THE INFLUENCE OF LANDFALL VARIATION ON TROPICAL CYCLONE LOSSES IN THE UNITED STATES AS SIMULATED BY HAZUS

by

KEVIN JOSEPH SHARP

B.A., University of Tennessee, 2007

A thesis submitted to the

Faculty of the Graduate School of the

University of Colorado in partial fulfillment

of the requirement for the degree of

Master of Arts

Department of Geography

2009

The thesis entitled:
The Influence of Landfall Variation on Tropical Cyclone Losses in the United States
as Simulated by HAZUS
written by Kevin Joseph Sharp
has been approved for the Department of Geography

Dr. William R. Travis

Dr. Peter D. Blanken

Dr. Roger A. Pielke Sr.

Date: July 9, 2009

The final copy of this thesis has been examined by the signatories, and we
Find that both the content and the form meet acceptable presentation standards
Of the scholarly work in the above mentioned discipline.

ABSTRACT

Sharp, Kevin Joseph (M.A., Geography)

The Influence of Landfall Variation on Tropical Cyclone Losses in the United States as Simulated by HAZUS

Thesis directed by Dr. William R. Travis

Tropical cyclone losses in the United States have shown an increasing trend since the beginning of the 20th century. This is mainly due to increased exposure along America's coast. The amount of coastal property at risk persistently increases due to inflation, wealth increase, and population growth. When researchers have normalized the loss record to remove the influence of exposure and vulnerability change, no trend can be discerned in the damage record. This has been used to refute the claim that tropical cyclones are becoming more potentially destructive, and to keep the locus of explanation firmly in socio-demographic trends. But physical variation, in storm size, intensity and location, still make a significant difference in the impact of any individual storm event. This fact occasionally induces calls for renewed efforts at hurricane modification and routinely evokes a sense of either relief or alarm at "close calls" that, except for a difference of a few miles in landfall location or a modest weakening of peak winds, separate hurricane disasters from catastrophes. This project examined the effect of landfall location on storm damage using the Federal Emergency Management Agency's (FEMA) risk assessment model, HAZUS. Thirty-mile track shifts were prescribed for the top 10 most damaging storms in the normalized record since 1988. The alternate storms yielded drastically different damage estimates from the original storms, indicating large spatial variations in exposure. Each landfall shift resulted in a rank change in the overall normalized record. The damage record is dominated by individual extreme events like those used in this analysis, and although random, differences in landfall location would presumably average out in a long record. The fact that a few storms account for a large majority of losses, and that small differences in their landfall yield large differences in impact, points to a very large noise to signal ratio that would make it difficult to discern a climate-induced trend, and may also obscure some dimensions of socio-economic exposure and vulnerability trends.

DEDICATION

This thesis is dedicated to my family. Their support and encouragement have led me to pursue an education that pertains to my passion for natural hazards and meteorology. Without them, I would not be who I am today.

ACKNOWLEDGEMENTS

This project would not have been possible without the assistance and instruction of many people at the University of Colorado. I would like to thank Gene Longenecker for providing and assisting with HAZUS. I would also like to thank Dr. Roger Pielke Sr. for his role in rekindling my passion for tropical cyclones. I owe a huge debt of gratitude to Dr. Bill Travis for all of his support throughout my graduate school career. His contribution to my educational experience has been invaluable. This project would not have been possible without the resources he generously provided.

TABLE OF CONTENTS

LIST OF TABLES

PAGE

LIST OF FIGURES

PAGE

I. INTRODUCTION

Tropical cyclones are large low-pressure storms that form over the tropical oceans of the Earth’s low latitudes, typically between 30°N and 30°S. These storms develop in every ocean except for the Arctic. Tropical cyclones are characterized by strong winds, heavy rain, storm surges, high waves, tornadoes, and mesovortices. Conversion of the ocean’s heat energy into latent heat provides the energy needed for a storm to develop and strengthen. Latent heat is released as evaporated water vapor condenses aloft (Pielke Sr., 1990). The average tropical cyclone can release 50 to 200 trillion watts of heat energy, which at the high end is similar to a ten megaton nuclear bomb exploding every twenty minutes (NCAR, 2006). Factors that influence the development of tropical cyclones include water temperature, air mass characteristics, upper-level wind velocity, equatorial proximity, and land proximity. Natural disasters can result when these powerful storms interact with landmasses and human populations.

The Atlantic hurricane season lasts from June 1 to November 30. The peak of the season is from August to October. The number of tropical cyclones in a given season depends on many factors. Local and global atmospheric and oceanic patterns influence tropical cyclone formation, making seasonal predictions nearly impossible. Some of the atmospheric patterns that influence tropical cyclone formation, such as the El Niño Southern Oscillation (ENSO), the Atlantic Multidecadal Oscillation (AMO), and the North Atlantic Oscillation (NAO), can take several years or decades to complete one cycle (Bell, 2008; Mayfield, 2005; Pielke Sr., 1990). Conditions that inhibit or aid in the development of hurricanes can last for several seasons.

Lives and property are put at risk when people settle in coastal areas that are affected by tropical cyclones. More tropical cyclones make landfall on the US than on any other nation (Shultz, Russell, & Espinel, 2005). Since the beginning of the 20th century, mortality rates due to hurricanes in the United States have decreased drastically while property damage has increased. Advances in forecasting and technology have led to more efficient early warning systems, which have saved numerous lives. Property vulnerability has increased as development continues along America's Gulf and Atlantic coasts (Pielke Jr. & Pielke Sr., 1997).

In the past decade, controversy has emerged over whether or not increasing damage due to hurricanes can be attributed to human-induced global warming. Expert analysts fall on both sides of the argument (Pielke Jr., Landsea, Mayfield, Laver, & Pasch, 2005). The 2004 and 2005 hurricane seasons were abnormally active and destructive with $50 billion and $128 billion in total damage respectively. The two year period set a record for number of tropical cyclones in the Atlantic and tied the record for major hurricanes, which was set in the 1950 and 1951 seasons (Blake, Rappaport, & Landsea, 2007). These unusually active seasons occurred during a time when climate change issues were gaining popularity. Hurricane Katrina in 2005 became the most damaging hurricane in America's history. Shortly thereafter, Al Gore gave a speech to the National Sierra Club Convention in San Francisco claiming that global warming was responsible for "unusually warm waters in the gulf," which provided Hurricane Katrina fuel to strengthen (Gore, 2005). Katrina made landfall as a category 3 hurricane in southeast Louisiana. The extraordinary damage caused by this storm was due more to its close proximity to vulnerable property than to any unprecedented intensity (vulnerability and exposure will be used interchangeably in this project). In fact, the trend of increasing overall damage due to hurricanes in the United States disappears when the data are normalized (Pielke Jr. et al., 2008). Using individual seasons or storms as benchmarks can provide a distorted view of the underlying factors that are responsible for the increase in vulnerability of America's coastal population.

Risk assessment models can be used to predict the impact of disasters on population and property. The Federal Emergency Management Agency's (FEMA) HAZUS-MH can be used to predict losses due to floods, hurricane winds, and earthquakes (FEMA, 2007). The user can input factors to simulate a landfalling hurricane on a coastal area of the United States. Though it is doubtful that the loss figures generated by HAZUS-MH closely match actual losses as they would be measured by assessment teams on the ground, the model does generate losses that can be compared among events, both real and simulated. The most destructive tropical cyclones in the history of the United States have one thing in common: They made landfall on highly developed areas. These storms would likely fall from the ranks had they made landfall on significantly less vulnerable areas. Minor shifts in landfall location could drastically change the damage figures. The entire hurricane damage record would look much different had all the storms made landfall on different locations. Slight adjustments to historical landfalls with HAZUS should reveal that the noise to signal ratio is very large in the loss record.

II: LITERATURE REVIEW

Long-term studies on hurricane damage trends in the United States have found that losses have been increasing since the beginning of the 20th century. This increase is most prominent in the last three decades. Figure 1 shows the trend in direct impact hurricane damage adjusted for inflation with an 11 year average. "Direct impacts" account for losses that occur as an immediate result of the hurricane, such as wind damage. "Secondary impacts" result from direct impacts, and include increases in disease following the storm. "Tertiary impacts" include delayed effects such as changes in tax revenue (Pielke Jr. & Landsea, 1998). Data for direct impacts are more comprehensive and comparable than data for secondary and tertiary impacts. Furthermore, secondary and tertiary impacts can be assumed to follow a similar trend to direct impacts.

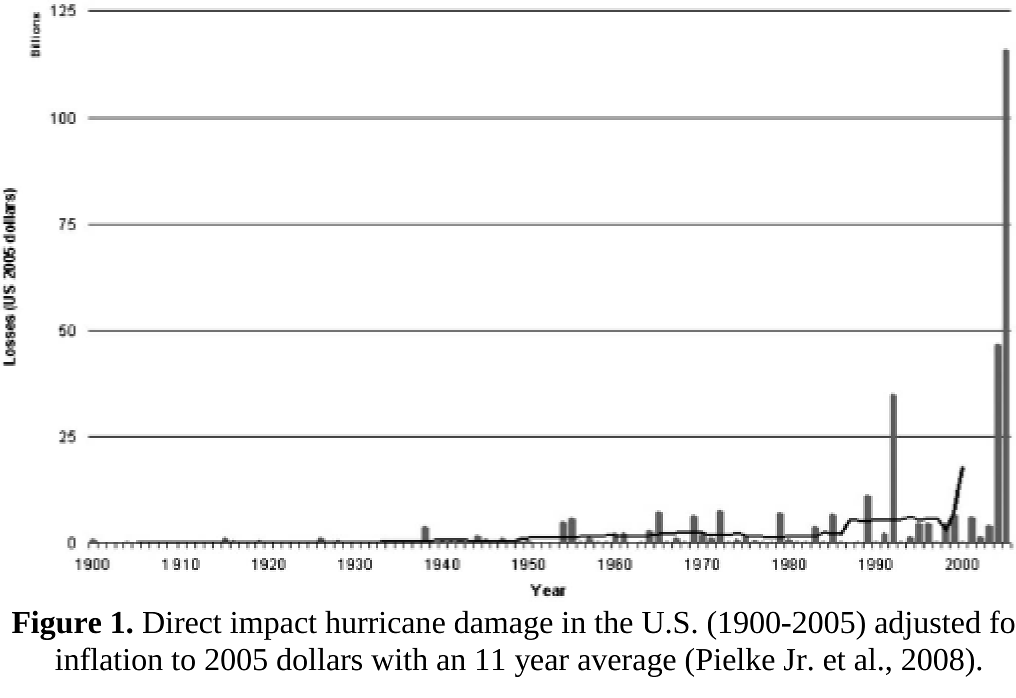


Figure 1. Direct impact hurricane damage in the U.S. (1900-2005) adjusted for inflation to 2005 dollars with an 11 year average (Pielke Jr. et al., 2008).

Figure 1 shows that total damage due to hurricanes has been increasing, especially in recent decades. Events that lead to unprecedented losses have also been increasing. This has led many to hypothesize that the increase in losses can be attributed to a corresponding increase in the number and intensity of hurricanes. In 1995, a U.S. Senate report claimed that hurricanes "have become increasingly frequent and severe over the last four decades as climatic conditions have changed in the tropics" (Senate, 1995). The data shows that there was actually a decrease in major hurricanes for the decades preceding the senate report. Though major hurricanes make up less than a quarter of the total number of tropical cyclones, they account for 85 percent of the total damage (Pielke Jr. et al., 2008). While the number of major hurricanes per season decreased in the latter decades of the 20th century, the total losses continued to increase. 1991-1994 was the most inactive 4-year period for the Atlantic in over 50 years. (Pielke Jr. & Landsea, 1998). Despite this, the United States saw its most damaging hurricane in history during this inactive period when Hurricane Andrew made landfall in southern Florida causing over $40 billion in total losses (adjusted to 2009 dollars). This suggests that the increase in damage cannot be directly attributed to a corresponding increase in the frequency or intensity of hurricanes.

Coastal Population Trends

The evidence shows that the upward trend in hurricane damage must be attributed to something other than a change in the characteristics of hurricanes. Population and development have continually increased on the United States coastline since the beginning of the 20th century. The amount of property at risk of damage from hurricanes is higher today than it has ever been. A storm that made landfall in 1950 would cause considerably more damage today because the amount of vulnerable property on the U.S. coast has increased drastically. Average wealth has also continued to increase so susceptible populations have more to lose than the populations of previous decades (Pielke Jr. & Pielke Sr., 1997).

Access to recreation, employment, waterway transport, energy, and tourism are among the many factors that make coastal areas attractive to Americans. In 2003, it was estimated that approximately 153 million Americans lived in coastal counties (Census, 2003). The National Oceanic and Atmospheric Administration (NOAA) defines a coastal county as one that has at least 15 percent of its land within a coastal watershed. About 90 million people live in the hurricane-prone coastal counties of the Gulf and Atlantic coasts, from Texas to Maine (Figure 2) (Census, 2003). Florida’s coastal population accounts for more than 20 percent of the Gulf and Atlantic total with over 16 million residents (Census, 2006). Coastal counties only make up about 23 percent of the land area in Gulf and Atlantic coastal states but contain more than 52 percent of their populations (Census, 2001). The average population density of these coastal counties is 328 people per square mile compared with the national average of 98 (Census, 2003). Between 1980 and 2000, Atlantic and Gulf coastal population increased by 12.5 million people, or 19 percent. Florida led the increase with 7.1 million new coastal residents, a 75 percent gain in only 20 years (Figure 3)

(Census, 1995; Census, 1996; Census, 2001; Census, 2004).

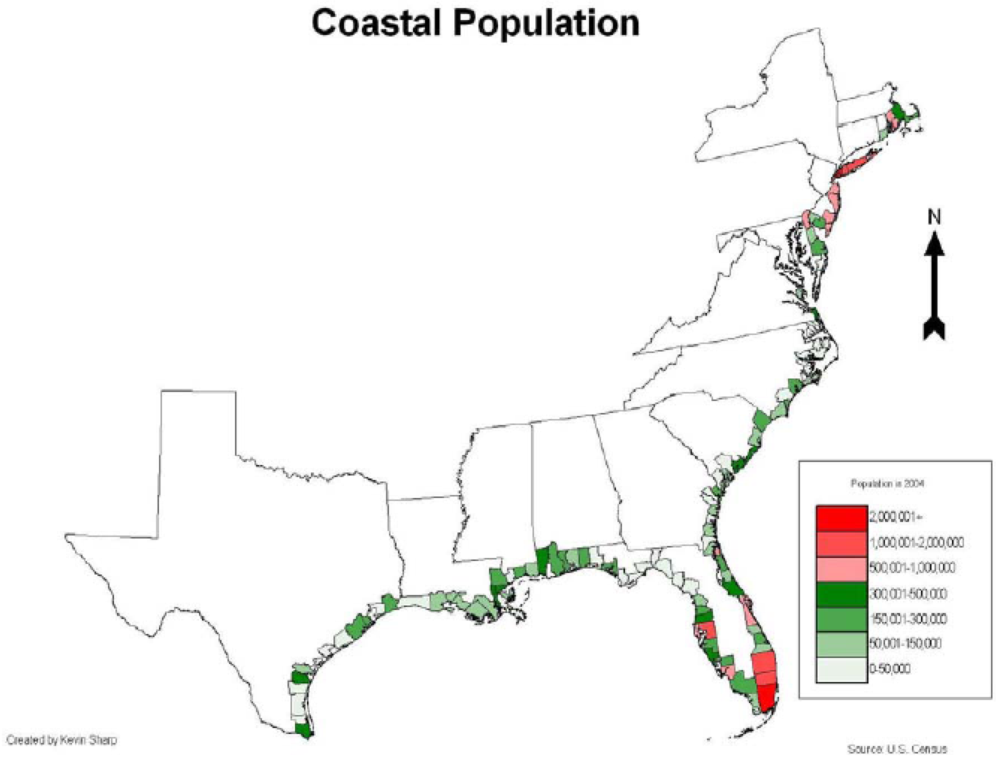


Figure 2. Coastal county population in 2004.

