

**ASSESSMENT OF THE POTENTIAL EFFECT OF CLIMATE CHANGE ON
HURRICANE RISK AND VULNERABILITY IN FLORIDA**

A Thesis

by

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ABSTRACT

Hurricanes are a yearly threat to the eastern and Gulf coasts of the United States. An increase in frequency and intensity of hurricanes is a possible and dangerous consequence of future climate change. To assess the threat of more frequent and intense hurricanes, this research will address how climate change will affect future hurricane activity in Florida. A greater understanding of how climate change will affect hurricanes is vital for regions, such as Florida, that are vulnerable to these powerful storms.

Hurricane return periods were calculated for all Florida counties based on 1900-2010. Hurricane landfalls were quantified using a dynamic wind model which allowed for the spatial extent of each storm to be examined. A meta-analysis of the existing literature on the effects of climate change on hurricane behavior was performed. Using the findings from the meta-analysis, a sensitivity analysis was performed to determine how climate change may affect hurricane damage and loss for Florida. The HAZUS-MH Hurricane Model was used to estimate losses and damage from hurricane winds based on Florida's growing population and increasing coastal development.

Results show that wind-derived return periods more accurately depict the distribution of a storm's wind field. Counties in southern Florida have the lowest return periods based on the track-derived and wind-derived return periods. Based on the meta-analysis, hurricane intensity is expected to increase by 2 to 11%. Hurricane frequency is expected to decrease or remain the same and storm tracks are not expected to change. The sensitivity analysis examined the influence of climate change on baseline (current),

moderate (15% increase), and extreme (35% increase) TC intensity scenarios. The most developed and populated regions are the most vulnerable to hurricane damages and losses. Based on the boxplots, the spread of percent values increases for building damage, economic losses, and shelter needs as storm intensity increases. The spread in the data shown in the scatterplots and boxplots is storm specific. This research found that southeastern Florida is at highest risk of future hurricane landfalls and most vulnerable to hurricane damages and losses.

DEDICATION

This thesis is dedicated to my parents and sister for always supporting me and encouraging me to follow my dreams.

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CHAPTER I

INTRODUCTION

An increase in the frequency and intensity of hurricanes is a possible and dangerous consequence of future climate change (Shepherd and Knutson 2007). This research will examine how climate change will affect hurricanes and their behavior. A greater understanding of the impacts of climate change is vital for regions that are vulnerable to these powerful storms (Pielke et al. 2005). Florida is one region that is extremely vulnerable to hurricanes since it is a peninsula that can be impacted from both the west coast and east coast. Although the relationship between hurricanes and climate change has been extensively studied (Elsner 2006; Emanuel 2005a; Emanuel 1987; Henderson-Sellers et al. 1998; Landsea et al. 2006), the relationship between climate change and hurricane event risk has not been quantified for Florida.

Every year, from June to November (a period known as hurricane season), tropical cyclones form over the North Atlantic Ocean and are a threat to the eastern coastline of the United States and the Gulf of Mexico (Elsner and Kara 1999). Florida is extremely vulnerable to hurricane landfalls as it is surrounded by both the Atlantic Ocean and the Gulf of Mexico. Valuable properties and growing populations are at risk of devastating hurricane landfalls (Elsner 2006). With a continuous increase in coastal populations, future climate change may greatly impact these populations (Sarewitz et al. 2003). An improved understanding of potential future changes in hurricane trends can help mitigate property damage and loss of life (Pielke et al. 2005). An awareness of

hurricane risk can aid local government officials and policymakers in improving evacuation planning and decisions and hurricane preparedness (Pielke et al. 2005). Improved preparation when facing the threat of a hurricane can help save property and lives.

Numerous studies have examined the relationship between climate change and hurricane activity, however, the results continue to be debated (Knutson et al. 2010). Hurricane event risk for vulnerable areas, such as Florida, has not been extensively quantified. Examining hurricane event risk for Florida can provide more information of the future effects of climate change. The findings of this study will allow researchers and scientists to apply similar methods to other vulnerable regions along the U.S. coastline. The application of a parametric wind field model may also provide a new perspective when examining the relationship between hurricanes and climate change since it has not been used in other studies. Further research on the impacts of climate change is vital in order to provide accurate information to affected populations and to prepare for the future.

1.1 Research Objectives

This thesis has three main objectives:

1. Quantify hurricane event risk for all Florida counties based on observed data for 1900-2010.
2. Quantify how climate change will influence hurricane event risk by performing a meta-analysis of the literature.

3. Perform sensitivity analysis using the findings from the meta-analysis to determine how climate change will potentially affect hurricane damage and loss for Florida.

In this study, the possible future changes in hurricane event risk due to climate change will be examined for all Florida counties. The future hurricane event risk for Florida's counties will be quantified through a meta-analysis of the literature on climate change and hurricanes. The findings will then be applied using HAZUS-MH, a risk assessment tool used for analyzing damage and loss, to quantify potential future changes in hurricane related damages and losses in Florida. An assessment of potential hurricane risk and vulnerability can help the public and officials make sound decisions that may help save lives.

CHAPTER II

BACKGROUND AND LITERATURE REVIEW

2.1 Hurricanes

A tropical cyclone is defined by Elsner and Kara (1999) as a closed circulation system that forms over warm water. Tropical cyclones are called hurricanes in the Atlantic and the Northeast Pacific ocean basins (Elsner and Kara 1999; Emanuel 2005c). Tropical cyclones also form in the Northwest Pacific, where they are called typhoons and in the Indian and Southwest Pacific oceans where they are referred to as cyclones (Elsner and Kara 1999; Emanuel 2005c).

Hurricanes are characterized by having a low central pressure that is typically around 950 millibars (mb) and sustained winds greater than 33 m s^{-1} (74 mph) (Elsner and Kara 1999). Tropical cyclones start as disturbances or waves that develop into tropical depressions (Elsner and Kara 1999). Tropical depressions are composed of a low-pressure center and have sustained winds less than 17 m s^{-1} (39 mph) (Elsner and Kara 1999). As the storm begins to strengthen, it becomes a tropical storm. Tropical storms are weaker than hurricanes, but heavy rains and strong winds are capable of causing damage (Elsner and Kara 1999). A tropical storm has sustained winds of 17 to 32 m s^{-1} (39 to 73 mph) (Elsner and Kara 1999). Hurricanes have sustained winds greater than 33 m s^{-1} (74 mph) and the strongest hurricanes can have sustained winds of more than 69 m s^{-1} (155 mph) (Elsner and Kara 1999). The calmest winds are found in the eye of a hurricane (Emanuel 2005c). The eye is the region that has the lowest atmospheric

pressure (Elsner and Kara 1999). The fastest winds are found in the eyewall and winds typically decrease with distance from the eyewall (Emanuel 2003; Emanuel 2005c).

Climate change has the potential to have a significant influence on hurricane activity (Emanuel 2005a; Kerr 2006). Although numerous studies have examined the relationship between climate change and hurricanes, there is a lack of consensus in the literature regarding the impact of climate change on hurricane intensity, frequency, and track. The potential impacts of climate change on hurricane behavior and trends will be discussed in detail in Chapter 5.

2.2 Hurricane Formation and Development

Hurricanes commonly start as easterly waves that form in sub-Saharan Africa and make their way west across the Atlantic Ocean (Emanuel 2005c). Easterly waves have the cyclonic vorticity or rotation and the atmospheric instability that is necessary for tropical cyclogenesis (Emanuel 2005c). An easterly wave is classified as a tropical depression when its winds begin to rotate counterclockwise around a low pressure center (Emanuel 2005c). If a tropical depression gains strength, it may develop into a tropical storm and if conditions remain favorable, the tropical storm can become a hurricane (Emanuel 2005c). Storms that develop from easterly waves are called Cape Verde hurricanes (Elsner and Kara 1999).

Tropical cyclogenesis can also be influenced by tropical upper-tropospheric troughs (TUTTs) (Elsner and Kara 1999). A TUTT is an upper-level trough that is located in the central subtropical Atlantic (Elsner and Kara 1999). TUTTs can produce

strong vertical wind shear which inhibits hurricane formation (Elsner and Kara 1999). Vertical wind shear occurs when winds along a column of air blow at different speeds (Elsner and Kara 1999). The difference in wind speeds at different altitudes prevent the storm from maintaining the symmetry of its circulation (Emanuel 2005c). The greater the difference in winds at two altitudes, the greater the wind shear and the lower the possibility of storm formation and/or development (Aiyyer and Thorncroft 2006; Elsner and Kara 1999). Regardless of where or how they form, storms need the right environmental conditions to continue to strengthen and develop as hurricanes.

There are certain conditions that must be met for a hurricane to form. An unstable atmosphere capable of producing strong thunderstorms is needed (Emanuel 2005c). Warm ocean water that is at least 27°C and at least 45 meters (150 feet) deep, a deep layer of humid air, little to no wind shear, and enough Coriolis force that will allow the system to develop a spinning motion are also necessary (Emanuel 2005c). Warm ocean waters provide a source of heat that acts as fuel during hurricane formation and development (Emanuel 2003). Ocean temperatures must reach at least 26-27°C for cyclones to form (Elsner and Kara 1999; Emanuel 2003). The surface layer of warm water must be deep to prevent colder water at greater depths from being mixed into the surface (Elsner and Kara 1999). Vorticity is vital for storm formation (Emanuel 2005c). Vorticity is a characteristic of tropical cyclones, and in the Northern Hemisphere, it causes storms to move in a counterclockwise motion (Emanuel 2003). The Coriolis force plays an important role in a storm's rotating motion (Elsner and Kara 1999). The Coriolis force is strongest at the poles and weakest at the equator (0°), therefore, storms

cannot form close to the equator because of the weak Coriolis force (Elsner and Kara 1999). Storms have difficulty developing in higher latitudes because of cooler waters (Emanuel 2005c). This limits the area in which a hurricane can form (Elsner and Kara 1999; Emanuel 2003). The majority of storms that form in the North Atlantic Basin form in a region between 10° and 20°N known as the Main Development Region (MDR) (Goldenberg et al. 2001).

2.3 Hurricane Damage

Hurricane damage is caused primarily by wind, rainfall, and storm surge (Stanturf et al. 2007). Damage caused by hurricanes is categorized using the Saffir-Simpson scale because it is a “hurricane potential damage scale” (Elsner and Kara 1999). Each category is based on wind speeds (one minute maximum sustained winds) (Emanuel 2005c). Category one winds range from 33 to 42 m s⁻¹ (74 to 95 mph), while category five hurricanes are capable of producing winds that are 69 m s⁻¹ (155 mph) or greater (Elsner and Kara 1999; Emanuel 2005c).

Storm surge occurs when ocean water is pushed onto shore by a storm’s winds and pressure (Emanuel 2005c). Storm surge is also influenced by factors such as astronomical tides and ocean bathymetry (Emanuel 2005c). The size and shape of a TC can also influence the amount of storm surge (Irish et al. 2008). Storm surge can cause massive flooding and result in significant damage (Emanuel 2005c).

Billions of dollars in damages have been caused by hurricane winds (Elsner and Kara 1999; Emanuel 2005c; Willoughby and Rahn 2004). Hurricanes Katrina and Rita

caused approximately \$2 to \$3 billion in wind damage (Stanturf et al. 2007). In addition, approximately 16% of wind-related deaths between 1970 and 1999 were caused by hurricanes (Willoughby and Rahn 2004). In comparison, storm surge-related drownings caused 82% of deaths during the same time period (Willoughby and Rahn 2004).

Although the number of wind-related deaths has significantly decreased, wind damage to structures has increased (Willoughby and Rahn 2004). For example, four storms made landfall in Florida within a six week time period in 2004 and they caused a total of \$20.5 billion in losses (Barnes 2007).

2.4 Event Risk, Outcome Risk, and Vulnerability

This thesis will examine event risk, outcome risk, and vulnerability due to TCs. There are various definitions for risk and vulnerability in the literature (Füssel 2007). However, for this study, we will employ the definitions set forth by Sarewitz et al. (2003). These definitions of risk and vulnerability have been widely used by others (Füssel 2007; Jones et al. 2010; Jones and Preston 2011; Stanturf et al. 2007). Event risk is defined by Sarewitz et al. (2003) and Pielke et al. (2005) as the risk of the occurrence of a specific phenomenon or extreme event, such as a category 3 hurricane. Vulnerability, as defined by Sarewitz et al. (2003), refers to the characteristics of a system that have the potential to cause damage. Outcome risk is the result of event risk and vulnerability. Sarewitz et al. (2003) define outcome risk as the “risk of a particular outcome,” such as specific economic losses that result from a particular hurricane. Sarewitz et al. (2003) state that vulnerability is not reliant on the exact probability of a

future event. In their example, Sarewitz et al. (2003) project TC losses based on changes in societal vulnerability from 2000-2050 using two scenarios. Under the first scenario, climate remains constant while societal (demographic and socioeconomic) changes occur (Sarewitz et al. 2003). In the second scenario, climate changes while societal vulnerability remains constant (Sarewitz et al. 2003). Loss estimates for the first scenario were projected to be 20 to 60 times greater than losses for the second scenario (Sarewitz et al. 2003). This suggests that societal vulnerability is a vital component of risk assessment.

Event risk is defined by Lindell and Prater (2007) as “hazard exposure”. Lindell and Prater (2007) apply event risk when delineating hurricane emergency response planning areas (ERPAs). For hurricane ERPAs, hurricane event risk is defined by examining storm surge and wind contours on hazards maps for storms of all categories on the Saffir-Simpson Scale (Lindell and Prater 2007).

Stanturf et al. (2007) examine coastal forest management in areas where hurricanes act as a disturbance to the ecosystem. They apply event risk, outcome risk, and vulnerability to develop an adaptive strategy to reduce hurricane damage to coastal forests (Stanturf et al. 2007). Stanturf et al. (2007) use Sarewitz et al.’s (2003) definitions of risk and vulnerability. Event risk applies to the risk of occurrence of a major hurricane and is defined by determining the frequency and intensity of landfalling hurricanes in the southern United States from 1851-2005 (Stanturf et al. 2007). The event risk was used to assess the ecological outcome risk and vulnerability of recovery areas for an endangered bird species (Hooper and McAdie 1995).

Event risk is applied to various fields such as medicine, ecology, and economics (Driessen 2005; Hooper and McAdie 1995; Stanturf et al. 2007; van Wijk et al. 2005). Event risk, outcome risk, and vulnerability are also examined in the climate change adaptation literature (Füssel 2007; Jones et al. 2010; Jones and Preston 2011; Lim et al. 2005; Nottage et al. 2010).

Event risk identifies the probability of occurrence of an event and cannot be manipulated by those who identify it (Stanturf et al. 2007). It can be dynamic, as observed in this study, since event risk may be altered by future climate change (Stanturf et al. 2007). Outcome risk cannot be altered directly, however, it can be reduced by altering the vulnerability (Hooper and McAdie 1995; Sarewitz et al. 2003).

This study aims to examine the impact of more intense and more frequent TCs making landfall in Florida. In this study, event risk will refer to the risk of the occurrence of high (low) TC frequency, high (low) TC intensity, and a change in TC tracks. Return periods for all storms will quantify Florida's hurricane event risk. Vulnerability will be examined by projecting the socioeconomic impacts from intensifying storms as a result of climate change. The outcome risk will result from the projected event risk and vulnerability for the effect of climate change on hurricane trends for Florida.

2.5 Hurricane Impacts in Florida

Florida is vulnerable to hurricanes every year. Previous studies examined the effects of specific storms, such as Hurricane Andrew (Powell et al. 1996). Powell et al.

(2005) created a model to assess the risk of residential damage due to hurricane winds in Florida. Jagger and Elsner (2006) used maximum wind speed values to create models of extreme hurricane winds near the coast of the United States (1899-2004). Their models were used to estimate the return periods for hurricane-force winds (Jagger and Elsner 2006). They found that the entire Florida coastline will experience hurricane winds of 55 m s^{-1} (108 kts), on average, every 5 years (Jagger and Elsner 2006).

Elsner and Bossak (2001) used a Bayesian approach to create a climatology of landfalling hurricanes along the U.S. coastline (Elsner and Bossak 2001). Their results indicated that 20 hurricanes should make landfall in Florida during the next 30 years.

Jagger et al. (2001) created a model for generating the annual probability of maximum hurricane wind speeds for coastal counties along the U.S. eastern coastline and it included all of Florida's coastal counties. Their results highlighted Florida's vulnerability to hurricane activity and they found southern Florida to have the greatest risk due to high probabilities for hurricane activity (Jagger et al. 2001).

CHAPTER III

DATA AND METHODS

3.1 Study Region

The state of Florida is a peninsula located in the southeastern United States. The Gulf of Mexico borders the western coast of Florida and the Atlantic Ocean borders the eastern coast. Florida's location between two large bodies of water increases its vulnerability to tropical storm and hurricane landfalls. Florida's warm climate and appealing beaches attract residents and tourists (Leatherman 1997). As coastal populations continue to increase, so does their vulnerability to hurricanes (Pielke et al. 2008). Not only are people at risk, but properties, such as highly valuable oceanfront properties, and wildlife are exposed to storm-related damages (Duever et al. 1994; Pinelli et al. 2004). According to Elsner and Bossak (2001), the entire Florida coastline accounts for approximately 35% of the U.S. eastern coastline (from Brownsville, Texas to Eastport, Maine). Because of its geographic location, Florida is affected by hurricanes more than any other state (Matyas et al. 2011). Hurricanes can have significant economic and societal impacts in this region (Jagger and Elsner 2006).

All Florida counties will be examined in this study. Although Florida's coastal counties are more vulnerable to storm landfalls than inland counties, inland counties will also be considered. Figure 3.1 displays all Florida counties. There are 67 counties in total. In Florida, storms can easily make landfall on one coast and move across the state, affecting inland counties as the storm moves. Tropical Storm Fay (2008), for example,

made landfall four times in the state of Florida (Beven and Brown 2009). Inland counties are susceptible to damages from wind, tornadoes, and freshwater floods (Rappaport 2000). Inland areas of Florida also experience an increase in tourism during hurricane season months (Matyas et al. 2011). Cities such as Orlando attract millions of tourists, typically during the summer months that coincide with hurricane season (Matyas et al. 2011). An increase in tourism greatly increases the population at risk (Pielke Jr 1997).

3.2 Datasets

This study uses data from the National Hurricane Center's hurricane database (HURDAT) (<http://www.aoml.noaa.gov/hrd/hurdat/>). This database provides 6-hourly data of latitude, longitude, wind speed, and pressure, as well as other variables, for storms dating back to 1851. HURDAT has been used in a number of previous studies (Elsner et al. 2006; Muller and Stone 2001; Brettschneider 2008). HURDAT also provides U.S. hurricane landfall data from 1851 to 2010 and county by county hurricane strikes for 1900 to 2010. HURDAT provides landfall data (from which frequency is determined) and track and intensity data (pressure and wind speed) to quantify hurricane event risk.

There are some limitations to using HURDAT. For example, data from southern Florida is missing prior to 1900 (Elsner and Bossak 2001). Before the use of satellites and aircraft reconnaissance, hurricane data were difficult to obtain (Landsea et al. 2006; Landsea et al. 2004a).



Figure 3.1. Map of Florida’s counties.

Most of the historical hurricane data were obtained from ship observations, land stations and buoys or when the storms made landfall (Chang and Guo 2007; Landsea et al. 2004a). There are several biases and errors found in HURDAT (Landsea et al. 2008). Measurements prior to 1931 were taken once a day and 6-hr positions and data were interpolated (Elsner et al. 2006). Interpolations were also made for 6-hr positions and data for hurricanes from 1931-1956 based off of twice daily measurements (Elsner et al. 2006). Observations made prior to aircraft reconnaissance and satellite observations are likely undercounted (Landsea 2007). Since data collection was limited, a large number of storms could have been undetected and unrecorded (Landsea et al. 2004a). For the storm data that were collected, not all parameters are available. Parameters such as central pressure are missing up to the mid-1970s. Due to the incompleteness of the dataset, the trends observed over the entire hurricane record may be skewed (Landsea et al. 2008; Landsea et al. 2004a). Since recent hurricane data are more accurate, hurricanes may seem to be more abundant and intense when compared to past records (Landsea et al. 2006). Increases in hurricane activity were observed in the 1970s and 1980s, this period also corresponded with the development of technology in the field. In order to remove the inconsistencies found in older hurricane data records, a re-analysis project is underway. The re-analysis project is responsible for going back in the dataset to revise and alter any erroneous data from the 1800s and early 1900s (Landsea et al. 2004a). Examples of changes that have been part of the re-analysis project are the addition of undocumented storms from past years (late 1800s and early 1900s) and the upgrade of

Hurricane Andrew's intensity at landfall from category 4 to category 5 (Landsea et al. 2004b; Landsea et al. 2004a). Hurricane data from 1900 to 2010 were used in this study.

The International Best Track Archive for Climate Stewardship (IBTrACS) (<http://www.ncdc.noaa.gov/oa/ibtracs/>) dataset provides hurricane track shapefiles that were used for mapping North Atlantic basin hurricane tracks using a GIS. IBTrACS was used to obtain hurricane track shapefiles for the years 1900 to 2010. IBTrACS combines tropical cyclone best track data from sources around the world to produce one uniform, standardized, and complete dataset (Knapp et al. 2010). The dataset is provided by the National Oceanic and Atmospheric Administration (NOAA)'s National Climatic Data Center. IBTrACS includes data from HURDAT and other regional specialized meteorological centers (RSMC) from around the globe (Knapp et al. 2010). By standardizing the data, a dataset that does away with discrepancies from different agencies is created (Knapp et al. 2010). Similar to the HURDAT dataset, there are inconsistencies in the dataset due to the lack of technology (satellites) or a difference in analysis techniques (Knapp et al. 2010). Certain parameters such as eye diameter, storm size and radius of maximum winds are not present in datasets like HURDAT (Knapp et al. 2010). By including missing parameters and creating a uniform dataset, IBTrACS can be an efficient and complete source of hurricane data (Knapp et al. 2010).

The Tropical Cyclone Extended Best Track Dataset (EBT) uses Advanced Microwave Sounding unit (AMSU) data to derive tropical cyclone parameters (Demuth et al. 2006). The EBT acts as a supplement to HURDAT by providing storm structure parameters such as radius of maximum wind, eye diameter, and pressure and radius of

outer closed isobar (Demuth et al. 2006). The dataset for the Atlantic Ocean extends from 1988 to present. EBT was used for case study storms that were analyzed using HAZUS-MH.

Not all data were obtained from the same source for all case study storms. Datasets were obtained based on their availability. For storms that formed prior to 1988, data were obtained from HURDAT. Data were obtained from EBT for storms that formed after 1988. Table 3.1 lists the case study storms by name, year of landfall, category at landfall, and data source. Radius of maximum wind (Rmax) values are unavailable for storms prior to 1988. Rmax values were calculated for storms with missing values by using an equation from Willoughby et al. (2006). Willoughby and Rahn (2004) used aircraft observations to validate the Holland (1980) model. The study continues in Willoughby et al. (2006) where sectionally continuous profiles are created to correct errors and improve the model from Willoughby and Rahn (2004). The equation used to calculate Rmax values was derived from the sectionally continuous profiles from Willoughby et al. (2006).

Name	Year	Category at landfall	Data Source
Great Miami Hurricane	1926	4	HURDAT
Labor Day Hurricane	1935	5	HURDAT
Agnes	1972	1	HURDAT
Andrew	1992	5	Extended Best Track
Georges	1998	2	Extended Best Track
Mitch	1998	TS	Extended Best Track
Irene	1999	1	Extended Best Track
Charley	2004	4	Extended Best Track
Frances	2004	2	Extended Best Track
Ivan	2004	3	Extended Best Track
Wilma	2005	3	Extended Best Track
Fay	2008	TS	Extended Best Track

Table 3.1. List of case study storms examined in this thesis and their data source.

Storms that formed prior to 1988 are also missing central pressure values. A scatterplot (Figure 3.2) was created for wind speed and central pressure values for all storms that passed through a 500 km buffer around Florida. Due to a lack of data, only values from 1975-2010 were used. Central pressure values were calculated using the linear regression equation derived from the scatterplot. The R^2 value for the linear

regression equation was 0.87. This indicates that there is a strong relationship between wind speed and central pressure. As a storm's wind speed increases, its central pressure decreases (Atkinson and Holliday 1977; Emanuel 1987; Holland 1980).

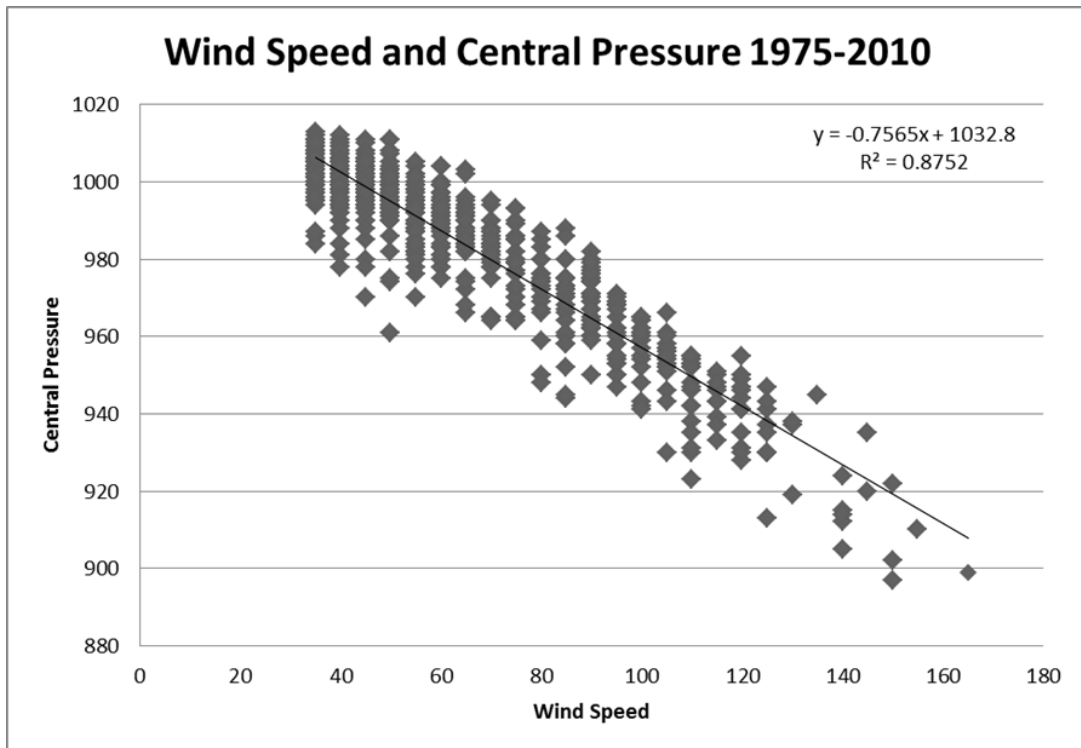


Figure 3.2 Scatterplot of wind speed and central pressure values for 1975-2010.

3.3 Methods

Objective 1: Quantify hurricane event risk for all Florida counties based on observed data.

Hurricane event risk for all Florida counties will be examined by quantifying hurricane landfalls for all counties in Florida. Several studies (Elsner and Kara 1999;

Muller and Stone 2001; Keim et al. 2007; Brettschneider 2008) have quantified hurricane landfalls using return periods. In these studies, hurricane landfalls have been quantified for the west and east coasts of Florida. Return periods indicate the average number of years between landfalls at a specific location (Elsner and Kara 1999; Muller and Stone 2001). In this study, return periods will be calculated for all storms. The return periods will be analyzed in four groups: all tropical storms and hurricanes, all tropical storms, all hurricanes, and all major hurricanes. Major hurricanes are those that are category 3 or higher (Elsner and Kara 1999). By creating a time series (Elsner and Kara 1999) and calculating the frequency of hurricane strikes (Brettschneider 2008), hurricane landfalls for Florida's counties can be quantified. This study will examine landfalls made by all tropical storms and hurricanes and examine landfalls made by major hurricanes (Elsner and Kara 1999). Tropical storms are still capable of impacting the areas in their path. For example, Tropical Storm Harvey (1999) made landfall on the southwest coast of Florida near Naples and deposited approximately 25 cm of precipitation (Davis et al. 2004). In 2008, Tropical Storm Fay made landfall in Florida four separate times (Beven and Brown 2009). The storm first made landfall near Key West, then near Everglades City in southwest Florida (Beven and Brown 2009). TS Fay crossed the state and then reached the Atlantic Ocean (Beven and Brown 2009). After reaching the Atlantic, the storm was steered westward and made landfall along the central eastern coast near Cape Canaveral (Beven and Brown 2009). TS Fay crossed the state once again, reaching the Gulf of Mexico and then making landfall one last time in the panhandle (Beven and Brown 2009). Other states, such as Alabama and Georgia, were affected by TS Fay as it

moved eastward across the southeastern U.S. (Brown et al. 2010). TS Fay's winds and heavy rainfall impacted the majority of Florida. Heavy rainfall was recorded across Florida, with the highest total reaching 70.2 cm in Melbourne (Beven and Brown 2009). TS Fay produced 19 tornadoes and flooded approximately 15,000 homes in Florida (Brown et al. 2010). TS Fay caused about \$560 million in damages in the U.S. (Brown et al. 2010).

Muller and Stone (2001) and Keim et al. (2007) created a model based on the average swath of hurricane-force winds to both the left and right of the center of the storm. This model does not adapt to individual storms, but the average of three groups of swath width (tropical storms, categories 1-2, and categories 3-5) are applied to each storm (Muller and Stone 2001). Since Muller and Stone's (2001) model does not allow for flexibility and adaptability, a dynamic wind model will be used in this study.

Willoughby and Rahn (2004) created a parametric wind model based on the Holland (1980) wind profile model. Holland's (1980) model used the radius of maximum wind, maximum wind, and measure of profile width to explain the variation in the axisymmetric winds of a storm (Willoughby and Rahn 2004). The parametric wind model describes how hurricane winds weaken as distance from the eyewall increases (Willoughby and Rahn 2004). The eye is the region of a hurricane with the calmest winds (Emanuel 2003). In this region, air is sinking and preventing air from rising and condensing to form clouds (Emanuel 2005c). The eyewall that surrounds the eye is the region that experiences the highest wind speeds (Emanuel 2003). Beyond the eyewall, wind speeds start to decrease as the distance from the eye increases (Willoughby and

Rahn 2004). Parametric wind models have been used to estimate how winds and storm surge can impact an area (Willoughby and Rahn 2004). However, the model does not always portray the wind fields of individual storms accurately (Willoughby and Rahn 2004). Parametric wind field models provide the basis for hurricane risk and catastrophe models (Vickery and Wadhera 2008; Willoughby and Rahn 2004). By considering a storm's spatial extent, the effect of hurricane winds can be examined for all areas affected by a storm.

The parametric wind model (Figure 3.3) will allow for the spatial extent of each storm to be examined. This model will be used when quantifying hurricane landfalls for Florida. To remain consistent with the rest of this study, the model will be run for all hurricanes from 1900-2010. A GIS will be used to display hurricane tracks for the years 1900-2010. The centroid of each county will be used to create a 500 km buffer. The buffer includes storm tracks that directly and indirectly affect Florida counties. A 500 km buffer has been used by Zhu and Quiring (2013) to examine spatial and temporal variations of tropical cyclone precipitation over Texas. Chu and Wang (1998) use a 463 km buffer when calculating tropical cyclone return periods for Hawaii and its vicinity. The radius of outer closed isobar for tropical cyclones is generally less than 550 km (Zhu and Quiring 2013). However, storms such as Hurricane Sandy have had wind fields that surpassed 500 km (Halverson and Rabenhorst 2013). Only the storm tracks that intersect the 500 km buffer will be considered in this study.

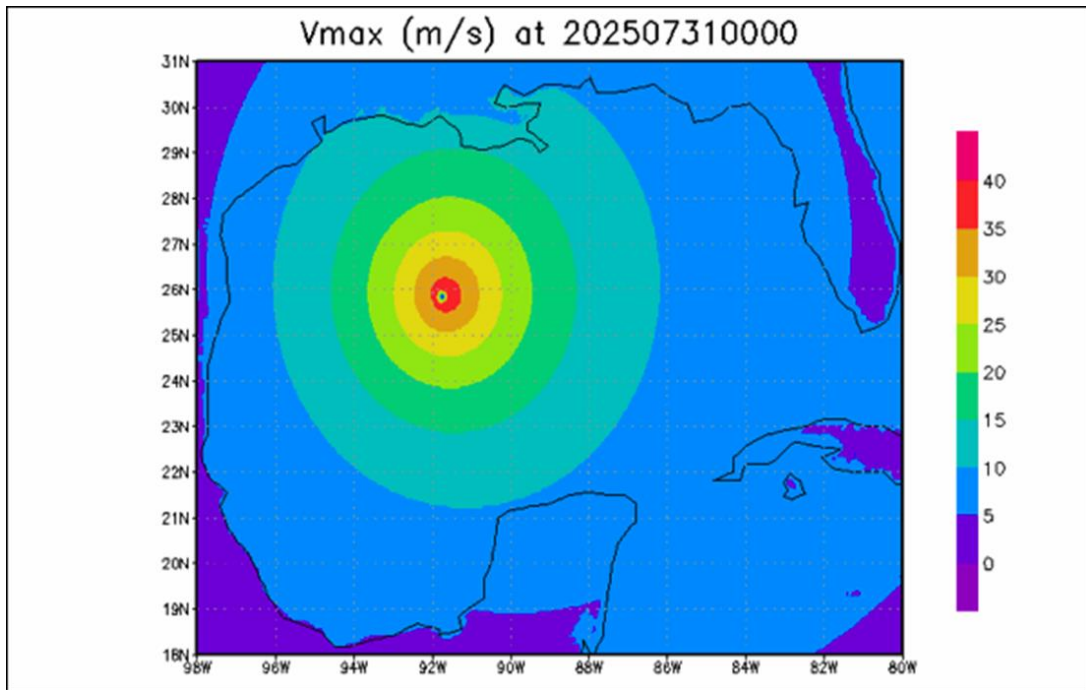


Figure 3.3. Parametric wind field model accounts for storm’s spatial extent.

Objective 2: Quantify how climate change will influence hurricane event risk by performing a meta-analysis of the existing literature.

For the second objective, the peer-reviewed literature that explores the relationship between hurricane event risk (occurrence of frequency, intensity, and change in track) and climate change will be examined. The meta-analysis will consist of examining the literature and organizing the findings by study area, time period, method, variables and conclusions. Summaries will then be created for the pertinent articles of the literature review and then used to perform an analysis of the findings. A meta-analysis is a type of research synthesis which is defined by Cooper et al. (2009) as “the

statistical analysis of a large collection of analysis results from individual studies for the purpose of integrating the findings.” Conducting an aggregate analysis may help in determining the frequency of scenarios found in the literature such as the studies that support the increase in hurricane trends due to climate change and those that do not (Cooper et al. 2009). The literature on hurricanes and climate change can be extensive, therefore, approximately 40-50 studies will be analyzed when conducting the meta-analysis (Cooper et al. 2009). The studies analyzed in the meta-analysis will be compared to find differences and similarities between them (Cooper et al. 2009). Comparing the different time periods, study regions, and methods will allow for more concise findings to be found among the confounding literature (Hunter and Schmidt 2004). The analysis will allow for the relationship between climate change and hurricane event risk to be quantified. The findings from this objective will be applied to Objective 3.

Objective 3: Perform sensitivity analysis using the findings from the meta-analysis to determine how climate change will potentially affect hurricane damage and loss for Florida.

Using the observed event risk (Objective 1) and the findings from the meta-analysis (Objective 2), the effect of climate change on the potential damage and loss for Florida will be determined by performing a sensitivity analysis. A sensitivity analysis allows for specific parameters in a model to be altered to observe changes (Laskey 1995; McCuen 1973). In this case, hurricane intensity will be altered according to the findings

from Objective 2. Based on their significance to Florida's hurricane history, two storms from each category (a total of 12 case study storms) will be selected for further analysis. Different future scenarios will be created based on the findings from the meta-analysis. The scenarios will reflect the effect of climate change on hurricane winds and intensity. For example, if a 20% increase in hurricane intensity is found in the literature, the parameters of the case storms will be modified to reflect this increase. Three scenarios are expected; baseline, moderate, and extreme. FEMA's HAZUS- MH Hurricane Wind Model will be run for all case study storms to determine how climate change will affect potential damage and loss for Florida under changing climatic conditions. The model will estimate building damage, economic losses, and social impacts from hurricane winds for all scenarios based on Florida's growing population and increasing coastal development.

This study focuses on hurricane event risk. Risk refers to the probability of occurrence, in this case, the probability of hurricanes becoming stronger/weak or more/less frequent as a result of climate change (Cuevas 2011). Vulnerability focuses on the socio-economic factors and exposure that determine how those at risk will be impacted (Cuevas 2011). It is possible that climate change will not greatly influence Florida's hurricane event risk in the future. However, an increase in Florida's populations and an increase in the building of properties will increase Florida's vulnerability regardless of its hurricane event risk (Pielke Jr 1997). To account for future changes in hurricane vulnerability for Florida's population, FEMA's HAZUS-MH Hurricane Wind Model will be used.

FEMA's HAZUS-Multi Hazard (MH) is a risk assessment tool used by local governments and emergency managers (Beckmann and Simpson 2006). HAZUS-MH aids communities in the preparation, mitigation, response, and recovery of natural hazards such as earthquakes, floods, and hurricanes (Beckmann and Simpson 2006). The Hurricane Model is a component of HAZUS-MH used for estimating losses and damages from hurricane wind and/or storm surge (Vickery et al. 2006a). It is used as a risk assessment tool for analyzing the impact of past, present, and future storms (Beckmann and Simpson 2006). The program allows the user to create hurricane scenarios using historical data. The model can be run for hypothetical storms using the user defined hurricane scenario which runs on user defined data input (Beckmann and Simpson 2006). HAZUS is also used for disaster planning and response in the event of an approaching storm (Beckmann and Simpson 2006).

The HAZUS-MH Hurricane Model is composed of a hurricane hazard model, terrain model, wind load/debris models, and damage and loss models (Vickery et al. 2006a). The hurricane hazard model is based on a hurricane wind field model and an empirical storm track model created by Vickery et al. (2000a; 2000b). The wind field model is a dynamic numerical model of the planetary boundary layer used by Vickery et al. (2000b). It differs from other models used in hurricane risk assessment in that it accounts for air-sea temperature differences and the influence of sea surface roughness on wind speed (Vickery et al. 2000b). The empirical storm track model is used to model a storm's track across the ocean, from its location of genesis to where it makes landfall (Vickery et al. 2000a). The physical damage model is based on load and resistance

analysis of building envelope elements (Vickery et al. 2006b). The economic building loss model estimates the cost of repairing and replacing building structures using implicit (building interior) and explicit (building exterior) cost functions (Vickery et al. 2006b). All components of the hurricane model have been validated using observational, wind tunnel, and insurance loss data (Vickery et al. 2006b). HAZUS-MH provides model output in charts, tables, and maps (Beckmann and Simpson 2006).

A limitation to using HAZUS is its lack of updated data (Beckmann and Simpson 2006). HAZUS provides data from a default database, however, it does not contain the most up-to-date storm and demographic data (Beckmann and Simpson 2006). The model provides data for building damage, economic loss, shelter requirement, return period, and damage to essential facilities for both historic and hypothetical storms (Beckmann and Simpson 2006). The HAZUS-MH Hurricane Model was run for each case study storm for a baseline, moderate, and extreme scenario. To create user defined hurricane scenarios in HAZUS, storm track data need to be input manually. Data for latitude, longitude, time, radius to maximum winds, wind speed, central pressure, and inland points are necessary for each user defined hurricane scenario. Historical data for storms of category 3 or higher are found in HAZUS's storm database and does not need to be provided by the user. Data for the baseline scenarios were found in the database for storms of category 3 or higher. Storms of category 2 or less require data to be provided by the user. Data for moderate and extreme scenarios for all storms were input manually. Rmax values remained constant as storm intensity was increased for moderate and extreme scenarios. Central pressure values were adjusted using the linear regression

equation for increases in intensity for moderate and extreme scenarios. The three intensity scenarios are explained further in Chapter 6.

Using HAZUS- MH, building damage, economic losses, and social impacts from hurricane winds for all three scenarios will be estimated based on Florida's growing population and increasing coastal development.

CHAPTER IV

HURRICANE EVENT RISK IN FLORIDA

4.1 Return Periods

The occurrence of non-periodic extreme events such as hurricanes, earthquakes, and floods can be defined by calculating their return periods (Elsner and Kara 1999). A return period is the inverse of the annual probability (Elsner and Kara 1999). In this study, a return period is referring to the inverse of the annual probability of a hurricane landfall. Return periods can be used to display the spatial distribution of hurricane landfalls for a specific region. The length of the study period may influence the return period's accuracy (Elsner and Kara 1999). A longer study period will provide better results since it will take into consideration the frequency of rare storm events (Elsner and Kara 1999). Although return periods may not accurately represent the hurricane climatology for a specific location, they are useful for emergency management, planning, and insurance purposes (Elsner and Kara 1999). By providing an estimate of hurricane landfalls, local governments and other agencies can use the information to guide their planning and decision making processes.

Past studies have calculated return periods for landfalls and for wind events using different methods. Early studies, such as Simpson and Lawrence (1971), found the probabilities of occurrence of hurricane landfalls from observations and from a Poisson distribution. Batts et al. (1980) used probabilistic models to calculate return periods for hurricane winds. Later studies calculated return periods for hurricane landfalls and wind

events by using historical hurricane records or results from Monte Carlo simulations to produce values that were fitted to probability distributions (Chu and Wang 1998; Jagger and Elsner 2006; Neumann 1991; Rupp and Lander 1996). Neumann (1991) used historical tropical cyclone records to calculate return periods for tropical cyclone events and tropical cyclone intensities for San Juan, Puerto Rico. The return periods were calculated by fitting maximum wind values from historical records to a Weibull distribution (Neumann 1991). These calculations were part of a development of methods for risk analysis for the National Hurricane Center Risk Analysis Program (HURISK). Risk analysis information is vital for decision makers of regions that are commonly affected by tropical cyclones (Chu and Wang 1998).

Jagger et al. (2001) examined the probability of wind events for coastal counties from Texas to North Carolina. They created a dynamic hurricane wind probability model that provides annual exceedence probabilities for maximum wind events of tropical cyclones (Jagger et al. 2001). The model can predict the probability that a specific county will experience hurricane wind events using climate data parameters from the Weibull distribution of maximum wind speeds and a dynamic model that includes climate variables such as ENSO and NAO (Jagger et al. 2001).

Elsner and Kara (1999) calculated the return periods of hurricane landfalls for coastal counties for a region stretching from Texas to Maine and their methods will be used in this study. First, the average annual probability of a hurricane landfall is calculated using

$$p = \frac{L}{N} \quad (1)$$

where p is the average annual probability of a landfall, L is the number of landfalls for a county, and N is the number of years in the study period (Elsner and Kara 1999). The return period is the inverse of the average annual probability of a landfall

$$T = \frac{1}{p} \quad (2)$$

Simpson and Lawrence (1971), Muller and Stone (2001), and Keim et al. (2007) calculated return periods for 50-mile segments along the Gulf Coast and Eastern Seaboard. Batts et al. (1980) also examined 50-mile segments along the Gulf and East Coasts and considered hurricane winds that measured up to 124 miles inland. Using 50 mile segments to calculate return periods results in an even distribution of area for each segment which makes comparison between segments easier. These segments, however, do not account for political boundaries which delineate segments at a county level. Elsner and Kara (1999) and Jagger et al. (2001) calculated return periods for coastal counties on the Gulf and Eastern Coasts. Calculating return periods at the county level may make comparisons between study regions difficult due to the unequal distribution of area between counties. However, an examination at the county level provides local governments with a more accurate assessment of tropical storm and hurricane wind impacts.

This study will be the first to calculate return periods for all counties in Florida. Florida's geographic location makes it extremely vulnerable to hurricane strikes since it is surrounded by the Gulf of Mexico and the Atlantic Ocean. Frequently, storms track across Florida, impacting inland counties as well as coastal counties. Inland counties

experience flooding and heavy rainfall events that can cause significant damages (Rappaport 2000). For this reason, inland counties are included as part of this study.

For each Florida county, a track-derived and a wind-derived return period were calculated based on HURDAT data from 1900-2010 and from the parametric wind field model. Return periods were calculated for all storms and maps were created to display the return periods for: all storms, tropical storms only, hurricanes only, and major hurricanes only (categories 3-5). The track-derived return period is based on the number of tracks that crossed each county during the study period. Track-derived return periods are calculated using Elsner and Kara's (1999) method (see Equation 2). This method accounts for direct tropical storm and hurricane landfalls for all counties. However, it does not account for a storm's spatial extent. A county that may not be in the storm's direct path will not appear to have been affected by the storm. A storm's wind swath typically extends far enough to affect more than one county (Muller and Stone 2001). Keim et al. (2007) found that the average hurricane's wind swath extends approximately up to 50 km to the left of the center of circulation and up to 100 km ahead of and to the right. The parametric wind field model provides wind speed values experienced by each county for each storm.

