

Land Use Factors Affecting Economic Damages From Tropical
Cyclones On The US Gulf and Atlantic Coasts

by

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Submitted in partial fulfilment of the requirements
for the degree of Master of Arts

at

Dalhousie University
Halifax, Nova Scotia
December 2014

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Abstract

This paper assesses the economic damages from 94 tropical cyclones between 1992 and 2012 along the US Gulf and Atlantic coasts. I used the Geographical Information System ArcGIS to buffer the digital track of each storm into 200 km wide swaths and extract data on the storm intensity, coverage of various land cover types, and nighttime light emissions. I built a double log model in which the ratio of economic damages to an estimated gross state product was regressed on maximum sustained winds, rainfall per hour, physical exposure and on wetlands. I also included a dummy variable that equals one when maximum sustained winds are less than 119km/hr and zero otherwise. I found that the wind speed of a tropical cyclone increases damages on average to the 6th power and that rainfall per hour significantly increases damages for hurricanes.

List of Abbreviations Used

BP/CW: Breush-Pagan/ Cook-Weisberg

CCA: Climate Change Adaptation

C-CAP: Coastal Change Analysis Program

CID: Commercial/ Industrial Development

CPI: Consumer Price Index

CRED: Centre for Research on the Epidemiology of Disasters

CRS: Community Rating System

DMSP OLS: Defense Meteorological Satellite Program's Operational Linescan System

DRR: Disaster Risk Reduction

FEMA: Federal Emergency Management Agency

GDP: Gross Domestic Product

GIS: Geographical Information System

GSP: Gross Spatial Products

HDI: Human Development Index

HIR: High Intensity Residential

HID: High Intensity Development

HPI: Housing Price Index

L&D: Loss and Damage

LE: Light Energy

MSW: Maximum Sustained Wind

NOAA: National Oceanographic and Atmospheric Association

OLS: Ordinary Least Squares

TSLs: Two Stage Least Square

Glossary

Damage: the physical impact and losses as monetized values, which could be direct or indirect in the form of economic follow-on effects (Surminski et al. 2014)

Disaster: a severe alteration in the normal functioning of a community or a society due to hazardous physical events interacting with vulnerable social conditions, leading to widespread adverse human, material, economic, or environmental effects that require immediate emergency response to satisfy critical human needs and that may require external support for recovery (Field, 2013, pg. 3).

Economic Damage: An estimate constructed by the National Oceanographic and Atmospheric Administration (NOAA) that doubles reported insurance losses. The doubling of insurance damage estimates from NOAA is an attempt to capture all uninsured losses (NOAA, 2014).

Flood Plain: is the relatively flat lowland that borders a river, which is usually dry but is periodically subject to flooding. Floodplain soils actually are former flood deposits (USGSb, 2014a).

Loss: negative impacts in relation to which reparation or restoration is impossible, such as loss of freshwater resources (Surminsky, 2014)

Maximum Sustained Winds: are the highest 2 min surface winds occurring within the circulation of the system. These "surface" winds are those observed to occur at the standard meteorological height of 10 m (33 ft) in an unobstructed exposure (i.e., not blocked by buildings or trees) (Powell et al. 1996).

The Estuarine System: consists of deep-water tidal habitats and adjacent tidal wetlands that are usually semi-enclosed by land but have open, partly obstructed, or sporadic access to the open ocean, and in which ocean water is at least occasionally diluted by freshwater runoff from the land. The salinity may be periodically increased above that of the open ocean by evaporation. Along some low-energy coastlines there is appreciable dilution of sea water. Offshore areas with

typical estuarine plants and animals, such as red mangroves (*Rhizophora mangle*) and eastern oysters (*Crassostrea virginica*), are also included in the Estuarine System (USGS, 2013a).

The Palustrine System: includes all non-tidal wetlands dominated by trees, shrubs, persistent emergents, emergent mosses or lichens, and all such wetlands that occur in tidal areas where salinity due to ocean-derived salts is below 0.5 ‰. It also includes wetlands lacking such vegetation, but with all of the following four characteristics: (1) area less than 8 ha (20 acres); (2) active wave-formed or bedrock shoreline features lacking; (3) water depth in the deepest part of basin less than 2 m at low water; and (4) salinity due to ocean-derived salts less than 0.5 ‰ (USGS, 2013b)

Exposure: is defined as “the presence of people; livelihoods; environmental services and resources; infrastructure; or economic, social, or cultural assets in places that could be adversely affected” (Field, 2012, p.3).

Risk: The term risk refers to the expected losses from a particular hazard to a specified element at risk in a particular future time period. Loss may be estimated in terms of human lives, or buildings destroyed or in financial terms (Peduzzi et al. 2002).

Watershed: “a watershed is an area of land that drains all the streams and rainfall to a common outlet such as the outflow of a reservoir, mouth of a bay, or any point along a stream channel” (USGS, 2014b).

Vulnerability: The propensity or predisposition to be adversely affected (Field, 2012 pg. 3).

Chapter 1:Introduction

Section 1.0: Introduction

Climate change has been cited as one of the most important global risks that decision makers will face in the years to come (IPCC, 2014). The complexity and scope of the adverse effects of climate change presents a unique challenge for economics due to the long-time horizons involved, the uncertainty associated with the risk and the unprecedented scale at which one needs to envision such a problem (Stern, 2007). Tropical cyclones of greater severity in the next century impose an economic problem that demands public policy planning under uncertainty, through time, and which imposes a high degree of risk applied to a very large geographic scale (IPCC, 2014).

With stronger storms comes a heightened importance for adaptation policy to mitigate the market and non-market loss and damages that result. In the regions they affect, tropical cyclones are often the most damaging storms and are of primary importance when assessing flood risk (Woodruff et al. 2013, pg.44). There is mounting evidence that land use characteristics in the path of these storms are important in determining the economic damage that will result from tropical cyclones in addition to their intensity (Zia, 2012). As such, policy makers must be informed on how these storms interact with land use and land cover of areas exposed to these storms. Adaptation to climate change and reducing the risk of disasters has been shown to be the most effective way to manage the economic damages that are expected to result from tropical cyclones through to 2050 (Pielke, 2007; Zia, 2012).

To create an effective climate change adaptation (CCA) plan for future storms, policy makers require assessment from many different perspectives, economics being just one. The purpose of this present paper is to inform policy makers on how economic damages from tropical cyclones may be explained by the interaction of a given storm's intensity, the physical exposure of the affected area and its vulnerability to disasters occurring. The results of this study are intended to strengthen CCA policies as people plan for future tropical cyclones influenced by a changing climate.

Section 1.1: Background

There is little agreement on whether climate change is causing an increase in damages from tropical cyclones at all (Pielke, 2007) or if the recent observations of high damages are due more to increases in physical exposure and/or vulnerability of cities to storms (Nordhaus, 2006; Zia, 2012). In addition to the disagreement surrounding the cause or existence of rising damages resulting from tropical cyclones, there are suggestions that storms may increase in their intensity and frequency into the 21st century (IPCC, 2014). With such disagreement in the literature and pressure to act quickly, policy makers are left with problems that transcend economics, ethics, and political science with little to guide policy in a direction that will bring the best result.

This paper is concerned with providing policy makers with an understanding of how economic damages from tropical storms on the US Gulf and Atlantic coasts may be a product of the intensity of storms and characteristics of land use and land cover. There is evidence that storm intensity (Nordhaus 2006), land-use characteristics such as the density of populations and structures (Peduzzi, 2002; Zia, 2012), presence of wetlands

and agriculture (Brody et al. 2007; Zia, 2012), vulnerability (Peduzzi et al., 2002; Zia, 2012) and physical exposure (Peduzzi 2002; Nordhaus 2006) have influenced the damages that result from tropical cyclones.

Nordhaus (2006), Pielke (2007), and Zia (2013) have pointed to the importance of managing our physical exposure and vulnerability to tropical cyclones, though the definitions of vulnerability have differed from paper to paper. Reliable sets of data on vulnerability and a reasonable proxy for exposure are lacking (Surminski, 2014) and represents a key area of focus for this present paper. I used the coverage of wetlands as a proxy for vulnerability for reasons described in chapter 3. In short, I use the findings presented by Brody et al. (2007) and Costanza et al., (2008) that wetlands may act as a natural buffer to storm flooding and therefore reduce the probability of flood damage in the area they protect.

Given the evidence presented, this paper will use regression analysis to attempt to statistically determine the contributions of maximum sustained winds, rainfall, frequency of storms, density of buildings, and spatial extent of wetlands in influencing economic damages from tropical cyclones in the US between 1992 and 2012.

To use the language of the IPCC (2014) and that of Peduzzi et al. (2002), the latter of whom has contributed to analysis for the United Nations Environment Programme Global Resource Information Database, this present paper will speak interchangeably about economic damages being a function of intensity, physical exposure and vulnerability to storms and the proxy measures for each where applicable. The intensity of a storm is measured as the maximum sustained winds (MSW) and total rainfall, while

physical exposure is a product of the frequency of storms and the area of densely developed urban areas. Vulnerability to storms is measured as the area (in km²) of two different wetland types as a proportion of the total area covered by each storm.

The contribution of wetlands to economic damages that result from tropical storms is a particularly interesting component of this analysis. While the main goal in this study is to understand how economic damages may fluctuate with changing intensities, exposure and vulnerabilities; the proportion of damages explained by wetland extent provides a monetary value for those wetlands. This monetary value should be added onto existing monetary figures for wetlands to give an overall value of a given area of wetland to be used in cost-benefit analysis and other such tools to inform policy decisions.

Chapter 2 provides a literature review to help understand what has been done and which characteristics of areas hit by tropical cyclones could determine the variations in economic damages that result. Chapter 3 presents a detailed description of the methods used in this present study to understand the variables important to explaining the variations in economic damages. The results of this paper and a discussion on their interpretation are presented in chapters 4 and 5, respectively.

Chapter 2: Literature Review

Section 2.0: Introduction

This chapter will review the literature on what can explain the variations in economic damages that result from tropical cyclones, how disaster risk is quantified, and the variables used to assess disaster risk. I review five recently published works on these topics in an effort to clarify the nuances of this present paper's research question as it pertains to the functional form that damages may take, the explanatory variables involved in the equation, and methods for assessing the relationship between explanatory variables and economic damages. What is of interest to this study is which characteristics of land use and specifically wetland extent have any relationship with the variations in economic damages.

Section 2.1: Literature Review

A paper by Peduzzi et al. (2002) used the UN (1971) definition to form three hypotheses about risks resulting from earthquakes, cyclones, floods and volcanoes. They suggested that risk is a function of some specified hazard occurrence probability, elements at risk and vulnerability (Peduzzi et al, 2002, pg. 4). The first hypothesis was that the three factors explaining risk should be multiplied together such that,

$$K = H \times Population \times \mathbf{Vulnerability} \quad [1]$$

In equation 1, K = risk of the potential loss resulting from a future hazard, H = hazard probability, Population = population exposed to a hazard and Vulnerability = a vector of vulnerability variables of individuals based on socio-politico-economic factors. Their

argument supporting this hypothesis went as follows. There is zero risk of a disaster if any number of vulnerable individuals are not exposed to a hazard. Moreover, at the other extreme, even if hazards are great, the risk is also zero if nobody lives in the area exposed to hazards (population=0) or if the population is invulnerable to hazards (Vulnerability=0).

Peduzzi et al. used human lives lost as a proxy for risk and suggested that hazard probability in [1] multiplied by the population could then be replaced by physical exposure. Expected human lives lost is now a function of physical exposure and vulnerability to a given hazard such that

$$K = \text{Phyexp} \times \text{Vulnerability}. \quad [2]$$

Peduzzi et al. (2002) hypothesized that physical exposure and vulnerability will influence the number of lives lost to some power, be it to the power of one or otherwise. What is of further interest is the relationship between the variables that make up vulnerability and physical exposure. Peduzzi et al. (2002) argued that products and ratios of variables allow for the identification of combined effects between different variables that make up both physical exposure and vulnerability. For example, rapid urban growth and low GDP per capita may lead to higher vulnerability, whereas the two factors taken individually cannot be related to vulnerability.

Adding a power term to each variable in equation [2] gives the multiplicative model:

$$K = C (\text{Phyexp})^\alpha (\mathbf{V}_i)^{\beta_i} \quad [3]$$

Note that there are subscript i 's on the vulnerability variable. This is because Peduzzi suggested that vulnerability is a vector of variables and used stepwise regressions to determine which of the vulnerability variables should be included in the regression. Peduzzi et al. wanted to estimate the relative effects of physical exposure and vulnerability on the number of lives lost from given hazards. To linearize [3] in order to give an estimate the coefficients on each variable, the natural logarithms of both sides of equation [3] were taken giving

$$\ln K = \ln(C) + \alpha \ln \text{Phyexp} + \beta_i \ln V_i \quad [4]$$

Now that the model has been described, I will look at the results from Peduzzi et al. (2002) and the variables used in their risk analysis are discussed. As discussed above, expected human lives lost were used as a proxy for risk. Human lives lost was used because other indicators such as wounded, homeless, and the number of people affected, either had variances too high for Peduzzi et al. (2002, pg. 9) to use in their analysis or were not usable because of large gaps in the data. For their analysis, they regressed human lives lost on physical exposure and vulnerability parameters to assess the expected lives lost for earthquakes, cyclones, volcanoes, and floods.

Since only the impact of tropical cyclones are of interest in this paper, the only two types of hazards from Peduzzi et al. (2002) that will be reviewed here are flooding and windstorm losses. When attempting to calculate the physical exposure to flooding, Peduzzi et al. (2002) ran into data problems in that they were unable to find a global database on floods. Due to the lack of information on the duration and severity of floods, only one class of intensity could be made, though this intensity class remains undefined in

their paper. In the Centre for Research on the Epidemiology of Disasters (CRED) database, a georeference of the floods was produced and a link between the watershed and the events was made.

Watersheds affected were mapped for the period of 1980-2000 and a frequency of flooding was derived for each by dividing the total number of events by 21 years. The watersheds were then split to follow country borders, and the population of individuals living within each watershed was extracted using Geographical Information Systems (GIS) and multiplied by the frequency of flooding events to get the average yearly physical exposure.