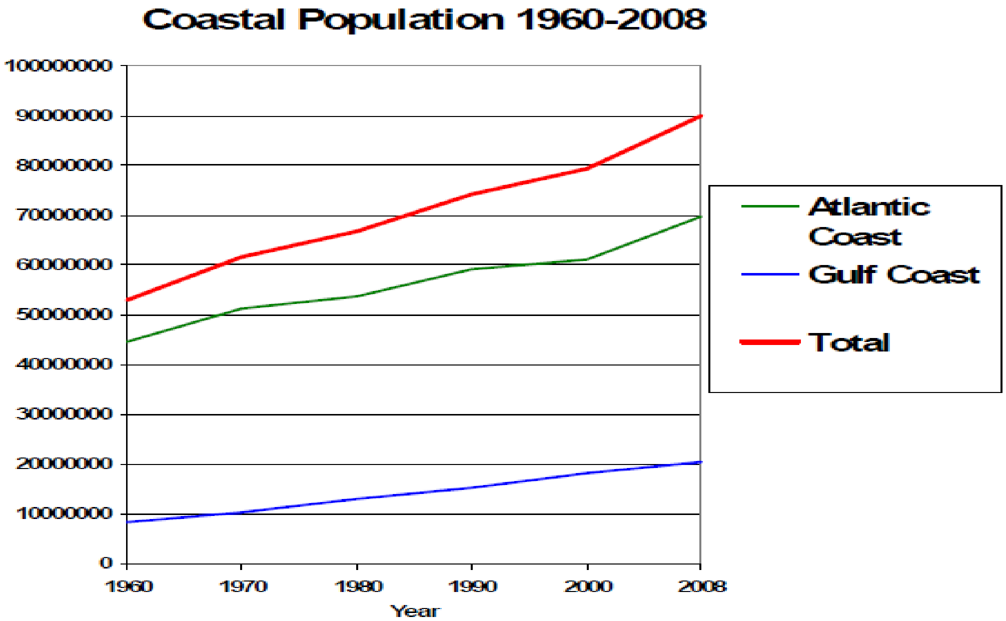


Figure 3. Coastal county population (1960-2008).

20th Century Tropical Cyclone Trends in the Atlantic Basin

Numerous studies have been conducted to determine whether or not the Atlantic basin is experiencing a change in the frequency and intensity of hurricanes. An increase in the average number of hurricanes per year would likely yield a corresponding increase in the average number of landfalling hurricanes. This would complement the effect that hazardous coastal growth patterns in the United States have on losses. Varying study methods reveal conflicting conclusions on past and future hurricane trends in the Atlantic.

Emanuel (1987) conducted a study to estimate the effect of increases in carbon dioxide (CO_2) on hurricane intensity in the Atlantic. A Carnot cycle model was used to predict the change in maximum intensity of tropical cyclones under warmer atmospheric conditions. The mean conditions over tropical areas were predicted by a general circulation model based on hypothetical CO_2 situations. The maximum pressure drop near the center of a storm was predicted based on estimated sea surface temperatures, ambient relative humidity, and thermodynamic efficiency. It was found that an increase in average sea surface temperatures by 3°C could lead to a 30-40% increase in the maximum pressure drop and a 15-20% increase in maximum winds. Furthermore, a doubling of CO_2 concentrations could lead to a 40-50% increase in the destructive potential of hurricanes. It was noted that a very small fraction of hurricanes actually reach their estimated maximum potential intensity and that results from climate simulations are extremely uncertain (especially in 1987). Models that relate oceanic dynamics and atmospheric circulation were very crude at the time and Emanuel noted that "better estimates of tropical cyclone intensities must await more sophisticated modeling efforts” (Emanuel, 1987). Nevertheless, this study suggests that maximum hurricane intensities could increase substantially in a warmer world.

Nearly two decades later, Knutson et al. (2004) conducted a similar study using climate change scenarios from nine different global climate models. They also used four different cumulus convective parameterizations. This allowed them to estimate the effects of various climate change situations on potential tropical cyclone intensity. Their findings were similar to Emanuel’s with elevated CO_2 scenarios leading to an estimated decrease in minimum central pressure and an increase in convective available potential energy (CAPE), maximum surface winds, and precipitation rates. A simulated increase in CO_2 concentrations by 1% a year for 80 years led to an estimated increase in maximum tropical cyclone surface winds of 6% in all basins. This experiment prescribed robust vorticity and did not allow for dynamical influences like changes in wind shear and tropical circulation to affect the development of tropical cyclones (Knutson & Tuleya, 2004). Therefore, it should be thought of as an experiment in maximum potential intensity and not a prediction of how hurricanes will actually react in a world with higher CO_2 concentrations.

Bengtson et al. (1996) conducted a similar study with a high resolution model and found that increasing concentrations of CO_2 in the atmosphere may actually lead to a decrease in the frequency of tropical cyclones. A global circulation model was run for the 100 year period of 1985 to 2085 with an increase in CO_2 concentrations of 1% each year. This led to a doubling of CO_2 concentrations in about 60 years. The model estimated the current number and distribution of storms reasonably well. A doubling of CO_2 concentrations led to a decrease in the estimated frequency of tropical cyclones in the northern hemisphere for every month except July (Figure 4). Bengtson et al. (1996) claim that the Emanuel (1987) study was flawed in its prediction that sea surface temperatures will react quickly and drastically to CO_2 concentration changes in the atmosphere. Most ocean-atmosphere models predict only a minor increase in sea surface temperatures as a result of a doubling of CO_2 concentrations. Their model predicts a noted change in the atmospheric circulation in a world with twice the amount of CO_2 in the atmosphere. The troposphere warms and the stratosphere cools due to an increase in outgoing infrared radiation. This leads to a larger temperature gradient between the poles and equator, which causes the subtropical jet to increase and move poleward. Their model estimated that this would lead to a decrease in vorticity and an increase in wind shear over the tropics. A weakening of the Hadley circulation is also estimated. These three factors work to inhibit the formation of tropical cyclones in their simulation (Bengtson, Botzet, & Esch, 1996).

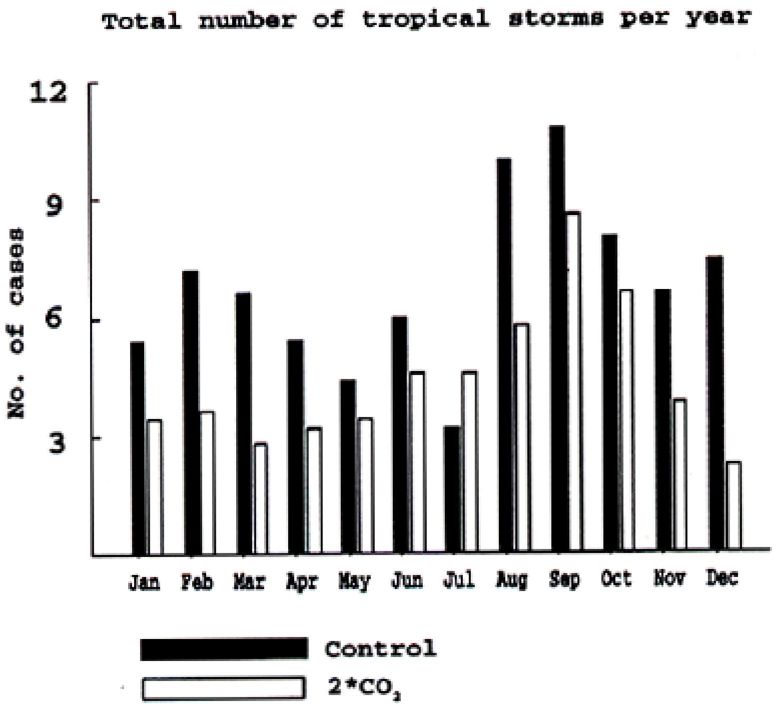


Figure 4. Estimated number of tropical cyclones in the northern hemisphere per month based on CO_2 concentration simulations (Bengtson et al., 1996).

Landsea et al. (1996) acknowledged the conflicting conclusions and analyzed the climate record in an effort to see whether or not the actual data shows any trends in hurricane intensity and frequency in the Atlantic basin. Consistent accurate tropical cyclone observations began in 1944 with the advent of regular aircraft reconnaissance flights. Therefore, they decided to conduct their analysis for the time period 1944-1995. On average, major hurricanes occurred in the Atlantic basin 2.2 times per year during the study period. Their analysis showed that the rate of major hurricanes per year decreased by .32 each decade, which was significant at the 2% level. The rate of minor tropical cyclones showed an insignificant increase while the rate of all tropical cyclones showed an insignificant decrease (Figure 5) (Landsea, Nicholls, Gray, & Avila, 1996).

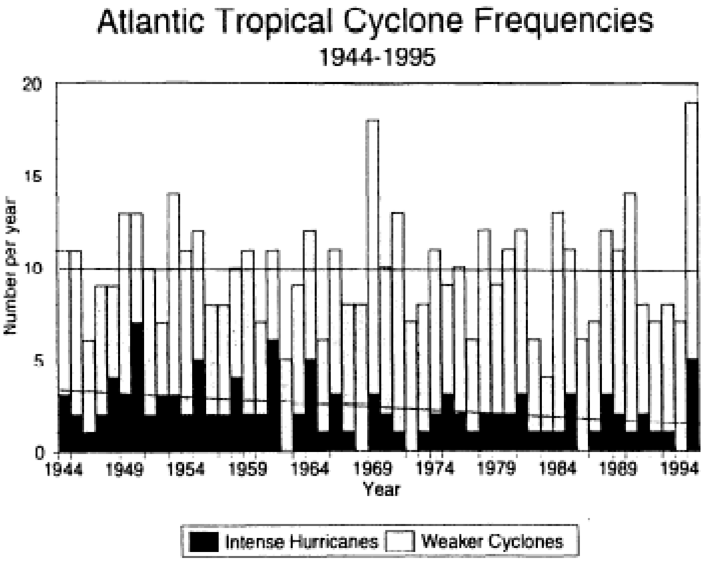


Figure 5. Time series of intense hurricanes (category 3, 4, and 5) and weaker cyclones (minor hurricanes, tropical storms, and subtropical storms) with lines of linear best fits (Landsea et al., 1996).

They noted that the large decrease in the occurrence of major hurricanes may seem counterintuitive due to the unprecedented damage caused by Hurricane Hugo in 1989 and Hurricane Andrew in 1992 (Landsea et al., 1996). Again, damage figures should not be used as a proxy for hurricane trends due to the major influences of population, development, and wealth change on losses. Prior to Hurricane Andrew, southeast Florida hadn't been directly hit by a major hurricane since Hurricane King struck as a category 3 in 1950. Between 1950 and 1992, the population of the area increased by more than 600% (Landsea, 1993). Hurricane King caused less than $300 million in damage in 2009 dollars (Norton, 1951). If the same storm had made landfall in 2005, it would likely have caused more than $4 billion in damage (Pielke Jr. et al., 2008). The mean intensity of tropical cyclones decreased during the period by .81 ms^{-1} per decade, which was significant at the 5% level. The maximum intensity did not show a significant trend (Figure 6) (Landsea et al., 1996). Despite the assertions by some (Senate, 1995) that hurricane frequency and intensity increased during the period, the actual data shows the opposite.

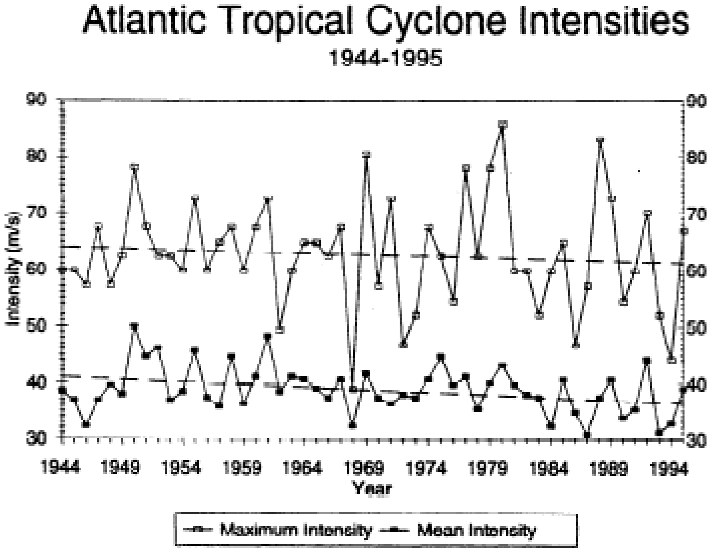


Figure 6. Time series of tropical cyclone maximum intensity and mean intensity with lines of linear best fits (Landsea et al., 1996).

Normalization

To put historical storms in today's context, one can attempt to normalize the past damage record. Normalization is conducted so that we can estimate the damage a historical storm would cause today. One type of normalization method is known as the "stage damage approach," where the amount of vulnerable property is estimated for the present day. Computer models then predict the impact of a given storm on the vulnerable property. Another normalization method is known as the "simulation approach," where the frequency and magnitude of events is studied instead of individual events (Pielke Jr. & Landsea, 1998). Pielke Jr. and Landsea (1998) attempted normalization without the use of catastrophe models to avoid the uncertainties involved with them. For their normalization, they assumed that hurricane losses are proportional to inflation, wealth, and population. To normalize to 1995, the following formula was used:

$$\mathrm{NL}_{95} = L_y \times I_y \times W_y \times P_{y,c}$$

where NL_{95}= storm loss normalized to 1995, y= year of storm's impact, c= county or counties of storm's landfall, L= storm's loss not adjusted for inflation, I= inflation factor, W= wealth factor, and P= population factor. They normalized the loss record from 1925 to 1995 for their initial study and found that the trend of increasing damage disappeared (Figure 7). In fact, the normalized record showed a pattern of more numerous costly hurricanes in the 1940s through the 1960s and less numerous costly hurricanes in the 1970s and 1980s. Not surprisingly, this pattern is consistent with the climatology of hurricane landfalls. At the time, Hurricane Andrew was the most damaging hurricane on record. The normalization showed that an unnamed hurricane in 1926 that hit southeast Florida and Alabama would likely cause more than twice the amount of damage in 1995 as Hurricane Andrew would. The normalized damage record also showed that the United States has at least a 1 in 6 chance of having a season with over $10 billion in damage each year (Pielke Jr. & Landsea, 1998).

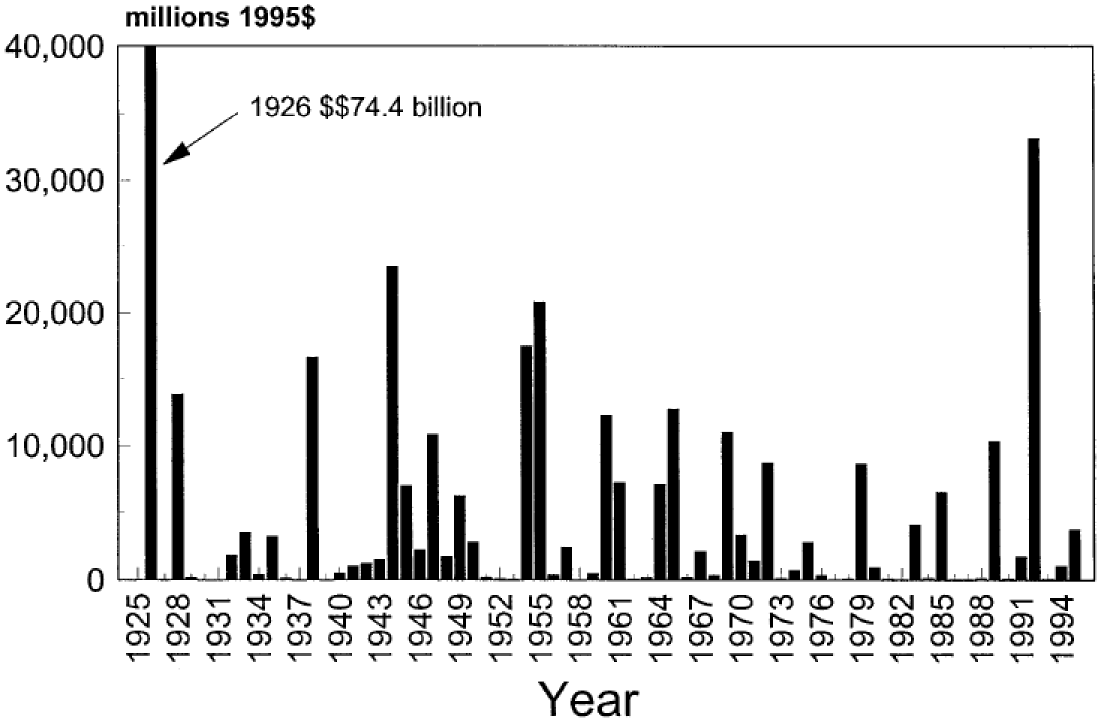


Figure 7. Normalized direct hurricane damage to 1995 conditions (Pielke Jr. & Landsea, 1998).

Pielke Jr. et al. (2008) updated their normalization to 2005 in a later study. They included an alternate normalization method from a different study, which also normalized damage based on wealth and inflation, but used housing units instead of population. It has been shown that using population instead of housing units may underestimate the present-day losses because property development often outpaces population growth. The wealth adjustment was also based on housing units instead of population. The formula for their normalization method stayed the same. The alternate normalization formula was:

$$D_{2005} = D_y \times I_y \times \mathrm{RWPHU}_y \times HU_{2005/y}$$

where D_{2005}= normalized damage to 2005, D_y= damage in given year not adjusted for inflation, I_y= inflation adjustment, RWPHU_y= real wealth per housing unit adjustment, and $HU_{2005/y}$=housing unit adjustment. Both normalization methods revealed the same result as the 1998 study. The trend of increasing losses disappeared (Figure 8). The lack of a trend in normalized damage is not surprising as there is also no evident trend in hurricane frequency or intensity at landfall (Pielke Jr. et al., 2008).