The wind speed frequencies from the histograms were used to calculate wind-derived return periods for each county. Equation 3 was used to calculate wind-derived return periods,

$$T = \frac{W}{N} \quad (3)$$

where T is the return period, W is the wind speed event frequency, and N is the number of years in the study period.

The track-based return periods underestimate the impact of tropical storms and hurricanes, creating a bias. However, the wind-derived return periods result in an accurate representation of the effect of wind events for Florida counties.

Results of the calculated return periods are displayed in Figures 4.3-4.10. The results were categorized by storm intensity. Risk factors were also calculated for each county. For each storm category (tropical storms, hurricane, and major hurricane), the mean wind speed was divided by its return period. The sum of the quotients for each category is the risk factor value. Risk factor values were calculated for each county and were calculated separately using track-derived return periods and wind-derived return periods. The risk factor values describe the likelihood of a county experiencing a wind event ranging from tropical storm force winds to major hurricane force winds.

4.2 Histograms

Histograms displaying the distribution of wind speed values were created for each county. The histograms include wind speed events for all tropical storms and hurricanes that impacted Florida between 1900-2010. Figure 4.1 displays the frequency of tropical cyclone wind based events for Miami-Dade, Orange, Hillsborough, Duval, Leon, and Escambia Counties. These counties were chosen because of their geographical location as well as for the major cities that are located in each county. Pensacola (Escambia County), Tallahassee (Leon County), Jacksonville (Duval County), Orlando

(Orange County), Tampa (Hillsborough County), and Miami (Miami-Dade County) contain the majority of Florida's population (U.S. Census Bureau 2013). Figure 4.2 shows the geographical location of the counties. Based on the 2010 US Census population data for the six cities, Pensacola has the lowest population (51,923), while Jacksonville has the highest (821,784) (U.S. Census Bureau 2013).

The histograms display the frequency of tropical cyclone wind based events based on the parametric wind field model. From the selected counties, Miami-Dade (Figure 4.1a), the southernmost county, experienced the most TC wind based events. For Miami-Dade, wind speeds ranged from 0 m/s to approximately 70 m/s. The majority of TC wind events were approximately 10 m/s. Miami-Dade experienced wind speeds approaching 70 m/s which are the highest wind speeds experienced by any of the six counties. Hillsborough and Orange Counties are located in the central part of the state. Hillsborough County is located off of Florida's western central coast while Orange County is located inland.

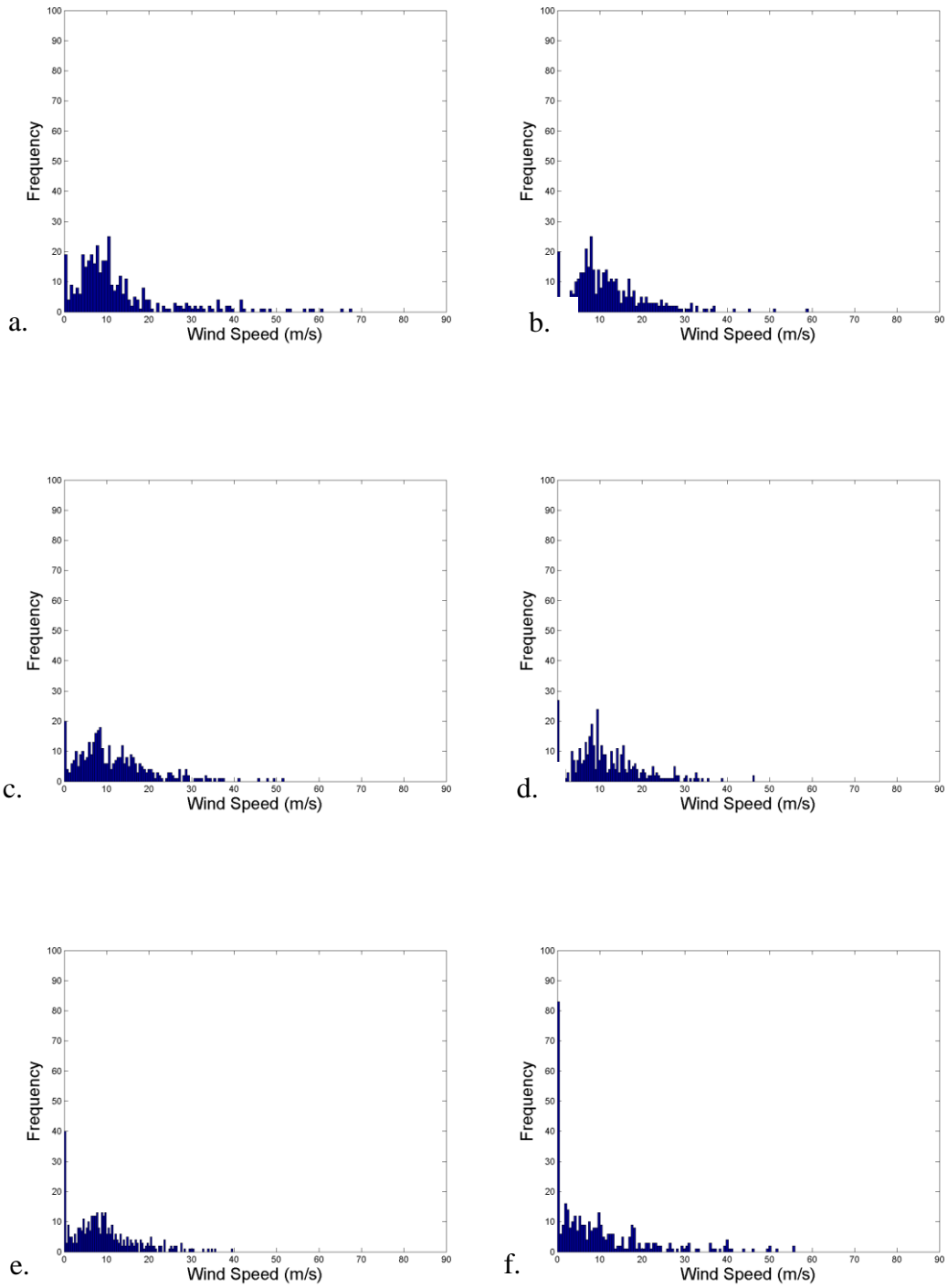


Figure 4.1. Histograms of the frequencies of tropical cyclone wind based events for a) Miami-Dade, b) Orange, c) Hillsborough, d) Duval, e) Leon, and f) Escambia Counties.

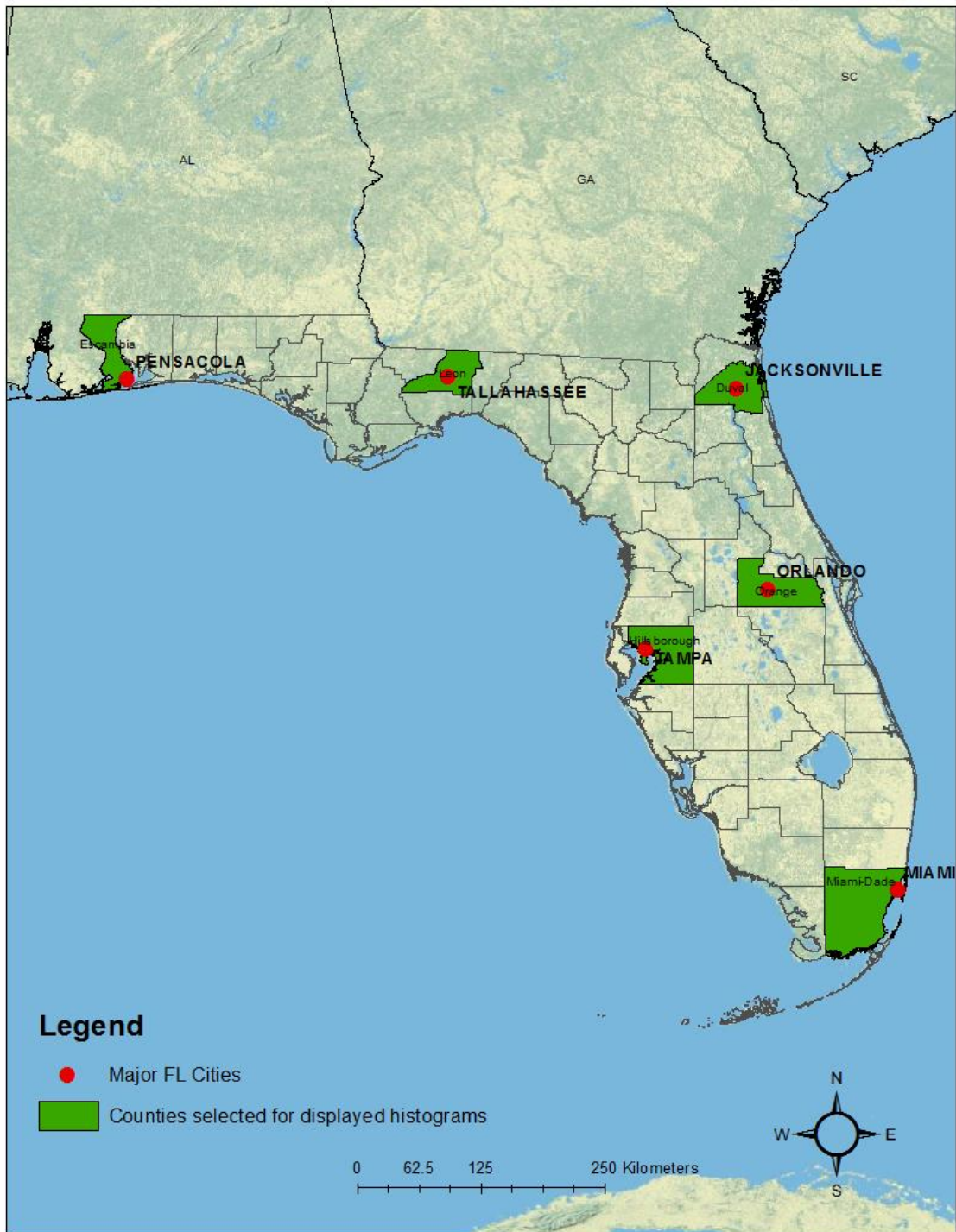


Figure 4.2. Map of counties selected for displayed histograms. Major cities located in the selected counties are also highlighted.

The histograms for Orange (Figure 4.1b) and Hillsborough (Figure 4.1c) counties have similar distributions, however, Orange County has a higher frequency of TC wind events. Specifically, Orange County has more TC wind events between 5 and 15 m/s than Hillsborough County. The majority of TC wind events for Orange County are found between 5 and 15 m/s.

The difference in the counties' geographical location (coastal vs. inland) is reflected in the difference of the distribution of TC wind events. Leon and Orange Counties are inland while the remaining four are coastal counties. The coastal counties generally had higher frequencies of TC wind events than the inland counties. However, latitude seems to play a larger role in wind speed frequencies. As a county's latitude increased, its frequency of TC wind events decreased. This may be the result of fewer storms passing through counties that are higher in latitude. The majority of storms pass through south and central Florida resulting in higher frequencies of TC wind events for the counties in those regions. When comparing the two inland counties, Orange County in central Florida had a higher frequency of TC wind events than Leon County in the panhandle. The counties that are centrally located (Orange and Hillsborough) have a higher frequency of TC wind events in comparison to counties to the north and in the panhandle. Duval County is located along the northeast coast of Florida. Duval County (Figure 4.1d) has a similar distribution to the central counties, however, it has significantly fewer events. The majority of events for Duval are between 5 and 15 m/s. Leon (Figure 4.1e) and Escambia County (Figure 4.1f) are part of the panhandle. In comparison to the histograms for Escambia and Leon, Duval has the highest frequency

of TC wind events in northern Florida. This may be explained by Duval County's location along the Eastern Seaboard; a region that is commonly affected by tropical storms and hurricanes (Elsner and Kara 1999). Escambia County is Florida's westernmost county and borders the Alabama-Florida state line. Leon County is part of the Big Bend region and it is located along the Florida- Georgia state line. The Big Bend region of Florida is located on the northwest coast and is where the Florida Peninsula joins the Florida Panhandle (Weatherly and Thistle 1997). The counties located in the region are Dixie, Franklin, Gadsden, Jefferson, Leon, Liberty, Madison, Taylor, and Wakulla County. Escambia County is located on the coast while Leon County is located inland. The histograms for these northern panhandle counties vary greatly from the rest of the histograms. Northern counties experienced fewer TC wind events than central and southern counties. Leon County has the lowest frequency of wind events out of all six counties. The majority of Leon County's TC wind events were between 5 and 10 m/s. Out of the six counties, it was the only county to not experience TC wind events over 40 m/s.

Based on the histograms, Miami-Dade County had the highest frequency of TC wind events and Leon County had the lowest. Inland counties generally experienced less wind events than coastal counties. When examining histograms for all counties, the counties with the highest frequencies were located in the southernmost region of Florida. The counties with the lowest frequencies were those that were located along the panhandle, close to the state borders between Florida and Georgia and Alabama, and in the Big Bend region.

4.3 Return Period Maps

4.3.1 All Storms

The majority of Florida counties have a track-derived return period between 0-10 years based on all storms (tropical storm and hurricane) (Figure 4.3). Counties with higher return periods were found mainly in northern Florida, the panhandle, central Florida and along the central western coast. Holmes, Washington, Gulf, Hamilton, Baker, Union, Gilchrist, Pinellas, and Manatee Counties all have track-derived return periods between 10-20 years and are all located along the panhandle and in northern Florida with the exception of Pinellas and Manatee Counties which are located along Florida's central western coast. Bradford and Sarasota counties have return periods between 20-30 years. Bradford County is in northern Florida and Sarasota is found along the central western coast. Seminole County, which is centrally located, is the only county with a track-derived return period of 30-40 years. Figure 4.3 suggests that the majority of the state is at risk of experiencing a tropical storm or hurricane landfall every 0-10 years. In comparison, the map for wind-derived return periods for all storms (Figure 4.4) shows that all Florida counties have a return period between 0-10 years. This indicates that all Florida counties can experience tropical storm or hurricane force winds every 0-10 years. Figure 4.4 highlights how every county is at risk from experiencing significant wind events within a short time span. Although Figure 4.3 displays counties which have experienced direct storm hits, Figure 4.4 more accurately represents which counties are impacted by tropical storms and hurricanes and when those effects are expected to occur.

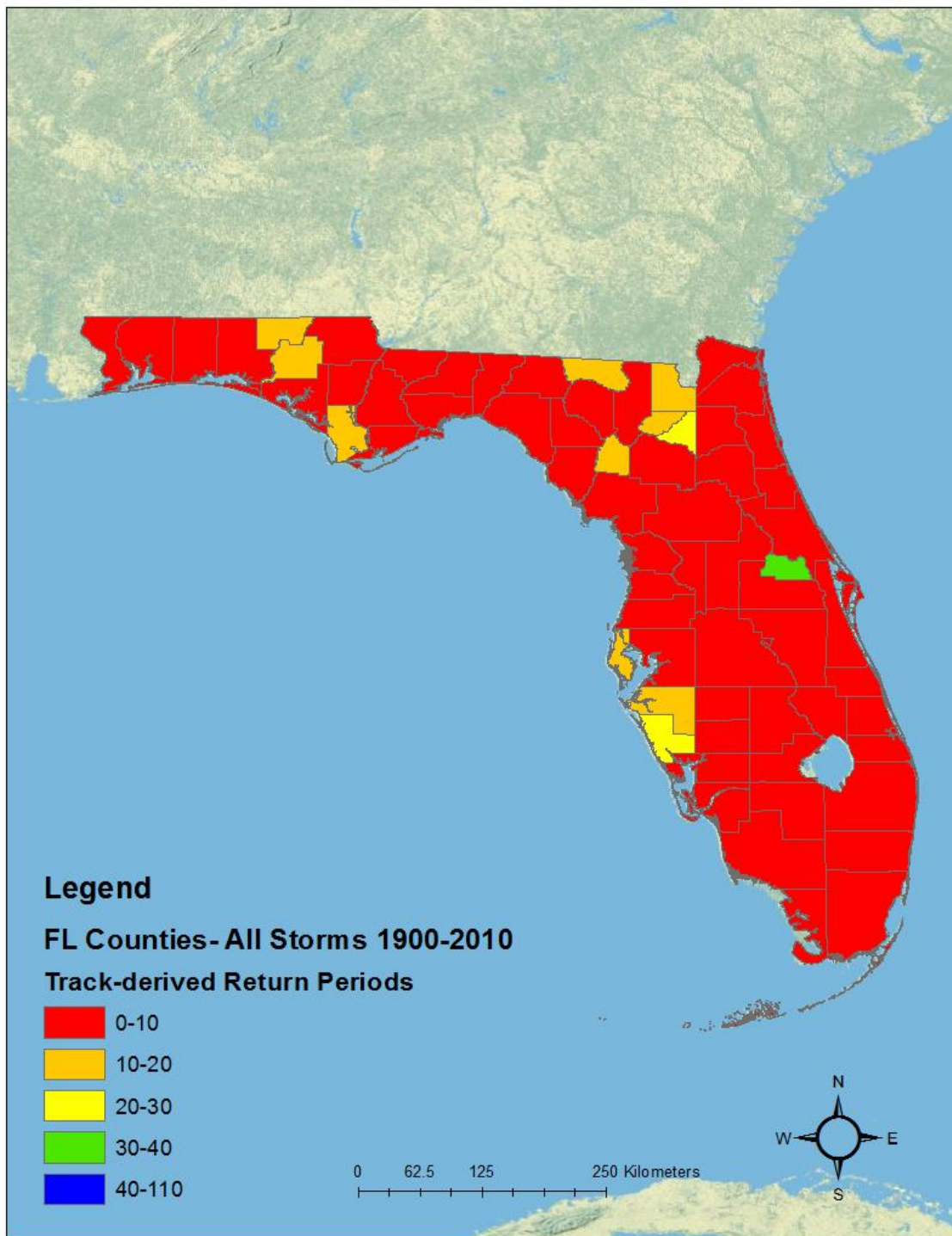


Figure 4.3. Calculated track-derived return periods (years) for all tropical storms and hurricanes based on 1900-2010 for all Florida counties.

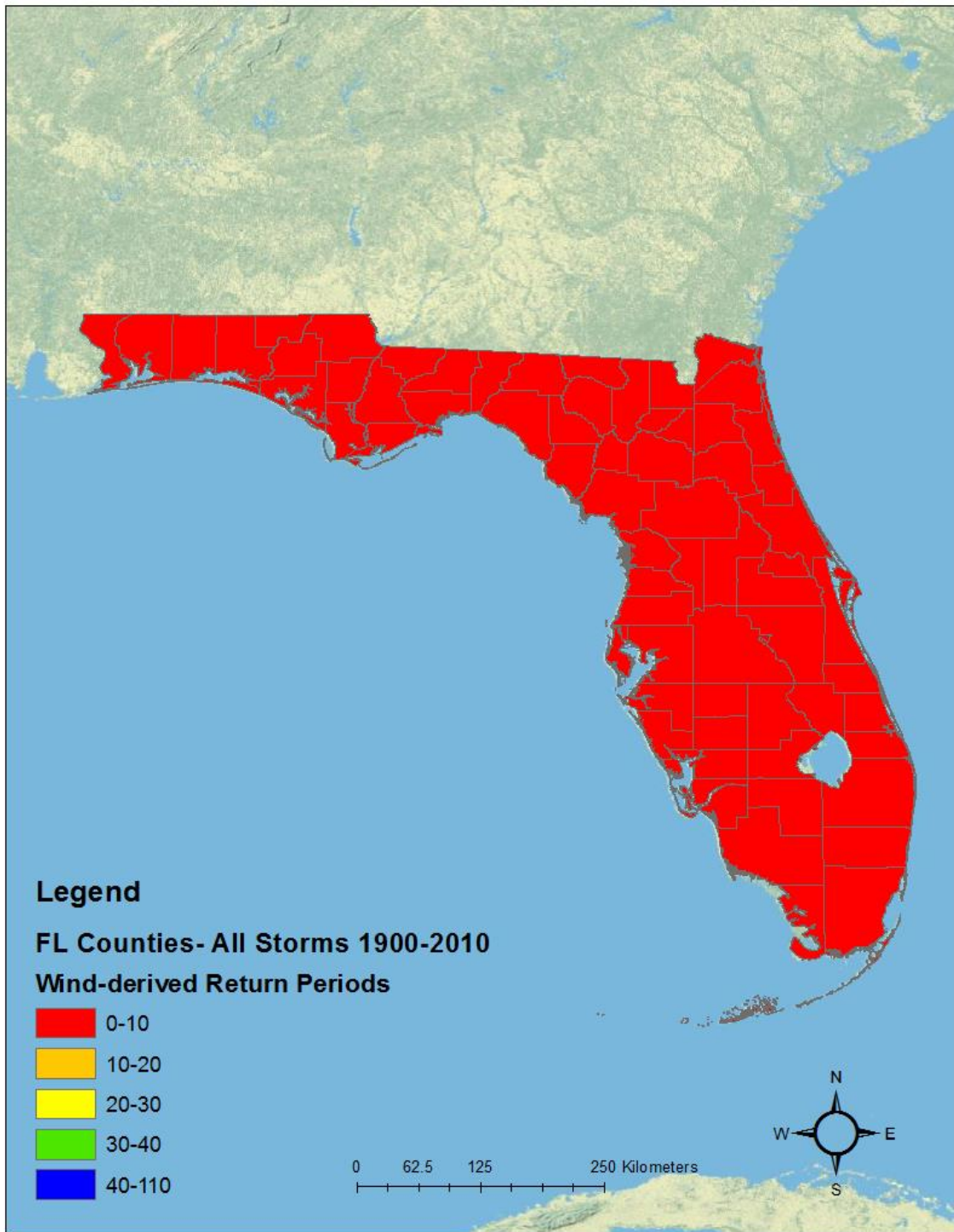


Figure 4.4. Calculated wind-derived return periods (years) for all tropical storms and hurricanes based on 1900-2010 for all Florida counties.

4.3.2 Tropical Storms Only

Figure 4.5 shows that the majority of Florida counties have track-derived return periods between 0-10 years for tropical storms only. Counties with track-derived return periods of 10-20 years were mostly located along the Florida panhandle and included Escambia, Santa Rosa, Holmes, Washington, Bay, Jackson, Calhoun, Gadsden, Liberty, Franklin, Madison, Hamilton, Baker, Union, and Gilchrist. The remaining counties were located along the central western and eastern coasts with Hillsborough, Manatee, and Hardee Counties to the west and Indian River, St. Lucie, and Martin to the east. Broward County stood out as the only county in southern Florida to have a track-derived return period between 10-20 years. Pinellas, Sarasota, and DeSoto Counties are located along the central western coast and have track-derived return periods between 20-30 years. Gulf County in the panhandle was the only county with a track-derived return period between 30-40 years. Bradford and Seminole Counties in north central Florida have track-derived return periods of 40-110 years.

For tropical storms, all counties have a wind-derived return period between 0-10 years (Figure 4.6). All counties are expected to experience tropical storm force winds every 0-10 years. Similar to the maps for all storms, there was a difference between the track-derived and wind-derived return period maps. The track-derived return period map (Figure 4.5) had counties with return periods ranging from 0-110 while the wind-derived return periods (Figure 4.6) only had return periods between 0-10 years. The track-derived return period map may inaccurately display where the effects from tropical storms can be felt.

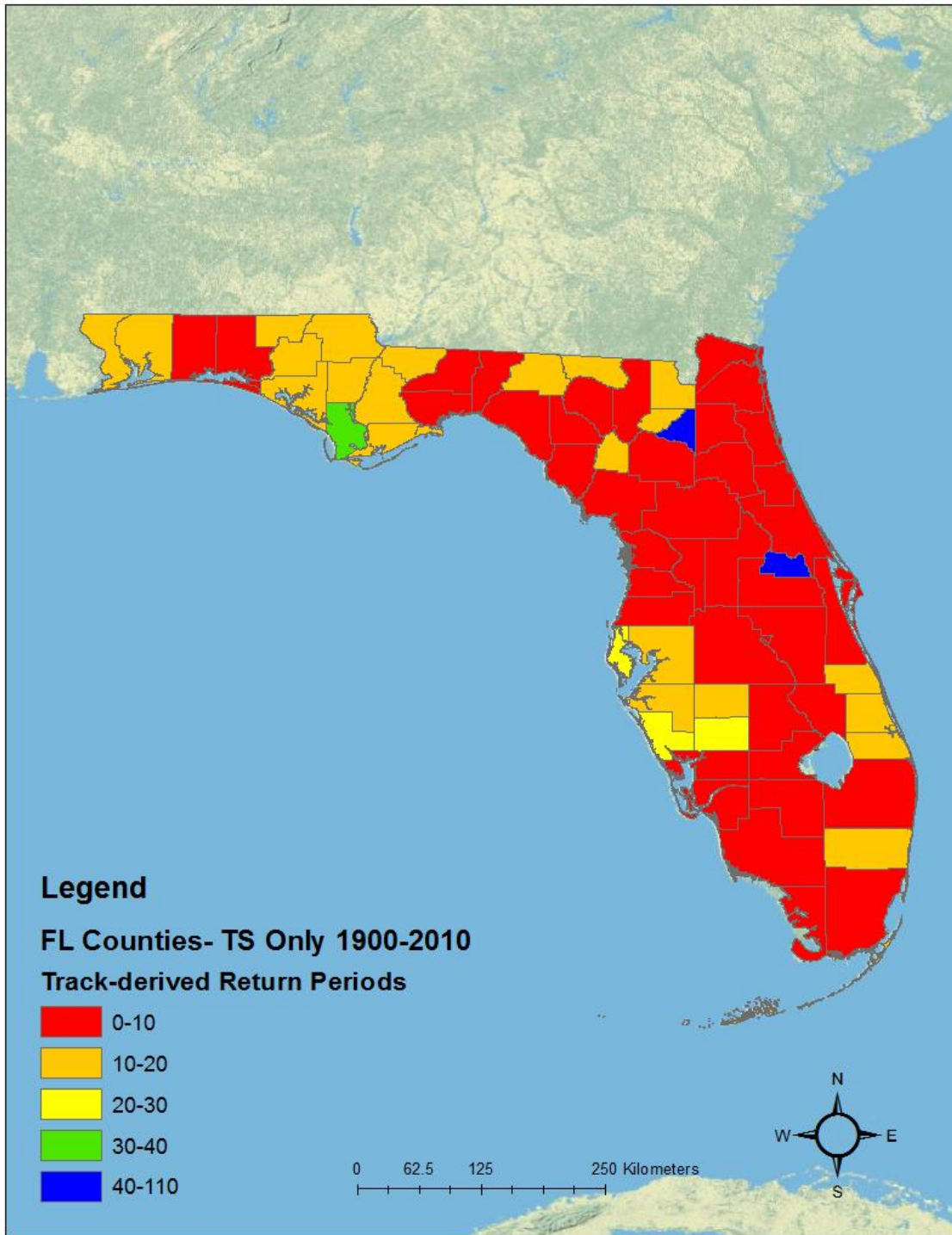


Figure 4.5. Calculated track-derived return periods (years) for all tropical storms based on 1900-2010 for all Florida counties.

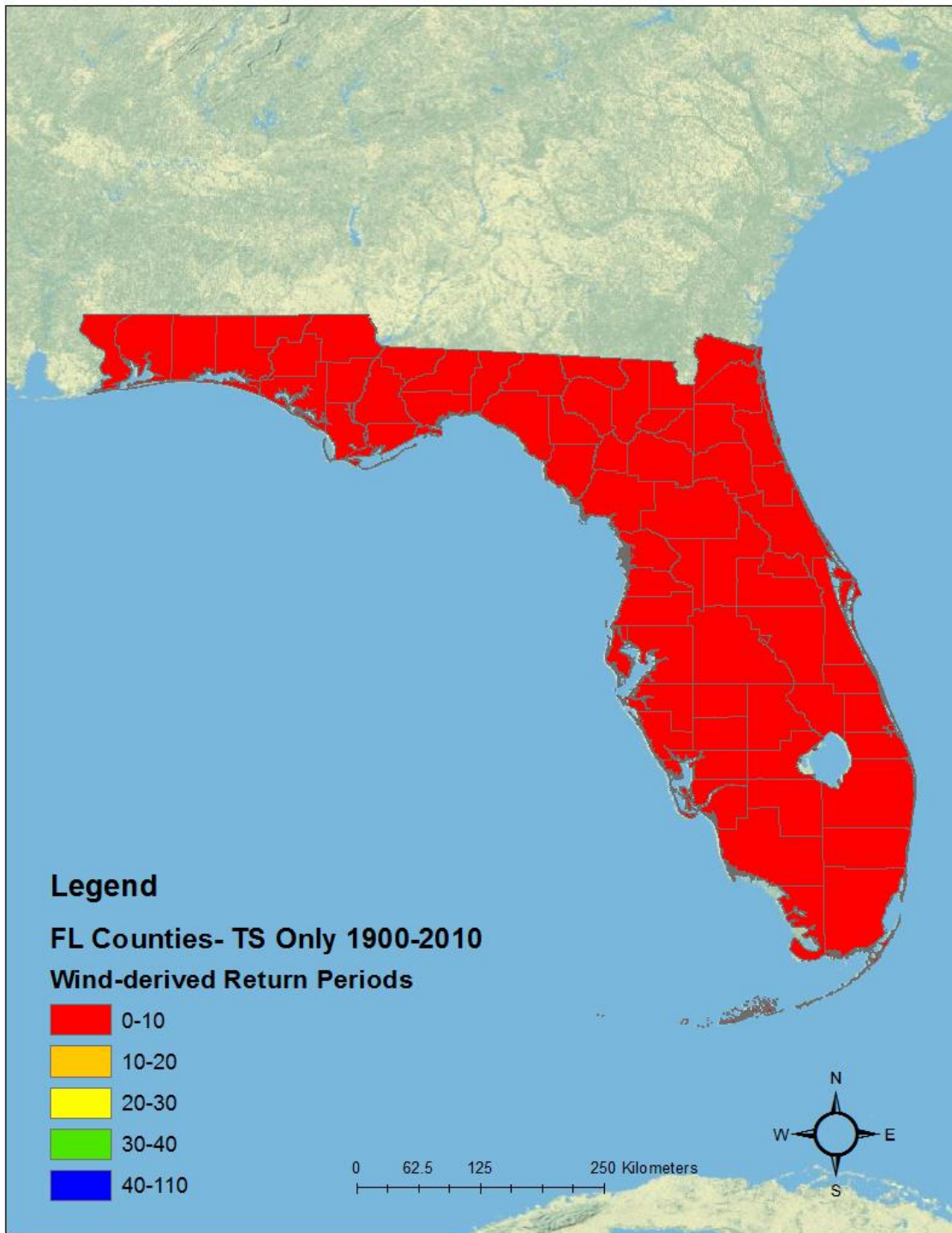


Figure 4.6. Calculated wind-derived return periods (years) for all tropical storms based on 1900-2010 for all Florida counties.

4.3.3 Hurricanes Only

For hurricanes only, counties in southwestern (Mainland Monroe and Collier) and southeastern (Martin, Palm Beach, Broward, Miami-Dade, and Florida Keys Monroe) Florida have a track-derived return period between 0-10 years along with Polk County which is located in central Florida (see Figure 4.7). The majority of counties in central Florida (Marion, Putnam, Citrus, Hernando, Pasco, Lake, Volusia, Brevard, Indian River, St. Lucie, Okeechobee, Highlands, Hardee, DeSoto, Lee) have a track-derived return period between 10-20 years. Bay County is the only county in the panhandle to have a return period between 10-20 years. Counties with return periods between 20-30 years are scattered along the panhandle (Escambia, Santa Rosa, Walton, Gulf, and Franklin) and central Florida (St. Johns, Sumter, Orange, Osceola, Charlotte). With the exception of Hillsborough and Hendry Counties located in central and southern Florida respectively, the counties with track-derived return periods 30-40 years are located along the panhandle (Okaloosa, Holmes, Washington, Jackson, Calhoun, Liberty, Taylor, and Union). Counties throughout the state had track-derived return periods between 40-110 years. They are located along the panhandle (Gadsden, Leon, Wakulla, Jefferson,), northern Florida (Madison, Hamilton, Suwannee, Lafayette, Columbia, Nassau, Duval, Clay, Bradford, Alachua, Levy, Flagler), central Florida (Seminole, Glades), and the central western coast (Pinellas, Manatee, Sarasota) of Florida. Return periods for Baker, Dixie, and Gilchrist Counties were 0 which is not a valid value for return periods since it is a result of dividing the number of landfalls,

which is 0 by the years in the study period. For those counties, return period values were not available.

The map for wind-derived return periods for hurricanes (Figure 4.8) looks more segregated than the track-derived return period map (Figure 4.7). Counties with wind-derived return periods between 0-10 years are found exclusively in the panhandle (Escambia, Santa Rosa, Okaloosa, Walton, Holmes, Washington, Bay, Calhoun, Gulf, Franklin, Liberty, Wakulla) and in southern Florida (Hillsborough, Manatee, Sarasota, Hardee, DeSoto, Highlands, Okeechobee, Osceola, Brevard, Indian River, St. Lucie, Martin, Palm Beach, Broward, Miami-Dade, Mainland Monroe, Florida Keys Monroe, Collier, Hendry, Lee, Charlotte, Glades). Gadsden, Leon, Suwannee, and Columbia Counties in the north had return periods between 20-30 years. Madison and Taylor Counties in the Big Bend region have wind-derived return periods between 30-40 years. Nassau, Hamilton, Jefferson, also in northern Florida, had return periods between 40-110 years. The remaining counties located mainly in central and north central Florida, with the exception of Jackson County in the panhandle, have wind-derived return periods between 10-20 years. Figure 4.8 clearly shows the areas affect most by hurricanes. Counties in the southern part of the state and in the panhandle are the most susceptible to hurricane force winds.

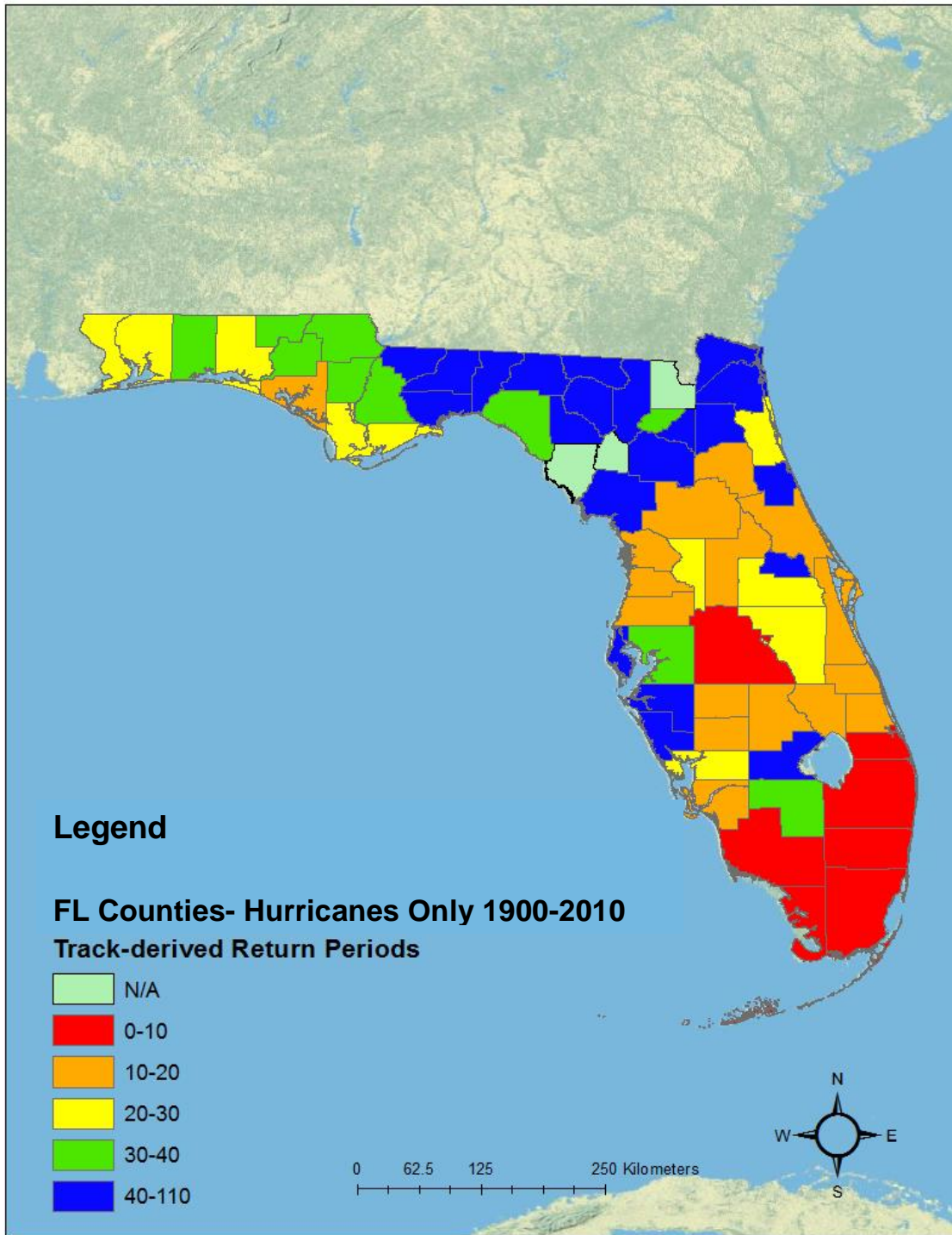


Figure 4.7. Calculated track-derived return periods (years) for all hurricanes based on 1900-2010 for all Florida counties.

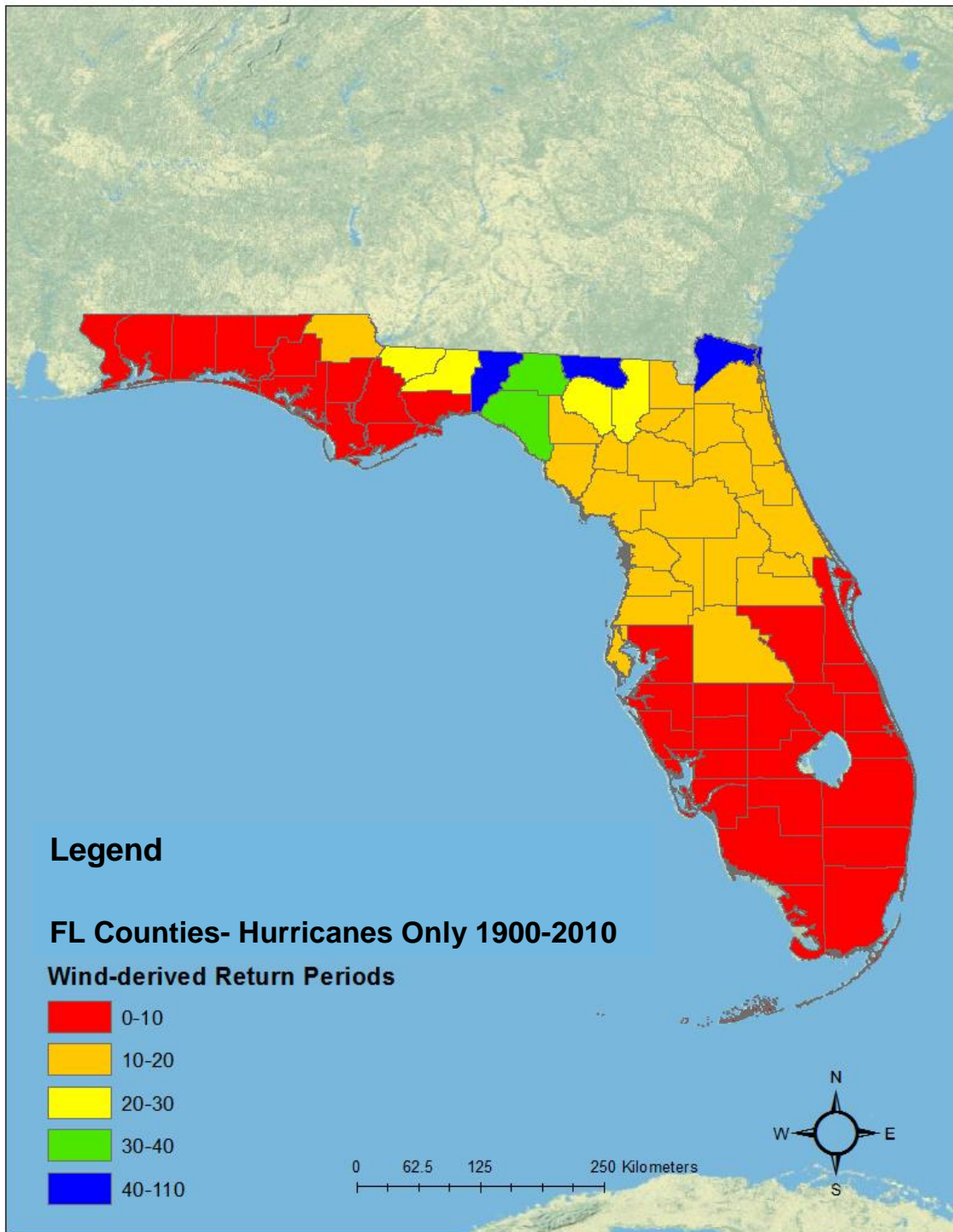


Figure 4.8. Calculated wind-derived return periods (years) for all hurricanes based on 1900-2010 for all Florida counties.

4.3.4 Major Hurricanes Only

As shown in Figure 4.9, the counties with the lowest track-derived return period between 10-20 years are found in the southern tip of Florida (Martin, Palm Beach, Miami-Dade, Mainland Monroe, Florida Keys Monroe, and Collier). Polk County also has a track-derived return period between 10-20 years but it is found in central Florida. A large number of storms pass through Polk County when they cross Florida. This may account for the county's high track frequency. Polk stands out from its surrounding counties in central Florida. Lee, DeSoto, and Highlands Counties have track-derived return periods between 20-30 years. Broward County is the only county in the southern tip of Florida to have a return period between 20-30 years. The counties surrounding it have return periods between 10-20 years. In central Florida, Pasco, Hardee, and Okeechobee Counties have track-derived return periods between 30-40 years. No counties had return periods between 40-50 years. Counties with track-derived return periods between 50-110 years are located in the panhandle (Escambia, Santa Rosa, Okaloosa, Walton, and Holmes), central Florida, (St. Johns, Flagler, Volusia, Orange, Lake, Sumter, Citrus, Hernando, and Hillsborough) and southern Florida (St. Lucie, Glades, Hendry, and Charlotte). The rest of the counties, the majority being in the Big Bend region and in north central Florida, have not been affected by a major hurricane. The legend for the major hurricane map (Figure 4.9) is different from the rest of the maps. No county had a return period between 0-10 for major hurricanes. The legend on the figures was adjusted so that the lowest calculated return period is 10 years.

The wind-derived return period map (Figure 4.10) for major hurricanes has the southern tip of Florida (Martin, Palm Beach, Miami-Dade, Mainland Monroe, Florida Keys Monroe, and Collier) as the region with highest risk since its counties have wind-derived return periods between 10-20 years. St. Lucie, Highlands, Hendry, Charlotte, and Lee Counties in south central Florida have wind-derived return periods between 20-30 years. Escambia County in the panhandle and Broward County in the southern tip of the state stand out in their regions with their return periods of 20-30 years. The counties surrounding Escambia have higher return periods of 50-110 years while the counties surrounding Broward have lower return periods of 10-20 years. Hardee, Glades, and Okeechobee Counties in south central Florida have wind-derived return periods between 30-40 years. No counties have wind derived return periods between 40-50 years. With the exception of Jackson, Washington, Bay, Calhoun, Gadsden, Liberty, Wakulla, Leon, Jefferson, Madison, Taylor, Hamilton, Baker, Nassau, Duval, Brevard, and Manatee Counties which have no available data, the remaining counties in the panhandle and central Florida have wind-derived return periods between 50-110 years.

