

**UNF Digital Commons** 

UNF Graduate Theses and Dissertations

Student Scholarship

2013

# Investigation Into The Relationship Between Hurricane Storm Parameters and Damage

Jeremy S. Young The University of North Florida

Suggested Citation

Young, Jeremy S., "Investigation Into The Relationship Between Hurricane Storm Parameters and Damage" (2013). UNF Graduate Theses and Dissertations. 437. https://digitalcommons.unf.edu/etd/437

This Master's Thesis is brought to you for free and open access by the Student Scholarship at UNF Digital Commons. It has been accepted for inclusion in UNF Graduate Theses and Dissertations by an authorized administrator of UNF Digital Commons. For more information, please contact Digital Projects. © 2013 All Rights Reserved



## INVESTIGATION INTO THE RELATIONSHIP BETWEEN HURRICANE STORM PARAMETERS AND DAMAGE

by

Jeremy S. Young

A thesis submitted to the School of Engineering in partial fulfillment of the requirements for the degree of

Master of Science in Civil Engineering

## UNIVERSITY OF NORTH FLORIDA SCHOOL OF ENGINEERING

February, 2013

i

Copyright (©) 2012 by Jeremy Scott Young

All rights reserved. Reproduction in whole or in part in any form requires the prior written permission of Jeremy Scott Young or designated representative.

The thesis "Investigation into the Relationship between Hurricane Storm Parameters and Damage" submitted by Jeremy Scott Young in partial fulfillment of the requirements for the degree of Master of Science in Civil Engineering has been

Approved by the thesis committee:

Date:

Christopher J. Brown, PhD PE

Dr. Don T. Resio, PhD

Dr. Paul Eason, PhD, PE

Accepted for the School of Engineering:

Dr. Murat Tiryakioglu, PhD, CQE Director of the School of Engineering

Accepted for the College of Computing, Engineering, and Construction:

Dr. Mark Tumeo, PhD, PE Dean of the College of Computing, Engineering, and Construction

Accepted for the University:

Dr. Len Roberson, PhD Dean of the Graduate School

#### ACKNOWLEDGEMENT

This study was funded by the Taylor Engineering Research Institute (TERI) through the University of North Florida and tuition was paid in part by Angela J. Hubbird.

In this research, there are many people who enabled me to pursue this degree and without their help this thesis would not have been possible. First, I would like to thank Dr. Brown, for not only, giving me the support and knowledge to complete my research; but also, for being my thesis advisor. In addition, I would like to thank, Dr. Eason and Dr. Resio for agreeing to serve on my master's thesis committee. Special thanks go to Dr. Irish and Dr. Resio for their previous work on the surge scale; meteorological and oceanic sciences have been a hobby for me, so I am glad to have the opportunity to expand on their work. Also, Jeffrey A. Gebert from the Army Corp of Engineers, Philadelphia District; his cooperation gave UNF a large of amount of information which has been used and referenced: these documents will continue to be a future source of information for an emerging coastal and water resource program.

It is rare to be able to praise the ones you love in such a formal manner: my mother, father(s) and sister helped me believe in my abilities. Finally, my kids, who have also sacrificed and understood my need to pursue my engineering career, special thanks are due.

Some of the Hurricanes presented in this paper I have personally experienced: Hurricane Frederic blew through my homeland, when I was a toddler. The other "big one" for the

iv

Pensacola and Mobile area was Ivan and my family nicknamed it "Ivan the Terrible", and it was terrible since it took us three weeks to remove the trees from the road, so that we could resupply on food. Of course later on in my life, I witnessed many more Hurricanes such as Erin, Dennis, Charlie, Jeanne, and Opal: each one I believe taught me something new in style and nature of destruction. I will never forget following Hurricane Katrina, how some people that moved to the Pensacola area because their homes were destroyed: many of those people have never moved back tocoastal Louisiana.

It was an honor to attend school at UNF and to work as a graduate assistant. My life has been shaped by events and people, as it is a natural way of growing into one's character.

v

## Table of Contents

| Chapter   | 1: INTRODUCTION  |
|-----------|--|
| Chapter   | 2: LITERATURE REVIEW   |
| 2.1       | Introduction to the Damage Function                            |
| 2.2       | Classification of Damage Categories and Types                  |
| 2.3       | The Effect of Storm Parameters on the Damage Function          |
| 2.4       | The Damage Normalization Methodology                           |
| 2.5       | Surge Scale – A Hydrodynamics Based Surge Scale for Hurricanes |
| 2.6       | Chapter Summary  |
| Chapter   | 3: TESTING AND RESULTS 11                                      |
| 3.1       | Hurricane Data   |
| 3.2       | Hurricane Damage Classification                                |
| 3.2.      | 1 H <sub>1</sub> Classification                                |
| 3.2.      | 2 H <sub>2</sub> Classification                                |
| 3.2.      | 3 H <sub>3</sub> Classification 19                             |
| 3.2.      | 4 H <sub>4</sub> Classification                                |
| 3.3       | Storm Parameters Comparison to Damages                         |
| 3.4       | Total Normalized Damages                                       |
| 3.4.      | 1 Inflation Adjustment   |
| 3.4.2     | 2 Real Wealth Per Capita Adjustment                            |
| 3.4.      | 3 Affected Coastal County Population                           |
| 3.4.      | 4 Future Normalized Damages                                    |
| 3.5       | Explanation of Surge Scale                                     |
| 3.6       | The Surge Damage Function                                      |
| Chapter 4 | 4: DISCUSSION OF RESULTS                                       |
| 4.1       | Coefficient of Determination Measurements                      |
| 4.2       | Developed Relationships  |
| 4.2.      | 1 Surge Scale and Damage Relationships                         |
| 4.2.2     | 2 Hurricane Parameter and Damage Relationships                 |
| 4.3       | Total Normalized Damage Relationship to Surge Scale            |

| 4.3.1         | Un-Sorted Data R value Results  |
|---------------|---|
| 4.3.2         | Potential Improvements in Damage Estimation Methods                                   |
| 4.3.3         | Additional Analysis: Improvements and Exclusion of "Micro-canes" 41                   |
| 4.4 Hur       | ricane storm parameters comparison to Total Normalized Damages                        |
| 4.4.1         | Radius to Hurricane Force Winds (R <sub>33</sub> ) Relationship to Damages            |
| 4.4.2         | Maximum Surge Elevation ( $\zeta_{max}$ ) Relationship to Damages                     |
| 4.4.3         | Alongshore Extent of Surge Greater Than 2 meters $(Y_2^m)$ Relationship to Damages 44 |
| 4.4.4         | Coastal Storm Specific Population Density ( $\rho$ ) Relationship to Damages          |
| 4.4.5         | Central Pressure $(c_p^{a})$ Relationship to Damages                                  |
| 4.4.6         | Area of Indunation (Ain) Relationship to Damages                                      |
| 4.4.7         | Other Parameter Relationship to Damages   |
| 4.5 The       | Process of Developing a Surge Damage Function   |
| 4.6 Cha       | pter Summary 52   |
| Chapter 5: CO | NCLUSIONS AND RECOMMENDATIONS   |
| APPENDIX A    |   |
| APPENDIX B    |   |
| APPENDIX C    |   |
| APPENDIX D    | 9   |
| APPENDIX E    |   |
| APPENDIX F    |   |
| APPENDIX G    | ÷   |
| APPENDIX H    | [   |
| APPENDIX I    |   |
| APPENDIX J    |   |

## FIGURES

| Figure 1: MSCIP 2010 Report   | 4    |
|---|------|
| Figure 2: Total Normalized Damages versus Surge Scale for Adjusted Damage                 | . 35 |
| Figure 3: Total Normalized Damages versus Surge Scale for Various Coastal Growth Scenario | s36  |
| Figure 4: Coastal Growth Influence on Total Normalized Damages by Storm Rank              | . 37 |
| Figure 5: Total Normalized Damages versus Surge Scale (1938-1969)                         | . 40 |
| Figure 6: Total Normalized Damages versus Surge Scale (1970-1969)                         | . 41 |
| Figure 7: Total Normalized Damages versus Surge Scale (1970-1969) - Exclusion of "micro-  |      |
| canes"  | . 42 |
| Figure 8: Mean Surge versus Surge Scale   | . 62 |
| Figure 9: Total Normalized Damage vs. Radius to Hurricane Force Winds                     | . 63 |
| Figure 10: Total Normalized Damage vs. Maximum Surge                                      | . 64 |
| Figure 11: Total Normalized Damage vs. Alongshore Extent of Surge                         | . 65 |
| Figure 12: Total Normalized Damage vs. Central Pressure                                   | . 66 |
| Figure 13: Total Normalized Damage vs. Offshore Normal Projection to 30 Meter Contour     | . 67 |
| Figure 14: Total Normalized Damage vs. Track Speed  | . 68 |
| Figure 15: Total Normalized Damage vs. Storm Duration                                     | . 69 |
| Figure 16: Total Normalized Damage vs. Storm Angle Measured from Normal Projection        | . 70 |
| Figure 17: Total Normalized Damage vs. 2010 Coastal Storm Specific Population Density     | . 71 |
| Figure 18: The 30 Meter Shelf Contour (Blue Line)   | . 72 |
| Figure 19: Offshore Profiles Corresponding to Figure 17                                   | . 73 |
| Figure 20: Surge Scale Comparison to Surge (R=0.72)                                       | . 74 |
| Figure 21: Alongshore Extent of Surge vs. Mean Surge                                      | . 75 |
| Figure 22: 2005 Population by County (Plan-view)  | . 76 |
| Figure 23: 2005 Population by County  | . 77 |
| Figure 24: US Wealth vs. Year   | . 78 |
| Figure 25: 2005 Hurricane Tracks  | . 79 |
| Figure 26: US Census National Historical Percent Growth in Population                     | . 80 |
| Figure 27: Hurricane Damage Correction Factor   | . 83 |
| Figure 28: Total Normalized Damage Predictions  | . 84 |
| Figure 29: 2010 Population Densities by County  | . 85 |

# TABLES

| Table 1: Damage Survey Categories  |
|--|
| Table 2: Description of Hurricane Classification Based on Damage and Surge Scale6                                |
| Table 3: Introduction to Hurricane Data  |
| Table 4: Hurricanes Classified   |
| Table 5: Storm Parameters by Hurricane  15   |
| Table 6: Qualitative Relationship between Hurricane Parameters and Surge Generation                              |
| Table 7: Approximate Range Storm Parameters for Hurricane Surge Scale Categories                                 |
| Table 8: General Information and Hurricane Damages   |
| Table 9: Future Damages  |
| Table 10: Damage Calculation Adjustment (2005-2020)  30  |
| Table 11: General Information and Hurricane Damages – Sorted (1938-1969)   |
| Table 12: General Information and Hurricane Damages – Sorted (1970-2010)   |
| Table 13: General Information and Hurricane Damages – Sorted (1970-2010) and Micro-canes       excluded       43 |
| Table 14: Storm Specific Coastal County Population Density Calculations       46                                 |
| Table 15: Damage Prediction  |
| Table 16: Summary of Equations and Associated Coefficient of Determination     53                                |
| Table 17: 2010 Population Densities by County  |

## ABSTRACT

"Economic damage, such as damage to property and infra-structure, from hurricane surges depends on two factors 1) the depth of coastal inundation and 2) the area covered by the surge" (Irish et. al 2007). Typically, damage estimates are developed after hurricanes have dissipated. To have the ability to predict hurricane damage in advance based upon various physical parameters would be a technical advance that could aid vulnerable coastal communities with hurricane planning. This thesis advances this goal forward by relating "Total Normalized Damage" to "Surge Scale" along with other key parameters. In this thesis Total Normalized Damages are compared to Surge Scale in three statistically significant ways: Un-separated Comparison, Separated Comparison and Separated Comparison without "micro-canes". An attempt at the surge damage function has been presented in this thesis as a cornerstone of the research work contained herein. This thesis also examines the effect of different damage components and their uncertainties on Total Normalized Damage. Such damage estimates include wind damage, surge damage, and inland flooding, which were separated into individual damage categories.

х

#### Chapter 1

#### INTRODUCTION

The most unpredictable and regionally destructive types of coastal storms, hurricanes, are becoming better understood thanks to technological improvements since the 1970s and beyond. In particular, Hurricane Katrina [2005], provided a large impetus for improving our understanding of hazards and risks associated with this type of storm. In spite of this progress, hurricanes and their impacts are still somewhat unpredictable. Understanding climate cycles can be realized through generations of experience and observation; however, the length of many of these cycles and the lack of good data before the middle of the last century make this difficult today. The damage costs each year due to hurricanes means, that as a nation, we should be more purposeful in our zoning, building codes, etc., to account for inevitable hurricanes since the relationship to a Coastal Construction Control Line (CCCL) (Dean et al., 2002) and damages is apparent. This thesis analyzes relationships between "Total Normalized Damage" and other key variables including population growth rates and population density, among others. This thesis analyzes the impact that population growth rates and population density have on damages. Perhaps society must prepare for higher damages with higher growth rates or otherwise restrict coastal growth rates to reduce damage liabilities. This is already being accomplished in several ways such as through government land purchasing into the United States National Park Service, or other state or local parks since many of these coastal areas are environmentally sensitive ecosystems. The CCCL is another way of allowing growth only in designated areas defined by risk.

In addition to analyzing the impact population growth rates have on damages; this thesis presents a perspective of how damage estimates accuracy is related to the methods used to estimate surges and damages available at the time of hurricane landfall through analyzing the connections of damages to Surge Scale (SS). It is not completely clear the exact survey methods that the Federal Emergency Management Agency (FEMA), Army Corps of Engineers (ACOE) and the National Oceanic and Atmospheric Association (NOAA) use to currently make damage estimates, though total damages without separation of the data is the reported source of information. Functional relationships between "Total Normalized Damages" and SS exist and are also discussed at length in this thesis.

Specifically, this thesis has been organized into five chapters. Chapter 1 presents an introduction to the thesis information. Chapter 2 presents a summary of historic literature on the subject and details the datasets required for the thesis. Chapter 3 describes Total Normalized Damages (TND) and the sample calculation to year 2010; it also describes the origins of SS. Chapter 4 describes the relationship between TND and other key variables along with the proposed damage prediction methodology. Finally, Chapter 5 gives the conclusions and recommendations that have been derived from the research conducted. Two of the chapters are considered the most important; Chapter 3 and Chapter 4.

#### Chapter 2

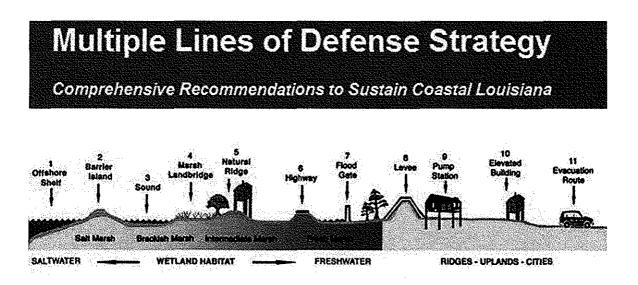
#### LITERATURE REVIEW

Following the very active 2004 and 2005 hurricane seasons, research into the quantification of hurricane damages has been escalating. It is not the intention of this paper to re-create the methodology for Normalized Damages formulated by Pielke (2008); rather, it will focus on developing a relationship between SS and various other key hurricane parameters to the Total Normalized Damages.

Pielke and Landsea (2008) builds on previous research complied into Pielke and Landsea (1998) and utilizes National Hurricane Center (NHC) loss estimates back to 1900. This paper presents the most comprehensive methodology to date on adjusting damages caused by Atlantic Hurricanes to a current year. Additionally, it shows areas along the Atlantic and Gulf coastlines that are particularly vulnerable to large damages due to population (See Appendix D.) In this thesis, research conducted by Malmstadt and Scheitlin (2009) were used as a resource for checking purposes for damage estimates presented in Pielke and Landsea (2008).

The Surge Scale or SS was initially developed by Irish and Resio (2007) and is a simplified approach to determining the magnitude of surges associated with hurricane events. The methodology in particular accounts for the size of a hurricane as well as bathymetry influences (a more detailed explanation can be found in Chapters 3 and 4). In tests with historical data, the SS was shown to produce the most accurate parametric means of estimating the hurricane surge response at the coastline. Resio and Westerink (2008) presents an approach to mitigating

damages, such as, wetlands that can influence surge levels. On coastlines with shallow offshore and/or onshore slopes a Multiple Lines of Defense Strategy is often utilizes for mitigating damages. Figure 1 shows a graphical example of this concept.





Based on upland topography, offshore bathymetry and the probabilities of hurricane occurrence, a "multiple lines of defense strategy" can reduce damages significantly. This strategy is similar to the Dutch approach of coastal disaster mitigation and coastal engineering issues; building surge infrastructure in multiple lines allows redundant protection from hurricane induced damages.

## 2.1 Introduction to the Damage Function

The Damage Function for surge (Irish and Resio, 2007) consists of several factors in which economic damage is related to storm parameters such as surge elevation, storm size, alongshore extent of surge, storm intensity, shelf and beach geometry (e.g. bathymetry, topography and shoreline orientation), forward speed, track, storm duration and population density. In order to compare the various storm parameters to damages to build the damage function for surge it is necessary to adjust the economic damage caused by hurricanes to the same year through the normalization procedure discussed in sections 2.3 and 2.4.

2.2 Classification of Damage Categories and Types

In order to understand damage derived from hurricanes, it is important to discuss Damage Survey Categories. Table 1 presents the categories of damage represented in official United States government (NOAA, 2011) estimates for damage. Table 2 presents a description of hurricane classification based on damage and SS.

| Category  | Description  |
|---|--|
| Wind Normalized Damage – ND <sub>w</sub>            | Damage determined to be derived from wind<br>and not flooding.                   |
| Inland Flooding Normalized Damage – ND <sub>f</sub> | Failures due to saturated soil or damage to upland infrastructure, misc. damage. |
| Surge Normalized Damage – ND <sub>s</sub>           | Damage determined to be caused by hurricane surge.                               |

| Table | 1: | Damage | Survey | Categories  |
|-------|----|--------|--------|-------------|
| 10010 |    | Danage | Sarrey | Outogoines. |

These Damage Survey Categories are a simple representation of contributing categories of normalized damage to the total normalized damage estimates such that:

$$TND = ND_w + ND_f + ND_s$$
(1)

where, TND is "Total Normalized Damage" and ND<sub>i</sub> is normalized damage category with subscripts defined in Table 1.

| Hurricane<br>Classification | Qualitative<br>Description         | Damage (US\$<br>Billions) | Surge Scale (SS) |
|-----------------------------|------------------------------------|---------------------------|------------------|
| H <sub>1</sub>              | Low to Moderate<br>Damage          | 0 – 17                    | 0-0.5            |
| H <sub>2</sub>              | Moderate to Extreme<br>Damage      | 6 – 19                    | 0.5 - 1.0        |
| H <sub>3</sub>              | Moderate to<br>Catastrophic Damage | 5 - 80                    | 1.0 - 3.0        |
| H <sub>4</sub>              | Catastrophic Damage                | 80+                       | 3.0+             |

| Table 2: Description of | Hurricane | Classification | Based on I | Damage and Surge Scale |
|-------------------------|-----------|----------------|------------|------------------------|
|                         |           |                |            |                        |

In addition to Damage Survey Categories, some hurricanes make multiple landfalls. In this case equation 1 would become:

$$TND_1 + TND_2 = TND_T = \Sigma TND \qquad (2)$$

where the notion used simply means that the Total Normalized Damage estimated is from multiple landfalls, making the task of classification particularly difficult since surge scale is calculated for each specific landfall and damage can be highly variable. In the specific case of Katrina [2005], the south Florida land fall was relatively benign and therefore represents a small amount of the TND. It is important to note that damage could be broken into a "per landfall" basis which would improve the correlations found later in Chapter 4.

## 2.3 The Effect of Storm Parameters on the Damage Function

The Damage Function was preliminarily investigated by Irish and Resio (2007). The authors assumed that the damage function could be written as:

$$D \approx \frac{\kappa(\gamma + \delta)}{m + 1} \zeta_{\max} R_{33}$$
(3)

where the Damage (D) is proportional to  $\kappa$ ,  $\gamma$ , and  $\delta$  which are all dimensionless constants. The parameter  $\zeta_{max}$ , is the maximum surge at the coast measured from the normal water level and R<sub>33</sub> is the radius to hurricane force winds measured from the center of circulation. The power constant, m indicates that damage is non-linearly dependent on storm surge for m not equal to 1; however, it depends only linearly on storm size. From equation 3, we see that damages can be especially high for large with which generate large maximum surges.