Peduzzi et al (2002) define tropical cyclones using the Saffir-Simpson tropical cyclones classification based on the maximum sustained surface wind (MSW) where MSW is defined as the peak 1-minute wind at the standard meteorological observation height of 10 m over unobstructed exposure (Schott et al. 2012). Tropical cyclones are considered to be storms where the maximum sustained surface wind speed is greater than 33m/s and is divided into four sub categories based on their geographical location. These categories are: "hurricanes", "typhoons", "severe tropical cyclones", "severe cyclonic storms" (Landsea, 2000). The authors looked at only 11 years worth of storms and don't describe the number of storms considered for their analysis, which throws the credibility of their results into question due to a shortage of observations.

For the compilation of physical exposure to cyclones, there were again problems with data collection and two approaches were used. Under the first approach, the authors used a horizontal wind structure model or the raster approach depending on the data

available (Peduzzi et al., 2002, pg. 17). “The horizontal wind structure model calculates the symmetric winds and it assumes that the tropical cyclone surface pressure field follows a modified rectangular hyperbola” (Peduzzi et al., 2002, pg 17). The raster approach delineates annual probabilities of occurrence of tropical cyclones into 5 x 5 decimal degrees cells. Probabilities are based on tropical cyclone activity of a specific record period, except for several estimated values attributed to areas that may present occasional activity but where no tropical cyclones were observed during the record period. A frequency per year is derived for each cell. Cells are divided to follow country border, then population is extracted and multiplied by the frequency in order to obtain the average yearly physical exposure for each cell (Peduzzi et al., 2002).

In an effort to extract the number of persons affected by a specific cyclone, information on tracks, sustained wind, and central pressure were obtained (Peduzzi et al., 2002, pg 17). The computation of a frequency could not be derived in absence of a coherent spatial unit (due to large discrepancies in country size). To overcome this difficulty, the computation was made by adding the population affected and then divided by the number of years (pg.18).

Peduzzi et al. (2002) selected variables for each type of hazard using numerous stepwise linear regressions in order to highlight significant independent variables using [4]. Peduzzi et al. validate each regression by evaluating R^2 , conducting variance analysis and detailed residual analysis. They showed that this model allows the identification of parameters leading to higher/lower risk and the estimation of coefficients. (p. 25).

The stepwise selection process and subsequent reliance on R^2 for model validation introduces significant problems with the results described in their paper. First, models using stepwise regression have been shown to frequently fail to replicate when applied to new sets of comparable data (Judd and McClelland, 1989). This drawback of not having external validity is problematic for policy makers who might use this information to create policy for areas outside of the specific locations used in Peduzzi et al. (2002).

Second, the reliance on stepwise regression produces R^2 values that are biased upwards (Judd and McClelland 1989). Since Peduzzi et al. (2002) relied on these R^2 values to select dependent variables and these R^2 values are higher than they ought to be, the results may not yield the true model for risk. Judd and McClelland (1989) sum up the problems with stepwise regression analysis quite succinctly in saying “It is our experience and strong belief that better models and a better understanding of one’s data result from focused data analysis, guided by substantive theory,” (p. 204). That said, results might be used to guide new theories that could then be tested using new data.

The variables selected by the statistical analysis for floods are physical exposure, GDP per capita and local density of population. These two socioeconomic vulnerability variables show that when a population is more physically exposed with fewer means to rebound from a flood, there will be a higher number of casualties. More surprisingly, countries with low population density were found to be more vulnerable than countries with high population density (pg. 34). The authors wondered whether this could be due to a higher level of organization in more densely populated areas resulting in faster response times and more general aid available.

This could indeed be the case and when the dependent variable in the model is lives lost, however the sign of the coefficient may change when considering economic damages. For example, if a higher population density has a better emergency response time, total lives lost could fall. However, building damages might be independent of emergency response and (assuming a higher population density brings a larger number of buildings) more buildings would cause damages to rise. That said, for a given frequency of storms, a greater population density may also bring better adaptation plans and lessen the vulnerability of the population to flood damage.

The stepwise regression results for cyclones suggest that besides the physical exposure, the Human Development Index (HDI) and the percentage of arable land are selected indicators for vulnerability to cyclone hazards (pg. 33). The resulting regression equation suggests that HDI is inversely related to lives lost while percentage of arable land is positively related to lives lost. Again, it should be expected that a higher HDI score be associated with a lower level of lives lost as a country with higher development should have the capacity to deal with cyclone related injuries far faster than a country with a lower score.

The percentage of arable land is an interesting variable to have included when the dependent variable is lives lost. Peduzzi et al. argue that those countries with a high dependence on agriculture would suffer greater lives lost due to cyclones. The causal link behind this relationship is not very well explored however and further discussion as to why this may be the case is unfortunately missing. It would be understandable to see this relationship exist if the dependent variable were economic damages, as the income of those affected would be significantly reduced immediately with large amounts of crop

damage. If storms destroy large percentages of agricultural land in regions where agriculture makes up a large share of GDP, then economic damages should not only be high but also lead to a disaster, as defined in chapter 1. It could be the case that this percentage of arable land variable shouldn't be in the model and is present because of the limitations in using stepwise procedures, for example due to a spurious relationship (Judd and McClelland, 1989).

One shortcoming of Peduzzi et al. (2002) is not taking into account variables relevant to individual hurricanes such as maximum wind speeds, rainfall, duration overland etc. As noted with regards to the next paper to be reviewed, there is a significant relationship between maximum sustained winds of a hurricane and the economic damages which result. One would expect higher number of persons killed as the MSW increases, though possibly not to the same degree as described below.

Nordhaus (2006) investigates several broad questions about trends in the frequency and power of hurricanes, trends in vulnerability to hurricanes, how maximum sustained winds at landfall relate to economic damages, and finally how ocean warming is likely to lead to stronger hurricanes. I will not discuss Nordhaus's work on the relationship between warming and strength of hurricanes as they are not directly related to the questions posed in this paper.

Nordhaus describes how, in a given year, damages statistically depend upon total output, the capital-intensity of output, the location of economic activity, the number of storms, the intensity of storms, and the geographical features of the affected areas (Part III, pg. 5) He suggests that the economic impact of storms is linear in frequency, i.e. that

more storms cause more damage in the same year. However, damages from individual events across years may not be linear in frequency because societies should be learning and adapting to storms. For example, an area that gets hit more frequently by storms year after year should be better equipped to prevent damages and have different building standards in comparison with prevent an area that rarely gets hit with storms. It could also be the case the a greater number of storms in the same year cause damages to rise exponentially as infrastructure meant to protect against storms gets diminished with repeated storms.

Nordhaus (2006, pg.7) investigated what he calls the “damage-intensity function”, which is the relationship between wind speed at landfall and damages. Nordhaus noted that the conventional assumption about the relationship between damages and wind speed is to assume that damages are a function of wind speed to either the second or third power (See the footnote in Nordhaus on pg. 6). He pointed out however that this presumption is based on an energy-wind speed relationship, which is not necessarily applicable to the impact of wind and water on damages to designed structures (Nordhaus, 2006, pg. 7).

Nordhaus used a simple OLS regression to estimate the relationship between economic damages and maximum sustained wind speed, while controlling for “drift factors” by including the year of the hurricane. He used a double log model in which damages per unit GDP were the dependent variable regressed on the log of wind speed and the year. Nordhaus (pg. 7) found that economic damages increase to the 8th power of wind speed. He mentioned three possible causes of this incredibly high result including potential biases because of the omitted storm variables, statistical bias, and the highly non-linear relationship between physical damages and wind stress.

Nordhaus discussed other important variables not included in the initial OLS regression, including measures of the entire time series of central wind speeds of the storm, the wind speeds for the entire region affected by the storm, and the quantity of vulnerable capital affected by the storm. For assessing the changes in vulnerability to hurricanes over time, Nordhaus uses his G-Econ Dataset to get a rough estimate of the “intrinsic vulnerability” by examining the magnitude of the nation’s capital stock that is in coastal areas and at low elevation (pg.4). To get a better resolution of vulnerability, Nordhaus, on pg. 5, further divided the country into subgridcells of 10’ by 10’ (approximately 15 by 15 kilometers) for the vulnerable Atlantic coast of the United States, and then estimated the capital stocks for each subgridcell (pg. 5).

Nordhaus found that accounting for vulnerable capital and the entire storm path not only improved the fit of the model, it also increased the coefficient estimate for wind speed to 8.5. Furthermore, the time trend in the OLS full-sample equation found that normalized damages rose by 2.9 percent per year, indicating *increased* vulnerability to storms of a given size (Nordhaus, 2006, pg.12)

Nordhaus correctly hypothesized that wind speeds calculated in years prior to 1960, when the use of satellite measuring came into popular use, were subject to more error. To ensure that there was no contamination of measurement error from wind speeds early on in the sample he used a TSLS approach using minimum pressure as an instrument for wind speeds (Nordhaus, 2006). Nordhaus found that the TSLS estimates yielded a high elasticity of damage per unit GDP with respect to wind speeds. He found that this elasticity was 9.1, which he says would be expected if the wind speed is measured with substantial error.

The final check on the relationship between wind speed and economic damages was to look at how designed structures interact with wind speeds when a fracture occurs in the structure. Nordhaus argued that structures are designed to take a certain wind stress load, which if exceeded causes the structure to crumble. If I were to estimate the elasticity of damages with respect to a stress (such as wind or water) on a building, it would be very small up to the fracture level and then extremely high as the material fractured. His argument is then that I see such high elasticity of damages to wind speed because of the relationship between the strength of a building relative to the strength of the storm. At wind speeds within the capability of buildings, there should be little to no damage occurring. At wind speeds greater than the intended use of a building, the building material will fracture and damages will exponentially increase. This is a logically sound argument but no information directly observing damages at lower wind speed relative to damages at hurricane strength wind speeds was presented. Having data on storms with lower wind speeds would help strengthen his argument if the data showed consistently lower damages at lower wind speeds.

Nordhaus concluded that damages statistically increase to the 8th power of MSW as the result is robust to several different measures and estimation techniques. What's more, economic vulnerability increases sharply with MSW and because hurricanes are rare events, I am likely to observe the wind speed – damage relationship at the point where sharply non-linear failures arise (Nordhaus, pg.12). In other words, when studying only hurricanes, we are observing damages that result from structural failure of buildings, which increases exponentially once an initial structural break happens and thus the elasticity of damages is not constant.

Section 2.2: Land cover variables for explaining economic damages

There are only two empirical studies utilizing regression methods to understand whether economic damages from flooding events can be explained by wetlands (Costanza et al. 2008; Brody et al. 2007). While neither study looked at risk or classified variables into physical exposure and vulnerability categories, Brody et al. (2007) did control for physical and socioeconomic characteristics while Costanza et al. (2008) controlled for wind speed. Further, Brody et al. (2007) did not look at hurricanes in particular but did assess economic damages in-relation to flooding events in general. They were unable to identify the specific source of a given flood but it is generally understood that these floods resulted from precipitation.

Brody et al. (2007) motivated their paper by saying that “despite the prevalence of policy and engineering measures to reduce the adverse impacts of floods, they remain one of the greatest threats to the property and safety of human communities in the United States among all natural hazards” (pg.1). Due to the lack of GIS data, the authors note that no study to date has thoroughly tested the impact of the human built environment based only on multiple flood events over time, at large spatial scales, while controlling for biophysical and socio-economic characteristics (pg. 2).

The authors argue throughout the introductory sections of the paper that increases in population density, the number of impervious surfaces, the alteration of hydrological systems and an overall diminishing capacity for these systems to hold and store surface water, contribute to an increase the damage due to flooding (Brody et al., 2007. pg. 4).

To address the current lack of research as noted above, Brody et al. (2007, pg. 5) assess

how the built environment influences flooding impacts in the eastern portion of Texas. This area was chosen because Texas experiences the highest amount of damages due to flooding in comparison to any other state. Eastern Texas specifically has been experiencing large increases in impervious surfaces and alteration of wetlands associated with rapid coastal development (pg. 5).

It is important to note that this study excluded tidal and storm-surge flooding and so only focused on flooding events due to rainfall. Why tidal and storm surge flooding were excluded is not very clear. The area of study is mostly coastal and it is well established that coastal wetlands help reduce storm surge flooding (Wamsely et al. 2010) and so there is some theoretical basis for their inclusion. The implication for Brody et al. (2007) is that coastal wetlands that should be excluded based on the exclusion of coastal flooding data may have been included in their analysis where they shouldn't be. To view a map of the study area, see Brody et al. (2007, pg. 10).

Furthermore, their study doesn't differentiate wetland types that have been shown to interact differently with storm surge and rainfall flooding (Wamsely et al. 2010). This reason for the lack of delineation of wetland types not explained and is especially confusing as the authors spend a few paragraphs detailing how different wetland types contribute in different ways to peak flood (the highest point of the flood water level).

The authors calculated property damage measured as the total dollar loss (consumer price index adjusted 1997 UD) resulting from 423 flood events between 1997 and 2001 at the county level. Using multiple regression analysis, the impact of wetland alteration, impervious surface, and dams on reported property damages was estimated

while controlling for biophysical and socio-economic characteristics (Brody et al. 2007, pg. 2).

They controlled for biophysical, built environment and socio-economic variables including precipitation, flood duration and flood plain overlap, impervious surfaces (calculated as the percentage of land covered by buildings and pavement in a county area), wetland alteration (measured as the cumulative total of spatially defined wetland permits¹ the day of a flood event), median household income (which is the sum of money income received in calendar year 1999 by all household members of 15 years and over, including household members not related to the householder, people living alone, and other non-family household members) and a Federal Emergency Management Agency (FEMA) rating score for each county.

The socio-economic variable ‘FEMA rating score’ is based on the FEMA Community Rating System (CRS). The CRS promotes mitigation of flood damage through insurance premium discounts and other financial incentives to counties, which have shown they have taken actions to mitigate flooding events (Brody et al. 2007, pg.8).