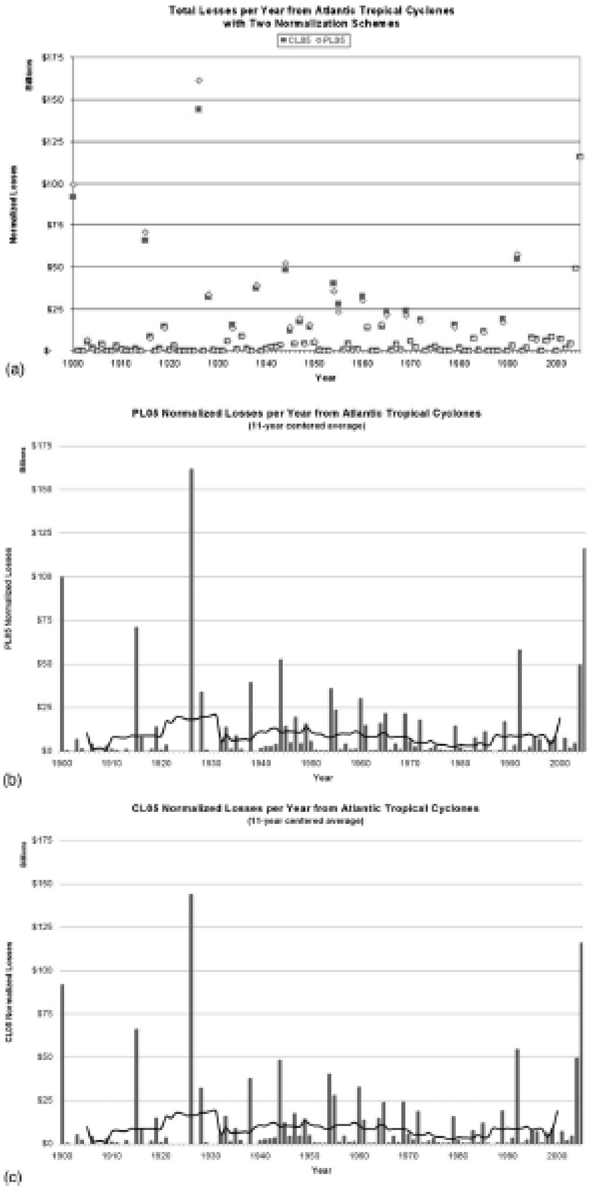
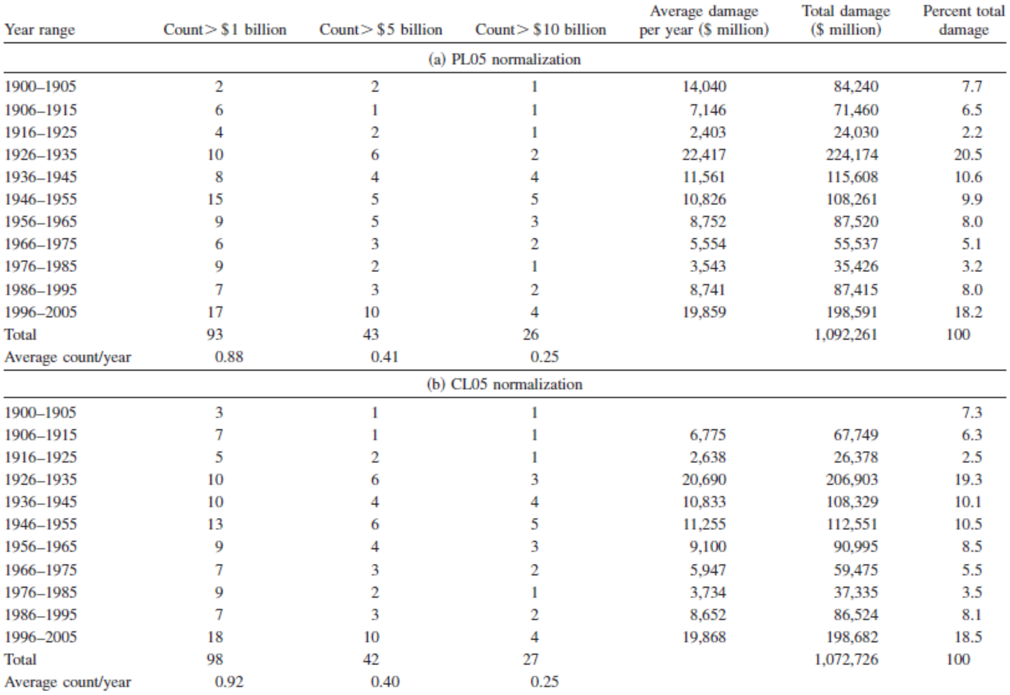


Figure 8. Damage record normalized to 2005 with an 11-year average. a) Both methods b) original method (PL05) c) alternate method (CL05) (Pielke Jr. et al., 2008).

Under both normalization methods, the 1926 hurricane remained the most destructive with greater than $140 billion in direct damage while Hurricane Katrina came in second with about $80 billion in direct damage. The 2004 and 2005 seasons contained 7 of the 30 most destructive storms in the record. This is quite significant considering that no other 2-year period in the record contained more than 3 of the top 30. Despite this, the decade of 1926-1935 had the most normalized damage with $224 billion while 1996-2005 came in second with $199 billion (Table 1). The totals were dominated by individual extreme storms with 70% of the 1926-1935 damage coming from the 1926 hurricane and about 40% of the 1996-2005 damage coming from Hurricane Katrina (Pielke Jr. et al., 2008). This shows that individual extreme events have a very large effect on the damage record.



Year range	Count> $1 billion	Count> $5 billion	Count> $10 billion	Average damage per year ($ million)	Total damage ($ million)	Percent total damage
(a) PL05 normalization						
1900–1905	2	2	1	14,040	84,240	7.7
1906–1915	6	1	1	7,146	71,460	6.5
1916–1925	4	2	1	2,403	24,030	2.2
1926–1935	10	6	2	22,417	224,174	20.5
1936–1945	8	4	4	11,561	115,608	10.6
1946–1955	15	5	5	10,826	108,261	9.9
1956–1965	9	5	3	8,752	87,520	8.0
1966–1975	6	3	2	5,554	55,537	5.1
1976–1985	9	2	1	3,543	35,426	3.2
1986–1995	7	3	2	8,741	87,415	8.0
1996–2005	17	10	4	19,859	198,591	18.2
Total	93	43	26		1,092,261	100
Average count/year	0.88	0.41	0.25			
(b) CL05 normalization						
1900–1905	3	1	1			7.3
1906–1915	7	1	1	6,775	67,749	6.3
1916–1925	5	2	1	2,638	26,378	2.5
1926–1935	10	6	3	20,690	206,903	19.3
1936–1945	10	4	4	10,833	108,329	10.1
1946–1955	13	6	5	11,255	112,551	10.5
1956–1965	9	4	3	9,100	90,995	8.5
1966–1975	7	3	2	5,947	59,475	5.5
1976–1985	9	2	1	3,734	37,335	3.5
1986–1995	7	3	2	8,652	86,524	8.1
1996–2005	18	10	4	19,868	198,682	18.5
Total	98	42	27		1,072,726	100
Average count/year	0.92	0.40	0.25			

Table 1. Normalized damage (to 2005) by decade using the normalization method a) weighted by population b) weighted by housing units (Pielke Jr. et al., 2008).

Pielke Jr. et al. (2008) found that the normalized losses had increased quite rapidly since their 1998 study. They found that most locations roughly double their normalized damage amount every 10 years due to development and cost increases. The 1926 hurricane caused $72.3 billion in damage normalized to 1995 dollars and $157 billion in damage normalized to 2005 dollars. It was noted that the effects of mitigation efforts were not taken into account for these studies. Stricter buildings codes could reduce losses by up to 40%. New building codes have only been enforced for some newer buildings though and their overall effect is still likely minimal. Future normalization studies will need to consider updated building codes as they become more widely enforced (Pielke Jr. et al., 2008).

Climatic Oscillations and their Influence on Tropical Cyclone Activity and Losses

There are many regional climatic oscillations that have been shown to affect the oceanic and atmospheric circulations over much of the globe. The El Niño-Southern Oscillation (ENSO), the Atlantic Multi-decadal Oscillation (AMO), and the North Atlantic Oscillation (NAO) appear to have the most marked effect on the conditions in the tropical cyclone formation zones of the Atlantic basin. The United States coastline has a higher risk of losses during certain phases of these oscillations.

ENSO has a warm phase (El Niño), a cool phase (La Niña), and a neutral phase. The phase is dictated by sea surface temperature fluctuations in the tropical eastern Pacific Ocean. The Southern Oscillation is the atmospheric signature of ENSO, and shows the monthly fluctuations in the air pressure difference between Tahiti and Darwin, Australia. During the normal Pacific pattern (neutral phase), easterly trade winds dominate, causing warm water to pool in the western Pacific with cool water upwelling in the eastern Pacific. This leads to persistent low pressure in the western Pacific and high pressure in the eastern Pacific. An El Niño pattern emerges when the easterly trade winds weaken, allowing for a pooling of warm water in the eastern Pacific. This warm phase officially begins when sustained sea surface temperature anomalies across the central Pacific rise above 0.4°C (Pielke Jr. & Landsea, 1999). The Southern Oscillation Index turns negative as surface pressures rise over eastern Australia and fall over Tahiti and the central/eastern Pacific Ocean. Drought ensues in the western Pacific while anomalously heavy rains fall in the eastern Pacific. A La Niña pattern emerges when the easterly trade winds are stronger than usual. Cool water upwelling occurs at a faster rate in the eastern Pacific and warm water pools in the western Pacific. This cool phase officially begins when sustained sea surface temperatures across the central Pacific fall below -0.4°C (Pielke Jr. & Landsea, 1999). Surface pressures fall over the western Pacific and rise over the central/eastern Pacific, causing the Southern Oscillation Index to turn positive.

ENSO has been shown to have a noticeable effect on tropical cyclone activity in the Atlantic basin. On average, El Niño years have the fewest named storms, hurricanes, and major hurricanes while La Niña years have the most. Neutral years fall between the two. The ENSO phase has its most marked effect on the number of major hurricanes in the Atlantic with them occurring at more than a 3:1 ratio in La Niña years versus El Niño years (Figure 10) (Bove, 1998) The United States coastline is at much higher risk of a landfalling major hurricane during non El Niño years with an average of .74 during La Niña and neutral years and an average of .25 during El Niño years (Gray, 1984). The probability of two or more hurricanes making landfall on the United States coast is 66% during La Niña years, 48% during neutral years, and 27% during El Niño years (Bove, 1998). The warm phase of ENSO causes anomalously strong westerly winds in the upper troposphere over the Atlantic basin. This leads to an increase in vertical wind shear, which inhibits the formation and development of tropical cyclones. The cool phase causes a relaxation of these westerly winds, which leads to a decrease in vertical wind shear and a more favorable environment for tropical cyclone development (Gray, 1984).

With increased activity during the La Niña phase, it can be assumed that the United States coastline is at a higher risk of losses during these years. A comparison of the ENSO record with normalized damage figures demonstrates this (Figure 9). Pielke Jr. and Landsea (1999) found a significant relationship between the ENSO phase and normalized losses for the period 1925-1997. The mean, median, and standard deviation of losses were calculated for all three ENSO phases (Table 2). The data shows that La Niña years have historically been much more damaging than El Niño years. The data were highly skewed, as demonstrated by the large differences between mean and median values. Because of this, a logarithmic transformation was used to calculate the significance of the mean values. This yielded log-mean damage values of 2.26 for El Niño years, 2.73 for neutral years, and 3.37 for La Niña years. The probability of experiencing at least $1 billion in damage (normalized to 1997) was 0.32 for El Niño years, 0.48 for neutral years, and 0.77 for La Niña years. Extreme events that cause over $10 billion in normalized damage did not show a strong relationship with a probability of .14 for El Niño years, .21 for neutral years, and .18 for La Niña years (Pielke Jr. & Landsea, 1999). This may be due to the fact that there is only a small sampling of extreme events.

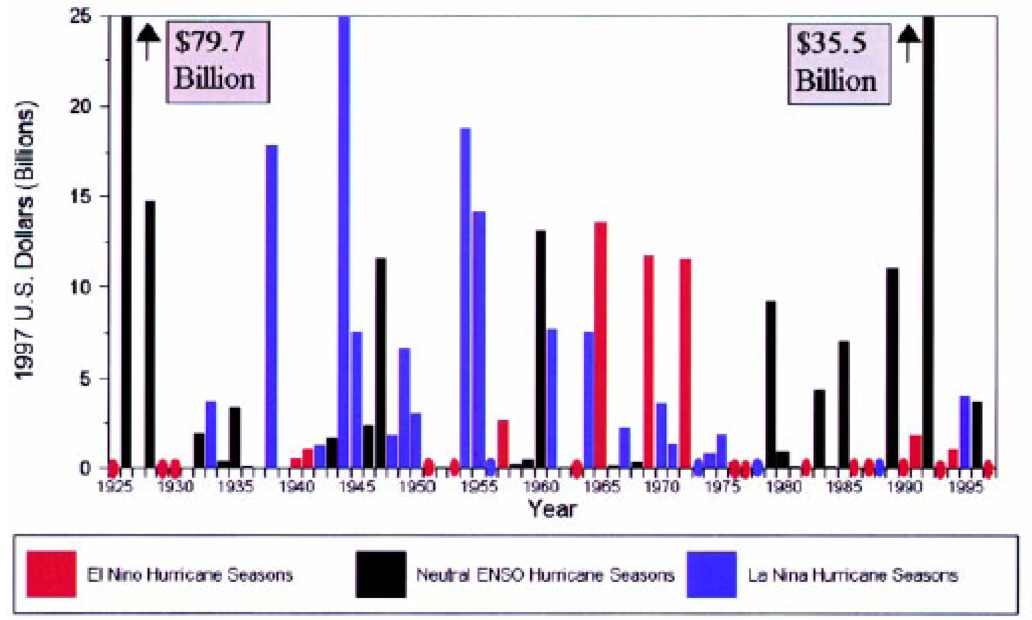


Figure 9. Losses normalized to 1997 compared with ENSO phase (Pielke Jr. & Landsea, 1999).

	Median ($ million)	Mean ($ million)	Std dev ($ million)
La Niña	3,292	5,887	6,991
Neutral	927	6,979	15,856
El Niño	152	2,056	4,228

Table 2. Median, mean, and standard deviation of hurricane losses (normalized to 1997) for the three phases of ENSO (Pielke Jr. & Landsea, 1999).

The AMO is a fluctuation of de-trended sea surface temperatures in the north Atlantic Ocean. It is measured by the AMO index, which is the 10-year running mean of sea surface temperature anomalies in the Atlantic north of the equator. The warm phase is associated with a faster thermohaline circulation. This causes an increase in the transport of warm equatorial waters to higher latitudes. The cold phase occurs when the thermohaline circulation slows and north Atlantic sea surface temperature anomalies turn negative. No correlation has been found between the AMO phase and the occurrence of tropical storms and minor hurricanes. Major hurricanes, on the other hand, occur twice as often during the warm phase as they do during the cold phase (Figure 10) (Appinsys, 2009). The AMO completes one cycle about every 70 years. Because major hurricanes cause the brunt of the damage in the landfalling record, the United States is at higher risk of losses when the AMO is in its positive phase.

