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PRE-LANDFALL INTENSITY AS PREDICTOR OF ECONOMIC LOSS FROM FLORIDA HURRICANES, 1900–2007

By

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I would like to dedicate this research to my parents, Kip and Lisa, who always reminded me that hard work pays off, and to my loving fiancé, Luke, who helped keep my spirits high when life was tough.

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ABSTRACT

Florida is uniquely susceptible to economic loss from hurricanes and has been affected by some of the most destructive hurricanes to ever reach the United States. In the wake of the devastation caused by Hurricane Andrew in 1992, risk assessment companies and reinsurance companies have spent millions of dollars to try and predict the economic loss from direct hurricane strikes. These companies base their predictions on historical hurricane events, and an important input to their risk models is the intensity of the hurricane at landfall. However, a large portion of economic loss from hurricanes comes from the storm surge, and storm surge is better predicted using intensities prior to landfall. In this study, the relationship between economic loss and hurricane intensity prior to landfall is analyzed using the best available data during the period 1900–2007. Results show that intensity 5 hours prior to landfall provides a better estimate of overall economic loss than the intensity at landfall. Based on this finding, a log-linear regression model is applied to the data to predict economic loss from pre-landfall intensity. Additional hurricane characteristics including size and location of landfall do not improve the model's ability to predict losses. Residuals are examined for model adequacy and hurricanes with the largest residuals are studied in more detail. It appears that the model under predicts loss amounts in areas of Florida that have seen rapid economic development, and an upward trend in the model residuals indicates a lingering bias in the renormalized loss data. The scientific merit of the research is a better understanding of the relationship between hurricane intensity and loss. The broader implications of this research are a relatively simple model for risk assessment.

CHAPTER 1

INTRODUCTION

Motivation

Often considered one of nature's most violent furies, hurricanes are incredibly powerful storms which wreak havoc on the United States' coastlines every year. Due largely to increasing development in vulnerable areas, the economic losses associated with these hurricanes have also been increasing. Risk assessment companies, such as *AIR Worldwide* and *Risk Management Solutions*, and reinsurance companies, such as *RenaissanceRE*, spend millions of dollars annually to estimate the overall economic loss expected to occur from individual hurricanes that make landfall on the U.S. coast.

The state of Florida is unique in its susceptibility to hurricane strikes because of its location surrounded by large, warm water bodies. Florida, like most of the coastal United States, has seen a building boom, and the increasing population and wealth of the incoming residents has forced insurers and citizens to rethink their overall exposure to hurricane damage. The *Insurance Information Institute* (Hartwig 2008) shows the value of insured coastal property in Florida ranks first in the nation and, as of 2007, was expected to exceed $2 trillion (AIR 2005).

The purpose of this research is to analyze total economic loss incurred by hurricanes affecting the state of Florida during the period 1900–2007. Present studies estimate economic loss based on historical hurricane events and the intensity of the event at landfall, usually using the maximum sustained wind speed as the intensity indicator. This research stems from an idea presented in Jordan and Clayson (2008), where pre-landfall intensities were used to predict storm surge. It was found that pre-landfall intensity correlated higher with storm surge than did landfall intensity, and since storm surge is a large part of overall economic loss, it is hypothesized here that pre-landfall intensity might be a better indicator of overall economic loss than landfall intensity. To test this hypothesis, this study statistically analyzes the relationship between pre-landfall intensities and normalized economic losses using data over the period 1900–2007 for the state of Florida.

The state of Florida is of particular interest to hurricane climatologists, since Florida is more vulnerable to hurricane strikes than any other state in the union. Overall vulnerability to hurricane damage is very high in Florida because of its close proximity to the warm waters of the North Atlantic (including the Gulf of Mexico and the Caribbean Sea). Economic losses for these hurricanes have been increasing in Florida, due to both increasing population and increasing wealth, and the concern for predicting the overall damage from these storms has grown. According to the data set presented in Pielke et al. (2008), 8 of the 10 most expensive U.S. land falling hurricanes have had some affect on the state of Florida, and have caused over $60 billion in insured losses.

The purpose of this study is to use pre-landfall hurricane intensity as an indicator of the overall economic loss felt by Florida from damaging hurricane characteristics, such as storm surge, rainfall, and severe winds. Figure 1 shows the Florida Peninsula, which has boundaries defined by latitudes ranging from 24° 30’ N to 31° N and longitudes ranging from 79° 48’ W to 87° 38’ W. Florida is affected by hurricanes that form in the North Atlantic Basin, shown in Figure 2, which includes the seas between North America, Europe, and Africa, and also includes the Gulf of Mexico and the Caribbean.

This basin supports hurricane formation because of the warm waters and low atmospheric wind shear experienced here during the months of June through November. The hurricanes usually form in the eastern Atlantic as areas of low pressure which, as a result of atmospheric instability, ultimately build into counterclockwise (in the Northern Hemisphere) rotating series of intense thunderstorms. Florida is also vulnerable to hurricanes that track northward from their origins over the western parts of the Caribbean Sea. These formations tend to occur in October and November. In either case, once the storm reaches sustained wind speeds of 64 knots (or 74 mph), it is considered a hurricane, and the warm waters of the North Atlantic supply the systems with enough fuel to travel westward throughout the basin and, possibly, make a direct strike to Florida.

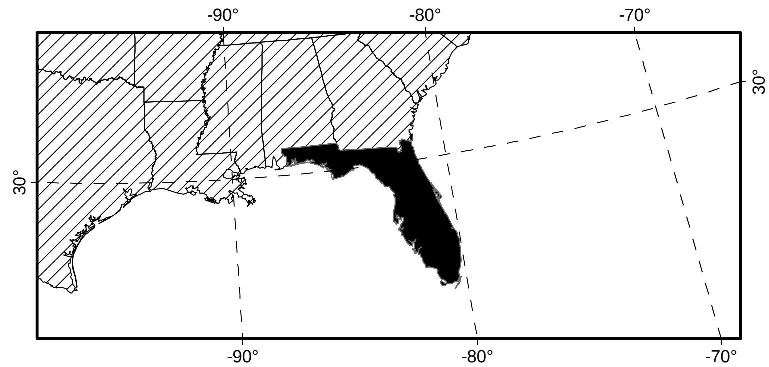

Figure 1: Map of study area depicting the state of Florida

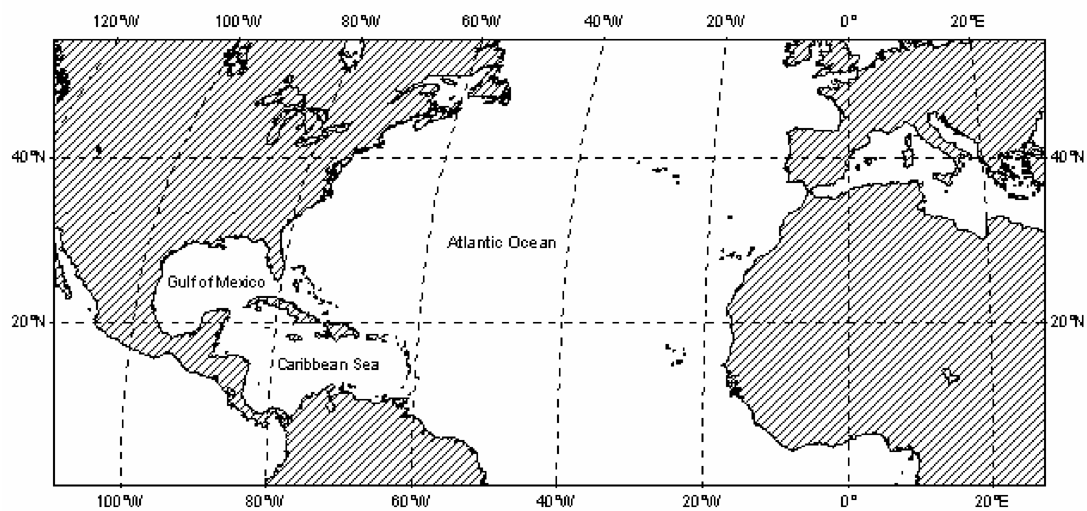

Figure 2: Map of the North Atlantic Basin. Basin consists of the North Atlantic Ocean, the Caribbean Sea, and the Gulf of Mexico.

Objective and Hypothesis

The goal for this research is to determine the statistical relationship between pre-landfall hurricane intensity based on wind speed and overall economic loss experienced in the state of

Florida. It is well documented that there is a relationship between landfall hurricane intensity and experienced economic loss, but based on the ideas presented in Jordan and Clayson (2008), there may be a stronger relationship when using intensity prior to landfall. The hypothesis for this research is that there will be a stronger relationship between intensity at 1–24 hours out from landfall and economic loss than the already established relationship between at landfall intensity and economic loss. This hypothesis originates from the idea that there is a time between the change in a hurricane storm system and the overall effects felt. This idea is explored thoroughly in the next chapter. Examples of hurricanes that changed intensity just before landfall are provided, and the aforementioned lag time between the ocean and atmosphere caused the storm surge and overall economic effects of the hurricane to be more reflective of the storm strength prior to the change in intensity. Since the intensity change in a hurricane just before landfall may not have adequate time to change the overall physical effects of the storm, pre-landfall intensity may be a better indicator of what will actually be felt at landfall (Jordan and Clayson 2008). The underlying premises and hypothesis are outlined below and will be discussed in the following chapters.

The first premise behind this research is that as a hurricane moves towards a coast, the storm surge is influenced by the geometry of the ocean basin and the continental shelf (Blain et al. 1994). The second premise is that storm surges, and the associated flooding, are a portion of the overall economic loss experienced from a landfalling hurricane (Sugg 1967). The final underlying premise is the idea presented in Jordan and Clayson (2008), that the expected storm surge at landfall is better predicted using hurricane intensities prior to landfall due to slow response time from the ocean. The hypothesis, as stated above, is that the expected economic loss incurred from hurricanes will be better estimated using wind intensities prior to landfall than using intensities at landfall.

The primary objective for this research is to find the relationship between landfall intensity and economic loss and compare that with pre-landfall intensity and economic loss to establish which method is a better indicator of expected loss. The data are examined using a correlation analysis, and a statistical model with losses is developed in order to predict economic loss in Florida using wind speed values prior to landfall. The adequacy of the model is checked using statistical tests, and, finally, the residuals of this model are analyzed to help explain more of the variability in the economic loss data.

The thesis begins with a literature review (Chapter 2) describing general hurricane characteristics, the climatology of Florida hurricanes, and early work on loss prediction. The data and methods are described in Chapter 3 followed by the results of a correlation study in Chapter 4. Chapter 5 describes the model developed based on the correlation results. A discussion of these results follow in Chapter 6, and the summary and conclusions are provided in Chapter 7.

CHAPTER 2

HURRICANES AND LOSSES

In order to understand the motivation for this research, it is important to understand where it lies within the scholarship of hurricane climate studies. This is explored through a literature review, which begins with a description of hurricane characteristics and the causes of intensification and decay. It then discusses hurricanes specifically in the state of Florida, and concludes with a discussion of past and present economic loss research.

Hurricane Characteristics

In the Northern Hemisphere, any closed, circular rotation of counterclockwise spinning air is referred to as a cyclone. When these phenomena occur over tropical bodies of water, mainly between 20° N and 20° S latitude, they are referred to as tropical cyclones. A tropical cyclone is a whirling mass of air that circulates around a center of low pressure, forming a nearly circular structure made up of deep clouds termed the central dense overcast (Elsner and Kara 1999). Near the center of these clouds, there is a hole, referred to as the eye. The eye of the tropical cyclone is generally free of clouds, winds are light, and the air is warm and dry. Surrounding the eye there is a band of cumulonimbus clouds, referred to as the eyewall, and it is here that the strongest winds and heaviest rains occur. Technically, a tropical cyclone landfall occurs when all or part of this eyewall crosses the coastline.

A tropical cyclone is referred to as a hurricane when it forms in the North Atlantic Basin and reaches full maturity. The National Hurricane Center (NHC) considers three categories of tropical cyclone maturity; tropical depressions, tropical storms, and hurricanes. A hurricane is the most severe of these categories. The NHC considers the tropical cyclone to be mature, and therefore a hurricane, when the sustained, near surface wind speeds reach 64 kt (74 mph). There are five categories of hurricane intensity, based on the Saffir-Simpson Scale, which estimates the overall damage potential of a hurricane based on wind speed. A Category 1 hurricane has wind speeds ranging from 64–82 kt. A hurricane of this intensity at landfall is expected to cause damage to unanchored mobile homes and trees, as well as some minor coastal flooding and pier damage. A Category 2 hurricane has wind speeds ranging from 83–95 kt and can be expected to cause damage to roofing materials, doors, and windows of most buildings. Category 3 hurricanes have wind speeds of 96–113 kt and will cause structures to fail and mobile homes to be destroyed. This is the first Category that is considered a major hurricane. The other two Categories considered major hurricanes are Category 4 and Category 5 hurricanes, which have wind speeds of 114–135 kt and >135 kt, respectively. Hurricanes of either of these magnitudes can be expected to cause damage to most structures and will flood most low-lying coastal areas. Evacuation is usually necessary when dealing with hurricanes of these intensities.

There are two main physical characteristics that are of interest to this study, and those are the tropical cyclone intensity and the radius to maximum winds (RMW). The first characteristic is important because only tropical cyclones which reach hurricane intensity and make landfall (as defined above) in Florida are considered for this study. The radius to maximum winds is the other important characteristic because it represents the hurricane size, which plays a large role in the overall economic loss experienced from a landfalling hurricane. This characteristic is considered as a possible explanatory variable for economic loss to be included in the developed model. Figure 3 shows an idealized radial profile for hurricane wind speeds. Winds are calm at the center of the hurricane and reach a maximum speed at a distance (RMW) from the center. Speeds decrease exponentially outward from the RMW.

Hurricane damage has been increasing throughout the coastal United States mainly because the amount of property and people living near vulnerable areas has vastly increased since the 2000 Census (Emanuel, 2005). According to the U.S. Census Bureau, Florida has the highest population growth among states affected by hurricanes, with an increase of 135% since 1970. With such a high population growth, the amount of development has also increased, and, because of the numerous amenities of coastal living, the majority of development has taken place on coastlines vulnerable to hurricane damage. The most damage-causing characteristics of a hurricane are high winds, storm surge, and large waves, and they each have the potential for total devastation of livelihoods and property. In order to fully understand the damage potential of a hurricane based on its intensity, it is crucial to understand the ways in which it intensifies or decays, as that will play a role in the overall economic loss experienced.