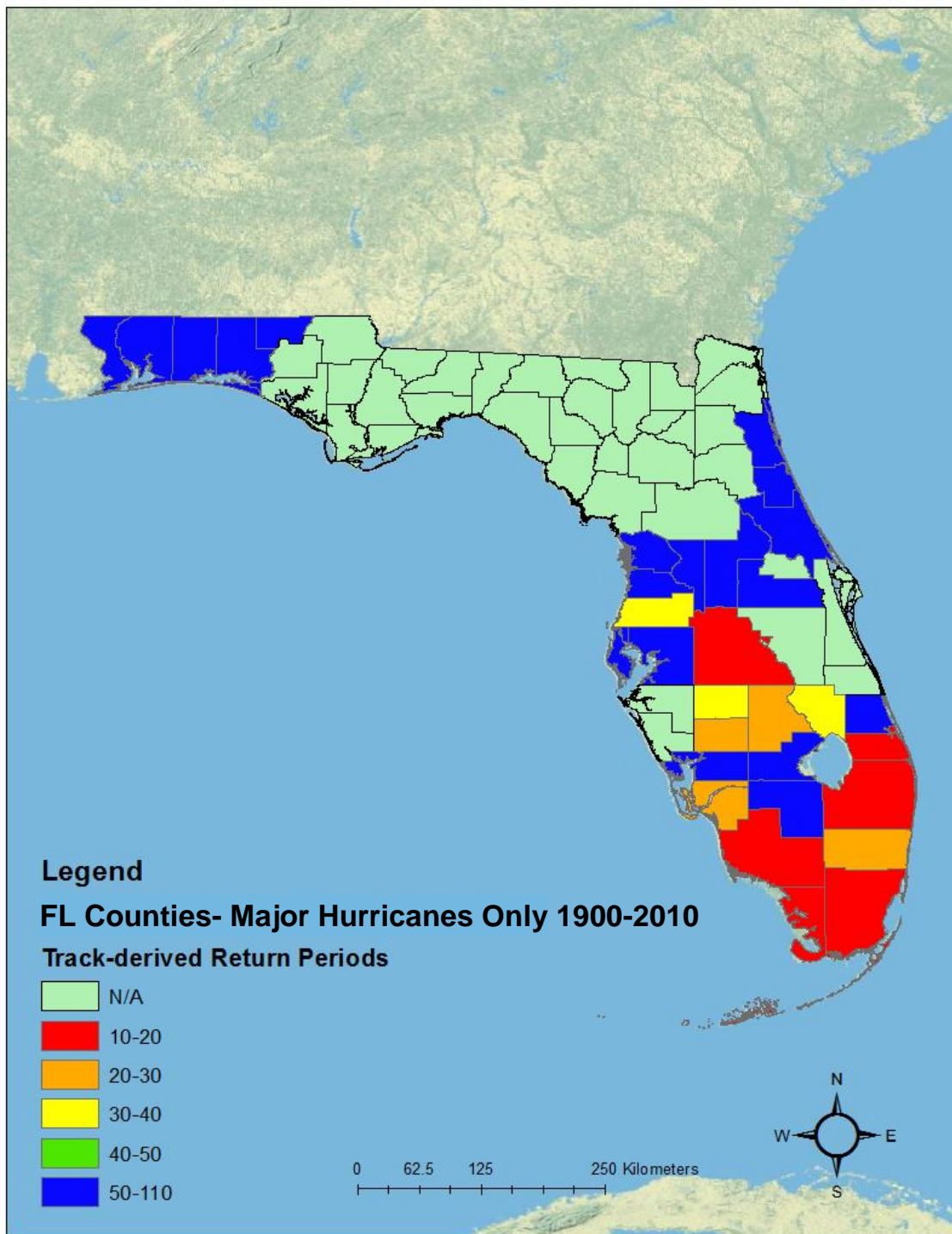


Figure 4.9. Calculated track-derived return periods (years) for all major hurricanes (categories 3-5) based on 1900-2010 for all Florida counties.

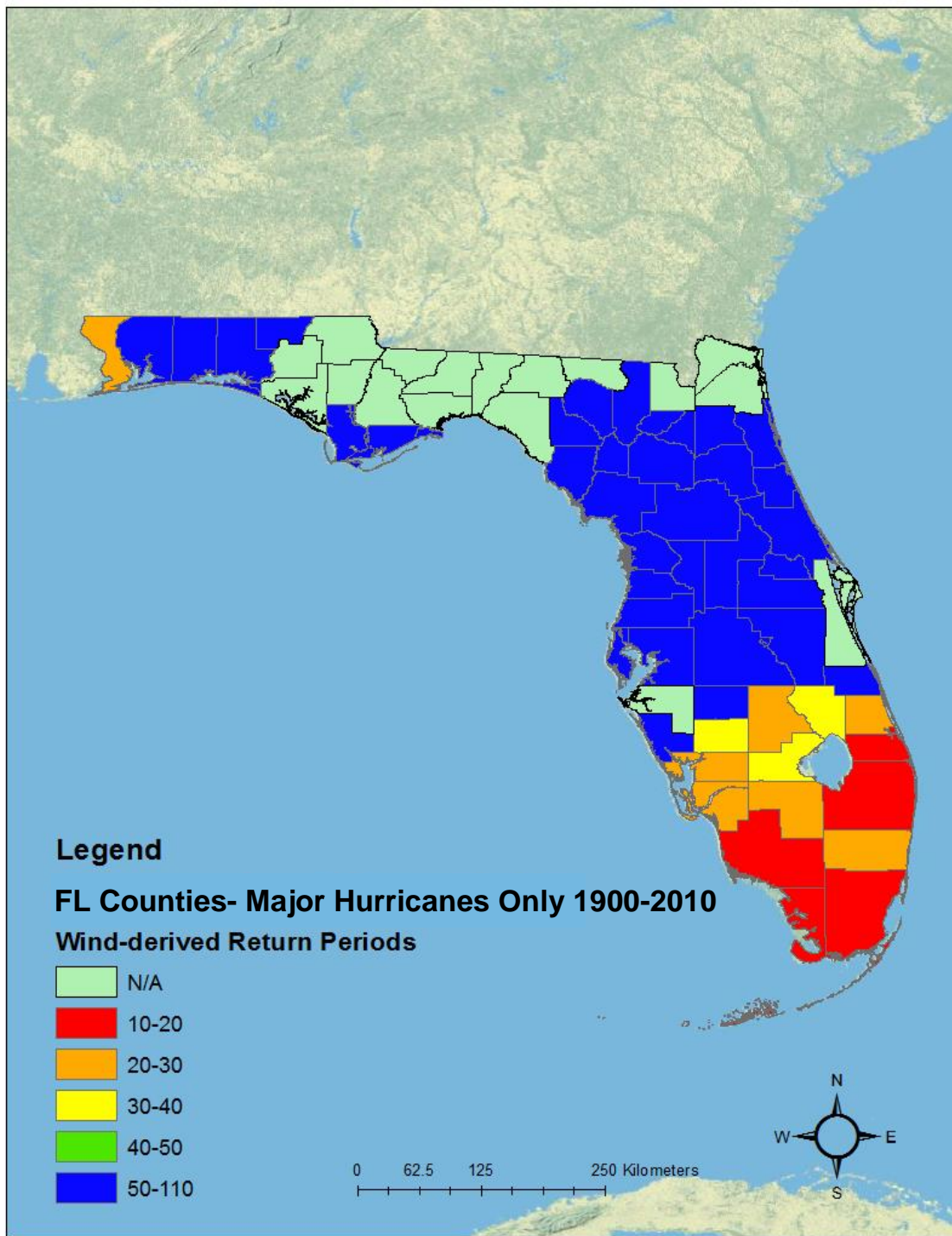


Figure 4.10. Calculated wind-derived return periods (years) for all major hurricanes (categories 3-5) based on 1900-2010 for all Florida counties.

4.4 Risk Factors

The risk factor maps have values ranging from 0-20. A county with a risk factor of 0 will have little to no risk of experiencing tropical storm or hurricane force winds while a county with a risk factor value of 20 has the highest risk of experiencing tropical storm or hurricane force winds. Risk factors were calculated separately using track-derived return periods and wind-derived return periods.

For risk factor values calculated using track-derived return periods (Figure 4.11), the majority of counties had a risk factor between 0-5 and were located in the panhandle, northern Florida, and central Florida. Counties with a risk factor value between 5-10 were located in southern (Highlands, Okeechobee, St. Lucie, Martin, Broward, Mainland Monroe, and Lee) and central (Citrus and Pasco) Florida. Counties in the southern tip of Florida (Palm Beach, Miami-Dade, Florida Keys Monroe, and Collier) had a risk factor value between 10-15. Polk County stands out in central Florida with a risk factor of 10-15. No counties had a risk factor value between 15-20. Counties in the southern tip of Florida have the highest risk of experiencing tropical storm or hurricane force winds based on track-derived return periods.

The map for risk factor values calculated using wind-derived return periods (Figure 4.12) shows large differences when compared to the map created using track-derived risk factor values (Figure 4.11). Only four counties have risk factor values between 0-5. These counties are Jefferson, Taylor, Hamilton, and Nassau and are located in the northernmost of Florida. The remaining counties in the panhandle and northern Florida have a risk value between 5-10. Counties in central Florida (Marion, Lake,

Volusia, Seminole, Orange, Brevard, St. Lucie, Indian River, Okeechobee, Highlands, Glades, Lee, Charlotte, DeSoto, Hardee, Sarasota, Manatee, Hillsborough, Pinellas, Pasco, Hernando, Polk, and Osceola) have risk factor values between 10-15 with the exception of Escambia and Franklin Counties in the panhandle and St. Johns in northern Florida. The entire southern tip of Florida has counties (Martin, Palm Beach, Broward, Miami-Dade, Florida Keys Monroe, Mainland Monroe, Collier, and Hendry) with a risk factor value of 15-20. In Figure 4.12, the southern tip of Florida has the highest risk of tropical storm and hurricane wind events which coincides with the results from Figure 4.11.

4.5 Conclusion

The results from the track-derived return periods differ from the wind-derived return periods. However, the return period maps coincide in having southern Florida as the region that is most likely to experience tropical storm and/or hurricane force winds. The risk factor maps also indicate that southern Florida has the highest risk of experiencing tropical storm and/or hurricane force winds. The regions with the longest return periods varied between the track-derived and wind-derived return periods. For the track-derived return periods, counties in north Florida, north central Florida, and the panhandle had the highest return periods and lowest risk factors. For the majority of wind-derived return period maps, counties in northern Florida, along the Florida-Georgia state line, had the highest return periods and lowest risk factors.

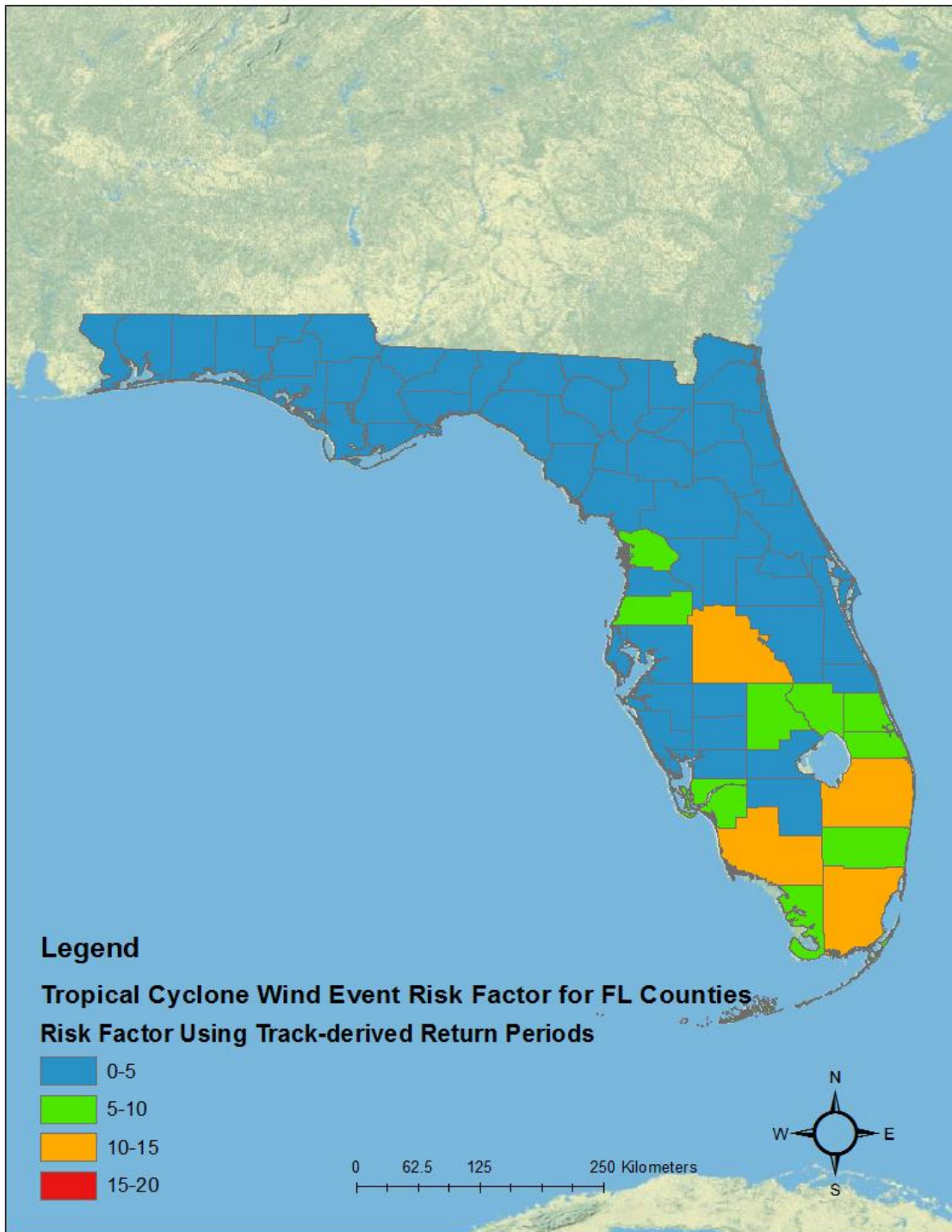


Figure 4.11. Calculated wind event risk factor using track-derived return periods for all tropical storms and hurricanes based on 1900-2010 for all Florida counties.

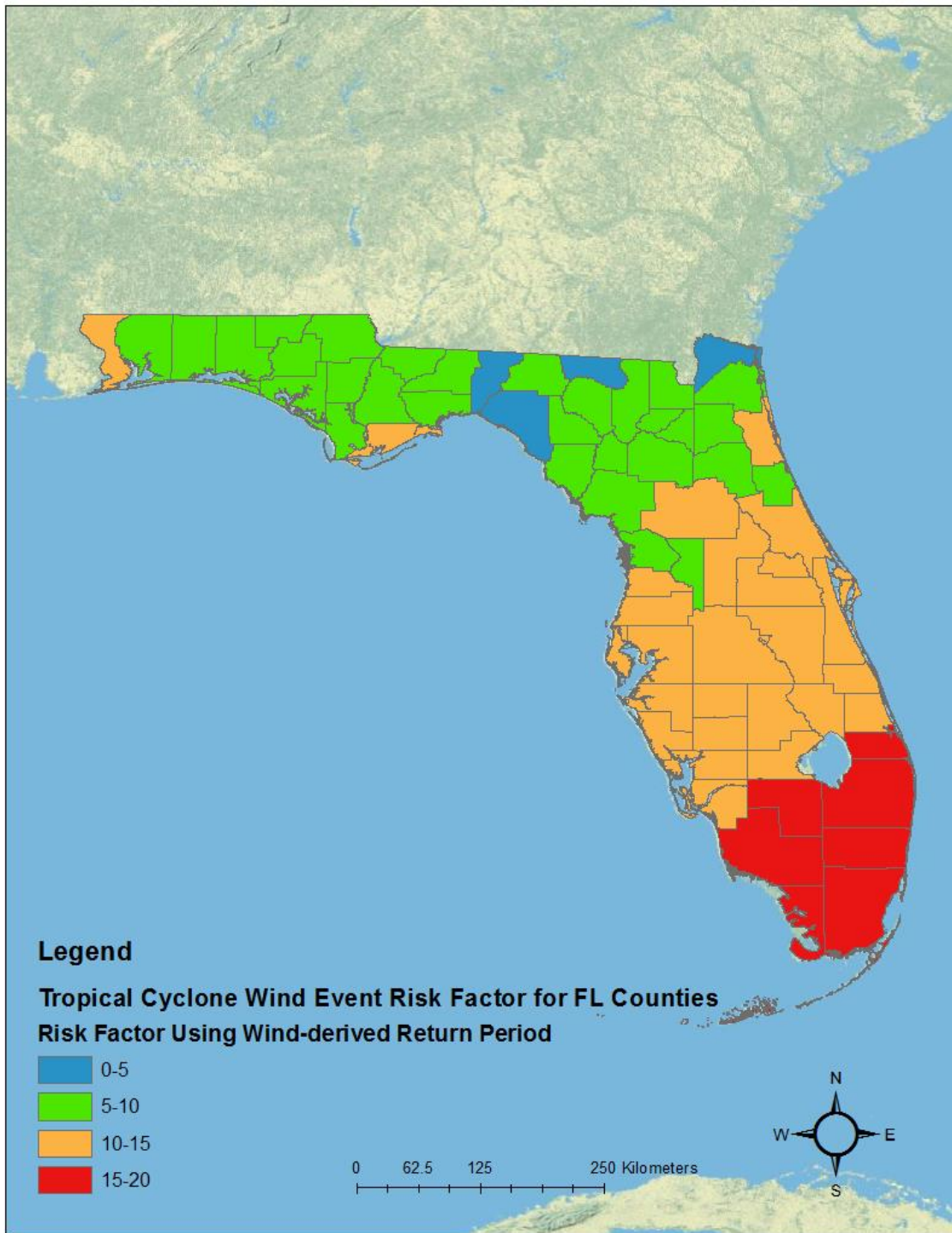


Figure 4.12. Calculated wind event risk factor using wind-derived return periods for all tropical storms and hurricanes based on 1900-2010 for all Florida counties.

For wind-derived return periods for major hurricanes, counties in central Florida and in the panhandle have the highest return periods.

According to Jagger et al. (2001), Miami-Dade County has a 10% chance of experiencing 41 m s^{-1} (80 kt) winds or greater in any one year and a 4% chance for a 51 m s^{-1} (100 kt) winds. The results from the calculated return periods and risk factors in this thesis coincide with Jagger et al.'s (2001) annual exceedence probabilities results for Miami-Dade County. Miami-Dade consistently has a return period between 0-10 years and has a high risk factor. Similar to the results from the return periods and the risk factors, the counties with the highest probabilities in Jagger et al. (2001) were those in southern Florida. Annual probabilities for category 1 hurricane winds ranging from 15-25% were calculated for southern Florida by their model (Jagger et al. 2001). The lowest probability values were less than 10% and were found along the northern region of the Florida peninsula. However, along the west coast of the Florida peninsula, the scale of the wind probability gradient increased as wind speed increased (Jagger et al. 2001). The gradient becomes stronger for storms of major hurricane intensity while the gradient is smaller for tropical storms (Jagger et al. 2001).

Jagger et al.'s (2001) dynamic probability model found that the region most at risk of hurricane wind events were in southern Florida and the region with the lowest risk was in the Big Bend region of Florida. The return period and risk factor maps also show that counties in the Big Bend region have high return periods and low risk factor values. Although the Jagger et al. (2001) study used a different methodology, it found similar results and therefore validates the results from this study.

Track-derived return periods may inaccurately represent the number of affected counties since they only account for the counties in which the eye of the storm passed through. Surrounding counties are not considered in this method. Wind-derived return periods account for the effects of a storm's wind swath as it makes landfall. Wind-derived return periods account for all counties affected by a storm's wind field. Knowing which counties have the highest risk of experiencing TC winds can help local governments make decisions such as whether or not to close public schools and public offices.

CHAPTER V

META-ANALYSIS OF THE INFLUENCE OF CLIMATE CHANGE ON HURRICANE EVENT RISK

5.1 Introduction

Increases in atmospheric concentrations of greenhouse gases such as carbon dioxide (CO₂) and methane (CH₄) have caused global temperatures to increase (Mathez 2013). This warming has been attributed to human activity based on increases in fossil fuel consumption (Mathez 2013). A changing climate leads to uncertainty about future hurricane behaviors and trends. Anthropogenic climate change may lead to changes in hurricane frequency, intensity, and movement. The influence of climate change on hurricane behavior has been examined by various authors (Elsner 2006; Emanuel 1987; Henderson-Sellers et al. 1998; Holland and Webster 2007; Knutson et al. 2010; Landsea et al. 2006; Pielke et al. 2005; Webster et al. 2005). Yet, there is no clear relationship between climate change and hurricane characteristics. There are conflicting results as to how climate change will impact hurricane behavior (Knutson et al. 2010). Natural variability in hurricane frequency, intensity, and movement has also been influenced by atmospheric teleconnections such as the El Niño/Southern Oscillation (ENSO). The effect of climate change on tropical cyclones is often examined at a global scale (Emanuel 2005a; Henderson-Sellers et al. 1998; Knutson et al. 2010). However, the influence of climate change on hurricane behavior may be more easily observed if the relationship were examined at a regional scale (Christensen et al. 2013; Pielke et al.

2005). This thesis will focus on the Atlantic basin (which includes the Caribbean and Gulf of Mexico) since this basin is most relevant to the study region. However, this chapter will also review and discuss global TC projections.

This chapter will examine the influence of climate change on potential hurricane behaviors and trends. A meta-analysis of the literature will quantify the expected changes in hurricane frequency, intensity, and movement as a result of climate change. The findings will be applied to the sensitivity analysis in Objective 3 that will determine how hurricane damage and loss will potentially be affected by climate change.

5.2 Hurricane Intensity and Climate Change

Emanuel (1987) used a Carnot cycle model and a general circulation model (GCM) to predict how maximum TC intensity will respond to increases in SST and increases in atmospheric CO₂. The Carnot cycle is a thermodynamic cycle which is used to explain the function of a heat engine. Similar to a heat engine, TCs use heat energy as a source of mechanical energy (Emanuel 2005c). Heat engines are composed of a heat source and a heat sink (Emanuel 2005c). The greater the temperature difference between the two, the more efficient the engine (Emanuel 2005c). Heat energy is provided mostly by latent heat of vaporization and by sensible heat (Emanuel 1987). Moisture is evaporated from the ocean surface and flows toward the center of the storm and upward into the eyewall (Emanuel 2005c). As moist air rises and condenses, energy is released as latent heat and transforms into sensible heat (Emanuel 2005c). The energy released is used by the storm to power its winds (Emanuel 2005c). Emanuel (1987, 2005c)

considers TCs to be ideal and efficient examples of a heat engine. What makes tropical cyclones exceptionally efficient is how they reuse energy (Emanuel 2005c). Some of the energy from the winds from the outer bands sinks back to the surface (Emanuel 2005c). The air then flows back toward the center where frictional dissipation takes place (Emanuel 2005c). Friction creates heat which is added to the air flowing into the eyewall at the inflow layer (Emanuel 2005c). Through this process, storms are able to increase their efficiency by reusing “waste heat” (Emanuel 2005c).

The Carnot cycle model was used to calculate the minimum sustainable central pressures and maximum wind speeds for TCs (Emanuel 1987). Relative humidity, surface pressure, and thermodynamic efficiency remained constant while central pressure and wind speeds varied as a function of SST (Emanuel 1987). The Carnot cycle model is dependent on changes in SST to determine changes in maximum TC intensity (Emanuel 1987). Emanuel (1987) found that a 3°C increase in SST led to a 30-40% increase in maximum pressure drop and a 15-20% increase in wind speed. These results indicate that small increases in SST lead can large changes in intensity (Emanuel 1987).

Emanuel (1987) used a GCM (the Goddard Institute for Space Studies General Circulation Model II), to study how doubling the amount of atmospheric CO₂ influences SST and maximum TC intensity. SSTs were simulated for five Augusts. Changes in SST ranged between 2.3°C and 4.8°C and were added to climatological August SSTs.

Emanuel (1987) found that the minimum sustainable pressures were lower in the Gulf of Mexico and the Bay of Bengal than in any other region. The model estimated a 40-50% increase in hurricane destructive potential with increases of up to 60% in some regions

(Emanuel 1987). He concluded that climatic changes from increases in CO₂ will result in increases in TC intensity. Emanuel (1987) did not examine changes in TC frequency.

Emanuel (2000) concluded that changes in potential intensity as a result of SST increases would influence the distribution of actual intensity. If potential intensity increased by 10-20% as a result of climate change, Emanuel (2000) concluded that actual intensity should increase by the same amount.

Emanuel et al. (2004) used a simple coupled ocean-atmosphere model to observe the influence of various environmental factors which impact hurricane intensity. Their model has an atmospheric component that calculates the intensity of a storm by taking into account its potential intensity. A hurricane's potential intensity is based on the storm's energy cycle and is the "maximum steady intensity" that a storm can reach (Emanuel et al. 2004). The atmospheric model is then combined with a one-dimensional ocean model is used to account for the role that upper-ocean dynamics play in storm formation and development. Emanuel et al. (2004) concluded that wind shear is the most important factor that influences intensity (Emanuel et al. 2004).

Knutson and Tuleya (2004) used nine global coupled climate models to create different scenarios to determine the influence of increased CO₂ on TC intensity and precipitation rates. The Geophysical Fluid Dynamics Laboratory (GFDL) R30 coupled model is used to run scenarios under current (control) and increased CO₂ conditions. Atmospheric CO₂ was increased by 1% for 80 years and this increased SST by 0.88° C to 2.48°C (Knutson and Tuleya 2004). Maximum surface wind speeds are expected to increase by 6% under warming conditions (Knutson and Tuleya 2004). The scenarios

only considered environmental factors from the GCMs and did not take vertical wind shear into consideration (Knutson and Tuleya 2004). Knutson and Tuleya (2004) also ran the model to evaluate changes in TC potential intensity based on Emanuel's (1987) theory. A 7.5% increase in potential intensity was found based on Emanuel's (1987) methods. Although the Knutson and Tuleya (2004) has limitations (e.g., it uses only a single model, it does not account for vertical wind shear), they concluded that under warming climate conditions, TC intensity is expected to increase as SST increases. In a later study, Knutson et al. (2008) found that maximum mean wind speed increases by 2.9% for all TCs and it increases by 1.7% for hurricanes.

Michaels et al. (2005) suggested that Knutson and Tuleya (2004) was inaccurate and unrealistic. Michaels et al. (2005) consider the GFDL model used by Knutson and Tuleya (2004) to be inaccurate at forecasting hurricane intensity. They also believe that a yearly 1% increase in CO₂ is unrealistic (Michaels et al. 2005). Michaels et al. (2005) suggest a 0.5% yearly increase in CO₂ which coincides with the increase of current CO₂ trends. After adjusting CO₂ values, Michaels et al. (2005) expect maximum TC wind speeds to increase by 3% which is half of what Knutson and Tuleya (2004) predicted.

Emanuel (2005a) calculates a power dissipation index (PDI) over the North Atlantic Ocean which determines the total power that was dissipated by a storm over its lifetime. Emanuel (2005a) uses PDI as an indicator of TC intensity. SST has a strong influence on PDI (Emanuel 2005a). Emanuel (2005a) states that theoretically TC peak wind speed should increase by 5% for every 1°C increase in SST. For example, an SST

increase of 0.5°C causes wind speed to increase by 2-3% and PDI to increase by 6-9%. The PDI is expected to increase by 8-12% when the increase in a storm duration is considered (Emanuel 2005a). Increases in wind speed and PDI are only partly explained by an increase of SST as a result of anthropogenic climate change (Emanuel 2005a). Other causes such as vertical wind shear may also play a role (Emanuel 2005a). Emanuel's (2005b) prediction that wind speed will increase by 10% based on a 2°C increase in SST is in agreement with Emanuel's (2005a) intensity theory of a 5% increase for every 1°C .

Webster et al. (2005) compared trends in observed SST and TC frequency and intensity from 1970 to 2004 for all ocean basins and found that hurricane intensity and frequency have increased since 1995. The number of hurricanes, intensity distribution, and number of storm days for all ocean basins were examined and compared to changes in SST trends (Webster et al. 2005). The short time period in this study is not ideal for definite relationships to be found, however, with the satellite era commencing in the 1960s, it provides the most complete data record available. Between 1970 and 2004, tropical SST increased by 0.5°C and they found a positive, statistically significant relationship between hurricane frequency and intensity, and SST. An increase in the number of intense hurricanes (categories 4 and 5) and a decrease in the number of storms in the North Pacific, Indian and Southwest Pacific ocean basins was also observed (Webster et al. 2005). An increase in the number of TCs and storm days was found in the Atlantic (Webster et al. 2005). The Atlantic Ocean basin also experienced an increase in intense hurricanes, however, it experienced the smallest increase out of all the ocean

basins (Webster et al. 2005). Webster et al. (2005) found that GCMs run under doubled CO₂ scenarios both generally agree that hurricane intensity will increase as the climate warms.

Landsea et al. (2006) used the Dvorak Technique, a method that uses satellites to calculate maximum sustained surface winds, to determine hurricane intensity. Since the technique was developed in the 1970s, hurricane intensity data may not be as accurate as data collected with today's satellite technology (Landsea et al. 2006). It is possible that some past storms may have been stronger than indicated by the Dvorak technique (Landsea et al. 2006). Due to this discrepancy in the data and to a lack in a consistency in the trends relating intensity and anthropogenic global warming, Landsea et al. (2006) concludes that it is not possible to determine whether hurricane intensity has increased significantly and whether hurricane intensity has been influenced by climate change.

Elsner (2006) examined the relationship between TC intensity and SST. Elsner (2006) used SST anomaly data and global mean temperature anomalies for the months of August to October for 1871-2005 and calculated a PDI similar to Emanuel (2005a). Elsner (2006) hypothesized that an increase in SSTs results from anthropogenic climate change or from the influence of the AMO. Regression models and Granger causality tests were used to test Elsner's (2006) hypotheses. The Granger causality test between hurricane activity, Atlantic SSTs, and PDI had a significant F value of 4.30. The influence of global temperature on Atlantic SST was also tested and had an F value of 7.07. Elsner (2006) concluded that anthropogenic climate change has a greater effect on SSTs and TC intensity than the AMO.

Trenberth (2007) examined the relationship between trends in hurricane activity and SST and found that although there may be natural causes for an increase in hurricane trends and SSTs, the increases may also be attributed to climate change. According to his findings, since 1970 climate change has increased global SSTs by 0.6°C which is enough to increase a hurricane's intensity by one category (Trenberth 2007).

To measure the influence of global warming on hurricane intensity, Kossin et al. (2007) created a new hurricane data record of satellite observations for 1983-2005 for all ocean basins. Kossin et al. (2007) found that PDI values increased in the North Atlantic basin over the study period. Since hurricane activity in the Atlantic accounts for less than 15% of global hurricane activity, Kossin et al. (2007) state that their results do not substantiate the theory that increasing SSTs are responsible for increased hurricane activity in the Atlantic.

Pielke (2007) performed a sensitivity analysis to examine the future economic impacts from TCs under climate and socioeconomic scenarios for 2050 and 2100. By 2050, intensity is expected to increase by 0-18% and frequency is expected to experience changes between -20% to +20%. By 2100, intensity is expected to increase by 0-36% and frequency is expected to experience changes between -40% to +40% (Pielke 2007). Pielke (2007) used intensity increases of 18% and 36% for 2050. Due to the disparity in frequency values, Pielke's (2007) sensitivity analysis assumed no changes in frequency. Results from the sensitivity analysis show that total damages significantly increase as TC intensity increases (Pielke 2007). Pielke (2007) used a baseline TC damage value of \$1.00. An 18% increase by 2050 would result in a damage value of \$4.60 while a 36%

increase would result in a damage value of \$7.04 (Pielke 2007). Damage values increase by approximately 360% from the baseline to the 18% increase scenario. From the 18% to 36% increase scenario, damage values increase by approximately 53%.

Although there are conflicting views on how climate change may affect hurricanes in the future, Knutson et al. (2010) conclude that hurricane intensity may increase by 2 to 11% and changes in frequency and track are unlikely to occur. The current assessment report from the IPCC (AR5) is in agreement with Knutson et al. (2010) and also projects hurricane intensity to increase by 2 to 11% (Christensen et al. 2013). Holland and Bruyère (2014) state that overall TC intensity is expected to increase by 5% for every °C increase in SST. Table 5.1 provides a summary of the findings regarding hurricane intensity and climate change. Based on Table 5.1, approximately 94% of the studies expect an increase in TC intensity.

Author(s)	Year	Increase/Decrease	Expected Changes
Emanuel	1987	Increase	3°C increase in SST results in 15-20% increase in wind speed
Emanuel	2000	Increase	If potential intensity increases, actual intensity will increase the same.
Knutson and Tuleya	2004	Increase	1% CO ₂ increase/year, SST increased 0.88°C to 2.48°C, wind speeds increase 6%
Emanuel	2005a	Increase	Wind speed increase of 5% for every 1°C SST
	2005b	Increase	Wind speed increase of 10% for every 2°C SST
Michaels et al.	2005	Increase	0.5% CO ₂ increase/year, wind speed increase of 3%
Webster et al.	2005	Increase	As climate warms
Landsea et al.	2006	Insufficient data	Difficult to determine due to inconsistent dataset
Elsner	2006	Increase	Anthropogenic climate change influences increases
Trenberth	2007	Increase	Global SST increased since 1970 by 0.6°C, enough to increase intensity by one category
Kossin et al.	2007	Increase	Increase in PDI in Atlantic basin
Pielke	2007	Increase	0-18% by 2050, 0-36% by 2100
Knutson et al.	2008	Increase	2.9% wind speed for all TCs, 1.7% for hurricanes
Knutson et al.	2010	Increase	2 to 11% based on 2.8°C increase by 2100 (A1B scenario)
IPCC AR5	2013	Increase	2 to 11% based on 2.8°C increase by 2100 (A1B scenario)
Holland and Bruyère	2014	Increase	Intensity increases 5% for every °C SST
Number of studies expecting an increase:		15 out of 16	

Table 5.1. Summary of expected changes in TC intensity.

5.3 Hurricane Frequency and Climate Change

The relationship between climate change and TC frequency is less clear than TC intensity. Emanuel (1987) states that there is no reason for TC frequencies to significantly decrease if atmospheric CO₂ levels were to double. The changes in hurricane trends over the last few decades have sparked the debate over whether those changes are occurring naturally or if they are being influenced by climate change (Kerr 2006).

Knutson and Tuleya (2004) focus on TC intensity and their study, which is described above, is not designed to measure changes in TC frequency. However, if TC frequency were to remain the same, they expect increases in the event risk of category 5 storms as a result of higher CO₂ conditions and warmer SSTs.

Emanuel (2005a) states that there is no trend in global annual TC frequencies. A number of studies (Henderson-Sellers et al. 1998; Knutson and Tuleya 2004) find relationships between SST and frequency inconclusive. According to Webster et al. (2005), global climate models run under doubled CO₂ scenarios have contradictory results regarding hurricane frequency. Some models predict an increase in hurricane frequency, while others predict a decrease (Webster et al. 2005). However, Webster et al. (2005) observed an increasing trend in TC frequency for the Atlantic basin from 1970 to 2005 (Webster et al. 2005).

However, other studies (Landsea 2007; Landsea et al. 2010; Mann et al. 2007) state that these relationships are likely a result of improved satellite observations and data collection, rather than the result of a warming climate. Landsea (2007) examined

undercount bias in the historical dataset when exploring the relationship between climate change and hurricane frequency. Prior to the use of satellites, hurricanes were observed when they approached land or by ships in the Atlantic (Landsea 2007). The number of TCs is likely underestimated prior to satellite era due to inconsistent data collection and undeveloped technology (Chang and Guo 2007; Landsea 2007). When storms missing from the record are accounted for, the number of hurricanes prior to the satellite era increases (Landsea 2007). An increase in hurricane activity in recent years is likely attributed to the technological advancements in hurricane detection and observations rather than a warming climate (Landsea 2007).

Using the ECHAM5 GCM, Latif et al. (2007) found a strong correlation between vertical wind shear and the Accumulated Cyclone Energy (ACE) Index. The ACE Index measures TC activity by considering the number, duration, and intensity of all TCs during a season (Latif et al. 2007). Latif et al. (2007) found an increase in SST over the Indian and Pacific Oceans due to an increase of vertical wind shear in the Atlantic. Latif et al. (2007) also found that an increase in SST in the North Atlantic relative to the warming of the Indian and Pacific Oceans resulted in a decrease in vertical wind shear. Vertical wind shear in the North Atlantic is dependent on the warming of Indian and Pacific Oceans (Latif et al. 2007; Wang and Lee 2008). A decrease in vertical wind shear results in an increase of hurricane activity (Latif et al. 2007). Latif et al. (2007) found that trends in TC frequency did not stray from the natural multidecadal variability of TC activity. For example, Latif et al. (2007) associate the decreases in TC activity in 2006 to

the small temperature gradient between the North Atlantic and Indian and Pacific Oceans as a result of El Niño.

Knutson et al. (2008) use a non-hydrostatic model and ensemble-mean global model projections to examine the role of increased SSTs on TC frequency. They found that an increase in Atlantic SST resulted in an 8% decrease in the frequency of major hurricanes (Knutson et al. 2008). Out of 27 model runs where the control is compared to warmer SSTs, 22 of those runs showed a decrease in tropical storm frequency (Knutson et al. 2008). Knutson et al. (2008) believe that environmental changes in moisture or circulation may be the cause for decreased storm frequency.

Knutson et al. (2010) used high resolution global models to project changes in hurricane behavior as a result of climate change. Some studies (Webster et al. 2005) state that trends in increased TC frequency have recently been observed. However other studies such as Landsea (2007), state that these relationships are more than likely a result of improved satellite observations and data collection rather than the result of a warming climate.

TC frequency is expected to remain the same or decrease in a warming environment (Knutson et al. 2010). The IPCC AR5 (2013) is also in agreement that TC frequency is expected to decrease or remain the same. However, the frequency of the most intense storms is expected to increase (Christensen et al. 2013). It is unlikely that an anthropogenic climate change signal has been present in the historical data record but it will likely show up in future TC activity and intensity trends (Holland and Bruyère

2014). Based on the studies shown in Table 5.2, 27% of studies expect an increase in the frequency of intense storms while 36% of studies expect a decrease or no change in TC frequency.

Author(s)	Year	Increase/Decrease	Expected Changes
Henderson-Sellers et al.	1998	Inconclusive	SST and frequency
Knutson and Tuleya	2004	Increase	in category 5 frequency
		Inconclusive	SST and frequency
Emanuel	2005a	No trend	
Webster et al.	2005	Increase	in frequency of intense hurricanes
Kossin et al.	2007	Inconclusive	Results do not support increase in activity due to increased SST
Pielke	2007		-20% to +20% by 2050, -40% to +40% by 2100
Landsea	2007	Inconclusive	Observed increases attributed to inconsistent dataset
Knutson	2008	Decrease	8% decrease in major hurricanes
Knutson et al.	2010	Remain same or decrease	
IPCC AR5	2013	Increase	Most intense storms
		Decrease	Overall, frequency expected to decrease or remain same
Number of studies expecting increase, decrease, or no change:		3 out of 11 (increase in intense storms) 4 out of 11 (decrease or stay the same)	

Table 5.2. Summary of expected changes in TC frequency.

5.4 Hurricane Track and Climate Change

There is a relatively strong consensus regarding how TC tracks will change as a result of a warming climate. Storm trajectories are dependent on factors such as SST and atmospheric circulations which are also dependent on the influence of climate change.

Using a K-means cluster analysis and a Poisson regression, Elsner (2003) found that during a negative NAO phase and during a La Niña year, hurricanes are more likely to make landfall along the Gulf Coast, from Texas and through South Carolina.

Hallegatte (2007) used synthetic hurricane tracks to assess the impact of climate change on hurricane risk analysis. Hallegatte (2007) modified hurricane intensity by 10%, but did not alter hurricane tracks because hurricane tracks are not expected to be effected by climate change (Hallegatte 2007).

Knutson et al. (2008) concluded that climate change is not expected to cause the region of TC formation in the Atlantic to expand. As tropical SSTs increase as a result of global warming, the temperature threshold for tropical cyclogenesis is expected to increase at the same rate (Knutson et al. 2008). This would result in little to no change in TC formation regions and storm trajectories (Knutson et al. 2008).

Emanuel et al. (2008) examined the influence of climate change on hurricane tracks by creating two track models. One model was based on historical track records and statistics and the other was a “beta and advection model” (BAMS) used to predict tracks based on large-scale wind fields (Emanuel et al. 2008). The spatial variability of the synthetic tracks created was in agreement with the historical tracks (Emanuel et al. 2008). Little to no variability in tracks was observed (Emanuel et al. 2008).

Variability in North Atlantic TC tracks is examined by Kossin et al. (2010). They separated historical tracks into four groups and analyzed each group individually. Clusters were defined by quadratic regression models and they found that tracks are greatly influenced by atmospheric circulation patterns such as NAO and El Niño since storms are steered by these patterns (Kossin et al. 2010). Storms need to form and develop over favorable regions to in order to strengthen (Kossin et al. 2010). Since storms are dependent on favorable conditions for development, track variability can greatly influence storm intensity and duration (Kossin et al. 2010).

Bender et al. (2010) found an increase in storm tracks in the western Atlantic (between 20°N and 40°N) for intense (category 4 or 5) hurricanes. Decreases in track density in the western Atlantic and increases in the middle and eastern Atlantic have been observed by long-term trend analyses (Knutson et al. 2010). However, these trends are most likely due to changes in storm observations in the eastern Atlantic (Knutson et al. 2010). Model projections show that large-scale changes in storm tracks are not expected to occur (Knutson et al. 2010). Climate change is not expected to result in a significant variation in storm tracks (Knutson et al. 2010). The spatial distribution of Atlantic SSTs as well as the influence of atmosphere-ocean circulations (such as ENSO and NAO) will have the most significant influences on the variability of TC tracks (Christensen et al. 2013). Based on the studies from Table 5.3, 50% of studies agree that TC tracks should expect little to no change.

Author(s)	Year	Expected Changes
Elsner	2003	Gulf coast landfall more likely during NAO (-), La Niña
Hallegatte	2007	Not expected to change
Knutson et al.	2008	Little to no variability
Emanuel et al.	2008	Little to no variability
Kossin et al.	2010	Changes dependent on atmospheric circulation patterns
Bender et al.	2010	Increase for cat 4 or 5 hurricanes in W. Atlantic
Knutson et al.	2010	No expected changes
IPCC AR5	2013	Changes dependent on SST distribution and atmosphere-ocean circulations
Number of studies expecting little to no change:	4 out of 8	

Table 5.3. Summary of expected changes in TC tracks.

5.5 Summary

A review of the literature indicate that climate change will cause TC intensity to increase by 5% for every 1°C increase in SST (Emanuel 2005a; Holland and Bruyère 2014). Intensity changes vary from an increase of 3% (Michaels et al. 2005) to an increase of 36% (Pielke 2007). According to the IPCC AR5, an increase in TC intensity of 2 to 11% is likely (Christensen et al. 2013; Knutson et al. 2010). Approximately 94% of the studies in the meta-analysis expect TC intensity to increase. The frequency of the most intense storms is expected to increase (Knutson and Tuleya 2004; Webster et al. 2005). However, there is no consensus on overall changes in TC frequency. It is most

likely that overall TC frequency will either decrease or remain the same according to 36% of the studies reviewed in this objective (Christensen et al. 2013; Knutson et al. 2010). TC tracks are dependent on SST patterns and on atmosphere-ocean circulations (Knutson et al. 2008). Half of the studies expect little to no change in TC tracks as a response to climate change (Emanuel et al. 2008; Knutson et al. 2010), although there will continue to be significant inter- and intra-annual variability in storm tracks.

For Objective 3, changes in TC intensity as a result of climate change will be based on findings from this chapter. Two TC intensity scenarios will be selected based on Pielke (2007). An increase of 15% will be applied to a moderate intensity scenario and a 35% increase will be applied to an extreme intensity scenario. No changes in TC frequency or track will be applied. Regardless of how climatic factors influence hurricane frequency, activity, and tracks in the future, an increase in both coastal and inland populations will increase Florida's vulnerability to hurricanes (Pielke et al. 2005).

CHAPTER VI

**SENSITIVITY ANALYSIS OF THE IMPACT OF CLIMATE CHANGE ON
HURRICANE DAMAGE AND LOSS IN FLORIDA**

HAZUS-MH Hurricane Model was used to determine the possible impact of climate change on hurricane damage and loss for Florida. The HAZUS Hurricane Model is composed of a hurricane wind field model and a damage and loss model. HAZUS was run for a baseline, moderate, and extreme climate change scenario for all case study storms. The baseline scenario assumes current climatic conditions. The moderate scenario reflects a 15% increase in storm intensity as a result of climate change and the extreme scenario reflects a 35% increase. All storm parameters are taken from past observations provided by the HAZUS database or from the datasets described in section 3.2.

