show that fertility decreases monotonically from positive to negative as the severity of the warning increases, with the largest negative effect for hurricane warnings. Of relevance for our study, they only find limited evidence for either a temporal displacement effect or a permanent reduction in births following a hurricane.

Hypothesis 2 asks whether disasters lead to a permanent fertility effect, i.e., a shock causes a long-term change in the total number of children born. For example, in the previous literature Lindstrom & Berhanu (1999) present strong evidence that shocks like war and famine have a negative long term fertility effect, while Rodgers *et al.* (2005) and Pörtner (2008) find positive effects. In the latter case the authors did not look specifically at events, but rather sought to discover where there is a 'harvesting effect' of natural disasters whereby people in storm hit areas have more children as insurance against future storms. Finally, Agadjanian & Prata (2002) observe negative short-term effects, which change to a positive effect in the longer term although their results vary depending on exposure to war, with more heavily affected areas

having a greater negative effect.

Our third testable hypothesis relates to the impact of natural disasters on the male-to-female (M/F) sex ratio. Known as the Trivers-Willard hypothesis the argument is that the M/F birth ratio falls (there are more female births) when mothers are stressed or have fewer resources available. Several papers have found evidence in favor of the this hypothesis. For example, Catalano (2005) shows that the sex ratio fell during periods of high unemployment in California. The same result was found for natural disasters such as floods (Lyster, 1974) and earthquakes (Fukuda *et al.*, 1998; D'Alfonso *et al.*, 2012). Other shocks such as the 9/11 attacks (Bruckner *et al.*, 2010) and generally stressful situations such as the troubled years in Northern Ireland, the Rodney King Riot, the Breivik terrorist attack and the Sandy Hook shooting (Grech, 2015) exhibit the same effect. An additional factor shown to influence the sex ratio is rainfall. In this regard, Grech & Scherb (2015) found that the M/F birth ratio following hurricane Katrina increased for states with excessive amounts of rainfall. At the same time, being exposed to hurricane Katrina alone did not affect one gender more than the other. An increased sex ratio following rainfall is also found by Lyster & Bishop (1965). Finally, it has been shown that fertility rates are sensitive to economic circumstances with unemployment rates and difficult economic conditions associated with lower fertility rates (Kelly and Cutright 1984 and Rindfuss et al. 1988).

Finally, hypothesis 4 is derived from the small number of studies that have proposed that the marital status of women affects post-disaster fertility. For example, Hamilton *et al.* (2009) finds a decrease in unmarried women giving birth relative to married women following hurricane Katrina. Also following hurricane Katrina, Zahran *et al.* (2011) finds that single mothers have poorer mental health than others and do not deal as well with life events as mothers with partners. Although it does not say anything specific about birth rates, it may imply that following a hurricane, single women are less likely to have children, in particular single women that already have one or more children.

For each of our four testable hypotheses early 20th century Jamaica arguably presents an ideal period in which to study effects of hurricanes on fertility. Jamaica is located in the Atlantic hurricane belt and experiences on average 10 tropical storms in each hurricane season which usually lasts from June until November. According to the National Library of Jamaica (2016) there were 16 hurricanes (7 of them considered major hurricanes) that struck Jamaica between 1901 and 1929 with estimated deaths of at least 250 people and many more being left homeless. For our period, the total number of births was around 1 million. Of the 16 hurricanes that damaged Jamaica, each affected on average 10 out of the 14 parishes. To replace those killed by hurricanes the total number of births would only have to increase by 0.025 percent. It is questionable if the death rate following the Jamaican hurricanes was high enough to cause a change in birth rates. However, if hurricanes have a longer term impact on reproductive health or fertility decisions then the actual change in the population either up or down may be substantially larger and one could potentially get similar effects to those found by Nobles *et al.* (2015).

Our period of study is convenient for two reasons. First, the damaging hurricanes that Jamaica experienced during this time are well distributed over time, with the two very strong hurricanes being fairly isolated, four similarly damaging ones being close together and finally a decade at the end of the period of almost no strong hurricanes.[2] Second, due to limited warning systems at the time there was effectively no anticipation prior to a hurricane strike, meaning that the impact would not have been affected by people evacuating an area or preparing more than they would normally during hurricane season. For example, the first hurricane report radioed from a ship in the Atlantic basin did not occur until 1909 (Landsea *et al.*, 2008).

To illustrate the type of damage that hurricanes caused during this period we briefly describe the impact of the November 1912 and August 1916 hurricanes. The Jamaica weather re-

[2]The main hurricanes during our period occurred on August 11th 1903 (65 deaths reported), June 13th 1904, November 10-18th 1912 (100 deaths reported), August 12-13th 1915 (11 deaths reported), September 24-25th 1915 (some loss of life due to flooding), August 15th-16th 1916 (17 deaths reported), September 23rd 1917 (57 deaths reported). See http://www.nlj.gov.jm/history-notes/HistoryofHurricanesandFloodsinJamaica.pdf for details.

port(number 411 pages 1-3) describes a cyclone with heavy rains that struck the north-eastern part of the island (St. Thomas, Portland, St. Andrew, and St. Mary) on the 10th, 11th and 12th and a second cyclone in the south-west of Kingston. By the 18th both cyclones produced a hurricane that struck Montego Bay and Kempshot in St. James. A total of 100 people died and severe damaged was caused by a tidal wave in Savanna-la-Mar. The 1916 hurricane in contrast struck the South coast which killed 17 and destroyed the entire banana crop all over the island.

To summarize our results, we demonstrate that hurricane strikes during the early 20th century in Jamaica resulted in an estimated 10,201 births not taking place, which is equivalent to approximately 1% ot total births. Although we present no evidence that hurricanes affected the sex ratio, we did find that marital status matters such that a significant percentage of the non-births were a result of single mothers not having a child in the 18 months after the hurricane events. Likewise, although there is no evidence that conception decisions were brought forward to avoid a hurricane season, the decision to conceive was delayed by up to 9 months such that birth rates only returned to normal rates 18 months after a hurricane.

The remainder of the chapter is organised as follows. Section 2 describes the data and provides some summary statistics. Section 3 describes our empirical strategy and Section 4 presents the results from tests of our four main hypotheses. Section 5 concludes.

5.2 Data and Summary Statistics

5.2.1 Geographical Unit of Analysis

Jamaica consists of 14 parishes (administrative divisions). For our analysis we treat Kingston and Saint Andrew as one parish, since the Kingston parish is relatively small in terms of area and the city itself extends into Saint Andrew. Hence, the regression analysis is based on 13 parishes. Jamaica's 10,991 km^2 is broken down into 13 geographical units which range in size

from 478 km^2 (Saint Andrew plus Kingston) to 1,213 km^2 (Saint Ann).

5.2.2 Population and Births Data

It became compulsory to register births in Jamaica on the 1st April 1878 following the implementation of Law 19 in 1877, 'A Law for the Registration of Births and Deaths in Jamaica', which was replaced by in March 1881 by Law 13 'the Registration (Births and Deaths) Act' (Registration Act, 1881). The 1881 law states that: '...every child born alive after the coming into operation of this Act, it shall be the duty of the father and mother of the child, ..., to give to the Registrar, within forty-two days next after such birth, information of the particulars required to be registered concerning such birth, ...'. In other words, from March 1881 onwards it became compulsory to register births within 42 days.

The Registration Act (1881) also states that "..., the word 'father' means a person who is married to the mother of the child at the time of conception or at any time thereafter and prior to the childs birth." Other paragraphs specify that a father can be registered if both the mother and the father acknowledge the paternity or in other circumstances such as the supposed father not denying paternity following a notice from the mother or a supreme court ruling. The assumption is that both parents are present during birth and contribute to the initial upbringing of the newborn when both register and that they, in most cases, had a stronger relationship post-conception than when only the mother is registered.

The complete birth records have been digitized and compiled in Civil Registration (1880) and provides us with a complete record of births in Jamaica in the early 20th century.[3] For the years 1901 through 1929, the records consist of approximately 1 million births. Each individual entry consists of a name (when known), birth date, parish of birth, gender, father's name (when known) and mother's name (when known).

To construct population level data we use the Blue Books of Statistics for Jamaica for the pe-

[3]The birth data covers the period for 1881-1929, but due to the availability of data for our weather variables we need to restrict our analysis to 1901 onwards.

riod 1891 through 1931 (Colonial Office, 1891-1931).[4] These provide census data for the years 1891, 1911, 1921 and 1931. At irregular intervals birth and death data is provided alongside limited migration data. By combining our birth data with official birth and death data we are able to calculate the net increase or decrease in the population for each year. In addition, we use information from Eisner (1974) and Graham (2013), which focus on Jamaican migration to Cuba for the years 1912 through 1940, to get a sense of the extent of the migration from Jamaica. Eisner (1974) points to Jamaican migration data being "worthless" throughout this period, with migration numbers being consistently understated and not even registered for some years. We have therefore opted to use Cuban migrant numbers to get a rough estimate of when the flows were large and when they were smaller, given that the Cuban numbers are considered to be more complete and that Cuba was the main destination for Jamaican migrants during this period.

Hence, the largest outflows from Jamaica occurred in the years leading up to the sugar crash in 1920, with very limited migration thereafter. When combined with a lower death rate the result was a significant increase in Jamaica's population during the 1920s. In our analysis we assume that any migration is relative to parish population levels and for the period 1911 to 1921 we use Cuban migration data as a proxy for overall migration flows, so that approximately 1/3 of the migration is assumed to happen for the years 1911-1915 and the remaining 2/3 for the years 1916-1920.[5] Once we corrected for net migration, we linearly extrapolated the data from one year to the next to obtain a time series of monthly population estimates. More precisely, we use the birth and population data to calculate the log birth rate, where the birth rate in parish i for month m, $b_{i,m}$, is given by:

$$b_{i,m} \equiv \frac{B_{i,m}}{pop_{i,m}} \tag{5.1}$$

[4]The most recent census prior to the beginning of our sample period was 1891.