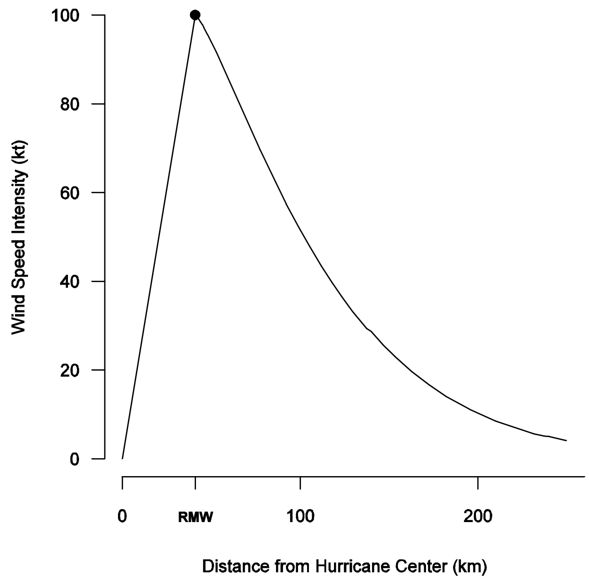

Figure 3: Idealized radial profile of hurricane wind speeds. Wind speeds increase away from the center to a maximum at some distance (RMW), then decrease exponentially.

Understanding the conditions which cause hurricanes to intensify or decay has been of interest to hurricane-climatologists for quite some time, one of the most notable studies being Emanuel's research on the maximum potential intensity (MPI) of tropical cyclones (Emanuel 1986; 1987). MPI can be thought of as the highest possible intensity that a hurricane can reach under ideal thermodynamic conditions. The actual maximum intensity of hurricanes will be quite variable because of the time-varying factors like wind shear and the contingency of landfall. Emanuel (1986) shows a strong relationship between the sea surface and the atmosphere, finding that hurricanes would avoid dissipation if the air-sea fluxes are maintained. Based on this relationship, Emanuel (1988) derives an equation for the MPI of hurricanes based on the minimum sustainable central pressure. This equation accounts for the thermodynamics of the hurricane and the effects of water substance on the system's density.

Emanuel (1986) illustrates that the thermodynamic structure of an idealized tropical cyclone resembles a simple Carnot heat engine, where sensible and latent heat are extracted from the ocean at one temperature and released as the outflow of the hurricane at another temperature. Emanuel (1988) shows that when there is no radial temperature gradient in the mixed layer and there is no dissipation except within the inflow, a Carnot-type engine drives the system's pressure lower, resulting in very high intensity (being as close as physically possible to the MPI). Although the actual occurrences of these ideal conditions are rarely met, the idea of an extraordinarily intense system (referred to as a hypercane) is theoretically possible. Elsner et al. (2008), motivated by this heat engine theory of hurricane intensification, show that the strongest tropical cyclones worldwide have increased over the past 25 years in response to warming oceans.

Hurricanes rely on the continuing air-sea interaction to maintain structure, so when this interaction is disrupted, the winds in a hurricane weaken (Emanuel 1986). This idea is described in detail by Kaplan and DeMaria (1995). Using the idea that the rate at which wind speeds subside is directly proportional to the wind speed itself, Kaplan and DeMaria (1995) create a simple empirical model that can predict the decay of tropical cyclone winds after the system makes landfall. This model includes corrections for the distance traveled inland, as well as the angle the hurricane makes landfall. The applicability of this model is that it can predict the maximum sustained surface winds after landfall, therefore improving the overall forecast of how long a system will maintain tropical cyclone status after making landfall.

The three main factors which contribute to a hurricane's intensity evolution are the cyclone's initial intensity, the thermodynamic state of the atmosphere over the lifespan of the hurricane, and the heat exchange between the system and the ocean it survives over (Emanuel 1999). This last factor is of the most importance to this research. The strong relationship between the atmosphere and the ocean plays a large role in the overall economic loss experienced from a hurricane. A large portion of the economic loss incurred from a direct hurricane strike comes from the storm surge damage (Sugg 1967). Storm surge is the rise in sea level associated with a hurricane, and it is heavily influenced by the relationship between the atmosphere and the sea surface (Resio and Westerink 2008).

Physically, the air-sea flux within a hurricane is the driving force behind the hurricane storm surge. Storm surge is created through the momentum flux between the energy exchange of the winds at the base of the hurricane and the waves at the top of the water column under the sea surface below the hurricane. This surge will change just prior to landfall because of the confinements of the continental margins (i.e. bathymetry, continental shelf). As the hurricane nears the continental shelf, the water column shortens and pushes more water towards the surface, ultimately leading to a larger swell at the surface (Blain et al. 1994). By direct interaction with the air flow, this change in swell will modify the wind stress (in this case, defined by air density and the turbulent fluctuations in vertical and horizontal velocities) and will, therefore, affect the exchange rate of the momentum flux between the ocean and atmosphere (Donelan et al. 1997). Depending on the environmental conditions within the hurricane at the time of change in momentum, the momentum flux will either increase or decrease, changing the overall characteristics of the storm surge (Resio and Westerink 2008). Since a large portion of overall hurricane damage comes from the storm surge, a change in the characteristics prior to landfall becomes vitally important to study because it will lead to changing estimates of expected economic loss.

Jordan and Clayson (2008) offer the idea that intensity prior to landfall is a better predictor of storm surge from a hurricane compared to the intensity at landfall. Storm surge prediction models in the past have been complex, and the use of pre-landfall intensities as the main predictor has generalized the process for the use of predicting tropical cyclone generated storm surge in any ocean basin. Hurricane Katrina (2005) and Hurricane Wilma (2005) are two recent examples of North Atlantic hurricanes that have shown the need for more accurate storm surge predictions.

Hurricane Katrina weakened just prior to landfall. Twelve hours prior to landfall on the Mississippi coast, Katrina's maximum sustained winds were approximately 140 kt. The National Hurricane Center's (NHC) 12-hour forecast for corresponding storm surge was for surge heights of 5.5–6.7 meters. At the time just prior to landfall, Katrina's winds decreased to 109 kt, and the NHC had lowered its surge forecast to 4.6–6.1 meters. Katrina's actual storm surge was 8.5 meters, much closer to the 12-hour intensity forecast than the landfall forecast (Jordan and Clayson 2008).

In contrast, Hurricane Wilma intensified from a moderate Category 2 hurricane to a strong Category 3 hurricane in the 12 hours prior to landfall in Southwest Florida. The actual intensity 12 hours prior was approximately 91 kt with a storm surge forecast of 2.8–5.2 meters. Just before landfall, the NHC increased the surge forecast to 3.7–5.5 meters because Wilma had strengthened to 109 kt. Similar to Hurricane Katrina, the 12-hour forecast was more accurate for Wilma as the actual observed storm surge was only 2.1 meters, much lower than the landfall forecast (Jordan and Clayson 2008).

Evidence suggests a lag time for the ocean to respond to a change in wind stress. Both Hurricane Katrina and Hurricane Wilma are examples of hurricanes where something within the physics of the storm changed prior to landfall, but because the ocean has a slower response time and it may not portray the effects of this change immediately, the 12-hour prior to landfall intensity is a much better indicator of what will actually occur at landfall.

Florida Hurricanes

Coastlines all over the world are vulnerable to strikes from cyclones and tropical cyclones. The state of Florida, however, is particularly vulnerable to hurricanes due to its close proximity to warm waters on both sides of the state. Therefore, Florida experiences a large portion of the overall U.S. economic loss from hurricanes. On average, at least one hurricane strikes Florida every two years, and a major hurricane (Category 3, 4, or 5) strikes Florida once every four years. Table 1 shows the annual probability of hurricane strikes in Florida based on the 67 known hurricane strikes from 1900–2007. The probabilities are based on the Poisson distribution for cyclone counts with a mean rate given by the set of 67 hurricanes. Major hurricanes have wind speeds of at least 96 kt and there are 25 major hurricanes of the 67 in the record.

Of the ten most expensive hurricanes ever to make landfall throughout the known historic record, eight of them have had some affect on Florida, causing in excess of $60 billion in insured losses. Therefore, it is not surprising that dollar losses from hurricanes are at the top of the list of catastrophic events (Pielke et al. 2008). Florida is also particularly vulnerable to hurricane damage because, according to the U.S. Census Bureau, Florida has the highest population growth among states affected by hurricanes and is expected to gain roughly 13 million people by 2030.

With this expected growth, damage is also expected to rise due to the increase in developed areas, and, thus, the increase in more vulnerable land.

Table 1: Annual probabilities of hurricanes and major hurricanes (Category 3, 4, and 5) affecting Florida based on the Poisson distribution. There are 67 known hurricanes to occur from the period 1900–2007, and 25 of them are considered major.

	Annual Probability of a Florida Hurricane	**Annual Probability of a Major Florida Hurricane (3+)**
0	47%	21%
1	34%	18%
2	11%	2%
3 or more	3%	0.2%

As noted in Malmstadt et al. (2009), there is an increase in the intensity (both minimum pressure and maximum wind speed) and size of Florida hurricanes (radius of maximum winds), as well as an increase in the normalized damage costs. Due to this increase in damaging hurricane characteristics and damage costs of Florida landfalling hurricanes, the importance of understanding the physical phenomena behind the hurricane has become even greater. In the previous section it is shown that physical changes in a hurricane prior to landfall may be an indicator of what the expected storm surge will be, and thus, the expected economic loss. Although the threat of severe damages has become more imminent in recent times, Florida is not new to experiencing economic loss from hurricanes, as the state has been ravaged by hurricanes throughout its history.

Hurricane Andrew (1992) was one of the most damaging hurricanes to affect Florida throughout the known historic record. This storm became a tropical depression on 16 August, 1992, and quickly became the season's first tropical storm on 17 August and first hurricane on 22 August. It struck southern Florida on the morning of 24 August, 1992 as a Category 4 hurricane. The results of Hurricane Andrew were devastating. Over 25,000 homes were destroyed and more than 100,000 homes were severely damaged (Landsea et al. 2004). According to Attaway (1999), over $1 billion (in 1992 dollar amounts) was lost from the agricultural sector of southeastern Florida's economy, and, Pielke et al. (2008) shows that Hurricane Andrew resulted in a total loss of just over $57 billion (in normalized 2005 amounts).

Economic Loss

The previous section discussed the status of hurricanes in the state of Florida, as well as the economic loss experienced throughout the state. Economic loss, as defined by Pielke et al. (2008), are the direct losses associated with a hurricane's landfall as determined in the time after the event. For the purposes of this study, the same definition will apply to economic loss, and will not include any longer-term macroeconomic effects, such as demand surge. Demand surge is considered the increase in construction costs, and therefore, the increase in insured losses, that occurs just after a catastrophic event. This type of loss is not considered here.

Interest in economic loss from hurricanes is not new, and was discussed in detail as far back as the early 1960s. Sugg (1967) discusses that although overall economic loss from hurricanes varies considerably from event to event, it is crucial for understanding the potential loss to have an accurate forecast prediction. Sugg (1967) also mentions, however, how an inaccurate prediction of landfall will cost money as preparations will be unnecessarily made. For example, Sugg (1967) offers the idea that errors of commission (inaccurate forecasts) would cost nearly $7 million (in 1967 dollars) for an average season (these costs come from the sum of protection, evacuations, and special interests that come from warning a population). On the other hand, Demsetz (1962) found that wind and rain damage from a hurricane striking Miami would be $13 million (in 1960 dollar amounts) if the city received no warning, but only $7.7 million (reduction in damage amounts along with the cost to prepare a city) if the city prepared for the hurricane. Anderson and Burnham (1973) discuss that the cost of protection and damages will always be less than no protection and damages alone. As seen with this example and in the previous sections, the knowledge of the physical phenomena behind a hurricane is vital to understanding the overall effects felt by the hurricane and, therefore, the amount of preparation that needs to be done to reduce the economic losses.

Research towards economic losses specifically in Florida has begun with the introduction of the Florida Public Hurricane Loss Projection Model by NOAA's Hurricane Research Division. This model was developed in order to accurately predict or estimate the overall economic loss from an individual future hurricane event. The overall components within this model include two atmospheric science components (for example, intensity and terrain influences), one engineering component (building structures), and one financial/actuarial component (computed insurance losses). The main purpose of this Florida Loss Projection model is to calculate the expected loss from an individual hurricane making landfall on a specific area of the Florida coastline.

This model is different than the economic loss model analyzed in this research because it is based on the specificities of a particular hurricane event and the particular expected place of landfall. The model from this research takes a more actuarial approach, utilizing information collected from Florida hurricanes (1900–2007) to calculate a general estimate for economic loss based on hurricane intensity prior to landfall.

Although wind speed is an adequate measure of the potential loss amount, it has been shown that minimum central pressure has a higher correlation with losses than wind speed alone (Malmstadt et al. 2009). Based on central pressure alone, Malmstadt et al. (2009) develops a Florida Hurricane Loss Index (FHLI). Using the FHLI it is shown that minimum central pressure alone explains 40% of the overall Florida loss amounts (log) versus the 28% explained by the Carvill Hurricane Index (an index used by the financial sector to price hurricane futures). It is important to note, however, that the FHLI does not consider the cyclone's forward speed and the rate at which the wind decays over land, and both of these variables will most likely increase the accuracy of the loss projection. That being said, knowing that the overall losses are better explained through using minimum central pressure by over ten percentage points, this index seems relevant to adopt.

This research is designed to show if pre-landfall intensity is a better indicator of overall economic loss than at landfall intensity for the historical set of Florida hurricanes. The main premise for this research comes from Jordan and Clayson (2008), which utilizes the 6, 12, 18, and 24 hourly interpolations of the given wind speeds in the HURDAT data set to predict storm surge using intensity prior to landfall. Using Pearson correlation and Spearman rank correlation, Jordan and Clayson (2008) found that the intensity 12 hours prior to landfall is a better predictor of overall storm surge. It has been discussed that storm surge is a large part of overall economic loss experienced from a hurricane. One would expect that if storm surge is better predicted prior to landfall, pre-landfall intensity would also be a better indicator of overall economic loss.

Although this study aims to use central pressure to estimate economic loss, the available 6 hourly data for pressures prior to landfall extends back only to 1975. However, in past research, hurricane wind speeds were substituted for pressure when pressure data were unavailable (Darling 1991), as it is understood that there is an inverse relationship between central pressure and wind speeds within a hurricane based on the physics of the atmosphere. It is the belief of the author that if pre-landfall intensity based on wind speeds are a better indicator of economic loss than at landfall intensity; it is plausible to think that the same will be true for minimum central pressure. The relationship between landfall pressure and landfall wind speed with economic loss is, fortunately, able to be compared because landfall pressure data dating back to 1900 is available. The relationship between landfall pressure and economic loss is tested to compare it with the relationship between landfall wind speed and economic loss to see if an inverse relationship exists and if pressure is, in fact, correlated higher with economic loss than wind speed.