For the baseline scenario, storms of category 2 or less were run using the user defined hurricane scenario and required all storm parameters to be provided by the user. The user defined scenario requires data for latitude, longitude, time, radius to maximum winds, wind speed, central pressure, and inland points to create a storm track. The historic hurricane scenario was run for storms of category 3 or higher. The data for these storms was provided by the HAZUS database. Storm parameters were not modified for the baseline scenario.

Using the findings from Objective 2, storm intensity was modified for the moderate and extreme climate change scenarios. Data for all case study storms were

input manually. The only storm parameters that were modified were wind speed and central pressure. Wind speed values were increased by 15% for the moderate scenario and by 35% for the extreme scenario. Central pressure values were modified to reflect increases in intensity by using the method described in section 3.2.

The damage and loss models were run for the data provided by HAZUS. The models were run for a total population of 15,982,378 based on 2000 U.S. Census data. The study region contains approximately 6.8 million buildings with a total replacement value of \$1.2 billion dollars (2006 dollars).

Structural damage from hurricane winds was estimated by the damage model by using a load and resistance methodology (Vickery et al. 2006b). Building damage categories are determined by the degree of damage done to the building envelope (Vickery et al. 2006b). There are five damage categories which range from no damage to complete destruction (Vickery et al. 2006b). As defined by Vickery et al. (2006b), the no damage category experiences little to no visible damage from the outside to the roof or windows. There is also little to no water damage. The minor damage category experiences damage to a maximum of one window, door, or garage door. There is also moderate roof damage and marks and dents to walls of the structure. Buildings experiencing moderate damage experience major damage to the roof and moderate breakage of windows. There is also some water damage to the building interior. The severe damage category experiences major damage to windows and roof, major roof loss, and extensive water damage to building interiors. The destruction damage category

experiences complete failure of the roof and/or wall frame and a loss of at least 50% of roof sheathing.

The damage categories described above are for residential buildings but similar descriptions are applied to other building types (Vickery et al. 2006b). For user defined storms, HAZUS provides an estimate of the average number of damaged buildings for each damage category (Vickery et al. 2006b). Only residential and commercial building types are considered in this study.

The economic loss model calculates estimates of building damage economic loss and calculates the total cost of all building components. Depending on the damage category of the building, the cost of rebuilding a damaged structure is calculated. Explicit cost functions are used to calculate loss for building exteriors and implicit cost functions are used to calculate loss for building interiors.

6.1 Case Study Storms

The HAZUS Hurricane Model was run for a total of 12 case study storms. In order to include storms of all categories in the sensitivity analysis, two storms were chosen for each storm category (tropical storm to category 5). The storms were chosen based on their historical and cultural significance. The majority of the storms have had significant societal and economic impacts in Florida. For example, the Great Miami Hurricane of 1926 made landfall in Downtown Miami a few years after the city experienced an economic and demographic boom (Barnes 2007). Miami's recovery after the storm was delayed by The Great Depression which occurred a few years after the

storm's landfall (Barnes 2007). A list of the case study storms is provided in Table 3.1. A map of the track is shown for each storm. Graphs were created for the model output for building damage by count for residential and commercial occupancy types, building economic estimated losses based on occupancy type and shelter needs and requirements.

6.1.1 Great Miami Hurricane (1926)

The Great Miami Hurricane of 1926 made landfall as a category 4 storm in southeast Florida (Figure 6.1) on September 18th, 1926. The city of Miami, which was named the “fastest growing city in the country” the previous year, was devastated by the storm's impacts (Barnes 2007). Miami's inexperienced population, as well as a lack of storm reports and timely warnings, contributed to the population's vulnerability (Barnes 2007). The storm also impacted the Pensacola area after crossing the state and entering the Gulf of Mexico. A report released by the Red Cross in October 1926 estimated the total death toll to be 373 (Barnes 2007). Approximately 43,000 people were left homeless and the property losses were estimated to be \$159 billion (Barnes 2007). Blake et al. (2011) estimated the death toll to be 372 and the damage costs to be \$164 billion when ranked using 2010 inflation, population, and wealth normalization values. The storm was also ranked as one of the ten most intense mainland storms with a minimum pressure of 930 mb at landfall (Blake et al. 2011).

6.1.1.1 Building Damage by Count

The majority of the residential buildings experienced no damage under the baseline conditions. Figure 6.2a shows the number of damaged buildings decreases as the damage type increases (e.g., minor damage (642,092), moderate (480,003), severe (233,020), and total destruction (77,903)). Under the moderate hurricane scenario, the majority of buildings experience no damage, however, the number of damaged buildings increased for severe and total destruction categories. For the extreme scenario, the number of buildings decreased in the no damage, minor damage, and moderate damage categories and increased in the severe damage and total destruction categories. There was a 6% (3%) decrease in the no damage category between the baseline and extreme (moderate and extreme) scenarios. The remaining damage categories also decreased between the baseline and extreme scenarios, except for the severe and destruction categories. The severe damage category increased by 81% (2%) from the baseline to extreme (moderate to extreme) scenario. The destruction damage category increased by 936% (86%) from the baseline to extreme (moderate to extreme) scenario. The total number of damaged buildings (minor, moderate, severe, destruction) increased by 20% (9%) from the baseline to the extreme (moderate to extreme) scenario. Most commercial buildings are in the no damage category (296,456) for the baseline scenario and there are fewer buildings in the minor (30,898), moderate (42,816), severe (48,557) and destruction (2,439) categories. The distribution of commercial buildings in the damage categories follows a similar trend for the moderate scenario and the extreme scenarios (Figure 6.2b).

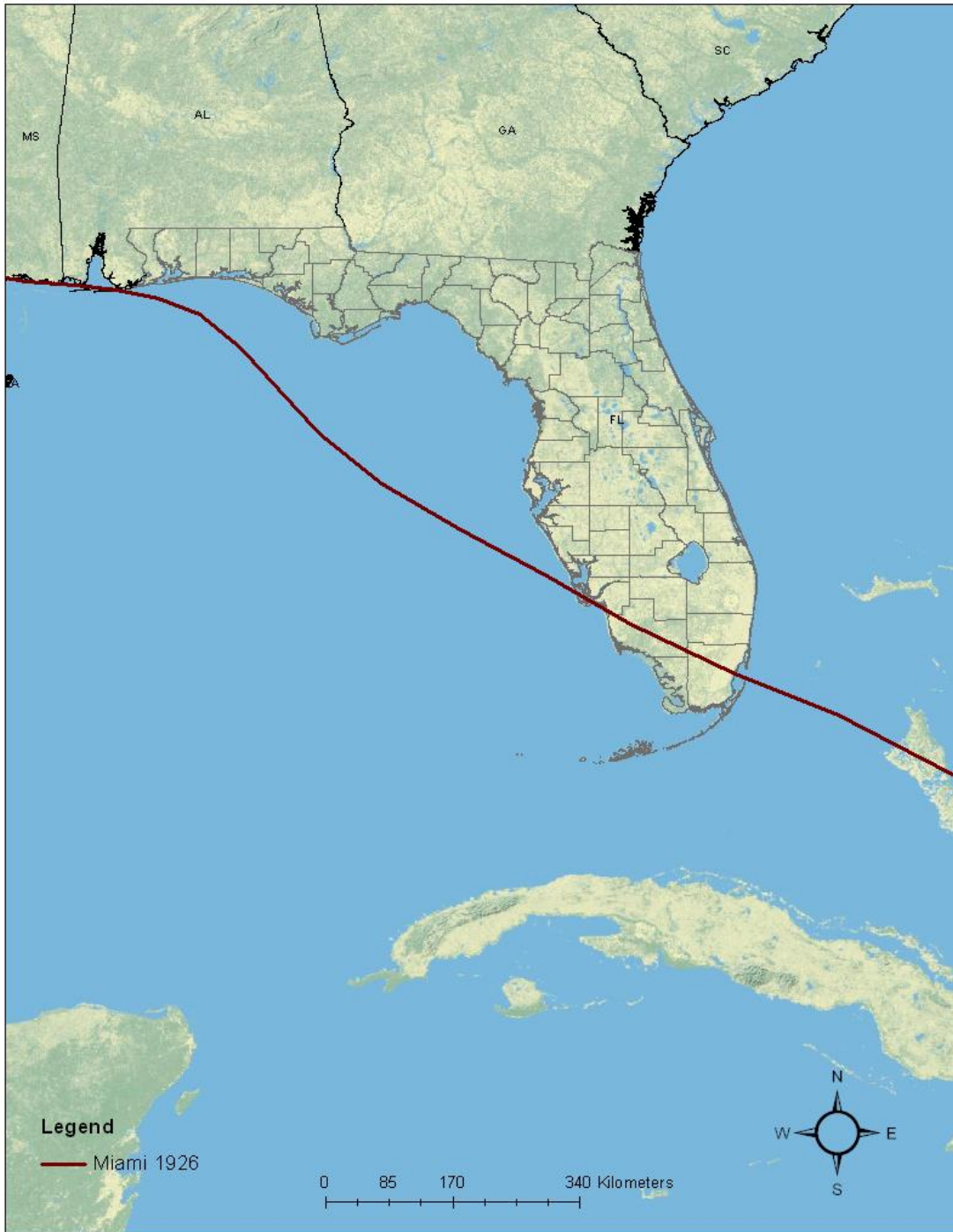
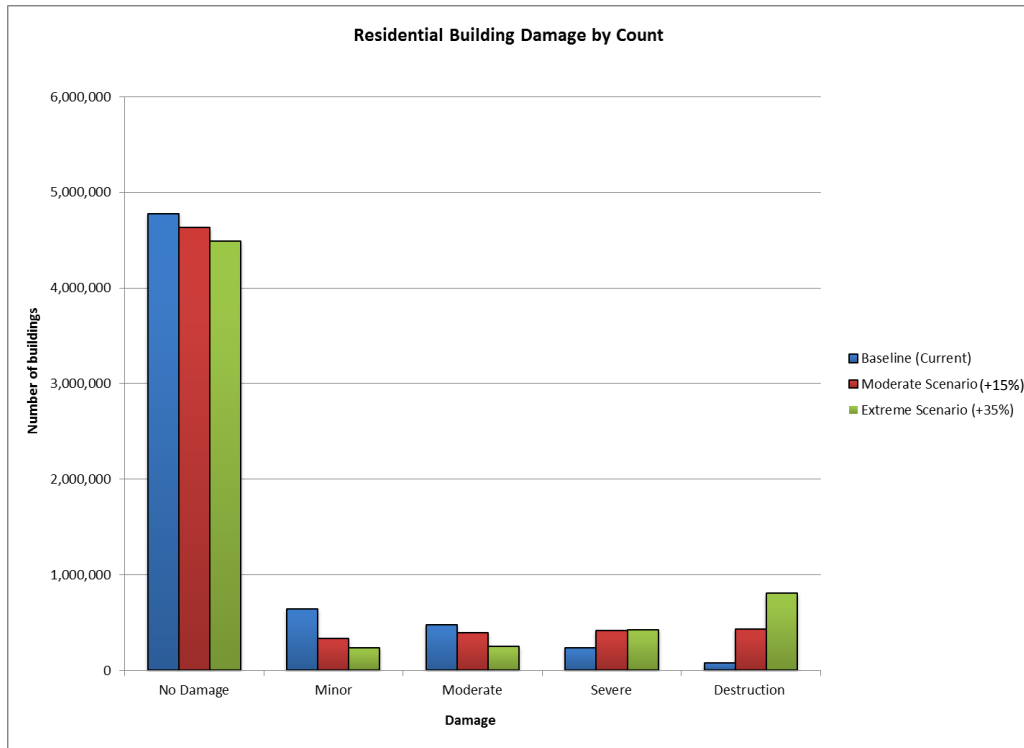
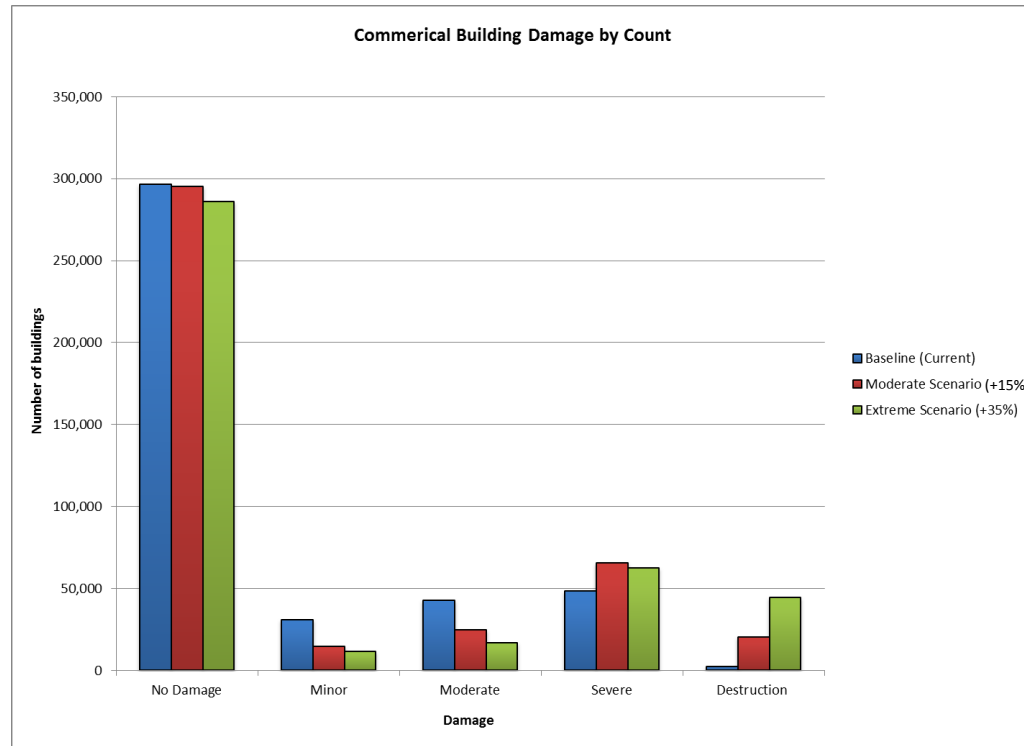


Figure 6.1. Track of the Great Miami Hurricane (1926).



a.



b.

Figure 6.2. Building Damage by Count for (a) Residential and (b) Commercial Occupancy Types

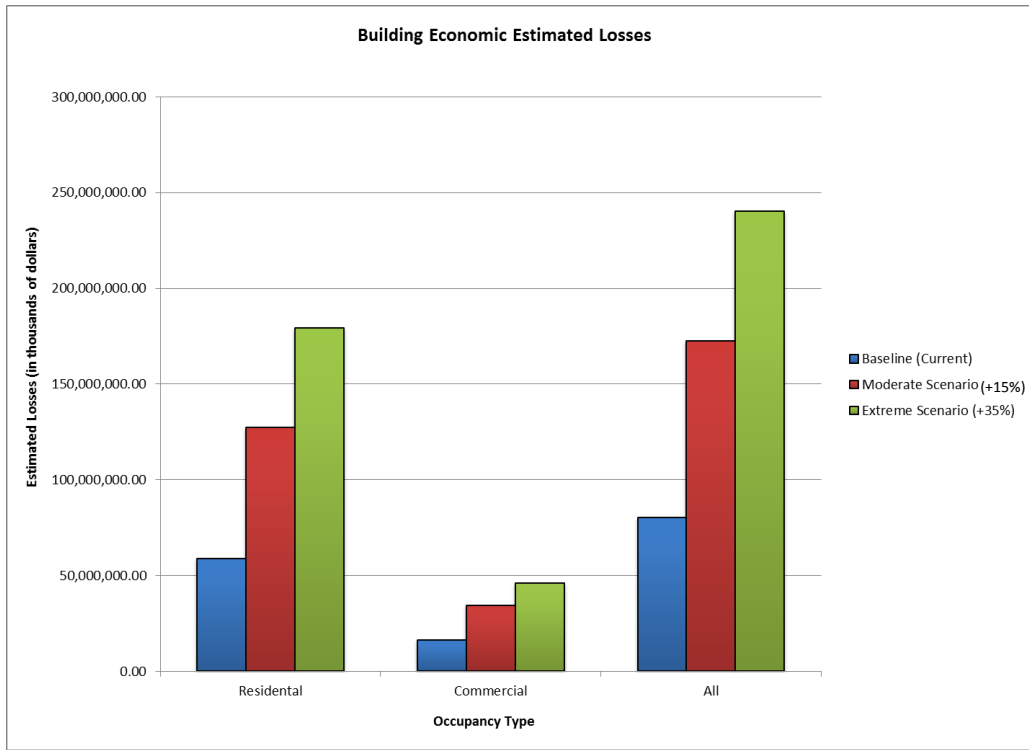
There is a 4% decrease in the number of commercial building in the no damage category between the baseline and extreme scenarios and a 3% decrease between the moderate and extreme scenarios. There was an increase of 8% (7%) between the baseline and extreme scenarios (moderate and extreme scenarios) in the total number of damaged buildings.

6.1.1.2 Building Economic Estimated Losses

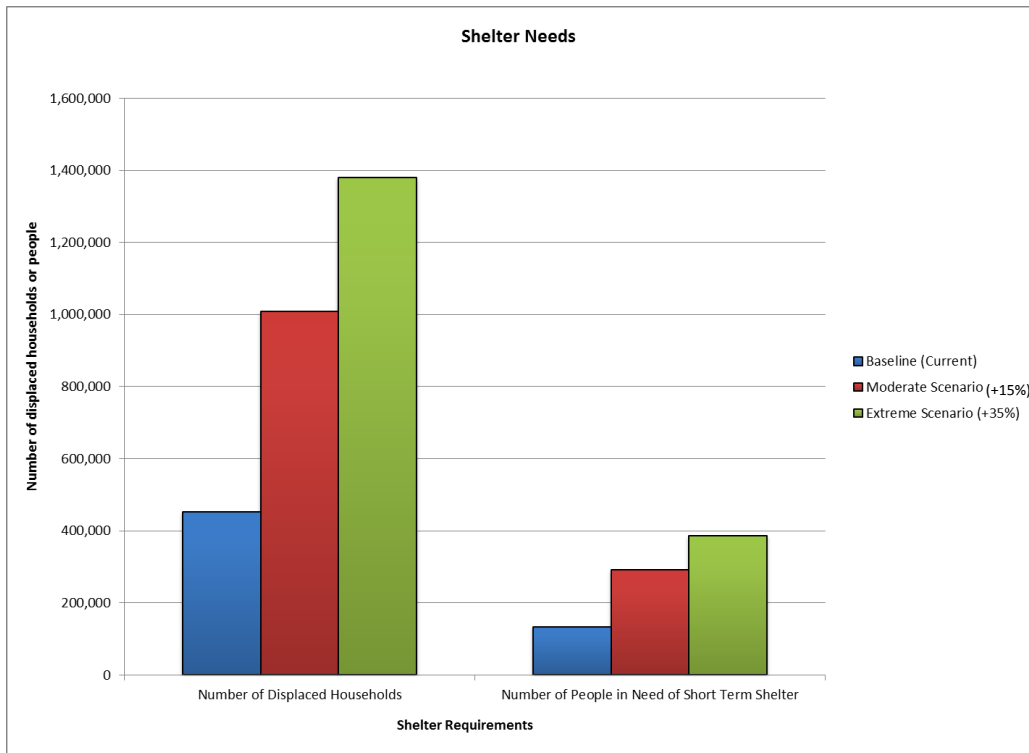
Figure 6.3a shows estimated economic losses for residential, commercial, and all occupancy types. Economic losses for residential buildings increased by 204% from the baseline to extreme scenario and by 41% from the moderate to the extreme scenario. Economic losses for commercial buildings increased by 182% (34%) from the baseline to extreme (moderate to extreme) scenario. All occupancy types (agriculture, commercial, education, government, industrial, religion, and residential) experienced an increase in losses of 199% (39%) from the baseline to the extreme (moderate to extreme scenario) scenario.

6.1.1.3 Shelter Needs and Requirements

The number of people and households affected by the change in storm intensity are shown in Figure 6.3b. The number of displaced households increases by 205% (37%) from the baseline to the extreme (moderate to the extreme) scenario. There is an increase of 190% between the baseline and extreme scenario and of 33% between the moderate and extreme scenarios for the number of people in need of short-term shelter.



a.



b.

Figure 6.3. (a) Building Economic Estimated Losses based on Occupancy Type and (b) Shelter Needs and Requirements

The Great Miami Hurricane of 1926 was a powerful storm that greatly impacted south Florida at a time when the region was rapidly developing. The baseline scenario displays the damage caused by the storm's intensity at landfall and the significant impact caused in Miami. An increase in storm intensity as a result of climate change would cause the region to experience increases of up to 20% in residential building damages, 8% in commercial building damages, up to 199% in economic losses for all occupancy types and up to 205% in the number of displaced households. Miami's growing population and coastal development exacerbate the city's vulnerability to intense storms.

6.1.2. Labor Day Hurricane (1935)

One of the most significant hurricanes in Florida's history is the Labor Day Hurricane of 1935. The powerful hurricane struck the Florida Keys on September 2, 1935 and made landfall over Long Key and Lower Matacumbe Key (Figure 6.4). During this time, the Overseas Highway connecting Key West with the Florida mainland, was being built by war veterans working for the Federal Emergency Relief Administration (FERA) (Barnes 2007). The Weather Bureau provided residents with warnings, but the storm intensified more rapidly than anticipated (Barnes 2007). The day prior to landfall, the storm was classified as a small tropical disturbance by the Weather Bureau and it made landfall as a category 5 hurricane (Barnes 2007). A train was sent from Miami to pick up the war veterans, residents, and visitors that did not evacuate in time (Barnes 2007). However, the train was washed off its tracks shortly after arriving in the Florida Keys due to the approaching hurricane's storm surge (Barnes 2007). The death toll was

estimated to have been 408 (Blake et al. 2011). The Labor Day Hurricane had a central pressure of 892 mb which is the lowest pressure recorded for a U.S. landfalling hurricane since record keeping began in 1851 (Blake et al. 2011). On September 4, the storm made a second landfall near Cedar Key. The building damage, loss, and shelter need values for this storm also account for the second landfall made along Cedar Key.

6.1.2.1 Building Damage by Count

The majority of residential buildings experienced no damage under baseline (6,122,197), moderate (5,179,103), and extreme (4,963,143) conditions (Figure 6.5a). The number of building in the no damage category decreased by 19% (4%) between the baseline and extreme (moderate and extreme) scenarios. The number of buildings in the minor damage category increased by 238% (9%) between the baseline and extreme (moderate and extreme) scenarios. Similarly, moderate damage increased from 14,716 to 210,116 (1328% increase) in the extreme scenario. The number of buildings in the severe and destruction categories increased from 2,960 (baseline) to 267,102 (extreme) and from 4,909 (baseline) to 550,667 (extreme), respectively. The total number of damaged buildings increased from 87,240 (baseline) to 1,246,293 (extreme), an increase of 1329%.

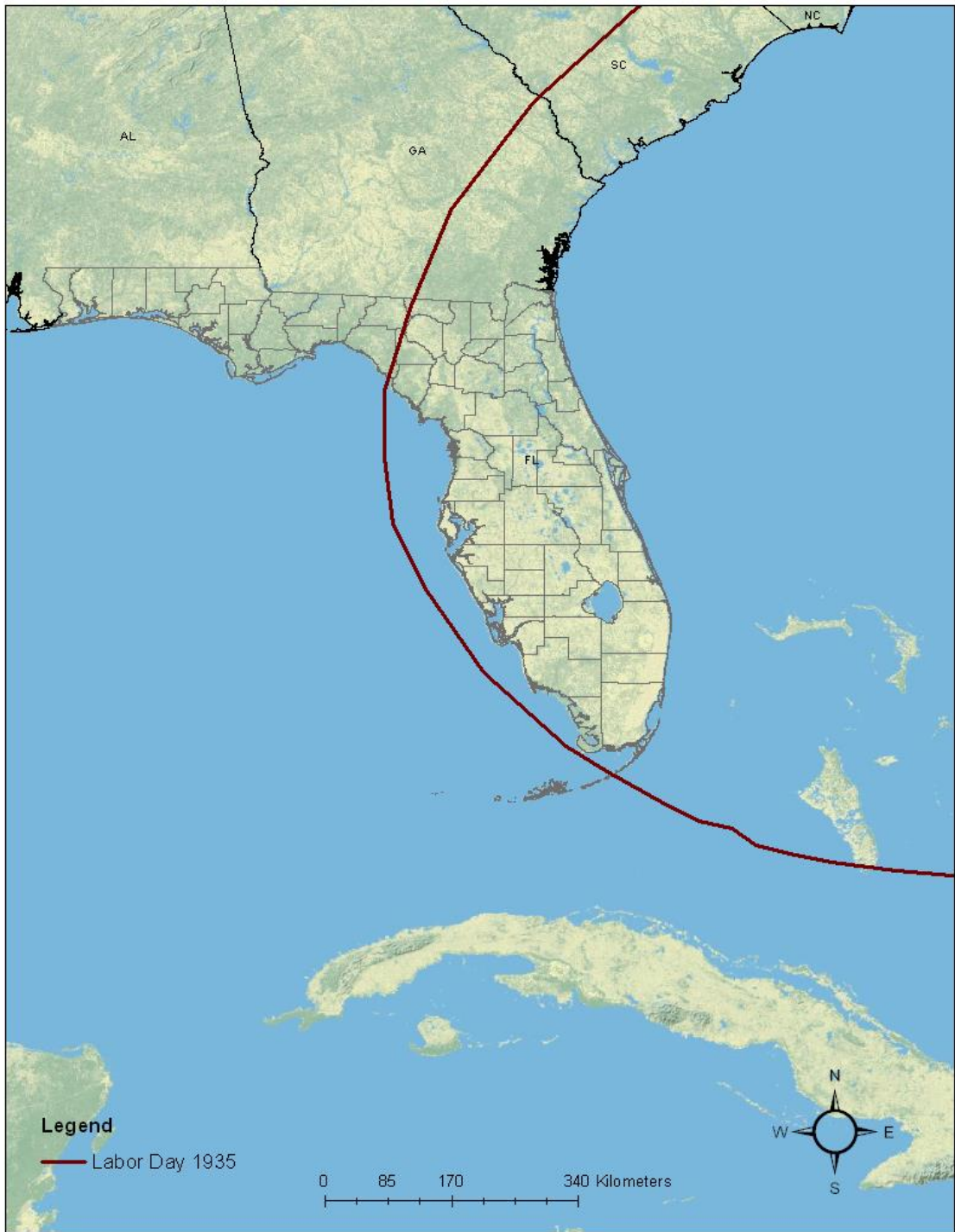


Figure 6.4. Storm track of the Labor Day Hurricane

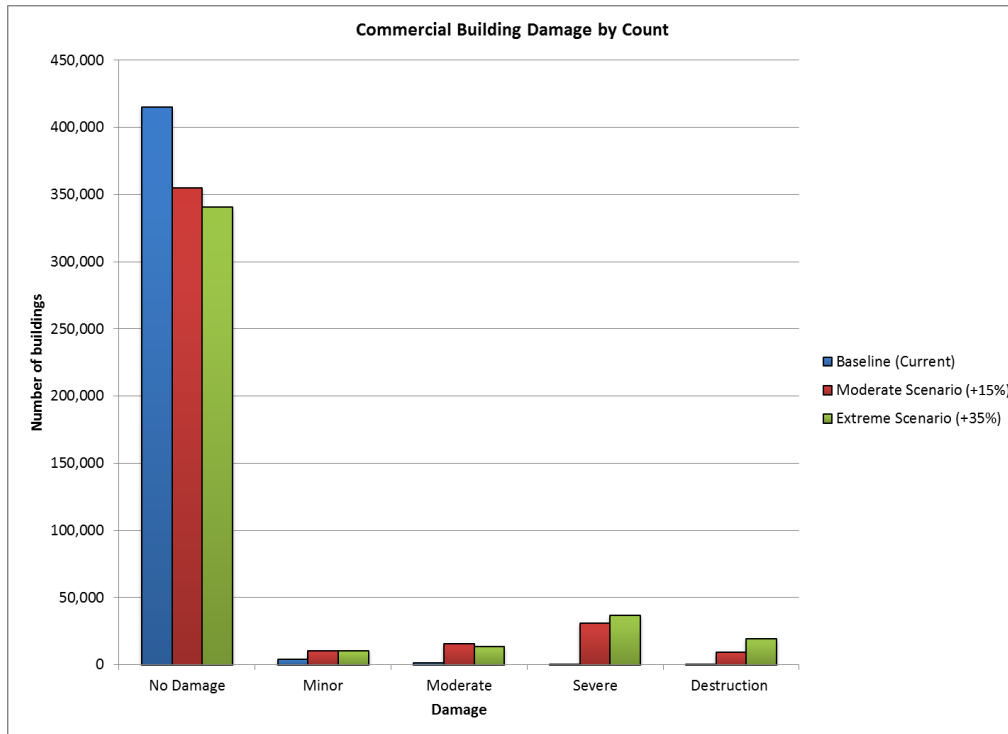
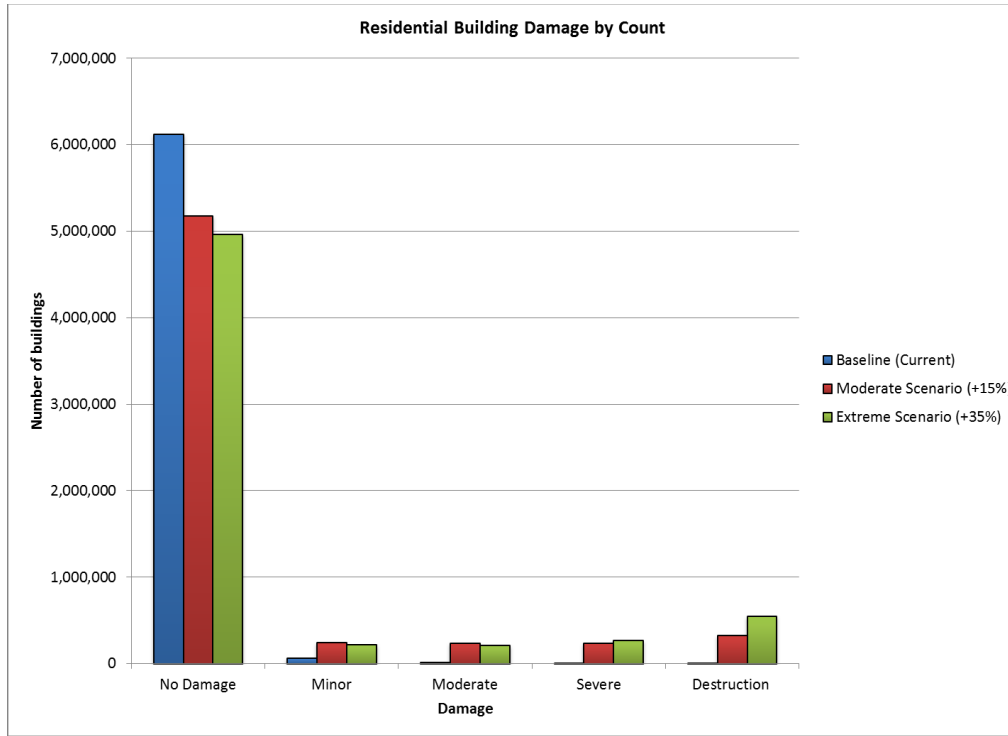


Figure 6.5. Building Damage by Count for (a) Residential and (b) Commercial Occupancy Types

For commercial buildings (Figure 6.5b) there was an 18% decrease between the baseline and the extreme scenarios and a 4% decrease between the moderate and the extreme scenarios for the no damage category. The number of buildings in the minor damage category increased by 157% from the baseline to the extreme scenario. The number of buildings in the moderate damage category increased from 1,442 to 13,603 from the baseline to the extreme scenario.

Severe damage increased from 501 buildings in the baseline scenario to 36,614 in the extreme scenario. The number of buildings in the destruction category increased from 172 (baseline) to 19,587 (extreme). The total number of damaged buildings increased from a baseline of 6,203 to 80,307 in the extreme scenario.

6.1.2.2 Building Economic Estimated Losses

For residential properties, the estimated economic losses for the baseline scenario are \$2.3 billion and increase to \$108 billion in the extreme scenario (Figure 6.6a). Residential economic losses increased by 42% from the moderate to the extreme scenario. Commercial building losses increased from \$3.4 million (baseline) to \$20 billion (extreme) and increased from the moderate scenario to the extreme scenario by 49% (Figure 6.6b). For all building occupancy types, baseline losses of \$2.7 billion increased to \$136 billion in the extreme scenario. There was a 44% increase in economic losses between the moderate and extreme scenarios.

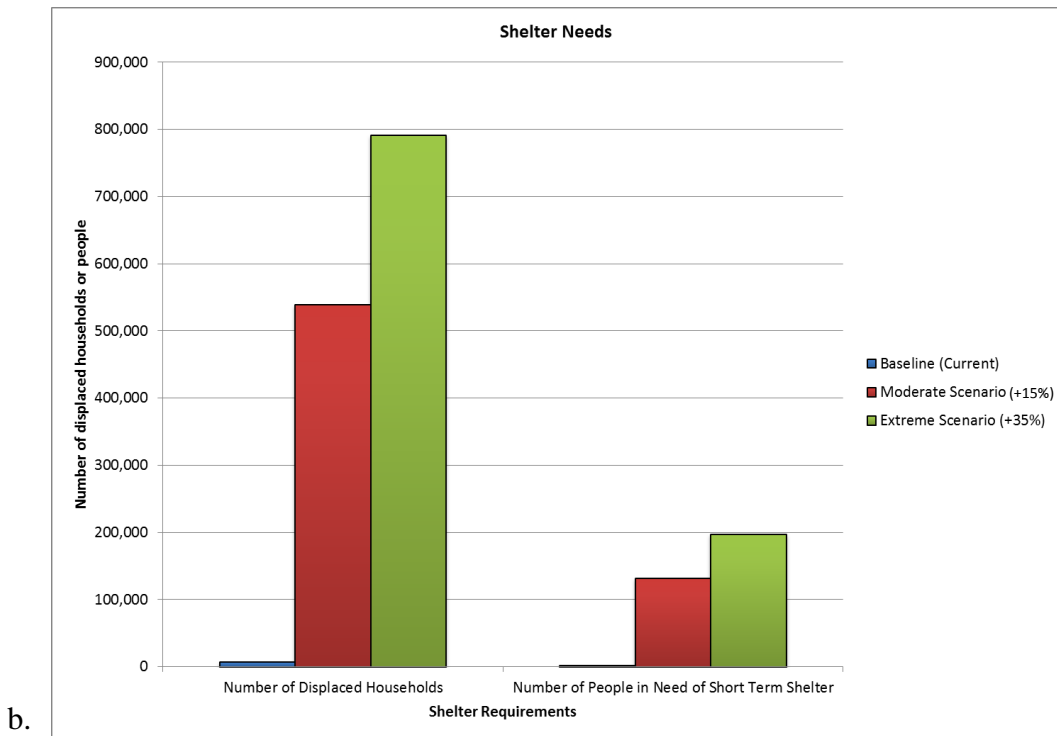
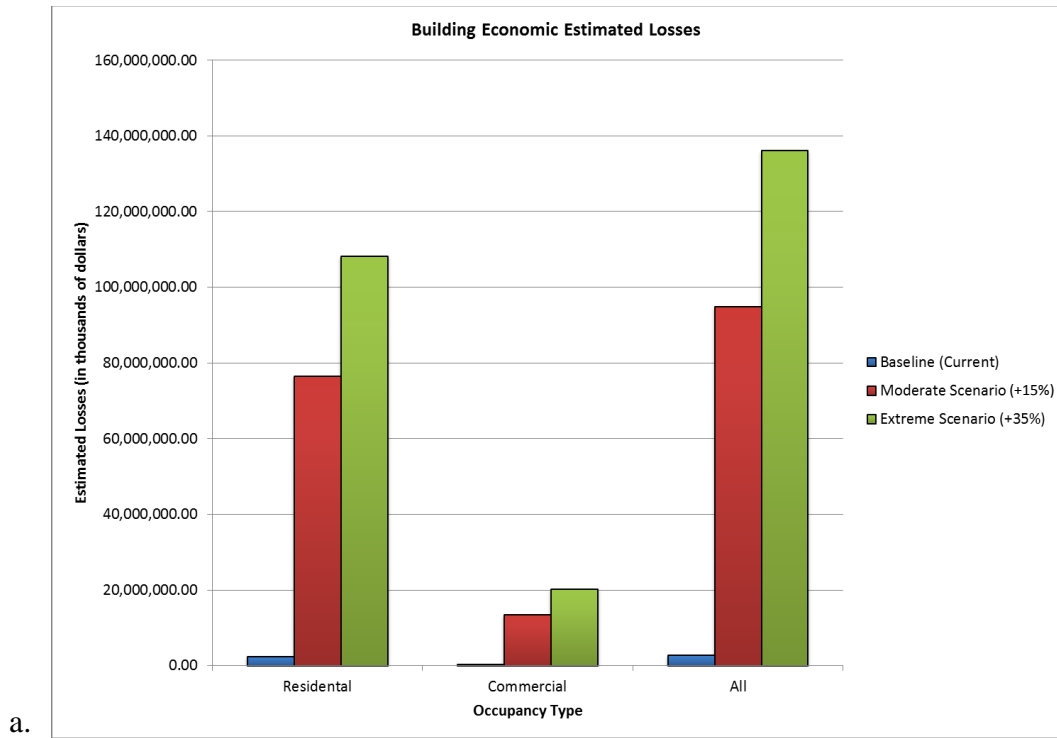


Figure 6.6. (a) Building Economic Estimated Losses based on Occupancy Type and (b) Shelter Needs and Requirements

6.1.2.3 Shelter Needs and Requirements

The number of displaced households increased from a baseline of 6,695 to an extreme scenario of 791,063 as shown in Figure 6.6b. The number of displaced households increased by 47% from the moderate to the extreme scenarios. The number of people in need of short-term shelter increased from 1,572 (baseline) to 196,962 in the extreme scenario (Figure 6.6b).

6.1.2.4 Summary

The Labor Day Hurricane of 1935 is one of the strongest hurricanes to have made landfall in the U.S. An increase in intensity of a storm such as the Labor Day Hurricane would result in devastating impacts in any region of Florida. Large increases from the baseline to the extreme scenario were observed for building damage, building economic loss, and shelter needs. The Labor Day Hurricane may have had a greater economic and societal impact if the storm had made landfall along the coast of mainland Florida.

6.1.3 Hurricane Agnes (1972)

Hurricane Agnes made landfall as a category 1 on June 19, 1972 along the Florida panhandle (Figure 6.7). Although Agnes was a weak storm when it made landfall, it was one of the costliest U.S. storms due to inland floods that resulted from heavy rain (Blake et al. 2011). Winds from Agnes caused above normal tides and fifteen tornadoes formed across Florida as the storm made landfall (Barnes 2007). In Florida,

Agnes was responsible for 9 deaths, 119 injuries, and more than \$40 million in damages (Barnes 2007). Agnes affected other states in the South and along Eastern Seaboard. There was a total of \$2.1 billion in damages in the U.S. and a total of 122 deaths (Barnes 2007).

6.1.3.1 Building Damage by Count

For Agnes, the majority of the residential buildings experienced no damage for all three scenarios (Figure 6.8a). In the baseline scenario, there were 6,209,055 buildings in the no damage category, 365 in the minor damage category, 16 in the moderate damage and 0 for both the severe and destruction categories. The moderate and extreme scenarios followed a similar trend. The differences between the no damage category for the baseline to extreme scenarios and between the moderate to extreme scenarios were both close to 0%. For the minor damage category, the number of buildings increase from 365 in the baseline scenario to 17,125 in the extreme scenario. For the moderate to extreme scenarios, the number of buildings increased from 2,744 to 17,125. Moderate damage buildings increased from 16 for the baseline scenario to 3,689 for the extreme scenario. The number of buildings in the severe damage category increased from 0 to 214 from the baseline to the extreme scenario. For the destruction damage category, there was an increase from 0 to 80 from the baseline to extreme scenarios. There were relatively few commercial buildings that were damaged and these values did not change much in the moderate and extreme scenarios (Figure 6.8b).



Figure 6.7. Storm track for Hurricane Agnes.

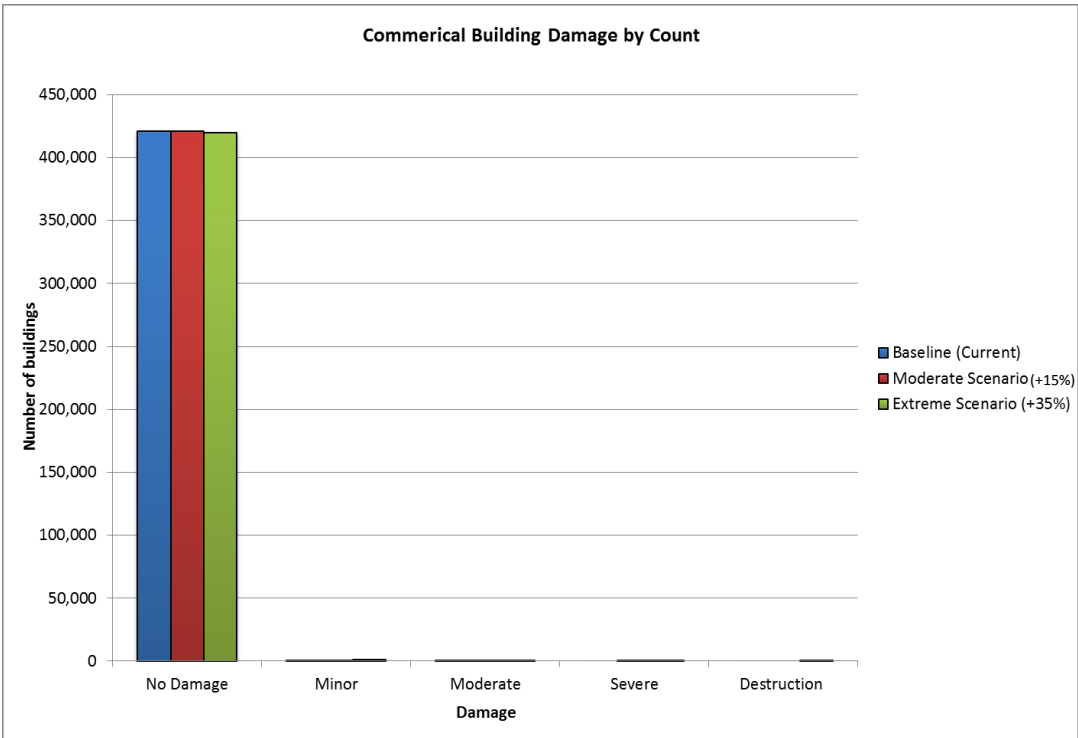
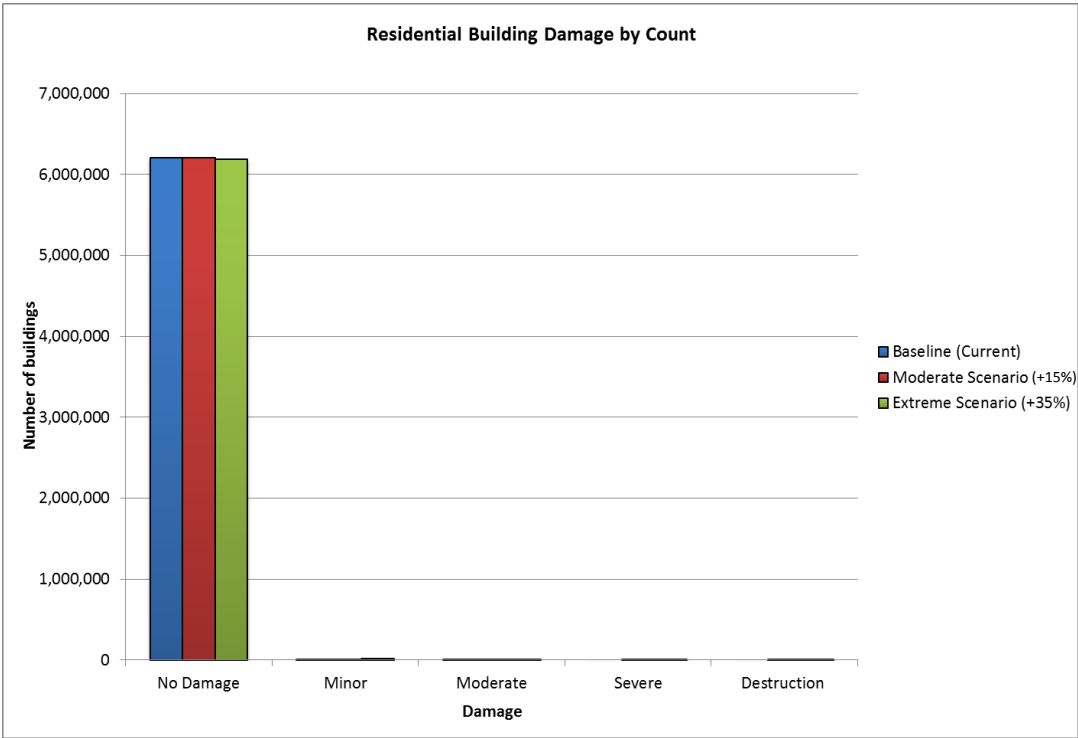


Figure 6.8. Building Damage by Count for (a) Residential and (b) Commercial Occupancy Types

6.1.3.2 Building Estimated Economic Losses

Building economic losses for residential occupancy types increase from approximately \$10 million for the baseline scenario to \$45 million for the moderate scenario and to \$203 million for the extreme scenario (Figure 6.9a). Commercial building economic losses increased for the baseline scenario from \$332,000 to about \$22 million for the extreme scenario. For all occupancy types, economic losses for the baseline scenario are approximately \$11 million and they increase to about \$235 million for the extreme scenario.