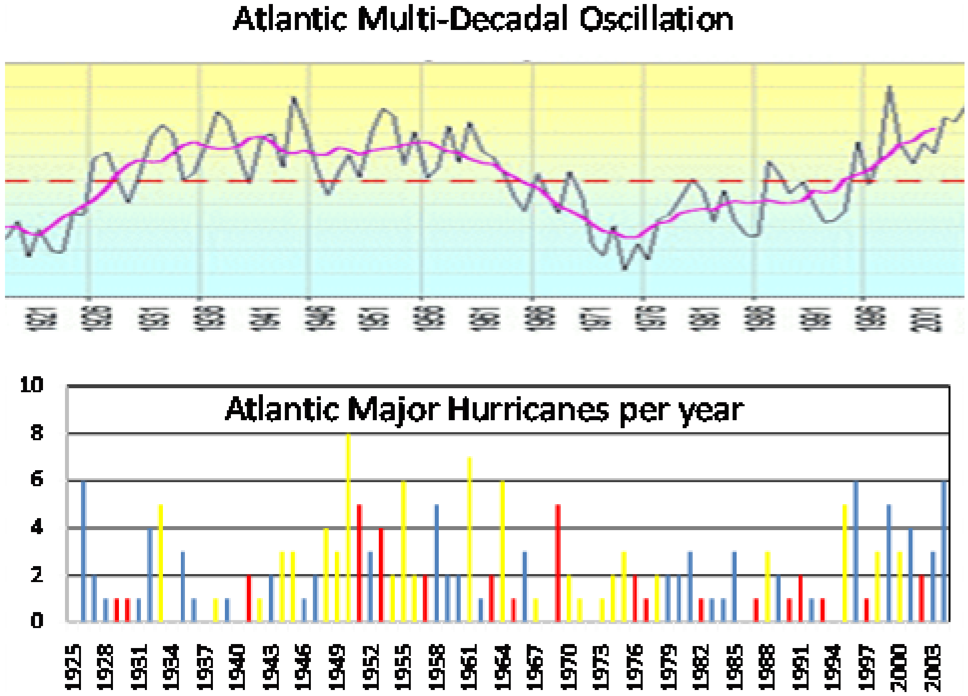


Figure 10. Number of Atlantic major hurricanes per year compared with the AMO phase and ENSO (La Niña in yellow, neutral in blue, and El Niño in red) (Appinsys, 2009).

The NAO is a fluctuation in the air pressure difference between the persistent Icelandic low and the persistent Bermuda high. The NAO is in its positive phase when the Bermuda high is strong and the Icelandic low is deep. It is in its negative phase when both are weak. The phase of the NAO has been observed to affect the tracks of Atlantic tropical cyclones. During its positive phase, the Bermuda high shifts east. The large pressure gradient causes an increase in the westerlies. The anomalously strong and eastern-lying anticyclone tends to cause tropical cyclones to avoid land by turning them north and then east over the open ocean. During the negative phase of the NAO, the Bermuda high weakens and shifts west. In this situation, tropical cyclones tend to make landfall in the United States as the anticyclone causes a northward turn further west in the Caribbean Sea or near the southeastern coast (Bell, 2008). The United States is at greater risk of losses when the NAO is in its negative phase due to the increased likelihood of landfall.

ENSO, the AMO, and the NAO are only a few of the climatic oscillations that affect conditions over the tropical Atlantic Ocean. Figure 11 shows the correlation between sea surface temperatures and Atlantic tropical cyclone activity. The negative correlation over the central/eastern Pacific and the positive correlation over the western Pacific demonstrate the ENSO effect. The positive correlation over the north Atlantic demonstrates the AMO effect. There is a greater likelihood of U.S. landfall during the negative phase of the NAO. The risk of losses is accentuated when these climatic oscillations act in conjunction to increase the likelihood of landfalling major hurricanes.

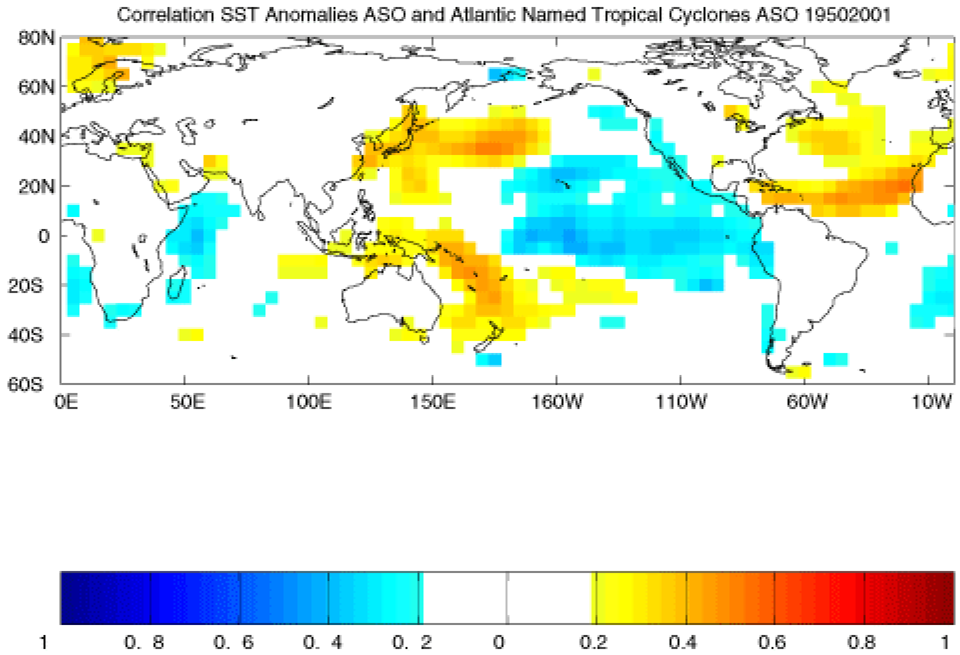


Figure 11. Correlation of sea surface temperature anomalies and Atlantic tropical cyclones (IRICS, 2008).

Recent Trends in Atlantic Tropical Cyclone Activity and Losses

The 2004 and 2005 hurricane seasons were extremely active in the Atlantic basin. 2005 was the most active season on record with 28 named storms, 15 of which became hurricanes. There were four category 5 hurricanes, the most ever recorded in one season. Hurricane Wilma became the most intense Atlantic hurricane on record with a surface pressure as low as 882 hPa. Hurricane Rita became the most intense hurricane to affect the Gulf of Mexico on record with a surface pressure as low as 897 hPa. Hurricane Katrina is now the most damaging tropical cyclone in history with over $100 billion in total losses (Trenberth & Shea, 2006). Not surprisingly, there are conflicting theories as to why these seasons were so active.

Multi-decadal variability can be seen in the Atlantic tropical cyclone record. The frequency of major hurricanes was above average during the 1940s through the

1960s and below average during the 1970s through the mid-1990s. Major hurricane activity began to rise again near the end of the 20th century as the AMO switched to its positive phase. The former director of the National Hurricane Center, Max Mayfield, testified to the U.S. Senate that the increase in activity could probably be attributed to natural variability, chiefly an increase in the AMO index. Furthermore, heightened activity can be expected to continue for at least another decade due to the fact that we have entered into a more favorable climatological pattern (Mayfield, 2005).

Emanuel (2005) defined an index of potential destructiveness of hurricanes by integrating the total dissipation of power over the lifetime of a tropical cyclone. Power dissipation reflects the total amount of power dissipated by a storm through its lifetime and is expressed in units of energy. Monetary losses and power dissipation rise approximately as the cube of wind speed. The formula for total power dissipation of a storm is:

$$\mathrm{PD} = 2\pi \int_0^{\tau} \int_0^{r_0} C_{\mathrm{D}} \rho |\mathbf{V}|^3 r \,\mathrm{d}r \,\mathrm{d}t$$

where PD= power dissipation, C_{D}= surface drag coefficient, ρ= surface air density, |V|= magnitude of surface wind, r= radius to an outer storm limit, and t= the lifetime of the storm. Historically, tropical cyclone radii have not been recorded so a simplified formula for a power dissipation index was developed as:

$$\mathrm{PDI} \equiv \int_0^{\tau} V_{\max}^3 \,\mathrm{d}t$$

where PDI= power dissipation index and $V_{\max}$= maximum sustained wind speed. Despite the fact that this is not a perfect formula for net power dissipation, Emanuel claims it provides a better measure of hurricane threat than tropical cyclone intensity and frequency alone. He acknowledges that no significant trend in tropical cyclone frequency can be found but asserts that potential destructiveness has risen in recent decades due to increases in storm lifetime and intensity. The data shows that the average annual total power dissipation has more than doubled in the last 30 years (Figure 12). There is a strong relationship between the sea surface temperatures and the total power dissipation in the tropical Atlantic with an r^2 of 0.65. Climatological phases that affect sea surface temperatures and tropical cyclone activity are evident in the findings. According to Emanuel, the most recent drastic increase in power dissipation “probably reflects the effects of global warming” (Emanuel, 2005). Total power dissipation may be underestimated for past seasons when observations were less comprehensive, especially for storms far from land. An increase in storm duration could reflect a tendency for tropical cyclones to avoid land where their lives are abruptly ended. A hurricane that avoids land, reaches category 5, and lasts for ten days would be considered much more “potentially destructive” than a hurricane that makes landfall, only reaches category 3, and lasts for four days. The latter storm would obviously prove more destructive.

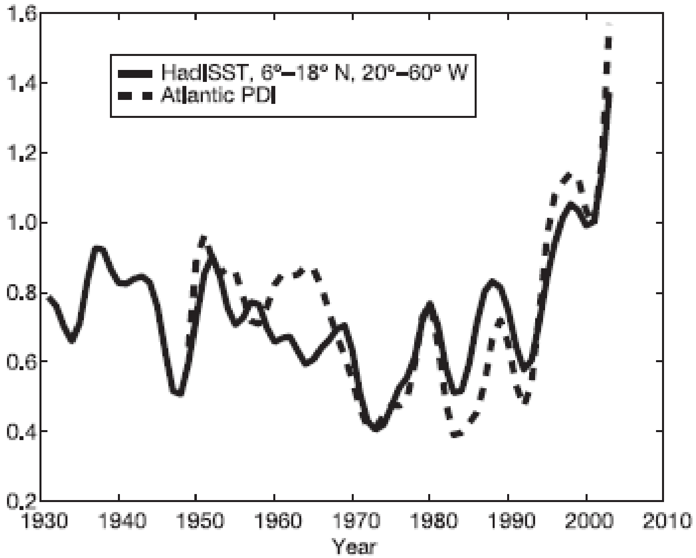


Figure 12. Total power dissipation index compared to September sea surface temperatures in Atlantic tropical cyclone formation zones (Emanuel, 2005).

In a 2005 article in *Nature*, Pielke Jr. claims that if tropical cyclones have indeed become drastically more destructive since the 1970s, the trend should reveal itself in the damage record. After removing societal changes through normalization, there is no apparent trend in damage. Between 1900 and 1950, there were .78 Atlantic tropical cyclones per year that caused over $1 billion in normalized damage with an average of $9.3 billion per storm. Between 1951 and 2004, there were .85 per year with an average of $7 billion per storm. Even after adding the 2005 season (which includes Hurricane Katrina), the differences are statistically insignificant. Analysis of the normalized damage record shows that Emanuel's total power dissipation index may not actually reflect the destructiveness of a hurricane season. If it does, then the drastic increase in the index since the 1970s may be due to inconsistent data or faulty methods as the normalized record does not show any significant trend in damage. With no identifiable trend in normalized damage, it is unlikely that researchers will be able to make a link between historical tropical cyclone trends and societal vulnerability. Furthermore, societal changes will likely continue to have a much greater effect on losses than climatological changes (Pielke Jr., 2005).

Despite the ongoing debate on whether climate change is affecting tropical cyclone activity, it is widely accepted that societal changes have had the greatest effect on vulnerability. The historical damage record is very noisy due to the fact that the brunt of hurricane losses can be blamed on isolated major events. Societal vulnerability from a given hurricane is highly influenced by the storm’s landfall location. An obvious hurricane activity signal is unlikely to ever be found through the analysis of normalized damage records due to the high noise to signal ratio. Slight differences in landfall location can lead to drastically different loss figures.

III: METHODOLOGY

This thesis takes initial steps in a different type of hurricane impact sensitivity analysis, by varying the landfall location in a loss simulation model. It is often commented that the apparently random fluctuations, or wobbles, in hurricane tracks make a large difference in impacts. Landfall variation could range from regional trends (such as more or fewer storms hitting the Northeast vs. Gulf Coasts), to meso-scale trends (such as changing likelihood of landfall in the coastal segments specified for warning and storm surge predictions), to micro-scale trends in location of the eyewall on the order of just a few miles. This thesis describes the first cut analysis of landfall variation at the micro- to meso-scale, varying landfalls on the order of tens of miles in the HAZUS loss simulator.

HAZUS

HAZUS was released in 1997 as an earthquake model by the Federal Emergency Management Agency (FEMA) and the National Institute of Building Sciences (NIBS). The model is a GIS-based tool that can be used to estimate the potential losses from an earthquake nationally. These loss estimates are used by governmental officials to plan for and mitigate the losses associated with earthquakes. The results have also been used for emergency response and disaster recovery planning. Shortly after the development of HAZUS, the software was upgraded to include loss estimations due to wind and flood hazards. HAZUS runs within the ArcView GIS platform, which allows for the modeling of these hazards and the estimated losses attributed to them (FEMA, 2007).

A hurricane model is included with HAZUS, which spatially estimates the sustained winds and maximum wind gusts based on user input. The hurricane model is the initial step to the development of a planned HAZUS wind model. The developers plan to include tornadoes, thunderstorms, extratropical storms, and hail in the final wind model. The current hurricane model can be run for the hurricane-prone areas of the United States, which are limited to the Atlantic coast, the Gulf Coast, and Hawaii (FEMA, 2007).

The overall wind model uses components from a hazard model, load model, resistance model, damage model, and loss model. Each of these models is developed and validated separately. The hazard model is used to depict the physical event. The load model is used to estimate the force exerted by the hazard on physical structures. The resistance model estimates the structural integrity of various building classes. The damage model estimates structural failure based on the load imposed by the hazard and the resistance demonstrated by the structure. The loss model estimates figures based on physical damage as well as repair and restoration estimates (Vickery, Lin, Skerlj, Twisdale, & Huang, 2006). The damage and loss models use the General Building Stock to estimate damage, direct economic losses, and building debris. The General Building Stock includes data on residential, commercial, industrial, agricultural, educational, and governmental buildings. This data includes occupancy type (what the building is used for) and building type (what the building is made of). (FEMA, 2007).

The Hurricane Model

The hurricane model takes into account the effects of wind pressure, windblown debris, tree blow down, rainfall, and storm duration. The developers of HAZUS aggregated models from several previous hurricane risk studies in order to create “the most advanced hurricane model currently in use for estimating hurricane wind speed risk” (Vickery et al., 2006). Existing boundary layer models were improved with the inclusion of dropsonde data, a theoretical model developed by (Kepert, 2001), and a physically based gust factor model that accurately estimates variation in wind gusts with surface roughness. An improved wind field model was created by using a full non-linear solution to the equations of motion for a tropical cyclone. Previous studies had used spectral or empirical models. The HAZUS hurricane wind field model uses physical models instead of empirical models to estimate the wind speeds within a tropical cyclone.

Validation with real hurricane data has shown that the HAZUS model demonstrates the actual wind field very well (FEMA, 2007). Vickery et al. (2006) conducted a 100,000 year simulation of major hurricane landfall rates in the Atlantic basin and compared it with observed data for the hurricane-prone regions of the Atlantic coast. HAZUS simulated a mean within the 95% confidence interval of the observed landfall rates for each region (Figure 13). Validation was further conducted by comparing the simulated and observed central pressures of landfalling hurricanes based on the return period (Figure 14). The simulated central pressures were remarkably close to the observed through the return periods (Vickery et al., 2006).

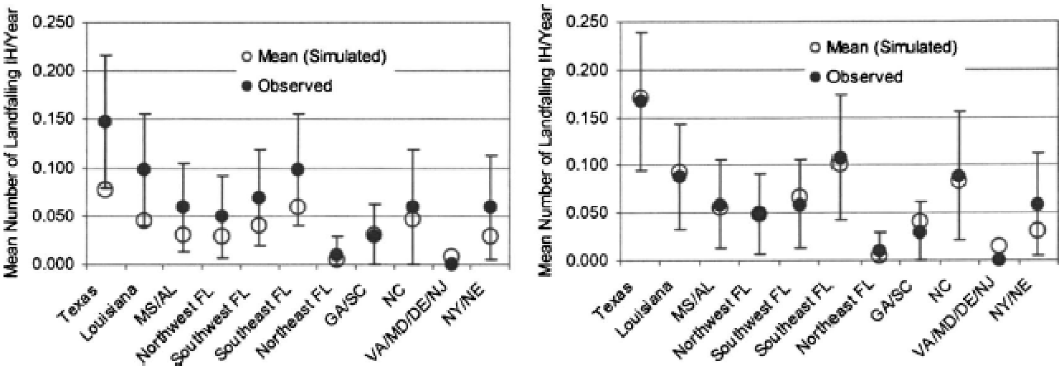


Figure 13. Simulated mean rate of landfalling major hurricanes compared with 95% confidence interval of observed mean rate – Major hurricanes categorized by wind speed on left and central pressure on right (Vickery et al., 2006).