This approach to the surge damage function suggests there is a way to relate economic damage in terms of hurricane storm surge parameters, which represents damage dissimilar to TND such that, TND is the estimated historical damage caused by a hurricane.

2.4 The Damage Normalization Methodology

A normalization methodology is used here to provide a consistent means of determining economic damage of past storms to current year levels of development and population. Otherwise, economic damage becomes highly dependent on the year of landfall, which would introduce a spurious relationship between the year of the hurricane and damages. The normalization methodology can be found in Pielke and Landsea (2008). Their equation is as follows:

$$D_{2005} = D_y * I_y * RWPC_y * P_{2005y}$$
(4)

The quantity  $D_{2005}$ , refers to hurricane damage adjusted to the year 2005, where,  $D_y$  is the reported economic damage in current-year dollars,  $I_y$  is the inflation adjustment,  $RWPC_y$  is the real wealth per capita adjustment and  $P2005_y$  is the coastal county population adjustment. This adjustment is a United States national level adjustment; whereas, some areas experience economic development faster/slower than others.

## 2.5 Surge Scale – A Hydrodynamics Based Surge Scale for Hurricanes

The SS is an empirical simplified approach to determining the magnitude of a surge event produced by hurricanes. Irish and Resio (2007) present SS as follows:

$$SS = (2.43 * 10E - 4) * \Delta p * L_{30m} * \phi_{x}(\frac{R_{33}}{L_{30m}})$$
(5)

The  $\Delta p$  is hurricane central pressure differential (mb),  $L_{30m}$  (km, also shown as  $w_{30}^{b}$ ) is the horizontal distance between the shoreline and the 30 meter depth contour. Additionally,  $\varphi_x$  is a

dimensionless storm size function and  $R_{33}$  is the radius to hurricane force winds from center of circulation.

The hurricanes presented in Chapter 3 reflect those that have a relatively normal to shoreline track (-60 to +45 degree strike angle). Hurricanes that make landfall near basin boundaries will tend to cause errors in the SS since Equation 5 assumes that a hurricane (forcing mechanism) has a sufficient length of coast to develop a surge. For multiple land falling hurricanes such as Donna [1960] and Gloria [1985]and even Floyd [1999] (not included in study) the tracks are such that they landed near basin boundaries, have oblique angles and are significantly more unrelated to the SS.

## 2.6 Chapter Summary

Hurricane related damages have been demonstrated to have a negative effect on the economic health of coastal communities that can persist for many years after landfall; however, this study will focus on the short-term damages since these are more directly quantifiable. The relationship between storm parameters and SS to damages is apparent. Classification of hurricanes in terms of damage, in particular focusing on surge specific damages will ultimately lead to a hurricane surge damage scale.

Previous studies, such as Powell and Reinhold (2006), have focused on the evaluation of hurricane surge damage potential ( $S_{DP}$ ) a function of storm parameters in the form of an integrated kinetic energy; however, this study focuses on using actual historical damage data to advance the cause of finding a surge damage function that will be related to the SS. Since SS has been shown to be an improvement over previous hurricane indices for surges (Irish, et al. 2007),

it is used here as a measure of surge impact for the estimation of surge damage. In Irish and Resio (2007), the authors also point out how the tide will sometimes have a measurable effect on total water elevation and thus damages. In this damage function the effects of wave action and run-up are assumed to be absorbed within other constants (i.e. produces a constant proportion of the damage) or can be neglected.

Other notable research for surge indices Kantha (2008) who presented the Hurricane Surge Index (HSI) which found a good positive relationship to surge; however, like the  $S_{DP}$  there is wider cone of uncertainty for the HSI when compared to Surge (m), particularly on the upper end of the scale.

#### Chapter 3

#### TESTING AND RESULTS

Chapter 3 presents a description of the data, data preparation, data comparisons and summarized test results. It's focus is to explore and explain correlations between various storm parameters, SS and normalized damages.

Historical hurricane storm parameters are chosen based on interest in effects on economic damage as suggested by Irish and Resio (2007) and others listed in section 2. Therefore, for this thesis only the most important parameters were considered. These include the radius to hurricanes force winds ( $R_{33}$ ) to reflect hurricane size, central pressure ( $c_p^a$ ) to incorporate intensity, maximum surge at the coast measured from the normal water level ( $\zeta_{max}$ ),offshore slope ( $w_{30}^{b}$ ) for bathymetry effects, alongshore extent of surge ( $Y_m^2$ ) and 2010 storm specific coastal population density ( $\rho$ ) and other parameters that are included in Appendix A &B.

## 3.1 Hurricane Data

The hurricane storm parameters data obtained in this thesis were taken are from Irish and Resio (2007) and NOAA (2012). Table 3 lists the hurricanes evaluated and their respective affected coastal counties. This data represents an estimate based on radius to hurricane force winds ( $R_{33}$ ) and the alongshore extent of surge greater than 2 meters ( $Y_m^2$ ). Additionally only US mainland land falling hurricanes are listed.

| Hurricane Name (Date) – Landfall State(s) | Affected Coastal Counties/Parishes                  |
|---|---|
| Katrina [2005] – Florida & Louisiana      | Baldwin, Mobile Al. Jackson, Harrison, Hancock      |
|   | MS. St. Mary, Terrebonne, Lafourche, St. Charles,   |
|   | St. John the Baptist, Jefferson, Plaquemines, St.   |
|   | Bernard, Orleans, St. Tammany, Tangipahoa LA.       |
| Andrew [1992] – Florida & Louisiana       | Miami-Dade FL. Iberia, St. Mary, Terrebonne LA.     |
| October [1944] – Florida                  | Monroe, Collier, Lee, Charlotte, Sarasota, Manatee, |
|   | Hillsborough, Pinellas, Pasco Fl.                   |
| Donna [1960] – Multi-State                | N/A – Most of East Coast                            |
| Ike [2008] – Texas                        | San Patricio, Aransas, Refugio, Calhoun, Victoria,  |
|   | Jackson, Matagorda, Brazoria, Galveston, Harris,    |
|   | Chambers, Jefferson, Orange TX. Cameron,            |
|   | Vermilion, LA.                                      |
| Wilma [2005] – Florida                    | Sarasota, Charlotte, Lee, Collier, Monroe FL.       |
| Betsy [1965] – Louisiana                  | Vermilion, Iberia, St. Mary, Terrebonne, Lafourche, |
| Deal) [1900] Dealbhain                    | St. Charles, St. John the Baptist, Jefferson,       |
|   | Plaquemines, St. Bernard, Orleans, St. Tammany,     |
|   | Tangipahoa, LA. Hancock, Harrison, MS.              |
| Camille [1969] – Louisiana                | St. Mary, Terrebonne, Lafourche, St. Charles, St.   |
|   | John the Baptist, Jefferson, Plaquemines, St.       |
|   | Bernard, Orleans, St. Tammany, Tangipahoa LA.       |
|   | Hancock, Harrison, Jackson, MS. Mobile, Baldwin     |
|   | AL.   |
| Hugo [1989] – South Carolina              | Chatham, GA. Jasper, Beaufort, Colleton,            |
|   | Charleston, Georgetown, Horry, SC. Brunswick,       |
|   | NC.   |
| Charley [2004] – Florida                  | Charlotte, Lee FL.                                  |
| Ivan [2004] – Florida/Alabama             | Jackson, MS. Mobile, Baldwin AL. Escambia,          |
|   | Santa Rosa, Okaloosa FL.                            |
| Carla [1961] – Louisiana                  | Kenedy, Kleberg, Nueces, San Patricio, Aransas,     |
|   | Refugio, Calhoun, Victoria, Jackson, Matagorda,     |
|   | Brazoria, TX.                                       |
| Rita [2005] – Louisiana/Texas             | Matagorda, Brazoria, Galveston, Harris, Chambers,   |
|   | Jefferson, Orange, TX. Cameron, Vermilion, Iberia,  |
|   | St. Mary, Terrebonne LA.                            |
| Fredric [1979] – Alabama                  | Plaquemines, St. Bernard, Orleans, St. Tammany      |
|   | LA. Hancock, Harrison, Jackson, MS. Mobile,         |
|   | Baldwin, AL. Escambia, Santa Rosa, Okaloosa, FL.    |
| Frances [2004] – Florida                  | Palm Beach, Martin, St. Lucie, Indian River,        |
|   | Brevard, FL.  |
| Opal [1995] – Florida                     | Gulf, Bay, Walton, Okaloosa, Santa Rosa,            |
|   | Escambia, FL.                                       |
| Celia [1970] – Texas                      | Calhoun, Aransas, Nueces, Kleberg, San Patricio,    |
| C   | Refugio, TX.  |
| Gustav [2008] – Louisiana                 | Vermilion, Iberia, St. Mary, Terrebonne, Lafourche, |
| T 1 1 100001 Nr. 4 C 1                    | Jefferson, Plaquemines                              |
| Isabel [2003] – North Carolina            | Brunswick, New Hanover, Pender, Onslow,             |
|   | Carteret, Pamlico, Beaufort, Hyde, Dare, Tyrrell    |
|   | Washington, Bertie, Chowan, Perquimans,             |
| D1-h [10/7]                               | Pasquotank, Camden, Currituck, NC.                  |
| Beulah [1967] – Texas                     | Cameron, Willacy, Kenedy, Kleberg TX.               |
| Audrey [1957] – Louisiana/Texas           | Brazoria, Galveston, Harris, Chambers, Jefferson,   |

## Table 3: Introduction to Hurricane Data

|                             | Orange, TX. Cameron, Vermilion, Iberia LA.       |
|-----------------------------|--|
| Eloise [1975] – Florida     | Escambia, Santa Rosa, Okaloosa, Walton, Bay,     |
|                             | Gulf, Franklin, FL.                              |
| Gloria [1985] – Multi-State | Carteret, Pamlico, Beaufort, Hyde, Dare, Tyrell, |
|                             | Washington, Bertie, Chowan, Perquimans,          |
|                             | Pasquotank, Camden, Currituck, NC. Atlantic,     |
|                             | Ocean, Monmouth, Middlesex, NJ. Richmond,        |
|                             | Kings, Queens, Nassau, Suffolk, Bronx, NY.       |
| Dennis [2005] – Florida     | Baldwin, AL. Escambia, Santa Rosa, FL.           |
| Hilda [1964] – Louisiana    | Cameron, Vermilion, Iberia, St. Mary, Terrebonne |
|                             | LA.  |
| October [1941] – Florida    | Bay, Gulf, Franklin, Wakulla, Jefferson, Taylor, |
|                             | Levy, Dixie, Monroe, Miami-Dade, Broward, Palm   |
|                             | Beach, FL.                                       |
| Allen [1980] – Texas        | Cameron, Willacy, Kenedy, TX.                    |
| Dolly [2008] – Texas        | Cameron, TX                                      |
| Lilli [2002] – Louisiana    | Cameron, Vermilion, Iberia, St. Mary, LA.        |
| September [1938] – New York | Atlantic, Ocean, Monmouth. NJ. Richmond, Kings,  |
|                             | Queens, Nassau, Suffolk, Bronx, Westchester, NY. |
|                             | Fairfield, New Haven, Middlesex, New London,     |
|                             | CT. Washington, Kent, Bristol, Newport, RI.      |
|                             | Bristol, Dukes, MA.                              |
| Bret [1999] – Texas         | Cameron, Willacy, Kenedy, Kleberg, TX.           |

The affected counties in Table 3 are used to calculate storm specific coastal population densities found later in this chapter. Although the Hurricane data extends over approximately 72 years, it is important to note the limitations of having a statistical sample approach used in this thesis versus a larger sample closer to statistical population of hurricane events on the order of centuries to more accurately reflect weather pattern effects on hurricane development and tracks.

## 3.2 Hurricane Damage Classification

Hurricane damage data was obtained from Pielke and Landsea (2008) and cross-checked against data from NOAA (2011) and Malmstadt and Scheitlin (2009). It should be noted that Malmstadt and Scheitlin (2009) was used as an additional reference for checking purposes as stated previously. Table 4 lists the hurricanes of interest and its SS/damage classification. The

following paragraphs attempt to describe each hurricane event listed in this study according to Hurricane Damage Classification.

| Hurricane State/Category | Hurricane  |
|--------------------------|--|
| $H_1$                    | September [1938], Ivan [2004], Frances [2004],<br>Opal [1995], Isabel [2003], Beulah [1967], Eloise                                      |
|                          | [1975], Gloria [1985], Dennis [2005], October  |
|                          | [1941], Allen [1980], Dolly [2008], Bret [1999],<br>Celia [1970]   |
| H <sub>2</sub>           | Andrew [1992], October [1944], Donna [1960],<br>Betsy [1965], Charley [2004], Hugo [1989], Carla<br>[1961], Fredric [1979], Lilli [2002] |
| H <sub>3</sub>           | Ike [2008], Wilma [2005], Camille [1969], Rita<br>[2005], Gustav [2008], Audrey [1957], Hilda [1964]                                     |
| H <sub>4</sub>           | Katrina [2005]   |

#### Table 4: Hurricanes Classified

As can be seen some hurricanes with moderate damages are in a lower category; however, these categories as shown in Table 2 are based on SS since damages within each category overlap. Notice, Katrina [2005] is the only  $H_4$  hurricane in this study. The recurrence interval is almost every 300 years for a storm capable of a 3.0+ SS and is informative in respect to what could be expected; however, probabilities are no guarantee of non-occurrence. (Please see Appendix H)

## 3.2.1 H<sub>1</sub> Classification

Table 5 gives a detailed list of the hurricane parameters utilized in this study. As shown in section 4 of this thesis patterns emerge inherent in those parameters that are related to damages. (See Appendices A& B)

| Storm     | Year         | R33(km) | w <sub>30</sub> b<br>(km) | <i>C<sub>p</sub><sup>a</sup></i><br>(mb) | Y2 <sup>m</sup><br>(km) | Storm<br>Angle<br>(2) | Track<br>Speed<br>(v -<br>kph) | Storm<br>Duration<br>over<br>land (Ω -<br>Hrs) | ζ <sub>max</sub><br>( <b>m</b> ) | Smean<br>(M) |
|-----------|--------------|---------|---------------------------|--|-------------------------|-----------------------|--------------------------------|--|----------------------------------|--------------|
| Katrina   | 2005         | 217     | 140                       | 919                                      | 404                     | -2                    | 20                             | 48   | 8.5                              | 8            |
| Andrew    | 1992         | 77      | 4                         | 949                                      | 32                      | 36                    | 20                             | 60   | 2.4                              | 2.4          |
| October   | 1944         | 179     | 53                        | 960                                      | 132                     | -47                   | 20                             | 48   | 3.4                              | 2.8          |
| September | 1938         | 233     | 10                        | 936                                      | 179                     | -12                   | 44                             | 30   | 3.5                              | 2.8          |
| Donna     | 1960         | 235     | 4                         | 970                                      | 200                     | 15                    | 15                             | 48   | 3.7                              | 3            |
| Ike       | 2008         | 195     | 92                        | 952                                      | 303                     | -18                   | 18                             | 30   | 5.9                              | 5.3          |
| Wilma     | 2005         | 179     | 118                       | 951                                      | 213                     | 3                     | 18                             | 4  | 2.4                              | 2.1          |
| Camille   | 1969         | 109     | 120                       | 910                                      | 189                     | 15                    | 24                             | 60   | 6.9                              | 6.6          |
| Charley   | 2004         | 40      | 57                        | 950                                      | 5                       | 22                    | 25                             | 28   | 2.1                              | 2.2          |
| Betsy     | 1965         | 195     | 52                        | 945                                      | 265                     | 18                    | 27                             | 76   | 4.8                              | 4.4          |
| Hugo      | 1989         | 146     | 56                        | 934                                      | 235                     | 5                     | 30                             | 24   | 5.7                              | 5.6          |
| Ivan      | 2004         | 128     | 31                        | 955                                      | 109                     | -10                   | 20                             | 64   | 3.1                              | 3            |
| Carla     | 1961         | 177     | 34                        | 936                                      | 188                     | -15                   | 11                             | 66   | 3.7                              | 3.5          |
| Rita      | 2005         | 230     | 119                       | 946                                      | 270                     | 7                     | 17                             | 60   | 4.6                              | 3.8          |
| Frances   | 2004         | 139     | 15                        | 960                                      | 16                      | -23                   | 10                             | 122  | 2.4                              | 2.2          |
| Frederic  | 1979         | 164     | 48                        | 950                                      | 184                     | 28                    | 20                             | 60   | 3.8                              | 3.7          |
| Opal      | 1995         | 169     | 21                        | 940                                      | 173                     | -23                   | 30                             | 36   | 3.7                              | 2.4          |
| Celia     | 1970         | 101     | 30                        | 944                                      | 68                      | 12                    | 25                             | 48   | 2.8                              | 2.8          |
| Gustav    | 2008         | 110     | 81                        | 957                                      | 151                     | 58                    | 25                             | 96   | 4.5                              | 4.4          |
| Isabel    | 2003         | 214     | 25                        | 957                                      | 20                      | -6                    | 20                             | 24   | 2                                | 1.9          |
| Beulah    | 1967         | 164     | 20                        | 950                                      | 100                     | -45                   | 15                             | 48   | 2.9                              | 2.6          |
| Audrey    | 1957         | 164     | 118                       | 964                                      | 181                     | -15                   | 12                             | 72   | 3.8                              | 3.6          |
| Eloise    | 1975         | 150     | 21                        | 955                                      | 255                     | -8                    | 25                             | 26   | 3.4                              | 2.6          |
| Gloria    | 1985         | 229     | 24                        | 951                                      | 74                      | -38                   | 50                             | 24   | 2.7                              | 2.3          |
| Dennis    | 2005         | 33      | 24                        | 952                                      | 4                       | 10                    | 15                             | 42   | 2.5                              | 2.1          |
| Hilda     | 1964         | 154     | 88                        | 960                                      | 94                      | 1                     | 15                             | 48   | 3                                | 2.6          |
| October   | 1941         | 143     | 40                        | 970                                      | 136                     | 5                     | 20                             | 30   | 3.24                             | 3.2          |
| Allen     | 1980         | 150     | 21                        | 945                                      | 116                     | -30                   | 20                             | 34   | 3.7                              | 2.8          |
| Dolly     | 2008         | 35      | 21                        | 967                                      | 20                      | -25                   | 12                             | 84   | 2.4                              | 2            |
| Lili      | 2002         | 133     | 84                        | 966                                      | 136                     | 34                    | 27                             | 24   | 3.6                              | 3.4          |
| Bret      | 1 <b>999</b> | 108     | 22                        | 953                                      | 0                       | -20                   | 14                             | 48   | 1.5                              | 2.1          |

# Table 5: Storm Parameters by Hurricane

 $R_{33}$  is the radius from center of the hurricane to hurricane force winds;  $w_{30}^{b}$  is the offshore normal distance to the 30 meter depth contour;  $c_p^{a}$  is the central pressure measured in millibars;  $Y_2^m$  is the alongshore extent of surge greater than 2 m;  $\theta$  is the storm angle measured from the shore normal; v is the forward track speed of the hurricane;  $\Omega$  is the storm duration over land;  $\zeta_{max}$  is the maximum water surface elevation measured vertically from the normal water level.  $\zeta_{mean}$  is the observed peak mean hurricane surge which is always somewhat less the  $\zeta_{max}$ .

Fourteen storms were classified as H<sub>1</sub>. For these storms, there was little to moderate damage; however, an assessment of each hurricane is necessary to understand why these storms fall under the H<sub>1</sub> classification. September [1938] which was rather large at  $R_{33}$ = 233 km and  $Y_2^{m}$ = 179 had a  $w_{30}^{b} = 10$  km which mitigated the surge; however, landed on a highly populated coastline which leads to higher damage through other forms of damage. Ivan [2004] was a small to moderately sized and moderately intense hurricane with an R<sub>33</sub> of 128 km at c<sub>n</sub><sup>a</sup> of 955 mb. The surge was approximately 3 meters at the highest; however, due to the size of the storm contributing to a relatively small alongshore extent of the surge, the ND<sub>s</sub> is suspected to be relatively small in comparison to the other forms of damage. The storm had a long duration over land and spawned many tornados; therefore, much of the damage related to this storm was of the type ND<sub>w</sub> and ND<sub>f</sub>. Frances [2004] was a hurricane that made landfall on a narrow section of the shelf with the  $w_{30}^{b}$  being 13 km which attenuated the majority of the storm surge. The high coastal county population density along with long storm duration over land indicates a high amount of  $ND_w$  and  $ND_f$  damage. Opal [1995] was a low to moderately damaging storm. The storm was intense at a central pressure of approximately 940 mb, R<sub>33</sub> of 169 km and an Y<sub>2</sub><sup>m</sup> of 175 km; however, the population density was low to moderate in this area along with a narrow continental shelf in this region.