CHAPTER 3

DATA

As stated throughout the previous chapters, this study is designed to test the relationship between hurricane intensity characteristics prior to landfall in the state of Florida and the economic loss associated with those hurricanes. This chapter will explain how the data are collected and manipulated to make suitable for use in this study. It also discusses how the data are utilized to explore this relationship, as well as the statistical methods executed to fully analyze the variables.

This study relies on the following principle sources of data.

1. For information regarding the historical hurricanes affecting Florida, the list employed to evaluate a risk model developed by the Florida Commission on Hurricane Loss Projection Methodology (FCHLPM) is used. This data set is very similar to the National Hurricane Center's HURDAT storm archive (Ho et al. 1987; Landsea et al. 2004) and can be found online at http://www.aoml.noaa.gov/hrd/lossmodel/AllFL.html. This dataset includes all storms which affected Florida since 1900 with their corresponding landfall dates and times (UTC), as well as intensity characteristics and storm size. Storm size is measured using the radius of maximum winds (RMW). It is proportional to the size of the area experiencing the most intense winds within the hurricane.

As stated earlier, this study aims to use the intensity characteristic minimum central pressure as the overall predictor of economic loss but, due to lack of hourly data since 1903, the analysis cannot be completed using that characteristic. However, in order to test the hypothesis that pressure is a more accurate predictor of economic loss compared to maximum wind speed, the landfall pressure data since 1900, also available at this data source, is used.

2. The focus of this study is on intensity prior to landfall, so the available hourly wind speed data per hurricane (hour 1 through hour 24 prior to landfall) provided by Jagger and Elsner (2006) is merged with the storm archive discussed above. Jagger and Elsner (2006) use the 6-

hourly best track data, described below, to create spline-interpolated wind speeds for hours before and after landfall, along with their positions (latitude and longitude). This data is merged with the data described above by using the available landfall dates and times (UTC) from the FCHLPM.

The 1960's marked the beginning of modern hurricane research with the introduction of detailed hurricane data compiled by the U.S. Weather Bureau, now known as the U.S. National Weather Service (Elsner and Kara 1999). These data have been maintained and analyzed by the National Hurricane Center (NHC), as well as additional analyses submitted by other organizations and private researchers, and are available to the public at http://maps.csc.noaa.gov/hurricanes. This best-track record, known as HURDAT, has been utilized in multiple publications since its development in the 1960's in order to analyze avenues such as hurricane development (Carlson 1971; Briegel and Frank, 1997), hurricane frequency (Cry and Haggard 1962; Elsner et al. 1999), and hurricane forecasting (Gray 1984; Willoughby 2007). It is the wind values in this data set that Jagger and Elsner (2006) used to create the spline interpolated values used in this study.

3. For losses from hurricanes that directly strike Florida, normalized loss data are taken from Pielke et al. (2008). There are two sets of loss estimates based on slightly different normalization procedures. The normalization is an adjustment of the loss in an attempt to match what the losses would be if the hurricane struck in the year 2005. The first procedure is the Pielke/Landsea (1998) normalization methodology, which is achieved by allowing for changes in inflation, wealth, and population. The Collins/Lowe (2001) methodology is a normalization that is achieved by allowing for changes in inflation, wealth, and housing units updated to 2005. Note that both normalization procedures are quite similar. Pielke et al. (2008) adjusted each of these procedures slightly to account for the changes in the included variables to 2005. The overall economic losses are aggregated from the entire state and do not necessarily cluster around the hurricane's landfall location. Economic loss is the direct loss associated with a hurricane's impact and does not include loss due to macroeconomic effects such as business interruption or demand surge. Further details of this normalization procedure can be found in Pielke et al. (2008). Table 2 shows all the hurricanes included in the data. The table includes the year, seasonal sequence number (Seq), name, month (Mo), day (Da), and hour (Hr) of the hurricane, as well as the time of landfall (UTC) and the location of the hurricane landfall in

longitude (Lon) and latitude (Lat). It also includes the maximum wind speed (*w*), the radius to maximum winds (RMW) and the minimum central pressure (Pmin), as well as the economic loss in $US (*L*), and whether or not the hurricane made landfall on the east coast (East), which stretches from Key Largo to Jacksonville.

Table 2: The entire data set when the 52 hurricanes made landfall. Refer to notes above for the descriptions of variables.

Year	**Seq**	**Name**	**Mo**	**Da**	**Hr**	**Time of Landfall (UTC)**	**Lon**	**Lat**	***w* (kt)**	**RMW (km)**	**Pmin (hPa)**	***L* ($US)**	**East**
1903	3	Storm3	9	13	22	2200	-85.6	30.0	81.6	50	975	5,206,457,013	F
1906	8	Storm8	10	18	11	1100	-80.9	25.1	105.7	40	953	1,419,379,689	F
1909	10	Storm10	10	11	18	1800	-81.0	24.7	100.0	25	957	433,320,008	F
1910	5	Storm5	10	18	6	0600	-82.0	26.5	95.0	14	955	814,232,250	F
1919	2	Storm2	9	10	7	0700	-82.1	24.4	115.6	17	929	719,625,394	F
1921	6	Storm6	10	25	20	2000	-82.7	28.1	87.4	21	952	3,201,735,033	F
1926	1	Storm1	7	28	6	0600	-80.6	28.3	75.0	16	960	3,599,433,103	T
1926	6	Storm6	9	18	12	1200	-80.3	25.6	115.0	22	935	129,000,000,000	T
1928	4	Storm4	9	17	6	0600	-80.1	27.1	115.0	32	935	31,842,991,619	T
1929	2	Storm2	9	28	18	1800	-80.7	25.1	85.0	32	948	255,541,019	T
1933	12	Storm12	9	4	5	0500	-80.1	26.8	114.7	15	948	1,361,044,627	T
1935	2	Storm2	9	3	5	0500	-80.7	24.8	132.5	7	892	3,105,119,662	F
1935	6	Storm6	11	4	17	1700	-80.1	25.9	65.0	12	973	5,554,281,127	T
1936	5	Storm5	7	31	15	1500	-86.7	30.4	75.2	22	973	125,914,494	F
1941	5	Storm5	10	6	10	1000	-80.2	25.4	104.4	21	954	361,980,468	T
1944	11	Storm11	10	19	7	0700	-82.4	27.1	62.0	29	962	35,587,059,722	F
1945	9	Storm9	9	15	22	2200	-80.3	25.4	116.8	14	940	10,147,966,555	T
1946	5	Storm5	10	8	2	0200	-82.7	27.5	52.3	30	989	991,035,044	F
1947	4	Storm4	9	17	16	1600	-80.1	26.4	131.2	30	947	11,612,664,951	T
1947	8	Storm8	10	12	2	0200	-81.1	25.3	72.0	15	980	539,953,323	F
1948	7	Storm7	9	22	0	0000	-81.2	25.6	100.0	8	963	3,619,996,492	F
1948	8	Storm8	10	5	19	1900	-81.2	24.6	106.9	18	977	565,294,842	F
1949	2	Storm2	8	27	0	0000	-80.1	26.8	130.0	26	954	13,468,454,482	F
1950	5	Easy	9	5	12	1200	-82.6	28.7	105.0	17	958	972,672,385	F
1950	11	King	10	18	6	0600	-80.2	25.8	90.0	7	988	3,725,252,507	T
1953	8	Florence	9	26	17	1700	-86.3	30.3	71.7	30	982	14,316,188	F
1956	7	Flossy	9	24	23	2300	-86.6	30.3	68.4	21	974	711,117,719	F
1960	5	Donna	9	10	7	0700	-80.8	24.8	115.4	21	930	28,920,699,579	F
1964	5	Cleo	8	27	10	1000	-80.1	26.0	87.0	8	968	4,653,166,631	T
1964	6	Dora	9	10	5	0500	-81.3	29.9	95.9	39	961	6,577,589,728	T

Table #2—continued

Year	Seq	Name	Mo	Da	Hr	Time of Landfall (UTC)	Lon	Lat	*w* (kt)	RMW (km)	Pmin (hPa)	*L* ($US)	East
1964	11	Isbell	10	14	21	2100	-81.3	25.7	110.3	12	964	624,127,559	F
1965	3	Betsy	9	8	11	1100	-80.5	25.1	110.5	23	952	4,013,938,352	F
1966	1	Alma	6	9	20	2000	-84.5	29.9	73.6	29	973	81,268,979	F
1966	9	Inez	10	4	18	1800	-80.5	25.0	75.0	17	984	130,663,800	F
1968	8	Gladys	10	19	5	0500	-82.7	28.8	70.1	20	977	495,114,445	F
1972	2	Agnes	6	19	21	2100	-85.4	30.1	55.5	23	983	411,000,086	F
1975	5	Eloise	9	23	12	1200	-86.3	30.2	110.0	16	955	2,834,851,643	F
1979	4	David	9	3	17	1700	-80.1	27.1	85.2	31	972	2,193,891,626	T
1985	11	Kate	11	21	23	2300	-85.3	30.0	81.2	12	967	1,088,138,521	F
1987	7	Floyd	10	12	22	2200	-80.4	25.1	62.4	47	993	2,649,286	F
1992	2	Andrew	8	24	9	0900	-80.2	25.5	123.7	12	922	52,340,623,758	T
1995	5	Erin	8	3	16	1600	-87.2	30.3	72.2	15	974	1,375,861,447	F
1995	15	Opal	10	4	22	2200	-87.1	30.3	89.9	50	942	6,339,955,773	F
1998	5	Earl	9	3	6	0600	-85.7	30.1	70.0	74	987	126,232,889	F
1998	7	Georges	9	28	11	1100	-88.9	30.3	91.5	44	975	1,046,295,571	F
1999	9	Irene	10	15	19	1900	-81.2	25.3	65.0	30	984	1,178,217,658	F
2004	3	Charley	8	13	20	2000	-82.1	26.8	113.1	5	947	16,297,047,080	F
2004	6	Frances	9	5	6	0600	-80.2	27.2	90.0	52	960	9,648,997,103	F
2004	9	Ivan	9	16	7	0700	-87.9	30.2	100.6	23	943	15,514,011,620	F
2004	10	Jeanne	9	26	4	0400	-80.2	27.2	99.6	45	951	7,496,264,391	T
2005	4	Dennis	7	10	20	2000	-87.1	30.4	90.3	8	946	2,230,000,000	F
2005	22	Wilma	10	24	11	1100	-81.4	26.0	96.8	46	950	20,600,000,000	F

In Table 2, there are four hurricanes that, at time of landfall, did not have wind speeds at hurricane intensity, and these are Storm 11 (1944), Storm 5 (1946), Hurricane Agnes (1972), and Hurricane Floyd (1987). However, all of these hurricanes exhibited hurricane force wind speeds (at least 64 kt) at hours just prior to landfall. Thus, they are included in this study. To provide a 'zoomed-in' view of the data set, a 14-hour swath of Hurricane Andrew (1992) is shown in Table 3. Hurricane Andrew made landfall at 0900 hours (UTC), shown in bold, on 24 August 1992. This table shows hurricane characteristics for Andrew beginning at ten hours to landfall, and ending with 3 hours past landfall (-3). As it is seen in Table 3, the maximum sustained wind speeds (*w*) change with every passing hour. All of the attributes in this table are the same as in Table 2.

Table 3: An example of the data used for this study. A 14-hour swath of Hurricane Andrew is shown with the variables used for the statistical analysis included. Note above for the description of the variables. Time of landfall is noted in bold.

Year	**Name**	**Mo**	**Da**	**Hr**	**Hours to Landfall**	***w***	***L* ($US)**	**RMW**
1992	Andrew	8	23	2300	10	127.7	52,340,623,758	12
1992	Andrew	8	24	0000	9	125.0	52,340,623,758	12
1992	Andrew	8	24	0100	8	124.2	52,340,623,758	12
1992	Andrew	8	24	0200	7	124.9	52,340,623,758	12
1992	Andrew	8	24	0300	6	126.4	52,340,623,758	12
1992	Andrew	8	24	0400	5	128.2	52,340,623,758	12
1992	Andrew	8	24	0500	4	129.6	52,340,623,758	12
1992	Andrew	8	24	0600	3	130.0	52,340,623,758	12
1992	Andrew	8	24	0700	2	128.9	52,340,623,758	12
1992	Andrew	8	24	0800	1	126.7	52,340,623,758	12
1992	**Andrew**	**8**	**24**	**0900**	**0**	**123.7**	**52,340,623,758**	**12**
1992	Andrew	8	24	1000	-1	120.5	52,340,623,758	12
1992	Andrew	8	24	1100	-2	117.4	52,340,623,758	12
1992	Andrew	8	24	1200	-3	115.0	52,340,623,758	12

It should be noted that before 1940, 32 hurricanes made landfall somewhere on the United States' coastline (not just Florida) with no reported losses in the official record, where only 8 such hurricanes have occurred since 1940 (Pielke et al. 2008). This suggests a likely undercount of the overall loss caused by hurricanes within the North Atlantic Basin prior to 1940, and, if at least one hurricane strikes Florida every two years, there is an undercount of Florida losses prior to 1940 as well. Therefore, the hurricane loss data prior to 1940 used in this research may not represent every hurricane to strike Florida and cause economic loss in the time period of this study, 1900–2007.

CHAPTER 4

ANALYSES

Florida Hurricane Climatology

The focus of this study is on the intensity of and losses from hurricanes which directly strike Florida. A direct strike is therefore considered to be one in which at least part of the hurricane's eyewall reaches the coast of Florida, including the Florida Keys. As an exception, the Florida Keys are only used as a landfall location if no other landfall was made in the state or if the intensity of the hurricane was higher at the island pass than at the mainland location. Hurricanes that fit these descriptions include Storm 10 (1909), Storm 2 (1919), Storm 2 (1935), Storm 8 (1948), Donna (1960), Betsy (1965), Inez (1966), and Floyd (1987).

Although there are 67 known hurricanes that have struck Florida from 1900–2007, only 52 of those hurricanes have an estimated economic loss value available in Pielke et al. (2008), and it is those 52 that are considered for this study. Figure 4 shows a bar chart representing the number of occurrences per month for the 52 Florida hurricanes, as well as a bar chart showing the distribution of hurricanes based on hour of landfall. The vast majority of Florida hurricanes occur during the months of September and October, while June, July, August, and November all have smaller numbers of occurrences. This is due to the warmer waters experienced in the North Atlantic Basin during the later months of the season, September and October. As seen in Figure 4 (b), the most common landfall time is 0600 (UTC). There is no evidence of a preferred landfall time of day.