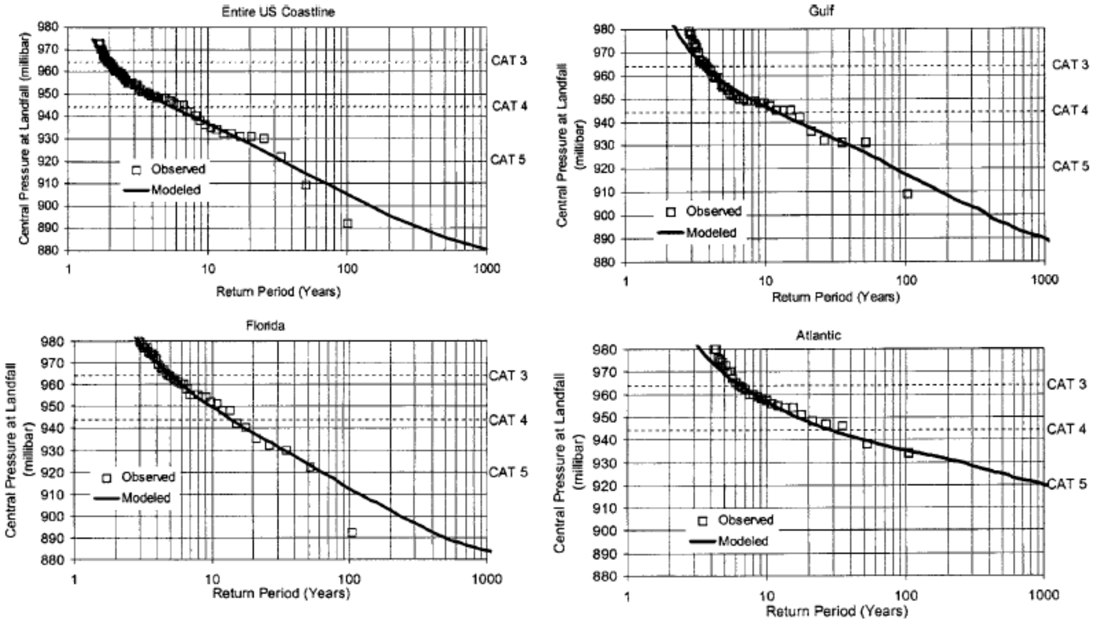


Figure 14. Simulated and observed central pressure at landfall plotted against return period (Vickery et al., 2006).

The hurricane model also estimates rainfall rates and includes damage caused by water entering buildings through broken windows or doors. These rainfall rates are not used to estimate flooding, which is not included in the HAZUS hurricane model (Vickery et al., 2006). Like the boundary layer model and wind field model, the HAZUS rainfall rate model is an upgraded form of a model used in a previous study.

Rodgers et al. (1994) created a rainfall rate model with data from 103 Special Sensor Microwave/Imager (SSM/I) observations of 18 Atlantic tropical cyclones between 1987 and 1989 (Rodgers, Chang, & Pierce, 1994). The empirical model uses the equation:

$$\mathrm{RR} = -5.5 + 110(R_{\max}/r) - 390(R_{\max}/r)^2 + 550(R_{max}/r)^3 \\ - 250(R_{max}/r)^4$$

where RR= rainfall rate (mm/h), $R_{\max}$= radius of maximum winds, and r= radius to point of interest (Vickery et al., 2006). HAZUS developers modified this model to account for the increase in rainfall rate with storm intensity (k), the effect of central pressure change rate (k_1), and the asymmetric distribution of rainfall (s), which depends on the storm's velocity. The HAZUS rainfall rate model uses the equation

$$\mathrm{RR}_{\mathrm{eff}} = k(\mathrm{RR})k_1 s$$

where $\mathrm{RR}_{\mathrm{eff}}$ is the rainfall rate in millimeters per hour (Vickery et al., 2006). The modeled rainfall rates were compared with observations of five hurricanes and found to be reasonably accurate estimates for most observation stations (Figure 15). However, the simulations tended to overestimate rainfall rates far from the storms' centers. To fix this, a calibration factor was included in the final rainfall rate model. Though the rainfall rate model provides reasonable estimates, variability is large due to the complexity of hurricanes and the atmospheric conditions surrounding them. As stated before, the HAZUS rainfall rate model is only used to estimate damage caused by water precipitating into damaged buildings and does not attempt to predict any losses associated with freshwater flooding. Storm surge and waves are also significant flooding hazards posed by hurricanes, but are not currently included in the HAZUS hurricane model either (FEMA, 2007).

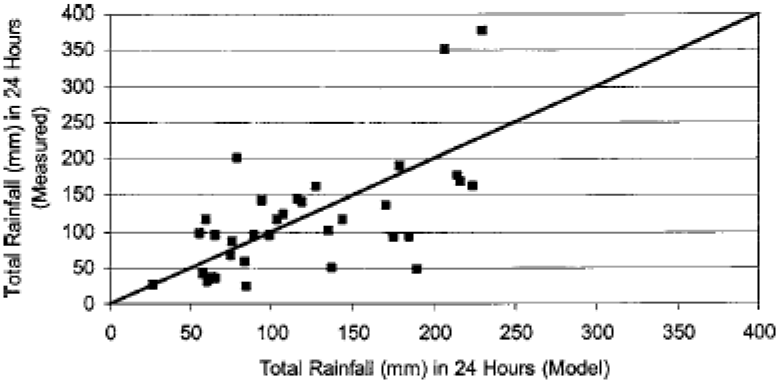


Figure 15. Simulated and observed total rainfall accumulation for one day (Vickery et al., 2006).

Terrain roughness has a noted effect on wind speeds near the surface. An urban area or a treed neighborhood has rougher terrain than an open field or waterfront location and is therefore less likely to experience severe winds. A structure in a forested area may experience half the wind load of a similar structure in an open vicinity (Vickery et al., 2006). Terrain roughness depends on the height and spacing of buildings, trees, and other obstructions on the surface. The HAZUS hurricane model combines its wind model estimates with terrain roughness data and upstream fetch to predict wind speeds for all locations being affected by the storm. There is currently no comprehensive database of terrain roughness for the United States so HAZUS uses estimates based on Land Use and Land Cover (LULC) data (Vickery et al., 2006). LULC data is distributed by the United States Geological Survey (USGS) and was created primarily through the manual interpretation of aerial photography. Land use maps and surveys were used as secondary sources. LULC data has 21 categories of land cover type and is available for the entire nation (USGS, 2009). By assigning values of terrain roughness to each LULC class, HAZUS developers were able to create a terrain roughness map for the entire nation. Topography is included in the hurricane model for Hawaii, but not for the continental United States due to the lack of significant elevation change near the coast in most areas (FEMA, 2007).

The Load Model

The wind load model uses an empirical approach to estimate the pressure exerted by wind on the exterior of various types of buildings. Pressure coefficient data were collected from the British and American wind loading codes as well as several wind tunnel tests. HAZUS uses different pressure coefficient models for various types of buildings including flat roof low-rise buildings, sloped roof low-rise buildings, mid-rise buildings, and high-rise buildings. The pressure coefficient (C_F) is defined as:

$$C_F = \frac{F}{\frac{1}{2}\rho U_H^2 A}$$

where F= peak wind induced force, ρ= air density, U_H= mean wind speed at roof height, and A= area of building (Vickery et al., 2006). The empirically modeled pressure coefficients were validated against the wind tunnel tests. Figure 16 shows that the HAZUS wind load model estimates the pressure exerted on buildings quite well. These pressure coefficients are modified by HAZUS to account for the effect of surrounding buildings.

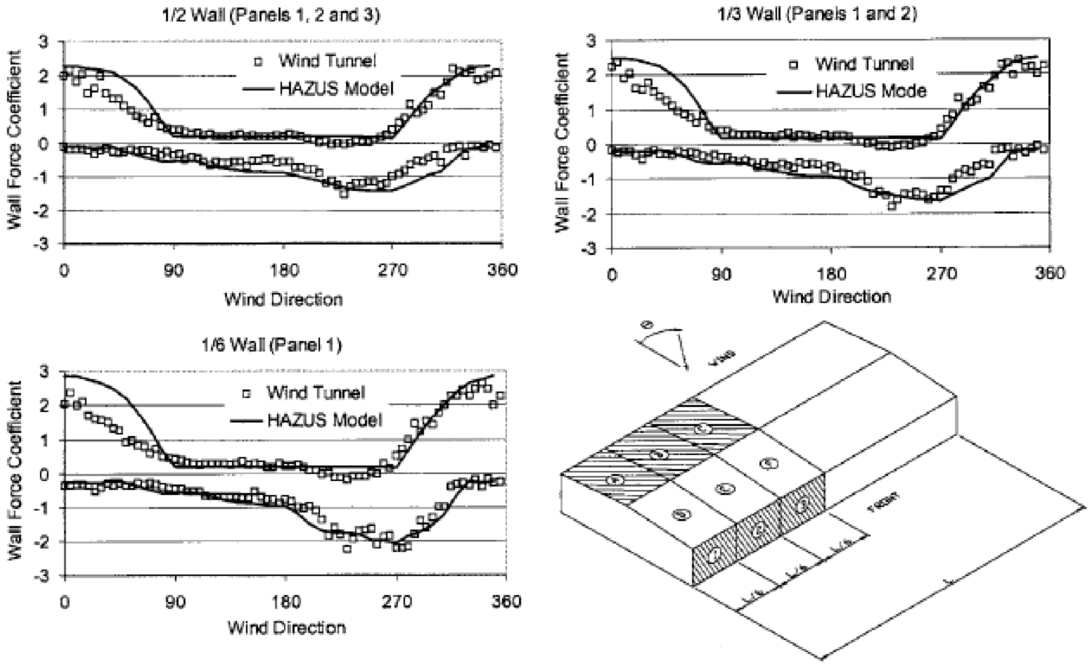


Figure 16. Pressure coefficients from HAZUS wind load simulations compared with wind tunnel experiments for a low-rise building (Vickery et al., 2006).

The wind load model also estimates uplift loads on the various building types. The uplift coefficient (C_R) is given by the equation:

$$C_R = \frac{R}{\frac{1}{2}\rho U_H^2 L}$$

where L= length of joist, R= uplift load per unit width of joist, ρ= air density, and U_H= mean wind speed at roof height (Vickery et al., 2006). The modeled uplift coefficients were also validated against wind tunnel tests and shown to be quite accurate (Figure 17). The HAZUS wind load model also includes estimations for windborne debris. The airborne debris model combines a residential debris model from a previous study with a newly developed rooftop gravel debris model designed especially for HAZUS.

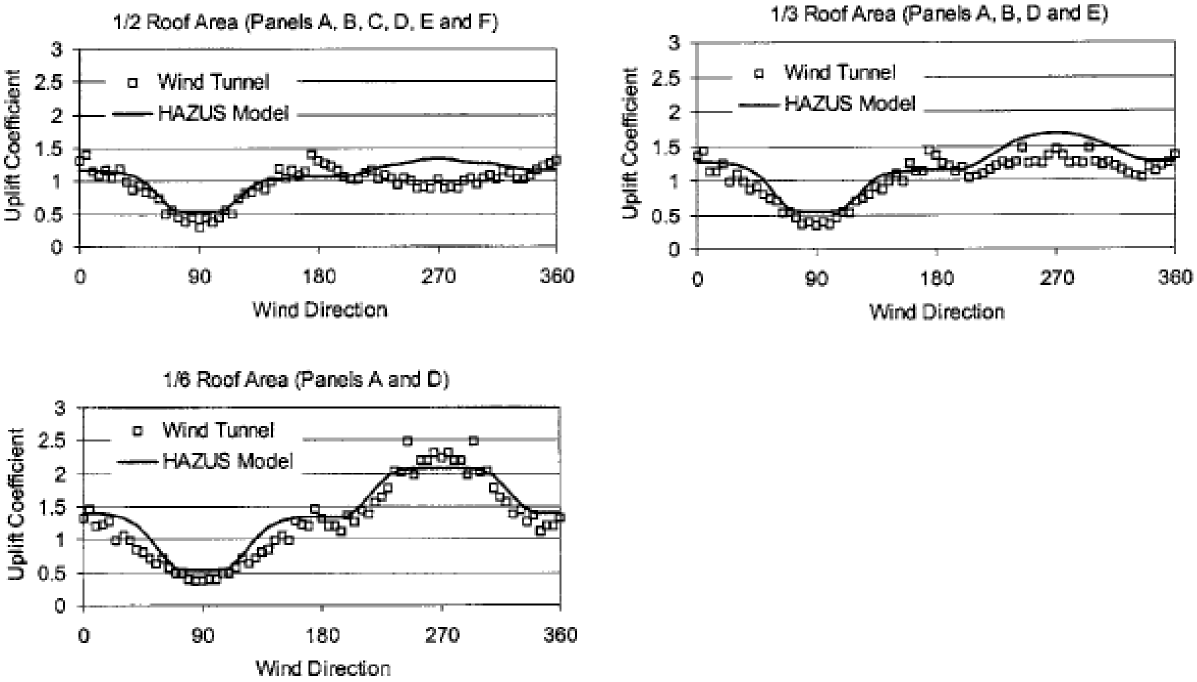


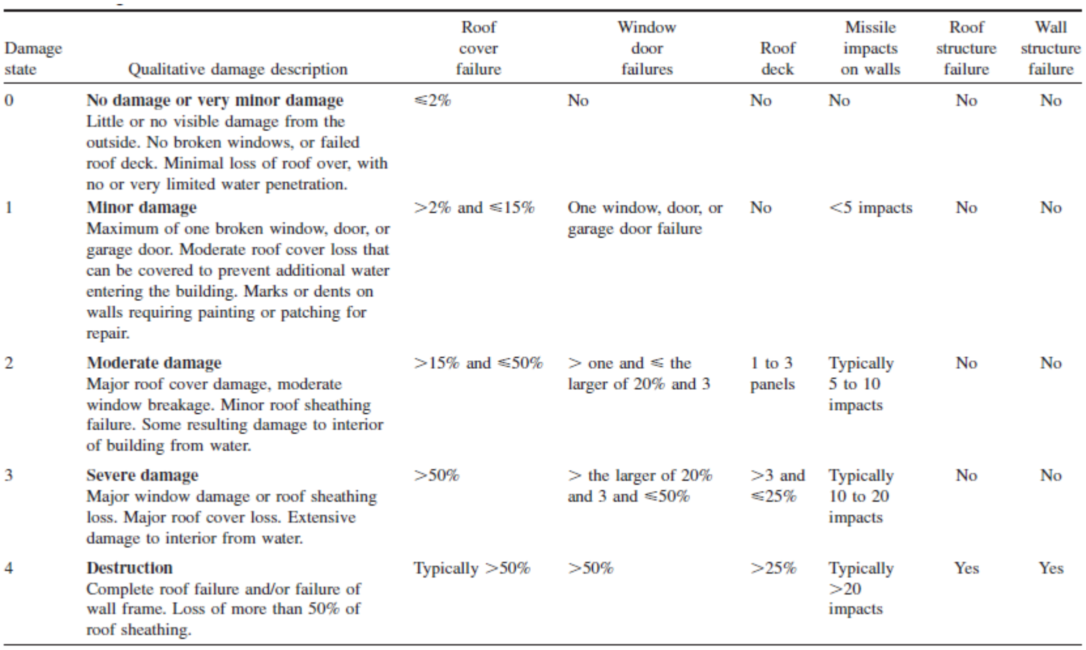
Figure 17. Uplift coefficients from HAZUS wind load simulations compared with wind tunnel experiments for a low-rise building (Vickery et al., 2006).

The Resistance Model

A load-resistance approach is used to estimate damage. Once the load is computed, HAZUS can determine whether certain building attributes will fail under such conditions. Engineering analyses and laboratory test data were combined to determine the resistance for single-family dwellings of one to two stories, multi-family dwellings of one to four stories, manufactured houses, pre-engineered metal buildings, low-rise retail buildings, industrial buildings, and high-rise buildings. Resistances were assigned to each component at risk of failure for the mentioned building types (Vickery et al., 2006).

The Damage Model

The damage model combines the estimates of the wind load model for a given storm with the resistance data to estimate building failures. HAZUS also takes into account the effect of storm duration by allowing for progressive failures and the weakening of structures while the storm lasts. The physical damage model focuses on the most commonly observed failures in buildings, which include windows, roof cover, roof deck, joints, and walls. The probability of impact from windborne debris is also included in the damage model. Once the damage model assigns building failures, it runs again and induces pressure on the interior of buildings with failed components. Further failures are then computed for the internally exposed structures. HAZUS then assigns each building with a damage state ranging from zero to four (Table 3). The mean number of buildings expected to experience each damage state is then estimated for each census tract. The damage model was validated against actual observations from three hurricanes. HAZUS was shown to demonstrate damage quite well, especially considering the large variation in resistance among buildings (Figure 18) (Vickery et al., 2006).