The second socio-economic variable, median income, was used because the authors presumed that wealthier communities have the financial capacity to mitigate flooding more effectively but at the same time can lose greater amounts of financial capital from damaging floods (Brody et al. 2007, pg. 8).

¹ Wetland Permits are permits to destroy wetlands for development and include general permits, nationwide permits, letters of permission and individual permits (Brody et al., 2007).

For their analysis the authors sequentially added the previously mentioned three suites of variables (biophysical; built; and socio-economic environments) to the model to test their effects both individually and as a group (Brody et al. 2007, pg. 9). The first iteration controlled only for biophysical variables and found the amount of rainfall the day before the event to be the greatest predictor of damage followed by the duration of the flood (pg. 9). When built environment and socio-economic variables were added to the model a surprising result was realized what is gained by dams in the mitigation of flood outcomes is statistically offset by development activities in wetlands (Brody et al. 2007, pg. 12). When only built environment and biophysical variables were included, the presence of dams as flood control reduced the amount of damage almost to the same degree to which damages were exacerbated by wetland alteration. Impervious surfaces were also highlighted as a statistically significant variable since increasing the area of impervious surfaces lead to an increase in flood damage.

When the fully specified model including socio-economic variables was used, the offsetting relationship between dams and wetlands expanded. Wetland alteration continued to have the largest effect on the dependent variable among built environment variables while the predictive power of the total number of dams within a county, representing structural solutions to flood mitigation, decreases (pg. 12).

This paper by Brody et al. provides a great start to understanding the relationship between our built environment and flood damages. Their methods could easily be applied to areas outside of Texas if wetland permit data is available, however; their work does not consider flooding from storm surge and so may not be accurate along coastal regions.

The next paper reviewed is by Costanza et al., (2008) where they used a very unique method for assessing the value of wetlands relative to hurricane damage in the United States. They investigated 34 hurricanes between 1980 and 2004 and created a dataset for the area of wetlands within a 100km wide X 100km inland swath of each hurricane. They then used nighttime light imagery to estimate the GDP within each swath; a method proven to be a very accurate estimate of GDP in recent literature, see Sutton et al. (2002). Estimating GDP with satellite imagery is not however without its critics when used in countries with sufficient data such as the US (Nordhaus, 2010).

Costanza et al. (2008) used this GDP proxy to normalize the associated economic damages from each hurricane. Normalization methods vary widely (see Pielke et al. 1998; Neumayer et al., 2011; Nordhaus, 2006) but the general goal is to adjust damages to allow better comparisons across geographic regions.

As impressive as the methodology in Costanza et al. (2008) is, there are a few gaps in their study. First, wetland data used was from only one year, yet their study covered hurricanes dating back to 1985. They used wetland data from the year 2000 as a layer² for every hurricane over all years in the study and only accounted for the decrease in wetland extent for Louisiana because of the substantial wetland loss over the period of study (Costanza et al. 2008, pg. 242). This method was employed in spite of the availability of wetland data from 1992-present compiled every five years by the NOAA.

² A layer in GIS is a slice or stratum of the geographic reality in a particular area, and is more or less equivalent to a legend item on a paper map. On a road map, for example, roads, national parks, political boundaries, and rivers might be considered different layers (Esri, 2014).

This oversight may have introduced substantial error for wetland extent outside of year 2000.

Another oversight in the Costanza et al. (2008) paper is that the regression equation used suffers from a similar draw back as Peduzzi et al. (2002) in that any theoretical basis for the explanatory variables being selected is seemingly arbitrary. For example, using the model presented in Costanza et al. (2008), economic damages can be explained by wind damage and wetland extent alone. They do control for one aspect of vulnerability in that they divided total damages by GDP but what about other potentially important factors such as density of buildings, impermeable surfaces, and physical exposure? These are important elements that could explain the variation in economic damages due to hurricane and are not explored in the paper.

One could argue, however, that the exclusion of socioeconomic variables and alike is not a problem if the omitted variables are not causing omitted variable bias or if one could not improve the fit of the model by including them. Costanza et al. (2008) does use Akaike's Information Criterion (AIC) to compare their model shown in equation 5 below, against a model containing only damages and maximum sustained winds. Their results suggest that the better model was

$$\ln \frac{TD_i}{GDP_i} = \alpha + \beta_1 \ln MSW_i + \beta_2 \ln w_i + \varepsilon_i, \quad [5]$$

Where ED_i/GDP_i represents total damages per unit GDP from hurricane i , MSW_i represent the maximum sustained wind speed of a given hurricane i , and w_i represent the hectares of wetlands present in the swath of the hurricane.

One problem with this test using AIC is that it only says that equation 5 is better than a more reduced model and doesn't extend to give suggestions about models with more variables. Furthermore, they did not test for omitted variable bias and so we aren't sure if their model could be improved by adding in other explanatory variables.

The results of their regression suggest that the coefficient on wind speed is different than that of Nordhaus (2006) but is in line with the standard relationship estimated between power and maximum sustained wind speed where the economic damages increases to the 3.878 power of speed (Costanza et al., 2008, pg. 243). While their estimate lines up with the relationship between power and wind speed and building destruction, this doesn't necessarily mean that the relationship between wind speed and economic damages behaves the same see Nordhaus (2006, pg.3).

Costanza et al. (2008) were able to differentiate between two wetland types, herbaceous wetlands and forested wetlands. They found that forested wetlands did not produce a significant result while herbaceous wetlands were significant. The estimated coefficient of the elasticity of damages per unit GDP with respect to wetland extent of -0.77 suggests that economic damages decrease quite rapidly with increases in wetland area. To calculate the marginal value of wetlands, Costanza et al., (2008, pg. 243) look at the avoided damages per unit area of wetlands. The difference in total damages from cyclone i (TD_i) with a loss of area a of wetland area (w_i) is represented by the equation

$$\Delta TD_i = e^\alpha \times MSW_i^{\beta_1} \times [(w_i - a)^{\beta_2} - w_i^{\beta_2}] \times GDP_i. \quad [6]$$

If a is small relative to w_i , this represents the marginal value per unit area of wetlands in preventing storm damage from a specific hurricane (Costanza et al. 2008, pg. 244).

Costanza et al. (2008) calculated the marginal value of wetlands for each of the 34 hurricanes covered in their study. They found the median value to be \$5000 ha⁻¹ with an average reduction in damages to be \$33,000 ha⁻¹ (Costanza et al., 2008, pg. 244). This information is very useful for policy makers at the state and municipal level because the marginal value of wetlands for storm protection gives a cost to developing over wetlands in hurricane prone areas. The authors go on to calculate the annual total value of wetlands for storm protection, however these calculations are outside the scope of this present study and thus will not be reviewed here.

The final paper reviewed is one by Zia (2012) which studies the long-term economic damage function while including land use and land cover trends in an effort to accurately forecast inflation adjusted expected damages under different climate change scenarios. His study developed a time series forecasting model to predict the inflation adjusted damages at different intensities of hurricanes, while controlling for housing densities of areas impacted by the hurricanes (Zia, 2012, pg. 920). This review only covers the beginning of Zia (2012) as this present study is not looking to predict changes in damages due to varying climate change scenarios.

Zia (2012) estimated that the average adjusted annual damages from hurricanes in the US was \$2937.73 million in 2005 dollars with an average of 1.62 hurricanes making landfall annually. Zia's estimate of average population density affected by hurricanes was 182 persons/square mile and on average 1.01 million houses were affected every year. Also, similar to Nordhaus (2006), Zia found an upward trend in annualized damages but no such trend between the frequency of hurricanes making landfall and the presence of La Nina or El Nino years.

Changing the functional form of the linear model by taking the log of damages sufficiently reduced the heteroskedasticity and, though still present, lessened the significance of autocorrelation (Zia, 2012). To account for the temporal autocorrelation, both Prais-Winsten and ARMA modeling approaches were used. Zia (2012) reported that the Prais-Winsten model appeared to be the most robust with no evidence for heteroskedasticity and first order autocorrelation. Their model predicted that a one percent increase in the average intensity of land falling hurricanes would be significantly ($p < 0.01$) correlated with a 130% increase in the log of annualized damages, holding all else constant. For context, Zia reported that the mean intensity of hurricanes was 1.71 on the Saffir-Simpson scale and the expected increase in storm intensity was between 8-16% over the 21st century (pg. 927). This change, according to his results would cause damages to increase by \$US 305.84 million to US\$611.69 million in 2005 constant dollars.

With respect to land use and land cover, their model predicted that a 1% increase in the agricultural land cover increases annualized damages by 1.51%, which is equivalent to approximately US\$ 44.35 million. This finding is intuitively understandable as total damages reported included damages to crops and livestock. If more agricultural land cover was affected by a given hurricane, one would reasonably expect there to be greater damages on average. Zia found that an average increase of 1 house per square mile of affected area resulted in a 2.68% increase in damages, or, in monetary terms, an increase of US\$ 78.73 million.

The summary of Zia's results is that the effects of housing density and agricultural land-cover have a significantly positive effect on damages from hurricanes (Zia, 2012, pg.

928). His paper suggests that a medium to long term land use adaptation, in the form of capping housing density and agricultural cover in the coastal states, can significantly reduce economic damages from intense hurricanes (Zia, 2012, pg. 931).

Section 2.3: Conclusion

The review suggests that storm intensity (Nordhaus, 2006; Costanza et al., 2008; Zia, 2013), a given population's physical exposure to hazards (Peduzzi et al. 2002) and its vulnerability (Nordhaus, 2012) are all significant variables to be considered when building a economic damages function. Furthermore, Brody et al. (2007) and to a more limited degree Costanza et al. (2008) show that wetlands have a significant influence on economic damages from flooding events. In the following chapter, a detailed description of the methods used to understand to what degree the aforementioned variables are important and with what functional form they are predicted to influence economic damages is presented.

Chapter 3: Data and Variables

Section 3.0: Introduction to methods

In this paper I am seeking to understand how the economic damages per unit gross spatial product (GSP) may be explained by the intensity of tropical cyclones, physical exposure and vulnerability of populations to storms occurring. Storm intensity is a vector containing MSW, total rainfall and the duration in hours of each storm. Vulnerability to storms is measured by the proportion of wetlands relative to the total area affected by each storm. I created a double log model to estimate the elasticity of economic damages per unit GSP to all three vectors. The regression equation used for estimation is

$$\ln(ED_i / GSP_i) = \alpha + \beta_1 \ln(Intensity_i) + \beta_2 \ln(Physical Exposure_i) + \beta_3 \ln(Vulnerability_i) + \varepsilon_i. [7]$$

The methods employed to generate data on dependent variables and the tracks of the storm were largely borrowed from Costanza et al. (2008). The work of Peduzzi et al. (2002) was drawn upon and modified with different variables to model the economic damages associated with tropical cyclones. This chapter outlines the variables used, the justification for their inclusion, their source and, where applicable, the details of the units of measure.

Section 3.1: Creating the dataset

Data on land classifications for wetlands and high intensity development, was downloaded from the NOAA Coastal Change Analysis Program (C-CAP) for years available (1992-2010) for 18 states: Texas, Louisiana, Mississippi, Alabama, Georgia, Florida, South Carolina, North Carolina, Virginia, Maryland, Delaware, Pennsylvania,

New Jersey, New York, Connecticut, New Hampshire, Massachusetts, and Maine.

Data on economic damages were downloaded from The National Hurricane Center and filtered to include all named tropical cyclones to come within 200 km of shore in the US between the years 1992 and 2012. The filtered results produced 94 hurricanes and tropical storms. The digital track of each storm was downloaded from the NOAA Historical Hurricane Tracker (NOAA, 2014) along with a detailed storm report explaining the meteorological characteristics, damages, and other detailed information throughout the life of the storm.

Using Geographical Information Systems (GIS) software, a distance of 100 km on either side of each storm track was measured to create a continuous swath until the storm became a tropical depression and/or was 200km or greater from the coast. See Figure 1 below for an example. The square area of each variable within the swath was measured and recorded (see Costanza et al. 2008).

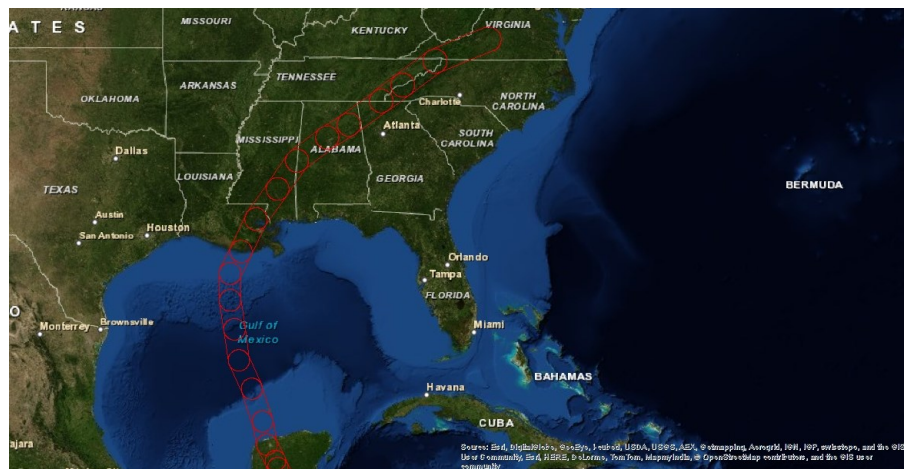


Figure 1: Swath for hurricane Bill overlaid on the US in ArcGIS.

Section 3.2: Hurricane Swath justification

In Costanza et al. (2008) the size of the swath was determined using visual observations of destruction. As discussed in the previous chapter, this is a poor estimate of the scale of flood damage and would be more appropriate if wind damage was the only dependent variable. The economic damage data used in this study was not disaggregated to reveal which proportion of total damages was from flooding or wind. As there is often substantial damage caused by both wind and flooding from tropical cyclones (NOAA, 2014), I could not use the wind field radius to provide information about the width of the swath.