[5]During the years 1914-1918 World War I was ongoing. According to an article in Jamaica Gleaner (Retrieved at http://old.jamaica-gleaner.com/pages/history/story0014.html) there were 10,000 men serving the British Empire during that period and it is unclear how these are accounted for in the migration numbers. Regardless, given that net outflow during the decade was more than 90,000, the accounting of the army men would not significantly shift the numbers.

where $B_{i,m}$ is the total number of births in parish i in month m and $pop_{i,m}$ is the total female population for the same month and parish.[6]

5.2.3 Hurricane Destruction Index

Following the work by Landsea *et al.* (2004) who re-analyze the Atlantic basin hurricane tracks, we are able to model local winds and construct a hurricane destruction index. The index is the same as that used in Emanuel (2011) and assumes a fraction of property is lost or damaged when wind speeds surpass a threshold in a cubic manner.[7] Formally our destruction index is given by:

$$f = \frac{v_n^3}{1 + v_n^3} \tag{5.2}$$

where f is the fraction of property lost or damaged and v_n is:

$$v_n \equiv \frac{\max[V - V_{thresh}, 0]}{V_{half} - V_{thresh}}$$

where V is the wind speed, V_{thresh} is the wind speed at and below which no damage occurs (set at 92.6km/h) and V_{half} is the wind speed at which half the property is destroyed (set at 203.7km/h).

By generating a destruction index in this way we are able to model the level of local exposure and to extend the work of Cohan & Cole (2002), Hamilton *et al.* (2009) and Grabich *et al.* (2015) who only use a simple exposure versus no exposure approach. This also differs from Evans *et al.* (2010), who use different categories of hurricane advisories to look at how many days of each warning or watch there had been 9 months prior to a birth. We believe that by modeling the wind speeds and creating a proxy for the kinetic energy of the hurricane, we are able to better capture the exposure level experienced by the population. Further justification for our approach comes from Strobl (2012) who finds that landfall dummies are not a good

[6] Our approach differs from Evans *et al.* (2010) and Burlando (2014) who use the log of births. Due to the length of the period and the significant population changes we believe that the change in the birth rate provides a better overall picture. In our sensitivity analysis we also estimate our results using the log of births. The results are qualitatively and quantitatively similar.

[7] Damages are related to wind speed in a cubic manner due to nature of energy dissipation of the hurricane.

proxy for estimating the negative growth impact of a hurricane at the local level. Likewise, wind damage shows a high power-law dependence on wind speed as shown in Pielke (2007) and Nordhaus (2010), implying that the experienced wind speed is a strong predictor of hurricane damage and exposure. Intuitively, using a dummy variable for the exposure that a parish experiences when it could be only minor damage and would be treated the same way as a parish that experiences severe damages is likely to lead to misclassification of exposure levels.

The wind speed data we use follows Strobl (2012), which in turn is based on a wind field model developed by Boose *et al.* (2004). The base equation stems from Holland (1980) and is given by:

$$V = GF\left[V_m - S(1 - sin(T))\frac{V_h}{2}\right]\left[\left(\frac{R_m}{R}\right)^B \exp\left(1 - \left[\frac{R_m}{R}\right]^B\right)\right]^{\frac{1}{2}} \tag{5.3}$$

where V is the wind speed at point P, V_m is the maximum sustained wind velocity anywhere in the hurricane, T is the clockwise angle between the forward path of the hurricane and a radial line from the hurricane center to the point of interest (the centroid of a Parish), P, V_h is the forward velocity of the hurricane, R_m is the radial distance from the center of the hurricane to point P, and G is the gust wind factor (water = 1.2, land = 1.5). Finally, F is a scaling parameter for surface friction (water = 1.0, land = 0.8), S is the asymmetry due to the forward motion of the hurricane (1.0) and B is the shape of the wind profile curve (1.2). These parameter values have been verified in Boose *et al.* (2001) and Boose *et al.* (2004).

The source for the localized wind speeds is the HURDAT database that provides the strength and tracks every 6 hours of all hurricanes that affected Jamaica during the period we have our birth data. Not all of these hurricanes had wind speeds that surpass our threshold, but it does provide an indication of the frequency with which hurricanes happen in the basin, the route that they tend to take and how many make landfall.[8]

[8]Despite the data being the most complete database available and having been extensively re-analyzed for the periods 1851-1910 (Landsea *et al.*, 2004), 1911-1920 (Landsea *et al.*, 2008) and 1921-1930 (Landsea *et al.*, 2012) there are still a small number of concerns regarding the completeness and accuracy of the data. There may be under-reporting of the number of hurricanes, inaccurate tracks and under-analyzed intensity. The errors in position is due to the limited ship sightings and it has been shown by Holland (1981) that even with numerous ships and buoys in the water, estimation errors of the centers of tropical cyclones are common, meaning that hurricanes passing over open sea are likely to contain some track error. The ones making landfall

5.2.4 Weather Data

In addition to the destruction index we also control for other climatic variables. Although wind speed is highly correlated with rainfall during a hurricane event our additional controls capture rainfall and the average temperature for each month. The rainfall data per month is measured in millimetres. The rainfall and temperature data are from the Climatic Research Unit (CRU) TS4.00 gridded time series data. We measure rainfall and temperature in the month of the hurricane and the month of the birth.

We define our rainfall and temperature variables in terms of anomalies as follows:

$$climate = \begin{cases} \frac{c_t - \overline{c}}{\sigma_c}, & \text{if } c_t - \overline{c} > \sigma_c \\ 0, & \text{otherwise} \end{cases}$$

where c_t is the rainfall or temperature in month t, $\overline{c}$ is the mean of rain or temperature, σ_c is the standard deviation and the value is zero if $c_t - \overline{c}$ is smaller or equal to σ_c.

5.2.5 Summary statistics

Throughout our time period, the number of births in Jamaica was fairly stable at approximately 35,000 per year, while the female population grew by about 25 percent from 1901 to 1929. Even though the annual numbers are fairly consistent, there is a large element of seasonality in the births data. In terms of the birth rate, it remained between 7.63 to 8.50 percent during the first two decades, while the 1920s saw it drop below 7 percent for the first time through a combination of fewer births and a larger population (driven by lower outward migration numbers). Eisner (1974) points to a fall in infant mortality and fewer legitimate children being born as

are more accurate, and these observations were made all across the Caribbean. For the intensity errors, the problem stems from instruments not being properly calibrated to deal with hurricane strength winds, and hence underestimating the intensity of the hurricanes. Overall, the goal of Landsea *et al.* in their series of papers was to correct the tracks and errors, although they admit that despite the reanalysis efforts there may be further changes if new information is discovered or if revised physical understanding is made available. While any revisions may impact the results of our analysis, as any new and updated track or intensity information will affect the modelled wind speed and hence the destruction index, we expect these changes to be minimal. Figure B1 shows all hurricanes in the Caribbean basin for the years 1901-1929.

other reasons for the trends in birth rates.[9]

The result of reduced migration flows and lower mortality rates was significant population growth in Jamaica. Despite these changes in population, the M/F ratio remained relatively stable at 102.3, which is slightly lower than the expected ratio found by James (1987), which was in the range 104-107. However, in the same article, he points to race being a factor in the sex ratio with some black populations having a slightly lower M/F ratio. Reassuringly, Visaria (1967), using a database for Jamaica for the period 1878 to 1950, finds the sex ratio to be identical to ours at 102.3.

In Table 5.1 we present summary statistics at the parish level including a summary of our destruction index. The top panel of Table 5.1 shows that there were on average more males than females in each parish and that there were more births to single mothers than to two parents (as recorded on the birth certificate). The second panel of Table 5.1 provides the summary statistics for the destruction index and modelled wind speeds (only values above our threshold of 92.6km/h are included). For the hurricanes included in our sample, the average hurricane destroyed 40 percent of the parish level property, while the most damaging hurricane to hit a parish destroyed 95 percent of the property. This demonstrates both the destructive power of a hurricane and the heterogeneity across space and time. It is worth noting that during the period 1901-1929 16 hurricanes had wind speeds over our 92.6km/h threshold, with 6 of these destroying more than 50 percent of the property in a given parish. At the same time, 6 of the hurricanes caused less than 10 percent damage. From the hurricane data we know that 4 hurricanes barely breached the threshold and caused less than 1 percent damage.

The bottom panel of Table 5.1 summarises our additional weather variables. As one would expect for a country in a temperate zone the temperature data is very stable with a difference of just 8 degrees between the maximum and minimum temperatures within a given month. For our rainfall variable, as expected, the standard deviation is considerably higher and the

[9] In Table B1 of Appendix B we present the summary statistics for the birth and population data at the national level. Figure B2 in Appendix B plots the birth data and also includes a plot of our destruction index for each year of our sample which we discuss later.

Table 5.1: Summary Statistics

	N	Mean	SD	Median	Minimum	Maximum
Birth and Population Statistics						
Monthly Parish Level Births	4,524	221.45	85.57	220	49	557
Monthly Parish Level Births - Girls	4,524	109.44	43.18	107	25	299
Monthly Parish Level Births - Boys	4,524	111.94	43.91	111	19	301
Monthly Parish Level Births - Single Mother	4,524	134.61	51.85	128	30	387
Monthly Parish Level Births - Parents	4,524	86.84	40.82	85	7	295
Parish Level Female Population	4,524	30,946	10,632	31,695	15,238	59,489
Parish Level Male Population	4,524	34,474	12,798	34,827	17,736	75,808
Annualized Parish Level Births per Female (%)	4,524	7.78	1.54	7.70	2.76	14.06
Destruction and Wind Statistics						
Destruction Index (Over threshold only)	166	0.40	0.38	0.26	0.00	0.95
Modeled Wind Speed (Over threshold only)	166	202.59	96.11	170.59	92.69	383.92
Destruction Index (All Months)	4,524	0.015	0.10	0	0	0.95
Modeled Wind Speed (All Months)	4,524	7.43	42.28	0	0	383.92
Climate Statistics						
Rain (mm)	4,524	187.79	201.51	121.4	6	2,499.7
Temperature (C)	4,524	24.48	1.49	24.5	20.2	28.3

difference between maximum and minimum is almost 250cm of rain over the course of a month.