Damage state	Qualitative damage description	Roof cover failure	Window door failures	Roof deck	Missile impacts on walls	Roof structure failure	Wall structure failure
0	**No damage or very minor damage** Little or no visible damage from the outside. No broken windows, or failed roof deck. Minimal loss of roof over, with no or very limited water penetration.	≤2%	No	No	No	No	No
1	**Minor damage** Maximum of one broken window, door, or garage door. Moderate roof cover loss that can be covered to prevent additional water entering the building. Marks or dents on walls requiring painting or patching for repair.	>2% and ≤15%	One window, door, or garage door failure	No	<5 impacts	No	No
2	**Moderate damage** Major roof cover damage, moderate window breakage. Minor roof sheathing failure. Some resulting damage to interior of building from water.	>15% and ≤50%	> one and ≤ the larger of 20% and 3	1 to 3 panels	Typically 5 to 10 impacts	No	No
3	**Severe damage** Major window damage or roof sheathing loss. Major roof cover loss. Extensive damage to interior from water.	>50%	> the larger of 20% and 3 and ≤50%	>3 and ≤25%	Typically 10 to 20 impacts	No	No
4	**Destruction** Complete roof failure and/or failure of wall frame. Loss of more than 50% of roof sheathing.	Typically >50%	>50%	>25%	Typically >20 impacts	Yes	Yes

Table 3. Characteristics of each damage state (Vickery et al., 2006).

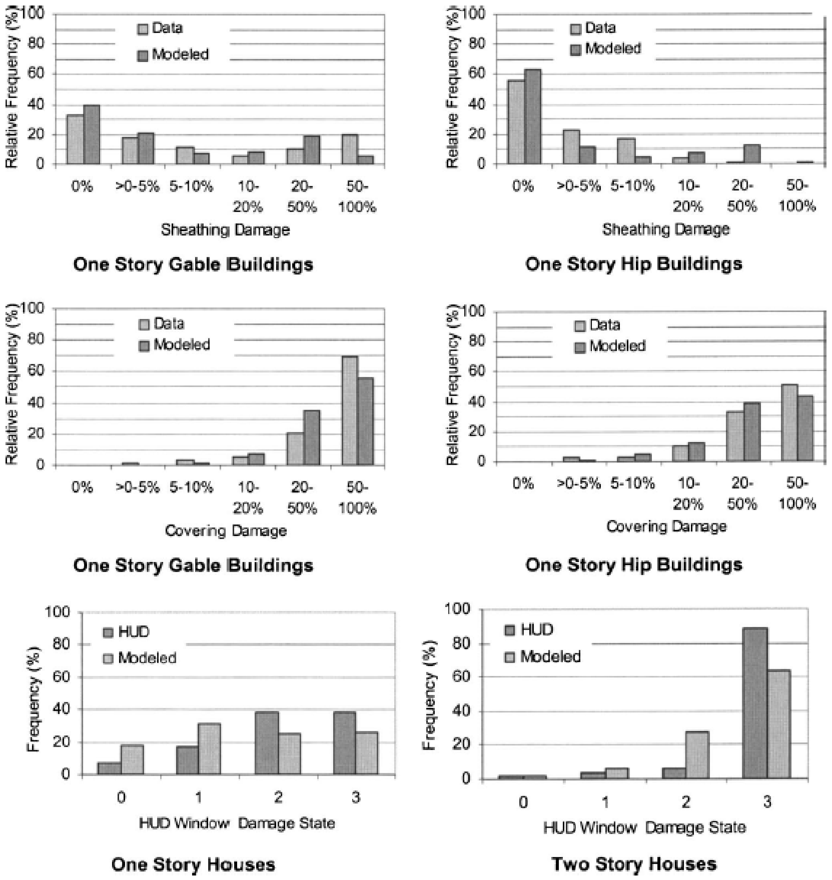


Figure 18. Simulated and observed building damage (Vickery et al., 2006).

The Loss Model

HAZUS runs its loss model with data generated from the damage model. Economic losses are estimated based on the costs of structural damage, inventory damage, and loss of use. Debris generation and the costs associated with cleanup are also estimated by the loss model. The model estimates the cost of each type of building and its components. These components include windows, roof cover, roof frames, structural framing, foundation, interior walls, and electrical among others. A combination of explicit and implicit loss functions are used to estimate the costs associated with rebuilding damaged structures. The repair or replacement cost due to exterior damage to the structure and its components is estimated with the explicit loss functions. Insurance company claim files were used to determine the amount of damage needed to require replacement of various components for residential, commercial, and industrial buildings. Because the damage model only estimates exterior damage, implicit loss functions were used to estimate interior damage. Engineering judgment and insurance loss data were used to develop empirical functions that estimate interior loss. The cost of interior damage is related to the total exterior damage coupled with rainfall penetration estimates. To estimate loss of use, the model calculates the probable length of time for reconstruction/repair and combines it with estimates of rental income, daily production output, and other economic factors (Vickery et al., 2006).

The loss model was validated with insurance data from Hurricane Andrew (Southern Florida), Hurricane Erin (Florida Panhandle), Hurricane Hugo (South Carolina), and Hurricane Opal (Florida Panhandle) (Vickery et al., 2006). The validation was conducted for single-family residential structures since insurance data was the most complete for losses associated with these types of buildings. Zip code averaged loss data were used instead of census tract data due to the collection and aggregation methods of insurance companies. Likewise, wind and surface roughness were estimated at the zip code scale for the validation study. Buildings were assumed to be randomly located within each zip code. The HAZUS loss model was shown to estimate hurricane losses quite well with a slight underestimation of the minor losses that occur at low wind speeds (Figure 19). This is expected since HAZUS does not predict minor damage associated with such components as chimneys, vents, driveways, decks, sheds, etc. while they are included in insurance figures (Vickery et al., 2006).

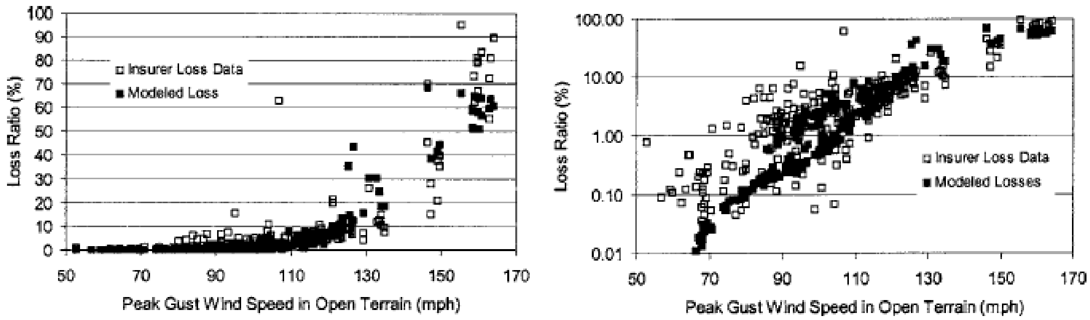


Figure 19. Modeled and observed loss ratios plotted against peak wind gust for Hurricanes Andrew, Erin, Hugo, and Opal - Linear scale (left) and logarithmic scale (right) (Vickery et al., 2006).

Summary

HAZUS is used to predict the losses associated with earthquakes, wind, and floods. The wind model is used for hurricanes and combines a hazard model, load model, resistance model, damage model, and loss model. For this study, the hurricane model is used as the principal hazard model. The hurricane model predicts the spatial pattern of a storm based on prescribed parameters. The load model uses data generated from the hurricane model to estimate the force exerted on structures. The resistance model predicts the strength of various types of buildings. The amount of force estimated by the load model is then compared with findings from the resistance model to predict damage. This damage and the loss of use of structures are then given an economic cost by the loss model. Validation of these models against observed data has shown that they all do reasonably well, especially considering the extreme variation in storms, terrain, buildings, and economic value. Regardless, precision between the estimated and observed losses is not necessary for this study since we are interested in the pattern of economic vulnerability and not the actual monetary cost attributed to each storm. We will assume that HAZUS accurately depicts the spatial variability of economic susceptibility in the United States. Therefore, loss estimates should reveal the importance of landfall location for a prescribed storm.

Research Methods

Varying the landfall of an historic hurricane should provide information on the noise to signal ratio associated with hurricane damage figures. A slight variation that leads to significantly different loss figures would reveal that the noise to signal ratio is very high. The alternate landfall locations should be relatively close to the original landfall locations so the effect of variations that are common to hurricane tracks can be seen. The simulated hurricanes will still affect the same general regions as the historic hurricanes, but their impacts will be distributed differently.

Several sources can be used to import historic storms into HAZUS. For this study, Hurricane Evacuation (HURREVAC) files are used. These files were created with data from National Hurricane Center (NHC) advisories (FEMA, 2007). These advisories have the most comprehensive and accurate information on historic storms. Using HAZUS, track modification is the most practical with HURREVAC files because storm attributes are given for every NHC advisory. The storm coordinates for each advisory can be altered. HURREVAC files are only available to HAZUS for storms that have occurred since 1988.

Though major hurricanes account for less than a quarter of all tropical cyclones, they are responsible for more than 85% of the damage (Pielke Jr. et al., 2008). Isolated extreme events are responsible for the most significant losses due to tropical cyclones. The normalized record estimates the damage that would be caused by historic hurricanes under present-day societal conditions. Simulating an alternate landfall for the most potentially destructive storms should reveal the sensitivity of damage figures to landfall location. If a minor track change results in dramatically different loss figures, it will suggest that societal development patterns are extremely influential to damage amounts. If the loss figures change very little, it will suggest that landfall location is not as important as storm characteristics. It is possible that prescribed landfall shifts will result in a reordering of the normalized record. This will also suggest that the noise to signal ratio for hurricane losses is very high and that landfall location is of chief importance. A company called ICAT Catastrophe Insurance updated the normalized record to 2009 using the same method as presented by Pielke Jr. et al. (2008) (ICAT, 2009). The hurricanes with the top 10 most normalized damage since 1988 will be used or this study. Table 4 shows the top 50 most damaging tropical cyclones (1900-2008) after normalization to 2009 and will be referred to as the “normalized record” from here on out.

In order to best observe the importance of landfall location, track shifts should be relatively minor. Hurricane sizes vary considerably, but the average diameter is about 300 miles. The eye of a hurricane is typically between 20 and 40 miles wide. (NHC, 1999). Locations under the hurricane’s eye are affected by the eyewall before and after its passage. The eyewall is the most violent part of the hurricane and can be assumed to cause the most wind damage. A hurricane’s eye tends to shrink as it strengthens (Pielke Jr. & Pielke Sr., 1997) Therefore, it can be assumed that the eyes of major hurricanes will typically fall near the bottom of the size range. For this study, the track of each storm will be shifted 30 miles to the left and right of the original landfall location. This should allow for adjacent areas to be affected by the storm’s eye and eyewall with little or no overlap. The same general areas will be impacted by each storm, but the varying effects will be shifted by 30 miles. This should reveal how important minor variations in landfall location are.

RANK	NAME	YR	ST.	CAT.	BASE DAMAGE	2009 DAMAGE
1	Great Miami	1926	FL	4	76,000,000	180,890,000,000
2	Galveston	1900	TX	4	30,000,000	94,060,000,000
3	Katrina	2005	LA	3	81,000,000,000	91,480,000,000
4	Galveston	1915	TX	4	50,000,000	75,630,000,000
5	Andrew	1992	FL	5	25,500,000,000	66,190,000,000
6	NA	1944	FL	3	63,000,000	46,720,000,000
7	New England	1938	NY	3	306,000,000	45,210,000,000
8	Donna	1960	FL	4	300,000,000	44,170,000,000
9	NA	1928	FL	4	25,000,000	42,320,000,000
10	Camille	1969	LA	5	1,421,000,000	25,630,000,000
11	Wilma	2005	FL	3	20,600,000,000	25,140,000,000
12	Diane	1955	NY	TS	600,000,000	23,530,000,000
13	Betsy	1965	LA	3	1,280,500,000	20,660,000,000
14	Hazel	1954	SC	4	281,000,000	20,610,000,000
15	Ike	2008	TX	2	20,000,000,000	20,100,000,000
16	Carol	1954	NY	3	460,000,000	18,810,000,000
17	Charley	2004	FL	4	14,110,000,000	18,740,000,000
18	Agnes	1972	NY	TS	2,000,000,000	18,520,000,000
19	Ivan	2004	AL	3	14,200,000,000	18,140,000,000
20	Hugo	1989	SC	4	7,000,000,000	17,890,000,000
21	Carla	1961	TX	4	400,000,000	17,840,000,000
22	NA	1947	FL	4	31,000,000	16,400,000,000
23	NA	1949	FL	3	45,000,000	15,600,000,000
24	Dora	1964	FL	2	250,000,000	14,850,000,000
25	NA	1945	FL	3	60,000,000	14,580,000,000
26	NA	1916	AL	3	31,000,000	13,780,000,000
27	NA	1919	TX	3	20,000,000	13,640,000,000
28	Diane	1955	NC	1	200,000,000	12,750,000,000
29	Frederic	1979	AL	3	2,300,000,000	12,240,000,000
30	Frances	2004	FL	2	8,900,000,000	11,800,000,000
31	Rita	2005	LA	3	10,000,000,000	11,270,000,000
32	NA	1944	NY	1	90,000,000	10,410,000,000
33	NA	1926	AL	3	29,000,000	9,520,000,000
34	Alicia	1983	TX	3	2,000,000,000	9,290,000,000
35	Jeanne	2004	FL	3	6,900,000,000	9,080,000,000
36	NA	1944	NC	3	10,000,000	8,090,000,000
37	Allison	2001	TX	TS	5,000,000,000	8,000,000,000
38	NA	1935	FL	2	5,500,000	7,770,000,000
39	Floyd	1999	NC	2	4,500,000,000	7,480,000,000
40	Freeport	1932	TX	4	7,500,000	7,220,000,000
41	Opal	1995	FL	3	3,000,000,000	7,160,000,000
42	Fran	1996	NC	3	3,200,000,000	6,960,000,000
43	Celia	1970	TX	3	454,000,000	6,670,000,000
44	NA	1909	FL	3	1,000,000	6,420,000,000
45	Cleo	1964	FL	2	128,000,000	6,390,000,000
46	Ione	1955	NC	3	88,000,000	6,290,000,000
47	Eloise	1975	FL	3	490,000,000	5,980,000,000
48	NA	1903	FL	1	670,000	5,670,000,000
49	King	1950	FL	3	28,000,000	5,380,000,000
50	NA	1947	FL	1	20,000,000	4,960,000,000

Table 4. Top 50 most damaging tropical cyclones (1900-2008) after normalization to 2009. Base damage is the direct damage at the time of impact. This study will use the top 10 most damaging storms in the normalized record since 1988 (in grey).

The hurricane characteristics and velocity will remain identical prior to and after landfall. The National Weather Service (NWS) radar website will be used to determine the coordinates of alternate landfall locations (NWS, 2009). An applet below each region's radar can be used to determine the coordinates of coastal locations 30 miles to the left and right of the original track. The original landfall location can be set as the origin and the applet will reveal the distance from origin and coordinates for anywhere on the map. Alternate landfall locations will be set on the coast at a straight-line distance of 30 miles to the left and right of the original landfall location. The alternate hurricanes will have the same velocity as the original hurricane, but their paths will be shifted based on landfall location. It is assumed that these minor shifts would not affect the storm characteristic parameters. The right-shifted hurricanes will be called "Storm Name-R" and the left-shifted hurricanes will be called "Storm Name-L" (Figure 20).