The ideal method for defining the size of the swath would be to use a combination of storm surge distribution along the coast and location of heavy rainfall relative to the center of the hurricane track. Neither of these two options had available or reliable data. In comparing the size of the swath used in Costanza et al. (2008) with the storm reports from NOAA, the 100 km total width and 100 km inland from the shore was too small to include damages reported in various locations in the storm reports. Creating a 200 km wide swath (100 km on either side) on the center of the storm tracks downloaded from NOAA was sufficient to cover the majority of the locations cited with damages in the storm report.

In further contrast to the methods employed in Costanza et al. (2008), this study continues the buffer throughout the life of the storm to include inland areas where damages from flooding were reported in addition to those damages reported along the

coast. I did this because NOAA reports substantial inland flooding damage from tropical storms and stopping the buffer only 100 km from the shore as done in Costanza et al. (2008) would not be accurate.

Section 3.3.0: Dependent variable

The dependent variable used in this study was economic damages (adjusted for inflation using the US housing price index to year 2000) per unit GSP. I used the unadjusted economic damages as reported by NOAA and then normalized them according to the methods described below. NOAA's method of calculating total damages is to take reported insurance damage from a given storm and double that number to account for damages not covered by insurance (Zia, 2012). This method of doubling insured loss data has been found to produce large errors in some estimates for individual counties within the US, but no statistically significant tendency to underestimate or overestimate (Downton et al., 2005). The methods used by NOAA to calculate damages are undesirable but at least consistent. As damages were reported unadjusted for inflation, I converted all damages to constant dollars for the year 2000 using the US Housing Price Index (HPI).

Section 3.3.1: Normalization of damages using nighttime satellite imagery

Based on earlier analysis, when comparing economic damages through time, those damages should be "normalized" to account for changes in GDP and population per capita (Pielke, 1998; Nordhaus, 2006; Neumayer et al. 2011). In this present paper, I did not look for trends in damages over time but was nonetheless comparing damages from different storms across space and years in an effort to understand how those damages

were influenced by the independent variables described below.

Unfortunately data on GDP, wealth per capita, or population in the US was only readily available at metropolitan or state levels. Yet the track for each storm cut across defined metropolitan lines and often only affects a portion of several metropolitan areas at the same time. Because of this, I was unable to collect data directly and had to appeal to alternative methods.

I applied a method used previously by Constanza et al. (2008) and Sutton et al. (2002) to estimate the Gross Spatial Product (GSP) within each swath by using nighttime satellite imagery. This method has been shown to be quite accurate in measuring the extent of urban land cover, population density, energy consumption, greenhouse gas emissions and other socio-economic parameters (Elvidge et al., 1997; Sutton et al., 1997; Doll et al., 2000). Estimating GSP, GDP and other such economic variables using satellite imagery is not without its critics, however, especially when used for developed countries such as the US, see (Chen and Nordhaus, 2011).

Using light imagery data from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP OLS) between 1992 and 2012, I used GIS to measure a total light energy value for each swath in this study. The DMSP OLS images have been screened for clouds and ephemeral lights such as lightning, forest fires, gas flares, and lantern fishing (Elvidge et al., 1999). The image is radiance calibrated so an integration of the values of the pixels over the land area of a given swath is a measure of total light energy (Sutton et al. 2002).

Once the light energy (LE) values were calculated for each storm, I used the

findings from Sutton et al. (2002) to estimate the GSP within each swath by

$$\ln(GSP) = -4.25 + 1.05 \ln(LE). \quad [8]$$

The coefficients in [8] were calculated for the year 1995 across the US by Sutton et al. (2002). The results of this conversion for each storm in our study can be found in Table 4a in the appendix where values are given in millions and constant year 2000 USD. The average GSP in this sample was \$67176.8 (million year 2000 US). Using the estimated GSP for each swath, I was then able to normalize economic damages by taking the ratio of real economic damages in swath i relative to the estimated real GSP present in the same swath to get,

$$\text{Normalized Economic Damages}_i = \text{Damages}_i / \text{GSP}_i. \quad [9]$$

From the papers reviewed in the previous chapter, there is a clear trend in the literature to take the natural log of damages (Costanza et al. 2008; Zia 2012; Nordhaus, 2006; Pielke et al. 2008). One problem encountered with this transformation, at least with respect to the data used in this present study, was that there were 16 storms for which economic damage was reported as zero and so applying a natural log was not possible. The smallest value, other than 0, for normalized economic damages was 0.0009 and so storms for which normalized economic damage was reported as zero, a value of 1×10^{-6} was used in place of zero.

Section 3.4: Storm intensity variables

The intensity of storms has been found to dramatically influence the economic damages associated with tropical cyclones; see Zia (2012), Costanza et al. (2008),

Nordhaus (2006) and Stern (2007). In Brody et al. (2007, pg. 12), the amount of rainfall the day prior to each flooding event was found to have a significant influence on the economic damages from a flooding event.

Variables used in this study as a proxy for intensity include maximum sustained winds at landfall (MSW) and the average amount of rain per hour of the storm over land. Storm intensity variables were taken from the storm reports presented by NOAA and the digital information contained in the downloaded track of each storm.

The digital track of each storm contains details on the maximum sustained winds (MSW) of the storm in knots every six hours of the storm's life. Using GIS, the MSW of each storm at landfall was recorded using information contained in the digital data, in accord with Nordhaus (2006). For storms that did not hit land but came within 200km of the shore, the MSW at the storm's closest point to land was used. Further, the time at which each storm either made landfall or was within 200 km of the coast was recorded until each storm was either more than 200 km from the coast or became a tropical depression. The time spent overland or duration for short is simply the total number of hours each storm spent within 200km of shore and/or overland.

There was sufficient information from all 94 storms to compute an average rainfall total from each storm though the method used to calculate the average was slightly different for some. For each storm with data on the amount of rainfall in (measured in mm) in each county affected by a given storm, all observations were recorded and then averaged over locations. For storms in which the rainfall location was not available, the storm report gave a range of rainfall that fell over all locations affected

by the storm. For storms with this level of detail, the average between the lowest and the highest figure was used.

Section 3.5: Frequency of storms

To test Nordhaus's (2006) assumption that damages increase at a rate greater than linear in frequency I hypothesize that the coefficient on frequency will be $\beta_i > 1$. I argue that each additional storm of similar intensity to make landfall in a given area creates more damages if critical infrastructure is destroyed from the previous storm. For example, if Tallahassee Florida is hit by two category 1 hurricanes in one year, the damages from the second should be greater than the first because infrastructure designed to lessen damages may have a diminished capacity to buffer the energy from the second hurricane.

To generate a measure of frequency, I counted the number of tropical cyclones classified as at least a tropical storm that passed through a 200km diameter circle centered at the landfall point of the storm being assessed and then divided that number by the number of years in this study.

Figure 2 below displays visually how I counted the frequency value for hurricane Alberto in 2006. First, the point of landfall (just to the South East of Tallahassee) was assigned to be the center of a 200km diameter circle. Then, all storms between 1992 and 2012 that passed through this circle were counted and then divided by the number of years in the study to get the average number of storms per year to strike the landfall location of Alberto.

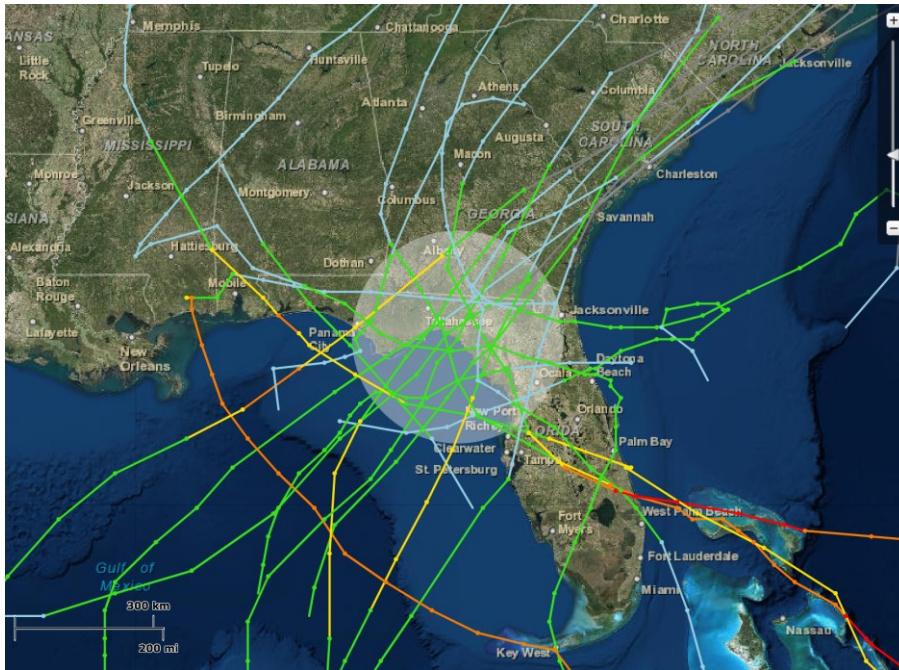


Figure 2: Tropical cyclones passing within a 200km circle centered on hurricane Alberto. Each line represents a different storm where the colour represents the intensity of the storm.

Section 3.6: Physical Exposure

Exposure to hazards can be understood as the “presence of human and ecosystem tangible and intangible assets and activities (including services) in areas affected by weather extremes (Field 2012, pg. 3). For Peduzzi et al. (2002), where human lives lost was the dependent variable, physical exposure was defined as the frequency of storms multiplied by population of a given country.

In this present paper, the use of population in place of elements at risk does not make sense with our dependent variable being only insured and non-insured losses. Since I am looking at economic damages that result from insured and non-insured losses, using the value of buildings, infrastructure, agricultural production, and services lost within a

storm track would be ideal. Unfortunately, data for these options was not directly available and so a proxy measure was used.

A variable called High Intensity Development (HID) was used as a proxy for elements in the storm track. High intensity development was the area (in km²) of the sum of high intensity residential (HIR) and commercial/ industrial development (CID). The argument for using HID in physical exposure is two fold. First, HIR and CID both require 80-100% of land cover to be constructed material and could be added together to find the total area of land covered by impervious surfaces. Second, while HIR includes such buildings as apartment complexes and row houses, CID includes areas of infrastructure (e.g. roads, railroads, etc. and all highly developed areas, which are not classified as high intensity residential). Therefore, it was reasonable to combine both into one variable that measures densely built, structures and infrastructure that could be at risk of being damaged in a storm.

Recall from chapter 2 that Brody et al. (2007) found that, between 1997 and 2001, the amount of impervious surfaces was significantly related to damages from flooding events while Zia (2012) found that the density of buildings had significant explanatory power for economic damages from tropical cyclones. It was then reasonable to hypothesize that, given a certain frequency of storms (as calculated above), a city would be more physically exposed to a tropical cyclone as the square area of HID increases. Therefore, explanatory variables in this paper will include frequency and high intensity development as a proportion of total land area in a given swath.

Section 3.6: Vulnerability

Field (2012, pg. 2) has a lengthy discussion on vulnerability being composed of two elements: the susceptibility of what is exposed to harm (loss or damage) and the capacity to recover from a hazard. The definition of vulnerability is the propensity or predisposition to be adversely affected (Field, 2012). Using this definition and considering that normalized economic damage is the dependent variable in this present paper, it follows that vulnerability to tropical cyclones should include those aspects of how much protection exists for individuals living in the path of a storm.

Given the evidence found in Brody et al. (2007) and Wamsley, et al. (2010) that wetlands may reduce damages due to flooding and storm surges, the presence of wetlands changes the probability of harm from flood and storm surge damages. In line with the definition of vulnerability from Field (2012), it can be argued that wetlands may lessen the vulnerability of a given area to damages from flooding and storm surge. In other words, an area is more vulnerable to storms if they have relatively less wetland area to lessen the impact of the storm.

There are two broader categories of wetlands used in this study (Estuarine and Palustrine) and there are several subtypes of wetlands that were included in the land cover data files. Palustrine wetlands may be situated shoreward of lakes, river channels, or estuaries; on river floodplains; in isolated catchments; or on slopes (USGS, 2014c). Estuarine wetlands are found exclusively near ocean shores where they are semi-enclosed by land but have open, partly obstructed, or sporadic access to the open ocean, and in

which ocean water is at least occasionally diluted by freshwater runoff from the land (USGS, 2013). More detailed classifications of Estuarine and Palustrine wetlands are illustrated in figures 3 and 4 respectively.

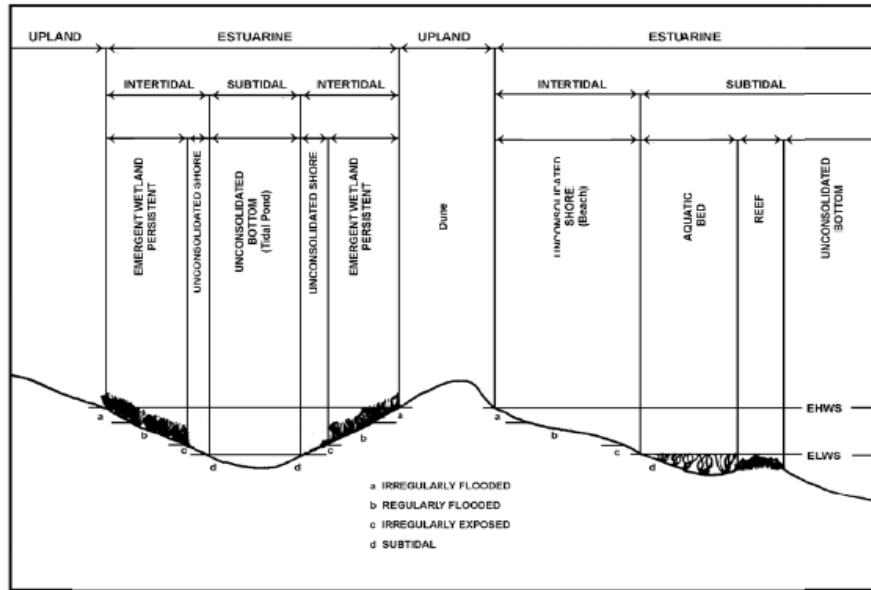


Figure 3 Classification of Estuarine wetlands as one progresses further from shore (left to right in the figure). Source: USGS (2013a).