Isabel [2003] was a large hurricane with and  $R_{33}$  of 214 km and an  $Y_2^m$  of estimated smaller size than the R<sub>33</sub>. Additionally, Isabel was an intense hurricane at 954 mb; however, the population density was relatively low in this region. Additionally, landfall was within 80 km of a shoreline angle change, which tends to allow some of the surge to escape into a "lower setup" through current bypassing Cape Hatteras, NC and thus lower damages. Beulah [1967] was a moderately intense hurricane at central pressure of 950 mb,  $R_{33}$  of 164 km and an estimated  $Y_2^m$  of over 100 km. On the day of landfall Beulah reached 160 mph wind speeds; however, had a non-normal track which would tends to reduce the surge and thus damages. Eloise [1975] was a moderately intense hurricane at 955 mb with an R<sub>33</sub> of 150 indicating a moderate size. Eloise [1975] was similar to Opal [1995] in regards to track and size. Eloise at a  $w_{30}^{b} = 21$  km indicates much of the damage was in the form of ND<sub>w</sub> and ND<sub>f</sub> damages. Gloria [1985] represented a minimal surge threat due to the steep beach  $(w_{30}^{b} = 30 \text{ km})$  along with an oblique angle. Gloria [1985] like Donna [1960] made landfall near a basin boundary which disperses the surge. Dennis [2005] was a "micro-cane" with an  $R_{33} = 33$  km similar to Charley [2004] and Andrew [1995]. So although Mobile, AL. experienced some low to moderate wind damage, Pensacola, FL. at 50 km away, there was little to no damage.

Oct. 1941 was a moderate sized hurricane at  $R_{33} = 143$  km and intensity of 970 mb; however, there were two landfalls in Florida. Important to note, the population in South Florida was not large until later in the twentieth century. Hurricane Allen [1980] was a fairly intense hurricane at landfall, briefly intensifying into a Saffir-Simpson Category 5 at approximately 180 mph with an  $R_{33}$  of 150 km; however, the population density was very low and the landfall happened to be on the Texas/Mexico border which would also tend to lower the damage estimate. Furthermore, the offshore slope in the area is steep and thereby reducing the surge and reducing damages.

Similarly, Dolly [2008] made landfall near the Texas/Mexico border and had a very small  $R_{33}$  of 35 km. Same with Allen [1980], the continental shelf is narrow in this area which helps to reduce the surge and thus damages. Bret [1999] was relatively small at  $R_{33} = 108$  km and also landed on a narrow section of the continental shelf, in fact the  $Y_2^m = 0$  km means that Bret [1999] was a benign surge threat. Celia [1970] like Opal was a moderately intense storm at 944 mb, but was significantly smaller at an R33 of 101 km and an  $Y_2^m$  of 75 km indicating that the wider continental shelf (bathymetry), storm duration or other storm parameters may dominate in terms of damages.

## 3.2.2 H<sub>2</sub> Classification

There were nine storms classified as H<sub>2</sub> storms. Andrew [1992], which was small at  $R_{33} = 77$  km and central pressure of 949 when land falling in southeast Florida which has a narrow  $w_{30}^{b} = 4$  km and therefore, most of the damage derived in Florida was mostly ND<sub>w</sub> damage and some ND<sub>f</sub> damage. Andrew was still small and less intense at 956 mb at land fall in Louisiana; however, forward speed decreased significantly after landfall and caused mostly ND<sub>f</sub> damage. Oct. [1944] had a highly oblique angle of  $\theta = -47^{\circ}$  to shore normal along with a track which is not hydrodynamically capable of producing large surges and thus the SS was very minimal at 0.7 and thus creating mostly ND<sub>w</sub> and ND<sub>f</sub> damage. Donna [1960] not only took a similar track to Oct [1944] in terms of angle, but also close to the basin boundary Gulf of Mexico and the Atlantic Ocean, producing mostly ND<sub>w</sub> and ND<sub>f</sub> damage. Additionally, October [1944] took an east coast track which involves large population densities.

Charley [2004] was a small sized hurricane with an alongshore  $Y_2^m$  of just 5 km and thus offered no major threat in terms of storm surge; however, caused heavy localized ND<sub>w</sub> damage; whereas, rapid intensification just prior to landfall to 944 mb and an R<sub>33</sub> of 40 km along with a high coastal population density along the storm track is indicative of high amounts of wind damage. Hugo [1989]  $R_{33} = 146$  km and an intense central pressure of 934, tracked on an almost shorenormal trajectory, thus a damaging surge was released in that  $Y_2^m = 235$  km. Carla [1961] was a large hurricane with an  $R_{33}$  of 177 km and an intensity of 936 mb. The SS = 0.6 is relatively small for this hurricane, but due to the steeper section offshore slope  $(w_{30}^{b} = 37 \text{ km})$  the surge was somewhat attenuated. Additionally the coastal population density was low in this area and since Carla [1961] took a track that included the Dallas/Fort Worth metropolis, the majority of damage is in ND<sub>w</sub> and ND<sub>f</sub> Damage Survey Categories. Land falling approximately 40 km west of Ivan, Fredric [1979] was larger at R<sub>33</sub> of 164 km at 950 mb. Similar to Ivan, Fredric's track was along a moderately steep offshore slope  $(w_{30}^{b} = 56 \text{ km})$ ; therefore, the surge was partially attenuated through depth. Lilli [2002] was a moderately intense storm at 966 mb, an R<sub>33</sub> of 133 km and making land fall on a relatively wide continental shelf: All of which would tend to increase damages; however, the damages remained low due to a low population density.

#### 3.2.3 H<sub>3</sub> Classification

There were seven storms classified as H<sub>3</sub> Storms. Recently Ike [2008] made landfall near Galveston, TX. With and  $R_{33} = 195$ , an  $Y_2^{m} = 303$  km and a shallow slope ( $w_{30}^{b} = 86$  m) caused a significant surge, SS = 1.3. Wilma [2005] was a large hurricane with an  $R_{33} = 179$  km at 951 mb. The offshore slope was also shallow in this area and therefore SS = 1.7 indicating relatively high damages; however, the track suggests that much of the damages was in the forms ND<sub>w</sub> and ND<sub>f</sub> since the landfall was in extreme southwest Florida in which there is no population along

the coast. (Everglades) Gustav [2008], a small to medium sized hurricane  $R_{33} = 110$  km at 957, took a track similar to Betsy [1965]; however, the  $w_{30}^{b}$  was much larger indicating more energy could be transferred to the shelf across the storm. Audrey [1957] was a moderately sized storm,  $R_{33}$  of 164 km and  $Y_2^{m}$  of 181 km, landed on a wide section of the continental shelf with a SS=1.3. The coastal population density was moderate leading to moderate damages. Hilda [1964]  $R_{33} = 154$  at 960 mb tracked onto a moderately sloping offshore profile. ( $w_{30}^{b} = 88$  km) The SS = 1.1 indicates the possibility of a moderate surge event and thus moderate damages. Additionally, Hilda weakened rapidly once it made landfall and thereby averting more damages, indicated by the low storm duration.

Betsy [1965] was a massive hurricane with an  $R_{33}$  of 195 km and an  $Y_2^{m}$  of 265 km and track included moderately populated areas of Louisiana; however, the track was such that much of the damage was through ND<sub>w</sub> and ND<sub>f</sub> damage. Interesting, is that a moderately steep beach slope and a helpful track that dissipates the surge energy to both sides of the Mississippi delta causes the surge to be less than a "Katrina like" normal to coastline track in which water piles up onto the Mississippi-Alabama Shelf. Camille [1969] was the standard New Orleans went by before Katrina [2005]. Camille [1969], a medium sized storm, took an almost identical track to Katrina thus producing a large surge. The storm had an  $R_{33} = 110$  km and a low 910 mb; therefore, illustrating the point that if the  $w_{30}^{b}$  (30 meter contour) is wide then any hurricanes larger than "micro-canes" pose a serious surge risk to coastal areas. Another interesting fact is the configuration of the southeast Louisiana coastline with respect to circulating counter-clockwise winds inevitably creates a "funnel" for surge energy into Lake Pontchartrain. Rita [2005] was a massive storm at an  $R_{33}$  of 230 km (Irish and Resio, 2007) and intensity of 946 mb. The coastal population density for this storm was low and the track went through a sparsely populated Texas/Louisiana border; otherwise, the damage from this storm could have been much greater.

3.2.4 H<sub>4</sub> Classification

Katrina [2005] was an outlier in so many categories. (See Table 7 and Appendix B) Not only was this storm massive in size, but also the offshore profile and coastline in respect to the track collaborated to create a devastating surge (SS = 3.1), which indicates a catastrophic combination of unfavorable storm/geophysical parameters.

3.3 Storm Parameters Comparison to Damages

The data collected from HURDAT (North American Hurricane Database, 2012) consisted of track information for location, wind speed, track speed along with assisting with estimating some land falling storm parameters which are related to the SS and damages. Irish and Resio (2007) also were used to determine other storm parameters of significance to storm surge generation. Given that the storm parameters were assessable through these mentioned sources, a qualitative relationship between storm parameters and contribution of storm surge is found in Table 6.

| Parameter                   | Negligible to low<br>Contribution | Low to Moderate<br>Contribution | Moderate to High<br>Contribution |  |  |
|-----------------------------|-----------------------------------|---------------------------------|----------------------------------|--|--|
| R <sub>33</sub>             |                                   | X                               |                                  |  |  |
| $\zeta^2_{\rm max}$         |                                   |                                 | X                                |  |  |
| W <sub>30</sub>             | X                                 | X                               |                                  |  |  |
| Y <sub>2</sub> <sup>m</sup> |                                   | X                               |                                  |  |  |
| θ                           | X                                 | X                               |                                  |  |  |
| $c_p^{a}$                   |                                   | X                               |                                  |  |  |
| V (Track Speed)             | X                                 |                                 |                                  |  |  |
| $\Omega$ (Storm Duration)   | X                                 |                                 |                                  |  |  |
| P (Population<br>Density)   |                                   | X                               | X                                |  |  |

Table 6: Qualitative Relationship between Hurricane Parameters and Surge Generation

Since damages from hurricanes can be very case-specific in terms of storm parameterized storm characteristics, Table 6 over-simplifies the complex and dynamic nature of these storms to some extent. In fact, if a surge damage function exists it may be a dynamic equation such that the equation changes along the coastline and for each hurricane type. This table has severe limitations; however, provides a basis for developing a surge damage function found in section 4.5. In appendix A, the correlations to TND helped to develop the qualitative relationship listed in Table 6.

As equation 3 states, the damage function for storm surge generation is not well understood; however, in comparing the storm parameters found in Table 5, it becomes apparent that certain parameters are more highly correlated to storm damage than others. The most highly correlated parameters and their respective ranges and hurricane classifications are shown in Table 7.

| Hurricane<br>Surge<br>Scale<br>Category | Surge<br>Scale | ζ <sup>m</sup> max<br>(m) | R33<br>(km) | Y2 <sup>m</sup><br>(km) | ρ<br>(Person/km²) | w30 <sup>b</sup><br>(km) | v (kph) | c <sub>p</sub> <sup>a</sup><br>(mb) |
|---|----------------|---------------------------|-------------|-------------------------|-------------------|--------------------------|---------|-------------------------------------|
| H <sub>1</sub>                          | 0 - 0.5        | 0 - 3.7                   | 30 - 233    | 0 - 179                 | 40 - 810          | 4 - 40                   | 10 - 50 | 936 -<br>970                        |
| H <sub>2</sub>                          | 0.5 -<br>1.0   | 2.1 -<br>5.7              | 40 - 195    | 5 - 265                 | 20 - 200          | 4 - 84                   | 11 - 30 | 934 -<br>970                        |
| H <sub>2</sub>                          | 1.0 -<br>3.0   | 2.4 -<br>6.9              | 77 - 230    | 32 - 303                | 23 - 236          | 4 - 120                  | 12 - 30 | 910 -<br>970                        |
| H <sub>4</sub>                          | 3.0+           | 7.0+                      | 150+        | 300+                    | 83+               | 120+                     | 20+/-   | 920-                                |

Table 7: Approximate Range Storm Parameters for Hurricane Surge Scale Categories

Since storm duration ( $\Omega$  – hours) and storm angle ( $\theta$  – degrees) mimics a normal distribution, the ranges could be obtained in terms of z-scores instead of the above Table 6. It can be seen from Table 7, the ranges of storm parameters overlap, have wide variability and a single parameter is not necessarily representative of hurricane category; therefore, the table is mostly for summary purposes.

#### 3.4 Total Normalized Damages

Normalized Damage as previously described in Peilke and Landsea (2008) was adjusted to the year 2010, since this is the last available year United States Census Bureau data is available.

Since SS is a measure of the magnitude of hurricane storm surge, SS was compared to TND in this thesis for the specific purpose of correlating the two. The limited duration of appropriate damage data (approximately 100 yr) relative to the estimated return periods for extreme events in specific locations (100-500 yr events) leaves the correlation between TND and SS, relatively weak when comparing the entire data set (R=0.295). Furthermore, there are weather pattern and climatic shifts that create additional uncertainty on these interrelationships.

In order to compare the SS and TND a sensitivity analysis was performed to determine the relative impact the adjusted year and coastal population growth have on the correlation of SS to TND. Please see Figures 2 and 3.

The TND is explained in detail in the following paragraphs which describe the procedures used to derive Tables 8, 9 and 10. Data for Normalized Damages to the year 2005 found in Pielke and Landsea (2008) was used along with other estimates from NOAA (2011) and Malmstad (2009); this study expands the data to 2010 and 2020 projections. The Columns in Table 8, 9 and 10 have been lettered for convenience referencing. Starting with Column A, the rank of the storms is based on the year 2010. Column B lists the hurricane name. Column C is the year of the hurricane event and Column D describes the state(s) of land fall. Column E is the simplified SS from Irish and Resio (2007) along with Donna (1960) and Eloise (1975) being estimated. Column F is from Pielke and Landsea(2008), which is the Normalized Damages to the year 2005. Column G is the TND adjusted to the year 2010.

Since Katrina is the most recent extreme event for Damages and SS (Ike [2005], Irene [2011], Sandy [2012] were also extreme events), a sample calculation explaining columns G through N can be found below within the Inflation Adjustment, Wealth Per Capita Adjustment, Affected Coastal County Population and Future Normalized Damages Adjustment sub-sections. TND as expressed in 2010 US Billion Dollars in column G is found from equation 4.

Column H is the coastal county population adjustment from the year 2005 to 2010. A list of affected counties can be found in Table 3. Column H represents a ratio of the 2010 population to

the 2005 population for the affected counties, with the exception of storms occurring in year 2008. Column I represents a low growth scenario for coastal county population adjustment. Column J represents a moderate growth scenario for coastal county population adjustment. Column K represents a high growth scenario for coastal county population adjustment. Columns L through N correspond to columns I through K in that only the affected coastal county population has been adjusted; whereas, a reasonable adjustment for national population growth was used to derive the Real Wealth Per Capita.

## 3.4.1 Inflation Adjustment

Reported Damages are adjusted from 2005 dollars ( $D_{2005}$ ). This is true for all cases except for Gustav, Ike and Dolly which were 2008 Hurricanes; therefore, the inflation adjustment was estimated from national inflation index(s): the implicit price deflator for gross domestic product (IPDGDP) and Consumer Price Index (CPI) (for 2008 hurricanes), reported by the Bureau of Economic Analysis (BEA) and the Bureau of Labor Statistics (BLS).So, the inflation adjustment can be found by the ratio of 2010 IPDGDP to 2005 IPDGDP. The IPDGDP for 2010 was approximately 111 and 100 for 2005. Therefore,  $I_Y = 111/100 = 1.11$ . There are obvious differences in what has been found in the BEA numbers for IPDGDP presented in Pielke, et al., 2008 vs. the IPDGPD numbers presented herein.

## 3.4.2 Real Wealth Per Capita Adjustment

According to the BEA (2011) real wealth for consumer durable goods for year 2005 was 40.98 trillion and for 2010, 45.82 trillion; where, real wealth for consumer durable goods is defined as "the net stock of equipment and software and of structures owned by business and government and the net stock of durable goods owned by consumers" (BEA, 2012). In other words Real

Wealth per Capita is a measure of how much stuff people currently own as compared to the past. Inflation, however, is the decrease in value of a currency over time. The ratio of 2010 and 2005 is 45.820/40.98=1.118. The inflation multiplier for 2005 was 1.11; therefore, the inflation corrected wealth adjustment is 1.118/1.11=1.007 or is called the Real Wealth Multiplier (RWM). The estimated United States population from the United States Census Bureau in 2005 was 297,777,921 and in 2010, 312,471,327 (USCB); thus, the United States population multiplier is the ratio of the 2010 estimate to the 2005: 312,471,327/297,777,921=1.049. Finally, the real wealth per capita (RWPC<sub>y</sub>) is 1.007/1.049=0.960. This information is found in Table 10.

| A    | B         | C    | D                                | E                      | F   | G   |
|------|-----------|------|----------------------------------|------------------------|---|---|
| Rank | Storm     | Year | State(s)                         | Surge<br>Scale<br>(SS) | PL <sub>05</sub><br>Damage<br>(USS<br>Billions) | PL <sub>10</sub><br>Damage<br>(USS<br>Billions) |
| . 1  | Katrina   | 2005 | FL, LA (Double Landfall)         | 3.1                    | 81  | 85.4  |
| 2    | Andrew    | 1992 | FL, LA (Double Landfall)         | 1                      | 57.7  | 64.4  |
| 3    | October   | 1944 | FL                               | 0.7                    | 38.7  | 44.9  |
| 4    | September | 1938 | NY                               | 0.2                    | 39.2  | 42.4  |
| 5    | Donna     | 1960 | Mult. St. (Multiple<br>Landfall) | 1                      | 29.6  | 33.0  |
| 6    | Ike       | 2008 | TX                               | 1.3                    | -   | 28.5  |
| 7    | Wilma     | 2005 | FL                               | 1.7                    | 20.6  | 24.6  |
| 8    | Camille   | 1969 | LA, MS                           | 2.7                    | 21.2  | 23.2  |
| 9    | Charley   | 2004 | FL                               | 0.6                    | 16.3  | 19.9  |
| 10   | Betsy     | 1965 | LA                               | 0.8                    | 20.7  | 18.6  |
| 11   | Hugo      | 1989 | SC                               | 1                      | 15.3  | 18.2  |
| 12   | Ivan      | 2004 | FL, AL                           | 0.4                    | 15.5  | 17.2  |
| 13   | Carla     | 1961 | LA                               | 0.6                    | 14.2  | 16.0  |
| 14   | Rita      | 2005 | LA, TX                           | 1.9                    | 10  | 11.5  |
| 15   | Frances   | 2004 | FL                               | 0.2                    | 9.7   | 11.2  |
| 16   | Frederic  | 1979 | AL, MS, FL                       | 0.7                    | 10.3  | 10.9  |
| 17   | Opal      | 1995 | FL                               | 0.4                    | 6.1   | 6.8   |
| 18   | Celia     | 1970 | TX                               | 0.5                    | 5.6   | 6.1   |

Table 8: General Information and Hurricane Damages

| 19 | Gustav  | 2008 | LA                  | 1.1 | -   | 5.1  |
|----|---------|------|---------------------|-----|-----|------|
| 20 | Isabel  | 2003 | VA, NC              | 0.3 | 4   | 4.7  |
| 21 | Beulah  | 1967 | TX                  | 0.3 | 4   | 4.6  |
| 2  | Audrey  | 1957 | LA, TX              | 1.3 | 3.8 | 4.4  |
| 2  | Eloise  | 1975 | · FL                | 0.4 | 2.8 | 3.1  |
|    |         |      | Mult. St. (Multiple |     |     |      |
| 24 | Gloria  | 1985 | Landfall)           | 0.3 | 2.4 | 2.6  |
| 25 | Dennis  | 2005 | FL                  | 0.3 | 2.2 | 2.5  |
| 26 | Hilda   | 1964 | LA                  | 1.1 | 2.2 | 2.4  |
| 27 | October | 1941 | FL                  | 0.4 | 2   | 2.2  |
| 28 | Allen   | 1980 | FL                  | 0.3 | 1.6 | 1.9  |
| 2  | Dolly   | 2008 | TX                  | 0.2 | -   | 1.3  |
| 30 | Lili    | 2002 | LA                  | 0.9 | 1.1 | 1.18 |
| 31 | Bret    | 1999 | TX                  | 0.3 | 0.1 | 0.12 |

### 3.4.3 Affected Coastal County Population

The affected coastal counties variable was based upon NOAA published data along with information shown from Figure 20, Pielke and Landsea (2008). Additionally, HURDAT (North American Hurricane Database) was used for determining storm size, track, along with 2011 NOAA billion dollar estimate reports were used as a method to determining coastal counties affected. County population data is available for 2000 and 2010 from the United States Census Bureau. The ratio of affected population of 2010 to 2005 for Hurricane Katrina [2005]is 2517648/2543485=0.99: A complete list of these ratios for the data is found in Table 9 and is under column H. Notice the ratio represents stagnant growth and some lives were lost while others were displaced by the storm; this is evidenced by a drop in population in counties hardest hit by the storm; however, some population growth in storm outlier counties.

