An Analysis of the Risk Posed by Tropical Cyclones along the Gulf Coast of the United States

THESIS

Presented in Partial Fulfillment of the Requirements for the Degree Master of Science in the Graduate School of The Ohio State University

By

Kenneth Morley

Graduate Program in Atmospheric Science

The Ohio State University

2014

Master's Examination Committee:

Dr. Jay S. Hobgood, Advisor

Dr. Jailin Lin
Abstract

Hurricanes have long been a major hazard for those living along this Gulf Coast of the United States. Significant research was conducted by previous researchers attempting to learn more about the risks posed from storm strength and track, while minimal research has evaluated the social risks associated with tropical cyclones.

This project developed a risk analysis model using storm as well as socio-economic values for the United States Gulf Coast. Data points collected and analyzed included social risk variables from the Social Vulnerability Index (SoVI), storm surge probabilities, storm cone of uncertainties, and evacuation times based on the strength of the storm and the given county.

Each of these variables played a major role in determining the risk of an approaching storm. Counties in Texas have a greater risk based on greater SoVI values, while counties in the other regions of the project area see increased risk from storm surge and long evacuation times. The results indicated that counties in Texas have much lower overall risk from tropical cyclones, while counties in Alabama, Mississippi, and Florida have greater risk values. The model revealed that the risk posed by a tropical cyclone is not confined to one variable or cause, but rather that risk must be assessed from numerous combinations of factors.
Acknowledgments

This thesis would not have been possible without my advisor Dr. Jay Hobgood. All your support and knowledge have made this project a pleasure to undertake. I would also like to thank my parents, Nate and Jamie Morley as well as my fiancé Jillian West for all your support and patience you gave me during the last two years.
Vita

May 2008 .................................................. St. Pius X High School, Albuquerque, NM

2012.......................................................... B.S. Atmospheric Sciences, University of Utah, Salt Lake City, Utah

2012 to present ........................................... Graduate Studies, The Ohio State University, Columbus, Ohio

Fields of Study

Major Field: Atmospheric Science
Table of Contents

Abstract ................................................................................................................................. ii
Acknowledgments ................................................................................................................... iii
Vita ........................................................................................................................................ iv
List of Figures .......................................................................................................................... vvi
Chapter 1: Introduction ........................................................................................................ 1
Chapter 2: Literature Review ................................................................................................. 4
Chapter 3: Science Objectives and Methodology ................................................................. 26
Chapter 4: Results .................................................................................................................. 45
Chapter 5: Conclusions and Future Work ............................................................................. 71
References ............................................................................................................................. 75
Appendix A: Hurricane Cones of Uncertainty ................................................................. 82
Appendix B: SoVI Variables .................................................................................................. 90
List of Figures

Figure 3.1 Gulf States Model Generation ................................................................. 41
Figure 3.2 Counties Model Generation ................................................................. 42
Figure 3.3 Cone of Uncertainty Model Generation ............................................... 43
Figure 3.4 Storm Surge Model Generation ............................................................. 44
Figure 4.1 Hurricane Ivan Advisory 48 Risk ......................................................... 57
Figure 4.2 Hurricane Ivan Advisory 51 Risk ......................................................... 58
Figure 4.3 Hurricane Ivan Advisory 52 Risk ......................................................... 59
Figure 4.4 Hurricane Katrina Advisory 19 Risk ..................................................... 60
Figure 4.5 Hurricane Katrina Advisory 23 Risk ..................................................... 61
Figure 4.6 Hurricane Katrina Advisory 25 Risk ..................................................... 62
Figure 4.7 Hurricane Ike Advisory 41 Risk ............................................................ 63
Figure 4.8 Hurricane Ike Advisory 45 Risk ............................................................ 64
Figure 4.9 Hurricane Ike Advisory 47 Risk ............................................................ 65
Figure 4.10 Hurricane Ida Advisory 20 Risk ......................................................... 66
Figure 4.11 Hurricane Ida Advisory 22 Risk ......................................................... 67
Figure 4.12 Tropical Storm Ida Advisory 24 Risk .................................................. 68
Figure 4.13 Tropical Storm Isaac Advisory 28 Risk ................................................. 69
Figure 4.14 Tropical Storm Isaac Advisory 30 Risk ................................................. 70
Chapter 1

INTRODUCTION

Hurricanes are one of the most destructive forces on Earth. They pose a massive threat to infrastructure, property, industry, and human life. Much of the research conducted on hurricanes revolves around the physical processes inside the storm. Numerous studies on rapid intensification, intensity, and dynamic and microphysical processes in the storms have been conducted over the past decades. This project approaches the impacts of hurricanes by examining their effects on human life and communities around the point of landfall and quantifies the risk posed to these communities by various types of hurricanes.