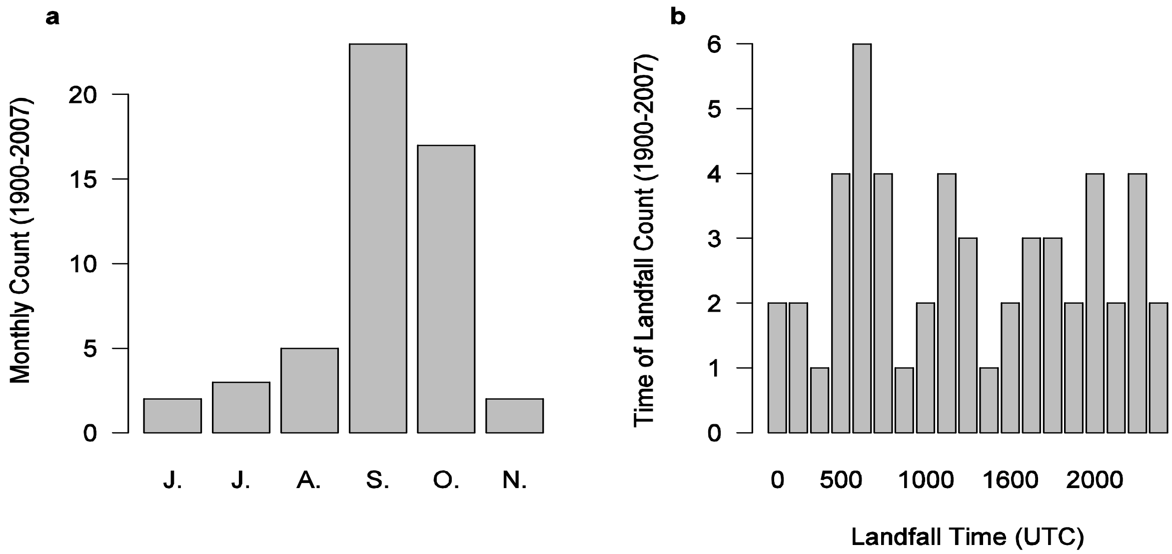

Figure 4: (a) Monthly bar chart. Months range from June to November. (b) Landfall hour bar chart. Landfall times are in UTC. Times range from hour zero to 2300.

In order to gain a better understanding of the characteristics common to this set of Florida hurricanes, a time series of the data and density plots for the radius to maximum winds, minimum central pressure, and maximum sustained wind speeds are provided in Figure 5. All characteristics are shown at time of landfall. As it is seen in Figure 5 (a), there are some years with no hurricane events and some years with more than one. 2004 had the most hurricane strike occurrences, with 4 direct landfalls. There is no significant trend in landfall counts over time. Figure 5 (b) shows the distribution in the size of Florida hurricanes (as measured by the radius to maximum winds). The mean of RMW is 24.87 km with a standard error of ± 1.98. The distribution is positively skewed with one cyclone having an RMW exceeding 70 km. Figure 5 (c) shows that the mean minimum central pressure for this set of hurricanes is 959.87 hPa with a standard error of ± 2.73. The distribution is negatively skewed with only one hurricane having pressure recorded below 900 hPa. Figure 5 (d) shows that the distribution of the maximum sustained wind speeds is symmetric, and the mean is 92.47 kt with a standard error of ± 2.87.

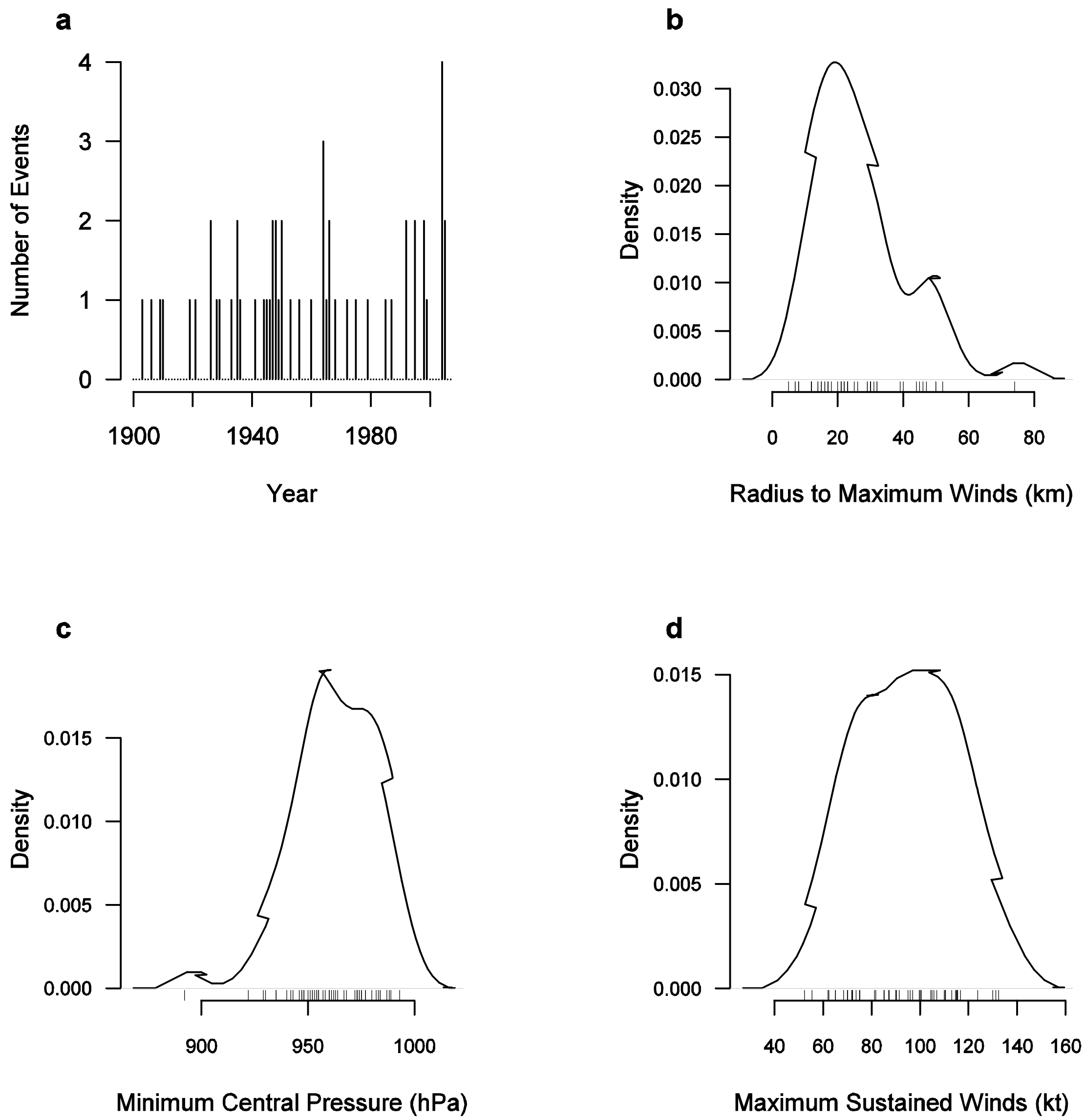

Figure 5: (a) Time series of Florida hurricane events from 1900–2007. (b) Density plot of the radius to maximum winds (km). The distribution is positively skewed since few cyclones exceeded 70 km. The mean of RMW is 24.87 km. (c) Density plot of the minimum central pressure (hPa). The distribution is negatively skewed, and the mean is 959.87 hPa. (d) Density plot of the maximum sustained wind speeds (kt). The distribution is symmetric since wind speeds vary greatly within a hurricane. The mean maximum wind speed is 92.47 kt.

Examples of direct hurricane strikes to Florida are provided in Figure 6. Examples include Storm 1 (1903), Storm 11 (1944), Hurricane Gladys (1968) and Hurricane Dennis (2005). The arrows show the direction of hurricane travel as it headed towards the coast.

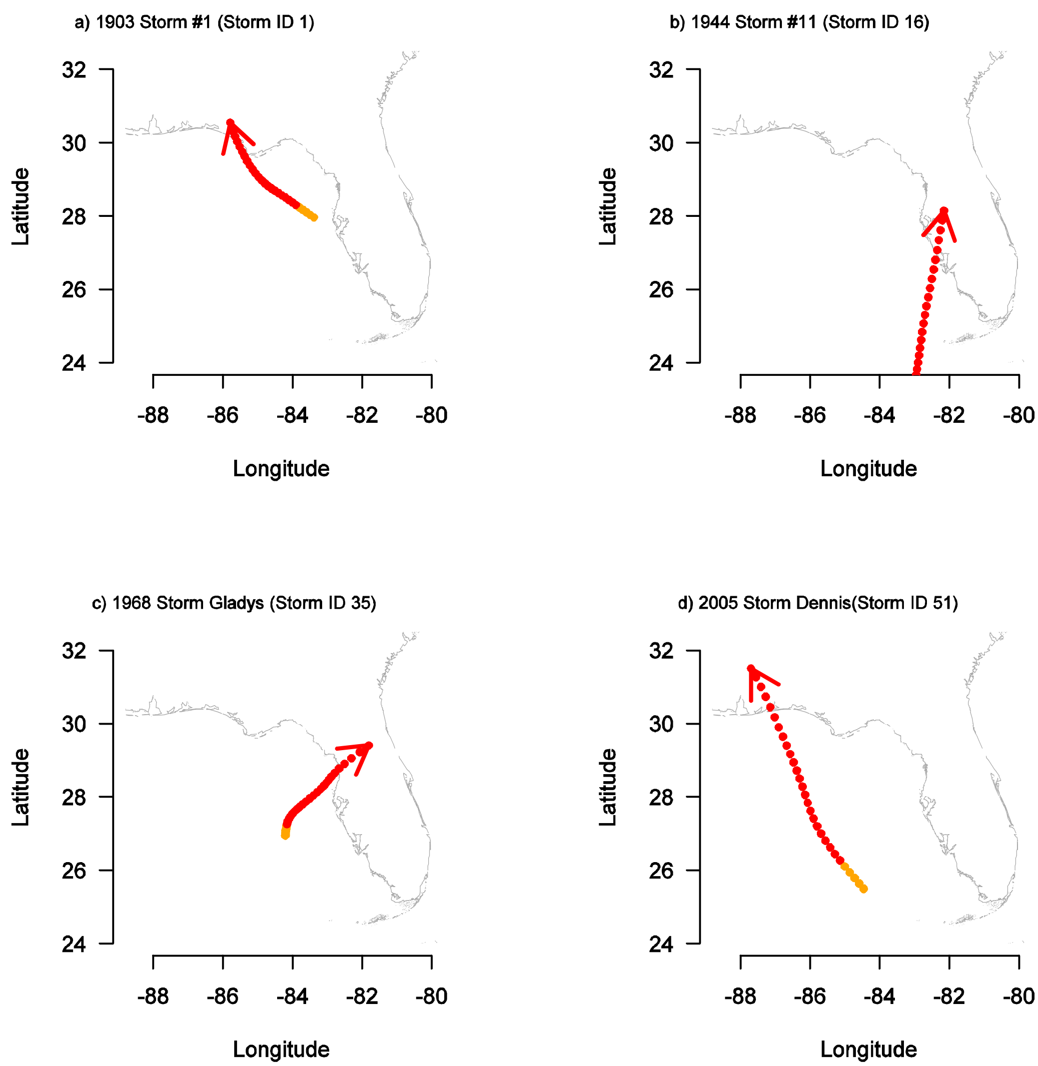

Figure 6: Examples of hurricane tracks within data set. Circles are coded for intensity. Orange denotes tropical storm status (34–63 kt) and red denotes Category 1 status (64–82 kt). The points indicate the hourly interpolated positions. Points farther apart indicate a faster moving hurricane.

A hurricane can make more than one direct hit on the state. This occurs, for instance, when a hurricane first strikes the peninsular region of Florida then moves out over the Gulf of Mexico before striking the panhandle region. For the purposes of this study, these events will be counted as one event. The landfall with the highest intensity is used since this study focuses on overall economic loss. When hurricanes travel over land, they tend to weaken so the intensity at second landfall is typically less than at first landfall. This is the case for all hurricanes in this data set except Storm 3 from 1903, Storm 5 from 1936, and Hurricane Erin from 1995. These hurricanes had higher intensities at their second landfall locations, and since this research is regarding intensity prior to landfall, it is noted that 1–24 hours prior to the second landfall location was not over land for these three hurricanes, so no complications arose in terms of pre-landfall being over land for these particular events.

The study includes 52 hurricane tracks that were considered at least Category 1 hurricanes (Figure 7). The first year in the data is 1900 and it extends through 2007. Not all years have at least one hurricane, and the first year with a storm is 1903. Although there are 67 known Florida hurricanes throughout this time period, only hurricanes which have affected Florida in terms of creating some type of economic loss are included. It is noted that Hurricane Georges (1998) and Hurricane Ivan (2004) made landfall outside of Florida, but both eyewalls still reached the Florida border and created economic loss within the state, and so are included for this study. Note there is only one Category 5 hurricane included in this data set, and it is denoted with a dark red circle and occurred in 1935.

Loss Data

Merging the first and second data sources described in the first section of this chapter provides the hourly-interpolated wind speeds per hurricane for the 24 hours prior to landfall needed to complete this research. Each hurricane is assigned an economic loss value based on the data provided by Pielke et al. (2008). There are two sets of loss data provided in Pielke et al. (2008) based on different normalization procedures, and, for the purposes of this analysis, the Collins/Lowe (2001) methodology (adjusted to 2005 in Pielke et al. (2008) already discussed) is adopted. It is noted that the Collins/Lowe (2001) methodology has a slightly higher correlation representing the relationship between economic loss and landfall intensity than the

Pielke/Landsea (1998) methodology, with values at 0.496 and 0.505, respectively. Although the Collins/Lowe (2001) methodology is adopted here, the results presented are not dependent upon the set of economic loss data used.