6.1.3.3 Shelter Needs and Requirements

The number of displaced households is 0 for the baseline scenario and increased to 24 for the moderate scenario and 449 for the extreme scenario (Figure 6.9b). The number of people in need of short-term shelter is 0 for the baseline scenario, 6 for the moderate scenario and 117 for the extreme scenario.

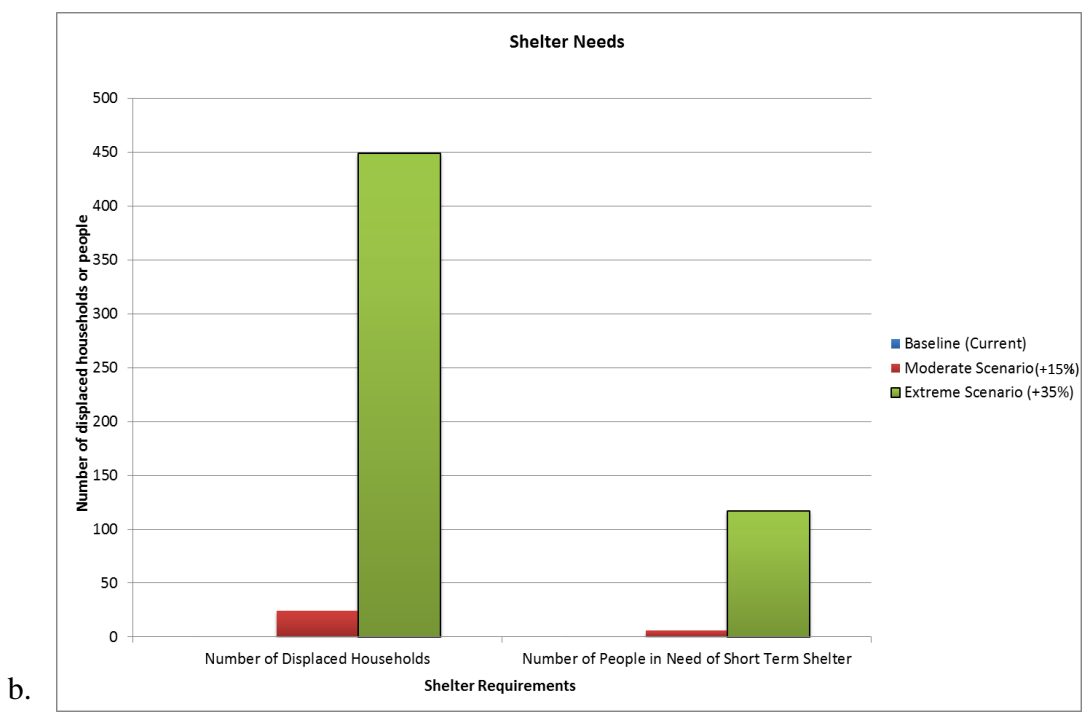
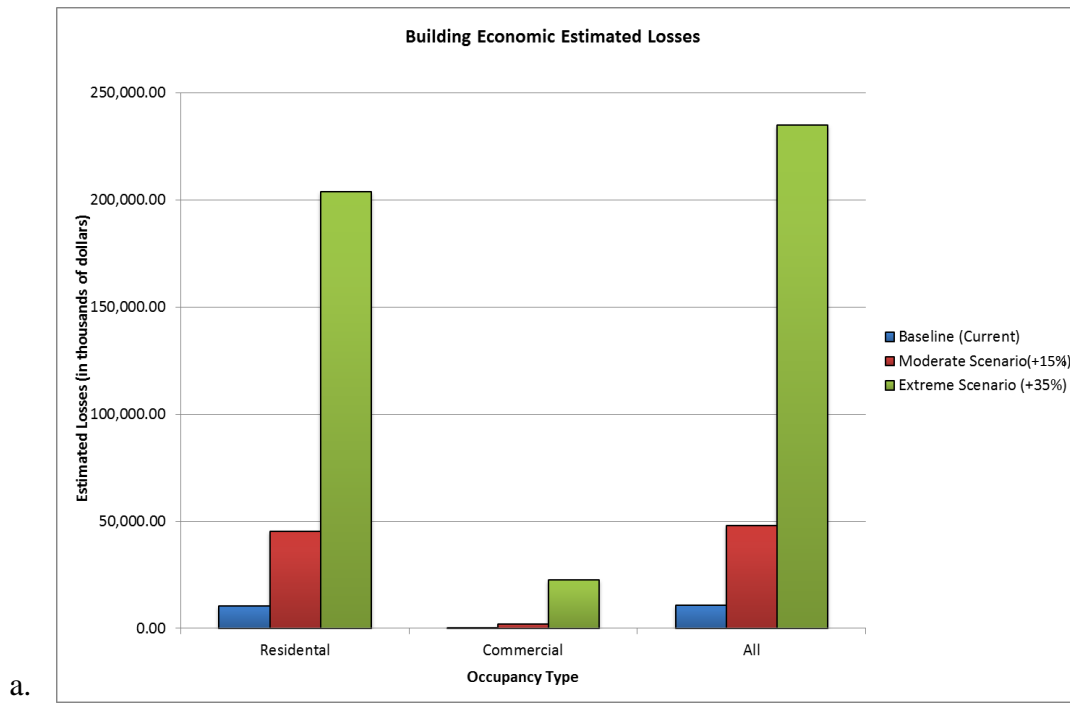


Figure 6.9. (a) Building Economic Estimated Losses based on Occupancy Type and (b) Shelter Needs and Requirements

6.1.4 Hurricane Andrew (1992)

On August 24, 1992, Hurricane Andrew made landfall in south Miami-Dade County as a category 5 storm that effected most of South Florida (Figure 6.10). Hurricane Andrew is the most intense storm to impact Florida since the Labor Day Hurricane in 1935 (Barnes 2007). The storm had maximum sustained winds of approximately 73 m s^{-1} (165 mph) and gusts up to 85 m s^{-1} (190 mph) (Barnes 2007). Most of the damage caused by Andrew was a result of high winds and storm surge (Barnes 2007). It weakened after making landfall but quickly re-strengthened to a category 4 before impacting Louisiana and Texas (Barnes 2007). As a result of Andrew, 700,000 people were evacuated, 175,000 were left homeless, 80,000 lived in shelters, and 25,000 homes were destroyed (Barnes 2007). It is estimated that Andrew caused 43 deaths and more than \$30 billion in damages (Barnes 2007).

6.1.4.1 Building Damage by Count

For the baseline scenario, the no damage category (5,861,084 buildings) had the highest number of buildings of all the damage types (Figure 6.11a). For the no damage category, there is an 8% decrease between the baseline and the extreme scenarios. The minor damage category for the baseline scenario is 137,854 and it increased by 9% in the extreme scenario. The moderate damage category

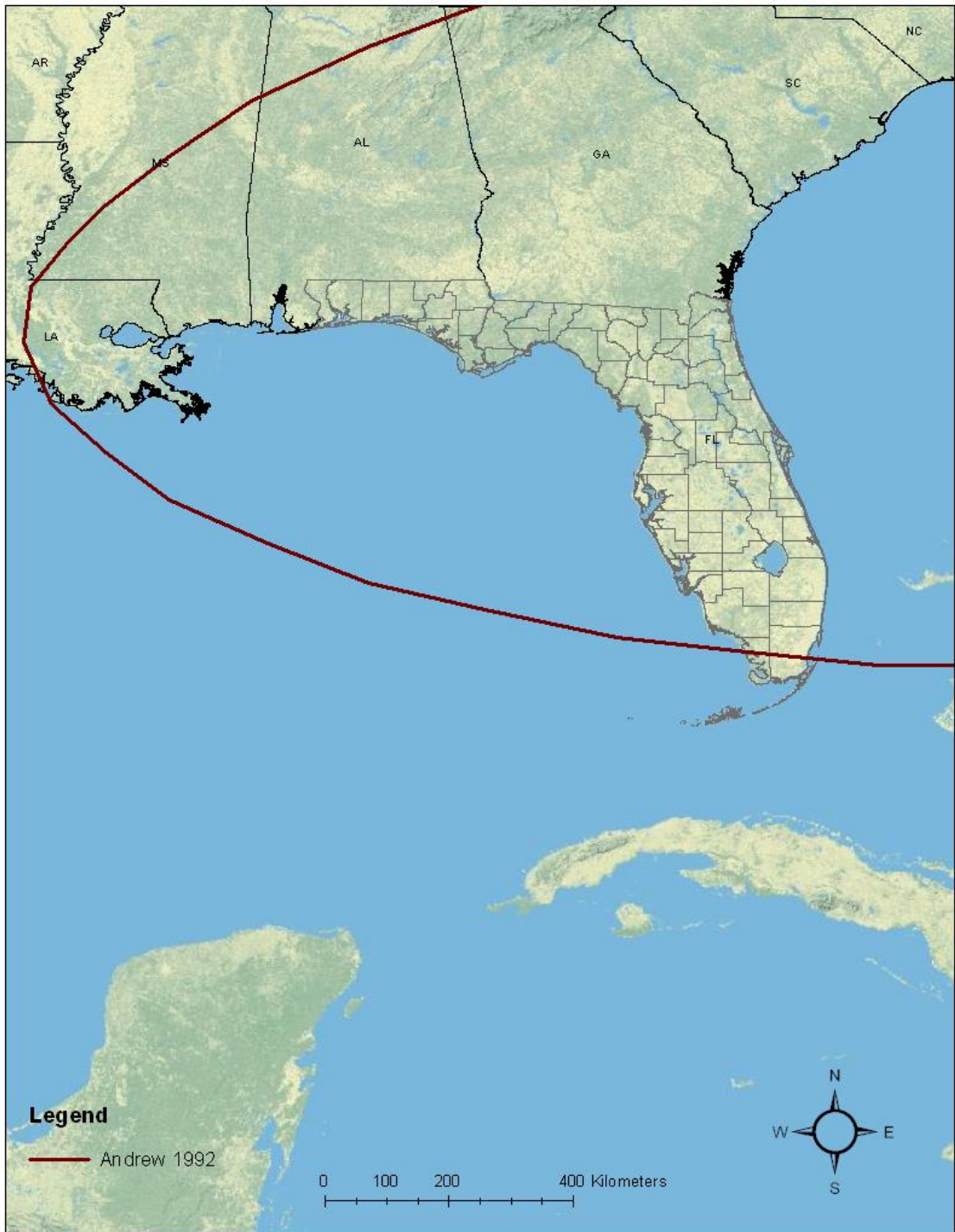


Figure 6.10. Storm track for Hurricane Andrew

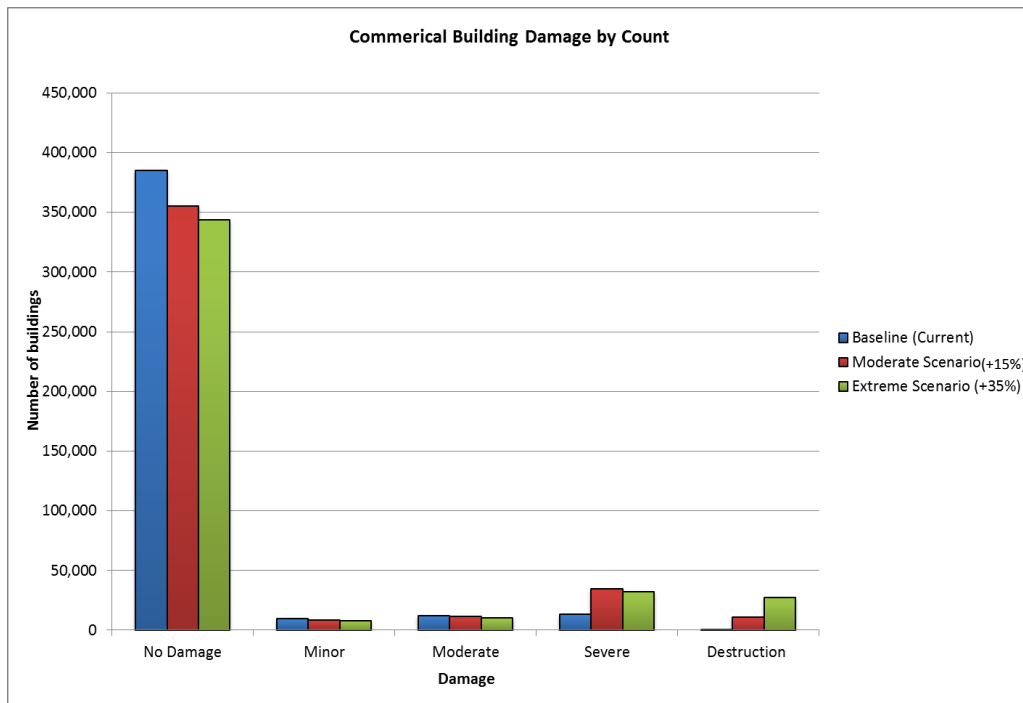
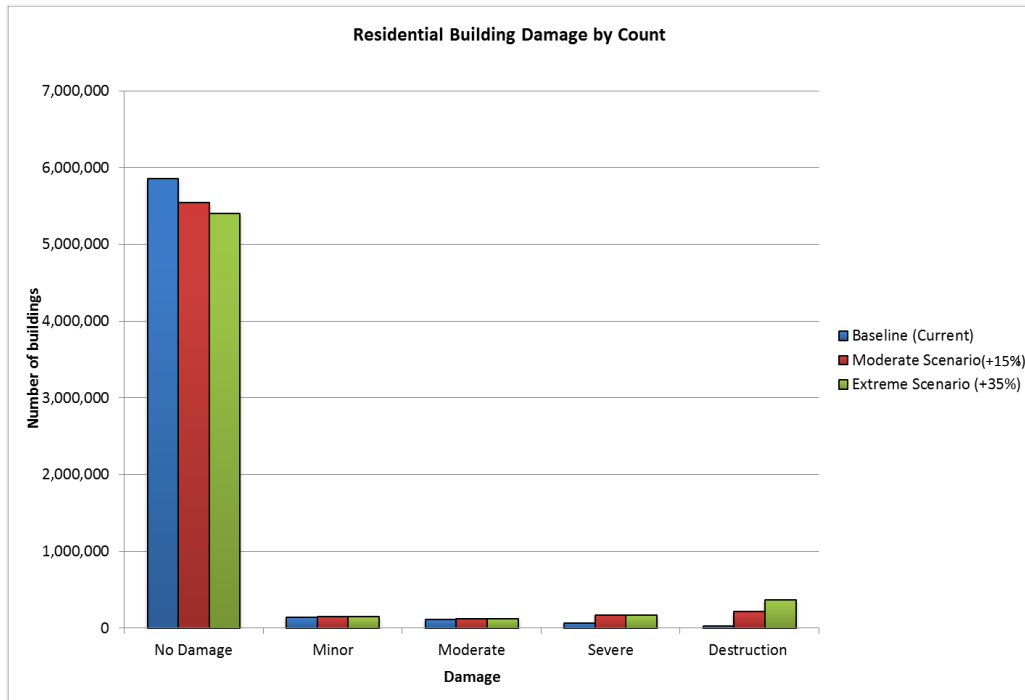


Figure 6.11. Building Damage by Count for (a) Residential and (b) Commercial Occupancy Types

increased from 113,782 buildings in the baseline scenario to 125,727 buildings in the moderate scenario. Severe damage increased by 146% from the baseline (68,182) to the extreme (167,583) scenario. There is an increase in 131% in the total number of buildings damaged from the baseline to the extreme scenario.

The number of undamaged commercial buildings decreased as the intensity of the scenarios increased (Figure 6.11b). Between the baseline and the extreme scenarios, the number of buildings in the no damage category decreased by 11%. The number of buildings in the minor damage category decreased by 18% from the baseline to the extreme scenario. The number of buildings in the severe damage category increased by 141% from the baseline to the extreme scenario. The number of buildings in the destruction category increased from 765 (baseline) to 27,294 (extreme). The total number of damaged buildings increased by 116% between the baseline and extreme scenarios.

6.1.4.2 Building Economic Estimated Losses

Residential properties experienced higher economic losses than commercial properties (Figure 6.12a). Economic losses for residential properties increased from \$16.5 billion in the baseline scenario to \$90.5 billion. An increase of 41% was observed between the moderate and extreme scenarios for residential buildings. Commercial buildings increased from \$4.2 billion (baseline) to \$28.6 billion (extreme). All occupancy types increased from \$21.9 billion between the baseline and extreme

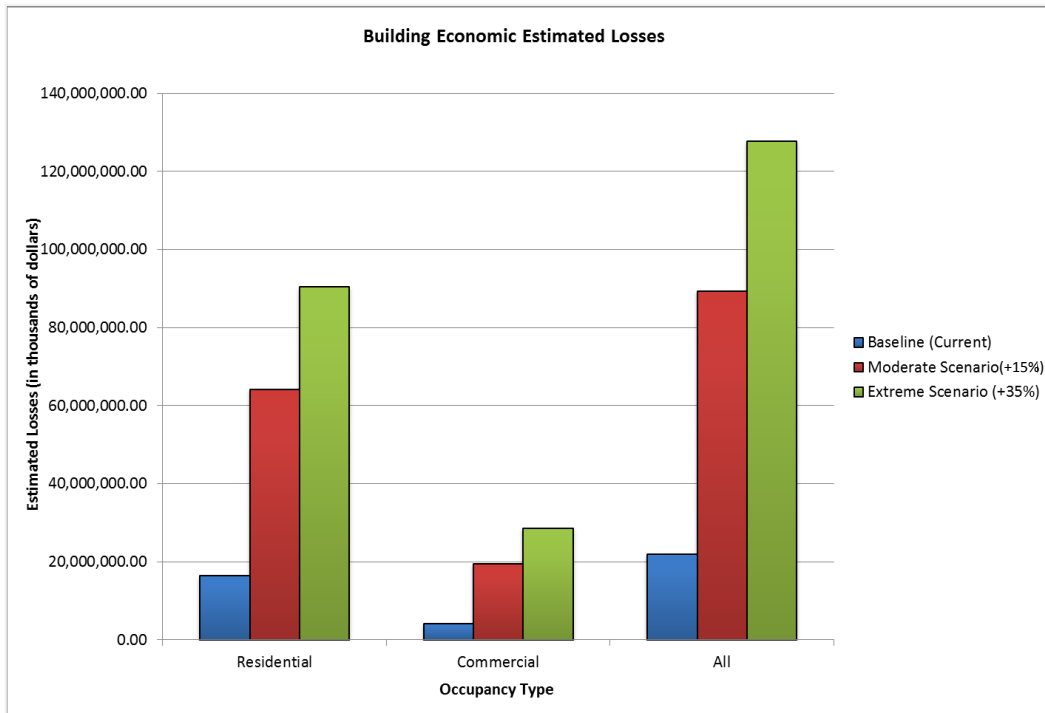
scenarios and by 43% (from \$89.3 billion to \$127.6 billion) between the moderate and extreme scenarios.

6.1.4.3 Shelter Needs and Requirements

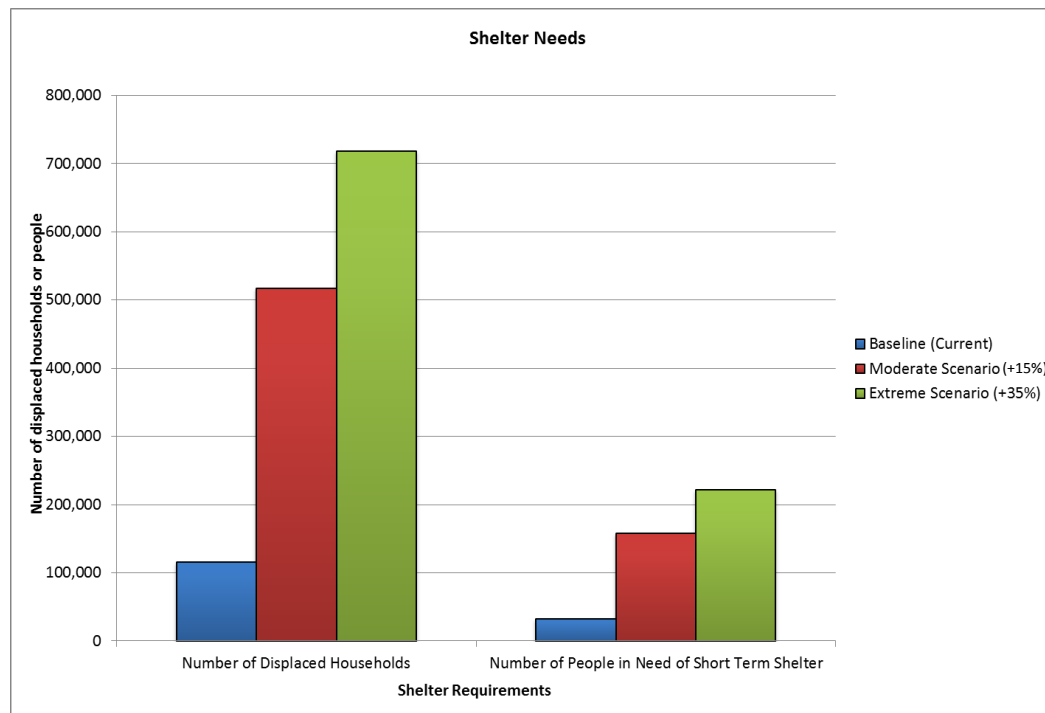
The number of displaced households and people in need of short-term shelter are higher in the baseline scenario for Andrew compared to other storms such as Agnes (Figure 6.12b). The number of displaced households increased from 115,180 in the baseline scenario to 718,620 in the extreme scenario (a 524% increase). The number of people in need of short-term shelter increased from 32,746 to 221,726 between the baseline and extreme scenarios and increased by 41% between the moderate and extreme scenario.

6.1.5 Hurricane Georges (1998)

Georges passed through the Florida Keys as a category 2 storm on September 25, 1998 (Figure 6.13). In Key West, a peak gust of 38 m s^{-1} (87 mph) was recorded and 21 cm (8.3 in.) of rain were reported (Barnes 2007). After crossing the Keys, Georges made landfall in Mississippi and then crossed along the Florida-Georgia border until it reached the Atlantic where it dissipated (Barnes 2007). Although the storm did not directly make landfall in Florida, the effects of Georges were experienced in regions across the state. In the panhandle, 61.7 cm (24.3 in.) of rain were reported at Elgin Air Force Base. Approximately 1,500 homes were damaged and 173 were destroyed in the lower Keys.



a.



b.

Figure 6.12. (a) Building Economic Estimated Losses based on Occupancy Type and (b) Shelter Needs and Requirements

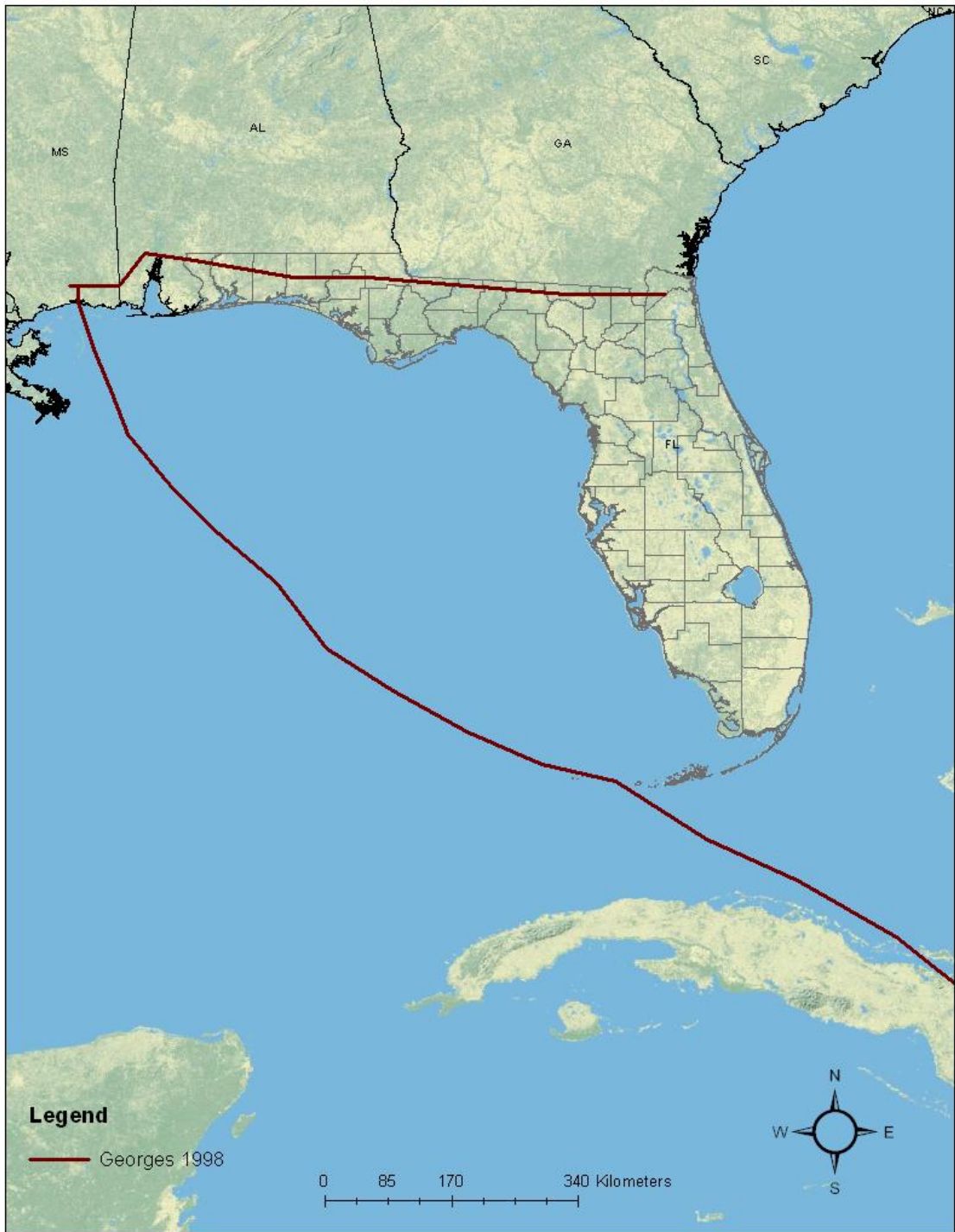


Figure 6.13. Storm track for Hurricane Georges

6.1.5.1 Building Damage by Count

The majority of residential buildings experienced no damage for all three scenarios (Figure 6.14a). For minor, moderate, and severe damage categories, the damage increased the most for the extreme scenario. Minor damage in the extreme scenario is five times greater than the baseline scenario. For the moderate damage category, the extreme scenario was almost nine times greater than the baseline scenario and almost 18 times greater for the severe damage category. Changes between the scenarios were insignificant for the destruction damage category.

Commercial building damages follow a similar trend to residential buildings. For all three scenarios, the majority of commercial buildings experienced no damage (Figure 6.14b). The highest number of buildings in the minor, moderate, and severe damage categories were for the extreme scenario. The greatest difference between the baseline and extreme scenarios was for the severe damage category. The extreme scenario was about 13 times greater than the baseline scenario. The number of buildings for the destruction category were under 500 for all three scenarios.

6.1.5.2 Building Economic Estimated Losses

The greatest economic losses were experienced by residential buildings in the extreme scenario (Figure 6.15a). Losses for residential buildings are approximately \$1.4 billion for the baseline scenario. The extreme scenario experienced losses of approximately \$9.6 billion for residential buildings. Commercial buildings also experienced the greatest loss in the extreme scenario. The economic losses for the

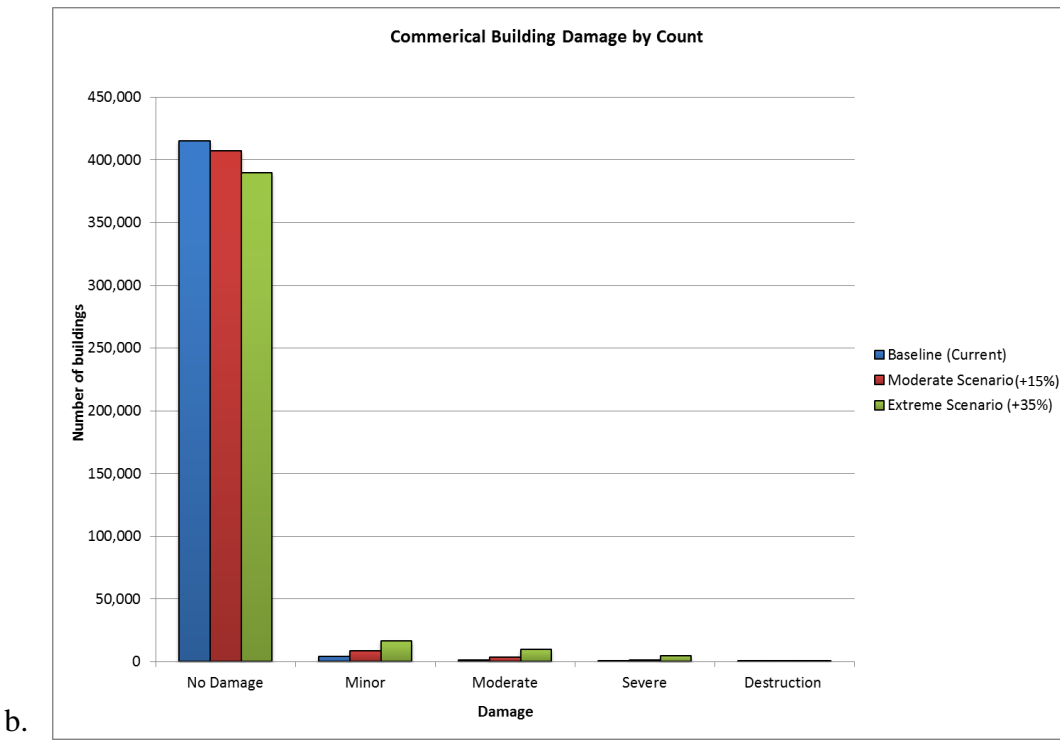
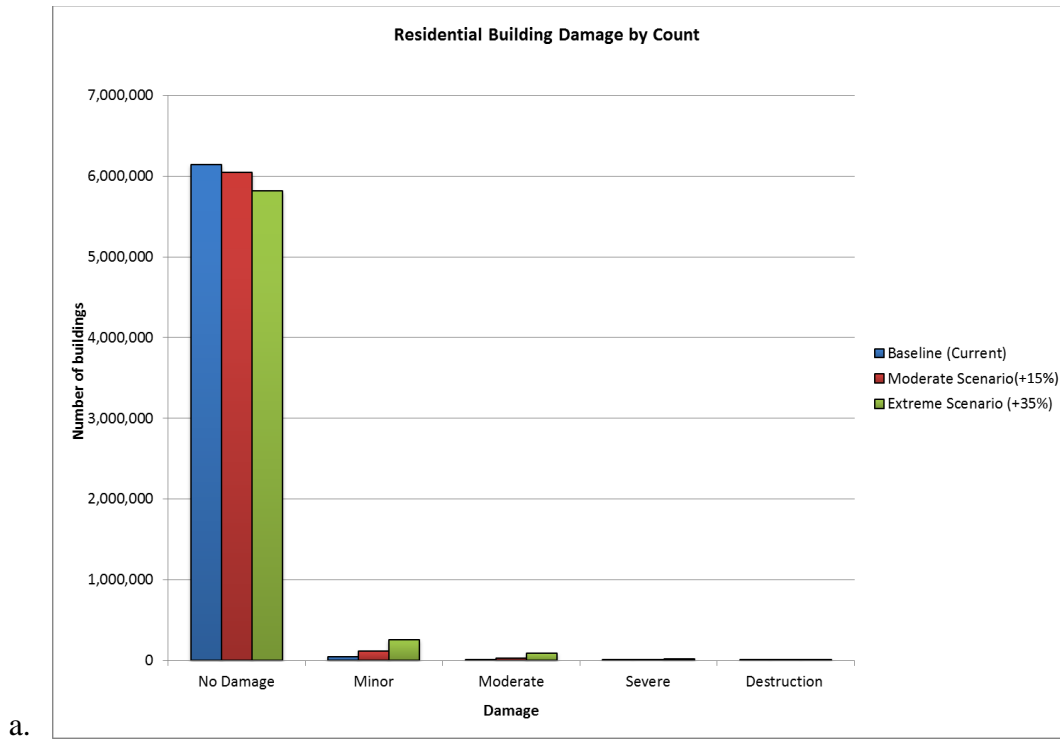


Figure 6.14. Building Damage by Count for (a) Residential and (b) Commercial Occupancy Types

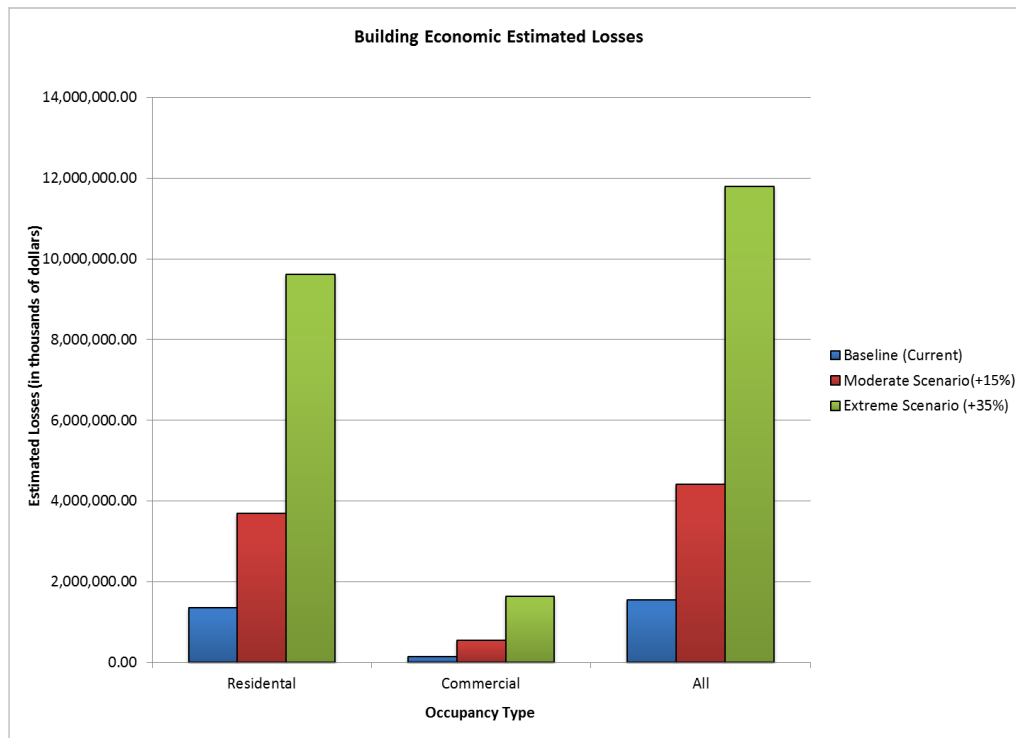
extreme scenario are about ten times greater than the economic loss for the baseline scenario. Overall, all occupancy types experienced economic losses of about \$1.5 billion for the baseline scenario and about \$11.8 billion in the extreme scenario.

6.1.5.3 Shelter Needs and Requirements

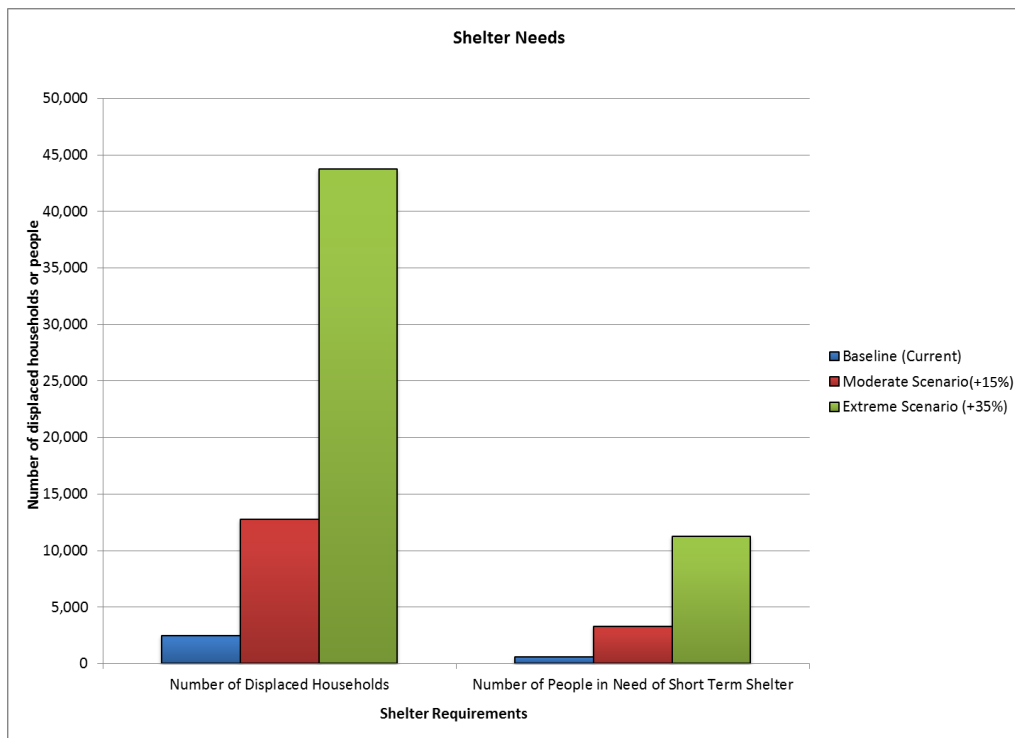
The number of displaced households and number of people in need of short-term shelter greatly increased between the baseline and extreme scenarios (Figure 6.15b). The number of displaced households is about 18 times greater for extreme scenario than the baseline scenario. The number of people in need of short term shelter increase from 600 to approximately 11,000 in the extreme scenario.

6.1.6 Tropical Storm Mitch (1998)

By the time TS Mitch reached Florida, it had already devastated Central America as a category 5 storm. The official death toll for Central America is 9,086 which made Mitch one of the deadliest Atlantic hurricanes (Barnes 2007). TS Mitch made landfall near Naples and affected the Florida Keys (Figure 6.16). Strong winds, heavy rains, and tornadoes resulted in 65 injuries and 645 destroyed homes (Barnes 2007).



a.



b.

Figure 6.15. (a) Building Economic Estimated Losses based on Occupancy Type and (b) Shelter Needs and Requirements

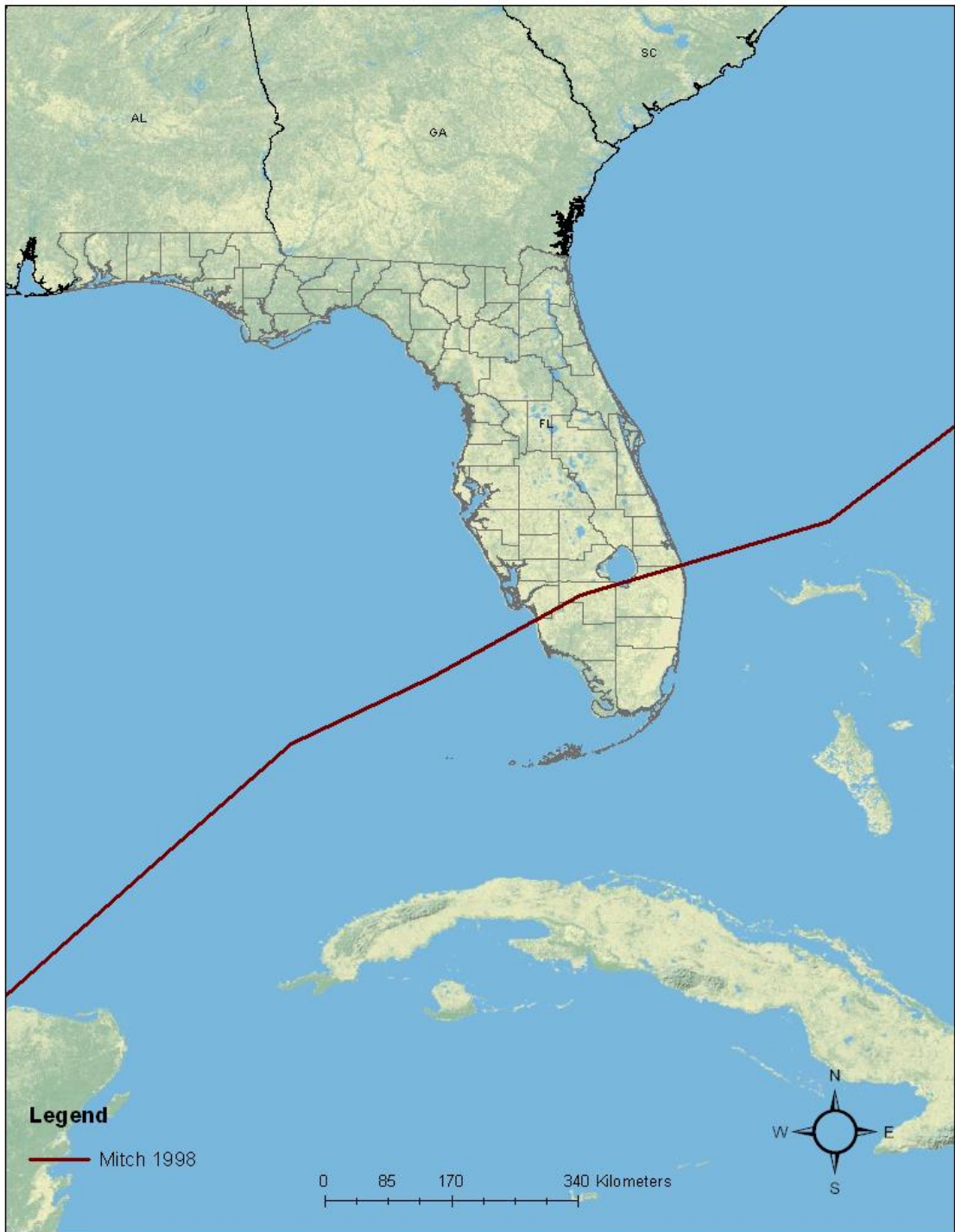


Figure 6.16. Storm track for Tropical Storm Mitch

6.1.6.1 Building Damage by Count

For residential occupancy type, the majority of buildings experienced no damage for all scenarios (Figure 6.17a). The number of damaged buildings in the no damage category decreased by 1% from the baseline scenario to the extreme scenario. In the minor damage category, the number of buildings increased from ~4,600 to ~60,000. In the moderate damage category, the extreme scenario is about 30 times greater than the baseline. The number of buildings in the severe damage category increased from 10 (baseline) to 200 in the extreme scenario.

The majority of commercial buildings are in the no damage category (Figure 6.17b). The number of buildings in this category decreased by 1% between the baseline and extreme scenarios. The number of buildings in the minor damage category increased from ~900 in the baseline scenario to ~5000 in the extreme scenario. The number of buildings in the severe and destruction categories are close to zero.

6.1.6.2 Building Economic Estimated Losses

Residential buildings experience greater economic loss than commercial buildings (Figure 6.18a). Economic losses for residential buildings are approximately \$150 million for the baseline scenario and increase to almost \$1.5 billion for the extreme scenario. Under the baseline scenario, commercial buildings experience losses of about \$7.2 million which is approximately 15 times less than the losses for the extreme scenario. For all occupancy types, losses under baseline conditions are about \$160 million and increase to about \$1.6 billion under the extreme scenario.