All parishes experienced population growth over this period, with Kingston and the surrounding areas being the most populous areas and the north-west being the least populous. No significant internal migration trends were found. Unfortunately, our census and migration data is not at frequent enough intervals for us to analyze internal migration patterns properly.[10]

Finally, we consider the full distribution of the 166 instances when a hurricane caused parish level damage, as a result of the 16 damaging hurricanes. We find that hurricanes are skewed towards the higher and lower destruction levels. From an analytical perspective it is useful to have hurricanes across the full destruction spectrum so that we are able to capture the birth effect at different exposure levels. The temporal distribution also helps, where some of the most devastating hurricanes are fairly isolated events whereas the last decade only had one hurricane in 1924 that caused significant destruction. This limits a confounding effect where birth decisions are affected by hurricanes that hit one after another in quick succession.[11]

[10]Figures B3 and B4 of Appendix B present the distribution of the population across Jamaica at the start and the end of our sample. In more recent studies, using a survey method, Smith & McCarty (1996) find that hurricane Andrew, which struck Florida 24 August 1992, caused significant migration effects both temporary and permanent. Likewise, Logan *et al.* (2016) find that population growth in high risk zones can be hampered for as long as 3 years following a hurricane with people either moving away and then not returning.

[11]Figure B5 of Appendix B shows the density distribution in graphical form

5.3 Empirical strategy

In the previous literature attempts to estimate the impact of a shock on fertility has tended to use dummies or a difference-in-difference approach to assess whether a population is exposed to a disaster or not (Cohan & Cole, 2002; Hamilton *et al.*, 2009; Grabich *et al.*, 2015). In this chapter, we take into account the extent of exposure by using our destruction index as a proxy for the damage experienced by the population of a parish. The empirical approach is partially based on the fixed effects model employed by Evans *et al.* (2010), where, instead of using ex ante hurricane forecasts, we use our own destruction index as the key independent variable. Hence, our empirical specification is given by:

$$\begin{aligned}\ln b_{i,t} = \beta_0 + \beta_1 X_{i,t-j} + \beta_2 rain_{i,t} + \beta_3 temperature_{i,t} \\ + \beta_4 rain_{i,t-j} + \beta_5 temperature_{i,t-j} + \beta_6 months_i + \beta_7 time + \theta_i + e_{i,t}\end{aligned} \quad (5.4)$$

where $\ln b_{i,t}$ is the log birth rate in parish i at time t, $rain_{i,t}$ and $rain_{i,t-j}$ captures rainfall during month t and $t-j$, while $temperature_{i,t}$ and $temperature_{i,t-j}$ are the same for temperature, β_0 is the intercept, $months_i$ are dummy variables for months, $time$ is a time trend following Evans *et al.* (2010)[12], θ_i are the parish fixed effects and $e_{i,t}$ is the error term. The variable $X_{i,t-j}$ is the destruction index value, f, in the month of the hurricane, which happened j months prior to month t. To correct for potential heteroskedasticity we use Huber-White covariances from White (1980).

Given the nature of Jamaica's climate, with stable and high temperatures and very limited cases of drought we decided not to use controls for low temperatures or relatively small amounts of rain. The weather variables are included for the hurricane month, $t-j$, to control for any rain or temperature effects that might be correlated with the hurricane. In principle our destruction index should also capture the damage due to rainfall during the hurricane. However, we include monthly rainfall as an additional control. Given how hurricanes are "fuelled" by water temperature one might also expect higher temperature months to have some correlation with

[12]Using parish specific time trends make little difference for coefficients and significance.

the strength of the hurricanes.[13] We thus also include rain and temperature controls for the month of birth to control for any impact of extreme weather on birth outcomes. For example, Wang *et al.* (2013) show that heat waves can lead to an increase in pre-term births. In addition, Lam & Miron (1996), find that summer temperature extremes tend to reduce conception.

Regarding our time variable t, we set it to be the month of birth where the hurricane happened j months previously. This is in line with the methodology used in Evans *et al.* (2010), Pörtner (2008) and Ball (2015) where they look at births j months after the shock (9 months in the latter two cases). One caveat with this approach is that the possibility of pre-term and still births can affect birth rates in earlier months. For example, Xiong *et al.* (2008) shows that exposure to hurricane Katrina led to an increase in pre-term births, implying that a hurricane can lead to an increase in the birth rate before 9 months have passed. Torche (2011) also find a decrease in gestational age following the 2005 Tarapaca earthquake in Chile. Similarly, Zahran *et al.* (2014) find that hurricanes Katrina and Rita led to an increase in foetal mortality which would not show up as an increase in births before 9 months. Given that our data set only has the number of live births by month we are unable to say anything specific about the effects on pre-term births and still births. We therefore chose to link each hurricane with the birth data j months later, i.e. a hurricane making landfall in January will be linked with the birth rates j months later (October if j is 9).

5.4 Results

In Table 5.2 we present the results for our different econometric specifications. The common factor in each specification is that the assumed threshold for our destruction index is 92.6km/h and that half the property value is destroyed when the wind speed reaches 203.7km/h. In all specifications we use monthly dummies and a time trend. The 13 parishes of Jamaica are our cross-sectional unit and the time interval is monthly. A panel unit root test on the log birth

[13] Hsiang (2010) points to sea surface temperatures being correlated with cyclone activity in the Atlantic. Similarly, Anttila-Hughes & Hsiang (2013) use rainfall and temperature controls to avoid any confounding weather behavior that might be correlated with typhoon incidence.

rate confirms that the panels are stationary.[14]

Column (1) shows the results for the basic specification that does not include any weather variables. We find that the strength of the hurricane negatively impacts birth rates at the 1 percent significance level. In Column (2) we introduce weather controls into our log of birth rate regression. In columns (3)-(5) we present the results for alternative measures of births. The temperature and rainfall variables in the month of birth are insignificant for all regressions. For the weather variables in the month of the hurricane, we find that rainfall remains insignificant but that temperature is now significant at the 1 percent level. Given how a hurricane gains energy from hot water and hot air, a higher than normal temperature combined with a hurricane, is likely to generate a very strong hurricane. If we only look at the hurricanes that happen in months that were unusually warm, there is a correlation of 0.814 between the destruction index value and the temperature variable.[15] In addition to the correlation with the destruction index, the results showing that heat causes fewer births is consistent with the findings of Barreca *et al.* (2015), where they find that heat waves cause a decline in the birth rate 9 months later. From Column (2) we can see that the inclusion of weather variables leads to a small reduction in the magnitude of our destruction index although the significance level is unchanged. In Columns (3)-(5) we perform a series of robustness checks with three alternative dependent variables. For example, Evans *et al.* (2010) and Pörtner (2008) used the log of births as their dependent variable. All specifications show the same negative effect and are significant at the 1 percent level.

To help interpret the demographic significance of our coefficients Table 5.3 shows the impact in terms of the number of births. It depicts two cases, one where we assume that the average hurricane hits, implying property values were reduced by 40 percent and a second case where we assume the maximum recorded hurricane for the period where 95 percent of the property value is destroyed. Each of these cases is broken down into parish and national level impacts, where the latter case assumes that the hurricane hits all 13 parishes with the same intensity.

[14] We used a Levin-Lin-Chu test from Levin *et al.* (2002) to test stationarity

[15] There are 22 instances where the temperature were more than 1 standard deviation higher than monthly mean and a hurricane struck

Table 5.2: Base case regressions (Births 9 months after hurricane)

Specification	Base Case	Base Case + Climate Variables			
Dependent Variable	Log of Birth Rate	Log of Birth Rate	Birth Rate[a]	Births	Log of Births
	(1)	(2)	(3)	(4)	(5)
Destruction Index	−0.059**	−0.053**	−0.386**	−14.535**	−0.053**
	(0.012)	(0.009)	(0.061)	(2.913)	(0.009)
Rainfall		−0.000	−0.005	−0.316	−0.001
		(0.001)	(0.008)	(0.266)	(0.001)
Temperature		−0.033	−0.000	−1.287	−0.005
		(0.004)	(0.025)	(0.970)	(0.004)
Rainfall during Storm		−0.007	−0.005	−0.521	−0.002
		(0.002)	(0.014)	(0.567)	(0.002)
Temperature during Storm		−0.015**	−0.104**	−3.742**	−0.013**
		(0.004)	(0.023)	(1.136)	(0.004)
Monthly and time trends	Yes	Yes	Yes	Yes	Yes
Climate Variables	No	Yes	Yes	Yes	Yes
Observations	4,524	4,407	4,407	4,407	4,407
R^2	0.350	0.364	0.000	0.278	0.291
Adjusted R^2	0.348	0.362	0.000	0.276	0.289

Notes: **Significant at the 1 percent level.
*Significant at the 5 percent level.
a. Coefficients and standard errors for birth rate multiplied by 1,000

Furthermore, we assume that the parish being hit has the mean population and that the dependent variable has the mean value.[16]

Overall, our results are fairly robust to our choice of dependent variable although using the log variables appears to result in a smaller reduction in the birth rate. When looking at the percentage change, an average hurricane leads to 2 percent less births 9 months later while a maximum strength hurricane leads to almost 5 percent fewer births.

As a further robustness check we re-estimate our results assuming different V_{half}-values (ranging from 130 to 370km/h compared to our assumed value of 203.7km/h) for two different threshold values is given by V_{thresh} at 92.6km/h and 185.2km/h, respectively.[17] The results are presented in Figures 5.1 and 5.2. The black lines show the coefficient values, and the blue lines are the

[16] A sensitivity check using median values resulted in only minor differences in our coefficients of interest.