#### 3.4.4 Future Normalized Damages

Although we cannot predict future damages deterministically, the methodology presented in this thesis provides a means to develop reasonable estimates of damage within an uncertainty range; this capability would be a step forward in estimating damage from a given storm surge. Furthermore, to adjust the future damage estimates, some basic understanding and assumptions are required in order to extrapolate reasonable estimates. Inflation indexes have averaged approximately  $1.1(I_y)$ , from year to year over the last two decades; therefore, a linear extrapolation was used to obtain the year 2020 IPDGDP of 123 and thus, giving an inflation adjustment to the year 2020 by 123/111=1.108. Due to the nature of the recent financial crisis, it will be difficult to ascertain the correct wealth; whereas, Appendix E shows the US wealth growth leveling off at 2008 and could cause errors in the 2020 predictions herein. Nevertheless, a modest wealth growth of 48.11 trillion USD for 2020 (45.82 trillion USD in 2005) was chosen. Wealth as shown in Appendix E looks hyperbolic until the years 2007-2010 are considered; it is shown that the numerator, the Real Wealth Multiplier (RWM) 2020 is 0.948 and the RWPC<sub>y</sub>=0.948/1.092=0.868 is less than 1 (Table 10).

# Table 9: Future Damages

| В         | C             | H       | I                                      | and <b>J</b> anaka              | K                                       | L                                       | М   | N  |
|-----------|---------------|---------|--|---------------------------------|---|---|---|--|
| Storm     | Year          | P2010/y | P <sub>2020/y</sub><br>(low<br>growth) | P2020/y<br>(moderate<br>growth) | P <sub>2020/y</sub><br>(high<br>growth) | PL2000w)<br>Damage<br>(USS<br>Billions) | PL <sub>20(mod)</sub><br>Damage<br>(US\$<br>Billions) | PL <sub>20(biss)</sub><br>Damage<br>(US\$<br>Billions) |
| Katrina   | 2005          | 0.99    | 0.79                                   | 0.99                            | 1.19                                    | 64.9                                    | 81.3  | 97.8   |
| Andrew    | 1992          | 1.05    | 0.85                                   | 1.05                            | 1.25                                    | 52.6                                    | 65.0  | 77.4   |
| October   | 1944          | 1.09    | 0.89                                   | 1.09                            | 1.29                                    | 38.3                                    | 46.9  | 55.6   |
| September | 1938          | 1.01    | 0.81                                   | 1.01                            | 1.21                                    | 33.2                                    | 41.4  | 49.5   |
| Donna     | 1960          | 1.05    | 0.85                                   | 1.05                            | 1.25                                    | 26.9                                    | 33.3  | 39.6   |
| Ike       | 2008          | 1.09    | 0.89                                   | 1.09                            | 1.29                                    | 24.5                                    | 30.0  | 35.5   |
| Wilma     | 2005          | 1.12    | 0.92                                   | 1.12                            | 1.32                                    | 21.8                                    | 26.6  | 31.3   |
| Camille   | 1969          | 1.03    | 0.83                                   | 1.03                            | 1.23                                    | 18.4                                    | 22.9  | 27.3   |
| Charley   | 2004          | 1.14    | 0.94                                   | 1.14                            | 1.34                                    | 18.0                                    | 21.9  | 25.7   |
| Betsy     | 1965          | 0.84    | 0.64                                   | 0.84                            | 1.04                                    | 11.5                                    | 15.1  | 18.7   |
| Hugo      | 1989          | 1.12    | 0.92                                   | 1.12                            | 1.32                                    | 16.1                                    | 19.7  | 23.2   |
| Ivan      | 2004          | 1.04    | 0.84                                   | 1.04                            | 1.24                                    | 13.9                                    | 17.3  | 20.6   |
| Carla     | 1961          | 1.06    | 0.86                                   | 1.06                            | 1.26                                    | 13.3                                    | 16.4  | 19.5   |
| Rita      | 2005          | 1.08    | 0.88                                   | 1.08                            | 1.28                                    | 9.8                                     | 12.0  | 14.2   |
| Frances   | 2004          | 1.09    | 0.89                                   | 1.09                            | 1.29                                    | 9.6                                     | 11.8  | 13.9   |
| Frederic  | <u>1979</u>   | 0.99    | 0.79                                   | 0.99                            | 1.19                                    | 8.3                                     | 10.4  | 12.5   |
| Opal      | 1995          | 1.05    | 0.85                                   | 1.05                            | 1.25                                    | 5.6                                     | 6.9   | 8.2  |
| Celia     | 1970          | 1.03    | 0.83                                   | 1.03                            | 1.23                                    | 4.9                                     | 6.1   | 7.2  |
| Gustav    | 2008          | 1.00    | 0.80                                   | 1.00                            | 1.20                                    | 3.9                                     | 4.9   | 5.9  |
| Isabel    | 2003          | 1.10    | 0.90                                   | 1.10                            | 1.30                                    | 4.0                                     | 4.9   | 5.8  |
| Beulah    | 1967          | 1.09    | 0.89                                   | 1.09                            | 1.29                                    | 4.0                                     | 4.8   | 5.7  |
| Audrey    | 19 <u>5</u> 7 | 1.08    | 0.88                                   | 1.08                            | 1.28                                    | 3.7                                     | 4.6   | 5.4  |
| Eloise    | 1975          | 1.05    | 0.85                                   | 1.05                            | 1.25                                    | 2.6                                     | 3.2   | 3.8  |
| Gloria    | 1985          | 1.02    | 0.82                                   | 1.02                            | 1.22                                    | 2.0                                     | 2.5   | 3.0  |
| Dennis    | 2005          | 1.07    | 0.87                                   | 1.07                            | 1.27                                    | 2.1                                     | 2.6   | 3.0  |
| Hilda     | 1964          | 1.02    | 0.82                                   | 1.02                            | 1.22                                    | 1.9                                     | 2.3   | 2.8  |
| October   | 1941          | 1.05    | 0.85                                   | 1.05                            | 1.25                                    | 1.8                                     | 2.3   | 2.7  |
| Allen     | 1980          | 1.09    | 0.89                                   | 1.09                            | 1.29                                    | 1.6                                     | 2.0   | 2.3  |
| Dolly     | 2008          | 1.04    | 0.84                                   | 1.04                            | 1.24                                    | 1.0                                     | 1.3   | 1.5  |
| Lili      | 2002          | 1.01    | 0.81                                   | 1.01                            | 1.21                                    | 0.9                                     | 1.1   | 1.4  |
| Bret      | 1999          | 1.09    | 0.89                                   | 1.09                            | 1.29                                    | 0.1                                     | 0.1   | 0.1  |

Decadal national population growth has decreased gradually from the early twentieth century value of approximately 20% to about 10% for the end of the twentieth century and early twenty-first century as can be noted in APPENDIX G, which depicts decline in the growth rate for national population. For damage parameters used in Equation 4refer to Table 10in order to adjust Pielke and Landsea 2005 to 2010 and 2020 Normalized Damages.

|  |            |  |       |       |                          |             | 1.77030794<br>1989 (2016)<br>1989 (2016) |       |                |
|--|------------|--|-------|-------|--------------------------|-------------|--|-------|----------------|
| I,   | <b>R</b> 2 | R <sub>i</sub>   | R     | RWM   | US Pop 1                 | US Pop 2    | Pop<br>Ratio                             | RWPC. | Adjust<br>Year |
| Jan State St | <u></u>    | and the second |       |       | aladie - adheann adheann |             |  |       | 2005-          |
| 1.110  | 45.818     | 40.980   | 1.118 | 1.007 | 297,777,921              | 312,471,327 | 1.049                                    | 0.960 | 2010           |
|  |            |  |       |       |                          |             |  |       | 2008-          |
| 1.037  | 45.820     | 45.670   | 1.003 | 0.967 | 304,094,000              | 312,471,327 | 1.028                                    | 0.976 | 2010           |
|  |            |  |       |       |                          |             |  |       | 2010-          |
| 1.108  | 48.111     | 45.820   | 1.050 | 0.948 | 312,471,327              | 341,114,336 | 1.092                                    | 0.868 | 2020           |

Table 10: Damage Calculation Adjustment (2005-2020)

#### 3.5 Explanation of Surge Scale

Previously the SS (Irish and Resio, 2007) was described in equation 5 in the simplest form. Additionally the storm parameters data used to estimate this data was included into Table 5.

Some storms will naturally produce small errors in any Simplified SS. The SS work identifies the storms which have the capability to produce large surges such as Katrina [2005]. Hurricane Andrew [1992] which was very intense and created high amounts of wind damage produced a minimal surge; whereas, the hurricane size was small and current was allowed to bypass through the Florida Straits. Cases such as these have been given more consideration and analysis in Chapter 4. SS in its more complicated form is described in the following:

$$SS = \frac{\zeta}{\overline{\zeta}} = (\frac{\chi \Delta p}{\overline{\zeta}}) \frac{L_*}{h_* \phi_*} \psi_x(\frac{R}{L_*}) \psi_t(\frac{t_*}{t_{in}})$$
(6)

In this equation,  $\zeta$  is the normal water surface elevation measured from normal water level and  $\zeta$  (bar) is a surge of 1 meter; therefore, SS is shown to be dimensionless.  $\chi$  is a dimensionless constant,  $\Delta p$  is the hurricane central pressure differential,  $L_*$  is the horizontal integration limit,  $h_*$  is the water depth at  $L_*$ ,  $\varphi_*$  is a dimensionless integral shape function,  $\psi_x$  is a dimensionless storm size function and R is the characteristic storm size. Additionally,  $\psi_t$  is a dimensionless storm duration function,  $t_*$  is the characteristic storm duration and  $t_{in}$  is the time required to reach steady-state equilibrium surge.

Simplification comes from recognizing that the interactive storm response to the land occurs in water shallower than 30 meters. The equivalent depth argument is found in Irish and Resio (2007), which effectively replaces the term  $L_*/h*\varphi*$  with  $L_{30m}$ . Once the equivalent depth argument is made, the storm size term in the equation (R/L\*) becomes  $R_{33}/L_{30m}$ . For Atlantic hurricanes,  $\psi_t$  can be approximated to be equal to 1 and if the proportionality constant between hurricane intensity and wind speed  $\lambda = 0.325$  and wind drag coefficient  $c_d = 0.0022$ , the dimensionless constant,  $\chi = 7.29(10)^8 \text{ kg/m}^3/\text{s}^2$ . With the above assumptions, and using hurricanes with  $\theta$  (Storm Angle) between -60° and +45°, the simplified SS shown in equation 5 works well with little loss in accuracy.

As previously noted, population has a significant effect on TND consistent with its exponential form in Equation 8. Equation 7 represents a dimensionless population factor. With the exception of Gloria [1985] in the sorted data set of 17 hurricanes the population densities are all below 200 persons/km; therefore, a benchmark in K is introduced.

$$K = \rho / 200$$
 (7)

A Surge-Only Damage Function (The Normalized Damage due to surge (ND<sub>s</sub>)) is termed the Hurricane Coastal Surge Damage Scale (HCSDS) here. An approach to finding the predicted TND is presented in this section. Shown as Figure 7, a linear relationship has been listed in Table 16 between SS and TND. The primary focus of this thesis is to present a beginning non-linear relationship by introducing a mathematical damping function using the storm parameters listed herein. The non-linear relationship for TND vs. SS:

$$TND_{P} = \left[ \left( \left( \left( SS * 21.852 \right) - 4.946 \right) * \left( e^{-K^{*}Hs} \right) \right) + \left( w_{30}^{b} / 30 \right) \right]$$
(8)

If the Hurricane Damage Correction Factor  $(H_s)$  is allowed to vary, when multiplied by K, the equation successfully dampens the predicted damage to the actual damage. Please see section 4.5 and Appendix I; whereas, a more detailed explanation of sensitivity and boundary conditions can be found.

#### Chapter 4

### DISCUSSION OF RESULTS

This thesis develops relationships between physical storm parameters and SS to damages in terms of hurricane state/category, as well as with the associated damages. This chapter begins with a discussion on the relationships developed for the hurricane damage events with SS and hurricane parameters. Finally, a table which incorporates all of the results from the developed relationships is presented. (Table 16)

## 4.1 Coefficient of Determination Measurements

The coefficient of determination, or  $R^2$  value was obtained for each relationship. The  $R^2$  value was used as a measure of how well each trend-line fits a given covariate data set. Trend-lines for each relationship were modeled by computing the least-squares fit regressions.  $R^2$  can range from 0 to 1.0. An  $R^2$  of 1.0 indicates that all points lie on the regression line, indicating that all of the variability is accounted for. As  $R^2$  values decrease from 1.0, less of the variability is accounted for in the relationship.

Considering that the hurricane events are natural phenomena, they are inherently variable with respect to interactions with the land masses. There is sparse research which relates hurricane parameters to damage; however, the following scale will be used here to provide a qualitative assessment of the relative importance of different  $R^2$  values. For this study, it is assumed that an  $R^2$  below 0.2 is a poor relationship, a  $R^2$  value between 0.2-0.7 is good, and a  $R^2$  value higher than 0.7 excellent.

## 4.2 Developed Relationships

Data on physical storm parameters, surge scale, and damages for thirty-one hurricane events were available. Parameters for these storms can be found in Table 14. Relationships were developed for the hurricane damage events with surge scale and hurricane parameters.

4.2.1 Surge Scale and Damage Relationships

Data from all of the hurricanes were combined to produce relationships in five categories. The first category is evaluated TND as a function of SS without sorting. The second category is evaluated TND as a function of SS by adjusted year. The third category is evaluated TND as a function of SS for coastal growth scenarios. The fourth category is evaluated TND as a function of SS sorted for technological improvements in damage surveying (Post 1970). The final category excludes "micro-canes" from the data which tend to produce high amounts of localized wind damage and thereby causes error in the correlation.

### 4.2.2 Hurricane Parameter and Damage Relationships

The majority of the relationships for the hurricane parameters contained a high degree of scatter. This scatter produced poor correlations between the parameters and damages indicated by a low coefficient of determination ( $\mathbb{R}^2$ ). Although there is high scatter in the data, and resulting poor correlations, R values above 0.1 will be discussed in further detail in section 4.4. Due to the infancy of research relating these relationships, even low correlations mean there is potential for these parameters to be included into the damage function. Graphs showing these relationships have been placed into Appendix B.

4.3 Total Normalized Damage Relationship to Surge Scale

Figure 2 illustrates the relationship between the TND and SS for the complete data set. The data comparisons are presented below in this section. The comparisons herein represent a leap forward in the understanding of actual historical damage and to storm surge in terms of parametric surge.

4.3.1 Un-Sorted Data R value Results

A sensitivity analysis was conducted for the influence of adjusted year and coastal growth (Figures 2 and 3) on the correlation between TND and SS. As can be seen from the figures, both the adjusted year and coastal growth make little impact on the correlation; however, examining Figure 4, one can observe an increase in the magnitude of damages for coastal growth.

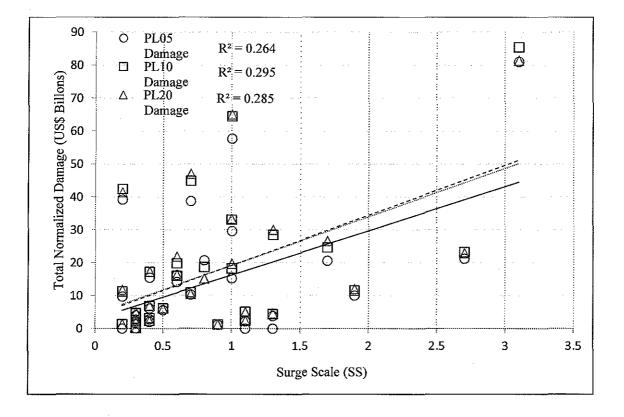


Figure 2: Total Normalized Damages versus Surge Scale for Adjusted Damage

Note that the correlation, regardless of adjusted year, remains near constant: Interestingly, the best correlation is found for year 2010; but these differences are not statistically significant. Additionally, Figure 3 shows that, for variable coastal growth rates, the correlation again remains relatively constant.

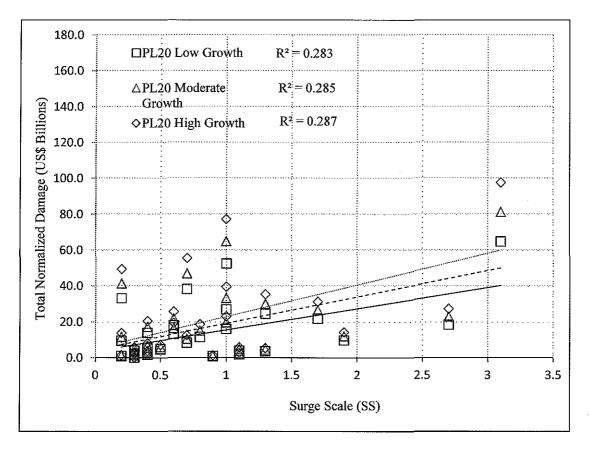


Figure 3: Total Normalized Damages versus Surge Scale for Various Coastal Growth Scenarios

As shown in these figures the R values are slightly less than 0.3; therefore, from our definition, the relationship is rated as good. Next, Figure 4 below shows the distribution of damages. It is important to realize that growth rates in population will strongly influence damages. For some hurricane events this will imply decreasing damages due to the negative growth rates in some areas along the coast.