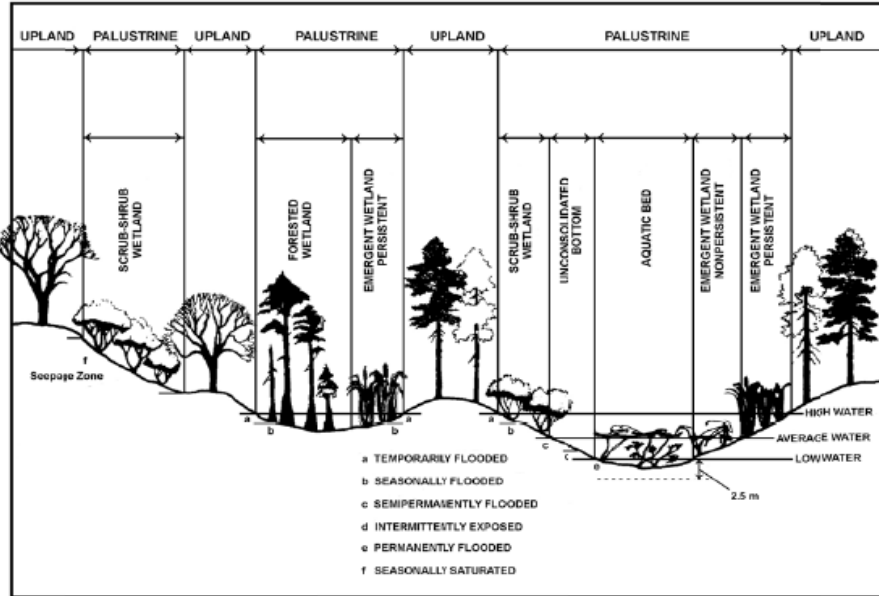


Figure 4 Classification of Palustrine wetlands relative to their positioning within an inland ecosystem. USGS (2013b).

As previously discussed, total wetland area was measured using GIS for each storm in this study. Each storm had a constant swath width of 200km, however the length of each swath may be different. As the total area covered by each storm was not constant, the ratio of wetland area to the total area was used to properly compare the effect of wetland extent on economic damages for different storm.

Section 3.7: Summary statistics

The first step in this analysis was to look at summary statistics for each variable, relationships between dependent and independent variables, distributions, and correlations between independent variables. The second step was to perform the necessary transformations of variables according to their kernel density plots. The summary statistics for all variables included in this study are displayed in Table 1 below.

The average HPI inflation adjusted damages over the study are \$2.9 billion (US

2000) per storm with a minimum value of 0 damages ranging to a maximum value of \$73 billion (US 2000). When damages are normalized using real GSP, the average damage was 11.3% of GSP with a maximum of 281% of GSP in the case of Hurricane Katrina. To give some context, Katrina caused damages of 280% of the GSP in the area that it affected. The average MSW at landfall was 116.9 km/hr (63 knots), which is a very strong tropical storm and just 3km/hr away from being classified a category 1 hurricane on the Saffir-Simpson wind scale. The average frequency of storms was 0.78 storms per year with an average rainfall of 6.35 mm/hr.

Table 1: Summary statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|--|-----|-------|-----------|--------|-------|
| Economic Damages (real yr. 2000 in millions) | 94 | 2913 | 9611 | 0 | 73004 |
| Normalized Damages | 94 | 0.113 | 0.367 | 0.0001 | 2.81 |
| MSW (km/hr) | 94 | 116.9 | 48.80 | 46.75 | 268.5 |
| Rain per hour (mm/hr) | 94 | 6.35 | 5.58 | 0.05 | 33.78 |
| Frequency (storms/year) | 94 | 0.786 | .2675 | .33 | 1.466 |
| High Intensity Development | 94 | 0.076 | 0.613 | 0.007 | 0.29 |
| Palustrine wetlands/ total area | 94 | 0.064 | 0.015 | 0.0013 | 0.867 |
| Estuarine Wetlands/total area | 94 | 0.092 | 0.111 | 0.0014 | 0.79 |

Section 3.8: Data analysis

There has been some interest in previous work about trends in economic damage from hurricanes (see Pielke et al. 1998). Figure 5 below shows the natural log of normalized economic damages spread over time and does not display any visible trend.

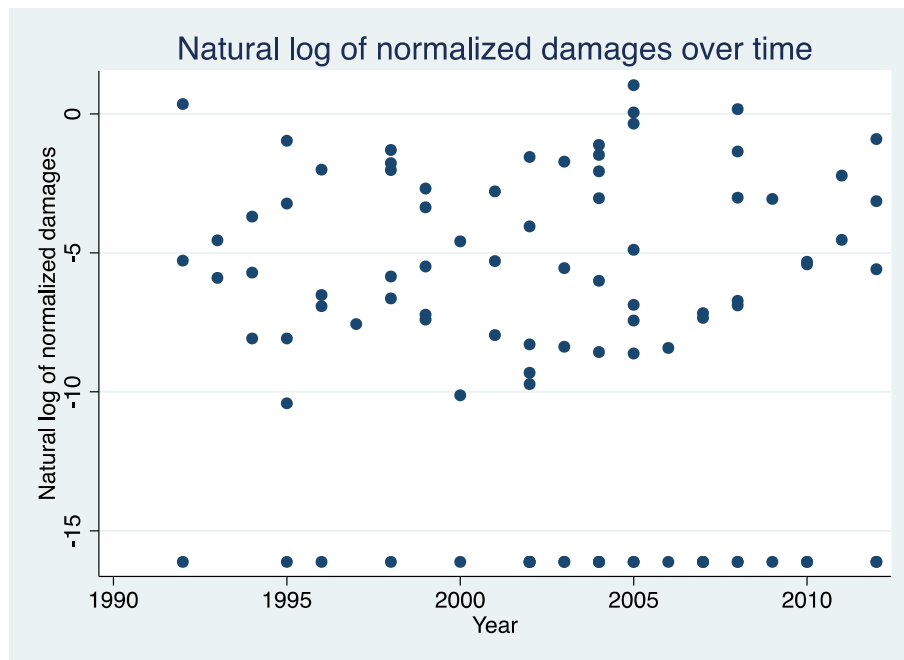


Figure 5: Natural log of normalized damages between 1992 and 2012

There has also been mention by Zia (2012) that policy makers ought to cap the density of development in hurricane prone areas. The concern in Zia (2012) is that the greater the amount of highly dense development, the higher economic damage ought to be. The data found in this present study can shed light on whether there are any observable trends in the level of development that exists in areas prone to tropical cyclones.

Figure 6 below shows a clear trend in the average amount of high intensity development areas (in km²) to be hit by tropical storms per year between 1992-2012. This

trend could be the result of more and more development along coastlines as mentioned in Nordhaus (2006) and Zia (2012).

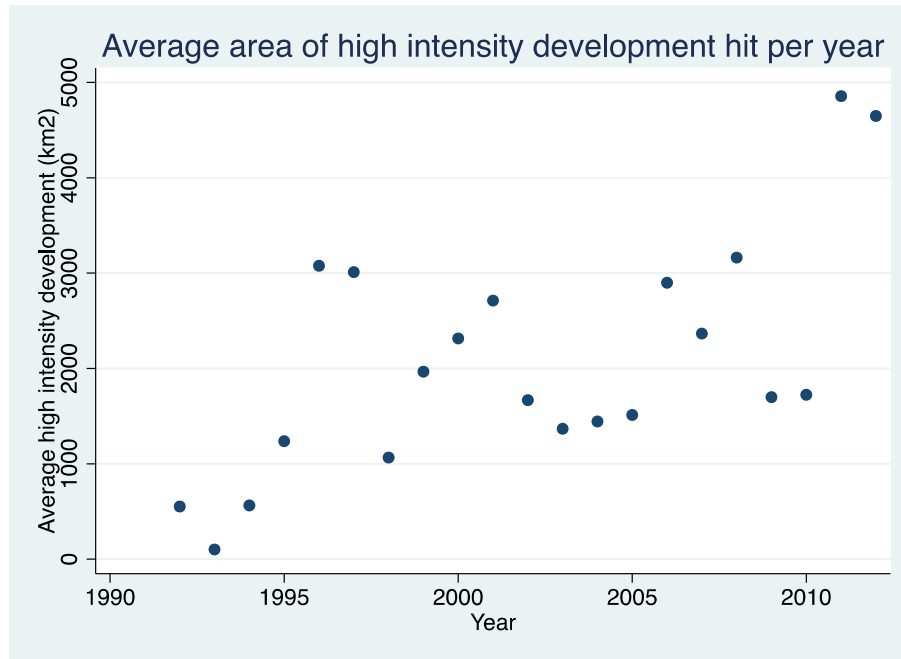


Figure 6: The average area of high intensity development hit by tropical cyclones per year

Section 3.9 Relations between normalized damages and maximum sustained winds

The first important relationship I observed was the relationship between the natural log of normalized damages and the natural log of maximum sustained winds as there is established evidence that suggests the relationship is exponential (Nordhaus, 2006; Costanza et al. 2008).

Figure 7 below shows a scatter plot of the natural log of normalized damages over the natural log of MSW. It was found that the variance of damages at lower wind speeds appears to be much greater than the variance of damages at higher wind speeds.

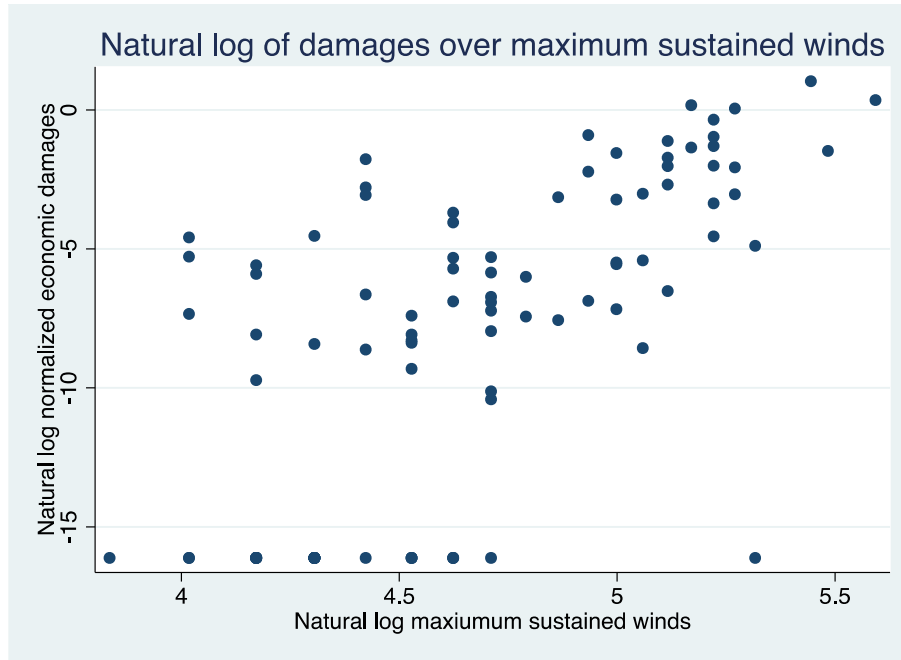


Figure 7: The natural log of normalized damages over the natural log of maximum sustained winds for all storms

Having an unequal variance over the sample causes concern for heteroskedasticity with this data. Further, it could be the case that damages vary more at lower MSW because other variables are more influential in causing damages than the winds. Therefore, a dummy variable was used such that $D = 1$ if MSW are below 116 km/hr, which is the sustained wind speed at which a storm becomes a category 1 hurricane, and $D = 0$ otherwise. This dummy variable will allow for the identification of a change in damages as storms become hurricanes.

Section 3.10: Transformation of different variables

When looking at the kernel density of unadjusted normalized economic damages (ED) as shown in Figure 9a, it is clear that a transformation was needed. Figure 10a shows that taking the natural log of normalized ED revealed a much more symmetric

distribution of damages. After adjusting for inflation using both HPI and CPI and normalizing for GSP, it was evident that taking the natural log was the appropriate transformation for them as well.

Looking at the kernel density of variables listed in Table 1 above revealed that they needed to be transformed by logs. The kernel density estimates for all log transformations are given in Figure 19a through Figure 115a. Given the necessary transformations using natural logs, using a log-linear regression was not an option with this data and a double log will be used.

As noted previously, there are 16 observations where economic damages are zero out of 94 total observations. Having almost 20% of the observations in the sample being zero, it was suggested that a probit specification maybe more appropriate. Since I am concerned about heteroskedasticity however, it makes sense to use a linear probability model with robust standard errors instead of a probit specification because probit models are more sensitive to heteroskedastic errors than are LPMs (Kennedy, 2003). The linear probability model allowed me to identify the change in the probability of normalized damages occurring with a dichotomous dependent variable that represents normalized economic damages (ED) where $ED = 1$ if normalized damages > 0 and $ED = 0$ otherwise. This model asks the same question as the probit but with less interference from violating the unequal variance assumption.

Chapter 4: Data Analysis and Results

Section 4.0: Regression equation

I have made the case over the course of the last few chapters that economic damage as a proportion of the total GSP in each swath can be modeled as a function of storm intensity, physical exposure and vulnerability. In model 1 below, intensity includes maximum sustained winds and the amount of rainfall per hour. Physical exposure includes the frequency of storms and the proportion of high intensity development in a swath while vulnerability contains the proportion of wetlands in a given swath and included both palustrine and estuarine wetlands. Further, as mentioned in the previous chapter, there is good evidence from figure 7 that the variance of damages at lower sustained wind speeds is greater than at higher sustained wind speeds. Therefore I included a dummy variable which is equal to 1 if MSW < 116km/hr and is 0 otherwise.