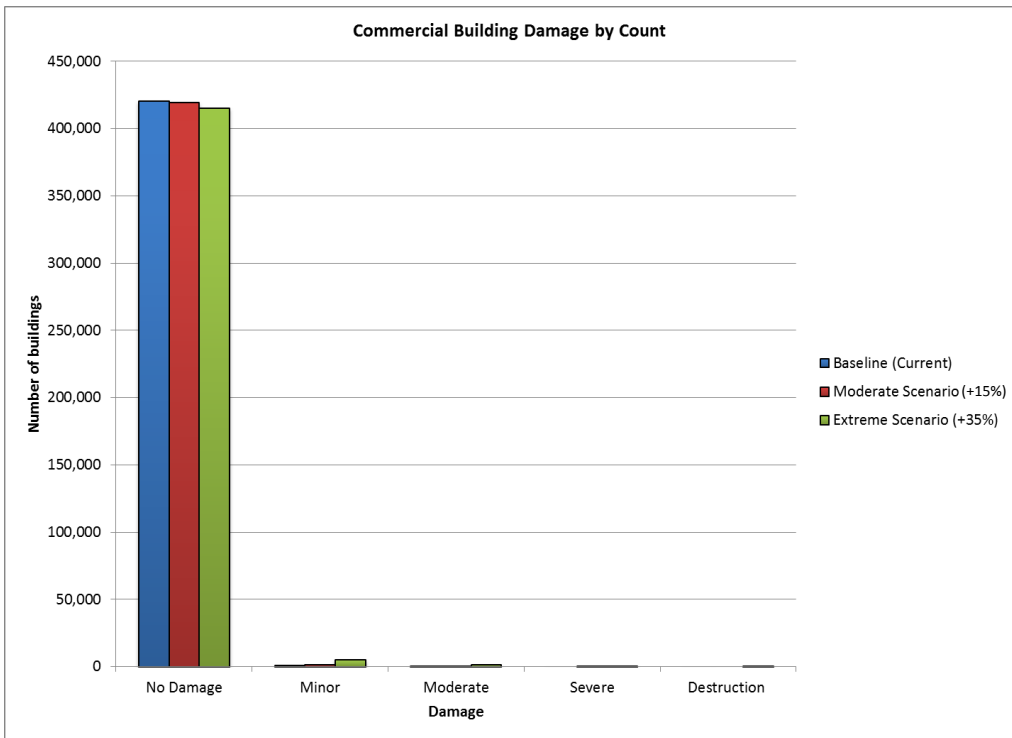
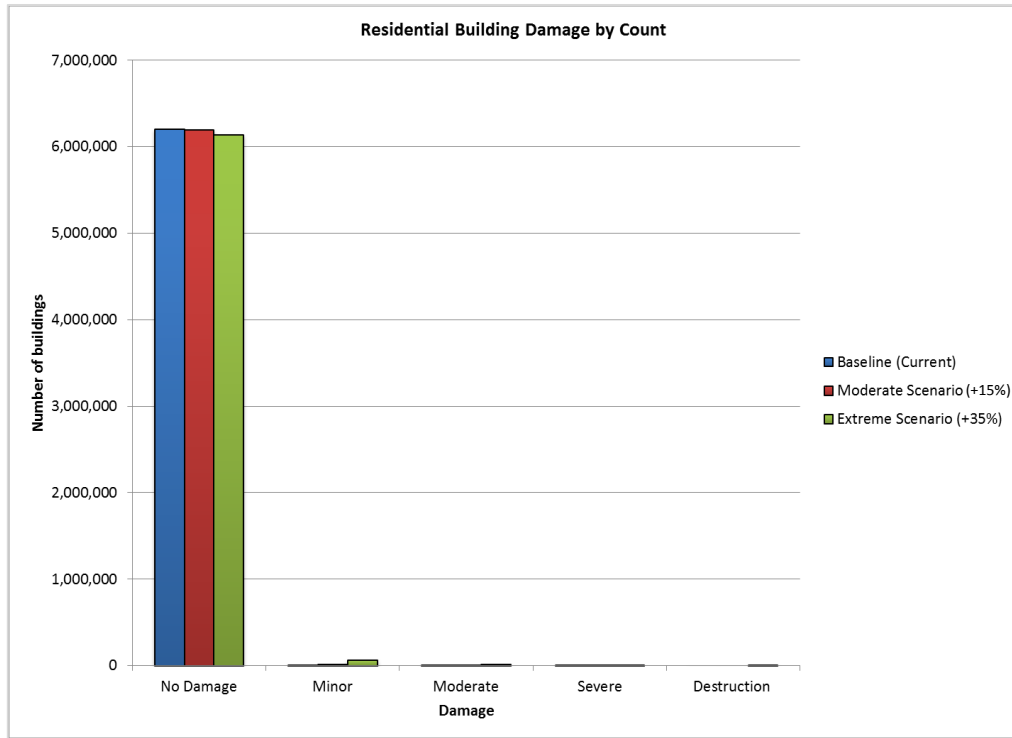
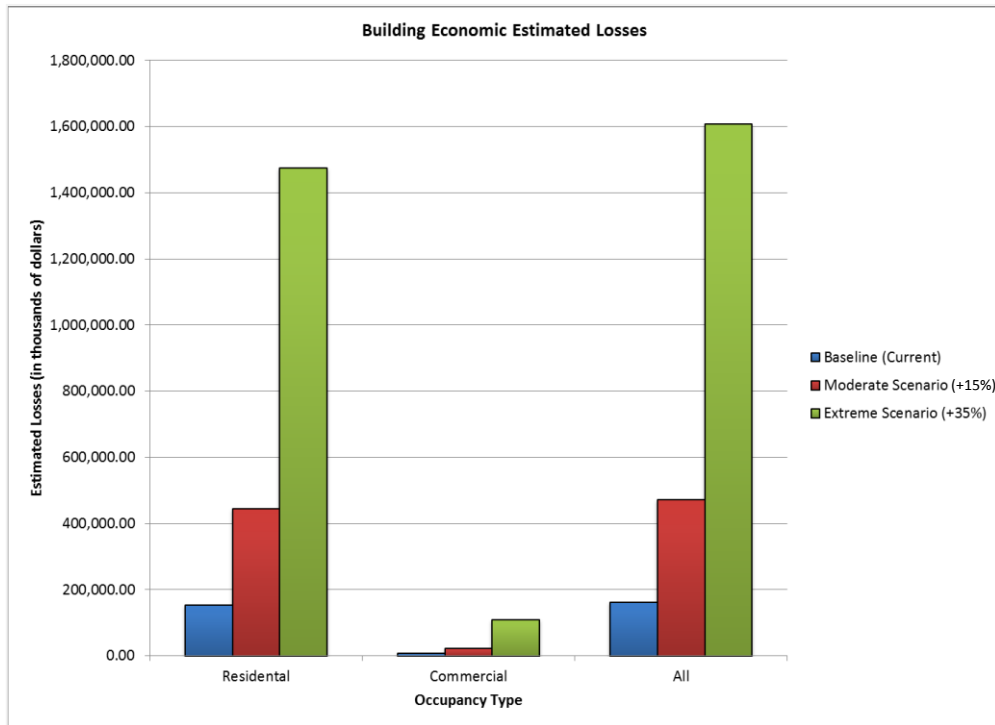
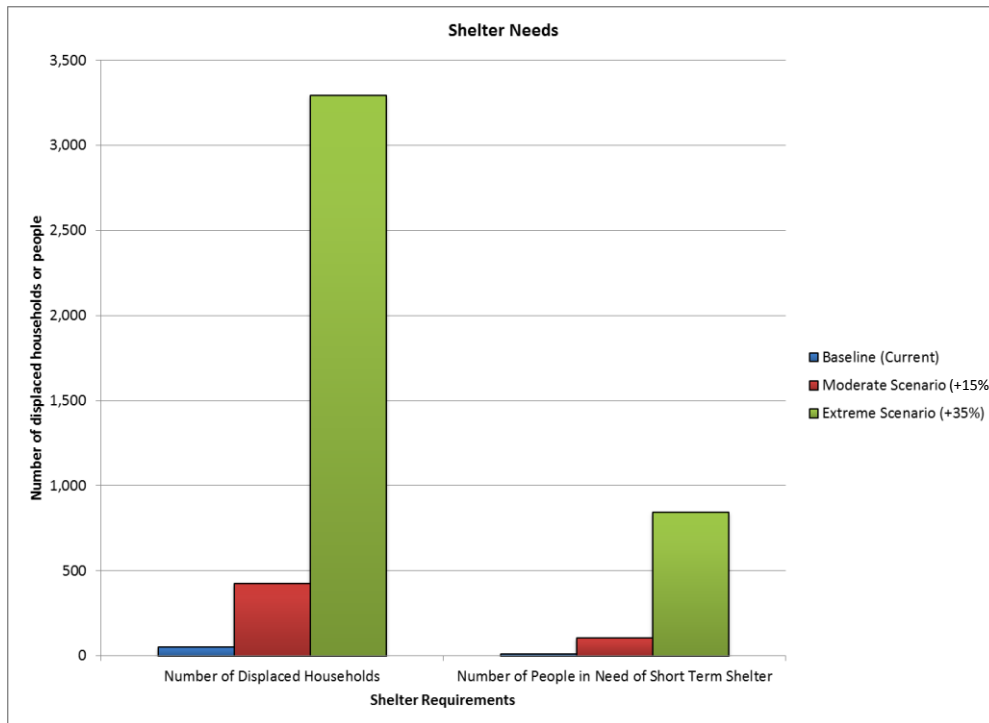


Figure 6.17. Building Damage by Count for (a) Residential and (b) Commercial Occupancy Types



a.



b.

Figure 6.18. (a) Building Economic Estimated Losses based on Occupancy Type and (b) Shelter Needs and Requirements

6.1.6.3 Shelter Needs and Requirements

The number of displaced households and number of people in need of short-term shelter greatly increased between the baseline and extreme scenarios (Figure 6.18b). The number of displaced households is about 60 times greater for the extreme scenario than the baseline scenario. The number of people in need of short-term shelter increased by 12 for the extreme scenario.

6.1.7 Hurricane Irene (1999)

Irene made landfall as a category 1 storm on October 15, 1999. The Keys and the Southern Florida mainland were impacted by Irene (Figure 6.19). After a near miss with Hurricane Floyd, which was expected to make landfall as a category 4, people did not adequately prepare for Irene because of its minimal strength (Barnes 2007). The majority of damages were caused by heavy rains and flooding (Barnes 2007). Most South Florida cities reported rainfall amounts of at least 25.4 cm (10 in.) (Barnes 2007). A total of 8 deaths and \$800 million in damages were reported (Barnes 2007).

6.1.7.1 Building Damage by Count

Residential buildings were mostly left undamaged for all scenarios (Figure 6.20a). The number of undamaged buildings decreased by 14% from the baseline scenario to the extreme scenario. The number of buildings in the minor and moderate damage categories are greater than for storms such as Georges and Mitch.

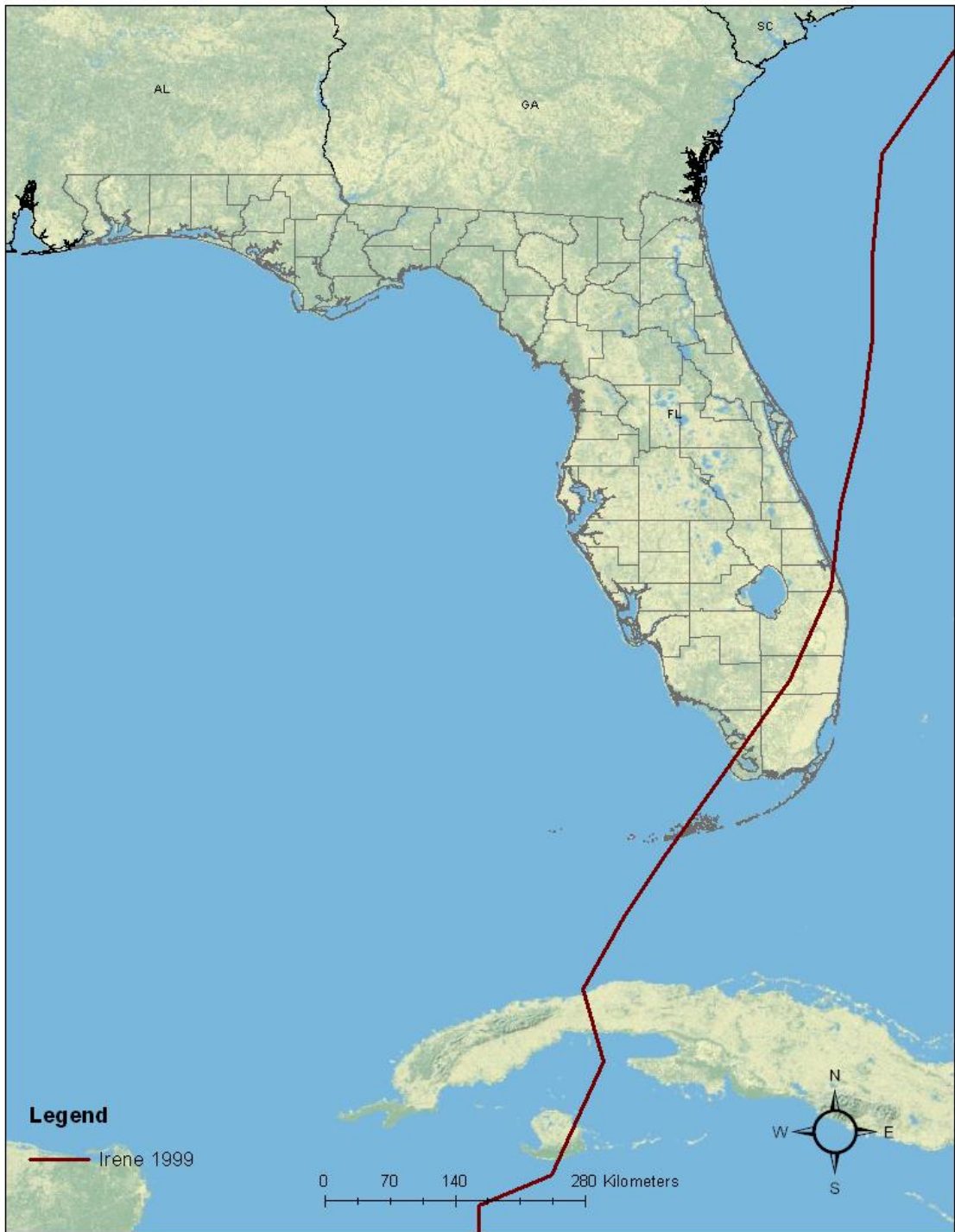
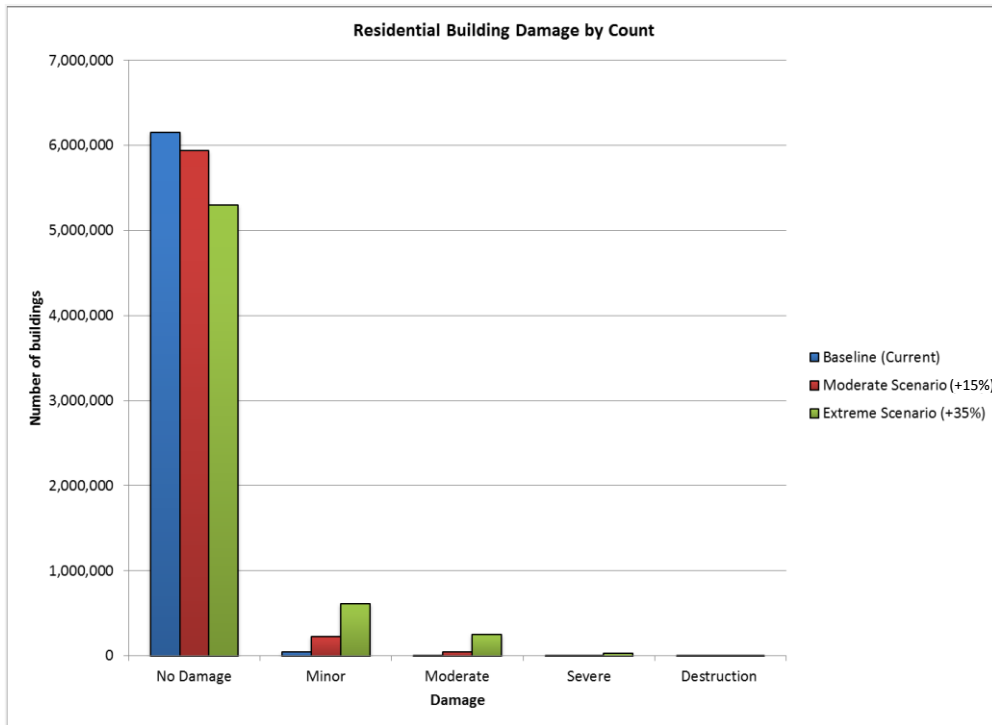
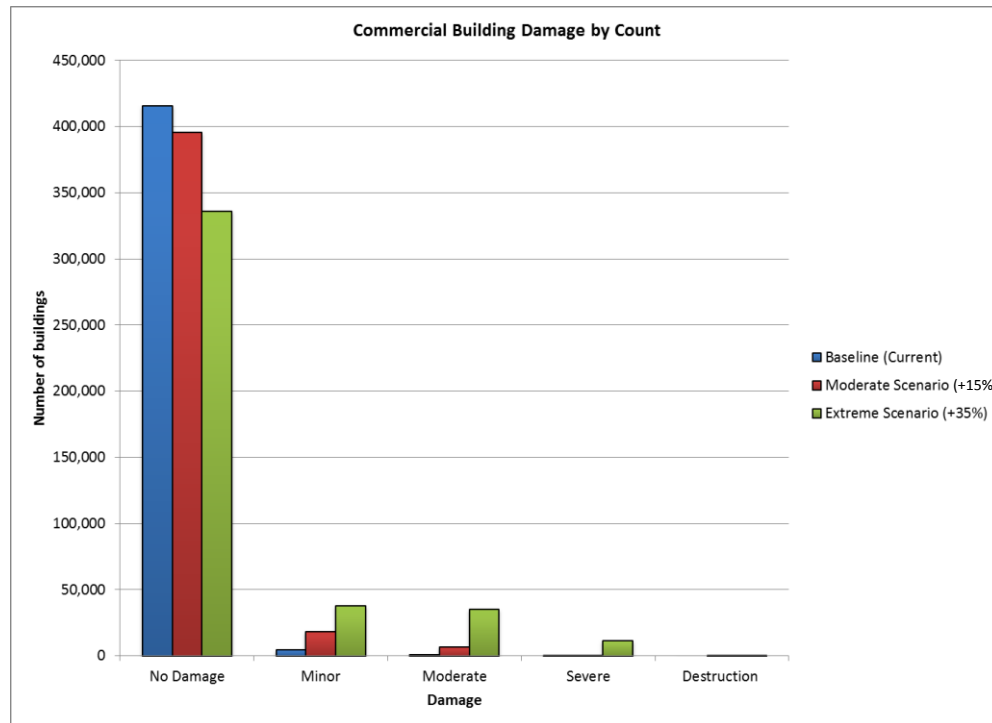


Figure 6.19. Storm track for Hurricane Irene



a.



b.

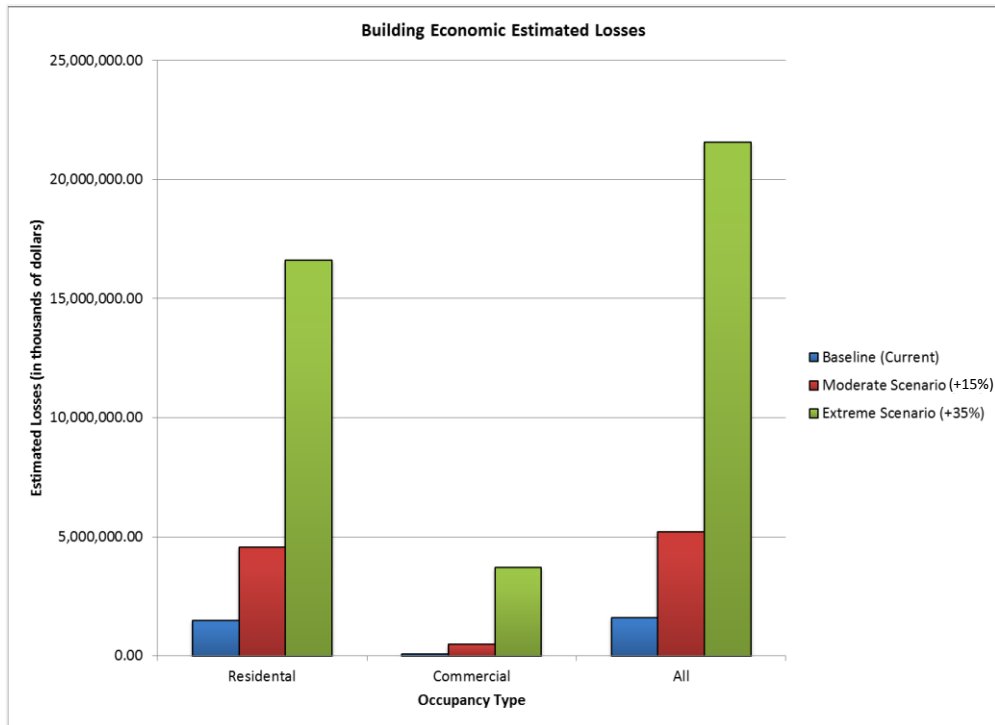
Figure 6.20. Building Damage by Count for (a) Residential and (b) Commercial Occupancy Types

The number of buildings in the minor (moderate) damage category is about 13 (35) times greater in the extreme scenario as compared to the baseline. There was a significant increase in the number of buildings in the destruction category between the baseline and extreme scenarios (from 1 to 6,628).

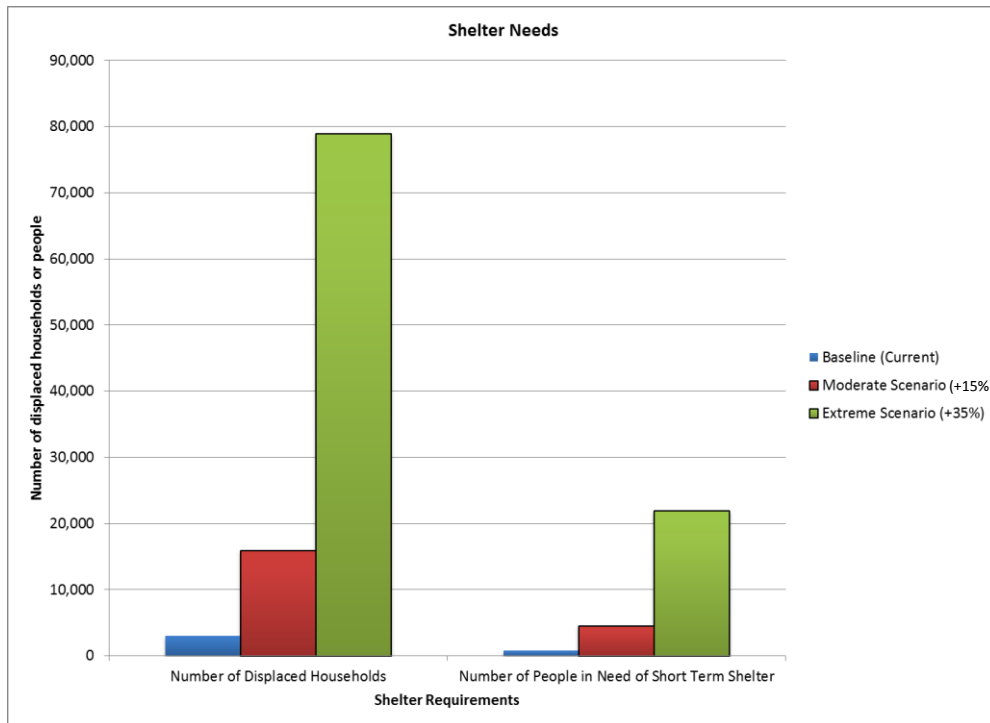
The majority of commercial buildings remained in the no damage category (Figure 6.20b). The number of buildings in the no damage category decreased by 19% from the baseline to the extreme scenario. There were ~35,000 buildings in the minor and moderate damage categories for the extreme scenario. For the severe damage category, the number of buildings increased from 22 (baseline) to 11,629 in the extreme scenario.

6.1.7.2 Building Economic Estimated Losses

Residential occupancy types experience greater economic losses than commercial occupancy types (Figure 6.21a). In the baseline scenario, residential building economic losses are approximately \$1.5 billion and increase to \$16.6 billion in the extreme scenario. Commercial building losses increase from \$85 million to approximately \$3.7 billion. Economic losses for all occupancy losses are approximately \$1.6 billion for the baseline scenario and increase to approximately \$21.5 billion in the extreme scenario.



a.



b.

Figure 6.21. (a) Building Economic Estimated Losses based on Occupancy Type and (b) Shelter Needs and Requirements

6.1.7.3 Shelter Needs and Requirements

Shelter needs for populations affected by Irene greatly increased as the intensity of the scenarios increased (Figure 6.21b). The number of displaced households for the baseline scenario increased from about 3,000 to about 80,000 for the extreme scenario. Under the extreme scenario the number of people in need of short-term shelter was 25 times greater than for the baseline scenario.

6.1.8 Hurricane Charley (2004)

On August 13, 2004, Hurricane Charley made landfall in Punta Gorda on the southwestern coast of Florida as a category 4 storm (Figure 6.22). Charley initially made landfall at 3:45 p.m. and then quickly crossed central Florida and reached Daytona Beach by midnight (Barnes 2007). The pressure dropped to 941 mb and sustained winds were recorded to have exceeded 64 m s^{-1} (145 mph) (Barnes 2007). Charley was a small storm with an eye diameter of 8 km (5 mi) (Barnes 2007). Consequently, winds were the main cause of damage from Charley (Barnes 2007). Those impacted by Hurricane Charley compared the damage it caused to the damage caused by Hurricane Andrew (Barnes 2007). An estimated 1 million people lived within ~48 km (30 mi) of where Hurricane Charley made landfall (Barnes 2007). 25 of Florida's 67 counties were declared disaster areas (Barnes 2007). Charley caused approximately \$15 billion in damages and 33 deaths (Barnes 2007).

6.1.8.1 Building Damage by Count

Charley caused significant damage to residential buildings in the moderate and extreme scenarios (Figure 6.23a). The number of buildings in the no damage category decreased by 24% from the baseline to the extreme scenario. The number of buildings in the minor damage category were about 5 times greater for the extreme scenario than the baseline scenario. The number of buildings in the moderate damage category increased from a baseline of about 40,000 to ~450,000 in the extreme scenario. The number of buildings in the severe damage category were about 25 times greater for the extreme scenario than the baseline scenario. The number of buildings in the destruction category increased from about 6,000 in the baseline scenario to ~370,000 in the extreme scenario.

Under baseline conditions, the majority of commercial buildings experienced no damage (Figure 6.23b). There is a 24% decrease from the baseline to extreme scenario in the number of buildings in the no damage category. For the extreme scenario, about 44,000 buildings were severely damaged, while 22,000 experienced minor damage, 32,000 experienced moderate damage, and 9,000 were destroyed.

6.1.8.2 Building Economic Estimated Losses

Economic losses for residential occupancy types increase from about \$3.3 billion in the baseline scenario to about \$86 billion in the extreme scenario (Figure 6.24a). Commercial occupancy types experience losses of around \$400 million in the baseline scenario. Those losses increase to about \$16 billion in the extreme scenario. For all

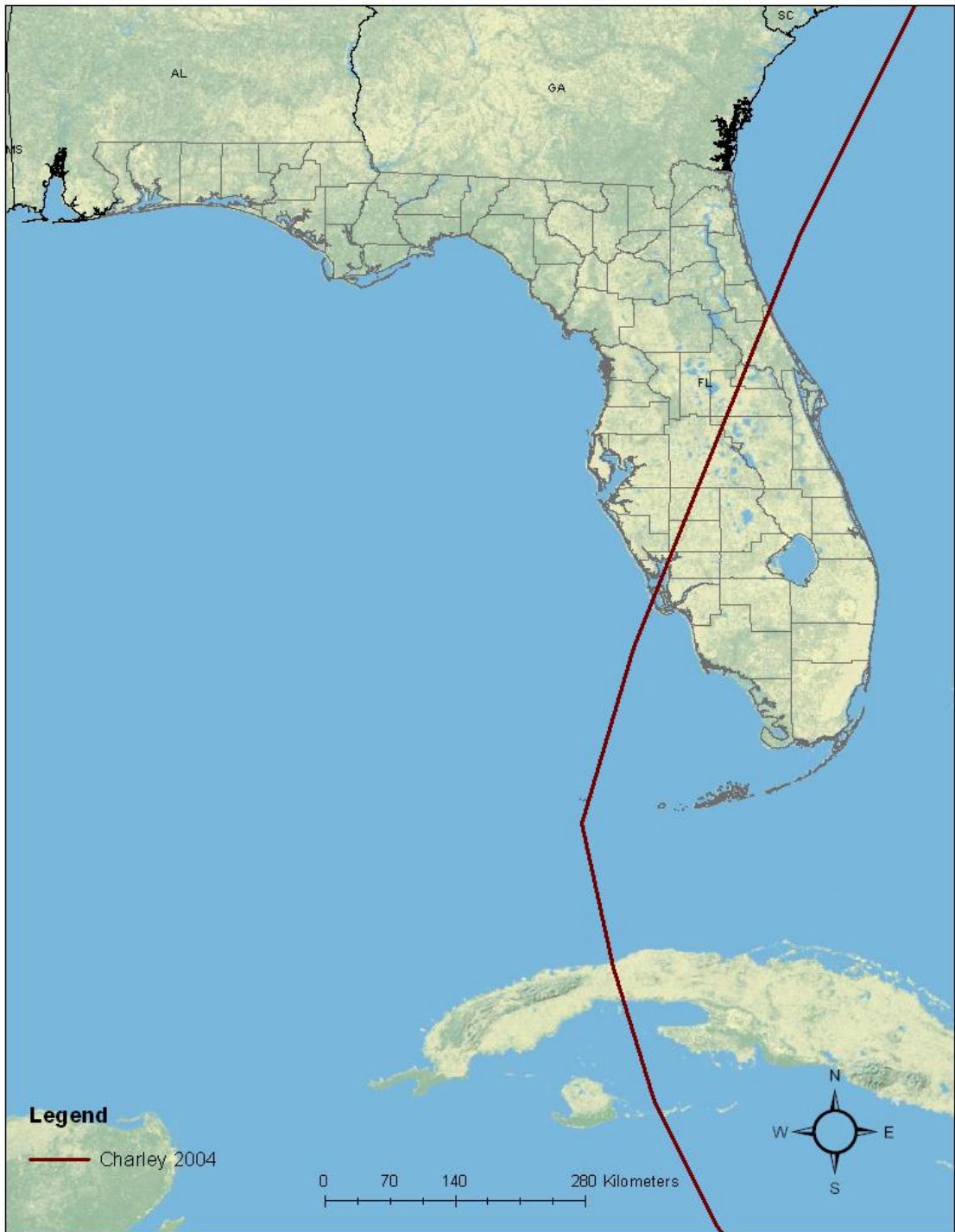


Figure 6.22. Storm track for Hurricane Charley

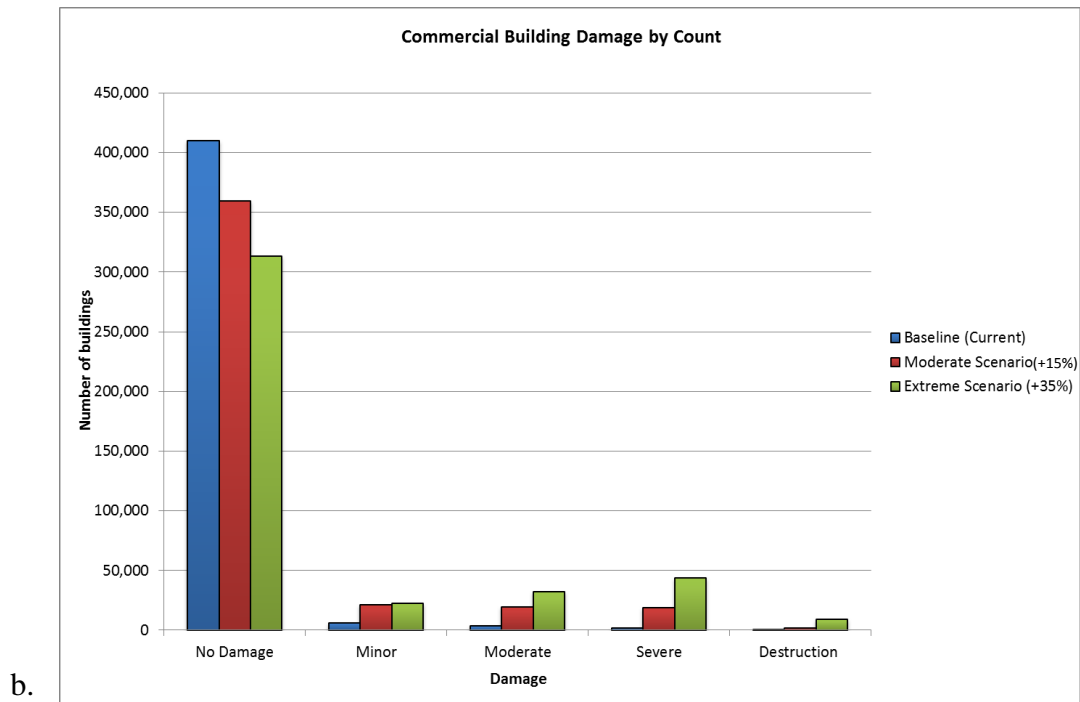
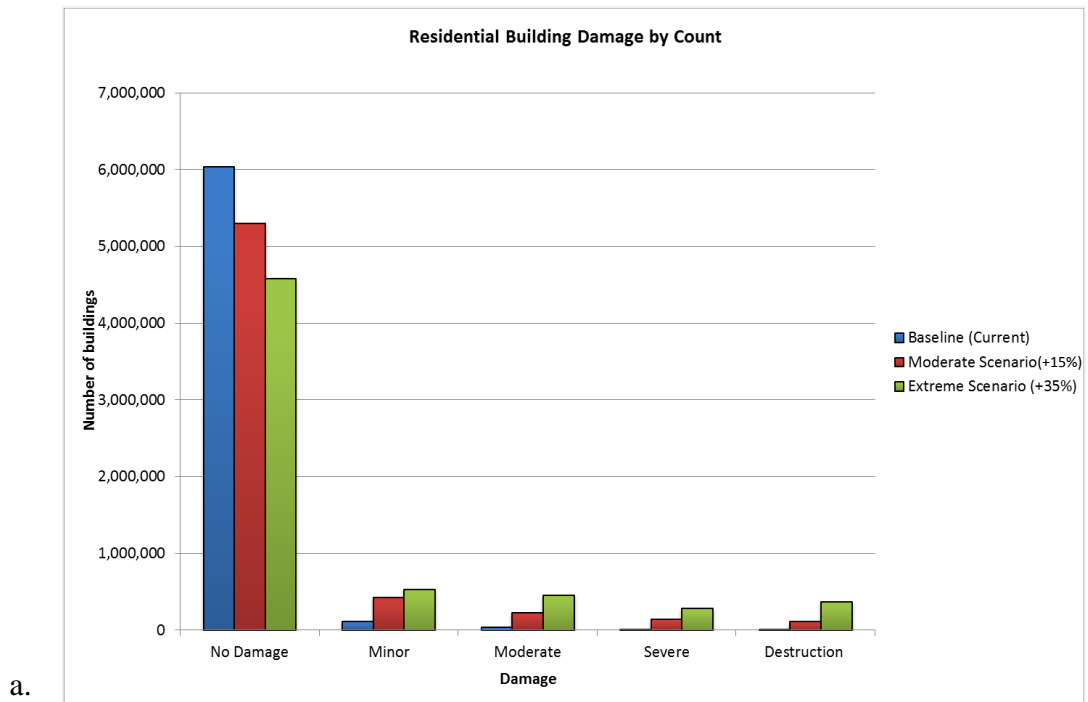


Figure 6.23. Building Damage by Count for (a) Residential and (b) Commercial Occupancy Types

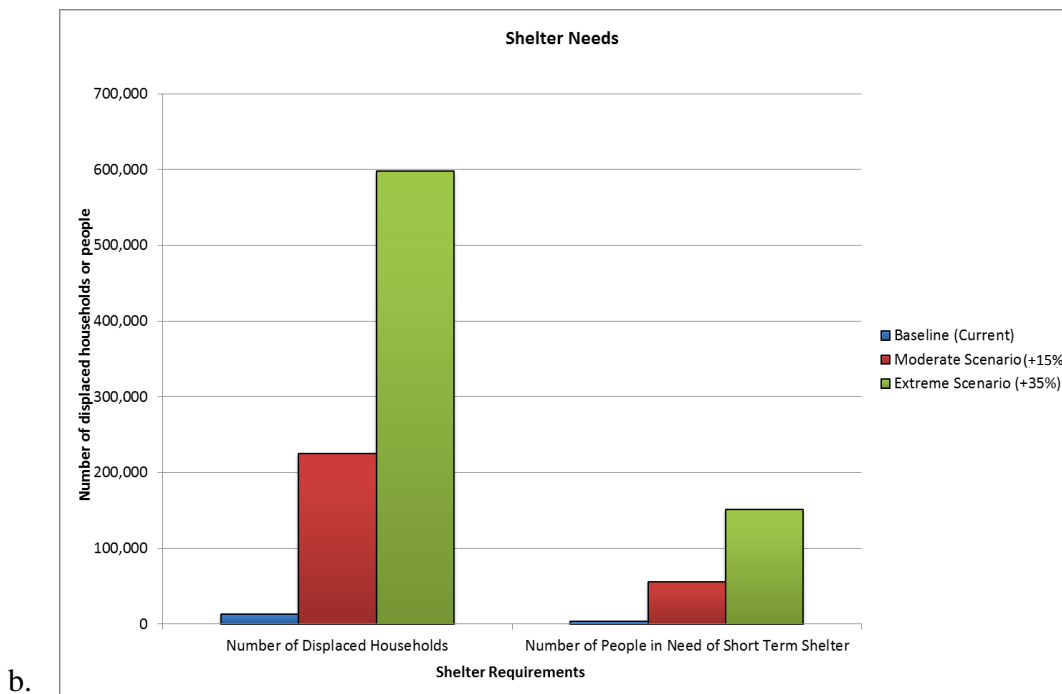
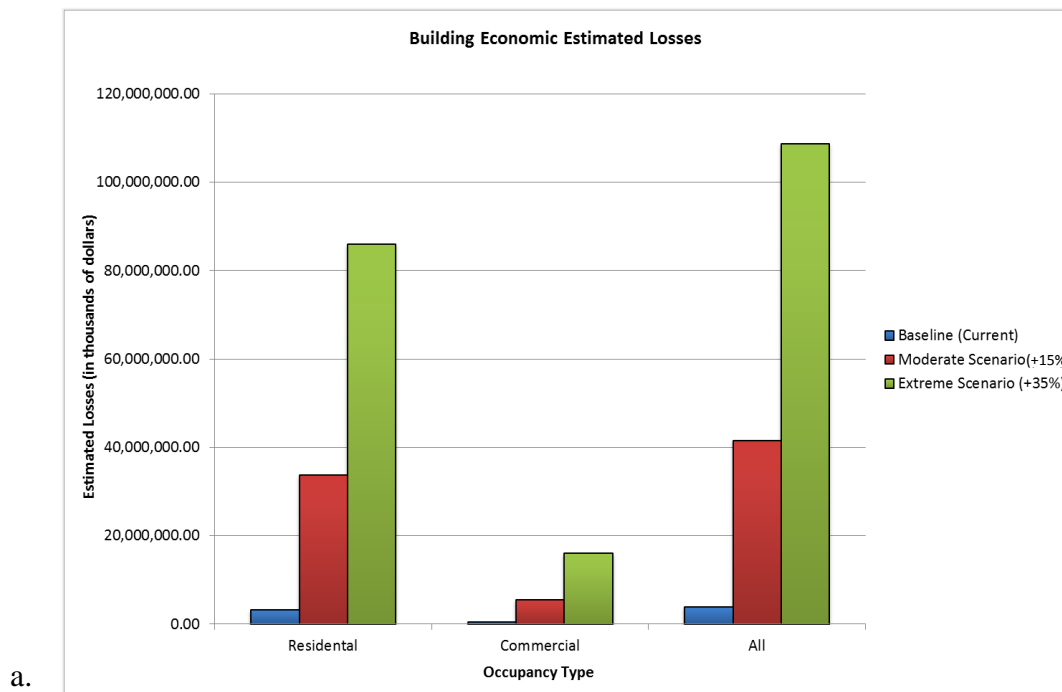


Figure 6.24. (a) Building Economic Estimated Losses based on Occupancy Type and (b) Shelter Needs and Requirements

occupancy types, baseline scenario losses are almost \$4 billion and increase to about \$108 billion in the extreme scenario.

6.1.8.3 Shelter Needs and Requirements

The number of displaced households and people in need of short-term shelter greatly increased between the baseline and extreme scenarios (Figure 6.24b). Displaced households increased from ~13,000 to almost 600,000 in the extreme scenario. The number of people in need of short-term shelter is 45 times greater in the extreme scenario than in the baseline scenario.

6.1.9 Hurricane Frances (2004)

Hurricane Frances made landfall as a category 2 in Martin County on September 5, 2004 (Figure 6.25). It moved to the northwest across Florida and into the Gulf of Mexico (Barnes 2007). Frances made a second landfall as a tropical storm along Florida's Big Bend region (Barnes 2007). The storm was approximately twice the size of Hurricane Charley (Barnes 2007). Peak wind gusts of 48 m s^{-1} (108 mph) were recorded in Fort Pierce and peak gusts between $38\text{-}42 \text{ m s}^{-1}$ (85-95 mph) were recorded in surrounding areas (Barnes 2007). There were measurements of up to 40.6 cm (16 in.) of rain in some areas and 23 tornadoes were reported (Barnes 2007). Frances is estimated to have caused \$9 billion in damages (Barnes 2007).

6.1.9.1 Building Damage by Count

The majority of residential buildings experienced no damage (Figure 6.26a). For the minor damage category, there was a 243% increase from the baseline scenario to the extreme scenario. Significant increases occurred in the severe and destruction categories. The severe damage category increased from 347 in the baseline scenario to 129,483 in the extreme scenario. For the destruction damage category, there was an increase from 69 to 106,010 in the extreme scenario.

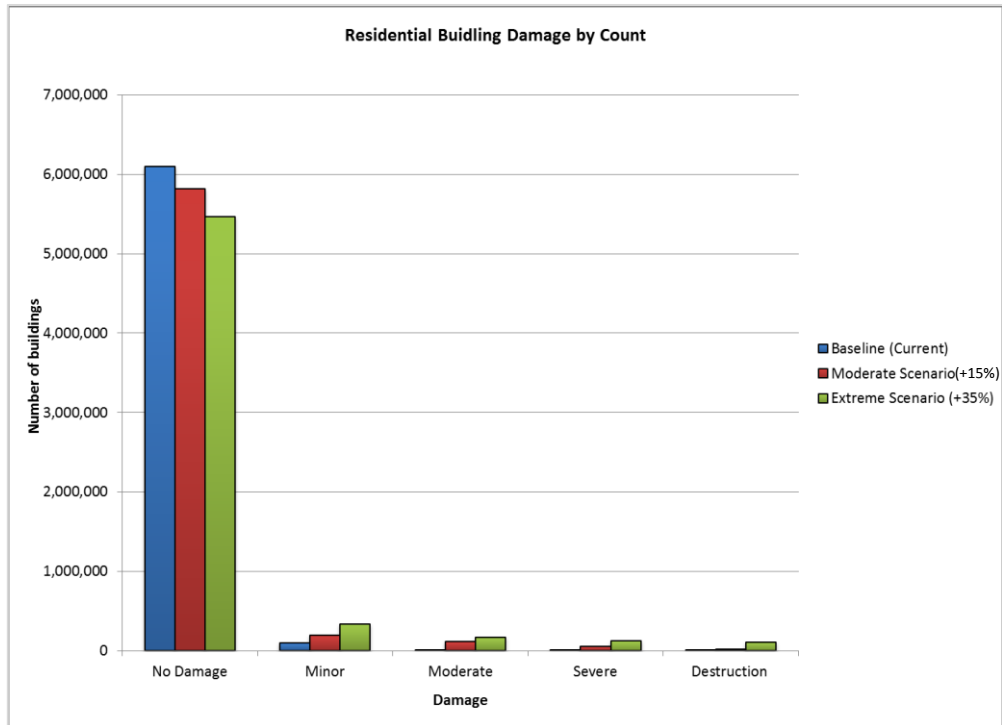
The majority of commercial buildings experienced no damage (Figure 6.26b). For the no damage category, the number of buildings decreased by 11% in the extreme scenario. The most significant increases were observed in the severe damage and destruction categories. For the severe damage category, 119 buildings were damaged in the baseline scenario and this increased to 19,047 in the extreme scenario. Two buildings experienced were destroyed under baseline conditions and this increased to 2,057 under the extreme scenario.