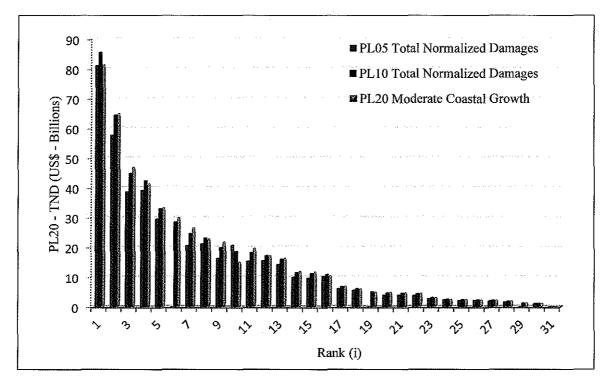


Figure 4: Coastal Growth Influence on Total Normalized Damages by Storm Rank

## 4.3.2 Potential Improvements in Damage Estimation Methods

The correlations between the SS and TND is somewhat weak though when considering a moderately long range (72 years) of data, which is likely due to a number of factors.For example, since 1970 many technological improvements have been made that allows for damage estimates to be more consistent and accurate. It is not the intention of this thesis to explain all the improvements that have been made; however, it is important to show the relative importance technological improvements have over the correlation between SS and TND. Table 11& 12 has been segregated into 1941-1969 and 1970-2010 intervals.

| A    | В         | С    | D                   | E                      | F  | G   | H                   |
|------|-----------|------|---------------------|------------------------|--|---|---------------------|
| Rank | Storm     | Year | State(s)            | Surge<br>Scale<br>(SS) | PL <sub>05</sub><br>Damage<br>(US\$<br>Billions) | PL <sub>10</sub><br>Damage<br>(USS<br>Billions) | P <sub>2010/y</sub> |
| 3    | October   | 1944 | FL                  | 0.7                    | 38.7   | 44.9  | 1.09                |
| 4    | September | 1938 | NY                  | 0.2                    | 39.2   | 42,4  | 1.01                |
|      |           |      | Mult. St. (Multiple |                        |  |   |                     |
| 5    | Donna     | 1960 | Landfall)           | 1                      | 29.6   | 33.0  | 1.05                |
| 8    | Camille   | 1969 | LA, MS              | 2.7                    | 21.2   | 23.2  | 1.03                |
| 9    | Betsy     | 1965 | LA                  | 0.8                    | 20.7   | 18.6  | 0.84                |
| 13   | Carla     | 1961 | LA                  | 0.6                    | 14.2   | 16.0  | 1.06                |
| 21   | Beulah    | 1967 | TX                  | 0.3                    | 4  | 4.6   | 1.09                |
| 22   | Audrey    | 1957 | LA, TX              | 1.3                    | 3.8  | 4.4   | 1.08                |
| 26   | Hilda     | 1964 | LA                  | 1.1                    | 2.2  | 2.4   | 1.02                |
| 27   | October   | 1941 | FL                  | 0.4                    | 2  | 2.2   | 1.05                |

Table 11: General Information and Hurricane Damages – Sorted (1938-1969)

For the period before 1970, the relationship between TND and SS exhibits a high degree of scatter, resulting in poor correlation as indicated by a low coefficient of determination ( $\mathbb{R}^2$ ). Graphs showing these relationships have been placed into Appendix A.

| A    | В        | С            | D                                | E                      | F  | G   | H       |
|------|----------|--------------|----------------------------------|------------------------|--|---|---------|
| Rank | Storm    | Year         | State(s)                         | Surge<br>Scale<br>(SS) | PL <sub>05</sub><br>Damages<br>D <sub>v2005</sub><br>(USS<br>Billions) | PL <sub>10</sub><br>Damages<br>D <sub>y2010</sub><br>(US\$<br>Billions) | P2010/y |
| 1    | Katrina  | 2005         | FL, LA (Double Landfall)         | 3.1                    | 81   | 85.4  | 0.99    |
| 2    | Andrew   | 1 <b>992</b> | FL, LA (Double Landfall)         | 1                      | 57.7   | 64.4  | 1.05    |
| 6    | Ike      | 2008         | TX                               | 1.3                    | -  | 28.5  | 1.09    |
| 7    | Wilma    | 2005         | FL                               | 1.7                    | 20.6   | 24.6  | 1.12    |
| 10   | Charley  | 2004         | FL                               | 0.6                    | 16.3   | 19.9  | 1.14    |
| 11   | Hugo     | 1989         | SC                               | 1                      | 15.3   | 18.2  | 1.12    |
| 12   | Ivan     | 2004         | FL, AL                           | 0.4                    | 15.5   | 17.2  | 1.04    |
| 14   | Rita     | 2005         | LA, TX                           | 1.9                    | 10   | 11.5  | 1.08    |
| 15   | Frances  | 2004         | FL                               | 0.2                    | 9.7  | 11.2  | 1.09    |
| 16   | Frederic | 1979         | AL, MS, FL                       | 0.7                    | 10.3   | 10.9  | 0.99    |
| 17   | Opal     | 1995         | FL                               | 0.4                    | 6.1  | 6.8   | 1.05    |
| 18   | Celia    | 1970         | TX                               | 0.5                    | 5.6  | 6.1   | 1.03    |
| 19   | Gustav   | 2008         | LA                               | 1.1                    | t  | 5.1   | 1.00    |
| 20   | Isabel   | 2003         | VA, NC                           | 0.3                    | 4  | 4.7   | 1.10    |
| 2    | Eloise   | 1975         | FL                               | 0.4                    | 2.8  | 3.1   | 1.05    |
| 24   | Gloria   | 1985         | Mult. St. (Multiple<br>Landfall) | 0.3                    | 2.4  | 2.6   | 1.02    |
| 25   | Dennis   | 2005         | FL                               | 0.3                    | 2.2  | 2.5   | 1.07    |
| 28   | Allen    | 1980         | FL                               | 0.3                    | 1.6  | 1.9   | 1.09    |
| 2    | Dolly    | 2008         | TX                               | 0.2                    | -  | 1.3   | 1.04    |
| 30   | Lili     | 2002         | LA                               | 0.9                    | 1.1  | 1.2   | 1.01    |
| 31   | Bret     | 1999         | TX                               | 0.3                    | 0.1  | 0.1   | 1.09    |

Table 12: General Information and Hurricane Damages – Sorted (1970-2010)

A comparison of Figures 5& 6 in this section show a large improvement in the correlation between SS and TND for post-1969 data as compared to the pre-1970 data. There is a "good" correlation ( $R^2 = 0.554$ ) between the SS and TND, based on the data presented post-1969. Whereas, the correlation was poor ( $R^2 = 0.001$ ) for the pre-1970 data, suggesting that hurricane damage estimates in the earlier era might not be sufficiently accurate to be used for quantifying this relationship. Though it is somewhat instructive to arrange data in descending order in terms of damage as Pielke and Landsea (2008) have presented, unfortunately a large portion of damage data has a questionable connection to SS because of technological improvements for damage estimates post-1969. Figure 5 indicates the pre-1970 relationship and Figure 6 shows the post-1969 relationship.

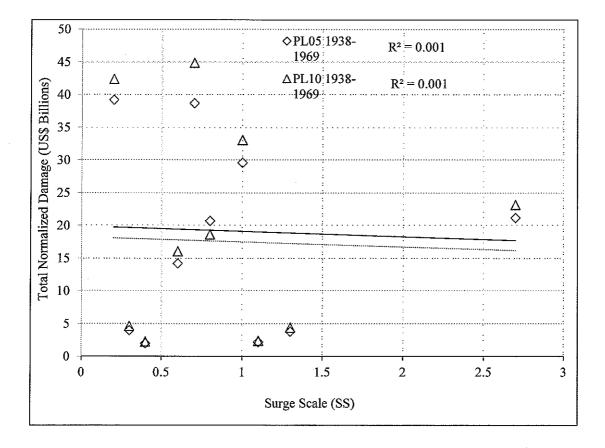


Figure 5: Total Normalized Damages versus Surge Scale (1938-1969)

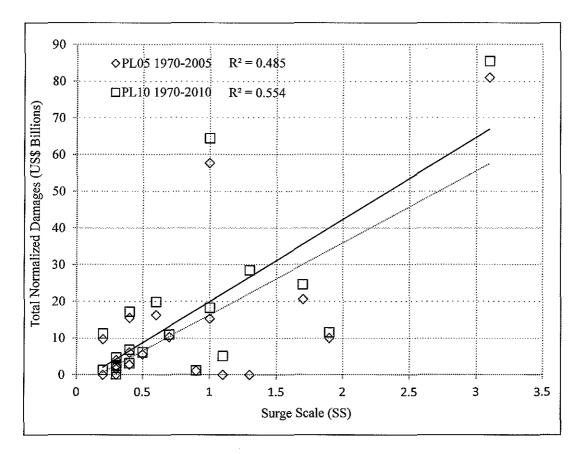


Figure 6: Total Normalized Damages versus Surge Scale (1970-1969)

#### 4.3.3 Additional Analysis: Improvements and Exclusion of "Micro-canes"

As discussed in section 2.2, there are three types of damages included in the damage estimates. To illustrate this point further additional hurricanes have been removed from the data set. Andrew [1992], Charley [2004], Dennis [2005] and Dolly [2008] had very small  $R_{33}$ , which is the radius to hurricane force winds. As shown in section 2.3, the damage function for surge depends on  $R_{33}$ . There are many hurricane parameters that are related to the surge damage function. Very small hurricanes, sometimes termed "Micro-canes" tend to produce high amounts of wind damage ( $ND_w$ ) with relatively small amount of inland flooding damage ( $ND_f$ ) and small amounts of surge damage ( $ND_s$ ); therefore, extracting them from the data set improves the correlation to R = 0.701 indicating a good to excellent correlation.

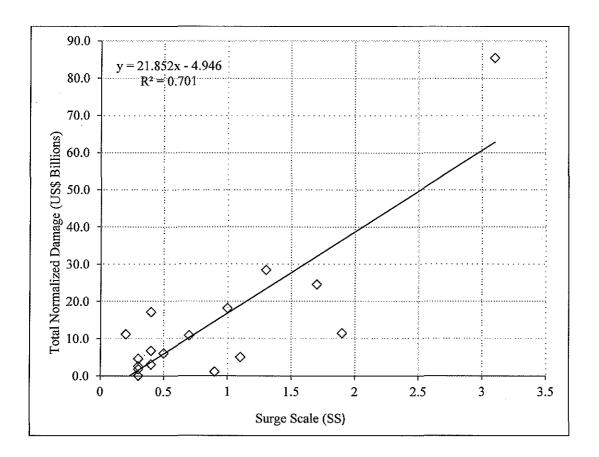


Figure 7: Total Normalized Damages versus Surge Scale (1970-1969) - Exclusion of "micro-canes"

The definition of micro-canes for the purposes in determining criteria to remove hurricanes from the data set is the following:

- RMW (radius of max winds)<20 km
- R<sub>33</sub><80 km

Hurricanes smaller than 80 km in size lack the potential to generate a significant surge, regardless of the other hurricane parameters or geophysical characteristics of a region. So, damage due to surge  $(ND_s)$  could be considered negligible in the damage estimates for these small hurricanes.

| Rank | Storm    | Year | State(s)                         | Surge<br>Scale<br>(SS) | PL <sub>05</sub><br>Damage<br>(USS<br>Billions) | PL <sub>10</sub><br>Damage<br>(US\$<br>Billions) | P <sub>2010/y</sub> |
|------|----------|------|----------------------------------|------------------------|---|--|---------------------|
| 1    | Katrina  | 2005 | FL, LA (Double Landfall)         | 3.1                    | 81  | 85.4   | 0.99                |
| 6    | Ike      | 2008 | TX                               | 1.3                    | -   | 28.5   | 1.09                |
| 7    | Wilma    | 2005 | FL                               | 1.7                    | 20.6  | 24.6   | 1.12                |
| 10   | Hugo     | 1989 | SC                               | 1                      | 15.3  | 18.2   | 1.12                |
| 12   | Ivan     | 2004 | FL, AL                           | 0.4                    | 15.5  | 17.2   | 1.04                |
| 14   | Rita     | 2005 | LA, TX                           | 1.9                    | 10  | 11.5   | 1.08                |
| 15   | Frances  | 2004 | FL                               | 0.2                    | 9.7   | 11.2   | 1.09                |
| 16   | Frederic | 1979 | AL, MS, FL                       | 0.7                    | 10.3  | 10.9   | 0.99                |
| 17   | Opal     | 1995 | FL                               | 0.4                    | 6.1   | 6.8  | 1.05                |
| 18   | Celia    | 1970 | TX                               | 0.5                    | 5.6   | 6.1  | 1.03                |
| 19   | Gustav   | 2008 | LA                               | 1.1                    | -   | 5.1  | 1.00                |
| 20   | Isabel   | 2003 | VA, NC                           | 0.3                    | 4   | 4.7  | 1.10                |
| 23   | Eloise   | 1975 | FL                               | 0.4                    | 2.8   | 3.1  | 1.05                |
| 24   | Gloria   | 1985 | Mult. St. (Multiple<br>Landfall) | 0.3                    | 2.4   | 2.6  | 1.02                |
| 28   | Allen    | 1980 | FL                               | 0.3                    | 1.6   | 1.9  | 1.09                |
| 30   | Lili     | 2002 | LA                               | 0.9                    | 1.1   | 1.2  | 1.01                |
| 31   | Bret     | 1999 | TX                               | 0.3                    | 0.1   | 0.1  | 1.09                |

# Table 13: General Information and Hurricane Damages – Sorted (1970-2010) and Micro-canes Excluded

The above data represent the best current estimate of SS relationship to TND. With further extraction of non-surge related damages, through correction factors based on rainfall amounts or wind field hyetographs, it is suspected that the correlation between  $ND_s$  and SS could improve even over what is seen here.

4.4 Hurricane storm parameters comparison to Total Normalized Damages

In an effort to illustrate the storm parameters that cause significant surge damage, the parameters in equation 3 will be discussed in some detail. This section covers current research in describing the damage function for hurricane surge. The damage function for surge is complex and there has

been considerable focus in this study on those hurricane parameters that are contributing factors to storm surge.

#### 4.4.1 Radius to Hurricane Force Winds (R<sub>33</sub>) Relationship to Damages

Some parameters also have connections to other types of damage:  $R_{33}$  is related to all three types of damage (ND<sub>w</sub>, ND<sub>f</sub>, ND<sub>s</sub>). Additionally,  $R_{33}$  is found in equation 3, being one of the largest contributors to damage. As Irish and Resio (2007) describe damage "depending linearly on storm size". In the comparison of TND and  $R_{33}$  only an R-value of 0.06 was found, which is somewhat counter-intuitive.

# 4.4.2 Maximum Surge Elevation (ζ<sub>max</sub>) Relationship to Damages

The storm parameter that was found to be most highly correlated to TND is  $\zeta_{max}$  with an R-value of 0.235. Fortunately, as shown by Irish and Resio (2007) there is a fair amount of maximum surge data; since, records of maximum surge elevation have been of general interest for some time. Again, once surge specific damage data is compared to  $\zeta_{max}$ , the correlation will be more representative of a parameter that cannot be connected to other types of damage.

4.4.3 Alongshore Extent of Surge Greater Than 2 meters (Y<sub>2</sub><sup>m</sup>) Relationship to Damages

The alongshore extent of surge greater than 2 m exhibits the next highest correlation to surge damages. In fact, this study shows an R-value of 0.185, which suggests that the Damage Function should include this parameter. It is intuitive that this parameter is related to surge damage as it is one of the parameters in determining the approximate area of inundation (Section 4.4.6).

#### 4.4.4 Coastal Storm Specific Population Density (ρ) Relationship to Damages

Coastal storm specific county population density is only accurate for surge, in that, the interior counties were not included in this study. Obviously, with many hurricanes the damage sustained is due to inland flooding and wind damage; therefore, it is suspected that the correlation between surge specific normalized damage will be well correlated to the coastal county population density. An R-value of 0.071 was calculated for the total data set indicating a somewhat deceptive relationship to the surge damage function: It was concluded here that a population density factor should be included. An unfortunate observation however, there is a large cone of uncertainty as illustrated by the Figure 17, Appendix B, especially on the upper end of the scale. Since there is a large cone of uncertainty, the correlation is negatively affected; however, most of the data trends are much better than the coefficient of determination indicate. The trend is positive and as shown in the section 4.3.1, growth scenarios can have large effects on future total normalized damages.

It is apparent that, even if in cases in which all other storm parameters indicated there would be large surge and thus damages, it is likely that the damages will be mitigated if the population is low. (An exception to this relationship is Katrina [2005] which was massive as to not only cover highly populated areas, but also include highly un-populated areas and thus lowering the population density significantly) Figure 7, Appendix A shows Rita [2005] as an example, was a massive hurricane capable of producing major damages, yet damages were lower than expected by the overall trend, due to the fact it made landfall along an unpopulated stretch of coastline at the Louisiana/Texas border. When analyzing Figure 17, data points (hurricanes) above the trend line indicate other forms of damage and those below have lower population densities.

| Year | Storm<br>Name | Area<br>(km²) | Storm<br>Year<br>Population | Storm Year<br>Specific<br>Coastal<br>Population<br>Density<br>(Person/km <sup>2</sup> ) | 2010 Year<br>Population | 2010 Storm<br>Specific<br>Coastal<br>Population<br>Density<br>(Person/km <sup>2</sup> ) | 2010<br>Normalized<br>Damage<br>(SUS<br>Billions) |
|------|---------------|---------------|-----------------------------|---|-------------------------|---|---|
| 2005 | Katrina       | 28,357        | 2,498,656                   | 88.1  | 2,517,648               | 88.8  | 85.4  |
| 1992 | Andrew        | 11,242        | 2,225,093                   | 197.9   | 2,736,185               | 243.4   | 64.4  |
| 1944 | 11<br>(Oct.)  | 20,481        | 368,516                     | 18.0  | 4,106,640               | 200.5   | 44.9  |
| 1938 | Sept.         | 18,451        | 8,162,408                   | 442.4   | 14,979,620              | 811.9   | 42.4  |
| 1960 | Donna         | -             | -                           |   | -                       |   |   |
| 2008 | Ike           | 33,437        | 5,157,529                   | 154.2   | 5,303,437               | 158.6   | 28.5  |
| 2005 | Wilma         | 13,186        | 1,396,114                   | 105.9   | 1,208,204               | 91.6  | 24.6  |
| 1969 | Camille       | 20,734        | 1,342,424                   | 64.7  | 2,517,648               | 121.4   | 23.2  |
| 2004 | Charley       | 3,878         | 661,002                     | 170.5   | 778,732                 | 200.8   | 19.9  |
| 1965 | Betsy         | 25,264        | 1,529,355                   | 60.5  | 1,913,962               | 75.8  | 18.6  |
| 1989 | Hugo          | 16,732        | 746,485                     | 44.6  | 927,910                 | 55.5  | 18.2  |
| 2004 | Ivan          | 15,981        | 1,298,493                   | 81.3  | 1,364,738               | 85.4  | 17.2  |
| 1961 | Carla         | 24,866        | 304,269                     | 12.2  | 839,294                 | 33.8  | 16  |
| 2005 | Rita          | 29,567        | 5,250,714                   | 177.6   | 5,407,430               | 1 <b>82.9</b>   | 11.5  |
| 2004 | Frances       | 11,975        | 2,194,130                   | 183.2   | 2,279,327               | 190.3   | 11.2  |
| 1979 | Frederic      | 24,773        | 1,879,923                   | 75.9  | 2,232,280               | 90.1  | 10.9  |
| 1995 | Opal          | 10,185        | 719,621                     | 70.7  | 869,571                 | 85.4  | 6.8   |
| 1970 | Celia         | 10,186        | 321,737                     | 31.6  | 481,173                 | 47.2  | 6.1   |
| 2008 | Gustav        | 15,162        | 855,751                     | 56.4  | 849,661                 | 56.0  | 5.1   |
| 2003 | Isabel        | 20,831        | 724,196                     | 34.8  | 777,234                 | 37.3  | 4.7   |
| 1967 | Beulah        | 9,922         | 171,229                     | 17.3  | 460,831                 | 46.4  | 4.6   |
| 1957 | Audrey        | 21,844        | 1,858,629                   | 85.1  | 5,204,218               | 238.2   | 4.4   |
| 1975 | Eloise        | 14,334        | 481,064                     | 33.6  | 881,120                 | 61.5  | 3.1   |
| 1985 | Gloria        | 22,773        | 10,301,250                  | 452.4   | 12,125,454              | 532.5   | 2.6   |
| 2005 | Dennis        | 8,482         | 430,572                     | 50.8  | 631,256                 | 74.4  | 2.5   |
| 1964 | Hilda         | 12,769        | 214,977                     | 16.8  | 304,588                 | 23.9  | 2.4   |
| 1941 | 5 (Oct.)      | 31,094        | 503,189                     | 16.2  | 5,959,319               | 191.7   | 2.2   |
| 1980 | Allen         | 7,666         | 455,530                     | 59.4  | 428,770                 | 55.9  | 1.9   |
| 2008 | Dolly         | 2,347         | 392,021                     | 167.1   | 406,220                 | 173.1   | 1.3   |
| 2002 | Lili          | 9,518         | 191,627                     | 20.1  | 192,728                 | 20.2  | 1.18  |
| 1999 | Bret          | 9,922         | 373,472                     | 37.6  | 460,831                 | 46.4  | 0.12  |

Table 14: Storm Specific Coastal County Population Density Calculations

# 4.4.5 Central Pressure $(c_p^{a})$ Relationship to Damages

Central Pressure is actually thought to be more related to wind damage  $(D_w)$  and somewhat to inland flooding damage  $(D_f)$ , and thus less disscussion is reserved for this parameter. There is a clear connection though, as R = 0.182; however, there is a negative relationship which is intuitive: more intense storms with lower central pressures produce more damage.

# 4.4.6 Area of Indunation (Ain) Relationship to Damages

Area of Inundation represents the area of water coverage over the uplands due to a hurricane surge. Equation 27 in Irish and Resio (2007) it is as Follows:

$$A_{in} = \frac{\zeta_{\max}}{2} * [(\gamma + \delta)R_{33}] * \cot\alpha \qquad (9)$$

Defining the unknowns:  $\gamma$  and  $\delta$  are dimensionless constants and cot  $\alpha$  is an upland topography function. While there will be continued effort towards inserting the parameters discussed herein into the above equation, there also should be a damage survey conformation of the proposed area of inundation equation. Surge damage will be highly correlated to the area of inundation.