[17] Emanuel (2011) uses a V_{thresh} of 92.6km/h, and two V_{half} values of 203.7km/h and 277.8km/h. We test for a full range of V_{half} and one V_{thresh} in accordance with the original paper as well as one close to the lower V_{half}

Table 5.3: Birth Impact of Hurricane (Number of Births 9 months after a hurricane)

Specification	Base Case	Base Case + Climate Variables			
Dependent Variable	Log of Birth Rate	Log of Birth Rate	Birth Rate[a]	Births	Log of Births
	(1)	(2)	(3)	(4)	(5)
Assuming Storm at mean level destruction of 40 percent					
Parish Level Impact	−5.1	−4.6	−5.3	−5.8	−4.3
National Level Impact	−65.8	−59.2	−68.7	−75.0	−55.8
Percent change in Births	−2.31	−2.08	−2.36	−2.60	−2.08
Assuming Storm at max level destruction of 95 percent					
Parish Level Impact	−11.9	−10.7	−12.7	−13.8	−10.1
National Level Impact	−155.1	−139.7	−164.5	−179.5	−131.6
Percent change in Births	−5.45	−4.91	−5.66	−6.24	−4.91

95 percent confidence intervals. The red lines are the R-squared values and lie within a narrow range of 0.2 percent of each other showing that the explanatory power of the model is not dependent upon the choice of V_{thresh} and V_{half}. The coefficient values have a local maxima at approximately 200km/h which is reassuringly close to the V_{half} value of 203.7km/h that we use in our base specification and helps to justify our parameter choice in our main results table.[18]. The results from Figures 5.1 and 5.2 imply that the results are robust to our parameter choices of the damage function. In the subsequent analysis we only present those results using a V_{half} of 203.7km/h and a V_{thresh} of 92.6km/h. In all cases we include weather controls and monthly trends as well as an overall time trend.

[18] As a final robustness check we examine the effect on the coefficient when we change values of V_{thresh} holding V_{half} held at 203.7km/h. The coefficient value tends towards zero as the threshold values increase. Increasing the threshold by which hurricanes can cause damage to property reduces the coefficient on births as expected as, by construction, we are reducing the number of hurricanes that may impact on fertility. The fact that it goes towards zero suggests the existence of attenuation bias as a result of measurement error. The results are shown in Figure B6 of Appendix B

Figure 5.1: Change in the Destruction Index Coefficient with Changing V_{half} assuming a V_{thresh} of 92.6km/h

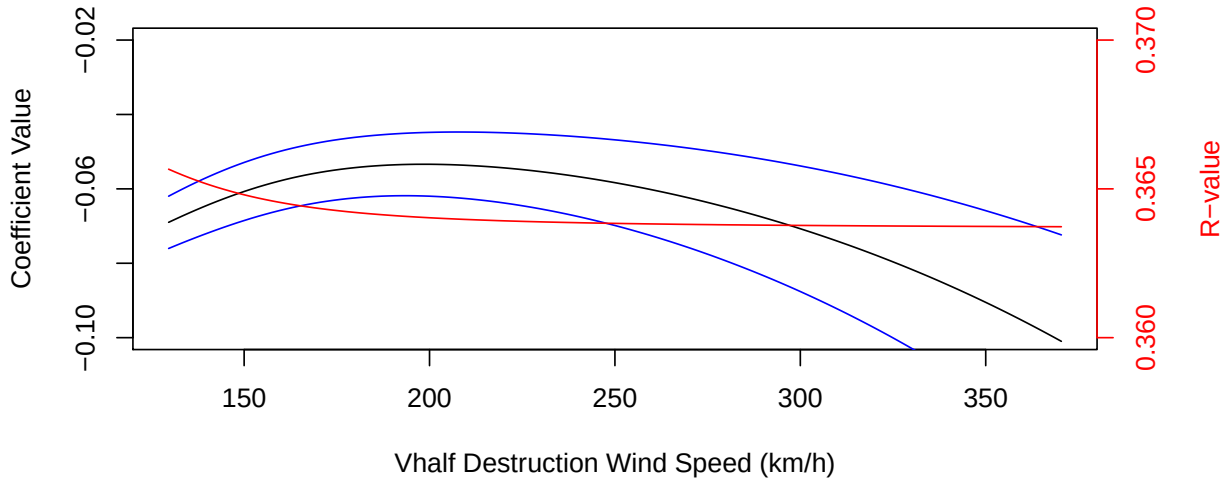
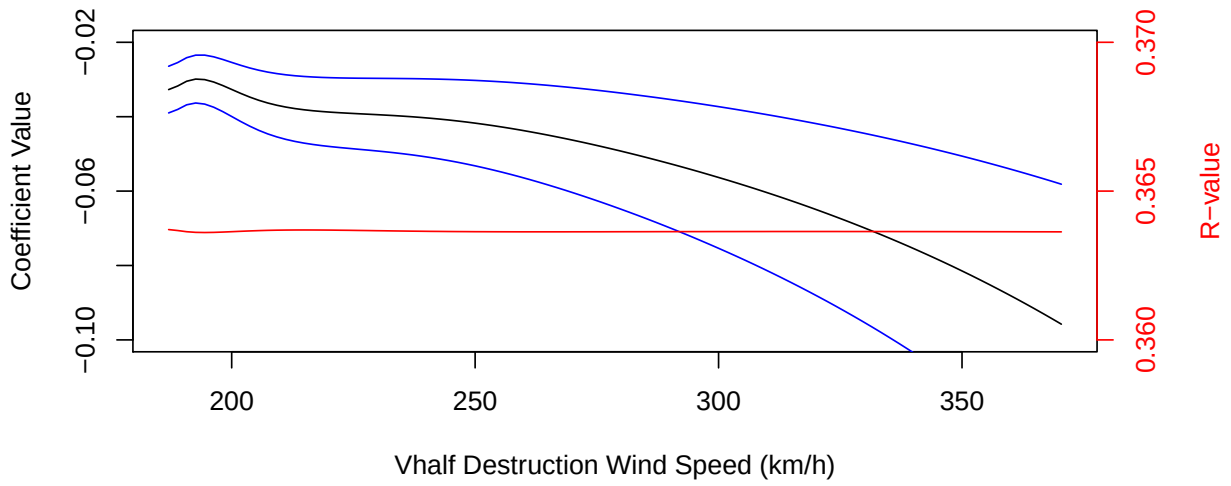


Figure 5.2: Change in the Destruction Index Coefficient with Changing V_{half} assuming a V_{thresh} of 185.2km/h



5.4.1 Hypothesis 1: Temporal fertility displacement

To investigate whether the conception decision is postponed or brought forward as a result of an upcoming hurricane or hurricane season we examine the impact of the hurricane for each month before and up to 18 months after a hurricane hits. In our case, the absence of an early warning system and the relatively infrequent nature of hurricanes in Jamaica means that bringing conception forward to avoid a hurricane is unlikely although we test for it anyway.

Table 5.4 presents our results and shows that there is a strongly significant and negative effect for all the months from month 9 through to month 17. In other words, our results suggest that it takes around 9 months after the hurricane for people to have sufficiently dealt with the aftermath of the hurricane to continue to have children at a rate that is not significantly different from pre-hurricane levels. We find no significant effect for births 7 and 8 months after the hurricane suggesting that there is no displacement in favour of earlier conception to avoid a hurricane or a hurricane season or an increase in pre-terms births. Our results show that the largest decreases in birth rates occur 11, 12 and 15 months after the hurricane suggesting that there are significantly fewer conceptions in the first six months following a hurricane with no effect found after eighteen months.

For the overall effect of a hurricane on total births and by month (using the same assumptions that we use for Table 5.3) we find that an average hurricane causes a decrease in births of 3.12 percent for the months 9 through 17. For a maximum strength hurricane, the decrease is 7.29 percent. Comparing this with the official death toll of approximately 250 following the hurricanes that occurred during the period 1901-1929 (National Library of Jamaica, 2016), we find that an average strength hurricane that affects all 13 parishes impacts 3 times as many lives through children not being born. Assuming an average strength hurricane and aggregating over all the 166 instances when a parish was damaged, our results estimate that hurricanes caused 10,201 fewer births to happen that would have happened otherwise. Finally, perhaps not surprisingly, we find no indication of a temporal displacement effect that would have shown up as an increase in births typically in the months 11-15 after a hurricane for delayed conception

and 7-8 months if conception is brought forward.[19]

Table 5.4: Birth Impact of Hurricanes for Months 7 through 18

	7 months	8 months	9 months	10 months	11 months	12 months
Destruction Index	−0.031	−0.028	−0.053**	−0.052**	−0.113**	−0.101**
	(0.014)	(0.019)	(0.009)	(0.011)	(0.010)	(0.018)
Monthly and time trends	Yes	Yes	Yes	Yes	Yes	Yes
Climate Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,433	4,420	4,407	4,394	4,381	4,368
R^2	0.360	0.361	0.364	0.367	0.370	0.368
Adjusted R^2	0.357	0.359	0.362	0.364	0.368	0.365

	13 months	14 months	15 months	16 months	17 months	18 months
Destruction Index	−0.081**	−0.096**	−0.119**	−0.060**	−0.045*	−0.012
	(0.014)	(0.018)	(0.015)	(0.016)	(0.015)	(0.013)
Monthly and time trends	Yes	Yes	Yes	Yes	Yes	Yes
Climate Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,355	4,342	4,329	4,316	4,303	4,290
R^2	0.365	0.363	0.363	0.362	0.364	0.365
Adjusted R^2	0.363	0.361	0.361	0.359	0.362	0.362

Notes: **Significant at the 1 percent level.
*Significant at the 5 percent level.