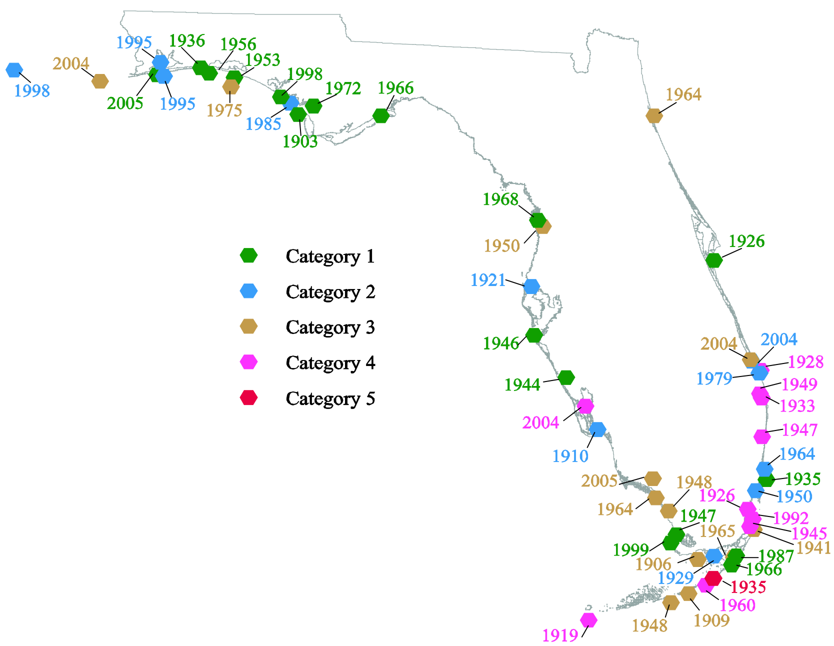

Figure 7: Florida landfalling hurricanes with available economic loss data from 1900–2007. Landfall locations are denoted with a symbol, and the landfall intensities are denoted by color (based on the categorization of the Saffir-Simpson Scale).

Loss events occurring throughout this time period are provided in Figure 8. There are years that have more than one hurricane, most notably 2004, which had the highest number of hurricane occurrences (refer to Figure 5a). Also, there are years that have no hurricane occurrences, such as 2000, 2006, and 2007. Those years, of course, have no loss values associated with them. The highest loss value occurred in 1926, with a value well above any other. This hurricane, if it occurred in 2005, would have caused over $120 billion in economic loss. This value, however, does not account for the changes in warning systems and evacuation procedures, so the devastation, if this hurricane did occur in 2005, may not have been quite so severe when these characteristics are taken into consideration.

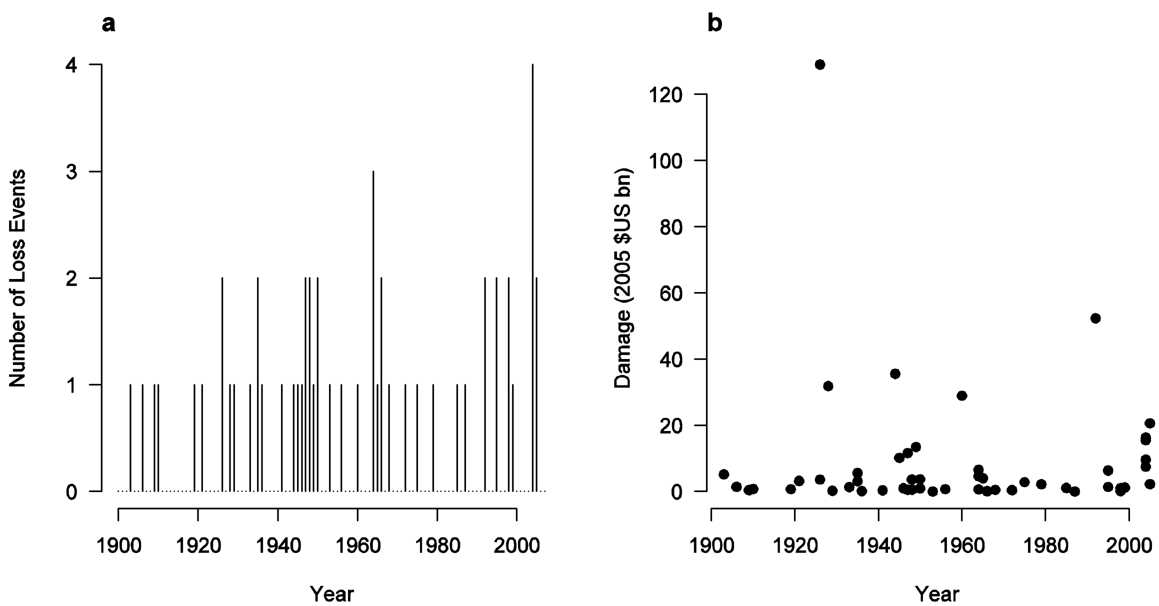

Figure 8: (a) Frequency of the number of loss events 1900–2007. (b) Loss amounts (2005 $US billion) 1900–2007.

To simplify the modeling procedure, the loss data from Pielke et al. (2008) are transformed using a logarithm (base 10) of the data. Without transformation, the economic loss data are positively skewed because there are only a few hurricanes with very high economic loss associated with them and a lot of hurricanes with low loss values. Figure 9 shows the original and transformed data. The original data are positively skewed with most hurricanes having small to moderate loss values (<$20 billion) and only a few with very large losses (>$120 billion). This skewness is reduced considerably after transforming the data using the logarithm (base 10) of the values.

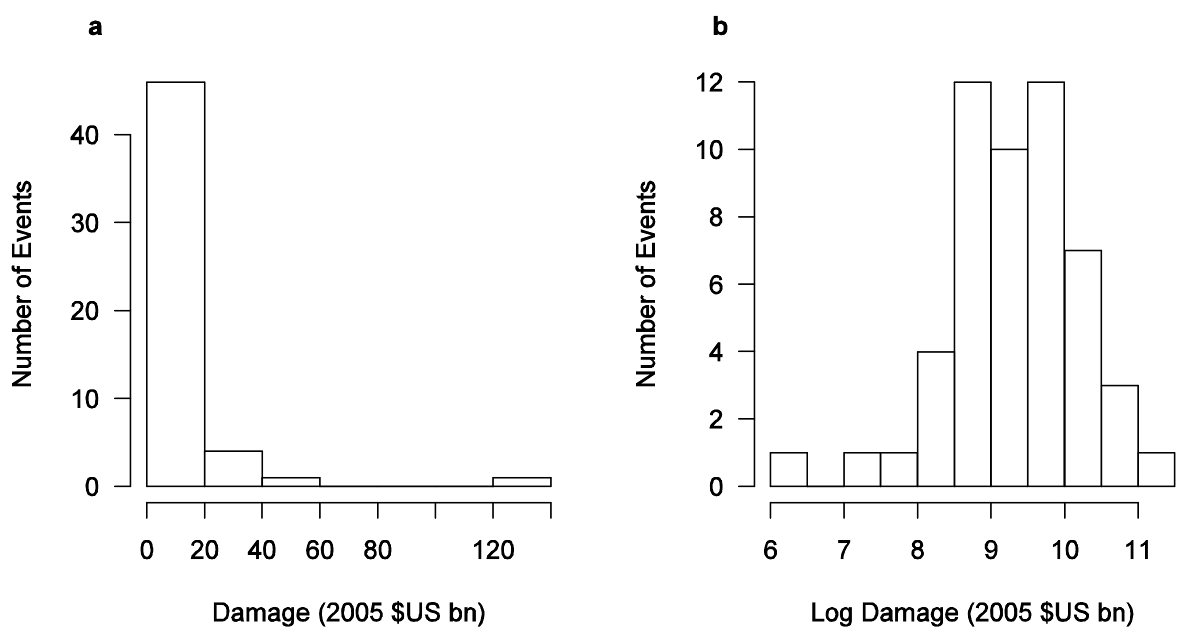

Figure 9: Histogram of normalized loss amounts from FL hurricanes 1900–2007 (in 2005 $US billions). (a) normalized loss amounts and (b) logarithm (base 10) of normalized loss amounts.

A plot including 5 hour tracks for all hurricanes within this data set, as well as their associated economic loss taken from the Collins/Lowe (2001) methodology presented and adjusted in Pielke et al. (2008) are presented in Figure 10. A 5-hour track for each of the 52 hurricanes included are shown and color-coded based on the economic loss data. The transformed loss values are also shown. The arrow shows the direction of hurricane travel as it crossed the coast. The majority of hurricane strikes happen in the southern portion of the peninsula and in the western portion of the panhandle. The 'bend' of Florida and the northeast coast experience the least amount of hurricane strikes.

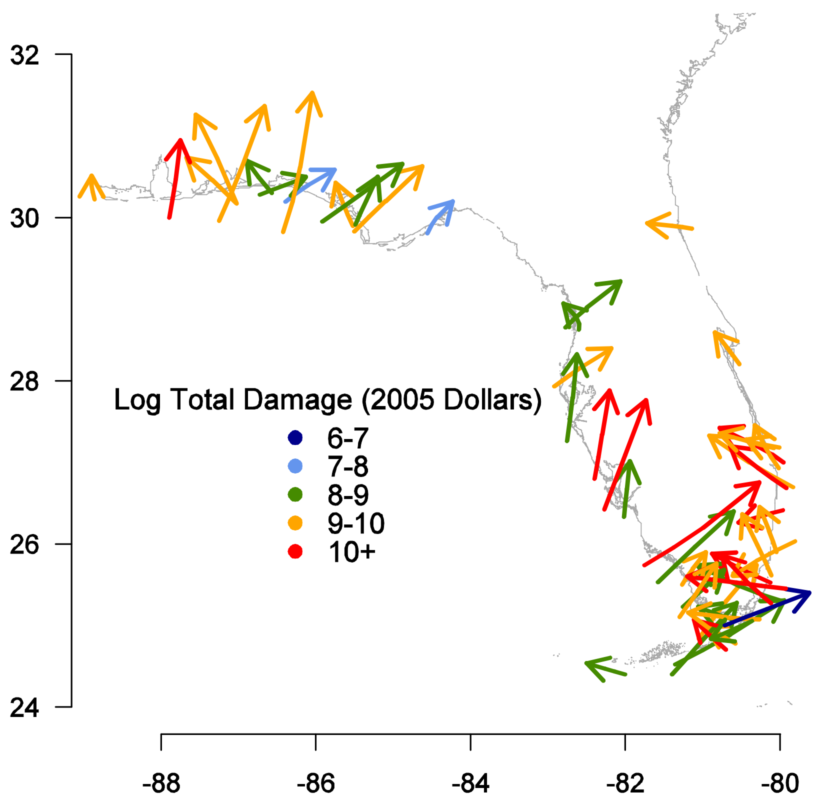

Figure 10: Five hour tracks of all 52 Florida hurricanes in data set with available economic loss data from 1900–2007. The normalized economic loss data (in logarithm base 10 values) are denoted by color. Note that 9 denotes $1 billion and the categories are exclusive.

Correlation between Loss and Wind Speed

The statistical analysis for this research is computed using the Pearson product-moment method of correlation. The Pearson correlation coefficients are calculated first to find the relationship between landfall intensity and the available economic loss data. Then the relationship is found between pre-landfall intensity and economic loss using the same method. Pre-landfall intensity is calculated for 1 hour out from landfall through 24 hours out from landfall. Those coefficients are then compared to the first computed to decipher which hour shows the greatest correlation value for overall economic loss in Florida.

As stated earlier, this study aims to use the intensity characteristic minimum central pressure as the overall indicator of economic loss but, due to lack of hourly data, is unable to do so. However, in order to show that minimum central pressure is a better indicator of economic loss than maximum wind speed, the available pressure values at landfall are correlated with the economic loss values. Those correlations are then compared to the correlations of landfall wind speeds and economic loss. If intensity based on pressure at landfall shows a stronger relationship with economic loss than using wind speed at landfall, and if the hypothesis that pre-landfall intensity is a better indicator of economic loss in Florida than intensity at landfall is correct, then it is intuitive to think that pre-landfall intensity based on minimum central pressure will be a better indicator of expected economic loss than pre-landfall intensity based on wind speeds.

After computing the correlation coefficients between pre-landfall intensity based on wind speed and economic loss, the coefficient of the highest value and significance is chosen, and a log-linear regression model is developed. An equation is derived from this regression model to be used for estimation of economic loss per Florida hurricane event in the future. After the model is developed, the adequacy of the model is checked by examining the distribution of the residuals. In order to explain more of the data, the residuals of the model are plotted and analyzed to decipher any patterns of under-prediction or over-prediction. Then two additional variables are considered. These variables include the radius of maximum winds (size of the hurricane) and whether the storm had an east coast landfall.

After these variables are examined, the Cook's distance values are computed for the model. Cook's distance calculates the influence an individual data observation has on the overall model. It measures the effect deleting an observation point from the data will have on the model's overall ability to describe the phenomenon. Model residuals are also examined and the hurricanes with the highest positive residuals and the hurricanes with the lowest negative residuals are described in further detail to try and allow for further insight into the analysis of the data (Chapter 6).

The goal of this study is to statistically analyze the relationship between pre-landfall hurricane intensity and economic loss in the state of Florida. This study uses data from 107 years of study, 1900–2007, and includes 52 individual hurricanes. Using Pearson correlation and regression analysis, the relationship between these two variables is determined and presented throughout the following results.

For clarity, let w_i represent the wind speed intensity at hour i from landfall, and L be the logarithm (base 10) of the total economic losses for the hurricane. Then the Pearson correlation coefficient between wind speed at landfall and loss is given by r $[w_0, L]$.

Figure 11 shows the Pearson correlation coefficients $r\ [w_i, L]$ between economic loss and hurricane intensity (maximum sustained wind speed) for the 25 hours analyzed. Hour zero denotes the landfall relationship, and hours 1–24 are the hours prior to the hurricane making landfall. The solid, black line represents the change in correlation values from hour zero (landfall) to 24 hours prior to landfall. The red, dashed line represents this relationship at landfall, and is included to show where the correlation values for other hours deviate from the landfall relationship. The gray, shaded area is included to show the 90% confidence intervals for these values. All of the specific values and their confidence intervals are shown in Table 4.

It is seen from Figure 11 and Table 4 that hurricane intensity five hours prior to landfall has the strongest relationship with economic loss for Florida when examining hours zero (landfall) through 24 hours before landfall. It is this variable that is used for all further statistical analyses. As mentioned in the Introduction, present studies base their economic loss estimations on historical hurricane events and the expected intensity of the current event at landfall. With the results presented in this study, it is shown that five hours prior to landfall is a better estimate of what the expected economic loss would be from an individual hurricane striking Florida. When examining the correlations further, wind intensities at hour one through hour 15 all have higher correlations with this economic loss data than the landfall intensity does. This can be seen where the black line deviates from the red, dashed line in Figure 11. However, since all of these values fall within the 90% confidence interval (gray, shaded area), it is safe to assume that

$r\ [w_i, \text{L}]$ are not significantly different from one another from a statistical standpoint. That being said, it seems the hurricane intensity roughly half-a-day before landfall might be a better estimator of economic loss than the expected at landfall intensity. This means that economic loss researchers could have an estimate up to 15 hours prior to landfall that would be a stronger estimate than what the expected intensity would give.