The main model we tested, model 1, is:

$$\ln\left(\frac{ED_i}{GSP_i}\right) = \alpha + \beta_1 \ln MSW_i + \beta_6 \frac{R_i}{HR_i} + \beta_2 \ln F_i + \beta_3 \ln HID_i + \beta_4 \ln\left(\frac{PW_i}{TA_i}\right) + \beta_5 \ln\left(\frac{EW_i}{TA_i}\right) + \beta_7 D_i + \varepsilon_i. \quad [11]$$

The subscript i denotes an individual storm. ED_i/GSP_i represents the economic damage per unit GSP, MSW_i represents the maximum sustained winds, F represents the frequency of cyclones, HID represents high intensity development, PW_i/TA_i is the area of palustrine wetlands present as a proportion of total area (TA_i) in the swath, EW_i/TA_i is the area of estuarine wetlands as a proportion of the total area, R_i/HR_i is the rainfall per hour, D is a dummy variable.

The linear probability model has a dichotomous variable ED, where ED= 1 if the economic damages per gross special product are greater than 0 and are 0 otherwise. The model is then,

$$ED_i = \alpha + \beta_1 \ln MSW_i + \beta_6 \frac{R_i}{HR_i} + \beta_2 \ln F_i + \beta_3 \ln HID_i + \beta_4 \ln \left(\frac{PW_i}{TA_i} \right) + \beta_5 \ln \left(\frac{EW_i}{TA_i} \right) + \beta_7 D_i + \varepsilon_i$$

Section 4.1: Regression results for double log and linear probability models

This section describes the regression results from the two models run for analysis. Table 2 below displays regression results for the OLS model and the LPM model. The results for the OLS model show that only maximum sustained winds and the dummy variable are significant at the 1% and 10% level, respectively. The LPM results are displayed but no significance was found, even for maximum sustained winds..

Table 2: OLS models where the natural log of normalized damages was the dependent variable and for the linear probability model it was a dichotomous variable.

| Variable Names | OLS Model | OLS Model with interactions | Linear Probability Model | Linear Probability model with interactions |
|-----------------------------------|-------------------|-----------------------------|--------------------------|--|
| Ln Maximum sustained winds | 6.18*** (2.13) | 6.18 (4.03) | 0.107 (0.17) | -0.148 (0.105) |
| Ln Frequency | -0.20 (1.53) | -0.425 (2.30) | -0.175 (0.12) | -0.014 (0.045) |
| Ln High Intensity Development | 0.326 (0.83) | 1.48 (1.95) | 0.058 (0.66) | 0.04 (0.04) |
| Ln Paulstrine Wetlands | 0.94 (1.94) | 4.24 (5.33) | 0.242 (0.15) | 0.315 (0.188) |
| Ln Estuarine wetlands | 0.25 (0.44) | 0.91 (0.70) | 0.013 (0.35) | 0.026 (0.193) |
| Ln Rainfall per hour | 0.29 (0.41) | 2.02* (1.07) | 0.617 (0.33) | 0.115 (0.050) |
| Dummy | -2.68* (1.82) | -16.54 (23.55) | 0.133 (0.145) | -2.36 (1.36) |
| Dummy* Ln Maximum sustained winds | | -0.89 (4.75) | | 0.404 (0.157) |

| | | | | |
|---|------------------|-------------------|----------------|-------------------|
| Dummy*Ln Frequency | -1.35 (3.14) | | | -0.39 (0.209) |
| Dummy*Ln High intensity development | -1.54 (2.18) | | | 0.028 (0.101) |
| Dummy*Ln Palustrine wetlands | -3.87 (5.73) | | | -0.065 (0.303) |
| Dummy*Ln Estuarine wetlands | -1.04 (0.91) | | | -0.026 (0.060) |
| Dummy*Ln Rainfall per hour | -2.22* (1.16) | | | -0.083 (0.07) |
| Constant | -21.99 (5.56) | -19.00 (20.94) | 0.74 (0.68) | 2.20 (0.680) |
| Observations | 94 | 94 | 94 | 94 |
| R2 | 0.41 | 0.49 | 0.23 | 0.23 |

Note: All standard errors are in parenthesis and * =10% **= 5% ***= 1% significance.

Section 4.2: Testing for Heteroskedasticity

One concern raised above with respect to the variance of damages at lower levels of lnMSW was that heteroskedasticity could be present in the data. Heteroskedasticity was further suspected based upon the results described in Zia (2012) who found heteroskedasticity to persist in economic damages as well. To test our own results for heteroskedasticity, the Breush-Pagan/ Cook-Weisberg (BP/CW) test was used and gave a chi square statistic of 9.25 ($p > \chi^2 = 0.0024$) for the OLS model. Given this large number, the null hypothesis of constant variance was rejected in favor of the hypothesis that heteroskedasticity was present.

Section 4.3: Accounting for Heteroskedasticity

To account for the heteroskedasticity and present more robust standard errors, White's robust standard errors were used; the results of these two methods appear in Table 4 below. For the OLS model, the robust standard errors are smaller for the lnMSW and the dummy variable than with the original model.

Table 3: Results of OLS using regular standard errors and OLS using White's robust estimates. The dependent variable is the natural log of normalized damages.

| Variable Names | OLS Model with regular standard errors | OLS Model with White's robust standard errors | OLS Model with interactions | OLS Model with interactions and robust standard errors |
|-------------------------------------|--|---|-----------------------------|--|
| Ln Maximum sustained winds | 6.18*** (2.13) | 6.18*** (2.09) | 6.18 (4.03) | 6.18*** (4.03) |
| Ln Frequency | -0.27 (1.53) | -0.27 (1.57) | -0.425 (2.30) | -0.425 (2.30) |
| Ln High Intensity Development | 0.326 (0.540) | 0.326 (0.564) | 1.48 (1.95) | 1.48 (1.95) |
| Ln Palustrine Wetlands | 0.551 (1.24) | 0.551 (1.65) | 4.24 (5.33) | 4.24 (5.33) |
| Ln Estuarine wetlands | 0.336 (0.288) | 0.336 (0.272) | 0.91 (0.70) | 0.91** (0.70) |
| Ln Rainfall per hour | 0.176 (0.270) | 0.176 (0.431) | 2.02* (1.07) | 2.02** (1.07) |
| Dummy | -2.69 (1.82) | -2.69* (1.58) | -16.54 (23.55) | -16.54 (17.46) |
| Dummy* Ln Maximum sustained winds | | | -0.89 (4.75) | -0.89 (3.59) |
| Dummy*Ln Frequency | | | -1.35 (3.14) | -1.35 (3.14) |
| Dummy*Ln High intensity development | | | -1.54 (2.18) | -1.54 (2.18) |
| Dummy*Ln Palustrine wetlands | | | -3.87 (5.73) | -3.87 (5.73) |
| Dummy*Ln Estuarine wetlands | | | -1.04 (0.91) | -1.04 (0.91) |
| Dummy*Ln Rainfall per hour | | | -2.22* (1.16) | -2.22** (1.16) |
| Constant | -31.99*** (8.57) | -31.99*** (9.71) | -19.00 (20.94) | -19.00 (20.94) |
| Observations | 94 | 94 | 94 | 94 |
| R2 | 0.45 | 0.45 | 0.49 | 0.49 |

Note: All standard errors are in parenthesis and * =10% **= 5% ***= 1% significance.

Section 4.4: Interpretation of OLS model with and without interaction terms.

From the OLS model without interaction terms one can expect a 1% increase in MSW to cause an increase in economic damages per unit GSP of 6.18%. The data for

economic damage per unit GSP has a skewness of 5.26 suggesting a fairly skewed distribution. As such the median economic damage per GSP of 0.00103 differs greatly from the mean of 0.113 and therefore using the median to calculate the change in normalized economic damages would possibly underestimate the impacts of the coefficients on normalized damages. From the OLS model with out interactions then, a 6.18% increase in the mean of normalized damages would cause the average damages per unit GSP to increase by 0.0069 or 0.6% of gross spatial product.

The dummy variable in the OLS model has a coefficient of -2.69 and as such when $D=1$, a -269% change in economic damages per unit gross spatial product can be expected. Therefore, a tropical storm is expected to cause much less damage than a hurricane; the average economic damage will decrease by 30% of the total GSP in the swath.

For the OLS model with interaction terms, once robust standard errors were used four variables returned significant results. Since I included interaction terms and the dummy variables used for these interactions are such that $D=1$ when $MSW < 119\text{km/hr}$, the variables without interaction terms give us the impact of those variables for hurricanes only. As such, for the natural log of MSW, a 1% increase in the MSW results in a 6.18% increase in damages for hurricanes only. The interaction between the dummy variable and $\ln MSW$ was not significant at even the 10% level.

The other variables that showed significance were estuarine wetlands, the natural log of rainfall per hour and the interaction term of the dummy and rainfall per hour. For estuarine wetlands, a 1% increase in the proportion of estuarine wetlands to total area affected by a storm results in a 0.91% change in damages, which is almost negligible. The

amount of rainfall per hour is significant as well both for hurricanes and for tropical storms. The natural log of rainfall per hour, without the interaction term, was 2.02 and so a 1% increase in the amount of rain per hour of a hurricane results in a 2.02% increase in damages. For the interaction term, and consequently for tropical storms, the impact of rainfall per hour is -2.22 and so the impact on damages is -0.2. This means that an increase in the rainfall per hour actually decreases the amount of damage slightly by 0.2%.

Section 4.5: Chapter Summary

In this chapter, I specified an OLS with and without interaction terms as well as a linear probability model. I found heteroskedasticity to be present in both models and so used White's robust standard errors to correct for the heteroskedasticity. The only two variables in the OLS model that were significant were the natural log of maximum sustained winds and the dummy variable. For the OLS model with interaction terms, the natural log of MSW, estuarine wetlands, the natural log of rainfall per hour, and the interaction term of rainfall per hour are significant.

Chapter 5: Discussion and concluding remarks

Section 5.0: Introduction

This chapter discusses the results found in the previous chapter and suggests possible improvements to the data gathering process described in chapter 3. This chapter will start with a discussion on importance of maximum sustained winds in describing economic damages. I will then discuss the insignificant variables and possible methods to improve the data collection process.

Section 5.1: Maximum sustained wind speed and economic damages

The elasticity of normalized damages to maximum sustained winds was 6.18, which is close to Nordhaus's (2006) finding and double that of Costanza et al's (2008) findings, which are both discussed in chapter 2. In chapter 4, the variance of the natural log of normalized damages was larger than at higher log MSW. At lower values of MSW, the variance of damages may be high because of a wide range of building codes, wetland extent, severity of floods, frequency of storms as well as other factors not considered in this study. This should mean that there is also potentially more error in damages at lower log MSW and so I plotted the square residuals against $\ln MSW$ as shown in Figure 8 below.

The relationship shows a clear negative relationship and a break just after the log MSW of 4. After the break, the errors are much lower than before the break as well as appearing to be more uniform. This is well in line with the uniform variance of log normalized damages at high MSW.

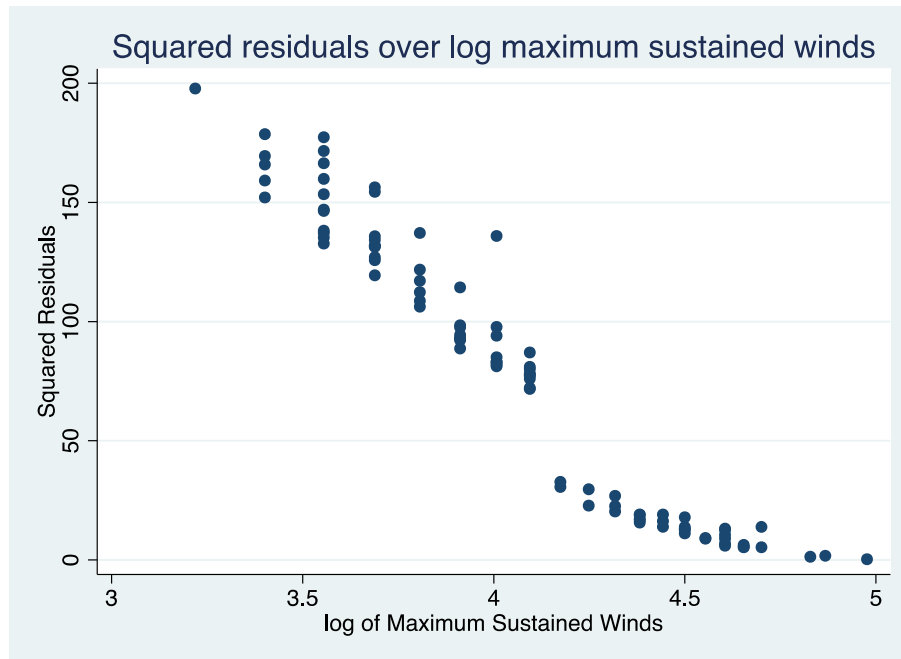


Figure 8: Squared residuals from the OLS model with robust standard errors presented as a function of the natural log of maximum sustained winds

It is quite clear from a comparison between Figure 7 and 8 that the results are consistent with Nordhaus’s (2006) structural failure theory. The OLS model and the OLS model with interaction terms show support for Nordhaus’ findings. After a storm becomes a hurricane, damages rise exponentially with much less error; one may be less likely to see structural damage from wind during a tropical storm than in a hurricane because the power being produced by the wind isn’t sufficient enough to cause a structural failure in buildings. At lower sustained wind speeds, the structural integrity of building isn’t compromised by the power of the wind and so damages should, at least on average, be less in total but also vary more. This greater variance could be the result of variables not included in this present study.

The OLS with interaction terms also showed that the natural log of estuarine wetlands to cause a significant, yet small, increase in damages for hurricanes. This result

is in contrast to Costanza et al's (2008) finding that coastal wetlands reduce economic damages from storms. In future research it would be good to interact estuarine wetlands with storm surge heights to get a clearer picture of how these wetlands interact with hurricanes.

For the amount of rainfall per hour, there is a significant and relatively large impact for hurricanes but a negligible impact for tropical storms. I looked at the average rainfall per hour for hurricanes and for tropical storms and found there to be no significant difference in their means. For tropical storms the average rainfall per hour was 0.7 mm/hr and for hurricanes it was 0.6mm/hr. In future studies, I would like to interact the amount of rainfall per hour with characteristics of land such as wetlands and impervious surfaces to get a better understanding of how these interact.