5.4.2 Hypothesis 2: Permanent Fertility Effects

In the previous section we find no evidence of a temporal displacement effect that would have shown up as an increase in births in the 18 months after the event. Our findings of a fall in births in the months following a hurricane suggests that there may be a permanent decrease in births. To investigate whether hurricanes have a permanent fertility effect such that the shock causes a change in the total number of children born we follow Evans *et al.* (2010) and estimate the following:

[19]The results are presented in Table B2 of Appendix B

$$\ln B_{i,t} = \beta_0 + \beta_1 X_{i,t} + \beta_2 rain_{i,t} + \beta_3 temperature_{i,t} + \beta_4 months_t + \beta_5 time + \theta_i + e_{i,t} \quad (5.5)$$

where $\ln B_{i,t}$ is the log of total births in parish i over t previous years, $rain_{i,t}$ is the level of rainfall for the hurricane month that happened t years ago, $temperature_{i,t}$ is the same for temperature, $months_t$ are dummy variables for months, β_0 is the intercept, $time$ is a time trend, θ_i are the parish spatial and time fixed effects and $e_{i,t}$ is the error term. The variable $X_{i,t}$ is the destruction index value, f, in the month of the hurricane, which happened t years ago.

Table 5.5 presents the results for specifications using 3, 5 and 10 year periods. Once again, we find a negative and significant effect of hurricanes on births for each of the three periods with the size of the coefficient falling as the period lengthens. Our results are in line with Evans *et al.* (2010) who finds that hurricane warnings have a negative permanent effect. One explanation for the absence of a 'harvesting effect' for Jamaica is that number of deaths is fairly limited, implying that the need to have additional children as an insurance against hurricanes is less than in other places where they may experience higher mortality rates due to hurricanes. In addition, given how regularly hurricanes strike and the fact that they impact the majority of the parishes, it may be that people have already accounted for the need to have more children, meaning that the aftermath of hurricanes results only in a fall in the overall number of births.

Using the same assumptions as before, the long term fertility effects of a hurricane shows that there may be a more prolonged effect than we found previously. At a parish level, there are 90 fewer births after 3 years assuming a hurricane of average strength, whereas 17 months after the hurricane there was a 'loss' of 61 births. This negative trend continues for up to 5 years, where another 32 births did not happen, bringing the total to 122. After 10 years we see a recovery in birth rates that brings us back to 3 year levels with 94 fewer births. Our results suggest that in the very long term, there may be a small up-tick in the birth rate to compensate, but it is still not sufficient to offset the total effect of the hurricane. From the percentages, we find

Table 5.5: Hurricane effects for 3, 5 and 10 year rolling aggregate births

	3 years	5 years	10 years
	(1)	(2)	(3)
Destruction Index	−0.030**	−0.025**	−0.010**
	(0.004)	(0.003)	(0.002)
Monthly and time trends	Yes	Yes	Yes
Climate Variables	Yes	Yes	Yes
Observations	4,056	3,744	2,964
R^2	0.045	0.026	0.018
Adjusted R^2	0.045	0.026	0.018

Notes: **Significant at the 1 percent level.
*Significant at the 5 percent level.

that an average strength hurricane caused a decline in births of 1.18 percent after 3 years, but only 0.40 percent after 10 years. Finally, we show that a maximum strength hurricane striking the entire island even 10 years later, there are almost 3,000 fewer children born, meaning that there are 0.95 percent fewer births over a 10 year period.[20]

5.4.3 Hypothesis 3: Sex-ratio Analysis

To test the Trivers-Willard hypothesis that proposes that the M/F birth ratio falls when mothers are stressed or have less resources available we split our sample into the number of boys and girls born by month following a hurricane. Table 5.6 presents the results. We find significance for the months 9 through 17 for both genders (with the exception of month 16 for boys). All months are negative and the negative impact appears to be slightly higher for girls than boys, with the exception of months 12 and 14.

To test for the equality of coefficients across the gender regressions we use the Paternoster *et al.* (1998) method. Looking at the Z-values in the 4th row of Table 5.6, we find that no months have a statistically significant difference between the two genders' destruction index coefficients. Overall, we find clear evidence that hurricanes had no effect on the sex ratio in Jamaica during

[20]Table B3 of Appendix B presents the long term fertility effects of a hurricane under the same assumptions as Table 3.

this period, a result similar to Grech & Scherb (2015).[21]

To calculate the total number of boys and girls lost for each month for our examples of an average and maximum strength hurricane we have only include significant months, meaning that we exclude month 16 for boys. The impact analysis shows that overall, girls are more affected than boys, with a total decline in births of 3.27 percent versus 2.83 percent for boys. However, as noted above, no single month had a significant gender difference.[22]

[21] As a sensitivity check we ran the same regressions with the sex ratio as the dependent variable. The results were similar in terms of significance although there were some minor changes in the coefficients. Results are available from the authors upon request.

[22] Tables B4 and B5 of Appendix B present the results.

Table 5.6: Boys v Girls - Months 7 through 18

	7m, Boys	7m, Girls	8m, Boys	8m, Girls	9m, Boys	9m, Girls
Destruction Index	−0.041	−0.020	−0.038	−0.017	−0.039*	−0.069**
	(0.023)	(0.013)	(0.027)	(0.020)	(0.016)	(0.014)
Monthly and time trends	Yes	Yes	Yes	Yes	Yes	Yes
Climate Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sign. Difference (Z-value)	-0.819		-0.644		1.377	
Observations	4,433	4,433	4,420	4,420	4,407	4,407
R^2	0.319	0.297	0.320	0.299	0.321	0.302
Adjusted R^2	0.317	0.295	0.318	0.297	0.319	0.300

	10m, Boys	10m, Girls	11m, Boys	11m, Girls	12m, Boys	12m, Girls
Destruction Index	−0.046*	−0.055*	−0.108**	−0.117**	−0.115**	−0.089**
	(0.017)	(0.019)	(0.008)	(0.017)	(0.019)	(0.024)
Monthly and time trends	Yes	Yes	Yes	Yes	Yes	Yes
Climate Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sign. Difference (Z-value)	0.363		0.49		-0.883	
Observations	4,394	4,394	4,381	4,381	4,368	4,368
R^2	0.323	0.304	0.327	0.307	0.326	0.304
Adjusted R^2	0.321	0.302	0.325	0.305	0.323	0.302

	13m, Boys	13m, Girls	14m, Boys	14m, Girls	15m, Boys	15m, Girls
Destruction Index	−0.080**	−0.083**	−0.103**	−0.089**	−0.117**	−0.122**
	(0.016)	(0.020)	(0.018)	(0.021)	(0.018)	(0.015)
Monthly and time trends	Yes	Yes	Yes	Yes	Yes	Yes
Climate Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sign. Difference (Z-value)	0.122		-0.499		0.21	
Observations	4,355	4,355	4,342	4,342	4,329	4,329
R^2	0.322	0.302	0.322	0.300	0.321	0.300
Adjusted R^2	0.320	0.300	0.320	0.298	0.319	0.298

	16m, Boys	16m, Girls	17m, Boys	17m, Girls	18m, Boys	18m, Girls
Destruction Index	−0.035	−0.085**	−0.046*	−0.047*	−0.012	−0.007
	(0.029)	(0.011)	(0.020)	(0.020)	(0.015)	(0.015)
Monthly and time trends	Yes	Yes	Yes	Yes	Yes	Yes
Climate Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sign. Difference (Z-value)	1.615		0.041		-0.21	
Observations	4,316	4,316	4,303	4,303	4,290	4,290
R^2	0.319	0.300	0.322	0.301	0.322	0.302
Adjusted R^2	0.317	0.298	0.320	0.299	0.320	0.300

Notes: **Significant at the 1 percent level.
*Significant at the 5 percent level.

5.4.4 Hypothesis 4: Marital status and fertility

To analyze whether marital status has an impact on fertility, we split our data into those births where both names are present on a birth certificate and those that include only the mother's name.[23] Table 5.7 shows the effect on births for the months 7 though 18. Compared to our sex-ratio analysis there are greater differences in both the magnitude and significance between the two groups. The coefficients for births to married couples are only negative and significant for the months 11, 12, 14 and 15, and in only one month is the coefficient higher than that recorded when only the mother's name is on the birth certificate.

The impact on actual births for the significant months show that an average strength hurricane leads to a reduction in births by 3.5 percent where only the mothers name is registered compared to a decrease of only 1.48 percent for married couples. For a maximum strength hurricane we find 8.15 percent and 3.44 percent fewer births for single mothers and married couples respectively. It should be noted that in our data set births where only the mother registers outnumber births with both parents registered with birth numbers of 135 and 81, respectively. In relative terms, it implies that 62.5 percent of children born in Jamaica only had the mothers name on the birth certificate but the decline in births to single mothers constitutes 79.6 percent of the total decline in birth rates.[24]

Once again we employ the test from Paternoster *et al.* (1998), and this time there are months when the coefficients significantly differ. Months 10 and 14 are significantly different at the 1 percent level and month 13 is fractionally outside the 5 percent significance level.[25] Looking at months 10, 13 and 14 only, there are 202 fewer births nationwide during an average strength hurricane versus 20 that are born to a married couple.[26]

Our results point to the fact that temporal displacement of the birth decision due to hurricanes

[23] In a small number of cases the birth certificates only the name of the father registered. These were dropped from the analysis

[24] The results are shown in Tables B6 and B7 of Appendix B

[25] Once again we ran the regressions with a ratio of children where only the mother registered over children where both parents registered and the results still remained the same, with significance in the same months.

[26] Using only the decrease in the significant month 14 and also using months 10 and 13 gives a total decrease of 38.2 births to two parents.