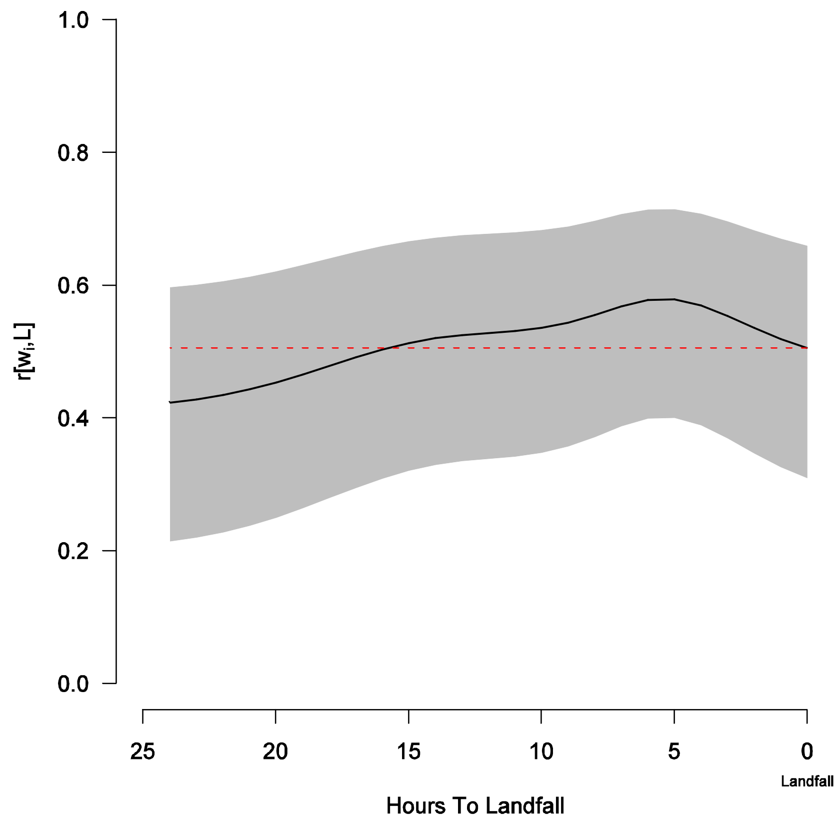

Figure 11: Pearson correlation coefficients (hours 24–0) representing relationship between pre-landfall hurricane intensity and economic loss in Florida. Hour zero denotes landfall relationship. The dashed red line represents the correlation between landfall wind intensity and losses. The solid black line represents the change in correlation values from 24 hours prior to landfall to the hour of landfall (hour zero). The gray shaded area represents the 90% confidence intervals for these relationships. w_i represents the maximum sustained wind speed of the hurricane at time i before landfall, when $i = 0, +1, +2, \ldots, +24$.

Table 4: The Pearson correlation coefficients representing the relationship between economic loss and wind intensity from hour zero (landfall) to 24 hours prior to landfall. The 90% confidence intervals are included to show significance.

Hours Out (*i*)	$r\ [w_i, L]$	**90% Confidence Interval**
0 (Landfall)	0.505	(0.311, 0.659)
1	0.519	(0.327, 0.669)
2	0.534	(0.348, 0.682)
3	0.554	(0.370, 0.696)
4	0.570	(0.390, 0.707)
5	**0.578**	**(0.401, 0.714)**
6	0.577	(0.400, 0.713)
7	0.568	(0.389, 0.706)
8	0.555	(0.372, 0.697)
9	0.544	(0.358, 0.688)
10	0.536	(0.348, 0.682)
11	0.531	(0.342, 0.679)
12	0.529	(0.339, 0.677)
13	0.526	(0.336, 0.675)
14	0.521	(0.330, 0.671)
15	0.514	(0.321, 0.666)
16	0.504	(0.309, 0.658)
17	0.492	(0.295, 0.650)
18	0.480	(0.280, 0.640)
19	0.467	(0.265, 0.630)
20	0.455	(0.250, 0.620)
21	0.444	(0.238, 0.612)
22	0.436	(0.228, 0.606)
23	0.429	(0.220, 0.600)
24	0.424	(0.214, 0.597)

CHAPTER 5

MODEL OF ECONOMIC LOSS

Model Equation

Now that the relationship is established between hurricane wind intensity at five hours prior to landfall and economic loss for the state of Florida, a log-linear regression model is developed and analyzed. The data and model are plotted in Figure 12. This figure represents the relationship between the logarithm of loss values and maximum wind speed at 5 hours prior to landfall. The solid, black line represents the model's best fit line and, for comparison purposes, the blue, dashed line represents the relationship for landfall wind speed and the logarithm of loss. This is included so differences between the two wind speed time variables can be easily compared. The 90% confidence intervals on the predicted model are included on this figure, and are denoted with dark red lines. After examining the y-intercept and the coefficient estimates of the log linear regression model, one can conclude the following: for every 1 knot increase in hurricane wind speed at five hours prior to hurricane landfall in Florida, the estimated economic loss will increase by a factor of 0.040, or $10^{0.04}$, or 9.6%. This is defined by the following equation

$$\hat{L} = 5.483 + 0.0401 \times w$$

where *L* refers to the logarithm of losses, the hat refers to the model estimate of the logarithm of losses, and *w* is the maximum sustained wind speed 5 hours prior to landfall (kt).

The adjusted R-squared for this model is 0.554, which suggests that 55% of the variability in the logarithm of losses is explained by using the interpolated maximum sustained wind speed values at five hours prior to landfall. This model represents statistically significant values against the null hypothesis of no relationship between wind speed and loss.

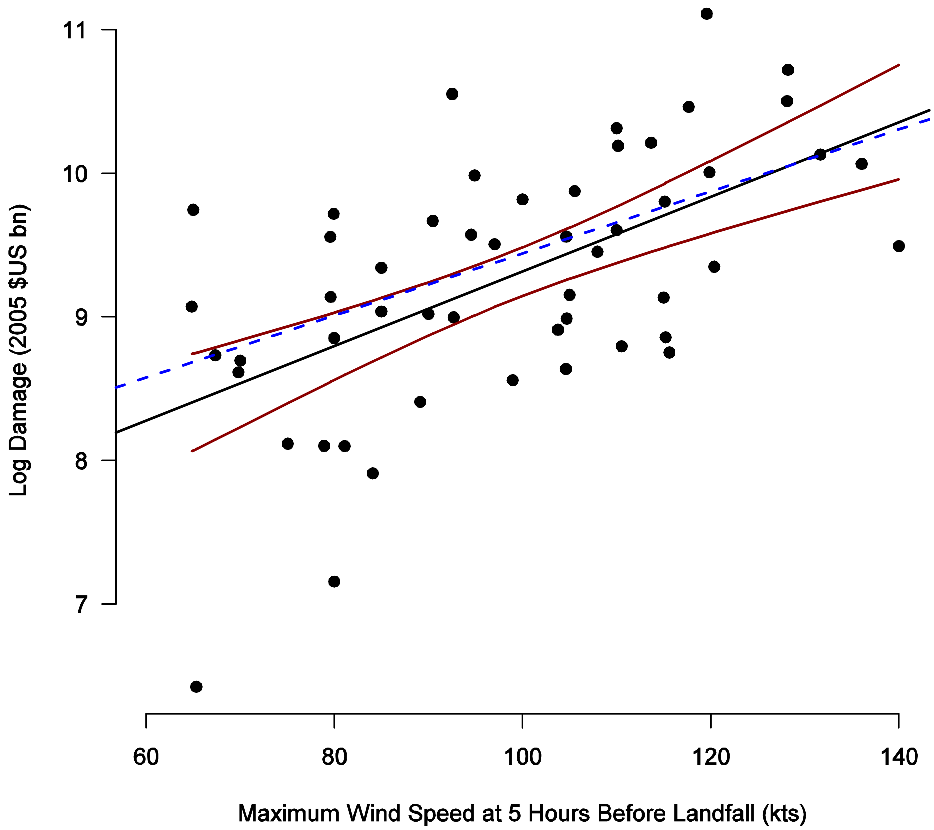

Figure 12: Regression model representing the relationship between the logarithm of loss amounts (2005 $US bn) and the maximum wind speed at 5 hours prior to landfall (kt). The solid black line represents the model's best fit line. The dark red lines represent the 90% confidence intervals on the predicted model, and the blue dashed line shows the relationship between landfall wind speed and loss.

This regression model plot is included to show how the model is predicting the economic loss values based on hurricane wind intensity at five hours prior to landfall. The lines of uncertainty (dark red lines) are included to show where one can expect the line of best fit to fall 90% of the time. Also included is a line representing the model for hour zero (landfall) and economic loss values. As shown in this figure, both lines fall within the 90% uncertainty lines, showing that they are not significantly different from one another. This is consistent with what

Figure 11 shows. However, the model itself is still significant statistically and could, therefore, tell something quite interesting about the relationship between economic loss and hurricane wind intensity at five hours prior to landfall.

Using the five hour intensity presented in this study, researchers could gain a greater understanding of the estimated economic loss in Florida even farther out from landfall. With this greater understanding, Florida citizens could be informed about the hurricane's nature in regards to economic loss and they could prepare their homes/infrastructure accordingly. At the very least, they would know the importance of evacuation even earlier because if the hurricane is expected to be severe in terms of economic loss, then people should definitely evacuate in order to reduce loss of life as well.

Model Adequacy

In order to check the adequacy of the model, the residuals are examined to see where any major outliers lie. A residual is defined as the difference between the observed value and the value predicted from the model (observed minus predicted). Positive (negative) residuals indicate the model under (over) predicts the actual value. Figure 13 shows the distribution of the accepted model's residuals. Figure 13 (a) shows the residuals based on the independent variable, maximum sustained wind speeds at 5 hours prior to landfall (kt). Figure 13 (b) shows a density plot of the model's residuals to show the density distribution of the residuals. As seen in Figure 13, the residuals for this model are normally distributed with few outliers. The two lowest negative outliers, Hurricane Floyd (1987) and Hurricane Florence (1953), and the three highest positive outliers, Storm 11 (1944), Storm 6 (1935), and Storm 6 (1926), are labeled. These specific residuals are looked at in more detail and explained in the next chapter. The density plot in Figure 13 (b) shows that the bulk of the model residuals are located between values -1 and 1, with the highest magnitude being located around zero.

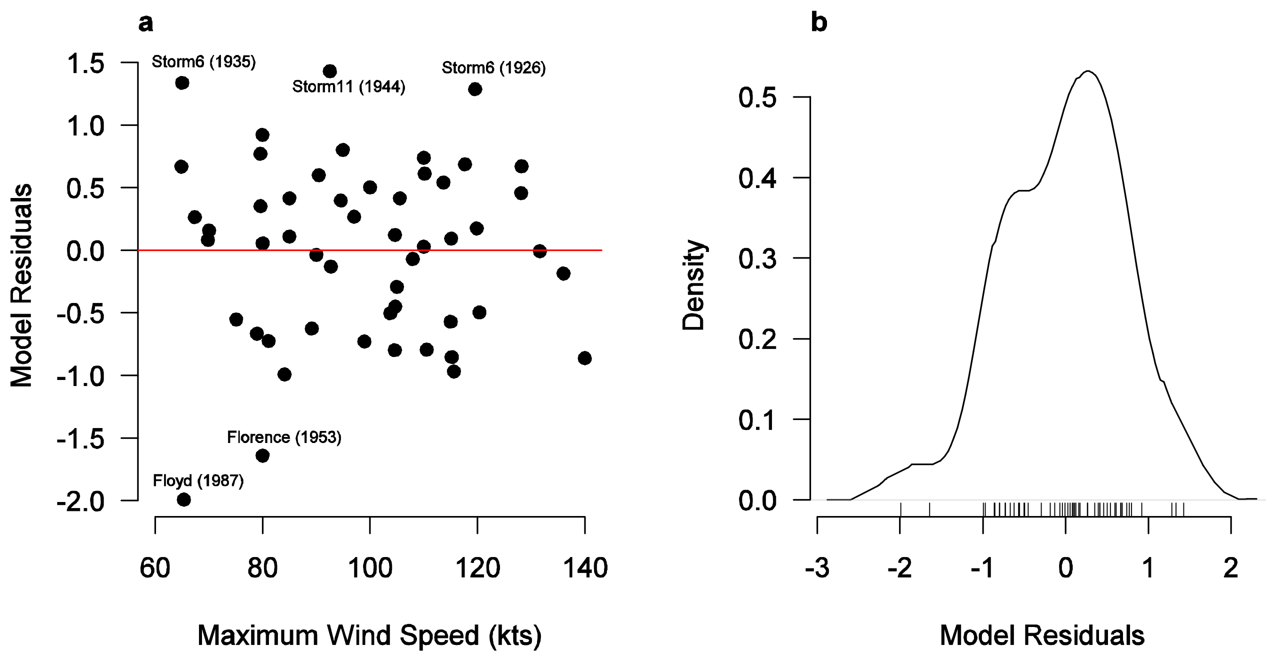

Figure 13: Distribution of model residuals. (a) Model residuals based on independent variable with line of best fit included. (b) Density plot of model residuals.

In order to examine the model residuals further, they are plotted based on landfall location and as a time series, as shown in Figure 14. Figure 14 (a) shows the magnitude of residuals for every hurricane in this sample. Extreme negative residuals are denoted by dark blue circles and extreme positive residuals are denoted with dark red circles. Figure 14 (b) shows a time series of the model's residuals through the span of this data set, 1900–2007. The line of best fit is included to show if there are any increasing/decreasing trends throughout this time period.