Section 5.2: Variables showing no significance

I first hypothesized in chapter 3 that normalized economic damages can be described by the maximum sustained winds, high intensity development, palustrine wetlands, and frequency of storms. The results from both OLS and the linear probability model suggest that only the maximum sustained winds, the rainfall per hour and, for hurricanes at least, estuarine wetlands are statistically significant explanatory variables for the variation in normalized damages.

It is unclear why there is such a contrast between the results in this study and those of Costanza et al. (2008), Zia (2012), Brody et al. (2007) who all found land characteristics to be significant predictors of economic damages in one form or another. It could be the case that there is some measurement error that resulted from the GIS

methods or that the selection of the buffer width was too large or too small. In future studies of this kind, different buffer widths, depths and potentially different GIS techniques could be considered to lessen the noise in the data. One method could be to measure land characteristics only 100km inland as done in Costanza et al. (2008) or to simply measure different characteristics. Another option would be to use the distribution of storm surge heights to inform the buffer width. The center of the buffer could be where the highest storm surge occurred and be as wide as the storm surge is above some determined number.

There could also be variables not included in this study that have significant explanatory power over normalized damages. Variables such as soil porosity, as used in Brody et al. (2007), and a dummy variable indicating whether or not the area affected by a storm is in a flood plane could be used. These are easily attainable using GIS and could be added to our model. Soil porosity could be important because, if the soil were dense or saturated at the time of a storm, one would expect less absorption and therefore more surface runoff to cause damages. Further, having development in a floodplain ought to be a significant predictor of damages, as observed with the flooding of Calgary in 2013.

Section 5.3: Conclusion

This chapter discussed the results highlighting several notable themes. First, the relationship between normalized damages and MSW at landfall is statistically significant and more in line with the findings of Nordhaus (2006) than with those of Costanza et al. (2008). Second, the frequency and percentage of land classified as high intensity development or as palustrine wetlands turned out to be insignificant. Future research

should be done on the contribution of the characteristics of cities and urban areas to economic damages as there may be a significant variable undiscovered in this study.

References

- Birkmann, J. (2006). Measuring vulnerability to promote disaster-resilient societies: Conceptual frameworks and definitions. *Natural Hazards: Towards Disaster Resilient Societies*. United Nations University New York
- Brody, S. D., Zahran, S., Highfield, W. E., Grover, H., & Vedlitz, A. (2007). Identifying the impact of the built environment on flood damage in Texas. *Disasters*, 32(1), 1-18.
- Brody, S. D., Peacock, W. G., & Gunn, J. (2012). Ecological Indicators. *Ecological Indicators*, 18, 493–500.
- Cameron, A. C., & Trivedi, P. K. (2009). *Microeconometrics using stata*. Stata Press College Station, TX.
- Chen, X., & Nordhaus, W. D. (2011). Using luminosity data as a proxy for economic statistics. *Proceedings of the National Academy of Sciences*, 108(21), 8589-8594.
- Costanza, R., P\'erez-Maqueo, O., Martinez, M. L., Sutton, P., Anderson, S. J., & Mulder, K. (2008). The value of coastal wetlands for hurricane protection. *AMBIO: A Journal of the Human Environment*, 37(4), 241-248.
- Doll, C. H., Muller, J., & Elvidge, C. D. (2000). Night-time imagery as a tool for global mapping of socioeconomic parameters and greenhouse gas emissions. *AMBIO: A Journal of the Human Environment*, 29(3), 157-162.
- Elvidge, C. D., Baugh, K. E., Kihn, E. A., Kroehl, H. W., Davis, E. R., & Davis, C. W. (1997). Relation between satellite observed visible-near infrared emissions, population, economic

- activity and electric power consumption. *International Journal of Remote Sensing*, 18(6), 1373-1379.
- Elvidge, C. D., Baugh, K. E., Dietz, J. B., Bland, T., Sutton, P. C., & Kroehl, H. W. (1999). Radiance calibration of DMSP-OLS low-light imaging data of human settlements. *Remote Sensing of Environment*, 68(1), 77-88.
- Field, C. B. (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation: Special report of the intergovernmental panel on climate change*. Cambridge University Press.
- Heij, Christiaan and De Boer, Paul and Franses, Philip Hans and Kloek, Teun and Van Dijk, Herman K and others. (2004). *Econometric methods with applications in business and economics* Oxford University Press.
- IPCC. (2014). Summary for policymakers. In C. B. Field, V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, L. L. White (Eds.), (pp. 1-32). Cambridge, United Kingdom, and New York, NY, USA: Cambridge University Press.
- Jonkman, S., Van Gelder, P., & Vrijling, J. (2003). An overview of quantitative risk measures for loss of life and economic damage. *Journal of Hazardous Materials*, 99(1), 1-30.
- Judd, C. M., McClelland, G. H. (1989). *Data analysis: A model comparison approach* Routledge.
- Kennedy, P. (2003). *A guide to econometrics* MIT Press
- Landsea, C. W. (2000). Climate variability of tropical cyclones: Past, present and future. *Storms*, 1, 220-241.

Neumayer, E., & Barthel, F. (2011). Normalizing economic loss from natural disasters: A global analysis. *Global Environmental Change*, 21(1), 13-24.

Nordhaus, W. D. (2006). *The economics of hurricanes in the United States*. National Bureau of Economic Research.

Peduzzi, P., Chatenoux, B., Dao, H., De Bono, A., Herold, C., Kossin, J., . . . Nordbeck, O. (2012). Global trends in tropical cyclone risk. *Nature Climate Change*, 2(4), 289-294.

Peduzzi, P., Dao, H., Herold, C., & Mouton, F. (2009). Assessing global exposure and vulnerability towards natural hazards: The disaster risk index. *Natural Hazards and Earth System Science*, 9(4), 1149-1159.

Pielke Jr, R. A., Gratz, J., Landsea, C. W., Collins, D., Saunders, M. A., & Musulin, R. (2008). Normalized hurricane damage in the United States: 1900--2005. *Natural Hazards Review*, 9(1), 29-42.

Pielke Jr, R. A., & Landsea, C. W. (1998). Normalized hurricane damages in the United States: 1925-95. *Weather and Forecasting*, 13(3), 621-631.

Pielke, R. A. (2007). Future economic damage from tropical cyclones: Sensitivities to societal and climate changes. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 365(1860), 2717-2729. doi:10.1098/rsta.2007.2086

Powell, M. D., Houston, S. H., & Reinhold, T. A. (1996). Hurricane Andrew's landfall in South Florida. part I: Standardizing measurements for documentation of surface wind fields. *Weather and Forecasting*, 11(3), 304-328.

Stern, N. (2007). *The economics of climate change: The stern review* Cambridge University press.

- Surminski, S., & Lopez, A. (2014). Concept of loss and damage of climate change--a new challenge for climate decision-making? A climate science perspective. *Climate and Development*, (ahead-of-print), 1-11.
- Surminski, S., Lopez, A., Birkmann, J., & Welle, T. (2012). Current knowledge on relevant methodologies and data requirements as well as lessons learned and gaps identified at different levels, in assessing the risk of loss and damage associated with the adverse effects of climate change. United Nations Framework Convention Climate Change
- Sutton, P. C., & Costanza, R. (2002). Global estimates of market and non-market values derived from nighttime satellite imagery, land cover, and ecosystem service valuation. *Ecological Economics*, 41(3), 509-527.
- Sutton, P., Roberts, D., Elvidge, C., & Meij, H. (1997). A comparison of nighttime satellite imagery and population density for the continental united states. *Photogrammetric Engineering and Remote Sensing*, 63(11), 1303-1313.
- United States Geological Survey. (2013a). Estuarine system. Retrieved November 2014, 2014, from <http://www.npwrc.usgs.gov/resource/wetlands/classwet/estuarin.htm>
- United States Geological Survey. (2013b). Paulstrine system. Retrieved November 2014, 2014, from <http://www.npwrc.usgs.gov/resource/wetlands/classwet/palustri.htm>
- United States Geological Survey. (2014a). The 100 year flood. Retrieved November 11th, 2014, from <http://pubs.water.usgs.gov/fs22996>
- United States Geological Survey. (2014b). What is a watershed? Retrieved November 11th, 2014, from <http://water.usgs.gov/edu/watershed.html>

Wamsley, T. V., Cialone, M. A., Smith, J. M., Atkinson, J. H., & Rosati, J. D. (2010). The potential of wetlands in reducing storm surge. *Ocean Engineering*, 37(1), 59-68.

Woodruff, J. D., Irish, J. L., & Camargo, S. J. (2013). Coastal flooding by tropical cyclones and sea-level rise. *Nature*, 504(7478), 44-52. Retrieved from <http://dx.doi.org/10.1038/nature12855>

Zia, A. (2012). Land use adaptation to climate change: Economic damages from land-falling hurricanes in the Atlantic and Gulf States of the USA, 1900--2005. *Sustainability*, 4(5), 917-932.

Appendix

Table 4a: Estimated GSP from each storm in the sample between 1992-2012

| Storm Name | GSP (millions year 2000) | Storm Name | GSP (millions year 2000) |
|------------|--------------------------|------------|--------------------------|
| Andrew | 22314 | Henri | 40319 |
| Dannielle | 95325 | Isabel | 15287 |
| Earl | 6359 | Alex | 19147 |
| Arlene | 9991 | Bonnie | 121701 |
| Emily | 5908 | Charley | 51057 |
| Alberto | 91753 | Frances | 24564 |
| Beryl | 284118 | Gaston | 18508 |
| Gordon | 24432 | Hermine | 53635 |
| Allison | 68245 | Ivan | 103711 |
| Dean | 52765 | Jeanne | 121480 |
| Erin | 21444 | Matthew | 44260 |
| Jerry | 105015 | Arlene | 54490 |
| Opal | 9600 | Cindy | 351906 |
| Arthur | 31618 | Dennis | 193634 |
| Bertha | 221853 | Emily (NT) | 11082 |
| Fran | 30658 | Katrina | 29084 |
| Josephine | 159480 | Ophelia | 44028 |
| Danny | 231336 | Rita | 14844 |
| Bonnie | 6258 | Wilma | 8895 |
| Charley | 19779 | Tammy | 79630 |
| Frances | 3350 | Alberto | 114997 |
| Georges | 10357 | Ernesto | 95597 |
| Hermine | 33627 | Andrea | 20963 |
| Mitch | 34816 | Barry | 195128 |
| Bret | 2162 | Erin | 26741 |
| Dennis | 91442 | Gabrielle | 18270 |
| Floyd | 110195 | Humberto | 53237 |
| Harvey | 26189 | Christobal | 21391 |
| Irene | 25976 | Dolly | 20472 |
| Gordon | 303884 | Edouard | 68487 |
| Helene | 164951 | Fay | 147501 |
| Leslie | 21482 | Gustav | 22701 |
| Allison | 91753 | Hanna | 111675 |
| Barry | 81917 | Ike | 21168 |
| Gabrielle | 43253 | Claudette | 55620 |
| Arthur | 24071 | Ida | 12308 |
| Bertha | 61217 | Bonnie | 69897 |
| Edouard | 37829 | Earl | 21598 |
| Fay | 46017 | Hermine | 47255 |
| Gustav | 5805 | Nicole | 23016 |
| Hanna | 70853 | Irene | 68928 |
| Isidore | 15103 | Lee | 71532 |
| Kyle | 71404 | Alberto | 195128 |
| Lili | 8282 | Beryl | 115379 |
| Bill | 55621 | Debby | 68101 |
| Claudette | 37652 | Isaac | 47052 |
| Grace | 76153 | Sandy | 125488 |