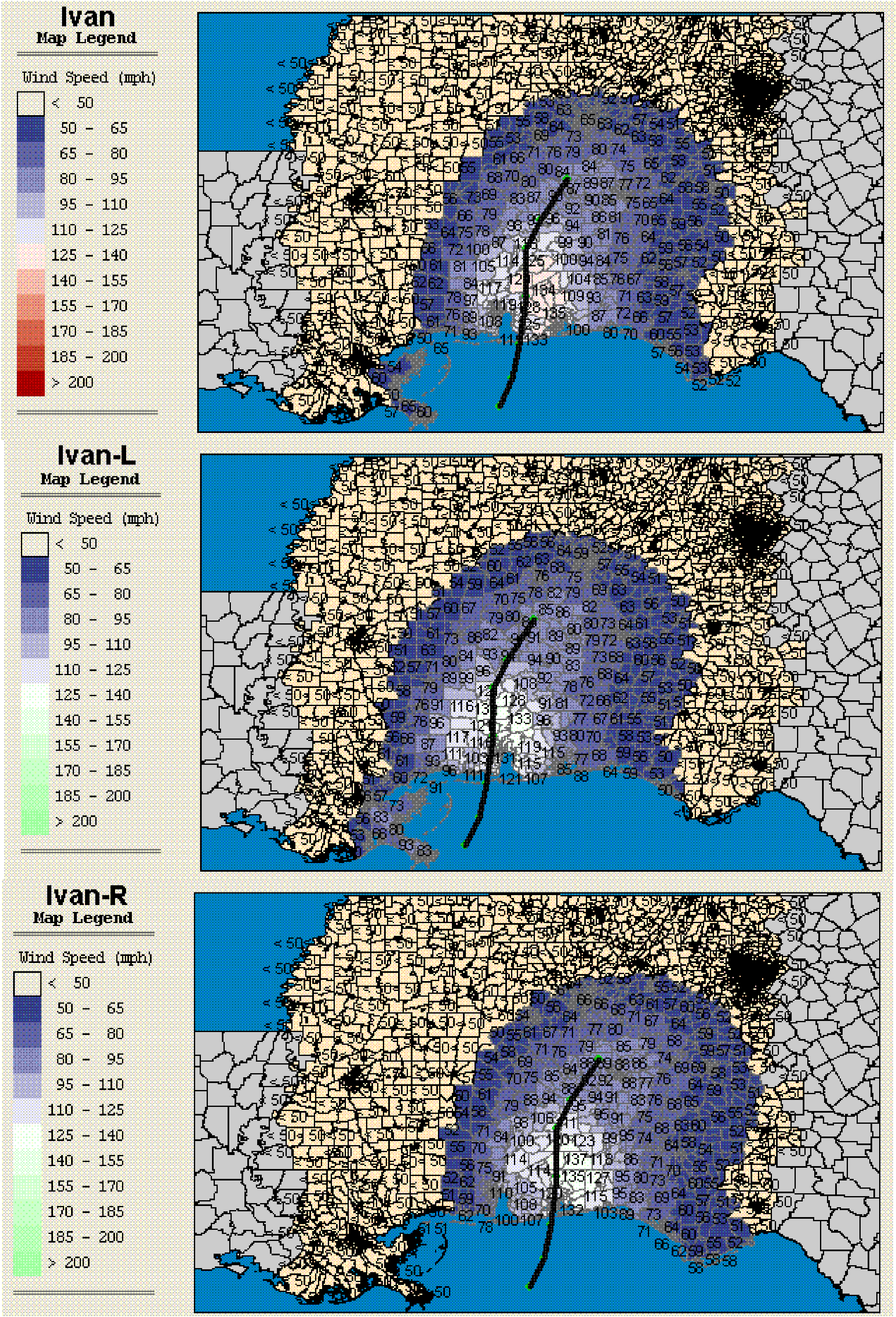


Figure 20. HAZUS estimated wind field for Ivan, Ivan-L, and Ivan-R.

Total direct physical damage estimates will be used for this analysis. Secondary and tertiary impact estimates are excluded in the interest of consistency with the normalized record. From here on out, any mention of “damage” will refer to direct damage. HAZUS should underestimate this value due to the fact that storm surge and freshwater flooding are not included. Regardless, precision for HAZUS damage estimates is unnecessary since we are predominantly interested in vulnerability differences among areas. It will be assumed that the difference between the HAZUS estimate and the normalized estimate for the original landfall location is proportional to that of the alternate landfall location. The HAZUS damage estimate for the original track will be adjusted to equal the normalized damage estimate for each hurricane. A proportional adjustment will then be prescribed for alternate landfall location damage estimates. This will reveal how damage may differ with respect to landfall location. The normalized damage record will then be updated to include the adjusted alternate landfall damage estimates. A significant reordering of the record would suggest that even normalized damage estimates are highly dependent on specific landfall location. The percentage of damage as compared to the original storm will also be calculated for each alternate landfall. Large changes will suggest that significant vulnerability differences exist within in the affected areas while small changes will suggest that vulnerability is relatively uniform.

The inability of HAZUS to include storm surge and freshwater flooding in its hurricane model poses some problems. While a hurricane’s wind behavior should not be highly dependent on exact landfall location, storm surge and freshwater flooding are. Alternate landfall locations can be expected to experience similar winds to the original landfall location. However, storm surge and freshwater flooding are highly dependent on local terrain. It will be assumed that the adjustment factor accounts for normalization and HAZUS's error for each original storm, and that it also represents the magnitude of error for alternate landfalls. This assumption is reasonable as the affected area will only change slightly for alternate cases. In order to use the same adjustment factor for the alternate landfalls, it must be assumed that unaccounted-for variables (e.g. storm surge) change proportionally to the HAZUS damage estimates for the three landfall situations. It is also assumed that the normalization parameters do not change as a result of the landfall shift. This assumption is valid because inflation and wealth changes are uniform among locations in the normalization scheme. The population change parameter would not change noticeably with such minor landfall shifts.

IV: RESULTS

Individual Storms

Hurricane Katrina

Katrina made landfall about 54 miles southeast of New Orleans, Louisiana in August of 2005 as a category 3 hurricane. It tracked due north and passed about 27 miles east of downtown New Orleans. About a week earlier, it made its initial landfall 17 miles north-northeast of Miami, Florida as a category 1 hurricane. It was the most damaging tropical cyclone in history causing over $100 billion in total losses. It is the third most destructive hurricane in the normalized record and would cause an estimated $91.48 billion in direct damage today. Both the Florida and the Louisiana landfalls were shifted for the alternate landfall scenarios.

HAZUS estimates that Katrina would cause $52.4 billion in direct damage. This must be multiplied by an adjustment factor of 1.75 to equal the 2009 normalized damage estimate of $91.48 billion. The right shift results in an initial landfall about 17 miles north of Fort Lauderdale, Florida and a second landfall at the southeastern tip of Louisiana. The center of Katrina-R tracks about 57 miles east of downtown New Orleans. It skirts the islands of Louisiana and makes a final landfall about 10 miles west of Biloxi, Mississippi. HAZUS estimates that Katrina-R would cause $19.2 billion in damage today. With the adjustment factor, the total rises to $33.6 billion, which would put Katrina-R at 16th in the normalized record. It causes less damage than Katrina because the New Orleans and Miami areas are spared of the most severe effects. The left shift results in an initial landfall about 16 miles south-

southwest of Miami, Florida and a final landfall about 90 miles south of New Orleans. The eye of Katrina-L goes directly over downtown New Orleans. HAZUS estimates that this storm would cause $92.6 billion in damage. With the adjustment factor, the total rises to $162.05 billion, which would put Katrina-L at second in the normalized record. It is much more damaging than Katrina because both Miami and New Orleans are affected by stronger winds. It is estimated that Katrina-L would be 77% more damaging than the original storm while Katrina-R would be 63% less (Table 5).

Storm	HAZUS direct damage estimate (billions $)	Adjustment factor	Adjusted to 2009 normalized direct damage (billions $)	Damage compared to original storm	Rank in original normalized record
Katrina	52.4	1.75	91.48	100%	3
Katrina-L	92.6		162.05	177%	2
Katrina-R	19.2		33.6	37%	16

Table 5. Hurricane Katrina.

Hurricane Andrew

Andrew made landfall about 16 miles south-southwest of Miami, Florida as a category 5 hurricane in August of 1992. After emerging over the Gulf of Mexico, it made landfall again about 57 miles southwest of Baton Rouge, Louisiana as a weak category 3 hurricane. It is estimated that it would cause $66.19 billion in damage today, making it the fifth most damaging tropical cyclone in the normalized record. Andrew-L makes its initial landfall over Key Largo, FL and its final landfall over rural south central Louisiana. It is estimated that Andrew-L would cause $34.64 billion in damage today, making it the 10th most damaging in the normalized record.

It does not cause as much damage as Andrew because less of the Florida peninsula is affected and the strongest winds avoid the Miami metropolitan area. Andrew-R makes its initial landfall about midway between Fort Lauderdale and Miami and its final landfall about 72 miles south-southwest of Baton Rouge. Andrew-R would cause an estimated $120.89 billion in damage today, making it the 2nd most damaging in the normalized record. It is more damaging than Andrew because the Miami metropolitan area is affected by stronger winds. Baton Rouge also sees more severe effects from Andrew-R. It is estimated that Andrew-R would be 83% more damaging than the original storm while Andrew-L would be 48% less (Table 6).

Landfall	HAZUS direct damage estimate (billions $)	Adjustment factor	Adjusted to 2009 normalized direct damage (billions $)	Damage compared to original storm	Rank in original normalized record
Andrew	18.05	3.67	66.19	100%	5
Andrew-L	9.44		34.64	52%	10
Andrew-R	32.94		120.89	183%	2

Table 6. Hurricane Andrew.

Hurricane Wilma

Wilma made landfall about 14 miles southeast of Naples, Florida as a category 3 hurricane in October of 2005. At one point, it had the lowest pressure ever recorded for an Atlantic basin hurricane. It is the 11th most destructive hurricane in the normalized record and would cause an estimated $25.14 billion in damage today. Wilma-L would cause an estimated $16.76 billion in damage today, making it the 22nd most damaging in the normalized record. It does not cause as much damage as Wilma because less of the Miami metropolitan area is affected. Wilma-R would cause an estimated \$34.44 billion in damage, making it the 9th most damaging in the normalized record. It is more damaging than Wilma because the eye crosses directly over the Miami metropolitan area. It is estimated that Wilma-L would be 70% more damaging than the original storm while Wilma-R would be 33% less (Table 7).

Landfall	HAZUS direct damage estimate (billions \$)	Adjustment factor	Adjusted to 2009 normalized direct damage (billions \$)	Damage compared to original storm	Rank in original normalized record
Wilma	19.1	1.32	25.14	100%	11
Wilma-L	12.7		16.76	67%	22
Wilma-R	34.44		42.82	170%	9

Table 7. Hurricane Wilma.

Hurricane Ike

Hurricane Ike made landfall on northern Galveston Island, Texas as a category 2 hurricane in September of 2008. Its eye skirted the northeast corner of the Houston/Galveston metropolitan area. It would cause an estimated \$20.1 billion in damage today, making it the 15th most damaging hurricane in the normalized record. Ike-L would cause an estimated \$43.63 billion in damage today, making it 6th in the normalized record. It is much more damaging than Ike because the eye goes directly over downtown Houston. Ike-R makes landfall about 70 miles east of Houston and would cause an estimated \$18.6 billion in damage today, making it 18th in the normalized record. It is less damaging than Ike because Houston is affected by weaker winds. It is estimated that Ike-L would be 141% more damaging than the original storm while Ike-R would be 7% less (Table 8).

Landfall	HAZUS direct damage estimate (billions $)	Adjustment factor	Adjusted to 2009 normalized direct damage (billions $)	Damage compared to original storm	Rank in original normalized record
Ike	18.19	1.11	20.10	100%	15
Ike-L	43.63		48.43	241%	6
Ike-R	16.76		18.60	93%	18

Table 8. Hurricane Ike.

Hurricane Charley

Charley made an initial landfall on Port Charlotte, Florida as a category 4 hurricane and skirted the South Carolina coast as a category 1 hurricane in August of 2004. It would cause an estimated $18.74 billion in damage today, making it the 17th most damaging hurricane in the normalized record. Charley-L would cause an estimated $38.80 billion in damage today, making it 10th in the normalized record. It is much more damaging than Charley because the Tampa/St. Petersburg metropolitan area experience stronger winds. Charley-L also affects more land area than Charley in South Carolina, including the city of Charleston. Charley-R would cause an estimated $7.54 billion in damage today, making it 39th in the normalized record. It is not nearly as damaging as Charley because less of the Tampa/St. Petersburg area and only the immediate coast of South Carolina are affected. It is estimated that Charley-L would be 107% more damaging than the original storm while Charley-R would be 40% less (Table 9).

Landfall	HAZUS direct damage estimate (billions $)	Adjustment factor	Adjusted to 2009 normalized direct damage (billions $)	Damage compared to original storm	Rank in original normalized record
Charley	9.92	1.89	18.74	100%	17
Charley-L	20.53		38.80	207%	10
Charley-R	3.99		7.54	40%	39

Table 9. Hurricane Charley.

Hurricane Ivan

Ivan made landfall on the eastern shore of Mobile Bay, Alabama as a category 3 hurricane in September of 2004. It was the strongest hurricane of the season. Ivan would cause an estimated $18.14 billion in damage today, making it the 19th most damaging hurricane in the normalized record. Ivan-L would cause an estimated $39.33 billion in damage today, making it 10th in the normalized record. Ivan-L is more than twice as damaging as Ivan because it makes landfall west of Mobile Bay, bringing its strongest winds into downtown Mobile. Ivan-R would cause an estimated $7.20 billion in damage today, making it 41st in the normalized record. It is much less damaging than Ivan because landfall occurs in a less developed area and downtown Mobile experiences weaker winds. It is estimated that Ivan-L would be 117% more damaging than the original storm while Ivan-R would be 60% less (Table 10).

Landfall	HAZUS direct damage estimate (billions $)	Adjustment factor	Adjusted to 2009 normalized direct damage (billions $)	Damage compared to original storm	Rank in original normalized record
Ivan	3.00	6.05	18.14	100%	19
Ivan-L	6.50		39.33	217%	10
Ivan-R	1.19		7.20	40%	41

Table 10. Hurricane Ivan.

Hurricane Hugo

Hugo made landfall near Charleston, South Carolina as a category 4 hurricane in September of 1989. It was the most damaging hurricane in history at the time. Hugo would cause an estimated $17.89 billion in damage today, making it the 20th most damaging hurricane in the normalized record. Hugo-L would cause an estimated $24.24 billion in damage today, making it 12th in the normalized record. It is more damaging than Hugo because all of Charleston is affected by the right eyewall. Hugo-L also tracks closer to the Columbia. Hugo-R would cause an estimated $11.04 billion in damage today, making it 32nd in the normalized record. It is less damaging because both Charleston and Columbia are spared from the strongest winds. It is estimated that Hugo-L would be 36% more damaging than the original storm while Hugo-R would be 38% less (Table 11).

Landfall	HAZUS direct damage estimate (billions $)	Adjustment factor	Adjusted to 2009 normalized direct damage (billions $)	Damage compared to original storm	Rank in original normalized record
Hugo	8.95	2.00	17.89	100%	20
Hugo-L	12.12		24.24	136%	12
Hugo-R	5.52		11.04	62%	32

Table 11. Hurricane Hugo.

Hurricane Frances

Frances made landfall near Port St. Lucie, Florida as a category 2 hurricane in September of 2004. After emerging into the Gulf of Mexico, it made its final landfall on the Florida panhandle as a tropical storm. Frances would cause an estimated $11.8 billion in damage today, making it the 30th most damaging hurricane in the normalized record. Frances-L would cause an estimated $19.63 billion in damage today, making it 16th in the normalized record. It causes more damage than Frances because landfall occurs closer to West Palm Beach and Miami. Frances-R would cause an estimated $8.57 billion in damage today, making it 36th in the normalized record. It causes less damage because the Miami metropolitan area is less affected. This effect is suppressed though because the Orlando area experiences stronger winds with Frances-R. It is estimated that Frances-L would be 66% more damaging than the original storm while Frances-R would be 27% less (Table 12).

Landfall	HAZUS direct damage estimate (billions $)	Adjustment factor	Adjusted to 2009 normalized direct damage (billions $)	Damage compared to original storm	Rank in original normalized record
Frances	8.71	1.35	11.8	100%	30
Frances-L	14.54		19.63	166%	16
Frances-R	6.35		8.57	73%	36

Table 12. Hurricane Frances.

Hurricane Rita

Rita made landfall in rural southwestern Louisiana as a category 3 hurricane in September of 2005. It is the 31st most destructive hurricane in the normalized record and would cause an estimated $11.27 billion in damage today. Rita-L would cause an estimated $12.14 billion in damage today, making it 28th in the normalized record. It causes more damage than Rita because the Houston/Galveston metropolitan area is affected by stronger winds. Rita-R would cause an estimated $10.88 billion in damage today, making it 32nd in the normalized record. It causes less damage because the strongest winds affect rural areas and the Houston/Galveston area is mostly spared. It is estimated that Rita-L would be 21% more damaging than the original storm while Rita-R would be 3% less (Table 13).

Landfall	HAZUS direct damage estimate (billions $)	Adjustment factor	Adjusted to 2009 normalized direct damage (billions $)	Damage compared to original storm	Rank in original normalized record
Rita	10.09	1.12	11.27	100%	31
Rita-L	12.14		13.60	121%	28
Rita-R	9.71		10.88	97%	32

Table 13. Hurricane Rita.

Hurricane Jeanne

Jeanne made landfall near Port St. Lucie, Florida as a category 3 hurricane in September of 2004. It came onshore two miles from where Hurricane Frances had made landfall three weeks earlier. Jeanne would cause an estimated $9.08 billion in damage today, making it the 35th most damaging hurricane in the normalized record. Jeanne-L would cause an estimated $17.24 billion in damage today, making it 22nd in the normalized record. It causes more damage than Jeanne because the Miami metropolitan area is affected by stronger winds. Jeanne-R would cause an estimated $8.08 billion in damage today, making it 37th in the normalized record. It causes less damage because Miami is affected by weaker winds. As was the case with Frances-R, the reduction in damage is probably not as marked because Orlando is more severely affected. It is estimated that Jeanne-L would be 90% more damaging than the original storm, while Jeanne-R would be 11% less (Table 14).