It may also be of some use to relate the area of inundation to damages by using approximations from parameters gathered herein,  $Y_2^{m}$  as well as  $w_{mean}$ , as a normal inland projection of average inundation and thus giving an approximate area of inundation.

$$A_{in} = Y_{am} * w_{mean} \tag{10}$$

It would be useful to relate area of inundation to a separated surge specific normalized damages and thereby, increasing the correlation between storm surge parameters and economical damage. This assumption may only be somewhat valid for a uniform upland topography.

4.4.7 Other Parameter Relationship to Damages

There were other parameters compared as a part of this study although the R-values are less than those included here and are expected to be less important for insertion into the surge damage function. One exception may be  $w_{30}^{b}$ , which is the width of the 30 m contour, R = 0.047. It is possible for a hurricane capable of creating a large surge to land fall on a very steep shelf; thereby attenuating the surge into deeper waters. As illustrated in Appendix C, Irish and Resio equivalent depth Figures 18 and 19: examples of these coastlines are particularly not conducive to high surge generation such as off-shore profiles for Northeastern US, Cape Hatteras, NC., Southeastern Florida, the panhandle of Florida and Southern Texas.

On the opposite end of the spectrum are those coastlines that are susceptible to large hurricanes surges due to the off-shore bathymetry and upland topography. Among these coastlines are the Texas-Louisiana border, the New Orleans area and Mississippi, the "Big-Bend" of Florida to Southwestern Florida and the Georgia and South Carolina coastlines. Other parameters compared to TND in this study are the angle from shore normal ( $\theta$ ), track speed (v) and storm duration ( $\Omega$ ). Storm Duration and Storm Angle mimics a normal distribution when compared to damages. (Please see Appendix B)

# 4.5 The Process of Developing a Surge Damage Function

The variable  $H_s$  is the Hurricane Surge Damage Correction Factor, which is a nonlinear varying parameter that "filters" out the ND<sub>f</sub> and ND<sub>w</sub> damages along with other errors such as multiple landfalls. The damping exponential function shown in Equation 8 is needed to properly curve fit the predicted damages to the actual damages. As a general rule those data points that lie beneath the trend line in Figure 7 often have relatively lower population densities, and data points above the trend line often have high ND<sub>w</sub> damages; thereby, requiring an exponential multiplier to dampen out the error from the trend line.

| Table | 15: | Damage | Prediction |
|-------|-----|--------|------------|
|-------|-----|--------|------------|

| Storm    | Surge<br>Scale<br>(SS) | w30 <sup>6</sup> (km) | Hurricane<br>Surge<br>Damage<br>Correction<br>Factor<br>(H <sub>S</sub> ) | Pop.<br>Factor<br>(K) | M-1<br>X | M-2 X<br>(TND <sub>P</sub> ) | Y<br>(TND <sub>A</sub> ) | (X-Y) <sup>2</sup> |
|----------|------------------------|-----------------------|---|-----------------------|----------|------------------------------|--------------------------|--------------------|
| Katrina  | 3.1                    | 140                   | -0.5704   | 0.44                  | 62.8     | 85.4                         | 85.4                     | 1.4E-08            |
| Ike      | 1.3                    | 92                    | -0.1047   | 0.77                  | 23.5     | 28.5                         | 28.5                     | 2.9E-10            |
| Wilma    | 1.7                    | 118                   | 0.8376  | 0.53                  | 32.2     | 24.6                         | 24.6                     | 1.1E-10            |
| Hugo     | 1                      | 56                    | 0.1545  | 0.22                  | 16.9     | 18.2                         | 18.2                     | 7.6E-11            |
| Ivan     | 0.4                    | 31                    | -3.5654   | 0.41                  | 3.8      | 17.2                         | 17.2                     | 1.0E-09            |
| Rita     | 1.9                    | 119                   | 1.7792  | 0.89                  | 36.6     | 11.5                         | 11.5                     | 1.4E-11            |
| Frances  | 0.2                    | 15                    | 20.9057   | 0.92                  | -        | 0.5                          | 11.2                     |                    |
| Frederic | 0.7                    | 48                    | 0.2820  | 0.38                  | 10.3     | 10.9                         | 10.9                     | 2.8E-10            |
| Opal     | 0.4                    | 21                    | -1.3427   | 0.35                  | 3.8      | 6.8                          | 6.8                      | 8.0E-12            |
| Celia    | 0.5                    | 30                    | 1.0075  | 0.16                  | 6.0      | 6.1                          | 6.1                      | 1.0E-10            |
| Gustav   | 1.1                    | 81                    | 7.3538  | 0.28                  | 19.1     | 5.1                          | 5.1                      | 6.9E-10            |
| Isabel   | 0.3                    | 25                    | -5.0368   | 0.17                  | 1.6      | 4.7                          | 4.7                      | 1.2E-09            |
| Eloise   | 0.8                    | 21                    | 9.8398  | 0.17                  | 12.5     | 3.1                          | 3.1                      | 7.3E-10            |
| Gloria   | 0.3                    | 24                    | -0.0494   | 2.26                  | 1.6      | 2.6                          | 2.6                      | 9.3E-12            |
| Allen    | 0.3                    | 21                    | 0.9887  | 0.30                  | 1.6      | 1.9                          | 1.9                      | 1.2E-09            |
| Lili     | 0.9                    | 84                    | 136.2641  | 0.10                  | 14.7     | 2.8                          | 1.2                      | 2.6E+00            |
| Bret     | 0.3                    | 22                    | 55.6390   | 0.19                  | 1.6      | 0.7                          | 0.1                      | 4.0E-01            |
|          |                        |                       |   |                       |          |                              | $\Sigma =$               | 3.0E+00            |

Referring to some undefined columns in the table above: M-1 (X) is damage prediction method 1, which uses only the linear relationship to damages. M-2 (X) is damage prediction method 2, which uses the full Equation 8. Y is the actual estimated 2010 damage estimates.

The  $H_s$  found in Equation 8 represents that part of the relationship that is still unknown. There is also a sensitivity problem inherent for those storms that are less that SS = 0.3; since, the

exponential function is not able to predict damage due to the boundary conditions of Equation 8. The predicted damage for Frances [2004] has been left blank due to this issue. There are also some tail effects for the lower damage hurricanes but since the lower end of the SS and damage are of less concern, there is no need to correct for these boundary conditions. (Not to say that 1.0-2.0 Billion is not significant) The strike angle ( $\theta$ ) and Storm Duration ( $\Omega$ ) becomes relatively unimportant to surge damages (ND<sub>S</sub>) if  $\theta$  is between the limits expressed in section 3.5 and if a storm doesn't stall causing large amounts of ND<sub>f</sub>. SS in general accounts for the majority of the damage in equation 8. There is a great deal of uncertainty for the variable H<sub>s</sub>. No combination of the parameters studied in this thesis can explain H<sub>s</sub>, which suggests the focus for future research should be to find accurate and predictable ways to extract non-related surge damage, then H<sub>s</sub> becomes less volatile and thus less damping will be required. This also suggests that other parameters such as rainfall (R), wind speed (V) and other factors may be involved in the formulation for H<sub>S</sub>. This thesis presents SS vs. TND for a wide spectrum of coastal areas and types of coastal development; therefore, there will inevitably be randomness in such a relationship.

For most hurricanes the TND can be predicted with the linear relationship to SS within 25 billion (which is significant): In most other cases the linear prediction is much closer to the actual TND. Additionally,  $w_{30}^{b}$  is shown to be a smaller part but critical in the addition term: without it the TND<sub>P</sub> ranges from 1 to 5 billion lower than the Actual Total Normalized Damage (TND<sub>A</sub>).

#### 4.6 Chapter Summary

Relationships between TND were developed for hurricane parameters and SS. The economical parameter of interest was TND. The hurricane parameters of greater interest were maximum surge elevation ( $\zeta^{m}_{max}$ ), radius of hurricane force winds (R<sub>33</sub>), the alongshore extent of surge greater than 2 meters (Y<sub>2</sub><sup>m</sup>), the central pressure (c<sub>p</sub><sup>a</sup>) and the coastal storm specific population density ( $\rho$ ).

The relationships for hurricane parameters and SS were displayed in terms of TND. In terms of the definitions adopted here the relationships provided poor to excellent correlations as indicated by the coefficient of determination ( $\mathbb{R}^2$ ) value. The majority of the relationships for the hurricane data contained a high degree of scatter and poor correlations between hurricane parameters as indicated by a low  $\mathbb{R}^2$  value. Due to the high degree of scatter in the data, and resulting poor correlations, these relationships were briefly discussed and the graphs showing these relationships can be found in Appendix B. The equations and coefficient of determination ( $\mathbb{R}^2$  values) for all of the relationships computed are summarized in Table 16.

| Property  |     | Independent Variable                  |   |  |  |  |  |  |  |
|-----------|-----|---------------------------------------|---|--|--|--|--|--|--|
|           |     | R33                                   |   | Cp <sup>a</sup>  | Y2 <sup>m</sup>  | ρ  |  |  |  |
| Variable  |     | $TND = 0.086R_{33} + 3.682R2 = 0.060$ | $TND = 0.109 w_{30}^{b} + 11.166 R^{2} = 0.047$ | TND = -<br>0.631c <sub>p</sub> <sup>a</sup> +<br>615.982<br>R <sup>2</sup> = 0.182 | $TND = 0.086Y_2^{m} + 4.419$ $R^2 = 0.185$                 | TND = $0.033\rho$<br>+ 11.476<br>$R^2 = 0.071$ |  |  |  |
|           | TND | θ                                     | v   | Ω  | $\zeta^m_{max}$  | SS   |  |  |  |
| Dependent |     | No Trend<br>Computed                  | N/A<br>$R^2 = 0.005$                            | No Trend<br>Computed   | $TND = 6.450\zeta^{m}_{max}$<br>- 6.687<br>$R^{2} = 0.235$ | TND = 21.852*SS - 4.946R2 = 0.701              |  |  |  |

Table 16: Summary of Equations and Associated Coefficient of Determination

The R<sup>2</sup>values range from 0.047 to 0.701. The 'No Trend Computed' entries in Table 17 indicate no relationships were determined. Appendix I contains Figures depicting the hurricane damages and their predicted values.

#### Chapter 5

#### CONCLUSIONS AND RECOMMENDATIONS

Thirty-one hurricane events were obtained from the Irish and Resio (2007) and Pielke and Landsea (2008) along with other sources listed in the References section of this thesis. The hurricanes were classified in terms of hurricane states. The hurricanes listed in the study were classified as  $H_1$  (small surge potential),  $H_2$  (moderate surge potential),  $H_3$  (high surge potential) and  $H_4$  (extreme surge potential). Aside from Surge Scale, classifications and investigations into hurricane parameter comparisons provide a basis for future research into the surge damage function. Fourteen of the hurricanes had questionable connections in terms of damage and SS. These hurricanes were either determined to have errors in the damage estimates or were "microcanes" which tend to produce somewhat anomalous surges at a coast.

The economic parameter of interest was Total Normalized Damages (TND). The hurricane/geophysical parameters of interest were the maximum surge elevation ( $\zeta^{m}_{max}$ ), radius of hurricane force winds ( $R_{33}$ ), the alongshore extent of surge greater than 2 meters ( $Y_2^{m}$ ), the central pressure ( $c_p^{a}$ ), the shore normal projection offshore to the 30 meter contour ( $w_{30}^{b}$ ), and the 2010 coastal storm specific population density ( $\rho$ ). Other parameters included in the study, yet were not discussed in detail were the storm angle measured from normal projection ( $\theta$ ), track speed (v) and the storm duration ( $\Omega$ ). A certain amount of scatter was present in all the data, but the best correlations were found between Surge Scale (SS) and Total Normalized Damage (TND), suggesting Surge Scale is inherently related to Damages in general and much more so to surge specific damages as suggested by elimination of "micro-canes" from the data set. Surge

Scale may provide the best chance for finding a surge damage function. Surge Scale could be additive, in that, adding the SS from multiple land falls may put data points closer to the trend line.

Future studies should include a further investigation into the area of inundation and surge specific damages (ND<sub>s</sub>) and SS relationship to surge specific damages, perhaps leading to a Hurricane Coastal Surge Damage Scale (HCSDS) (Similar to the Dolan-Davis classification for Northeast storms (Hondula, et. al. 2010) or Beaufort Force for winds. This future research may include gathering information on an average inland extent of surge ( $w_{mean}$ ) and further investigation into surge specific damage, thereby separating out the damages due to surge and increasing the correlation. The research conducted in this study and studies mentioned herein in the References section, should be a "bridge" to finding a HCSDS which could be used as a public warning system for assessing damage potential prior to landfall.

As Irish and Resio (2007) points out "While a number of hurricane indices already exist, the surge scale (SS) proposed in their paper is the first to be based specifically on simplified approximations to the hydrodynamic equations governing surge generation and has been shown to be well-correlated with observed historical maximum hurricane surges." (Please see Figure 20, Appendix C)Therefore, for practical usage, if the damage estimate errors/correction factors for other types of non-surge related damages are found (damage survey categories) and continued research between the surge specific damage and SS is accomplished, then the general damage function consisting of the several components could be analyzed in more detail. As of now, the damage function stands as an elusive equation, yet to be fully understood.

Damage Estimates for surge may be more highly correlated at the local level instead of using a macro perspective to the comparisons made herein. Surveying the damage into distinct damage survey categories will be of particular interest to separate those types of storms that have high potential for damage based on SS, which has been the focus of this thesis. Reporting of data in these categories will allow FEMA and the scientific community to better access the surge damage potential realized in devastating storms such as Katrina (2005).

There are currently ways of separating the survey damage categories forensically, even though, the best way is through historical damage survey reporting. There will always be a "grey" area into whether some damages were caused by flood, surge or wind; however, most damages should be separated without much problem by observation during damage surveying. The forensic ways could be to investigate cumulative historical wind hyetographs and NEXRAD radar cumulative rainfall in order to determine the relative amounts of each survey damage category's contribution to Total Normalized Damages. There is of course some software for these applications: HEC-FDA developed by the Army Corp. of Engineers for determining inland flooding damage and HAZUS for determining damages due to several types of natural phenomena: earth quakes, hurricanes, tsunamis, etc. This type of damage simulations require extraordinary amounts of time, money, effort and verification to historical record for model calibration, but could provide the basis of future damage assessments.

Katrina [2005] exposed some vulnerable infrastructure problems with Levees: In addition, the New Orleans proximity and susceptibility to historically devastating surges is of great interest

while engineers and scientists reassess our coastal disaster risk due to hurricane surges. Coastal wetlands (Resio, et al. 2008) and other forms of coastal defense in mitigating disaster will continue to be a focus for future researches. Katrina [2005] exposed some weaknesses in the coastal planning process in Louisiana just as Andrew [1992] exposed building code weaknesses in Florida: Planning in respect to our coastal population is of paramount importance.

It is stressed that much more data will be needed in order to obtain the correct surge damage prediction equations. This study took into account only 72 years of data (40 sorted) and since climatology in respect to advanced measurement equipment has only been around 50 +/- years, we will need several centuries to have a more process-based damage relationship to surge, instead of an extrapolative approach used in this thesis. Time scales are paramount when it comes to dynamic relationships such as normalized hurricane damage prediction. Damage Prediction for hurricane surge is fertile ground for the future research described in this chapter.

It is suggested that future research conduct damage scenarios in order to simulate hurricane data across centuries, thereby, testing equation 8 and updating as necessary. Additionally, it is inferred in this thesis that  $H_s$  includes  $ND_f$  and  $ND_w$  damages and additional study will be needed for inland counties to better assess the relationship of TND to SS. Otherwise, survey categories will provide a fairly linear relationship of  $ND_s$  to SS. The historical data and information herein and in referenced work can provide a basis for calibrating a surge damage model.

Perhaps damages will be derived from "Geographic Information Systems (GIS)" as (Wheeler, et al., 2008) suggests these systems "have become an important tool for the spatial modeling and

analysis of many coastal zone issues." Structural studies for wind damage (Jean-Paul Pinelli, et al., 2004) may provide a basis for separating damage estimates into the proper damage survey categories. Separating the damage data into damage survey categories should be a priority in future research and damage surveying since insurance companies and FEMA will help bear the cost of wind and flooding damage, respectively. Every extreme event will give vital information statistically for overall coastal impact in respect to economic, physical and biological processes.

There are two suggestions for future research in order to improve the relationship in terms of accuracy for Eq. 8, found herein. Amplification of surge damage often happens as a result of two factors not included in this thesis: "Hydraulic Funnels" (ie: bays and shoreline angle change) and time of landfall in relation to tidal cycle. Both of these concepts/parameters definitely affect surge damage and therefore amplification factors which could be addressed in the calculations for predicted damages.

Actual occurrence of hurricane events or event prediction; however, is beyond the scope of this thesis; whereas, this involves longer periods of record than we have data, since climate cycles vary over centuries. Nonetheless, the damage function will need continuing research in terms of historical reporting and future synthetic hurricane modeling so that investigation into physical inundation limits and analyzing the hurricane parameters mentioned in this thesis for further correlation to damages. It is thought that through these connections between actual population growth rates and damage scenarios, this will allow us to more adequately plan America's hurricane coastal disaster risk.

#### REFERENCES

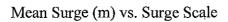
**Print Publications:** 

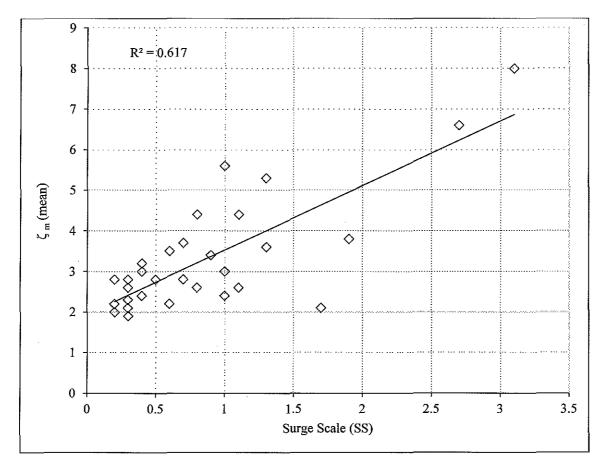
- A.C.O.E. (Army Corp. of Engineers), "The Corps of Engineers and Shore Protection History, Projects, Cost (IWR Report 3)," National Technical Information Service (2003), pp. 29-35
- A.C.O.E., "Hydraulic Engineering Center-Flood Damage Analysis," Institute for Water Resources, CPD-72 User Manual (2008) Retrieved from: http://www.hec.usace.army.mil/publications/pub\_download.html
- A.C.O.E., "Advanced Circulation Model" *Coastal and Hydraulics Laboratory*, Vicksburg (2012) Retrieved from: <u>http://chl.erdc.usace.army.mil/adcirc</u>
- A.C.O.E., "Mississippi Coastal Improvements Program Hancock, Harrison and Jackson Counties," <u>Comprehensive Plan and Integrated Programmatic Environmental Impact</u> <u>Statement.Vol 5 – Appendix E: Engineering</u> (2009) pp. 17- 29 <u>http://www.mrgo.gov/ProductList.aspx?ProdType=reference&folder=213</u>
- Ashley Naimaster, Christopher J. Bender, William Miller. "Modeling to Revise Coastal Inundation and Flooding Estimates in Georgia and Northeast Florida," *Taylor Engineering*, (2012) <u>http://www.fsbpa.com/2012TechPresentations/AshleyNaimaster.pdf</u>
- Bureau of Economic Analysis (BEA) "Consumer Durable Goods Current Cost Net Stock," Washington, D.C. (2011) Retrieved from: <u>http://www.bea.gov/national/FA2004/Details/Index.html</u>
- Bureau of Labor Statistics (BLS) "Consumer Price Index," Washington, D.C. (2012) Retrieved from: <u>http://www.bls.gov/cpi/cpi\_dr.htm</u>
- Dalrymple, R. A., & Dean, R. G. <u>Coastal Processes with Engineering Applications</u>, Cambridge University Press, Cambridge, 2002.
- David M. Hondula, Robert Dolan "Predicting Severe Winter Coastal Storm Damage," <u>Environmental Research Letter</u> 5, (2010), 3 pp. 2-4 Retrieved from: 2012,<u>http://iopscience.iop.org/1748-9326/5/3/034004/pdf/1748-9326\_5\_3\_034004.pdf</u>
- Donald T. Resio, Joannes J. Westerink. "Modeling the Physics of Storm Surges," <u>Physics Today</u>, 61 (2008), 9, pp. 33-38 Retrieved from: <u>http://nd.edu/~coast/reports\_papers/2008-PHYSICSTODAY-rw.pdf</u>
- Donald T. Resio "White Paper on Estimating Hurricane Inundation Probabilities," (ACOE). Coastal Hydraulics Laboratory (2007) pp. 1-125