Risk analysis has become big business with several large consulting firms specializing in analysis of risks from potential disasters ranging from hurricanes to drought. Insurance companies are the major clients of these firms and they use detailed information from various models to set premiums and establish risk related deductibles for their customers. Insurance companies must understand the risks posed in an area so they are able to charge the appropriate rates and, in the event of a disaster, help their customers while still realizing a profit (Anderson and Brown, 2005).
Consulting firms that specialize in disaster modeling charge a substantial rate for their services. This is because the computer power required to run the models is extensive. The EQEQAT consulting company quoted a cost in the “high tens of thousands of dollars,” for use of one of their data sets related to risk analysis (Freimarck, 2013). It is obviously not feasible to create a model of that complexity for this project. The models utilized by the consulting firms incorporate very specific data regarding hurricane wind fields, wind decay rates, industry, and insurance loss calculations among others. These, and other similar data points, will be used in a less complex manner that reduces the computing power and cost associated with compiling the information necessary for this project.

A perfect risk analysis model would include very specific information regarding all aspects of the event that is occurring, in this case, a hurricane. That is the reason no perfect model exists. It is impossible to achieve the amount of detail necessary to draw a perfect picture of the situation. A model can only hope to draw the best possible conclusions from the data entered into it. The model created for this project assesses risk to a specific area along the Gulf Coast of the United States through examination of hurricane properties, as well as the general composition of the target area. However, what makes this model truly unique is the detail associated with the demographic information of the individuals living in the high-risk areas. Previous research has not concentrated on characteristics of the human population along the path of the hurricane that contribute to survivability and risk. That emphasis is the major focus of this project.
To properly develop a risk analysis model, five separate variables must be quantified. These variables include:

1. The hazard faced by an area
2. The area’s vulnerability
3. The elements at risk
4. The mitigation techniques used in the area
5. The resilience.

Each of these variables consists of sub-values that represent the socio-economic state of the various areas used in this project. This project quantifies socio-economic variables in order to develop a reliable risk analysis model.

The conceptual framework for this project was informed by a review of relevant literature on risk analysis and hurricanes. This literature review familiarizes the reader with the processes of hurricane formation, the science of risk and risk analysis, details of the project area being studied, and finally, how a risk analysis model is created. The objective of the project is to more accurately quantify the risk posed by hurricanes by creating a model that focuses on demographics, characteristic, and attributes of the residents in the project area.
Chapter 2

LITERATURE REVIEW

2.1 Tropical Cyclone Formation

A tropical cyclone is one of the most powerful and destructive forces on Earth. A tropical cyclone is defined as “a rotating, organized system of clouds and thunderstorms that originates over tropical or subtropical waters and has a closed low-level circulation (NOAA).” Tropical cyclones maintain a warm-core structure. Other types of cyclones include extra-tropical and sub-tropical systems. An extra-tropical cyclone is a cold-core low-pressure system usually located in the middle latitudes while a sub-tropical cyclones form over sub-tropical waters and exhibit characteristics of both tropical and extra-tropical systems.

There are several distinct theories as to how a tropical cyclone forms (Frank, 1987). Frank (1987), theorized that the hurricane creation process includes three stages -- genesis, development, and intensification. Genesis is the development from a simple atmospheric disturbance to a tropical depression with a more defined circulation. Development occurs as the depression strengthens and transitions into a tropical storm.
This theory describes the strengthening of a tropical storm into a hurricane as the intensification stage.

Other theorists have slightly different definitions related to hurricane creation. McBride (1995) described growth as first needing a large-scale formation and progressing into core development. During Frank’s work with Tory, they described the process as having large-scale effects on tropical cyclone genesis and then vortex construction (Tory and Frank, 2010). Several possible large-scale features can cause these effects. Tropical disturbances, such as tropical waves originating off the African Coast, have been known to develop into tropical cyclones. Other causes include, monsoon disturbances, subtropical cyclones, upper level lows, and mesoscale convective systems (Tory and Frank, 2010). It is most likely that not a single factor will determine whether a tropical cyclone will form. A combination of features must be present to result in cyclogenesis.