Table 5.7: Single Mother v Married Couple - Months 7 through 18

	7m, Single	7m, Parents	8m, Single	8m, Parents	9m, Single	9m, Parents
Destruction Index	−0.026	−0.021	−0.048	0.008	−0.057**	−0.040
	(0.016)	(0.022)	(0.023)	(0.023)	(0.014)	(0.024)
Monthly and time trends	Yes	Yes	Yes	Yes	Yes	Yes
Climate Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sign. Difference (Z-value)	-0.174		-1.726		-0.602	
Observations	4,433	4,433	4,420	4,420	4,407	4,407
R^2	0.247	0.465	0.248	0.466	0.250	0.469
Adjusted R^2	0.245	0.462	0.246	0.463	0.249	0.465

	10m, Single	10m, Parents	11m, Single	11m, Parents	12m, Single	12m, Parents
Destruction Index	−0.076**	−0.002	−0.122**	−0.093**	−0.116**	−0.075**
	(0.010)	(0.020)	(0.016)	(0.022)	(0.021)	(0.020)
Monthly and time trends	Yes	Yes	Yes	Yes	Yes	Yes
Climate Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sign. Difference (Z-value)	-3.297**		-1.097		-1.413	
Observations	4,394	4,394	4,381	4,381	4,368	4,368
R^2	0.252	0.471	0.255	0.473	0.254	0.472
Adjusted R^2	0.251	0.467	0.254	0.470	0.252	0.468

	13m, Single	13m, Parents	14m, Single	14m, Parents	15m, Single	15m, Parents
Destruction Index	−0.105**	−0.042	−0.117**	−0.048*	−0.109**	−0.125**
	(0.014)	(0.029)	(0.022)	(0.020)	(0.013)	(0.027)
Monthly and time trends	Yes	Yes	Yes	Yes	Yes	Yes
Climate Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sign. Difference (Z-value)	-1.953		-2.369**		0.529	
Observations	4,355	4,355	4,342	4,342	4,329	4,329
R^2	0.253	0.471	0.252	0.470	0.251	0.470
Adjusted R^2	0.251	0.468	0.250	0.466	0.249	0.467

	16m, Single	16m, Parents	17m, Single	17m, Parents	18m, Single	18m, Parents
Destruction Index	−0.068**	−0.028	−0.039*	−0.054	−0.011	0.005
	(0.020)	(0.025)	(0.017)	(0.026)	(0.019)	(0.021)
Monthly and time trends	Yes	Yes	Yes	Yes	Yes	Yes
Climate Variables	Yes	Yes	Yes	Yes	Yes	Yes
Sign. Difference (Z-value)	-1.24		0.46		-0.593	
Observations	4,316	4,316	4,303	4,303	4,290	4,290
R^2	0.251	0.469	0.254	0.469	0.252	0.470
Adjusted R^2	0.249	0.465	0.252	0.466	0.251	0.466

Notes: **Significant at the 1 percent level.
*Significant at the 5 percent level.

is less likely for married couples than for single mothers, potentially as a result of married couples being better equipped to deal with shocks such as hurricanes. This may be due to having more resources (in monetary terms) or by having a broader support network.

5.4.5 Overall fertility effects

Finally, in Table 5.8 we summarize our findings of the sub-sections of Section 4. Once again we estimate the number of births that did not happen as a result of an average strength hurricane and a maximum strength hurricane in Jamaica. This is done by aggregating the impact on births from the 166 instances when a hurricane caused parish level damage. Our results show that births fell by 10,201 or that there were 1 percent fewer births than would otherwise have been born over the period of our study. Comparing the decrease in births with the number killed as a result of hurricanes which is estimated to be around 250, we show that hurricanes have a much larger effect on population numbers through fertility choices and reproductive health than through mortality.

One striking result from Table 5.8 is that single mothers had 1.15 percent fewer children versus 0.46 percent fewer children for married couples. Given that children where both parents register are more likely to be from a wealthier family and where the father is more involved in the pregnancy and birth of the child, it shows how family planning is less affected by major events when the family has more resources and both parents are involved.

Table 5.8: Summary of Birth Impacts for Jamaica Across All Storms

	National Level		All Storms Effect	Births	Percentage Decline
	Mean	Max			
Base Case	-799	-1,867	-10,201	1,001,850	-1.02
Boys	-365	-853	-4,666	506,432	-0.92
Girls	-412	-963	-5,263	495,107	-1.06
Single Mothers	-549	-1,280	-7,013	608,967	-1.15
Married couples	-140	-328	-1,794	392,883	-0.46

5.5 Conclusions

In this chapter we have investigated the impact of hurricanes on birth rates in early 20th century Jamaica. Overall, we found strong evidence that hurricanes had a significant impact on the number of births. Using our destruction index we show that the level of exposure to hurricane damage has a negative effect on births and that the magnitude of the effect differs with the level of damage. Our results also demonstrate the importance of accurately capturing exposure at the local level which we do using a wind field model.

In line with Evans *et al.* (2010) we find no evidence for temporal displacement of births. However, there is a strong negative effect both in the medium and long term, which is more in line with the findings of Lindstrom & Berhanu (1999). Our results show no support for the Trivers-Willard hypothesis and that, at least for this period in Jamaica, hurricanes have no effect on the sex ratio.

However, we do discover a significant difference between birth rates for those births where both the mother and father were registered compared to those births when only the mother's name was recorded on the birth certificate. This is a similar finding to that found by Hamilton *et al.* (2009) in a modern US context.

Having found such strong effects in a historical context, future research could be done with more modern data to see whether more advanced warning systems and preparations for hurricanes have alleviated the significantly negative effect of hurricanes on birth rates in the Caribbean. However, as Hamilton *et al.* (2009) show for Katrina, there are still events that can have a profound effect on fertility.

Appendix A

A.1 Nominal Expenditure Data

Table A1: Descriptives of Expenditure data by Economic Sectors

Statistic	N	Mean	St. Dev.	Max
General Administration	4,762	151,816	144,886	3,584,915
Public Law and Order	3,458	5,286	5,656	107,046
Economy	4,679	11,088	12,844	221,310
Environment	4,376	9,821	27,006	898,914
Housing and Public Facilities	3,658	8,618	19,250	286,751
Health	4,690	44,489	50,860	1,777,818
Tourism and Culture	4,254	2,976	6,118	204,020
Religious Affairs	717	1,660	3,684	50,718
Education	4,697	167,218	170,056	3,298,403
Social Protection	4,229	4,195	5,697	127,606
Infrastructure	4,689	76,533	99,461	3,145,709
Agriculture	4,679	19,469	22,635	1,061,025
Total	5,305	441,703	447,503	13,328,544

In RP million

Table A2: Descriptives of Expenditure data by Economic Categories

Statistic	N	Mean	St. Dev.	Max
Capital Expenditures	4,770	124,863	127,322	1,817,070
Goods and Services	4,775	97,234	83,776	1,210,640
Other expenditures	4,747	46,846	53,648	731,533
Personnel Expenditures	4,790	262,931	216,098	1,908,810
Total	5,305	479,115	423,606	4,942,255

In RP million

A.2 Regression Results

Table A3: Regression results for Unbalanced 2 year Sector Data

Sector	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami
Agriculture	0.094***	0.092	-0.038	-0.285***
	(0.033)	(0.170)	(0.047)	(0.051)
Economy	0.069**	-0.120	-0.023	-0.094***
	(0.029)	(0.153)	(0.056)	(0.031)
Education	-0.253*	0.514	0.581***	0.726***
	(0.136)	(1.423)	(0.178)	(0.280)
Environment	-0.027	-0.401	-0.026	-0.015
	(0.024)	(0.339)	(0.021)	(0.062)
General Administration	-0.327***	1.624	-0.134**	-0.529*
	(0.117)	(1.418)	(0.064)	(0.290)
Health	0.124**	0.208	0.151***	-0.045
	(0.060)	(0.221)	(0.033)	(0.074)
Housing and Public Facilities	-0.096	-0.036	-0.072	0.007
	(0.068)	(0.216)	(0.162)	(0.028)
Infrastructure	0.331***	-0.033	-0.380**	-0.119
	(0.093)	(0.869)	(0.179)	(0.154)
Public Law and Order	-0.028*	-0.238**	0.006	
	(0.015)	(0.119)	(0.026)	
Social Protection	0.034	0.010	0.014	-0.003
	(0.021)	(0.119)	(0.048)	(0.044)
Tourism and Culture	0.073**	-0.287*	-0.003	0.009
	(0.035)	(0.151)	(0.045)	(0.026)
Observations	15,152	15,152	15,152	15,152

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
[a] Coefficients and standard errors multiplied by 1,000.

Table A4: Regression results for Unbalanced 2 year Sector Data with lags

Sector	Flood[a]	Earthquake	Volcanic Eruptions[a]	Tsunami
Agriculture	0.108***	0.083	-0.049	-0.173***
	(0.030)	(0.193)	(0.041)	(0.027)
Economy	0.070***	-0.132	-0.038	-0.073***
	(0.027)	(0.127)	(0.043)	(0.026)
Education	-0.307**	0.154	0.671***	0.607*
	(0.131)	(1.543)	(0.156)	(0.312)
Environment	-0.028	-0.377	-0.037*	0.004
	(0.026)	(0.329)	(0.019)	(0.060)
General Administration	-0.381***	2.400*	-0.186**	-0.555**
	(0.105)	(1.411)	(0.090)	(0.273)
Health	0.127**	0.245	0.144***	-0.025
	(0.059)	(0.220)	(0.027)	(0.076)
Housing and Public Facilities	-0.086	-0.109	-0.070	0.019
	(0.069)	(0.195)	(0.172)	(0.049)
Infrastructure	0.374***	0.010	-0.404**	-0.037
	(0.095)	(0.911)	(0.162)	(0.157)
Public Law and Order	-0.023	0.003	-0.001	
	(0.018)	(0.128)	(0.021)	
Social Protection	0.032	0.011	0.008	0.009
	(0.019)	(0.091)	(0.045)	(0.039)
Tourism and Culture	0.073**	-0.341***	-0.009	0.028
	(0.034)	(0.124)	(0.043)	(0.025)
Agriculture Lag	0.104***	0.546**	-0.032	
	(0.038)	(0.254)	(0.036)	
Economy Lag	0.045*	0.617***	-0.091*	
	(0.027)	(0.170)	(0.051)	
Education Lag	-0.426**	-4.006**	0.529***	
	(0.206)	(1.832)	(0.196)	
Environment Lag	0.017	0.721***	-0.072**	
	(0.028)	(0.259)	(0.030)	
General Administration Lag	-0.316**	5.058**	-0.180*	
	(0.154)	(2.003)	(0.100)	
Health Lag	0.048	0.473***	-0.030	
	(0.042)	(0.198)	(0.034)	
Housing and Public Facilities Lag	0.063	-0.268	0.009	
	(0.161)	(0.374)	(0.203)	
Infrastructure Lag	0.270	1.810*	-0.141	
	(0.171)	(0.998)	(0.175)	
Public Law and Order Lag	0.048**	0.237**	-0.038*	
	(0.020)	(0.119)	(0.023)	
Social Protection Lag	0.014	0.384***	-0.024	
	(0.020)	(0.137)	(0.045)	
Tourism and Culture Lag	0.028	0.516***	-0.030	
	(0.036)	(0.121)	(0.045)	
Observations	15,152	15,152	15,152	15,152

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
[a] Coefficients and standard errors multiplied by 1,000.