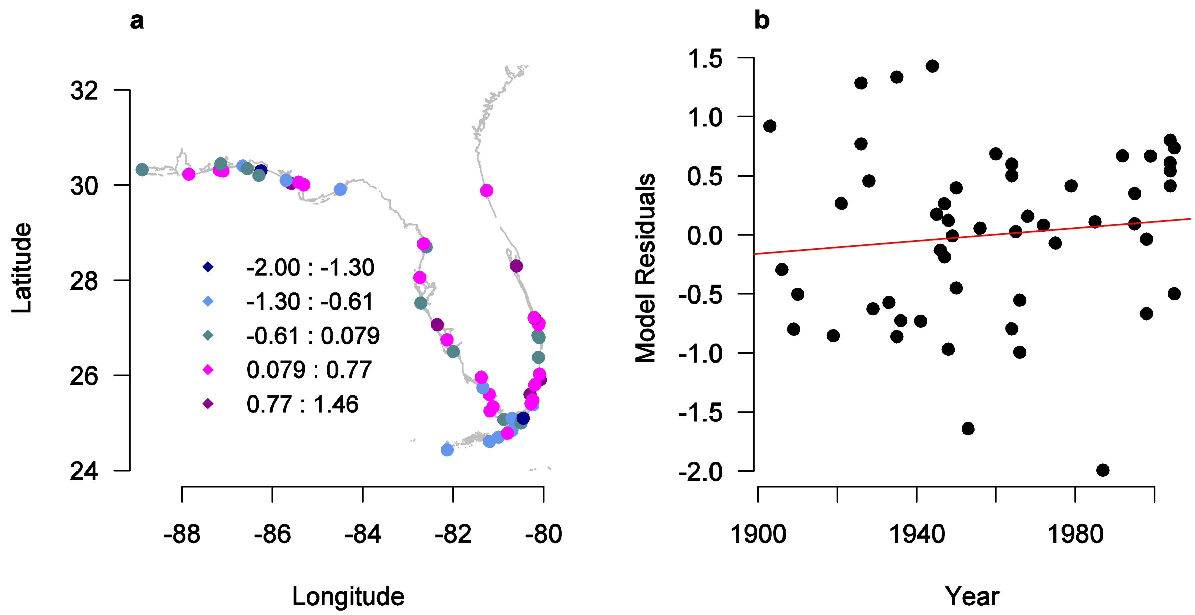

Figure 14: (a) Residuals plotted based on hurricane landfall location. The color denotes the magnitude of the residual values. (b) Time series of model residuals from 1900–2007 with the line of best fit included. There is an upward trend in the residuals. The p-value in the slope is 0.431 indicating no statistical significance against the null hypothesis of no trend.

As shown in Figure 14, there is a clustering of positive residuals at the southern tip of Florida, excluding the Keys, and along the peninsular region. On the other hand, the negative residuals are clustered at the Florida Keys and in a small region along the Florida panhandle. This means that the model is underestimating losses at the peninsula and, especially, at the southern tip. Also, the model is overestimating the losses in the Keys, as well as the panhandle region. It is possible the model is underestimating losses in those regions mentioned because there has been more economic development at the peninsula and at the southern tip, with more developed infrastructures, and therefore more potential for loss. The model is not accounting for the increase in damage possibility. For that same reason, the model is overestimating the losses in the panhandle and the Keys because there has been less development in those regions and the model is not taking the lessened loss potential into consideration. The increasing trend in model residuals suggests a temporal bias in the loss data with fewer cyclones today able to hit areas that have not seen economic development.

In order to examine these residual values further, the model residuals representing the relationship between landfall wind intensity and economic loss are compared with the accepted model for this study (5 hour wind speed intensity). Figure 15 (a) shows the accepted model's residuals based on landfall location (as seen in Figure 14 (a)). Figure 15 (b) shows the model representing landfall intensity, also based on landfall location. This is completed to analyze any major shifts from negative to positive (or vice versa) in the two models' residuals. As before, the largest negative residuals are denoted by dark blue circles and largest positive residuals are denoted with dark red circles.

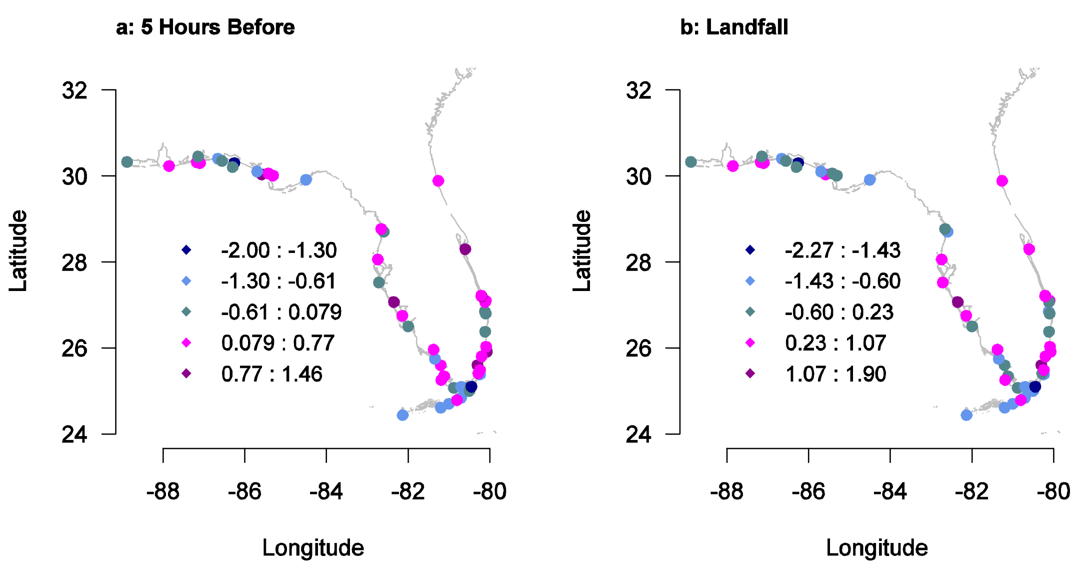

Figure 15: Comparison of model residuals. (a) Model residuals representing 5 hours prior to landfall. (b) Model residuals representing landfall. Residuals are plotted based on hurricane landfall location and the color denotes the magnitude of the residual values.

The comparison between Figure 15 (a) and Figure 15 (b) show no major shifts in clustering from positive to negative residuals. Therefore, in order to try and explain the remaining variability from the accepted model, or offer insight to the possible physical phenomenon at 5 hours prior to landfall, two variables are considered. The first is whether or not the hurricane made landfall on the east coast. This is considered because the majority of Florida's population is clustered throughout the east coast of the state, and perhaps the increased population throughout that coastline has caused the model to underestimate the total economic loss. This variable is included in the model and provides a p-value of suggestive but inconclusive significance. The value is 0.14, which by normal statistical standards, suggests a possible relationship but nothing conclusive. This variable also decreases the adjusted R-squared for the overall model from 0.55 to 0.43. Therefore, this variable is not considered useful for this study.

The second variable considered is the size of a hurricane, measured by the radius to the maximum winds (RMW). This variable is included because it is intuitive to think that the size of a hurricane would ultimately affect the overall economic loss experienced from that hurricane. It is shown in Malmstadt et al. (2009) that the size of a hurricane does not significantly increase the ability to estimate economic loss from hurricanes. However, in that study it was considered with the intensity at landfall and economic loss relationship, so, for the purposes of this study, it is tested because it is considered to have possible relevance.

The RMW (km) is found to have no significance in this model. The p-value is 0.82 on this term when it is added to the model, which is well above the accepted statistical significance threshold. The adjusted R-squared then, as expected, has decreased to 0.31. Even though this variable is not considered significant for this study that does not mean to imply that size is not important when dealing with economic loss from hurricanes. As stated previously in this study, hurricane storm surge plays a significant influence into the overall economic loss experienced from a hurricane. It is well known that the intensity and the size (RMW) of the hurricane contribute to the storm surge, so it is possible that this variable is not significant for this study because of the type of economic loss data being analyzed. Pielke et al. (2008) use the total, aggregate economic loss from the entire state, but these values are largely based on insurance values. Most insurance companies in Florida do not cover water damage, only wind, so wind speed damage is what is included in these loss values, not storm surge damage. This plays an important role because the size of the hurricane would not necessarily play a large role in the overall wind damage experienced. If these loss values incorporated surge damage as well as wind damage, the size of the hurricanes would potentially show a more significant statistical relationship in this model.

Cook's Distance

As neither of the above variables improved the ability of the model to explain variability of economic loss, one last attempt at further explaining the model is conducted. Cook's distance values are computed for every hurricane in this data set to determine the overall importance of an individual event in skewing the model's results. Cook's distance calculates the influence an individual data observation has on the overall model. It measures the effect deleting an observation point from the data will have on the model's overall ability to describe the phenomenon. Figure 16 shows these values plotted with the four highest values denoted with their year and storm sequence number (or the hurricane name when applicable). It is noted here that three of these labeled values are the same hurricanes as the residual outliers of the model (Florence, Floyd, and Storm 6 (1935)). The possible relationship between these hurricanes as residual outliers and as high Cook's distance values is explored in the next chapter. Also, the four hurricanes labeled in Figure 16 are also explored in further detail in the next chapter, along with the descriptions of the residual outliers.

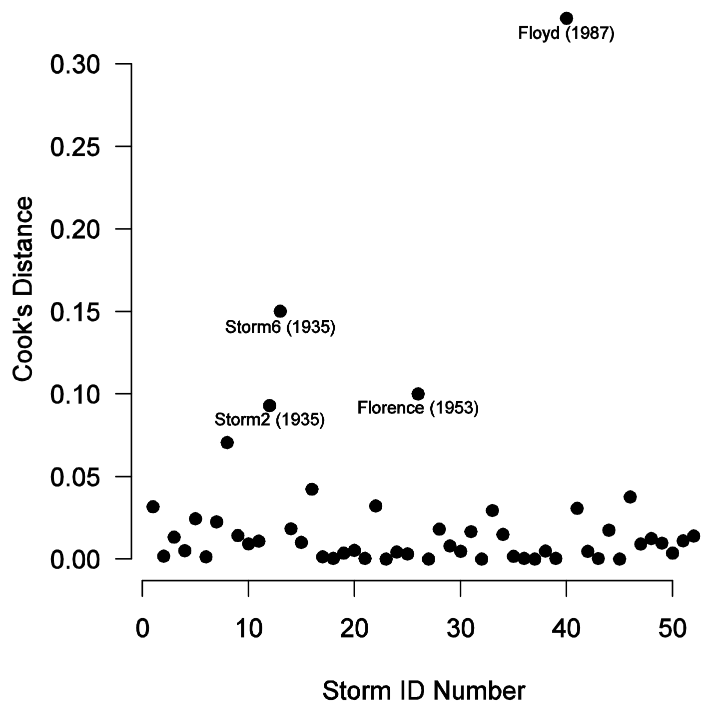

Figure 16: Cook's distance values based on data set's hurricane ID number. The largest four values are labeled.

Central Pressure

As previously discussed, this study aims to use minimum central pressure to estimate economic losses. It is shown in Malmstadt et al. (2008) that minimum central pressure has the strongest relationship with economic loss. However, due to lack of available data for hours prior to landfall, this study could not be completed using that variable. Fortunately, there is landfall pressure data available throughout the time period of this study, so, for comparison purposes, the correlation coefficients for economic loss and landfall intensity (both wind and pressure) are analyzed, as shown in Table 5.

Table 5: The correlation coefficient (Pearson) between the logarithm of losses and landfall winds and minimum central pressure. 90% confidence intervals are included.

	***r* [*w₀*, *L*]**	**90% Confidence Interval**
Minimum Central Pressure (hPa)	0.51	(0.31, 0.66)
Maximum Sustained Wind (kt)	-0.58	(-0.71, -0.40)

The *r* coefficient representing the relationship between landfall wind intensity and economic loss is 0.51, while the *r* coefficient representing the relationship between landfall pressure intensity and economic loss is -0.58. This means that pressure at landfall has a stronger relationship with economic loss than wind speed at landfall. If pressure has a stronger relationship with economic loss at landfall, it is plausible to think that pressure would have a stronger relationship with economic loss prior to landfall similar to the wind speed relationship. The results presented in this chapter will be discussed in Chapter 6. Possible explanations for these results are offered.

CHAPTER 6

MODEL RESIDUALS

It is vital to note that the expected economic loss from a hurricane event to the state of Florida is going to be highly dependent upon where the hurricane makes landfall, the size of the hurricane, the forward rate of movement, and many other characteristics. In order to try and test for some of these variables, the residuals of the model were examined to try and discern any major patterns of model over/under prediction. The model seems to under represent losses (positive residuals) in two major clusters. The first is at the southern tip of Florida, excluding the Florida Keys. The second cluster of model under prediction is along the peninsular region of the state, most notably below 30° N. The negative residuals, where the model is over representing losses, seem to cluster at the Florida Keys and along a small bend in the Florida Panhandle.

The clustering of positive residuals is interesting because the model is estimating losses to be lower than the observed at the southern tip of Florida and along the peninsula. These are regions where the population is very high and clustered, and when a hurricane actually does make landfall here, the losses experienced are more severe than the model expects, possibly, because of the increased infrastructure and population. The clustering of negative residuals is also interesting for the same reason. The model is expecting losses to be greater in the regions of the panhandle and the Florida Keys, possibly because of population and infrastructure. Although the Keys are built up, the building codes are designed to protect against hurricane damage as best as possible, so the damages experienced may not be as severe. Also, in the region of the panhandle where the model is over predicting, the population is much less so the damage would not be as great. Also, after thorough residual examination, it is found that many of the hurricanes in this region experienced large decreases in their maximum sustained wind speeds in the hours just prior to landfall. This large decrease could be caused by any number of characteristics, such as the continental shelf, increased vertical wind shear, influencing weather phenomena, etc. However, the large decrease in wind intensity would definitely decrease the overall loss experienced, which is a possible explanation for the over prediction of the model. Table 6 shows the top five negative and positive residuals for the model. Of these ten residuals, five of them are are explored in more detail in the next section.

Table 6: Top five positive and negative residuals for the model with the associated hurricane name.

Positive Residuals	Negative Residuals
1.43 (Storm 11 1944)	1.99 (Floyd 1987)
1.34 (Storm 6 1935)	1.64 (Florence 1953)
1.29 (Storm 6 1926)	0.99 (Alma 1966)
0.92 (Storm 3 1903)	0.86 (Storm 2 1935)
0.80 (Frances 2004)	0.85 (Storm 2 1919)

Individual Cyclones

The five residual outliers, the three highest positive and two lowest negative, are explored further to try and discern any particular patterns that would make these hurricanes outliers. The three highest positive residual outliers are Storm 11 (1944), Storm 6 (1935), and Storm 6 (1926). The two lowest negative residual outliers are Hurricane Floyd (1987) and Hurricane Florence (1953).

Storm 11 (1944)

This hurricane had the highest positive residual, with a value of 1.43. The hurricane formed in late October, 1944, and has since become known as the Havana-Florida hurricane (Barnes 2007). It tracked from southwest Florida stretching across the entire state towards northeast Florida.

The model greatly under predicted the losses from this hurricane. This is possible because the storm had many tornadoes associated with it, as well as a very large surge. There was massive flooding from one end of the state to the next, and the damage was very severe. This hurricane tracked across the entire state of Florida, damaging almost every developed area, causing much more economic loss than if it had missed these rapidly developing places. The model cannot account for the potential for more economic loss because it assumes a constant level of development across the whole state. This allows some insight as to why the model would so greatly under predict these losses, having not taken any of these influential characteristics into consideration.