Landfall	HAZUS direct damage estimate (billions $)	Adjustment factor	Adjusted to 2009 normalized direct damage (billions $)	Damage compared to original storm	Rank in original normalized record
Jeanne	7.21	1.26	9.08	100%	35
Jeanne-L	13.68		17.24	190%	22
Jeanne-R	6.41		8.08	89%	37

Table 14. Hurricane Jeanne.

Overall Results

For each storm, both track shifts resulted in sufficient difference to cause a rank change in the normalized record. The most significant differences were found for storms that affected large metropolitan areas. The largest difference was found with Hurricane Ike, where Ike-L caused an estimated 141% more damage than the original storm. This is not surprising because the original storm tracked just to the east of downtown Houston, sparing it of the most severe winds. Ike-L tracked through western Houston and pummeled the downtown area with its most severe effects. The smallest difference was found with Hurricane Rita, where Rita-R caused only 3% less damage than the original storm. No highly developed areas were affected by these tracks so the shift did not result in much of a vulnerability change.

Using the most damaging storms in the normalized record assured that most of our cases would involve large cities. The original landfall location had the median estimated damage out of the three landfalls for each storm. This is due to the fact that large cities don’t tend to be near each other and because development density usually decreases away from city centers. The damage estimates increased with a shift toward downtown areas and decreased with a shift in the opposite direction. A decrease in both directions should only occur if the original storm struck the most vulnerable location in the affected area.

Adding the results to the normalized record causes a marked reordering of the list. This suggests that the normalized record would look entirely different had each storm made landfall on a slightly different location. Table 15 gives the normalized record with each alternate landfall included.

RANK	NAME	YR	ST.	CAT.	BASE DAMAGE	2009 DAMAGE
1	Great Miami	1926	FL	4	76,000,000	180,890,000,000
2	Katrina-L	2005	LA	3		162,050,000,000
3	Andrew-R	1992	FL	5		120,890,000,000
4	Galveston	1900	TX	4	30,000,000	94,060,000,000
5	Katrina	2005	LA	3	81,000,000,000	91,480,000,000
6	Galveston	1915	TX	4	50,000,000	75,630,000,000
7	Andrew	1992	FL	5	25,500,000,000	66,190,000,000
8	Charley-L	2004	FL	4		57,700,000,000
9	Ike-L	2008	TX	2		48.430,000
10	NA	1944	FL	3	63,000,000	46,720,000,000
11	New England	1938	NY	3	306,000,000	45,210,000,000
12	Donna	1960	FL	4	300,000,000	44,170,000,000
13	Wilma-R	2005	FL	3		42,820,000,000
14	NA	1928	FL	4	25,000,000	42,320,000,000
15	Ivan-L	2004	AL	3		39,330,000,000
16	Andrew-L	1992	FL	5		34,630,000,000
17	Katrina-R	2005	LA	3		33,600,000,000
18	Camille	1969	LA	5	1,421,000,000	25,630,000,000
19	Wilma	2005	FL	3	20,600,000,000	25,140,000,000
20	Hugo-L	1989	SC	4		24,240,000,000
21	Diane	1955	NY	TS	600,000,000	23,530,000,000
22	Betsy	1965	LA	3	1,280,500,000	20,660,000,000
23	Hazel	1954	SC	4	281,000,000	20,610,000,000
24	Ike	2008	TX	2	20,000,000,000	20,100,000,000
25	Frances-L	2004	FL	2		19,630,000,000
26	Carol	1954	NY	3	460,000,000	18,810,000,000
27	Charley	2004	FL	4	14,110,000,000	18,740,000,000
28	Ike-R	2008	TX	2		18,600,000
29	Agnes	1972	NY	TS	2,000,000,000	18,520,000,000
30	Ivan	2004	AL	3	14,200,000,000	18,140,000,000
31	Hugo	1989	SC	4	7,000,000,000	17,890,000,000
32	Carla	1961	TX	4	400,000,000	17,840,000,000
33	Wilma-L	2005	FL	3		17,760,000,000
34	Jeanne-L	2004	FL	3		17,240,000,000
35	NA	1947	FL	4	31,000,000	16,400,000,000
36	NA	1949	FL	3	45,000,000	15,600,000,000
37	Dora	1964	FL	2	250,000,000	14,850,000,000
38	NA	1945	FL	3	60,000,000	14,580,000,000
39	NA	1916	AL	3	31,000,000	13,780,000,000
40	NA	1919	TX	3	20,000,000	13,640,000,000
41	Rita-L	2005	LA	3		13,600,000,000
42	Diane	1955	NC	1	200,000,000	12,750,000,000
43	Frederic	1979	AL	3	2,300,000,000	12,240,000,000
44	Frances	2004	FL	2	8,900,000,000	11,800,000,000
45	Rita	2005	LA	3	10,000,000,000	11,270,000,000
46	Hugo-R	1989	SC	4		11,040,000,000
47	Rita-R	2005	LA	3		10,880,000,000
48	NA	1944	NY	1	90,000,000	10,410,000,000
49	NA	1926	AL	3	29,000,000	9,520,000,000
50	Alicia	1983	TX	3	2,000,000,000	9,290,000,000
51	Jeanne	2004	FL	3	6,900,000,000	9,080,000,000
52	Frances-R	2004	FL	2		8,570,000,000
53	NA	1944	NC	3	10,000,000	8,090,000,000
54	Jeanne-R	2004	FL	3		8,080,000,000
55	Allison	2001	TX	TS	5,000,000,000	8,000,000,000
56	NA	1935	FL	2	5,500,000	7,770,000,000
57	Floyd	1999	NC	2	4,500,000,000	7,480,000,000
58	Freeport	1932	TX	4	7,500,000	7,220,000,000
59	Ivan-R	2004	AL	3		7,200,000,000
60	Opal	1995	FL	3	3,000,000,000	7,160,000,000
61	Fran	1996	NC	3	3,200,000,000	6,960,000,000
62	Celia	1970	TX	3	454,000,000	6,670,000,000
63	NA	1909	FL	3	1,000,000	6,420,000,000
64	Cleo	1964	FL	2	128,000,000	6,390,000,000
65	Ione	1955	NC	3	88,000,000	6,290,000,000
66	Eloise	1975	FL	3	490,000,000	5,980,000,000
67	NA	1903	FL	1	670,000	5,670,000,000
68	Charley-R	2004	FL	4		5,650,000,000
69	King	1950	FL	3	28,000,000	5,380,000,000
70	NA	1947	FL	1	20,000,000	4,960,000,000

Table 15. Top 70 most damaging storms normalized to 2009 including alternate landfalls.

V. CONCLUSION

Tropical cyclone damage in the United States has shown an increasing trend since records began. This trend has been apparent even through relatively inactive periods. No significant long-term trend in tropical cyclone activity or intensity can be found. A persistent increase in coastal vulnerability has given way to the obvious rise in hurricane losses. More development and property value is exposed on the coast than ever before. Normalizing the damage records eliminates the influence of vulnerability differences by taking into account population change, wealth growth, and inflation (Pielke Jr. & Landsea, 1998). A damage trend is no longer evident after normalization. The lack of a trend in the normalized record has been used to refute the claim that tropical cyclones are becoming increasingly destructive (Pielke Jr., 2005).

But development is far from evenly distributed on the coasts, and this study finds that relatively small variations in landfall location (variations that are typical for hurricanes as they respond to steering currents and exhibit wobble) yield large changes in damage. It is unlikely that a temporal trend exists in the tendency of hurricanes to strike more or less developed segments of coastline (and this research was not designed to reveal a trend, were it to exist) though the nature of American urbanization and land use patterns certainly spreads development out along more of the coastline over time. This work does reveal the large noise in hurricane impact: a 30-mile difference in landfall can demote the most destructive storms in the record to more typical events, and, presumably, could transform less destructive storms into catastrophes. This is demonstrated by the noteworthy reordering of the normalized record. A minor leftward shift would have caused Hurricane Katrina to be second in the normalized record while a minor rightward shift would have dropped it all the way to 16th. The majority of the damage in the normalized record comes from isolated extreme events like those used in this analysis. For instance, about 66% of the normalized damage between 1986 and 1995 came from Hurricane Andrew (Pielke Jr. et al., 2008). This means that Andrew-R would have led to 55% more normalized damage for that decade while Andrew-L would have led to 31% less. These findings show that minor track differences for historic storms would also significantly change the long-term record of normalized damage.

This amount of variation suggests that changes in hurricane numbers, intensity, and even landfall frequency observed in the historical record, and predicted to accompany global warming, would be difficult to discern in the loss data. The findings also suggest that seasonal forecasts of numbers of landfalling storms, unless they can pinpoint landfall location, offer little skill for anticipating impacts. A minor track shift yielded a greater than 50% increase in estimated damage for 8 of the 10 analyzed storms. Because major hurricanes account for 85% of the damage in the record, it can be assumed that at least one was present in years with high normalized damage values. However, it should not be assumed that those years had more major hurricane activity than years with low normalized damage values. Two category four hurricanes that make landfall on a rural coastline would cause much less damage than one category three hurricane that makes landfall on an urbanized coastline.

Some continuously-monitored regional climatic oscillations show significant correlations to tropical cyclone activity in the Atlantic basin. Studies show that the

United States is at higher risk of a major hurricane landfall during the La Niña phase of ENSO, the positive phase of the AMO, and the negative phase of the NAO. Though impacts cannot accurately be predicted due to the large influence of landfall variation, the relative risk of a landfalling major hurricane (based on climate phases) can be predicted with some skill. Because major hurricanes account for the majority of losses, there is a greater likelihood of catastrophe when their landfall is more probable. Without an incredibly accurate track forecast, storm impacts are unpredictable until the specific landfall location reveals itself.

REFERENCES

Appinsys. (2009). *Oceanic Oscillations and Correlation to Climatic Phenomena.*, Retrieved June 11, 2009, from http://www.appinsys.com/GlobalWarming/PDO_AMO.htm#amo

Bell, I. (2008). *North Atlantic Oscillation.*, Retrieved June 11, 2009, from http://www.ldeo.columbia.edu/res/pi/NAO/

Bengtson, L., Botzet, M., & Esch, M. (1996). Will Greenhouse Gas-induced Warming over the Next 50 Years Lead to Higher Frequency and Greater Intensity of Hurricanes*? Tellus A, 4*8(1), 57-73.

Blake, E., Rappaport, B., & Landsea, C. (2007). The Deadliest, Costliest, and Most Intense United States Tropical Cyclones from 1851 to 2006*. NOAA Technical Memorandum.*

Bove, M. C. (1998). Effect of El Nino on U.S. Landfalling Hurricanes, Revisited*. Bulletin of the American Meteorological Society, 7*9, 2477.

Census. (1995). Population in Coastal Counties: 1960-1980*. Census Bureau.*

Census. (1996). Population in Coastal Counties: April 1, 1990 and July 1, 1994*. Census Bureau.*

Census. (2001). *County and City Data Book: 2000 (13th edition*). Washington, DC.

Census. (2003). 2003 County Population Estimates*. Census Bureau.*

Census. (2004). 2004 County Population Estimates*. Census Bureau.*

Census. (2006). 2006 Hurricane Season Begins*. Census Bureau.*

Emanuel, K. A. (1987). The Dependence of Hurricane Intensity on Climate*. Nature, 32*6(6112), 483-485.

Emanuel, K. A. (2005). Increasing Destructiveness of Tropical Cyclones over the Past 30 Years*. Nature, 43*6(7051), 686-688.

FEMA. (2007). *Multi-hazard Loss Estimation Methodology - Hurricane Model - User Manua*l. Federal Emergency Management Agency.

Gore, A. (2005). *On Katrina, Global Warming.* Speech given at the National Sierra Club Convention. Retrieved June 11, 2009, from http://www.commondreams.org/views05/0912-32.htm

Gray, W. M. (1984). Atlantic Seasonal Hurricane Frequency. Part 1: El Nino and 30 mb Quasi-biennial Oscillation Influences*. Monthly Weather Review, 11*2, 1649.

ICAT. (2009). *ICAT -Damage Estimator*. Retrieved June 26, 2009, from http://www.icatdamageestimator.com/faq#6q

IRICS. (2008). *ENSO and North Atlantic Hurricanes*. Retrieved June 11, 2009, from http://iri.columbia.edu/climate/ENSO/globalimpact/TC/Atlantic/sst.html

Kepert, J. (2001). The Dynamics of Boundary Layer Jets Within the Tropical Cyclone Core. Part I: Linear Theory. *Journal of the Atmospheric Sciences, 5*8(17), 2469-2484.

Knutson, T. R., & Tuleya, R. E. (2004). Impact of CO2-induced Warming on Simulated Hurricane Intensity and Precipitation: Sensitivity to the Choice of Climate Model and Convective Parameterization. *Journal of Climate, 1*7(18), 3477-3495.

Landsea, C. W. (1993). A Climatology of Intense (or Major) Atlantic Hurricanes. *Monthly Weather Review, 12*1(6), 1703-1713.

Landsea, C. W., Nicholls, N., Gray, W. M., & Avila, L. A. (1996). Downward Trends in the Frequency of Intense Atlantic Hurricanes During the Past Five Decades. *Geophysical Research Letters,* 23.

Mayfield, Max (2005). Written testimony for oversight hearing before Committee on Commerce, Science, and Transportation: Subcommittee on Disaster Prevention and Prediction, U.S. Senate, on "the lifesaving role of accurate hurricane prediction." Retrieved June 14, 2009, from http://www.legislative.noaa.gov/Testimony/mayfieldfinal092005.pdf

NCAR. (2006). *Hurricanes - Keeping an Eye on Weather's Biggest Bullies*. Retrieved June 11, 2009, from http://www.ucar.edu/news/features/hurricanes/index.jsp

NHC. (1999). Hurricane Basics. *National Hurricane Center.* Retrieved June 13, 2009, from http://www.nhc.noaa.gov/HAW2/english/basics.shtml

Norton, G. (1951). *Hurricanes of the 1950 Seaso*n. Miami, FL: Weather Bureau Office.

NWS. (2009). *National Weather Service Doppler Radar Images*. Retrieved June 20, 2009, from http://radar.weather.gov/

Pielke Jr., R. A. (2005). Meteorology: Are there Trends in Hurricane Destruction*? Nature, 43*8(7071), E11-E11.

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

Pielke Jr., R. A., & Landsea, C. N. (1999). La Niña, El Niño and Atlantic Hurricane Damages in the United States. *Bulletin of the American Meteorological Society, 8*0(10), 2027-2033.

Pielke Jr., R. A., & Landsea, C. W. (1998). Normalized Hurricane Damages in the United States: 1925--95. *Weather & Forecasting, 1*3(3), 621.

Pielke Jr., R. A., Landsea, C., Mayfield, M., Laver, J., & Pasch, R. (2005). Hurricanes and Global Warming. *Bulletin of the American Meteorological Society, 8*6(11), 1571-1575.

Pielke Jr., R. A., & Pielke Sr., R. A. (1997). *Hurricanes: Their Nature and Iimpact on Societ*y. England: John Wiley and Sons.

Pielke Sr., R. A. (1990). *The Hurrican*e. England: Routledge Press.

Rodgers, E. B., Chang, S. W., & Pierce, H. F. (1994). A Satellite Observational and Numerical Study of Precipitation Characteristics in Western North Atlantic Tropical Cyclones. *Journal of Applied Meteorology, 3*3(2), 129-139.

Senate. (1995). *U.S. Senate Bipartisan Task Force on Funding Disaster Relie*f. Federal Disaster Assistance. 104-4.

Shultz, J. M., Russell, J., & Espinel, Z. (2005). Epidemiology of Tropical Cyclones: The Dynamics of Disaster, Disease, and Development. *Epidemiologic Reviews, 2*7(1), 21-35.

Trenberth, K. E., & Shea, D. J. (2006). Atlantic Hurricanes and Natural Variability in 2005. *Geophysical Research Letters,* 33.

USGS. (2009). *Land Use and Land Cover (LULC)*. Retrieved June 06, 2009, from http://eros.usgs.gov/products/landcover/lulc.php

Vickery, P. J., Lin, J., Skerlj, P. F., Twisdale, J.,Lawrence A., & Huang, K. (2006). HAZUS-MH Hurricane Model Methodology. I: Hurricane Hazard, Terrain, and Wind Load Modeling. *Natural Hazards Review,* 7(2), 82-93.

Vickery, P. J., Skerlj, P. F., Lin, J., Twisdale, J.,Lawrence A., Young, M. A., & Lavelle, F. M. (2006). HAZUS-MH Hurricane Model Methodology. II: Damage and Loss Estimation. *Natural Hazards Review,* 7(2), 94-103.