Appendix B

Table B1: Selected birth data

Year	Births	Mean Females	Mean Males	Birth Rate (%)	Boys	Girls
1901	30,570	386,045	353,239	7.92	15,529	15,029
1905	34,892	410,532	376,175	8.50	17,582	17,302
1910	34,937	434,063	397,768	8.05	17,655	17,270
1915	34,279	449,524	404,808	7.63	17,243	17,027
1920	36,449	446,843	390,268	8.16	18,624	17,812
1925	33,614	489,959	432,112	6.86	16,822	16,768
1929	35,762	535,040	477,193	6.68	17,990	17,761
Total	1,001,850	448,172	402,311	7.78	506,432	495,107

Table B2: Birth Impact of Hurricanes by Month

	Mean Hurricane			Maximum hurricane		
	Parish	National	Percentage	Parish	National	Percentage
9 Months	4.6	59.2	-2.08	10.7	139.7	-4.91
10 Months	4.5	58.1	-2.04	10.6	137.2	-4.82
11 Months	9.6	124.8	-4.38	22.3	289.7	-10.18
12 Months	8.6	111.8	-3.93	20	260.4	-9.15
13 Months	6.9	90	-3.16	16.2	210.8	-7.41
14 Months	8.2	106.4	-3.74	19.1	248	-8.72
15 Months	10.1	131.2	-4.61	23.4	304.2	-10.69
16 Months	5.2	67	-2.35	12.1	157.7	-5.54
17 Months	3.9	50.4	-1.77	9.2	119.1	-4.18
Total	61.4	798.8	-3.12	143.6	1866.6	-7.29

Table B3: Long Term Birth Impact of Hurricanes

	3 years	5 years	10 years
	(1)	(2)	(3)
Parish level			
Mean	-90.0	-122.3	-94.0
Max	-213.7	-290.9	-224.4
National level			
Mean	-1,170	-1,590	-1,222
Max	-2,778	-3,781	-2,918
Percentage			
Mean	-1.18	-0.99	-0.40
Max	-2.81	-2.35	-0.95

Table B4: Boys - Birth Impact of Hurricane by Month

	Mean Hurricane			Maximum Hurricane		
	Parish	National	Percentage	Parish	National	Percentage
9 Months	-1.7	-22.1	-1.54	-4	-52.3	-3.64
10 Months	-2.0	-26.0	-1.81	-4.7	-61.4	-4.28
11 Months	-4.6	-60.3	-4.19	-10.8	-140.1	-9.75
12 Months	-4.9	-64.1	-4.46	-11.4	-148.7	-10.35
13 Months	-3.5	-44.9	-3.12	-8.1	-105.1	-7.32
14 Months	-4.4	-57.0	-3.97	-10.2	-132.7	-9.24
15 Months	-5.0	-65.2	-4.54	-11.6	-151.1	-10.52
16 Months						
17 Months	-2.0	-26.0	-1.81	-4.7	-61.4	-4.28
Total	-28.1	-365.4	-2.83	-65.6	-852.8	-6.6

Table B5: Girls - Birth Impact of Hurricane by Month

	Mean Hurricane			Maximum Hurricane		
	Parish	National	Percentage	Parish	National	Percentage
9 Months	-2.9	-37.8	-2.7	-6.8	-88.7	-6.34
10 Months	-2.3	-30.2	-2.16	-5.5	-71.2	-5.09
11 Months	-4.9	-63.5	-4.54	-11.3	-147.1	-10.52
12 Months	-3.7	-48.5	-3.47	-8.7	-113.4	-8.11
13 Months	-3.5	-45.3	-3.24	-8.2	-106.1	-7.58
14 Months	-3.7	-48.5	-3.47	-8.7	-113.4	-8.11
15 Months	-5.1	-66.1	-4.73	-11.8	-153.1	-10.94
16 Months	-3.6	-46.4	-3.32	-8.3	-108.5	-7.76
17 Months	-2.0	-25.8	-1.85	-4.7	-61.1	-4.37
Total	-31.7	-412.2	-3.27	-74.0	-962.6	-7.65

Table B6: Mother only - Birth Impact of Hurricane by Month

	Mean Hurricane			Max Storm		
	Parish	National	Percentage	Parish	National	Percentage
9 Months	-3.0	-39.0	-2.24	-7.1	-92.0	-5.27
10 Months	-4.0	-51.8	-2.97	-9.3	-121.5	-6.97
11 Months	-6.3	-82.4	-4.73	-14.7	-190.9	-10.94
12 Months	-6.0	-78.5	-4.5	-14.0	-182.0	-10.43
13 Months	-5.5	-71.2	-4.08	-12.7	-165.6	-9.49
14 Months	-6.1	-79.1	-4.54	-14.1	-183.5	-10.52
15 Months	-5.7	-73.8	-4.23	-13.2	-171.6	-9.84
16 Months	-3.6	-46.4	-2.66	-8.4	-109.1	-6.26
17 Months	-2.1	-26.8	-1.54	-4.9	-63.5	-3.64
Total	-42.2	-549.2	-3.50	-98.4	-1279.8	-8.15

Table B7: Married Couple - Birth Impact of Hurricane by Month

	Mean Storm			Max Storm		
	Parish	National	Percentage	Parish	National	Percentage
9 Months						
10 Months						
11 Months	-2.9	-38.3	-3.62	-6.9	-89.4	-8.46
12 Months	-2.4	-31	-2.93	-5.6	-72.7	-6.88
13 Months						
14 Months	-1.5	-20	-1.89	-3.6	-47.2	-4.46
15 Months	-3.9	-51.2	-4.84	-9.1	-118.4	-11.20
16 Months						
17 Months						
Total	-10.8	-140.5	-1.48	-25.2	-327.8	-3.44