6.1.9.2 Building Economic Estimated Losses

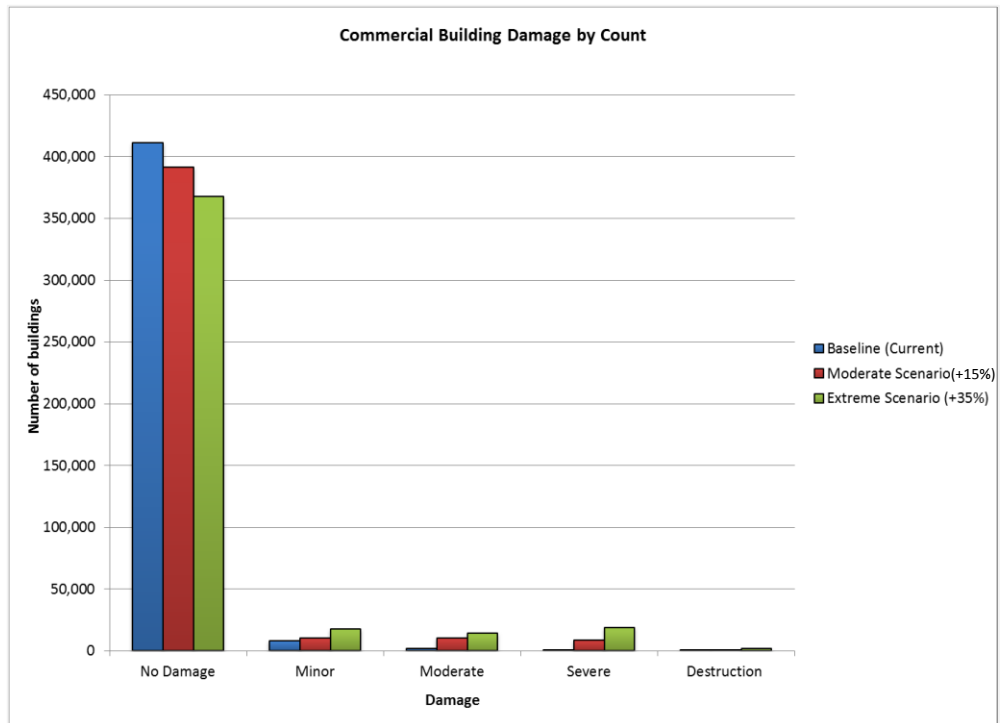
Residential occupancy types experienced greater economic losses than commercial occupancy types (Figure 6.27a). Under the baseline scenario, residential economic losses were about \$2.2 billion. Residential economic losses increased to approximately \$33 billion under the extreme scenario. Commercial economic losses for the baseline scenario are about \$150 million and the losses increase to about \$6.5 billion



Figure 6.25. Storm track for Hurricane Frances



a.



b.

Figure 6.26. Building Damage by Count for (a) Residential and (b) Commercial Occupancy Types

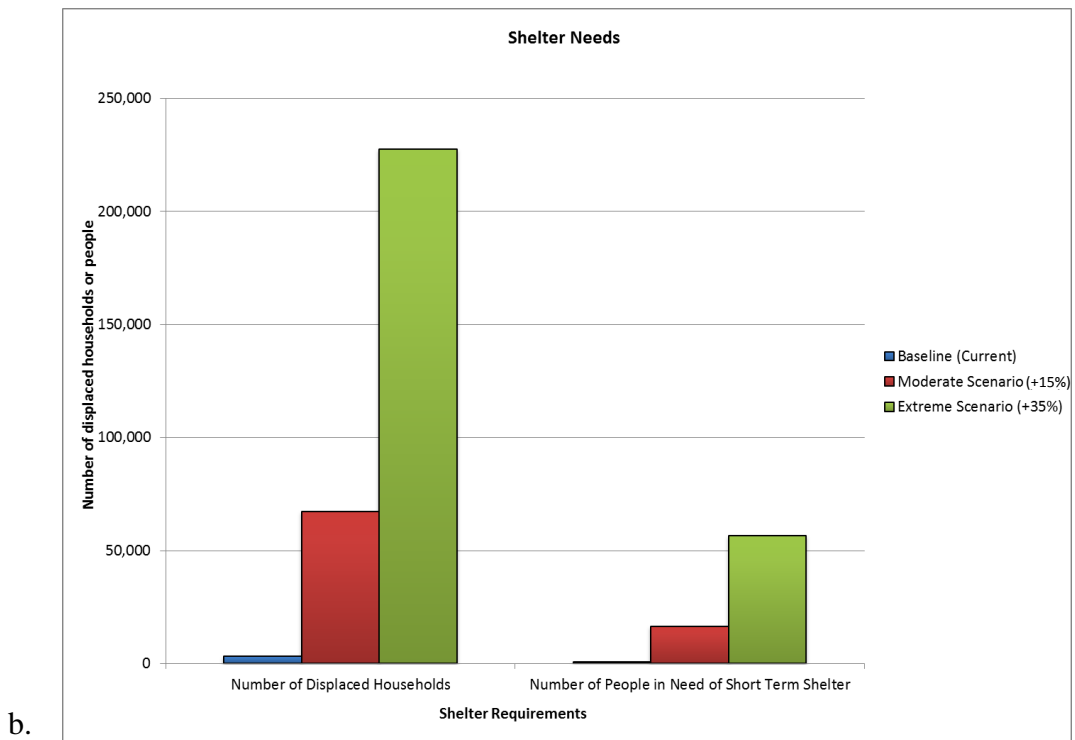
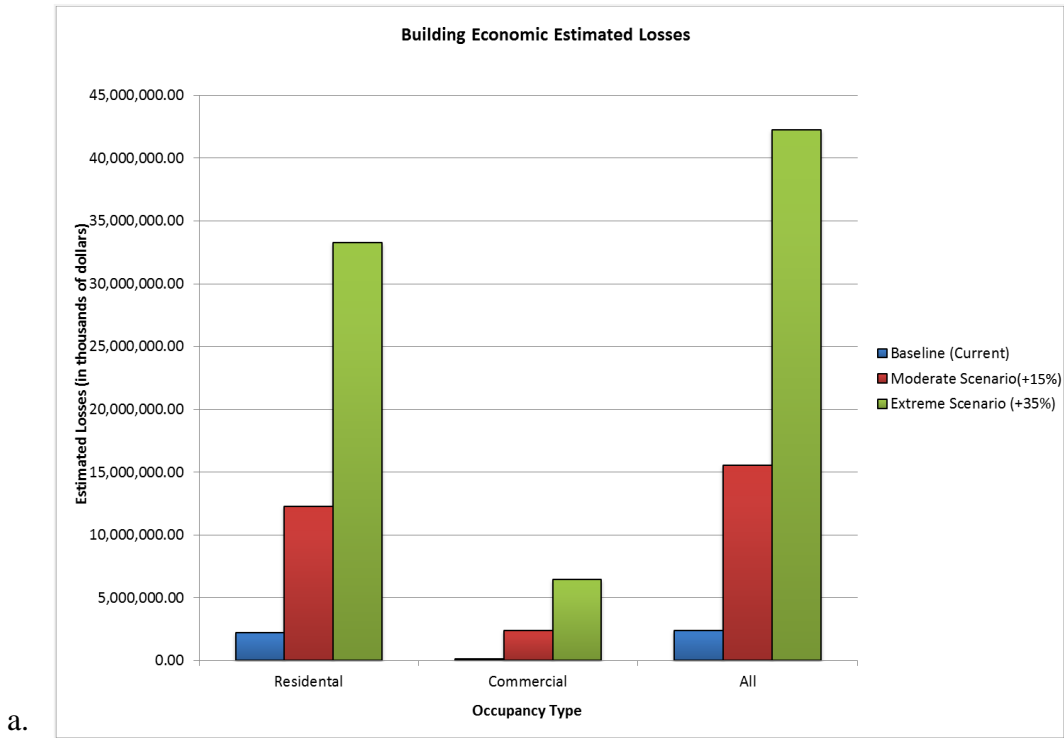


Figure 6.27. (a) Building Economic Estimated Losses based on Occupancy Type and (b) Shelter Needs and Requirements

under the extreme scenario. Total economic losses for all occupancy types are \$2.4 billion under baseline conditions and \$42 billion under extreme conditions.

6.1.9.3 Shelter Needs and Requirements

Shelter needs greatly increased between the baseline scenario and extreme scenarios (Figure 6.27b). The number of displaced households under baseline conditions is 3,352 and it is 227,569 under the extreme scenario. There are 850 people in need of short-term shelter for the baseline scenario and 56,740 people under the extreme scenario.

6.1.10 Hurricane Ivan (2004)

Hurricane Ivan made landfall along the Alabama-Florida border on September 16, 2004. Ivan was a category 3 at landfall and it continued to move northeastward towards Virginia (Figure 6.28). After reaching the Atlantic, Ivan became an extratropical low and it was steered southward towards Florida (Barnes 2007). The remnants of Ivan crossed southern Florida and made it into the Gulf of Mexico where it regained tropical storm status and made landfall in Louisiana (Barnes 2007). The highest peak gust recorded at landfall was 47 m s^{-1} (107 mph) at Pensacola Naval Air Station (Barnes 2007). Ivan produced 18 tornadoes and heavy rainfall which resulted in flooding for most regions in Ivan's path (Barnes 2007). The storm was responsible for 14 deaths and \$8 billion in damages in Florida (Barnes 2007).

6.1.10.1 Building Damage by Count

For all three scenarios, the majority of residential buildings experienced no damage (Figure 6.29a). When compared to no damage category, the number of buildings in the other damage categories are insignificant. Minor damage increased by 33% from the baseline scenario to the extreme scenario. For the moderate, severe, and destruction damage categories, the number of buildings greatly increased from the baseline to the extreme scenario. The largest increase occurred in the destruction category where the number of buildings increased from 109 in the baseline scenario to 7,709 in the extreme scenario. The majority of commercial buildings were in the no damage category (Figure 6.29b). The severe damage category experienced the greatest difference between the baseline and extreme scenarios. Under baseline conditions, there were 145 buildings in the severe damage category and this increased to 2,206 under the extreme scenario.



Figure 6.28. Storm track for Hurricane Ivan

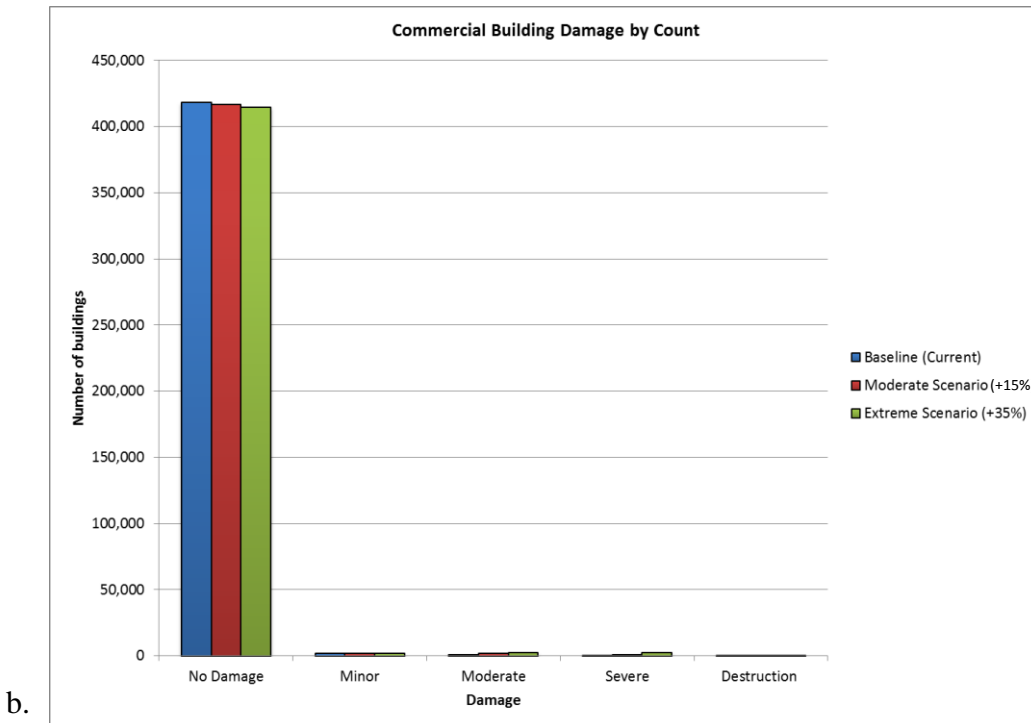
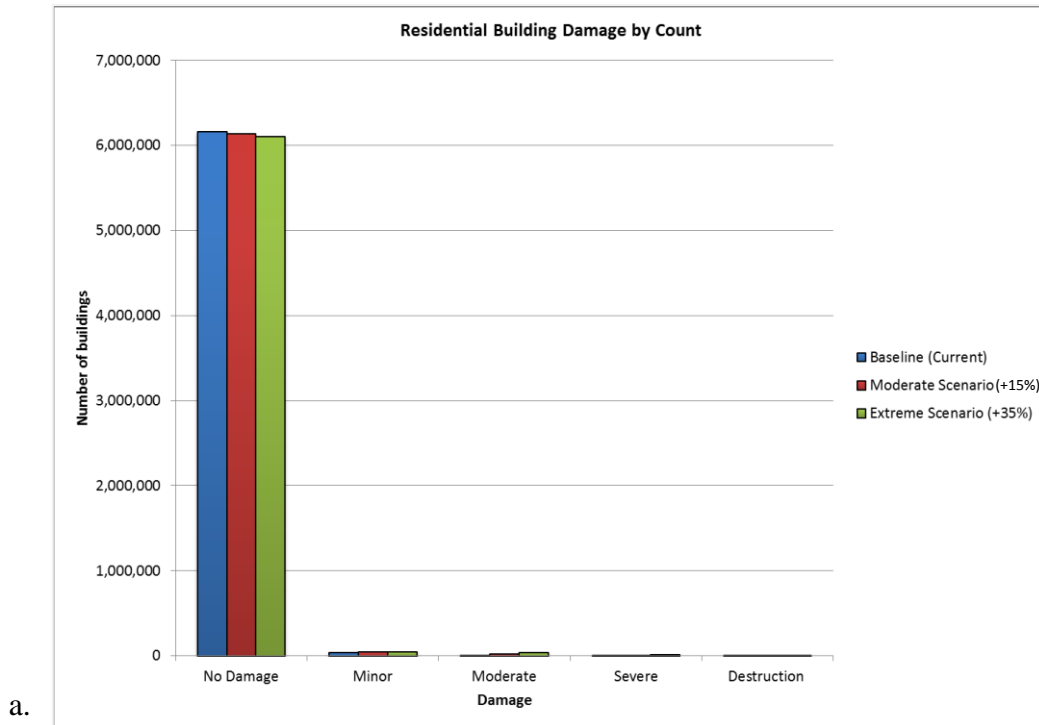
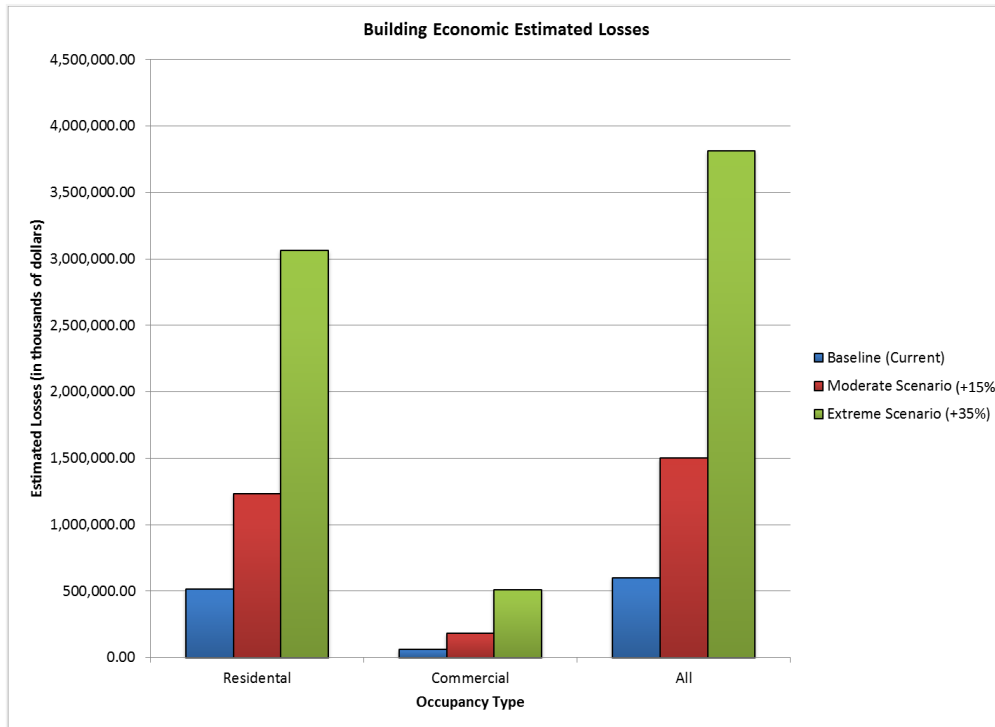
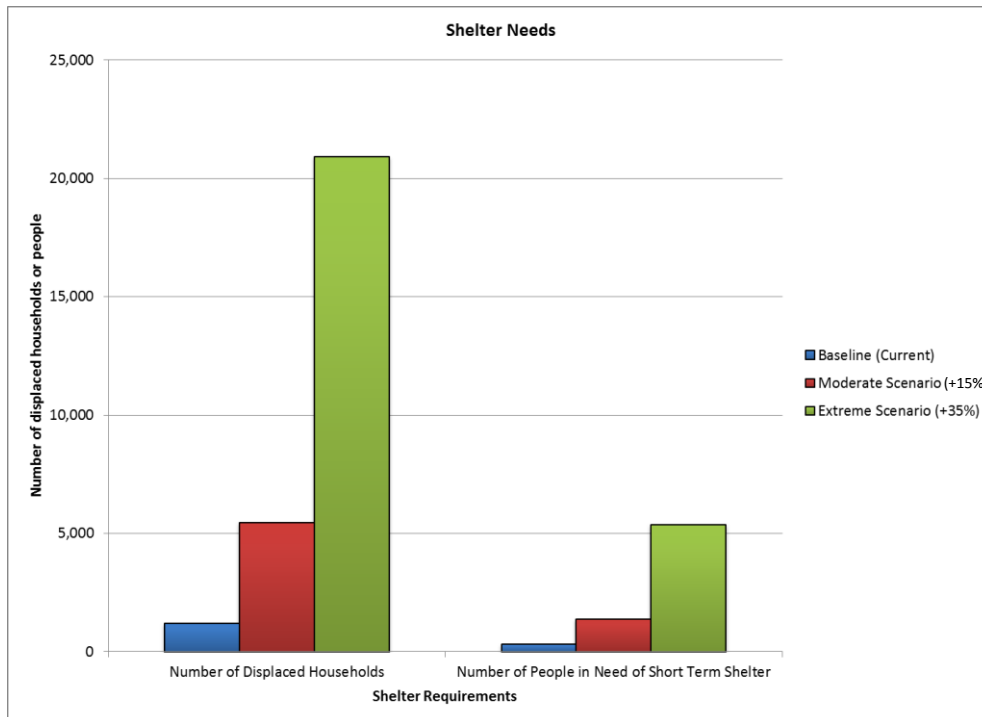


Figure 6.29. Building Damage by Count for (a) Residential and (b) Commercial Occupancy Type



a.



b.

Figure 6.30. (a) Building Economic Estimated Losses based on Occupancy Type and (b) Shelter Needs and Requirements

6.1.10.2 Building Economic Estimated Losses

Economic losses for residential occupancy losses were about \$500 million under baseline conditions (Figure 6.30a). Losses increase to \$3 billion under extreme conditions. Commercial economic losses were approximately \$60 million for the baseline scenario and are about ten times greater for the extreme scenario. The losses for all occupancy types for the baseline scenario were approximately \$600 million and \$3.8 billion for the extreme scenario.

6.1.10.3 Shelter Needs and Requirements

Hurricane Ivan greatly affected the shelter needs of the population (Figure 6.30b). The number of displaced households increased from 1,196 to 20,926 as the intensity of scenarios increased from the baseline to extreme. The number of people in need of short-term shelter in the baseline scenario was 315 and it increased to 5,373 in the extreme scenario.

6.1.11 Hurricane Wilma (2005)

Hurricane Wilma made landfall on October 24, 2005, making it the second latest storm to make a U.S. landfall during a hurricane season (Blake et al. 2011). Wilma made landfall as a category 3 in Everglades City in Southwest Florida (Figure 6.31). With an eye diameter of 96 km (60 mi), Wilma greatly impacted Southern Florida as it crossed towards the Atlantic (Barnes 2007). Storm surge caused by Wilma led to significant flooding (Barnes 2007). Power outages affected approximately 6 million people making

it the most widespread outage in the state's history (Barnes 2007). Wilma was responsible for 6 deaths and \$12 billion in damages (Barnes 2007).

6.1.11.1 Building Damage by Count

Although the majority of buildings experienced no damage, Wilma caused minor to severe damages to buildings in all three scenarios (Figure 6.32a). The number of buildings in the no damage category decreased by 12% in the extreme scenario. The number of buildings in the minor damage category decreased by 7% lower in the baseline scenario. Moderate damage increased by 200% from the baseline to the extreme scenario. The number of buildings in the destruction category increased from 1,041 (baseline) to 221,948 (extreme).

The majority of commercial buildings remained undamaged in all scenarios (Figure 6.32b). Under baseline conditions, ~28,000 buildings experienced minor damage and only about 50 buildings were classified as destroyed. Buildings in the minor damage category decreased by 28% in the extreme scenario.

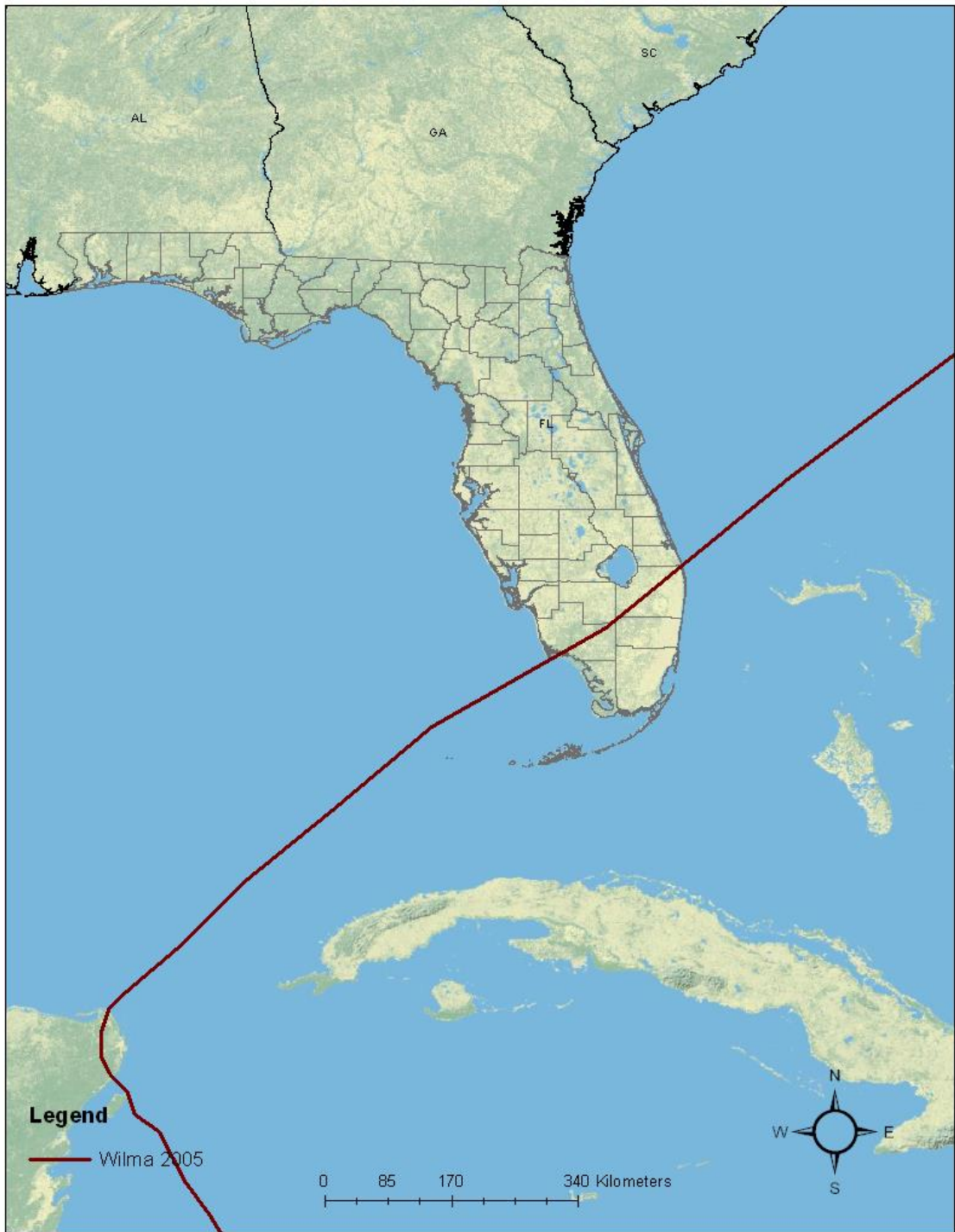
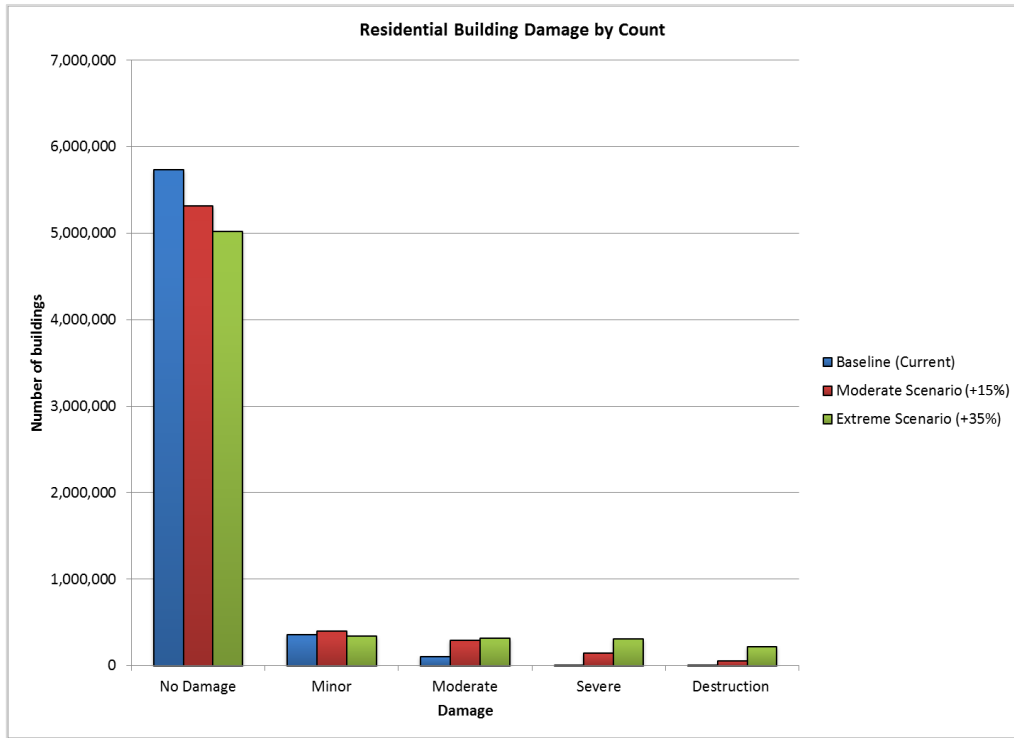
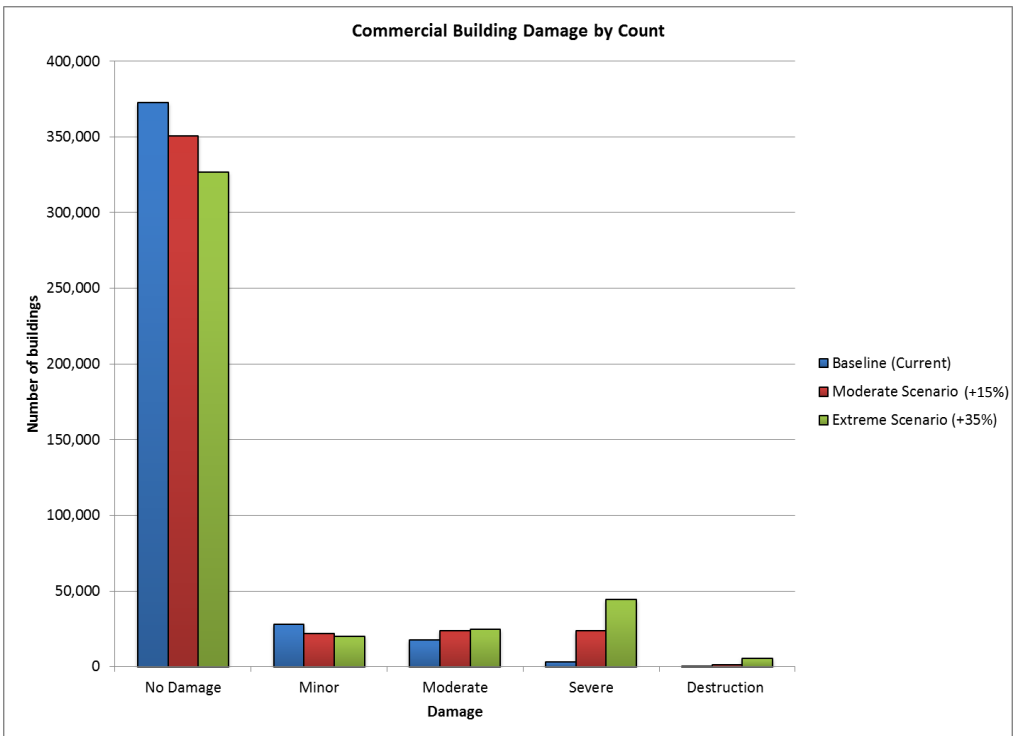


Figure 6.31. Storm track for Hurricane Wilma



a.



b.

Figure 6.32. Building Damage by Count for (a) Residential and (b) Commercial Occupancy Types

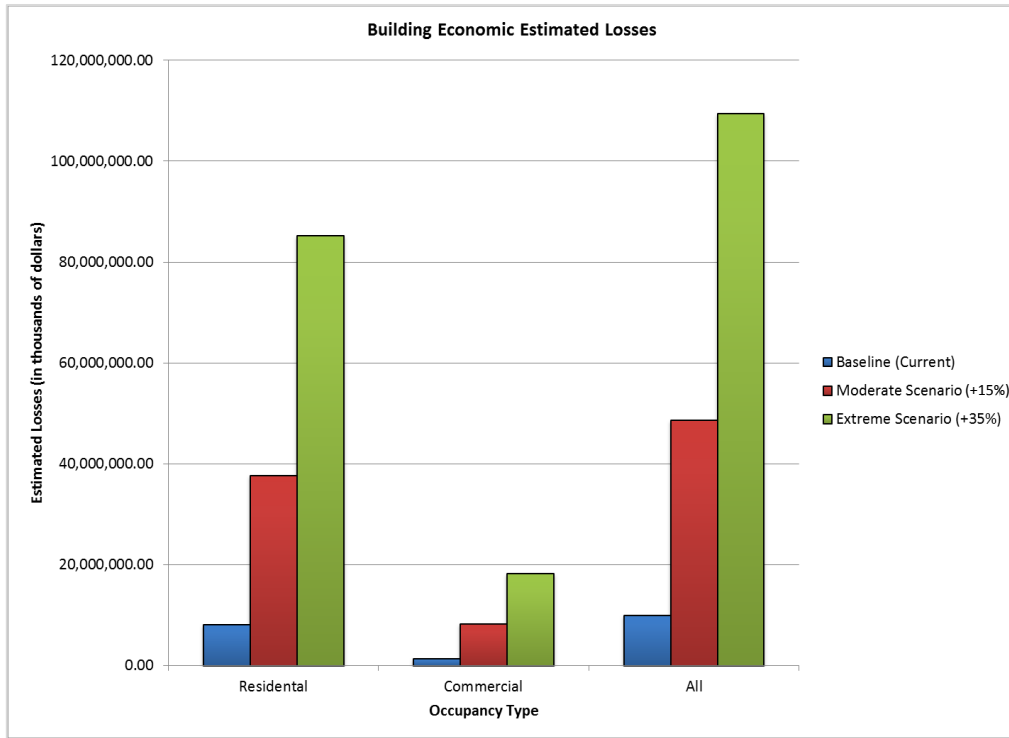
In the extreme scenario there are 125 times more buildings that were destroyed than in the baseline scenario.

6.1.11.2 Building Economic Estimated Losses

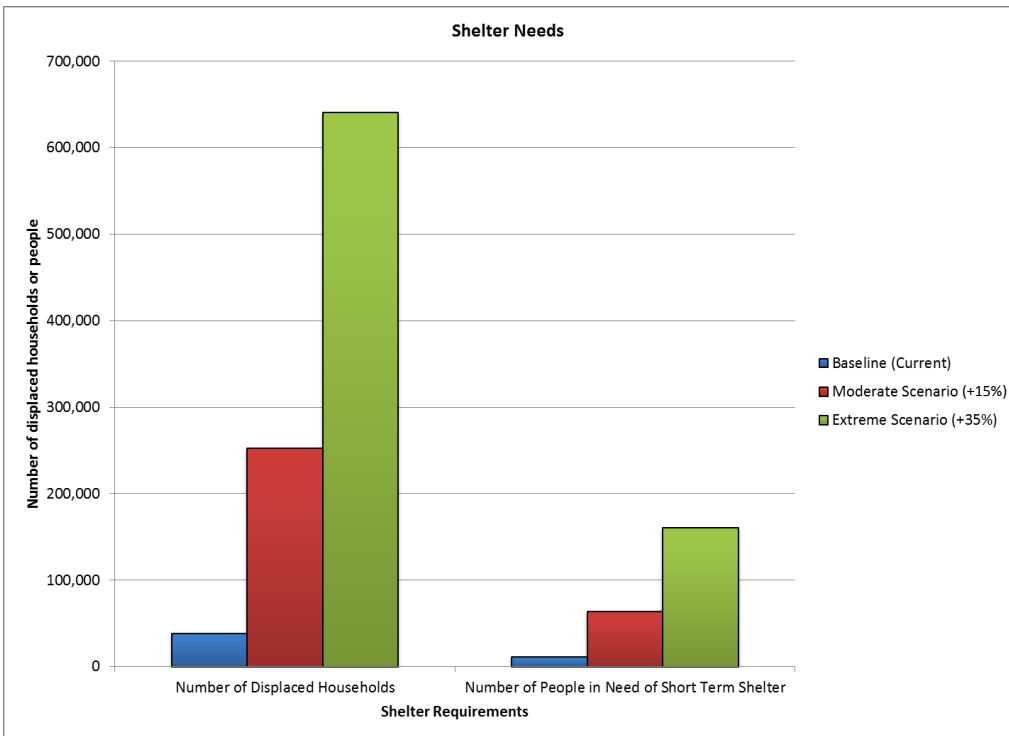
Economic losses were significant for both residential and commercial occupancy types under baseline conditions (Figure 6.33a). Residential buildings experienced economic losses of approximately \$8 billion under baseline conditions and about \$85 billion in losses under the extreme scenario. The difference in losses between the baseline and extreme scenarios for commercial buildings isn't as significant as the difference for residential buildings. Commercial building losses in the baseline scenario were \$1.4 billion and \$18 billion in the extreme scenario. For all occupancy types, losses were almost \$10 billion under baseline conditions and \$109 billion under extreme conditions.

6.1.11.3 Shelter Needs and Requirements

A significant number of Florida's population were displaced from their homes or placed in shelters as a result of Hurricane Wilma (Figure 6.33b). Hurricanes Ivan and Wilma made landfall as a category 3 storm, however, a greater number of people had shelter needs and requirements for Wilma. Under baseline conditions, the number of displaced households was 37,977 and the number of people in need of short-term shelter was 10,909. This increased to 640,787 and 160,343, respectively, in the extreme scenario.



a.



b.

Figure 6.33. (a) Building Economic Estimated Losses based on Occupancy Type and (b) Shelter Needs and Requirements

6.1.12 Tropical Storm Fay (2008)

Tropical Storm Fay formed on August 14, 2008 and made its first Florida landfall over Key West on August 18 (Figure 6.34). The next day, TS Fay made its second landfall in Southwest Florida, near Cape Romano (Beven and Brown 2009). On August 20, TS Fay passed Cape Canaveral and entered the Atlantic (Beven and Brown 2009). The storm made a third landfall along the Flagler-Volusia county lines on August 23 (Beven and Brown 2009). The storm made landfall a total of eight times, four of those landfalls were in Florida (Beven and Brown 2009). The strongest peak gust recorded was 34 m s^{-1} (78 mph) and up to 70.2 cm (27.65 in.) of rain were reported in Melbourne (Beven and Brown 2009). The storm also produced 19 tornadoes and minimal storm surge (Stewart and Beven 2009). In Florida, TS Fay was responsible for five deaths and approximately \$195 million in damages (Stewart and Beven 2009).

6.1.12.1 Building Damage by Count

The majority of residential buildings experienced no damage or only minor damage in all scenarios (Figure 6.35a). The largest differences between the baseline and extreme scenario are in the moderate, severe, and destruction damage categories. Moderate damage increased from 87 buildings in the baseline scenario to 14,726 in the extreme scenario. Only four buildings were severely damaged under the baseline scenario as compared to 491 buildings in the extreme scenario. For baseline conditions, no buildings were in the destruction category. Under extreme conditions, 228 buildings were in the destruction category.

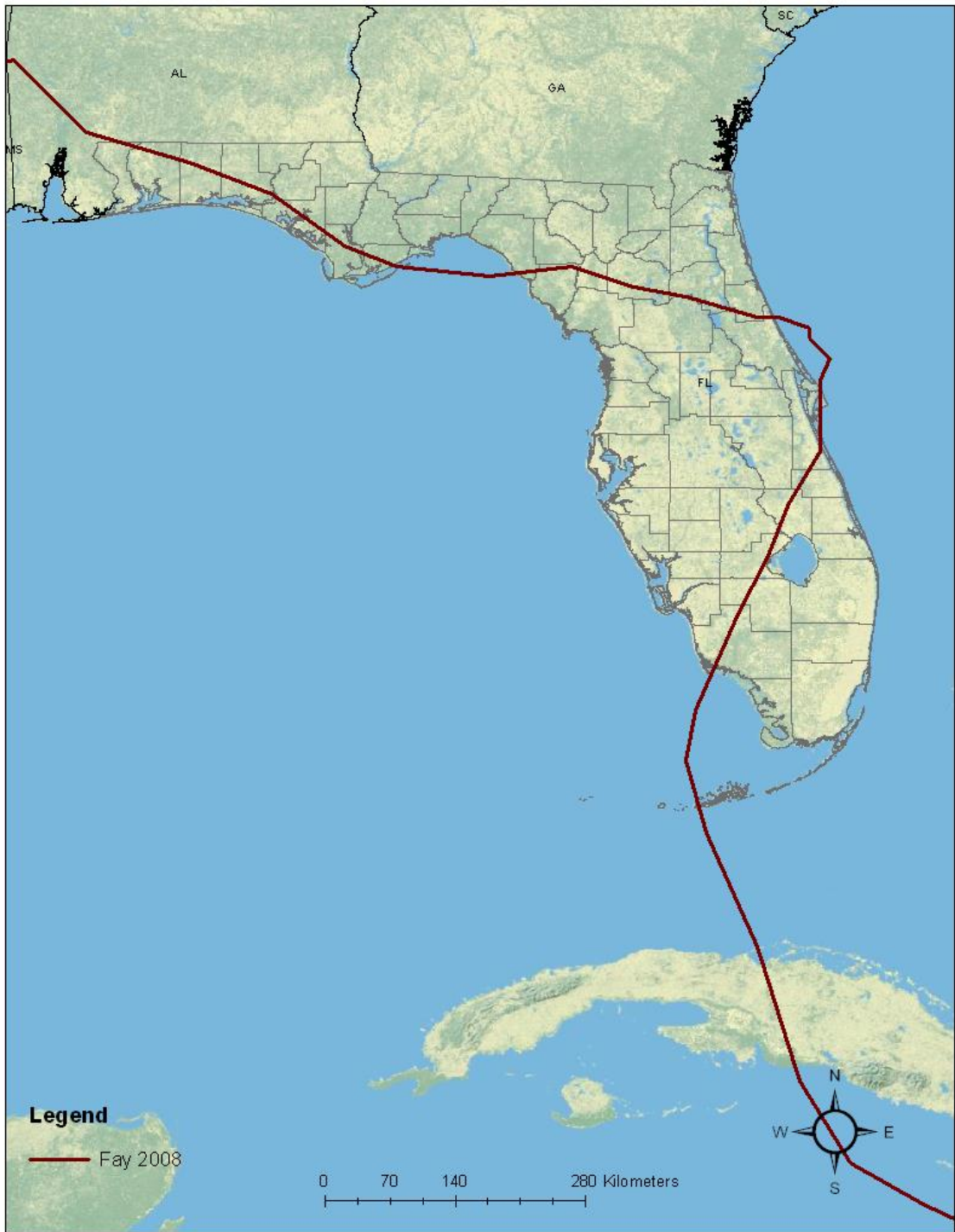


Figure 6.34. Storm track for Tropical Storm Fay

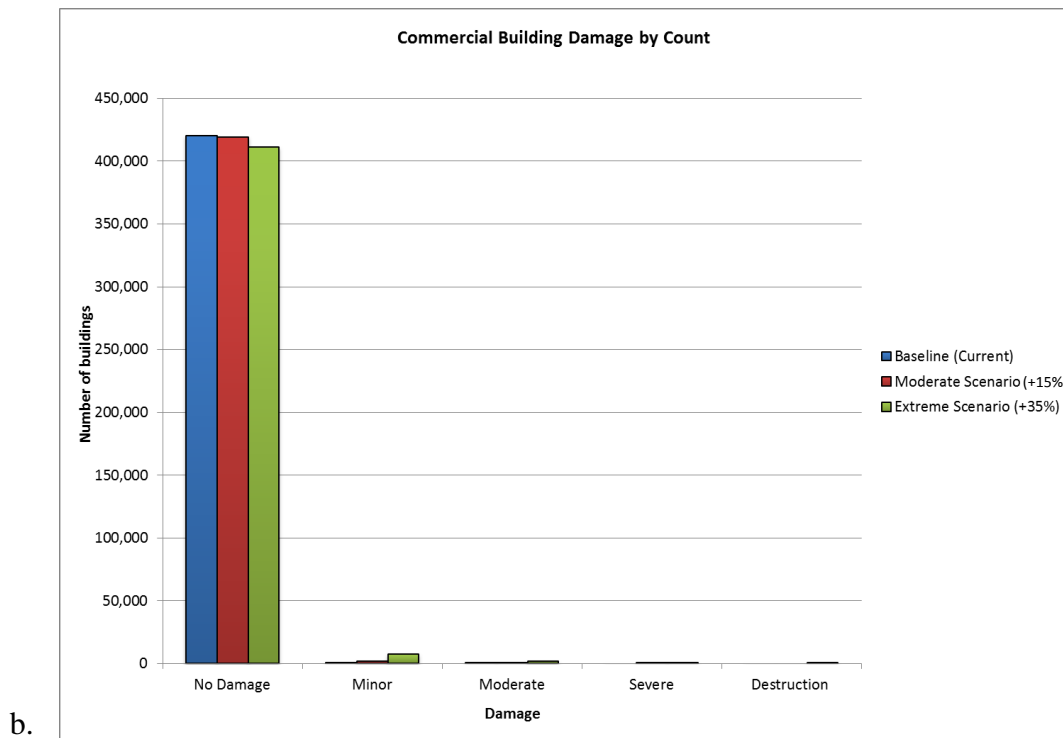
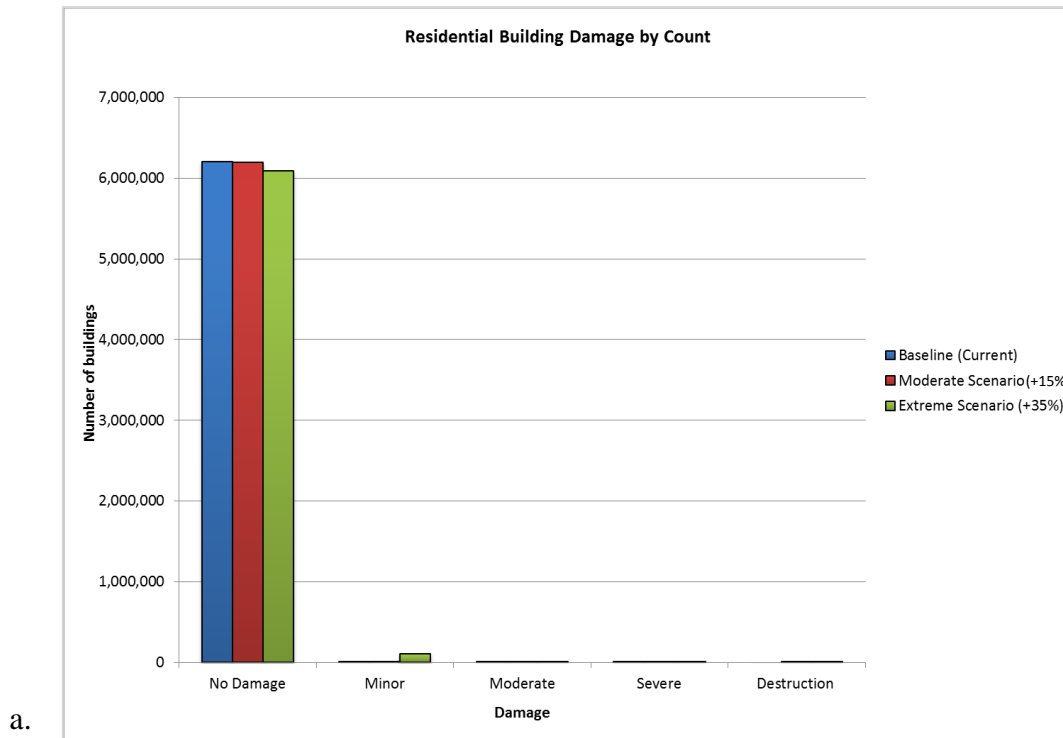


Figure 6.35. Building Damage by Count for (a) Residential and (b) Commercial Occupancy Types

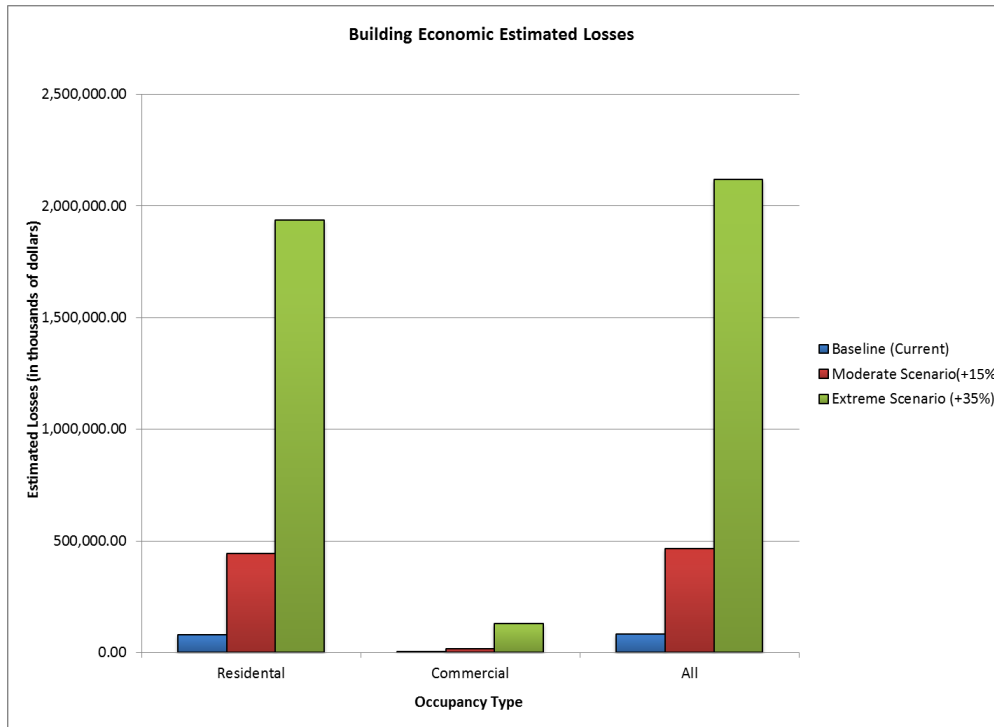
Commercial buildings were mostly in the no damage category for all scenarios (Figure 6.35b). The number of buildings with minor damage was almost 13 times greater in the extreme scenario than the baseline. Moderate damage increased from 7 buildings in the baseline scenario to 1,955 in the extreme scenario. No buildings were classified under the severe and destruction damage categories for the baseline scenario and less than 200 buildings are classified under severe and destruction damage categories for the extreme scenario.