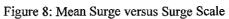
- Eric S. Blake, Christopher W. Landsea. "NOAA Technical Memorandum NWS NHC-6," National Oceanic and Atmospheric Administration (NOAA). (2011) Retrieved from: <u>http://www.nhc.noaa.gov/pdf/nws-nhc-6.pdf</u>
- Florida Department of Environmental Protection "Coastal Construction Control Line Review Studies Escambia-Nassau,".Florida State University. Tallahassee, FL. (2007) Retrieved from: <u>http://www.dep.state.fl.us/beaches/publications/tech-rpt.htm</u>
- Federal Emergency and Management Agency (FEMA) "HAZUS Multi-Hazard Loss Estimation Software," Wahington D.C. (2012) Retrieved from <u>http://www.fema.gov/protecting-our-</u> <u>communities/hazus</u>
- Jean-Paul Pinelli, Emil Simiu, Kurt Gurley, Chelakara Subramanian, Liang Zhang, Anne Cope, et. al., "Hurricane Damage Prediction Model for Residential Structures," Journal of <u>Structural Engineering</u>. (2004) pp. 1685-1691. Retrieved September 30, 2012,http://www.cs.rice.edu/~devika/evac/papers/Hurricane%20risk%20prediction.pdf,
- Jennifer L. Irish, Donald T. Resio "A hydrodynamics-based Surge Scale for Hurricanes," <u>Ocean</u> Engineering, 37 (2010), 1, pp. 69-81
- Jill Malmstadt, Kelsey Scheitlin, James Elsner. (2009) "Florida Hurricanes and Damage Costs," Southeastern Geographer 49 (2009), 2, pp. 108-131 Retrieved from: <u>http://myweb.fsu.edu/jelsner/PDF/Research/MalmstadtEtAl2009.pdf</u>
- Kantha "Tropical Cyclone Destructive Potential" <u>American Meteorological Society Journal</u> (AMS). 89 (2008), 2, pp. 219-221 Retrieved from: <u>http://www.aoml.noaa.gov/hrd/Powell/BAMS\_IKE\_Paper\_final.pdf</u>
- Mark D. Powell, Timothy A. Reinhold."Tropical Cyclone Destructive Potential By Integrated Kinetic Energy" American Meteorological Society. 88 (2006), 4, pp. 513-526 Retrieved from: <u>http://www.aoml.noaa.gov/hrd/Powell/BAMS\_IKE\_Paper\_final.pdf</u>,
- Mr. P.J. Wheeler, Mr. M.L.F. Coller, Mr. J. Kunapo1, Associate Professor J.A. Peterson, and Mr. M. McMahon. "Facilitating Coastal Zone Inundation Awareness Using GIS-Based Scenario Modeling and Multimedia Visualization," Queensland Spatial Conference (2008) 2, pp. 1-10
- National Oceanic and Atmospheric Administration (N.O.A.A.). "National Hurricane Center (NHC) Data Archive" Miami (2012), Retrieved from: <u>http://www.nhc.noaa.gov/pastall.shtml#hurdat</u>
- N.O.A.A. "National Hurricane Center (NHC) Data Archive-Re-analysis Project" Miami (2012) Retrieved from: <u>http://www.aoml.noaa.gov/hrd/hurdat/Data\_Storm.html</u>
- N.O.A.A. "Billion Dollar U.S. Weather/Climate Disasters" (2012) Retrieved from: http://www.nedc.noaa.gov/billions/events

- N.O.A.A. "NEXRAD radar data" (2011) Retrieved from: http://hurricane.ncdc.noaa.gov/pls/plhas/has.dsselect
- N.O.A.A. "Slosh Model" (2011) Retrieved from: http://www.nhc.noaa.gov/ssurge/ssurge\_slosh.shtml
- N.O.A.A. Coastal Services Center. "Historical Hurricane Tracks Coastal Population Tool" (2011) Retrieved from: <u>http://www.csc.noaa.gov/</u>
- Roger A. Pielke Jr., Joel Gratz, Christopher W. Landsea, Douglas Collins, Mark A. Saunders, and Rade Musulin."Normalized Damage in the United States 1900-2000". <u>Natural Hazards</u> <u>Review</u>, 9, 1 (2008), pp. 29-42 Retrieved from: <u>http://www.sip.ucar.edu/sourcebook/hurricanes/pdf/Pielke2005norm.pdf</u>
- Robert Wang, Michael Manausa. "Hurricane Ivan and Storm Tide Evaluation" Florida Department of Environmental Protection (FDEP) Report. (2005) Retrieved from: <u>http://bcs.dep.state.fl.us/reports/strmtide/ivan.pdf</u>
- United States Census Bureau (USCB) "Population Estimates by County, State and National Levels" (2010) Retrieved from: <u>http://www.census.gov/population/www/cen2010/cph-t/cph-t-1.html</u>

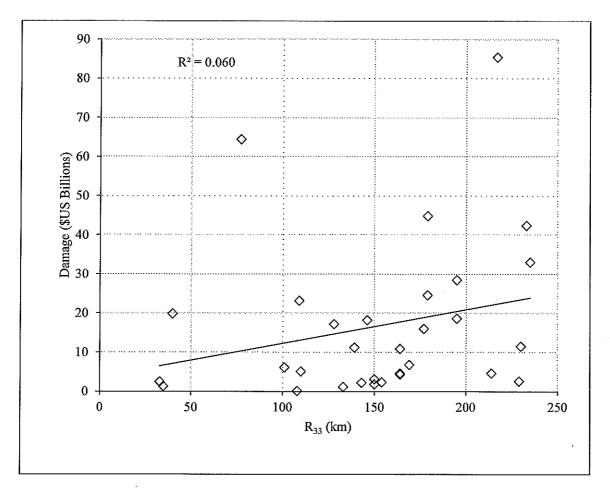
### APPENDIX A





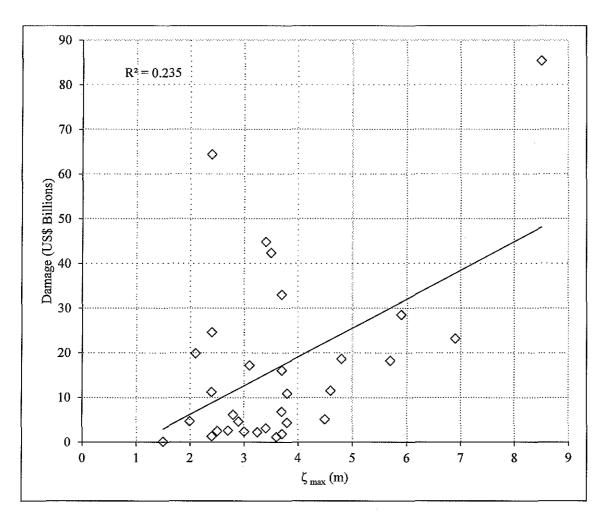


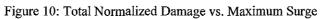




Storm Parameters Comparison to Total Normalized Damages

Figure 9: Total Normalized Damage vs. Radius to Hurricane Force Winds





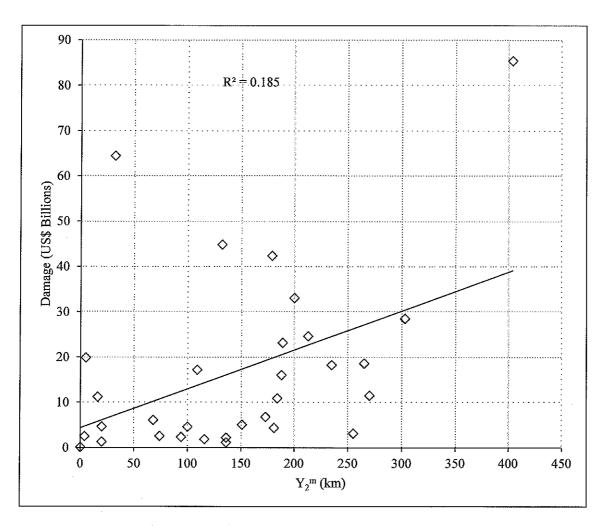


Figure 11: Total Normalized Damage vs. Alongshore Extent of Surge

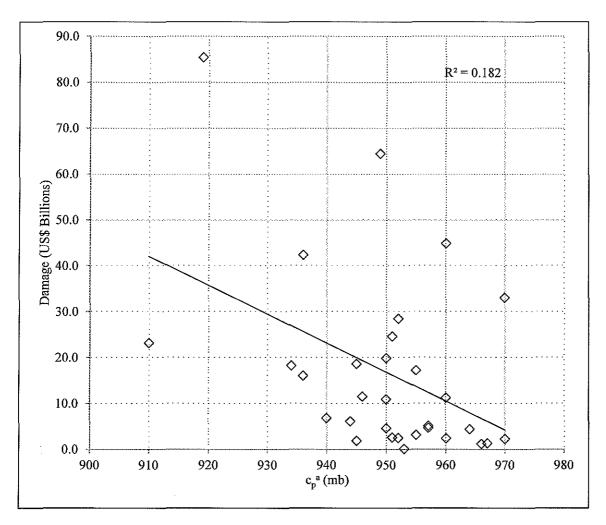


Figure 12: Total Normalized Damage vs. Central Pressure

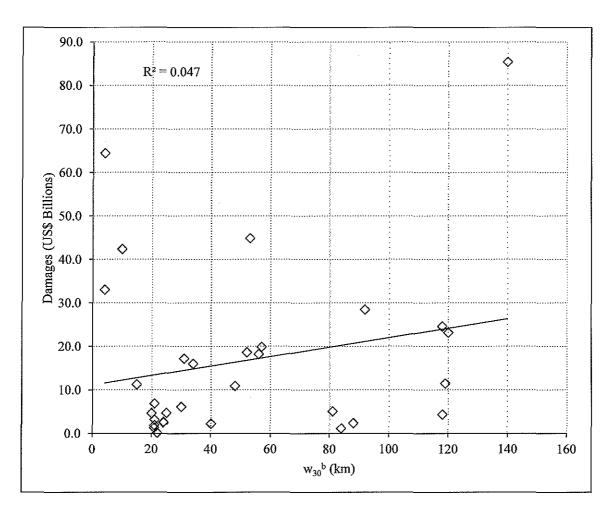
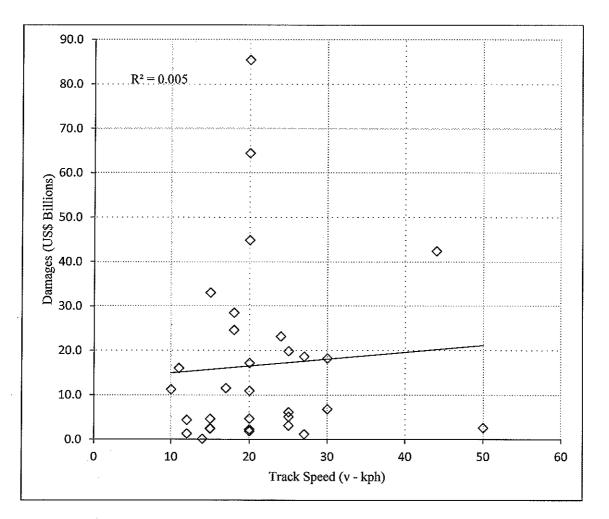
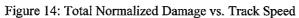


Figure 13: Total Normalized Damage vs. Offshore Normal Projection to 30 Meter Contour





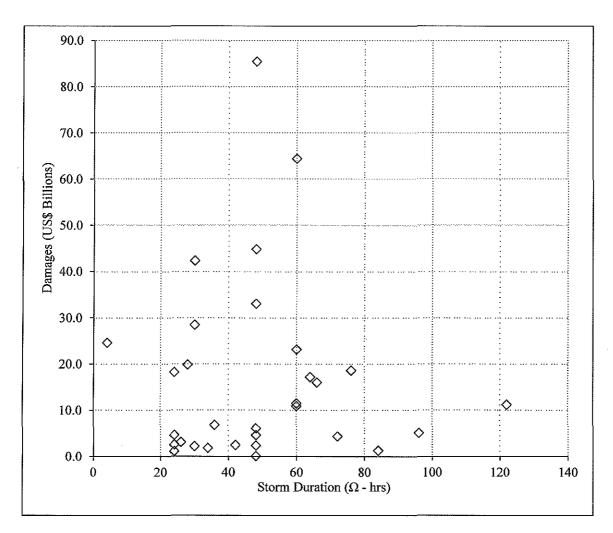


Figure 15: Total Normalized Damage vs. Storm Duration

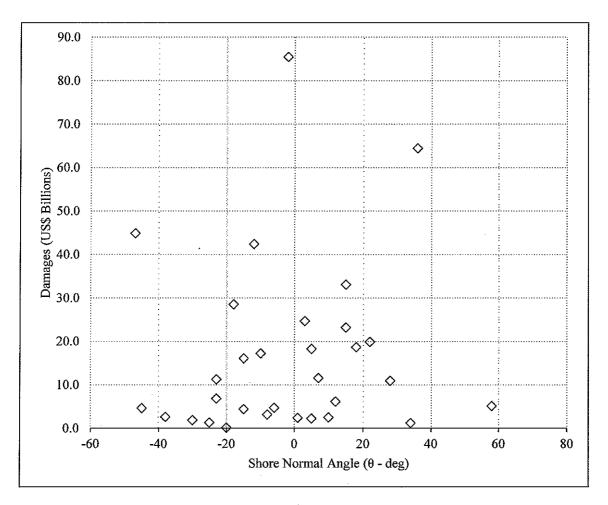
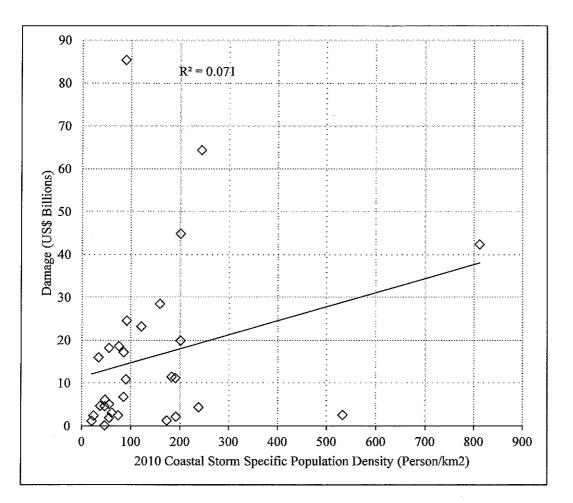
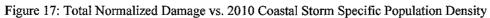


Figure 16: Total Normalized Damage vs. Storm Angle Measured from Normal Projection





## APPENDIX C

## Figures from Irish and Resio (2007)

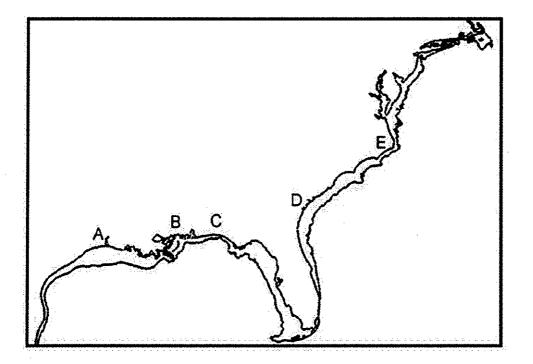
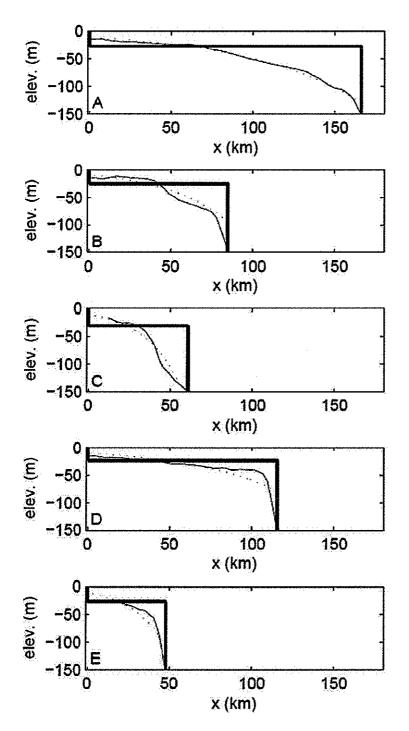
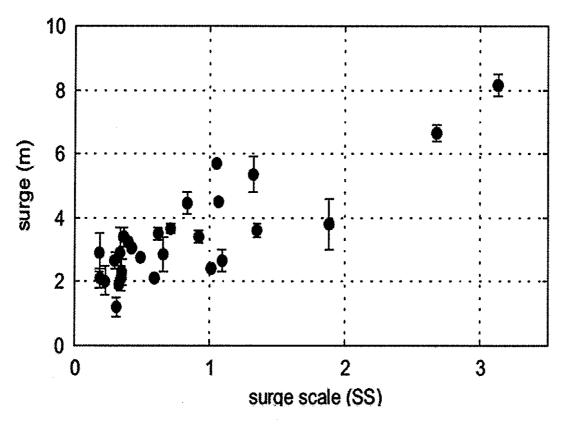
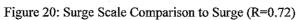


Figure 18: The 30 Meter Shelf Contour (Blue Line)









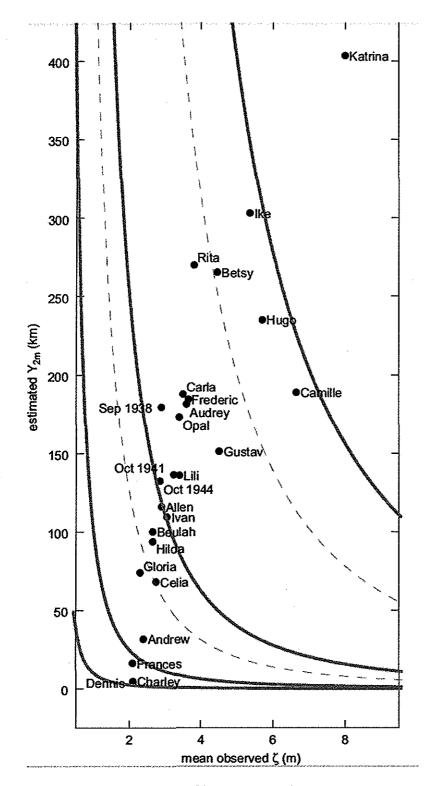


Figure 21: Alongshore Extent of Surge vs. Mean Surge

### APPENDIX D

### Figures from Pielke and Landsea (2008)

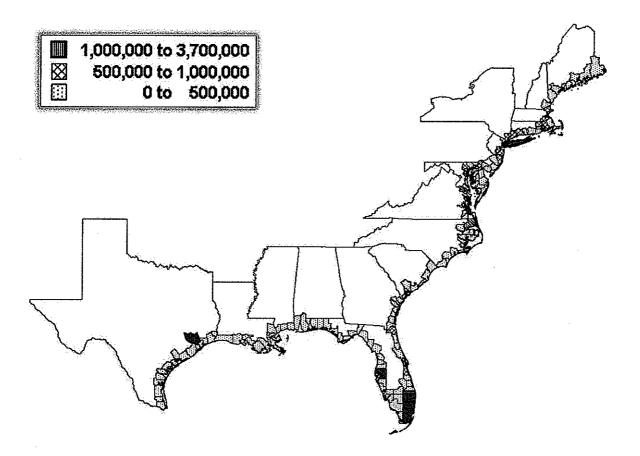
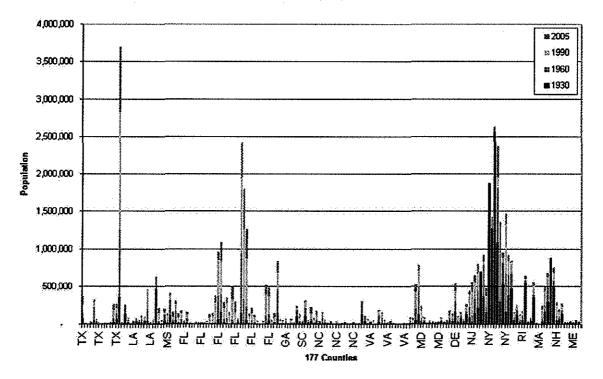
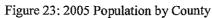


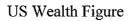
Figure 22: 2005 Population by County (Plan-view)