Figure B1: IBTracks All Storms Caribbean Basin 1901-1929

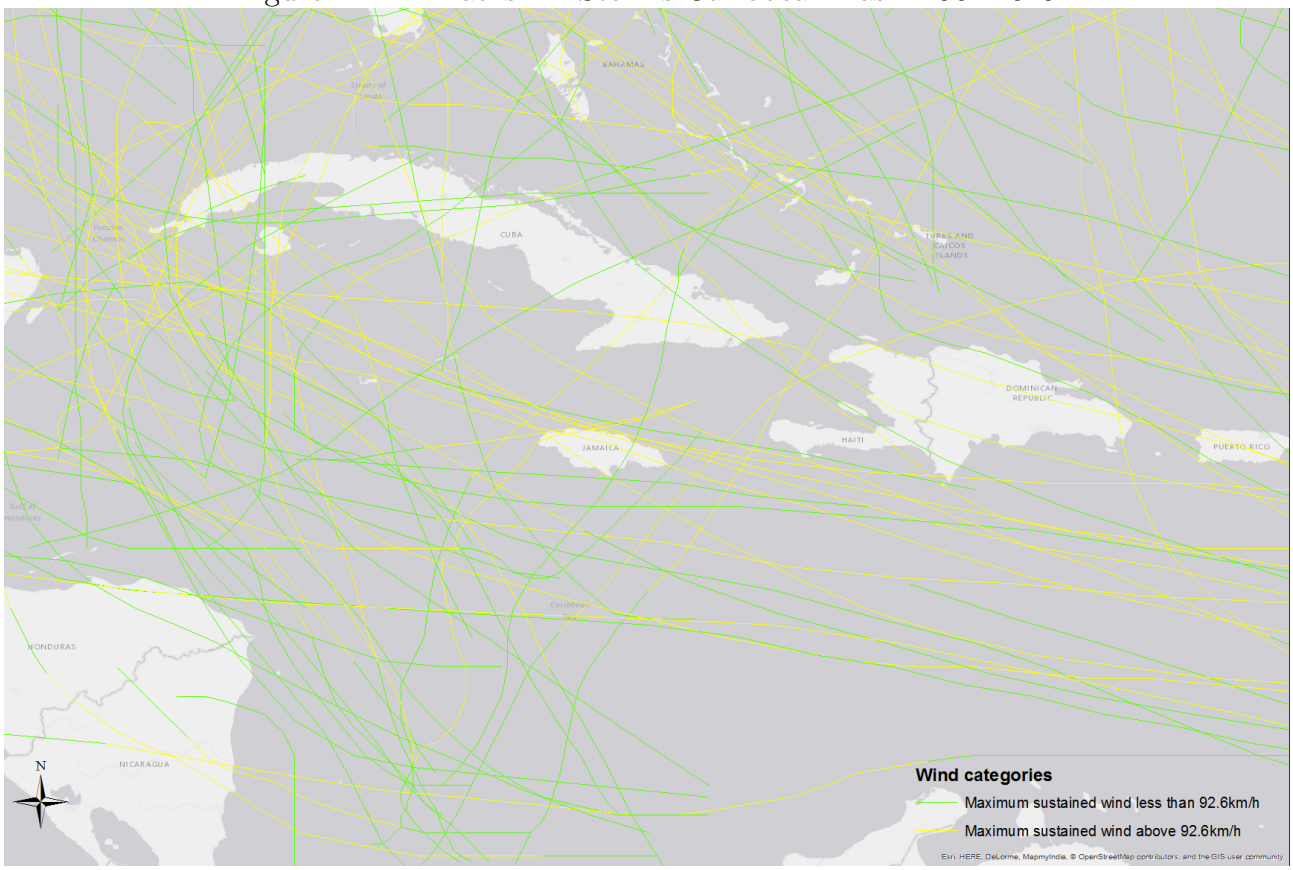


Figure B2: Births and Storms

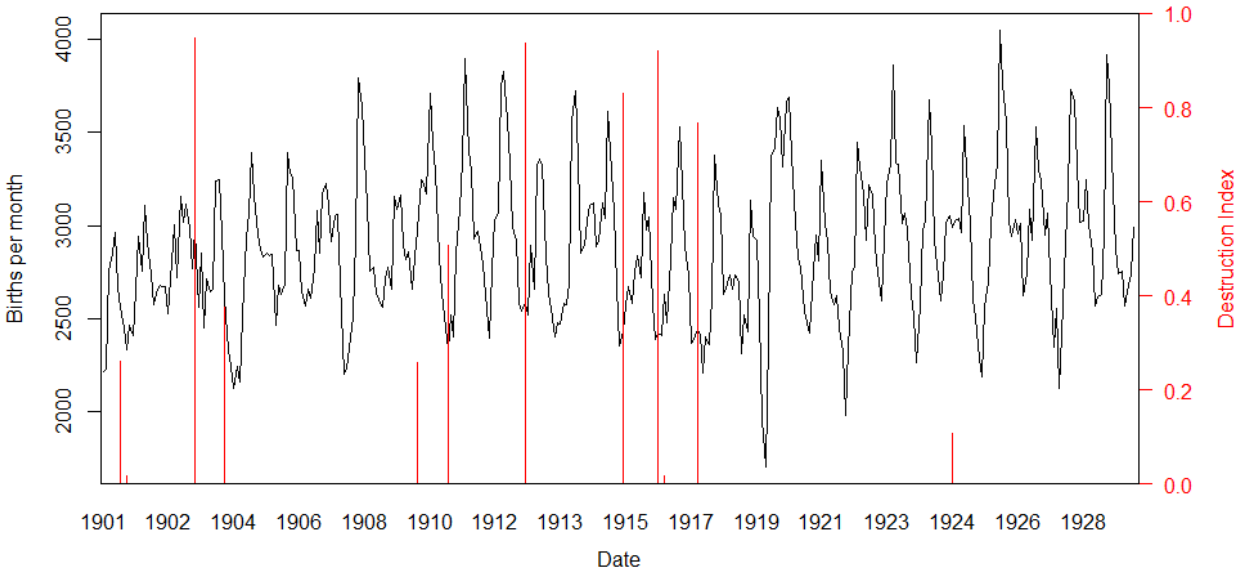


Figure B3: Population densities 1901

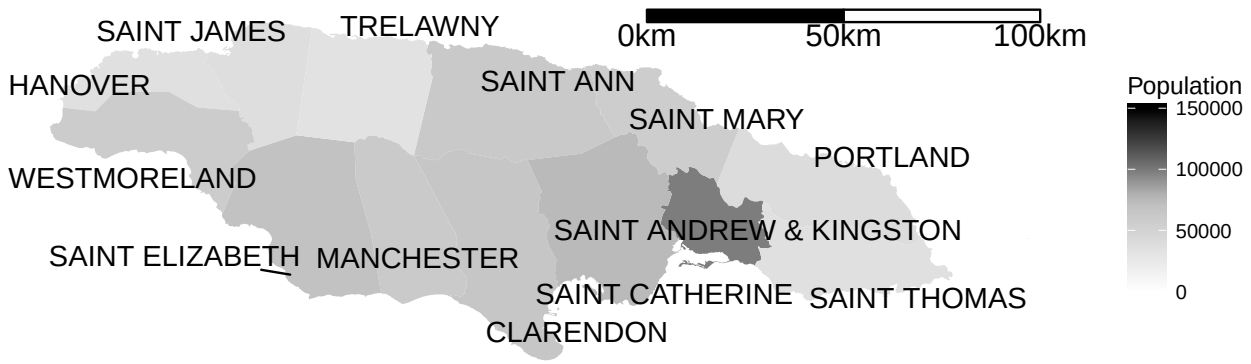


Figure B4: Population densities 1929

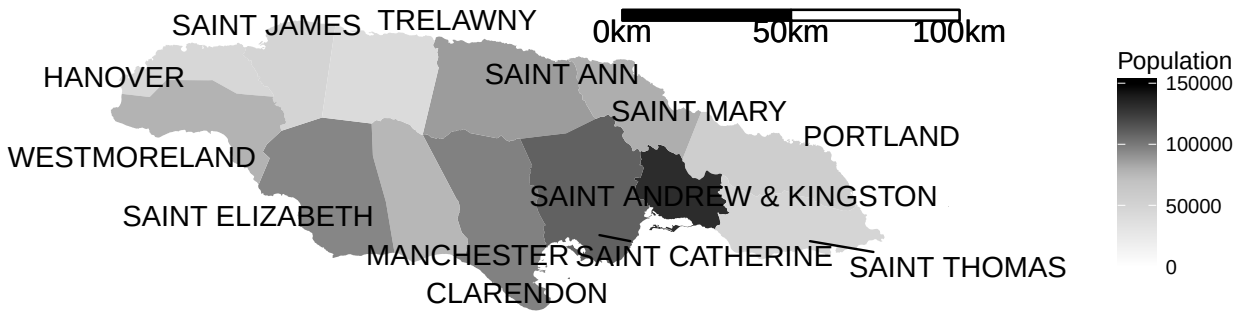


Figure B5: Density of Storms

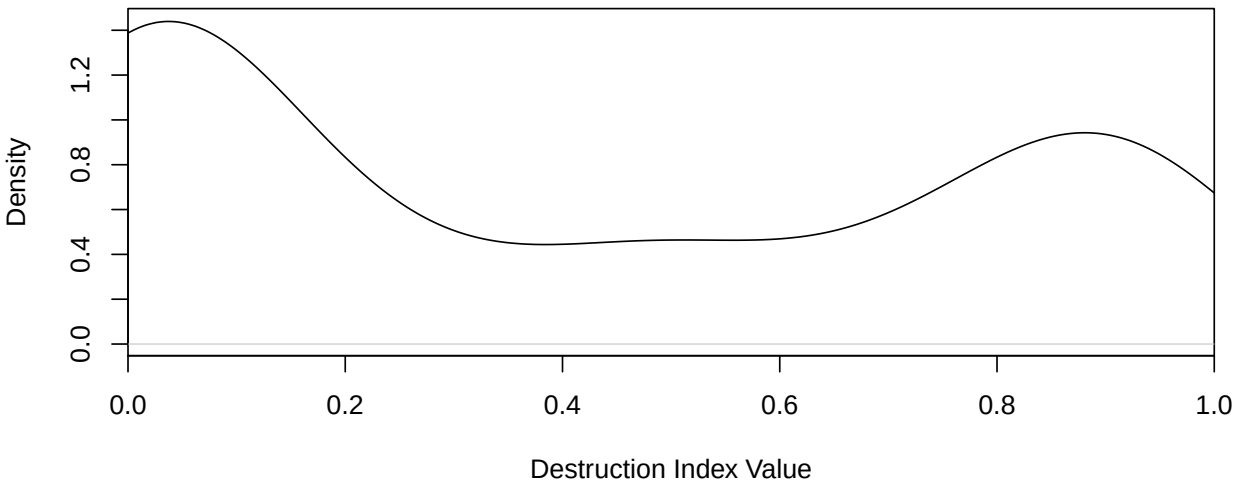
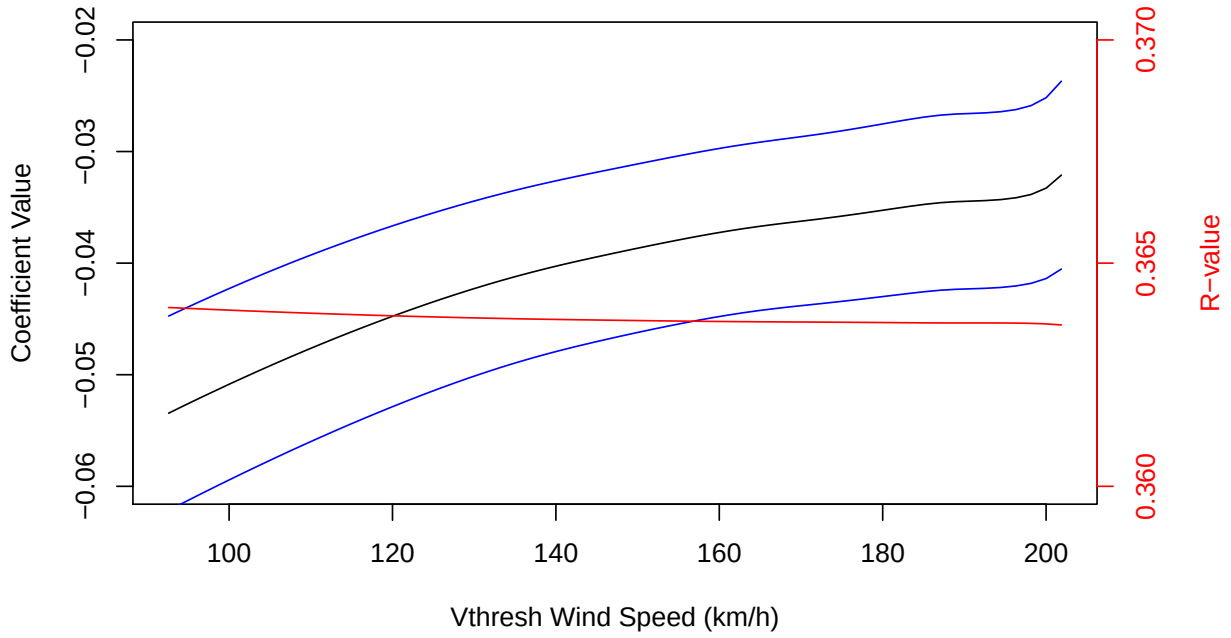


Figure B6: Change in the Destruction Index Coefficient with Changing V_{thresh} with V_{half} of 203.7km/h



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