6.1.12.2 Building Economic Estimated Losses

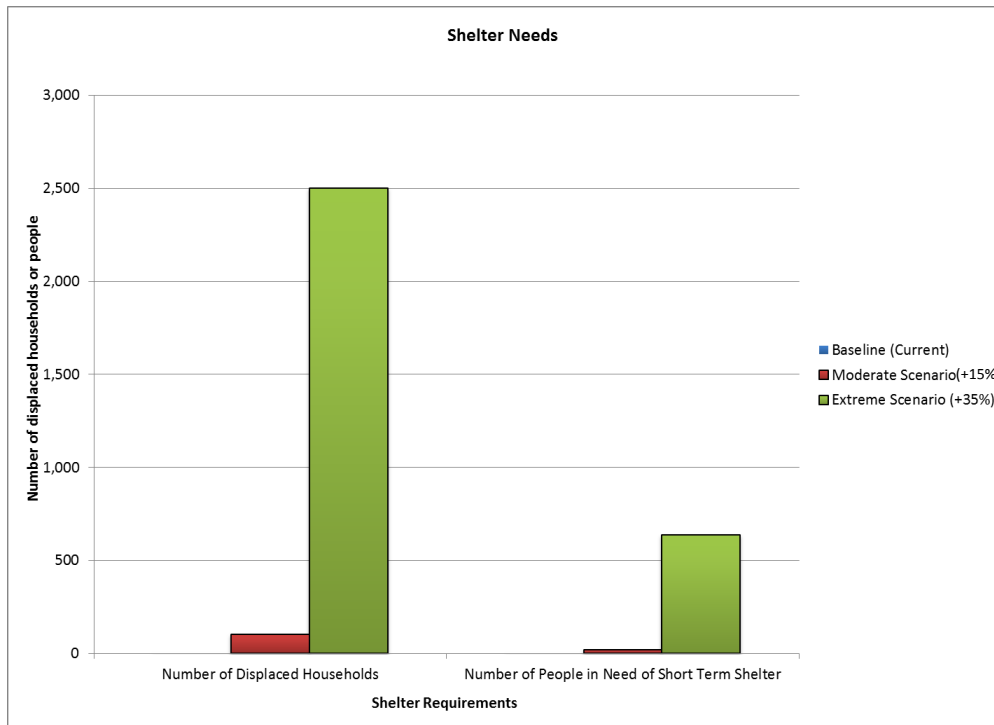
Economic losses for Tropical Storm Fay were not as significant as losses caused by other storms such as Hurricanes Andrew or Charley (Figure 6.36a). Loss estimates were lower for TS Fay when compared to TS Mitch. Residential losses were approximately \$80 million for baseline conditions and approximately \$2 billion under extreme conditions. For commercial buildings, losses were \$2.8 million under baseline conditions and increased to approximately \$130 million in extreme conditions. For all occupancy types, losses were approximately \$83 million for the baseline scenario and increased to \$2.1 billion for the extreme scenario.

6.1.12.3 Shelter Needs and Requirements

TS Fay had a minimal impact on shelter needs and requirements (Figure 6.36b). Under the baseline scenario, there were no displaced households and no people in need of short-term shelter. Under the extreme scenario, the number of displaced households



a.



b.

Figure 6.36. (a) Building Economic Estimated Losses based on Occupancy Type and (b) Shelter Needs and Requirements

increased to 2500 and the number of people in need of short-term shelter increased to 637.

6.2 Conclusion

The case study storms in this analysis represented the past and potential future hurricane impacts experienced by Florida. Using the HAZUS-MH Hurricane Model, building damage, economic losses, and social impacts from hurricane winds for all three scenarios were estimated based on Florida's growing population and increasing housing and property development. Storms classified as major hurricanes were expected to have the greatest impact as their intensity was increased in the climate change scenarios. However, results show that storm intensity is not an accurate indicator of building and economic losses. The values for building damage, economic losses, and social impacts for all case study storms are summarized in Tables 6.1-6.3.

Residential buildings typically experienced more damage than commercial buildings. Major hurricanes generally caused the greatest building damages in Florida. Damage values for the extreme scenario greatly increased from the baseline scenario for major hurricanes. All major hurricanes followed this trend except for Hurricane Ivan. Although Ivan was a category 3 at landfall, the values for damage categories (except for no damage category) were insignificant. Economic losses for all occupancy types for Ivan under the extreme scenario were approximately \$4 billion. Hurricane Wilma, which was also category 3 at landfall, experienced losses of almost \$110 billion under the

Storm Name	Residential Building Damage by Count					Economic Losses			Shelter Needs	
	No Damage	Minor	Moderate	Severe	Destruction	Residential	Commercial	All	Displaced Households	Short Term Shelter
Miami 1926	4,776,418	642,092	480,003	233,020	77,903	59,039,383.34	16,356,432.73	80,508,243.26	453,323	133,368
Labor Day 1935	6,122,197	64,655	14,716	2,960	4,909	2,313,824.61	335,505.68	2,738,871.09	6,695	1,572
Agnes	6,209,055	365	16	0	0	10,381.55	332.40	10,824.99	0	0
Andrew	5,861,084	137,854	113,782	68,182	28,535	16,490,143.02	4,218,721.89	21,980,109.57	115,180	32,746
Georges	6,144,896	51,129	11,501	1,359	552	1,360,910.21	150,537.18	1,552,477.29	2,447	618
Mitch	6,204,456	4,666	303	12	0	152,896.99	7,241.56	161,787.83	52	12
Irene	6,154,391	48,452	6,474	119	1	1,497,746.45	85,356.41	1,600,781.56	3,018	834
Charley	6,038,361	111,798	41,714	11,654	5,910	3,310,680.52	412,010.02	3,894,417.06	13,533	3,536
Frances	6,098,319	97,501	13,202	347	69	2,218,823.98	149,803.50	2,411,232.60	3,352	850
Ivan	6,164,591	36,824	7,534	379	109	516,585.78	59,155.00	597,147.84	1,196	315
Wilma	5,735,003	361,481	105,606	6,306	1,041	8,142,415.75	1,415,574.35	9,980,630.59	37,977	10,909
Fay	6,206,932	2,414	87	4	0	79,019.30	2,775.07	83,216.06	0	0

Table 6.1. Summary of building damage, economic losses, and shelter needs for all case study storms under the baseline (current) scenario.

Storm Name	Residential Building Damage by Count					Economic Losses			Shelter Needs	
	No Damage	Minor	Moderate	Severe	Destruction	Residential	Commercial	All	Displaced Households	Short Term Shelter
Miami 1926	4,635,393	334,382	391,440	413,912	434,310	127,252,050.14	34,470,861.55	172,514,344.87	1,008,233	291,731
Labor Day 1935	5,179,103	240,168	235,863	232,846	321,457	76,443,337.02	13,472,234.87	94,847,784.32	538,961	131,219
Agnes	6,206,447	2,744	240	5	1	45,257.92	2,109.18	48,005.25	24	6
Andrew	5,548,865	148,685	125,727	165,450	220,710	64,186,458.19	19,553,757.30	89,334,519.51	517,187	157,635
Georges	6,043,209	120,549	33,492	8,225	3,961	3,701,840.01	547,924.64	4,412,376.96	12,764	3,271
Mitch	6,194,471	13,533	1,401	32	0	445,114.27	22,886.17	472,696.88	426	104
Irene	5,936,825	227,633	43,572	1,202	205	4,571,999.28	486,975.84	5,192,398.06	15,887	4,464
Charley	5,302,748	424,285	230,312	140,974	111,117	33,767,815.28	5,547,501.32	41,492,949.77	225,412	56,070
Frances	5,817,805	196,683	122,315	52,565	20,069	12,249,585.44	2,391,129.17	15,560,841.63	67,412	16,583
Ivan	6,135,282	47,087	21,270	4,178	1,620	1,234,748.38	182,345.55	1,501,076.36	5,465	1,385
Wilma	5,319,361	395,615	288,919	148,625	56,918	37,589,620.32	8,320,275.96	48,588,231.25	252,779	64,053
Fay	6,193,950	14,509	950	23	4	443,925.10	16,412.91	466,835.05	102	20

Table 6.2. Summary of building damage, economic losses, and shelter needs for all case study storms under the moderate (15%) scenario.

Storm Name	Residential Building Damage by Count					Economic Losses			Shelter Needs	
	No Damage	Minor	Moderate	Severe	Destruction	Residential	Commercial	All	Displaced Households	Short Term Shelter
Miami 1926	4,493,427	234,076	252,898	421,768	807,269	179,199,810.05	46,141,953.69	240,370,158.10	1,380,477	387,120
Labor Day 1935	4,963,143	218,408	210,116	267,102	550,667	108,252,563.52	20,119,415.10	136,214,987.70	791,063	196,962
Agnes	6,188,329	17,125	3,689	214	80	203,748.55	22,779.77	234,965.29	449	117
Andrew	5,406,226	149,638	119,858	167,583	366,132	90,487,409.27	28,641,612.74	127,657,160.58	718,620	221,726
Georges	5,816,709	260,186	90,671	24,849	17,022	9,623,834.09	1,643,375.59	11,798,098.04	43,731	11,250
Mitch	6,138,522	60,902	9,757	228	28	1,474,147.53	108,940.16	1,607,341.99	3,292	842
Irene	5,302,476	614,725	253,239	32,369	6,628	16,604,910.87	3,723,375.52	21,562,466.55	78,864	21,893
Charley	4,577,278	525,293	450,099	287,976	368,791	86,014,767.94	16,096,691.89	108,613,465.63	598,029	151,220
Frances	5,465,823	334,170	173,951	129,483	106,010	33,281,367.94	6,453,370.51	42,266,284.45	227,569	56,740
Ivan	6,099,919	48,909	37,423	15,477	7,709	3,061,294.81	511,723.07	3,814,905.06	20,926	5,373
Wilma	5,020,899	337,725	316,443	312,423	221,948	85,188,745.69	18,169,649.13	109,381,299.39	640,787	160,343
Fay	6,087,055	106,937	14,726	491	228	1,936,121.08	129,198.25	2,118,897.75	2,500	637

Table 6.3. Summary of building damage, economic losses, and shelter needs for all case study storms under the extreme (35%) scenario.

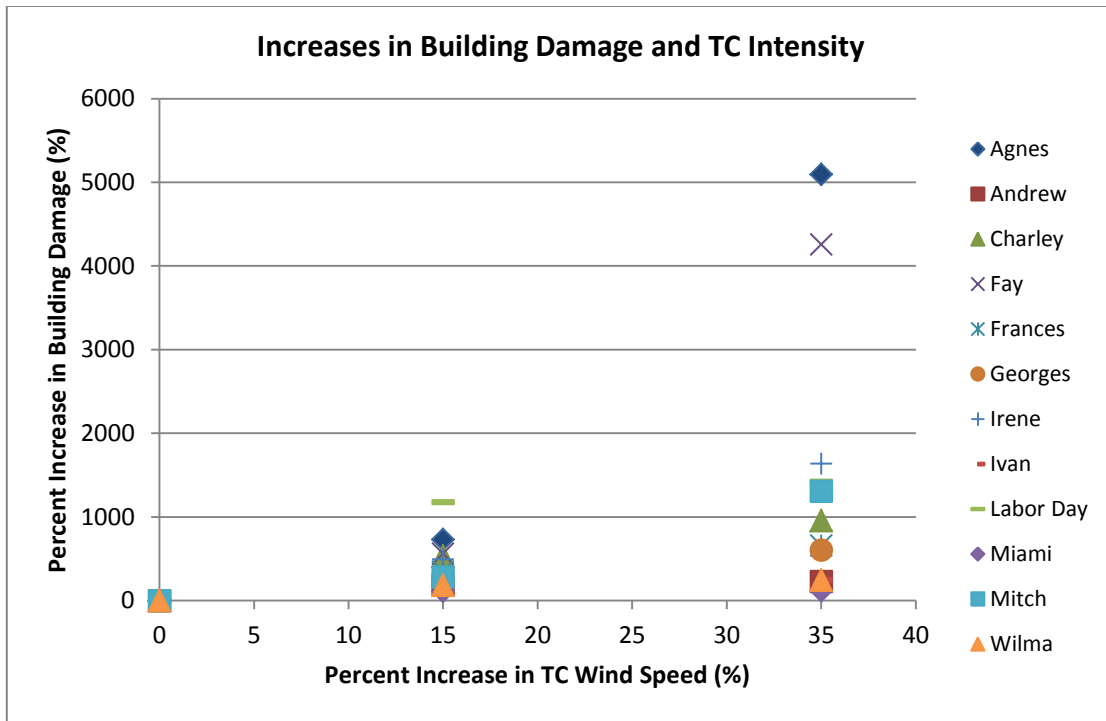
extreme scenario for all occupancy types. A similar trend can be seen for shelter needs and requirements values between Ivan and Wilma where values are greater for Wilma than for Ivan. This may be a result of the location of landfall for both storms. Hurricane Ivan made landfall in the Florida Panhandle, while Wilma made landfall in South Florida. Wilma impacted a more populated region and affected major cities such as Fort Lauderdale and Miami.

Hurricanes Irene and Frances were not major hurricanes when they made landfall, yet they greatly affected the regions where they made landfall. Hurricane Irene made landfall as a category 1 storm. It had a significant impact on the Keys and then made landfall in southwest Florida. Irene also had an impact on southeast Florida. Hurricane Frances was a category 2 storm when it made landfall in southeastern Florida. Frances crossed central Florida and then made landfall in the Big Bend region. Both storms made landfall in regions that are highly populated. Under extreme scenario conditions, Irene caused minor and moderate damages to both residential and commercial buildings. Frances caused damages in all the damage categories. The increases in scenario intensity made a difference in the impact Frances had on South Florida. Economic losses for all occupancy types under extreme conditions were approximately \$22 billion for Irene and \$42 billion for Frances. For Irene, the number of displaced households is approximately 80,000 under extreme conditions and about 20,000 people are in need of short-term shelter. Shelter needs were higher for Frances. Approximately 200,000 households were displaced and over 50,000 people were in need of short-term shelter under the extreme scenario. Building damage, economic loss, and

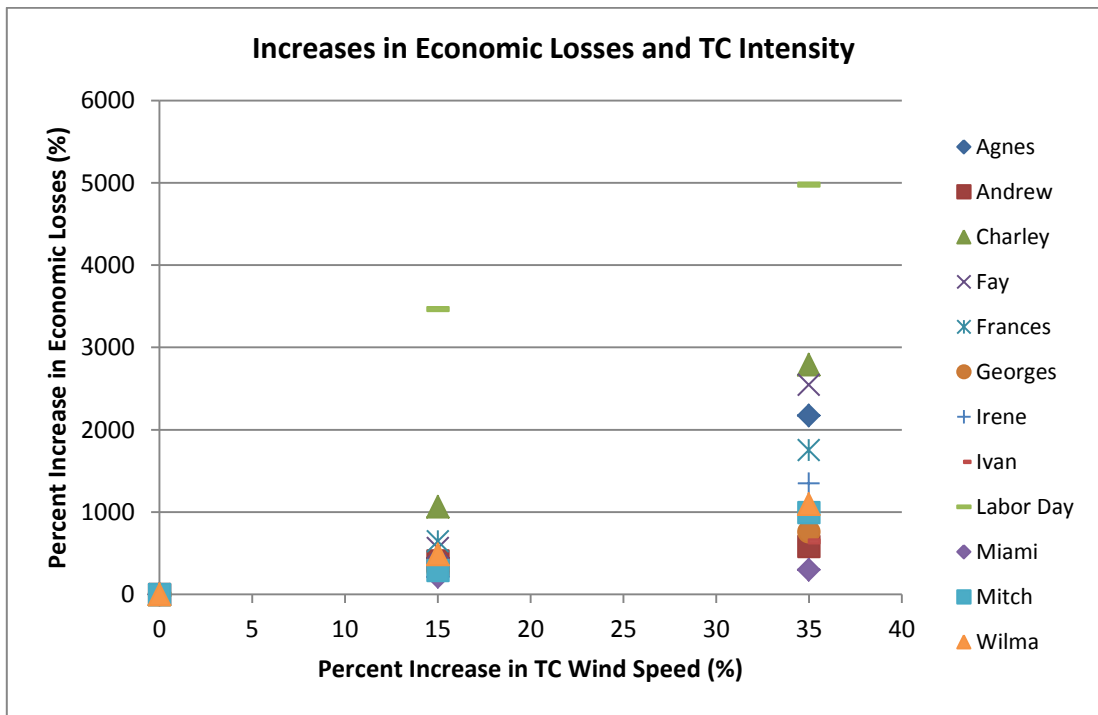
shelter needs were higher for Irene and Frances than for Agnes (category 1) and Georges (category 2). Although Agnes and Georges were of a similar intensity, they had less of an impact because they made landfall in less populated regions.

The 2004 hurricane season was extremely active for Florida. In a six week period, Hurricanes Charley, Frances, Ivan and Jeanne all made landfall in Florida (Barnes 2007). Out of those four storms, only Ivan did not cross through central Florida. Polk County is located in central Florida (Figure 3.1). It stands out among the counties in central Florida because of its track-derived return periods. The track-derived return periods from Objective 1 for Hurricanes Only (Figure 4.7) and for Major Hurricanes Only (Figure 4.9) are lower for Polk County than for its surrounding counties. The 2004 storm tracks partially validate the calculated track-derived return periods for Polk County. According to Barnes (Barnes 2007), the four storms caused damages that totaled \$20.5 billion in losses. Hurricane Jeanne was not included as a case study in this objective. The total building economic losses under baseline conditions for the three storms (Charley, Frances, and Ivan) were approximately \$7 billion. Under the extreme scenario, the economic losses increased to approximately \$155 billion. There were approximately 846,000 displaced households and 213,000 people in need of short-term shelter as a result of Charley, Frances, and Ivan under the extreme scenario.

The percent increases in building damages, economic losses, and shelter needs and the percent increase in TC intensity were compared in Figures 6.37a to 6.37c. The scatterplots help determine which storms experience the greatest increase in values

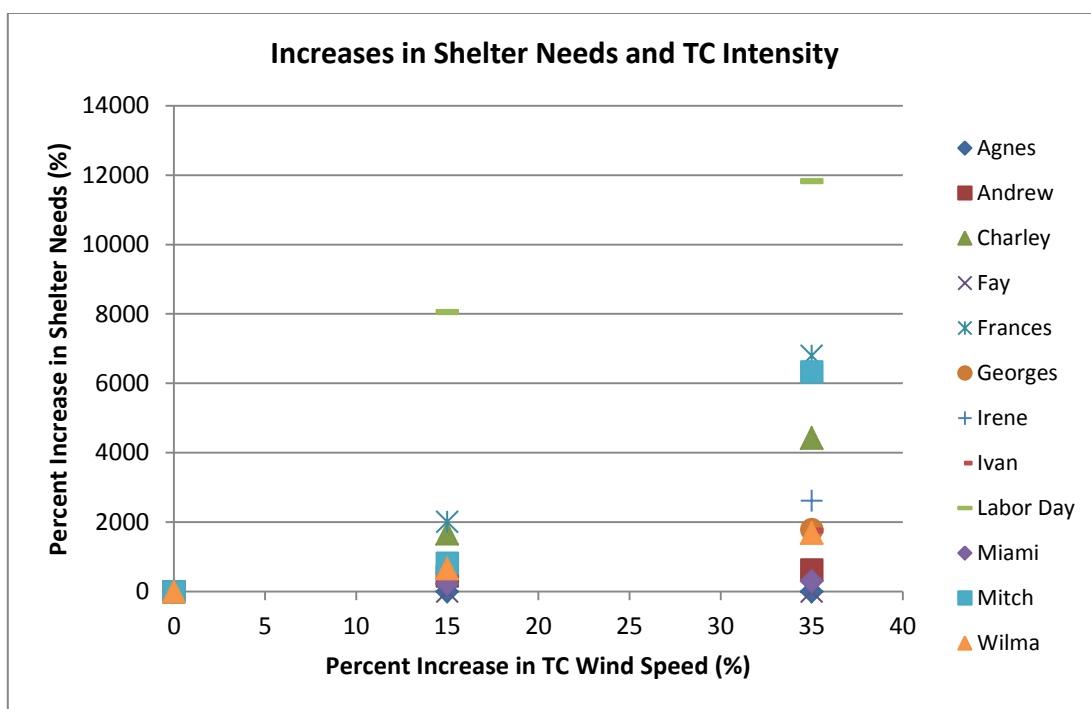


a.



b.

Figure 6.37. Comparison of percent increase in (a) building damage, (b) economic losses, and (c) shelter needs versus percent increase in TC intensity.



c. **Figure 6.37.** Continued.

between the baseline and moderate intensities and the baseline and extreme intensities. For building damage, weaker storms such as Agnes and Fay had a greater percent increase between the baseline and extreme intensity scenarios (Figure 6.37a). The percent increases correspond with the histograms for the storms which had the majority of the damage values in the no damage category (Figures 6.8a and 6.35a). However, the Labor Day hurricane had the highest percent increase for the 15% intensity increase. For economic losses, major hurricanes such as the Labor Day hurricane and Charley had the greatest percent increases for both the 15% and 35% intensity increases (Figure 6.37b). These storms affected regions in southern Florida that are densely populated. The Labor Day hurricane also had the greatest percent increase in shelter needs (Figure 6.37c). TS

Mitch and Hurricane Frances followed the Labor Day hurricane with the second and third highest percent increase values. The changes in shelter needs are the most sensitive to intensity increases for the Labor Day hurricane, TS Mitch, and Hurricane Frances. The storms vary in category but all made landfall in densely populated areas throughout central and southern Florida. The population of the landfall locations may account for the storms' percent increase values. The Labor Day hurricane is among the highest values for all scatterplots. This storm made landfall as a category 5 and there would be serious implications if a similar yet more intense storm were to make landfall in Florida in the future.

The boxplots show the spread of the ranges of the data for the moderate and extreme intensity scenarios. The baseline intensity scenario was not included since the values are all zero. For building damage, the average percent increase is 350% and the range of increase is 100-800% for the moderate (15%) intensity scenario. For the extreme (35%) intensity scenario, the average increase is 740% and the spread is 100-1700% (Figure 6.38a). For economic losses, the moderate intensity scenario had an average of 390% and a spread of 200-650%. The extreme intensity scenario had an average of 1400% and a range of 300-2800% (Figure 6.38b). The average for the moderate intensity scenario for shelter needs is 406% and the range of the percent increases is from 0-800%.

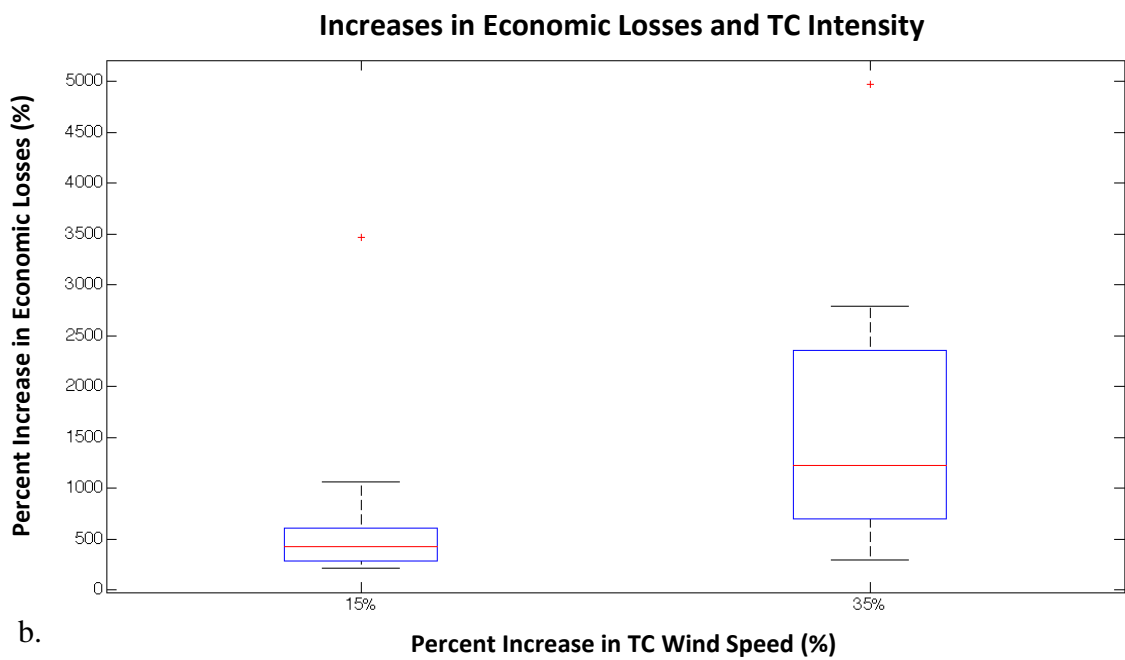
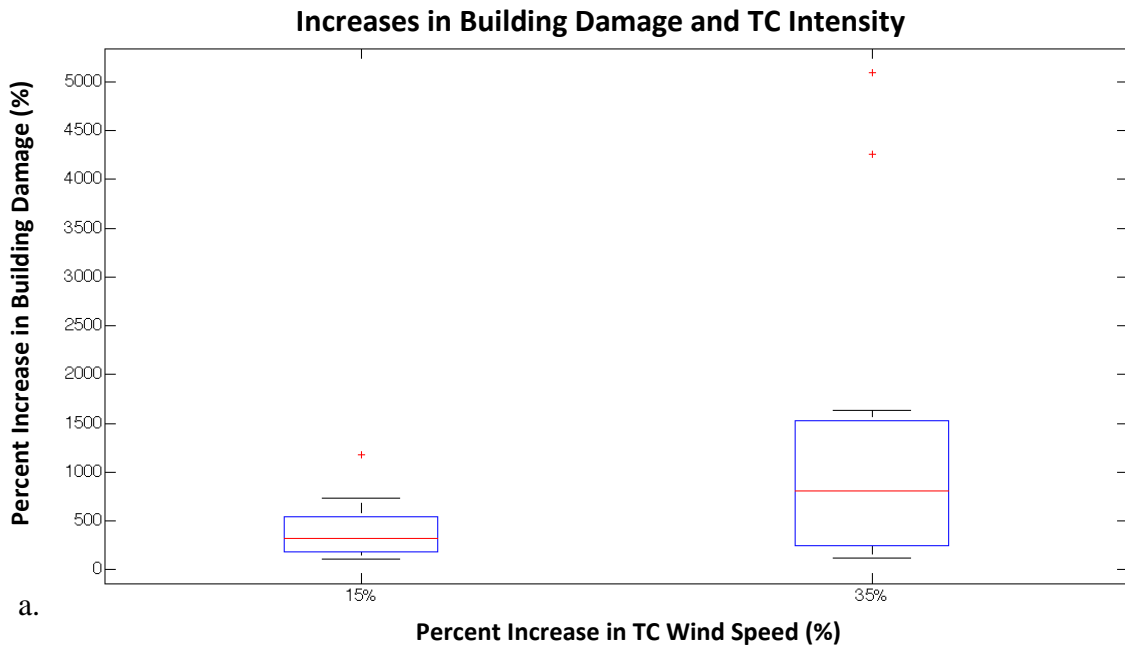


Figure 6.38. Boxplots of percent increase in (a) building damage, (b) economic losses, and (c) shelter needs versus percent increase in TC intensity.

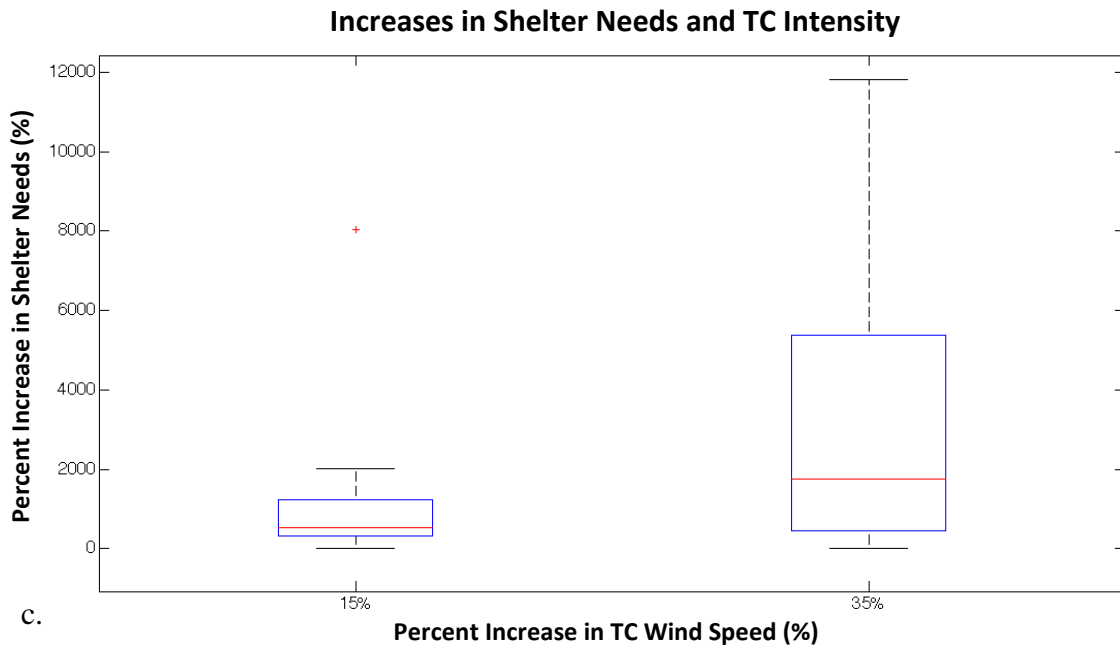


Figure 6.38. Continued.

The average is 1500% for the extreme intensity scenario and the range is 0-4500% (Figure 6.38c). As the storm intensity increases, the spread between the values increases for building damage, economic losses, and shelter needs. The results of the spread shown by the scatterplots and boxplots are storm specific. The 12 case study storms influenced the spread based on their intensities at landfall and their location of landfall. Including more storms in the sensitivity analysis would provide more precise results.

There are limitations to the methodology performed for Objective 3. The results of this analysis were sensitive to the subjective decisions that were made. Two case study storms from each category on the Saffir-Simpson scale (including tropical storms)

were subjectively chosen to display the distribution of storm intensities. These 12 storms, however, may not be fully representative of all storms that have made landfall in Florida. Objective 3 only examines the influence of a warming climate on TC intensity. The intensity scenarios were subjectively chosen based on the findings from Objective 2. Changes in TC frequency and track are not observed in this analysis. The results from the analysis are not fully representative of the effects of climate change on hurricane behavior. The findings may not be generalizable to other regions but illustrate how storms influenced by climate change may affect Florida.

Location of landfall significantly determines a storm's impact. A storm's category does not accurately determine the impact it can have on a region. The greatest effects of a storm will be experienced in densely populated areas in spite of climatic changes. The majority of case study storms in this analysis made landfall in South Florida. South Florida is a highly populated region that continues to grow and develop. Regardless of what changes in storm intensity occur in the future, the population of South Florida will remain extremely vulnerable to storm impacts as a result of its continuous growth.

CHAPTER VII

CONCLUSION

7.1 Summary

In this study, the potential influence of climate change on hurricane characteristics and impacts was analyzed for Florida. In Objective 1, track-derived and wind-derived return periods were calculated for all Florida counties. Results were categorized into four groups; all storms, tropical storms only, hurricanes only, and major hurricanes only. The track-derived return periods reflect the number of times a storm has crossed through a county. Wind-derived return periods account for the spatial extent of a storm's wind field. Both track-derived and wind-derived return periods show southern Florida as the region that is most prone to TC landfalls and winds for all categories. Risk factors were calculated for all counties with South Florida having the highest risk factor values. Results from Objective 1 show that south Florida counties have the highest risk of experiencing TC landfalls and wind impacts in the future based on past observations.

The effects of a warming climate on hurricane behavior and trends remain a contested topic in the literature. Objective 2 examined the role of climate change in future TC frequency, intensity, and tracks. Potential changes in TC behaviors may be attributed to anthropogenic climate change or to natural variability. Globally, storm frequency has not changed significantly since 1970 (Knutson et al. 2010). In the Atlantic basin, trends of increasing storm frequency have been observed. However, the increases are likely attributed to the increased storm counts as a result of a storm undercount in the

pre-satellite era (Landsea 2007). An increase in short duration storm counts may have also biased the trend of storm frequency for the Atlantic basin (Landsea et al. 2010). Although a variety of models have been used to project a change in storm frequency, there is no consensus among them. Models predict an increase in the frequency of the most intense storms for the Atlantic basin (Bender et al. 2010; Knutson et al. 2010). TC frequency is expected to either remain the same or to decrease (Knutson et al. 2010).

According to theory and climate model projections, an increase in SST will likely result in an increase in TC intensity (Emanuel 2005a). It is still difficult to determine whether increases in intensity can be attributed to a warming climate or if the trends are a result of natural variability. Model simulations project mean maximum wind speed to increase globally by 2-11% by 2100 (Knutson et al. 2010). According to Pielke (2007), global TC intensity is projected to increase by 0-18 % by 2050 and by 0-36% by 2100.

Bender et al. (2010) showed an increase in storm tracks for category 4 or 5 hurricanes in the western Atlantic (between 20°N and 40°N). However, model projections show that large-scale changes in storm tracks are not expected to occur (Knutson et al. 2010). Storm tracks are not expected to vary as a result of climate change (Knutson et al. 2010). Natural variability in TC frequency, intensity, and tracks can be attributed to atmospheric oscillations. Ocean-atmosphere circulation patterns can influence SST, vertical wind shear, and other factors that influence TC activity, intensity, and tracks (Goldenberg et al. 2001).

Pielke (2007) examines the economic and societal impacts of future influences of climate change on TCs. He used an increase of 18% and 36% for the sensitivity analysis

in his study (Pielke 2007). Based on the findings in the literature, three hurricane intensity scenarios were created for Objective 3. A baseline scenario reflecting current climate conditions, a moderate scenario reflecting a 15% increase in storm intensity and an extreme scenario with a 35% storm intensity increase were used in Objective 3.

In the final objective, twelve case storms were chosen to simulate how climate change may potentially affect hurricane damage and loss for Florida. Using the HAZUS-MH Hurricane Model, each case storm was run under three storm intensity scenarios. The baseline scenario simulated what would happen if the storm were to make landfall under current conditions. The moderate scenario examines impacts under a 15% increase in storm intensity. Under the extreme scenario, storm intensity is increased by 35%. Results show that landfall location plays a significant role on the impacts caused by TCs. Storm intensity at landfall also determined the degree of damages and losses caused by the storm. Based on the boxplots, the spread of percent values increases as storm intensity increases for building damage, economic losses, and shelter needs. The spread in the data shown in the scatterplots and boxplots is storm specific. Changes in TC intensity as a result of climate change will have the greatest impact on economic losses.

In Objective 1, Florida's hurricane event risk was defined by the calculated return periods. The counties most likely to experience TC landfalls were found in southeastern Florida. Based on the damage and loss values obtained from Objective 3, Florida's vulnerability is dependent on where a storm makes landfall. Damage and loss values will be greater in more populated and developed areas. Outcome risk is the product of event risk and vulnerability. Case study storms were analyzed to determine

the effect of intensified storms in Florida. Based on its landfall history and high population, southeastern Florida has the highest outcome risk of intense landfalling storms.

A storm can be classified as a major hurricane yet not cause as much damage or losses as a weaker storm if it made landfall in a less populated area. Although storm intensity can be used to predict the impact a storm will have at landfall, where it makes landfall is just as significant. Regardless of how TC intensity changes as a result of future climate change, regions that are densely populated will remain the most vulnerable to TC related damages and losses.

7.2 Implications

The results of this study have various implications for regions vulnerable to hurricane landfalls. Climate change can potentially exacerbate hurricane impacts for regions, such as Florida, that already experience devastating effects from hurricanes.

The hurricane seasons of 2004 and 2005 were record-breaking and significant for Florida. In 2004, there were 14 named storms, 9 of which became hurricanes and four of those made landfall in the U.S. (Kantha 2006). All four U.S. landfalling hurricanes made landfall in Florida within a six week period (Barnes 2007). The 2005 hurricane season was a record-breaking season. There were 27 named storms of which 14 became hurricanes (Anthes et al. 2006). Three of the fourteen hurricanes reached category 5 (Katrina, Rita, Wilma) and all made a U.S. landfall. Hurricane Wilma made landfall in Florida as a category 3. Wilma was the last major hurricane to make landfall in the U.S

in October 2005. Complacency can result from such a gap between hurricane landfalls (Pielke Jr 1997). According to sociologists, the worst impacts of a hurricane are remembered by people for approximately seven years (Blake et al. 2011). Although Florida has been impacted by tropical storms, such as Fay, since Wilma, residents may perceive their risk to have decreased as a result of the large gap between landfalls. This complacency can result in a lack of preparedness and concern.

The methodology used in this study can be applied to other hurricane prone regions. The application of a parametric wind field model may also provide a new perspective when examining the relationship between hurricanes and climate change since it has yet to be done by other studies.

This study can benefit federal, state and local governments in evacuation decisions and disaster planning. Local governments are often in charge of issuing evacuation orders and the role of local emergency management is also important during disasters (Burby 2006). Emergency management consists of four major roles; hazard mitigation, emergency preparedness, emergency response and disaster recovery (Lindell 2004). The Federal Emergency Management Agency (FEMA) provides funds to populations impacted by a natural disaster as well as mitigation funds in order to lessen the impact of natural disasters in areas that are vulnerable (Dynes 1992). Non-profit organizations such as the American Red Cross also provide vulnerable populations with resources to prepare and recover from an event (Lindell 2004). Information on how hurricane trends are expected to change in the future can help government, agencies and organizations in preparing for any changes in their actions.

Knowing how hurricanes will affect a certain area in the future can provide the public with the knowledge necessary to increase their preparedness (Lindell 2004). Hurricane preparedness and education can help increase awareness and could lead to informed decisions when faced with a storm (Lindell 2004).

Disaster mitigation is important in preparing a vulnerable area for the possible effects of a natural hazard. Mitigation allows for the effects of threatening events to be lessened by preparing the public. As coastal populations continue to increase, the number of lives and properties at risk greatly increases as well (Dawson 2006). Understanding how climate change may affect future hurricane trends in vulnerable areas can play a vital role in protecting both property and lives.

7.3 Limitations

Limitations in this study include the use of hurricane data starting from 1900. Data from the pre-satellite era may result in an undercount of storms (Landsea 2007). This may result in an inaccurate number of storms included in the return period calculations. Storm data were collected for 12 case study storms for Objective 3. The data were obtained from different datasets. Central pressure and Rmax values were provided for storms that formed after 1988. For earlier storms, the values were calculated and may not be as accurate as the values collected from observations. HAZUS-MH Hurricane Model was used to estimate damages and losses in Objective 3. The model only considers changes in hurricane intensity and does not consider changes in frequency or track. Results do not include all storms and may not be a representative

sample of the effects of a warming climate. The intensity scenarios chosen for this study were subjectively selected and the results may be sensitive to those decisions. Although HAZUS-MH was an appropriate choice for the analysis performed in this study, the results from this study may not be precise for predicting the effects that storms will have on damages and losses.

Future research could utilize the same methodology employed in this study to investigate hurricane impacts in other coastal states. The HAZUS-MH Hurricane Model could also be run for a larger number of storms to validate the results of this study.

7.4 Conclusion

Florida is one of the most vulnerable regions in the U.S. when it comes to TC impacts. The effects of a warming climate have the potential to devastate an already vulnerable region. Regardless of how climate change affects TC frequency, intensity, and track in the future, the population at risk of TC impacts will increase as cities across Florida continue to grow and develop.

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