#### 2005 Coastal County Population





### APPENDIX E



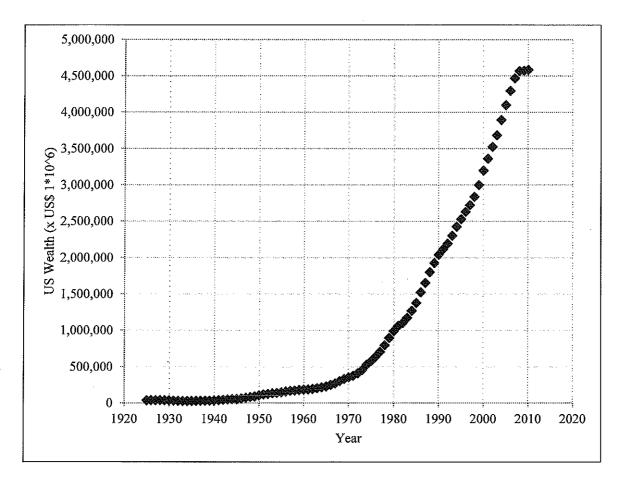


Figure 24: US Wealth vs. Year

#### APPENDIX F

#### 2005 Hurricane Season

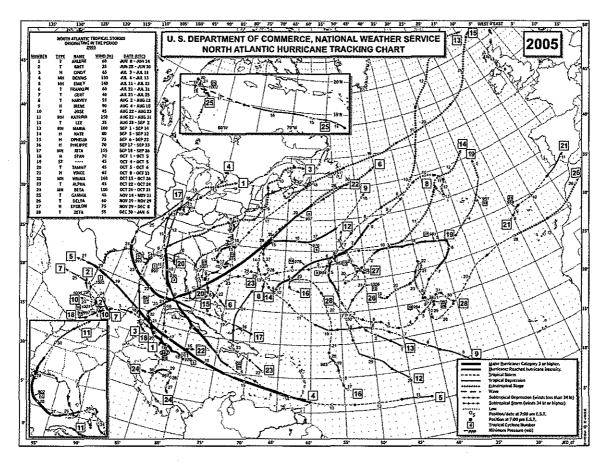


Figure 25: 2005 Hurricane Tracks

#### APPENDIX G

#### US Census Bureau Figure

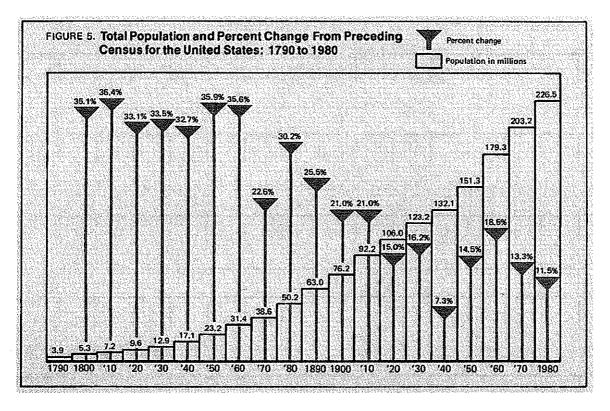


Figure 26: US Census National Historical Percent Growth in Population

### APPENDIX H

# Gumbel Distribution for Damages

| i (rank) | D     | D <sub>i</sub> - μ | (D <sub>i</sub> - μ) <sup>2</sup> | f(D_i) | -LN(-LN(f(x))) |  |
|----------|-------|--------------------|-----------------------------------|--------|----------------|--|
| 1        | 88.7  | 71.0               | 5040.405                          | 0.992  | 4.779          |  |
| 2        | 67.1  | 49.39581           | 2439.946                          | 0.970  | 3.501          |  |
| 3        | 64.2  | 46.49581           | 2161.86                           | 0.965  | 3.329          |  |
| 4        | 44.4  | 26.69581           | 712.6661                          | 0.891  | 2.157          |  |
| 5        | 33.0  | 15.29581           | 233.9617                          | 0.797  | 1.482          |  |
| 6        | 28.5  | 10.79581           | 116.5494                          | 0.743  | 1.216          |  |
| 7        | 23.5  | 5.795806           | 33.59137                          | 0.671  | 0.920          |  |
| 8        | 22.0  | 4.295806           | 18.45395                          | 0.647  | 0.831          |  |
| 9        | 21.5  | 3.8                | 14.40815                          | 0.639  | 0.802          |  |
| 10       | 19.9  | 2.195806           | 4.821566                          | 0.611  | 0.707          |  |
| 11       | 19.8  | 2.095806           | 4.392405                          | 0.609  | 0.701          |  |
| 12       | 17.3  | -0.4               | 0.163372                          | 0.563  | 0.553          |  |
| 13       | 16.2  | -1.50419           | 2.262598                          | 0.541  | 0.488          |  |
| 14       | 11.5  | -6.20419           | 38.49202                          | 0.445  | 0.210          |  |
| 15       | 11.3  | -6.40419           | 41.0137                           | 0.440  | 0.198          |  |
| 16       | 11.0  | -6.70419           | 44.94621                          | 0.434  | 0.180          |  |
| 17       | 6.8   | -10.9042           | 118.9014                          | 0.343  | -0.068         |  |
| 18       | 6.2   | -11.5042           | 132.3465                          | 0.330  | -0.104         |  |
| 19       | 5.1   | -12.6042           | 158.8657                          | 0.306  | -0.169         |  |
| 20       | 4.6   | -13.1              | 171.7199                          | 0.295  | -0.199         |  |
| 21       | 4.4   | -13.3042           | 177.0016                          | 0.291  | -0.210         |  |
| 22       | 4.3   | -13.4042           | 179.6724                          | 0.289  | -0.216         |  |
| 23       | 3.2   | -14.5042           | 210.3716                          | 0.266  | -0.281         |  |
| 24       | 2.6   | -15.1042           | 228.1367 0.253                    |        | -0.317         |  |
| 25       | 2.5   | -15.2042           | 231.1675                          | 0.251  | -0.323         |  |
| 26       | 2.4   | -15.3042           | 234.2183                          | 0.249  | -0.329         |  |
| 27       | 2.3   | -15.4042           | 237.2892                          | 0.247  | -0.335         |  |
| 28       | 1.9   | -15.8042           | 249.7725                          | 0.239  | -0.358         |  |
| 29       | 1.3   | -16.4042           | 269.0976                          | 0.227  | -0.394         |  |
| 30       | 1.2   | -16.5042           | 272.3884                          | 0.225  | -0.400         |  |
| 31       | 0.13  | -17.5742           | 308.8523                          | 0.204  | -0.463         |  |
| Σ        | 548.8 |                    | 14087.73                          |        |                |  |

### Katrina [2005]

| $T_{\rm R} = 1/(\lambda(1-f(D_i)))$ |          |          |  |  |  |  |  |
|-------------------------------------|----------|----------|--|--|--|--|--|
| λ=                                  | 0.43     |          |  |  |  |  |  |
| $T_R =$                             | 277.51   | Years (1 |  |  |  |  |  |
| $P_e =$                             | 0.003603 | Probabi  |  |  |  |  |  |
| P <sub>ne</sub> =                   | 0.996397 | Probabi  |  |  |  |  |  |

Years (Return Period) Probability of Exceedance Probability of Non-Exceedance

### APPENDIX I

### Predicted Damage Figures

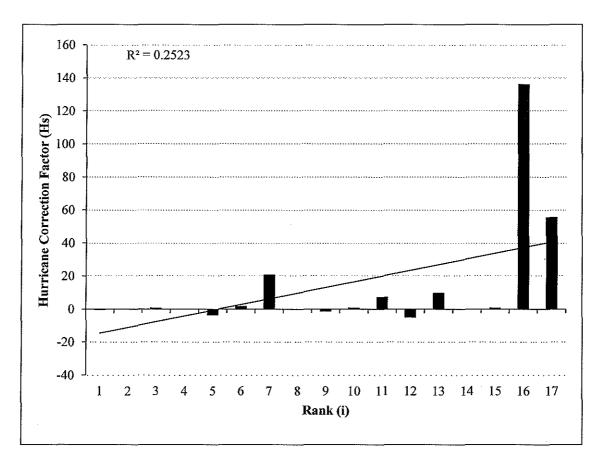


Figure 27: Hurricane Surge Damage Correction Factor

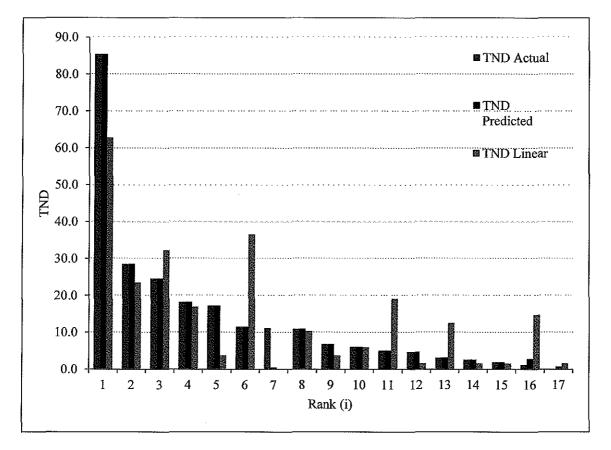


Figure 28: Total Normalized Damage Predictions

### APPENDIX J

# County Densities

| County<br>Number | County/Parishes         | State | Land<br>Area<br>(mi <sup>2</sup> ) | Land Area<br>(km <sup>2</sup> ) | 2010<br>Population | 2010<br>Population<br>Density<br>(Person/km <sup>2</sup> ) |
|------------------|-------------------------|-------|------------------------------------|---------------------------------|--------------------|--|
| 1                | Cameron                 | TX    | 906                                | 2347                            | 406,220            | 173.1  |
| 2                | Willacy                 | ТХ    | 597                                | 1546                            | 22,134             | 14.3   |
| 3                | Kenedy                  | TX    | 1457                               | 3774                            | 416                | 0.1  |
| 4                | Kleberg                 | TX    | <b>8</b> 71                        | 2256                            | 32,061             | 14.2   |
| 5                | Nueces                  | TX    | 836                                | 2165                            | 340,223            | 157.1  |
| 6                | San Patricio            | TX    | 692                                | 1792                            | 64,804             | 36.2   |
| 7                | Aransas                 | ΤX    | 252                                | 653                             | 23,158             | 35.5   |
| 8                | Refugio                 | TX    | 770                                | 1994                            | 7,383              | 3.7  |
| 9                | Calhoun                 | TX    | 512                                | 1326                            | 21,381             | 16.1   |
| 10               | Victoria                | TX    | 882                                | 2284                            | 86,793             | 38.0   |
| 11               | Jackson                 | TX    | 829                                | 2147                            | 14,075             | 6.6  |
| 12               | Matagorda               | TX    | 1114                               | 2885                            | 36,702             | 12.7   |
| 13               | Brazoria                | ΤХ    | 1386                               | 3590                            | 313,166            | 87.2   |
| 14               | Galveston               | TX    | 398                                | 1031                            | 291,309            | 282.6  |
| 15               | Harris                  | TX    | 1729                               | 4478                            | 4,092,459          | 913.9  |
| 16               | Chambers                | TX    | 599                                | 1551                            | 35,096             | 22.6   |
| 17               | Jefferson               | TX    | 904                                | 2341                            | 252,273            | 107.7  |
| 18               | Orange                  | TX    | 356                                | 922                             | 81,837             | 88.8   |
| 19               | Cameron                 | LA    | 1313                               | 3401                            | 6,839              | 2.0  |
| 20               | Vermilion               | LA    | 1174                               | 3041                            | 57,999             | 19.1   |
| 21               | Iberia                  | LA    | 575                                | 1489                            | 73,240             | 49.2   |
| 22               | Saint Mary              | LA    | 613                                | 1588                            | 54,650             | 34.4   |
| 23               | Terrebonne              | LA    | 1255                               | 3250                            | 111,860            | 34.4   |
| 24               | Lafourche               | LA    | 1085                               | 2810                            | 96,318             | 34.3   |
| 25               | St. Charles             | LA    | 284                                | 736                             | 52,780             | 71.8   |
| 26               | St. John the<br>Baptist | LA    | 277                                | 717                             | 45,924             | 64.0   |
| 27               | Jefferson               | LA    | 307                                | 795                             | 96,318             | 121.1  |
| 28               | Plaquemines             | _LA   | 845                                | 2189                            | 23,042             | 10.5   |
| 29               | Saint Bernard           | LA    | 465                                | 1204                            | 35,897             | 29.8   |
| 30               | Orleans                 | LA    | 181                                | 468                             | 343,829            | 735.1  |
| 31               | Saint Tammany           | LA    | 846                                | 2191                            | 233,740            | 106.7  |

# Table 17: 2010 Population Densities by County

| 32              | Tangipahoa              | LA       | 790                                    | 2046 | 121,097           | 59.2                  |
|-----------------|-------------------------|----------|--|------|-------------------|-----------------------|
| 33              | Hancock                 | MS       | 477                                    | 1235 | 43,929            | 35.6                  |
| 34              | Harrison                | MS       | 581                                    | 1505 | 187,105           | 124.3                 |
| 35              | Jackson                 | MS       | 727                                    | 1883 | 139,668           | 74.2                  |
| 36              | Mobile                  | AL       | 1233                                   | 3194 | 412,992           | 129.3                 |
| 37              | Baldwin                 | AL       | 1596                                   | 4135 | 182,265           | 44.1                  |
| 38              | Escambia                | FL       | 662                                    | 1715 | 297,619           | 173.5                 |
| 39              | Santa Rosa              | FL       | 1016                                   | 2632 | 151,372           | 57.5                  |
| 40              | Okaloosa                | FL       | 936                                    | 2423 | 180,822           | 74.6                  |
| 41              | Walton                  | FL       | 1058                                   | 2739 | 55,043            | 20.1                  |
| 42              | Bay                     | FL       | 764                                    | 1978 | 168,852           | 85.4                  |
| 43              | Gulf                    | FL       | 555                                    | 1436 | 168,852           | 117.6                 |
| 44              | Franklin                | FL       | 544                                    | 1410 | 11,549            | 8.2                   |
| 45              | Wakulla                 | FL       | 607                                    | 1571 | 30,776            | 19.6                  |
| 46              | Jefferson               | FL       | 598                                    | 1548 | 14,761            | 9.5                   |
| 47              | Taylor                  | FL       | 1042                                   | 2699 | 22,570            | 8.4                   |
| 48              | Dixie                   | FL       | 704                                    | 1823 | 16,422            | 9.0                   |
| 49              | Levy                    | FL       | 1118                                   | 2897 | 40,801            | 14.1                  |
| 50              | Pasco                   | FL       | 745                                    | 1929 | 464,697           | 240.9                 |
|                 | Pinellas                | FL       | 280                                    | 725  | 916,542           | 1264.2                |
| 52              | Hillsborough            | FL       | 1051                                   | 2722 | 1,229,226         | 451.6                 |
| 53              | Manatee                 | FL       | 741                                    | 1919 | 322,833           | 168.2                 |
| 54              | Sarasota                | FL       | 572                                    | 1480 | 379,448           | 256.3                 |
| 55              | Charlotte               | FL       | 694                                    | 1796 | 159,978           | <u> </u>              |
| 56              | Lee                     | FL       | 804                                    | 2081 | 618,754           | 297.3                 |
| 57              | Collier                 | FL       | 2025                                   | 5246 | 321,520           | 61.3                  |
| 58              |                         |          | <u> </u>                               | 2582 |                   |                       |
|                 | Monroe<br>Minuti Dada   | FL FL    | 1898                                   | 4915 | 73,090            | 28.3                  |
| <u> </u>        | Miami-Dade              | FL       | ······································ | 3122 | 2,496,435         | 507.9                 |
| 60              | Broward                 | FL_      | 1,205                                  |      | 1,748,066         | 559.9                 |
| 61              | Palm Beach              | FL_      | 1974                                   | 5113 | 1,320,134         | 258.2                 |
| 62              | Martin<br>St. Lessia    | FL       | 556                                    | 1439 | 146,318           | 101.7                 |
| <u>63</u><br>64 | St. Lucie               | FL_      | 572<br>503                             | 1483 | 277,789           | 187.4                 |
| 65              | Indian River<br>Brevard | FL<br>FI | 1018                                   | 2637 | 138,028           | 105.9                 |
| <u> </u>        | Chatham                 | FL<br>GA | 438                                    | 1135 | 543,376           | <u>206.1</u><br>233.7 |
| <br>67          | Jasper                  | SC       | 656                                    | 1135 | 265,128<br>24,777 | 14.6                  |
| 68              | Beaufort                | SC<br>SC | 587                                    | 1520 | 162,233           | 14.0                  |
| <u> </u>        | Charleston              | SC       | 919                                    | 2380 | 350,209           | 147.1                 |
|                 | Colleton                | SC SC    | 1056                                   | 2735 | 38,892            | 147.1                 |
| 71              | Georgetown              | SC       | 815                                    | 2111 | 60,158            | 28.5                  |
| 72              | Horry                   | SC       | 1134                                   | 2937 | 269,291           | 91.7                  |
| 73              | Brunswick               | NC       | 855                                    | 2214 | 107,431           | 48.5                  |
| 74              | New Hanover             | NC       | 199                                    | 515  | 202,667           | 393.2                 |
| 75              | Pender                  | NC       | 871                                    | 2256 | 22,099            | 9.8                   |

| 76  | Onslow      | NC | 767        | 1987        | 177,772   | 89.5            |
|-----|-------------|----|------------|-------------|-----------|-----------------|
| 77  | Carteret    | NC | 520        | 1347        | 66,469    | 49.4            |
| 78  | Bertie      | NC | <u>699</u> | 1810        | 21,282    | 11.8            |
| 79  | Pamlico     | NC | 337        | 873         | 13,144    | 15.1            |
| 80  | Beaufort    | NC | 828        | 2145        | 47,759    | 22.3            |
| 81  | Hyde        | NC | 613        | 1588        | 5,810     | 3.7             |
| 82  | Dare        | NC | 384        | 995         | 33,920    | 34.1            |
| 83  | Tyrrell     | NC | 390        | 1010        | 4,407     | 4.4             |
| 84  | Washington  | NC | 348        | <b>90</b> 1 | 13,228    | 14.7            |
| 85  | Chowan      | NC | 173        | 448         | 14,793    | 33.0            |
| 86  | Perquimans  | NC | 329        | 852         | 13,453    | 15.8            |
| 87  | Pasquotank  | NC | 227        | 588         | 40,661    | 69.2            |
| 88  | Camden      | NC | 241        | 624         | 9,980     | 16.0            |
| 89  | Currituck   | NC | 262        | 679         | 23,547    | 34.7            |
| 90  | Atlantic    | NJ | 556        | 1439        | 274,549   | 190.8           |
| 91  | Ocean       | NJ | 629        | 1629        | 576,567   | 354.0           |
| 92  | Monmouth    | NJ | 469        | 1214        | 630,380   | 519.2           |
| 93  | Middlesex   | NJ | 309        | 800         | 809,858   | 1012.2          |
| 94  | Richmond    | NY | 58         | 151         | 468,730   | 3094.7          |
| 95  | Kings       | NY | 71         | 183         | 2,504,700 | 13 <u>695.9</u> |
| 96  | Queens      | NY | 109        | 283         | 2,230,722 | 7884.3          |
| 97  | Nassau      | NY | 287        | 743         | 1,339,532 | 1802.1          |
| 98  | Suffolk     | NY | 912        | 2362        | 1,493,350 | 632.2           |
| 99  | Bronx       | NY | 42         | 109         | 1,385,108 | 12733.2         |
| 100 | Westchester | NY | 433        | 1121        | 949,113   | 846.3           |
| 101 | Fairfield   | СТ | 626        | 1621        | 916,829   | 565.7           |
| 102 | New Haven   | СТ | 606        | 1569        | 862,477   | 549.8           |
| 103 | Middlesex   | CT | 369        | 956         | 165,676   | 173.2           |
| 104 | New London  | СТ | 666        | 1725        | 274,055   | 158.9           |
| 105 | Washington  | RI | 333        | 862         | 126,979   | 147.2           |
| 106 | Kent        | RI | 170        | 440         | 166,158   | 377.4           |
| 107 | Bristol     | RI | 25         | 65          | 49,875    | 770.3           |
| 108 | Newport     | RI | 104        | 269         | 82,888    | 307.7           |
| 109 | Bristol     | MA | 556        | 1440        | 548,285   | 380.7           |
| 110 | Dukes       | MA | 104        | 269         | 16,535    | 61.5            |