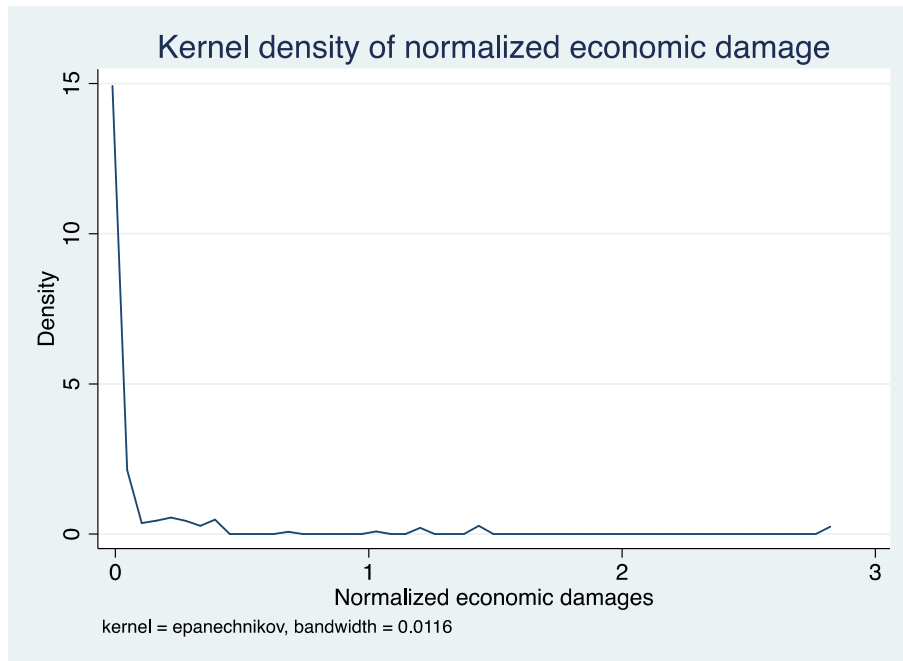


Figure 9a: Kernel density for normalized economic damage

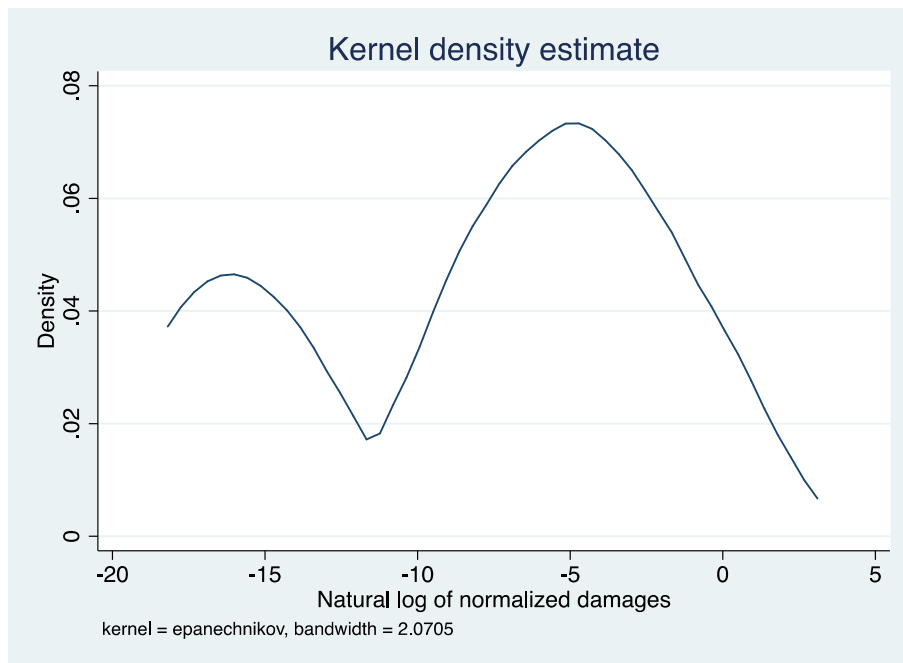


Figure 10a: Kernel density for log normalized economic damage

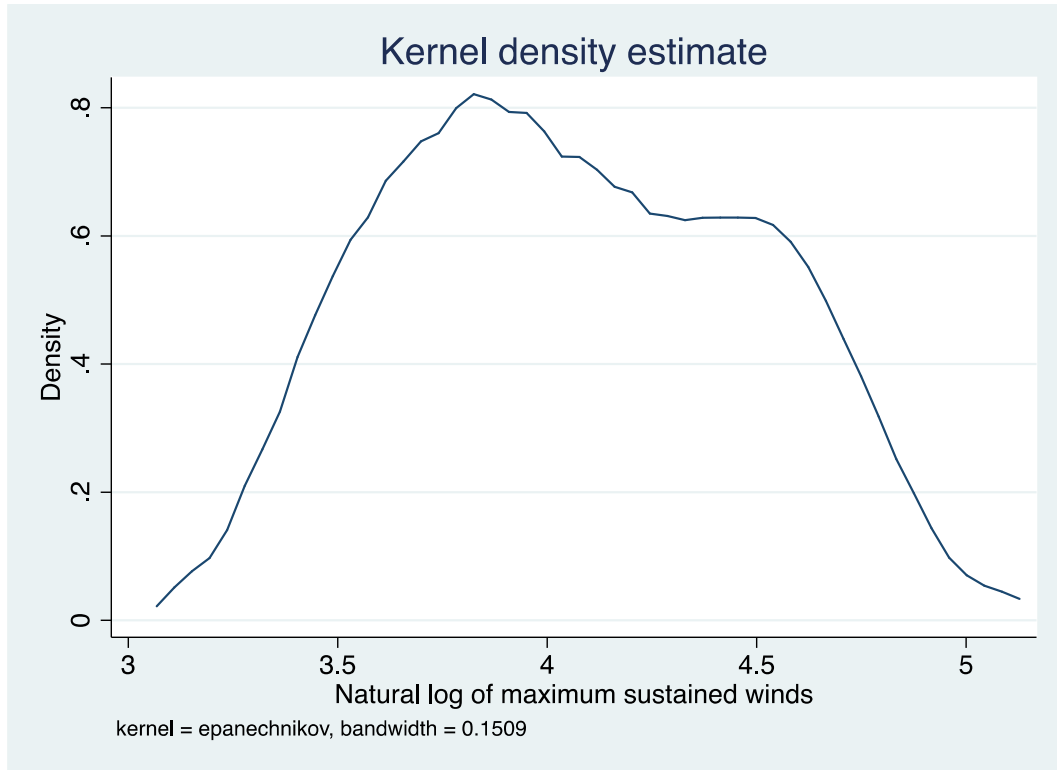


Figure 11a: Kernel density of the natural log of maximum sustained winds

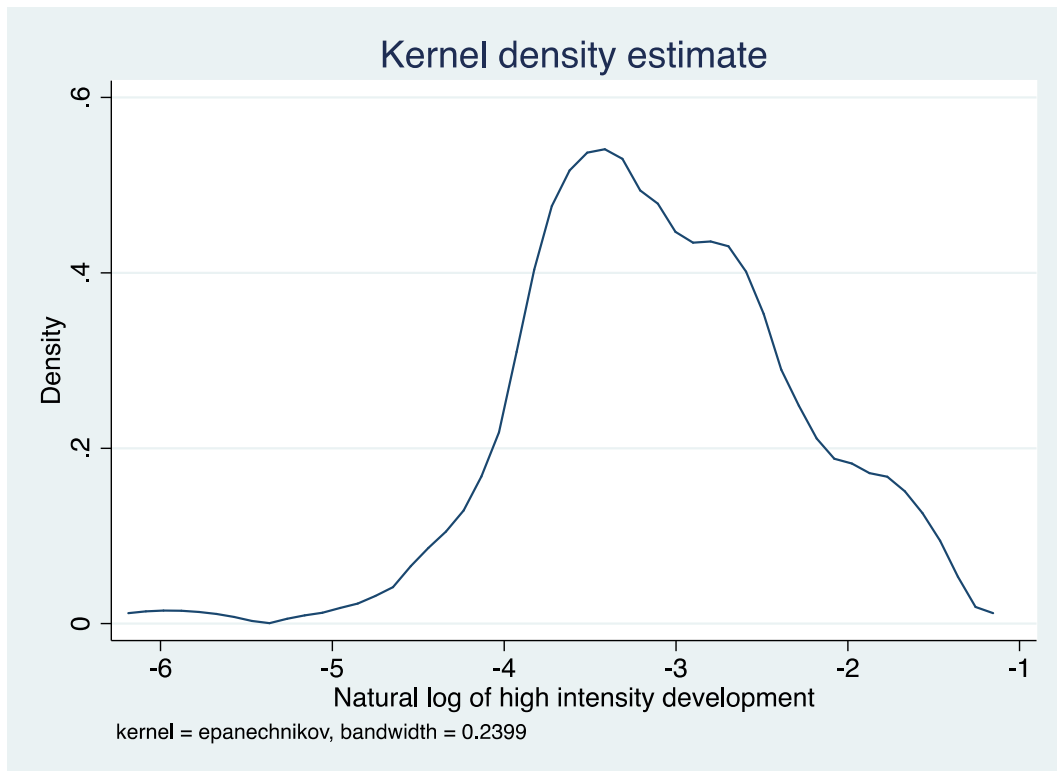


Figure 12a: Kernel density of the natural log of high intensity development

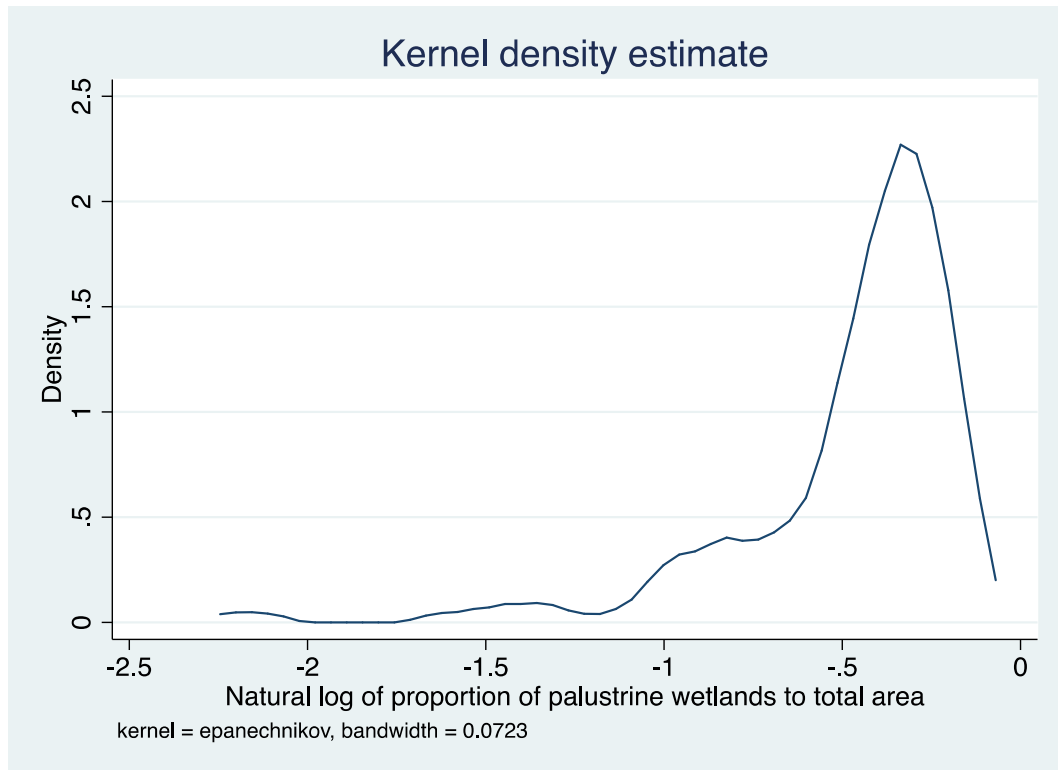


Figure 13a Kernel density of the natural log of palustrine wetlands as a proportion of total area

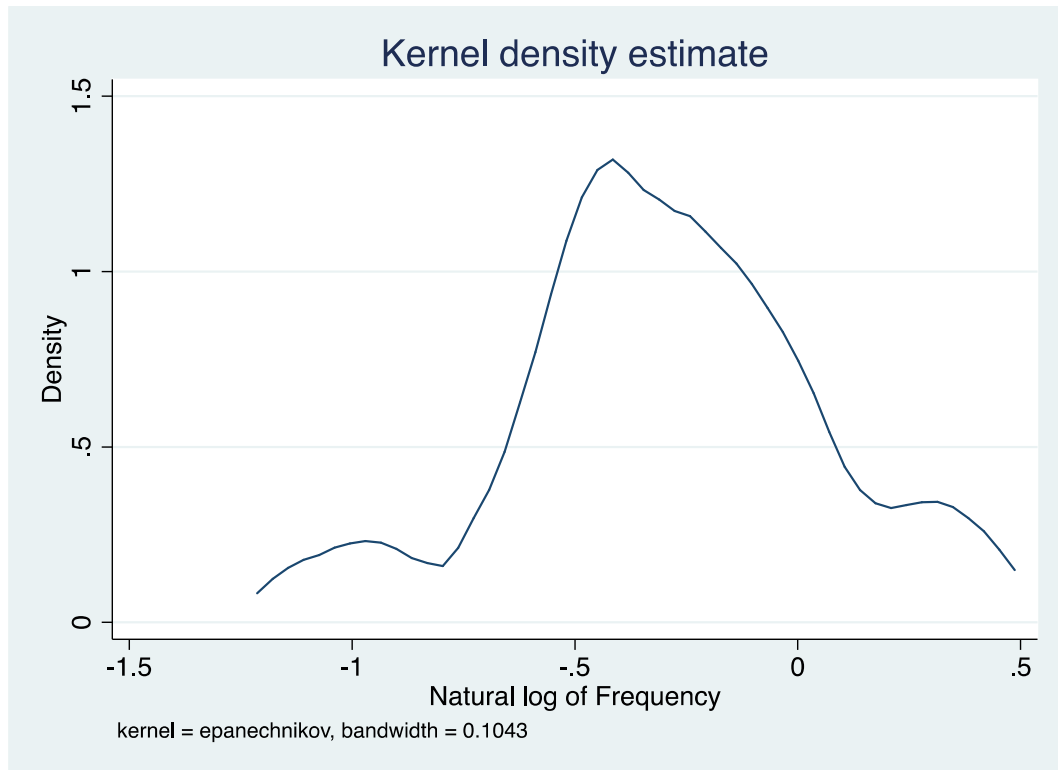


Figure 14a Kernel density of the natural log of frequency

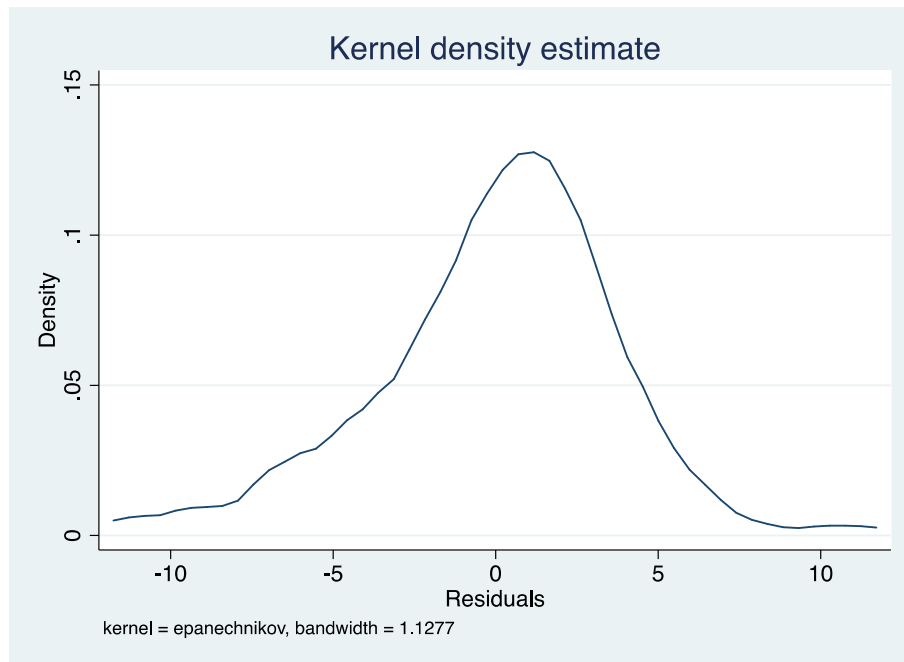


Figure 15a: Kernel density of residuals from OLS