Storm 6 (1935)

This hurricane has very little about it which is unique or particularly interesting as to why it is an outlier in this data set. The major difference about this hurricane is the irregular path it took late in the season and the timing of landfall. The hurricane occurred during the first week of November, 1935, just months after the very severe 1935 hurricane (to be discussed when exploring Cook's distances), and had a track directly across South Florida. It seemed to linger and move very slowly over the previously devastated area, which ended up causing more damage than was expected (Barnes 2007). The area from St. Augustine to Key West was exceptionally vulnerable at this time, and the model could not account for the increased vulnerability. The model under predicted the losses from this hurricane, resulting in a high positive residual value of 1.34.

Storm 6 (1926)

This hurricane is the last positive residual outlier to be discussed, with a value of 1.29. This hurricane is most likely an outlier because it was the most expensive hurricane to strike Florida in this data set. The loss value associated with this hurricane, to be known as the Great Miami Hurricane, is $129 billion (2005 $US). The model under predicted these losses because it does not account for infrastructure, and this hurricane tracked directly across Miami from east to west. In 1926, Miami was the most populated region in Florida, experiencing rapid economic development. In 1925 alone, Miami saw over $60 million worth of new construction (Barnes 2007). This hurricane is largely responsible for turning Miami's boom of 1925–1926 into a bust due to its catastrophically devastating nature. Since the destruction from this hurricane was so widespread, it is difficult to know how many lives were lost, and the extent of monetary losses, but with an estimated loss value of such a large amount, it is safe to assume this was a very dangerous hurricane occurring at the height of economic development. It is, therefore, not surprisingly under estimated by this model.

Hurricane Floyd (1987)

The greatest negative model residual outlier is Hurricane Floyd (1987), with a value of -1.99. Looking at the data set used for this study, Hurricane Floyd has the lowest loss amount of any other hurricane in this data set. If it would have struck in 2005, it would have caused $2 million in losses in the Florida Keys region. Luckily, the Florida Keys are developed, but are done so in a way that the infrastructure and housing are somewhat protected from the intense characteristics of hurricanes. Also, vital economic infrastructure is minimal in this area, as it is a place for tourists and vacationers, and is not as much of an economic hub as a place like Miami. According to Barnes (2007), Hurricane Floyd was not a great nuisance in the state of Florida, and the majority of the losses came from utility lines and agricultural damage. Since this hurricane caused such little loss throughout the state, it being an observation in this data set may be skewing the model's ability to predict because the loss was so much less than would be expected from a hurricane. The model has predicted the losses from this hurricane to be greater than they were which is consistent with the hurricane report in Barnes (2007).

Hurricane Florence (1953)

This hurricane is the last residual to be discussed, with a value of -1.64. This hurricane, similar to Hurricane Floyd, had very little loss in the state of Florida. If it would have struck in 2005, it would have caused $14 million in losses. Hurricanes Florence and Floyd had the two lowest loss values by over 70 million dollars. The next lowest was Hurricane Alma (1966), which had a 2005 loss of $85 million. Hurricane Florence struck in the panhandle region where there are a significant number of more negative residuals. This hurricane did not have the impact of Florida storms from previous years, and was considered very mild by most Florida residents (Barnes 2007). This hurricane struck in a region that is notably less developed than the rest of Florida. The panhandle, especially in 1953, had very few residents, and virtually no major economic infrastructure. The majority of the losses from this hurricane were felt in the agricultural sector of Florida's economy, similar to Hurricane Floyd. The model over predicted the losses from this hurricane because it, again, could not account for the varying degrees of economic development across the state.

In summary, it is noted that positive residuals are more likely in areas that have seen rapid economic development and negative residuals are likely in areas with little economic development. It was the case that when a hurricane tracked over an area with major economic infrastructure, the model under predicts the losses from that hurricane. The opposite is also true. When hurricanes track over areas with little economic infrastructure, the model over predicts the losses from that hurricane. This explanation is consistent with the upward trend of residuals noted in Figure 14 (b). As the state continues its economic development, older historical hurricane losses will be able to be readjusted to be consistent with the newer losses.

Model Improvements

In order to test the possible influence of population or a physical element on this set of Florida hurricanes, two other variables were included in the model. The physical element used is size, as measured by the radius to the maximum winds (RMW), and the population element included is whether or not the hurricane made an east coast landfall, as the east coast is where the majority of the large clustering of Florida's citizens is. As mentioned in the previous chapter, neither of these variables have statistical significance when including them in the model.

The size variable, although seemingly very important, has been shown to play a small role when estimating economic loss. Malmstadt et al. (2009) show that the size of the hurricane, as measured by the RMW, has the weakest relationship when dealing with economic loss from Florida hurricanes, and has been shown to have a much more counterintuitive relationship. Although the relationship was weak, as the hurricane increases in size, the economic loss decreases (Malmstadt et al. 2009). The exact reason for this is unknown at the present time, but this somewhat puzzling observation could be explained by the fact that hurricane intensity is inversely related to hurricane size for this set of hurricanes. Thus, the larger hurricanes tend to be weaker and cause less damage than at a smaller, more structured stage. The other possible explanation is that the economic loss values chosen for this study are not appropriately representing the losses caused from storm surge (which is heavily influenced by hurricane size). This is mentioned briefly in the previous chapter, but may play an important role in why size is seemingly insignificant. If the loss values for this study do not incorporate surge damage (as they are highly dependent upon insured values, which notably do not cover water damages in

Florida), then size would seem unimportant because the loss values are based solely on wind damages that would not be greatly influenced by the size of the hurricane. If it is possible to include surge damage values into the economic loss values used in this study, it may be shown that size plays a much larger role than shown here.

The population variable, whether or not the hurricane made an east coast landfall, is obviously not the best way to represent population. However, when dealing with economic loss values that are aggregated from the entire state, dissecting populations becomes difficult and messy. That being said, the best way for this study to represent population was to base it off of landfall location. It is possible that this population variable is not significant for this study because of this inaccurate way of establishing population. Another way to increase the accurateness of this variable would be to include housing values. This is a possibility for a future study.

Since neither of the discussed variables increased the model's ability to explain variability in the economic loss values, one final attempt to discern patterns was conducted. The Cook's distance values for the model, which show the influence that a particular observation point has in the model, were examined and the top four values are analyzed. The four hurricanes, in order of highest value first, include Hurricane Floyd (1987), Storm 6 (1935), Hurricane Florence (1953), and Storm 2 (1935). Three of these hurricanes are the same as the residual outliers previously discussed, Hurricane Floyd, Storm 6 (1935), and Hurricane Florence, and are, therefore, not analyzed again. Possible reasons for this storm pattern are explored, however, after a description of Storm 2 (1935).

<u>Storm 2 (1935)</u>

This hurricane is known as the 1935 Labor Day storm. It has received this title because it was the most severe hurricane to strike the Florida Keys throughout the known record up to this point. This hurricane has high influence in this data set because it is the most intense storm to make landfall in Florida and is considered the only Category 5 hurricane in this set of Florida hurricanes. This storm had the lowest recorded pressure up to date, and, although the economic loss was not as severe as was expected, the loss of life for this hurricane was catastrophic. The residual value for this hurricane is negative, showing that, based on the wind intensity for this hurricane, the model predicted the losses to be higher than what they actually were. If this hurricane were to strike today, the loss of life would not be so severe (enhanced warning systems, better evacuation measures, etc.), but the economic loss would be quite different because of the increased infrastructure and population in the area struck.

It is intuitive that 3 of the hurricanes with the highest positive and lowest negative residuals are the same as 3 of the hurricanes that play the largest influence to the data set. Many of these hurricanes were either more intense or less intense than was expected so the model predicted them accordingly. If the model is predicting something different than the actual, it would be intuitive to think that those hurricanes being under/over predicted would have large influences on the overall model's ability to explain/predict economic loss. Whatever the reason, each of the hurricanes that have a description provided for it has a particular uniqueness to it that would enable it to play a larger role in influencing the data set than the other Florida hurricanes not described.

As previously mentioned throughout this research, this study aims to use minimum central pressure as the estimator for economic loss. This is founded on the Malmstadt et al. (2009) study that shows minimum central pressure to be the strongest indicator of economic loss. Due to the lack of available data for pressure prior to landfall, this research focused on the use of maximum sustained wind speed. However, since there is a long standing inverse relationship between wind speed and minimum pressure, if wind speed prior to landfall is a better indicator of economic loss than at landfall wind intensity, it is intuitive to believe that minimum pressure prior to landfall would also be a better indicator. In the previous chapter, it is shown that the landfall pressure variable, when comparing it to the landfall wind variable, is a better estimate of economic loss. If pressure is a stronger variable at landfall than wind speed, it makes sense to think pressure prior to landfall would also be a stronger variable than wind speed prior to landfall.

Although this study is trying to establish a better way to estimate economic loss than what is currently being used, it is important to note the major limitation of this study. It is well known that the amount of hurricane damage is highly dependent on many variables, such as the locale of landfall, the population, the amount of infrastructure, the mitigation measures, the forward rate of the hurricane, the average rate of decay in the hurricane, etc. The purpose of this research is not designed to ignore these factors, but to instead provide a more general understanding to the relationship between hurricane intensity and economic loss in the state of Florida. By using intensity at five hours prior to landfall, economic loss researchers and concerned citizens can gauge a better estimate of the expected economic loss than what is currently being used, the at landfall intensity. With a better estimate of economic loss, all concerned can be better prepared.

CHAPTER 7

SUMMARY AND FUTURE RESEARCH

Hurricanes affecting Florida and the rest of the United States have an infamous reputation for causing mass destruction and mayhem to the livelihoods of American citizens. It was the goal of this study to statistically analyze the hurricanes affecting Florida from 1900–2007, in the known record, and explore their relationship to the economic loss associated with them. The hypothesis of this study was that the intensity characteristic, maximum sustained wind speed, would be able to explain some of the variability of economic loss in Florida when using those intensities prior to the hurricane actually making landfall in the state better than when using those intensities at landfall.

The main, important result provided from this research is that there is a strong relationship between the intensity (maximum sustained wind speed) of hurricanes in Florida prior to their actual landfall in the state and the economic loss of those associated hurricanes. The highest correlated wind speed value with economic loss was at 5 hours prior to landfall. Although the wind speed values used for this study are interpolated values (except the 0, 6, 12, and 18 hourly values), this value is still statistically significant and can therefore be considered quite important.

The model developed in this research explains 55% of the variability in the economic loss data set used in this study. Further variables, the size of the hurricane (RMW) and a population variable accounted for by landfall location, were tested to try and improve the model, but provided little significance. The population variable, whether or not the hurricane made an east coast landfall, did provide suggestive, but inconclusive, evidence, so it is possible that the population variable could benefit from further examination. The residuals of the model were explored further to decipher any trends or patterns. Five hurricanes with residual outliers were discussed further, Storm 11 (1944), Storm 6 (1935), Storm 6 (1926), Hurricane Floyd (1987), and Hurricane Florence (1953), and it is found that if damage from a hurricane was more/less intense than what was expected, the residual will most likely be an outlier. Also, if the hurricane has a track over a notably developed, or notably underdeveloped, place, the model will not account for the amount of development, and the hurricane will most likely be a residual outlier. The final attempt to explain more of the model was done by analyzing the Cook's distance values for the hurricane. This allowed for a more detailed description as to the possible reasons behind a hurricane's ability to influence the model. Four hurricanes, Hurricane Floyd (1987), Storm 6 (1935), Hurricane Florence (1953), and Storm 2 (1935), had much higher values than any other hurricane in the data set, and Storm 2 (1935) was discussed (as the others had already been). The results highlight a bias in the loss data. As the state continues with its economic development, the bias will be diminished.

The final statistical test that is conducted in this study is the correlation comparison between the intensity at landfall of, both, minimum central pressure (hPa) and maximum sustained wind speed (kt) and the economic loss data used in this study. It is found that, although they both have fairly strong correlations with economic loss, the minimum central pressure variable has a slightly stronger relationship with economic loss than the maximum sustained wind speed variable.

Limitations, Further Research, and Broader Impacts

There are three main limitations to this study. The first limitation is in the economic loss data set. As previously mentioned, prior to 1940 there were 32 hurricanes that made landfall somewhere on the United States' coastline with no reported losses in the official record, where only 8 such hurricanes have occurred since 1940 (Pielke et al. 2008). This suggests a likely undercount of the overall loss caused by hurricanes within the North Atlantic Basin prior to 1940. Since at least one hurricane strikes Florida every two years, there is a likely undercount of Florida losses prior to 1940 as well.

Another main limitation is that the economic loss experienced from a hurricane is highly variable and depends on a number of factors, not just wind speed intensity and size. Some of the other numerous factors which could be considered in later studies to help estimate economic loss are the location of landfall, wind gusts, the forward speed, the storm surge, terrain features, distance from coastline, and local building codes.

There is one more limitation worth noting. The data used for this research, as with any research, relies on collection methods which have errors inherent to their very structure. It is not possible to know all of the hurricanes which have affected Florida during any period prior to modern data collection, nor is it possible to know all of the resulting economic loss experienced in Florida. That being said, this study is conducted using the most accurate data sources available, and, therefore, provides an accurate description of intensity prior to landfall for Florida hurricanes and their associated economic loss. Even with these inherent errors, the results from this study could be used for many possible avenues.

It would be beneficial to apply the idea of pre-landfall intensities being beneficial to other areas of the United States' coastline, in order to provide other areas with the best possible indicator of economic loss. Also, the other variables listed above could be tested to further explore the relationship between pre-landfall intensity and economic loss. An interesting study could take the sloping of the continental shelf into consideration and see how that may play a role into changing the storm surge prior to landfall and the associated economic effects. Another possible research avenue would be to break up the aggregate economic loss values to county values and then add county level population to the model to try and improve it.

It is well documented that hurricane intensity affects the economic losses experienced at location of landfall. However, previous studies have looked at the intensity at landfall to accurately predict economic loss without taking into account the hurricane before landfall. This research investigates the idea that using intensity prior to landfall as the main estimator for overall economic loss experienced in Florida will provide a better estimate than using intensity at landfall. This same principle could be utilized for all future estimation forecasts for all areas of the United States' coastlines affected by hurricanes, not just the state of Florida. People living in vulnerable areas could then take more precautionary measures to prepare their homes and property from any oncoming damaging hurricanes, and, hopefully, reduce the amount of damage experienced by preparing appropriately.

Risk assessment companies and reinsurance companies spend millions of dollars annually to try and estimate economic losses and, put very simplistically, they base their information on historical hurricanes and the expected intensity of the event at landfall. This study offers them a new way to approach the estimation of economic loss. It proposes that using intensity at five hours prior to a hurricane making landfall will allow them to gain a greater understanding of the expected economic loss of the event at hand. In a world where time is money, having an extra five hours, can save a lot.

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