In order to understand how a tropical cyclone will influence an area, it is important to know the structure of the storm. A tropical cyclone can be broken into four distinct sections: The eye, inner eye, also known as the eye wall, outer eye, and outer rain bands. Each of these sections has unique features at different intervals of the storm. The eye of the storm contains the lowest central pressure. The inner eye wall is comprised of the most convective portions of the storm while the outer eye contains mostly stratiform precipitation. The outer rain bands are much more variable and may have stratiform precipitation but mostly contain small convective cells. The size of each region will vary based on the size and shape of any given storm.
The tropical cyclone can also be broken into four quadrants depending on the direction of the shear. Hence and Houze Jr. (2012) used both of these techniques in their research, which used the TRMM Precipitation Radar to analyze the rainbands in tropical cyclones. The tropical cyclone can be separated based on the shear direction into the downstream left, downstream right, upstream left, and downstream right quadrant. Each of these quadrants has unique characteristics based on the size and shape of the storm. As with the eye and rain band regions, the size and shapes of the quadrants will vary based on the uniqueness of the tropical cyclone. Most of the convective activity is restricted to the downstream quadrants, particularly the downstream right. This is important when distinguishing risk because the convective areas are usually accompanied by the heaviest rain, winds, which effect flooding, and storm surge values. In most cases, as a hurricane makes landfall, the heavier damage estimates are seen in the downstream right quadrant of the storm because of this higher convective activity.

2.2 Risk and Risk Analysis

The subject of risk is broad and expansive. Risk assessment is most commonly associated with monetary loss or gain when evaluating the dangers of investing in the stock market, gambling, or providing a principle investment in a start-up company. This project assesses the risk from tropical cyclones on the individuals of the Gulf Coast. “Societal risk is formally defined as the risk of a number of fatalities occurring (King et al., 2010).” For the purpose of this investigation, the formal definition of risk above does not provide enough detail. For this reason, other societal impacts of tropical cyclones,
such as property destruction, interruption of basic services, disruption of transportation, unemployment, and the stress on society will be included. The use of these additional variables will more accurately represent the full effect of a tropical cyclone on an area.

This thesis includes information about components of a risk assessment model. A governing equation must be developed in order to quantify the risk posed by an approaching storm. One example of an equation quantifying risk is:

\[ Risk = \frac{\text{Hazard} \times \text{Vulnerability} \times \text{Elements at risk}}{\text{Mitigation} \times \text{Resilience}} \]  

(King, 2010)

This equation incorporates five separate variables that contribute to the overall threat that a hurricane poses to an area or community. Each of these variables is broken into sub-variables that are given values based on the effects they have on a given area during a storm. Sub-variables may fit into more than one of the five governing variables. The equation used for this project utilized these variables in a simplified format in order to incorporate the various data sets.

A tropical cyclone damages multiple aspects of human life. In order to lessen the impact of such storms, people must have knowledge of their vulnerabilities. If a particular vulnerability is discovered prior to a catastrophic event, such as a tropical cyclone, it is easier to adapt and recover. In addition, mitigation strategies can be utilized to reduce the impact of the storm at the vulnerable points.

In order to understand the risk assessment model, each element of the formula above must be explained. The “elements at risk” is a variable describing what objects a storm
will influence. This can range from human life, to business and industry. The “resilience” is the ability to recover from a catastrophic incident, which in this case, is a tropical cyclone. Measures of resilience include factors such as the number of charitable organizations present in an area and the proportion in the population that consider themselves religious. The “impact of the hazard” is defined as having a sudden occurrence without warning. Technology, such as satellite imagery and aircraft reconnaissance, has substantially extended warning times. According to the Texas State Historical Association, the residents of Galveston, Texas were warned about the massive storm of 1900 by listening to the local weather bureau official as he rode down the street in his horse-drawn cart-telling people to leave. Most did not heed his warning and as a result, 10-12 thousand people lost their lives (Texas State Historical Association). Today, the advent of new weather technology can help prevent such a catastrophe, but only if those in the impact area obey the warnings of scientists and government officials.

“Impact” can be separated into two distinct parts: physical impact and social impact. The physical impacts of a storm relate to the destruction of property by processes such as wind, rain, and storm surge (King et al., 2010). The severity of each of these physical impacts is a function of the strength and size of the storm. For example, a more intense storm will most likely have a lower central pressure, which will cause higher wind speeds. Similarly, the physical impacts are related to the characteristics of the area in which they occur. This is seen when comparing storm surge values in locations of varying slopes and heights. Storm surge has less of an impact on steeper, elevated coastal zones.
The social impact of a storm is much more difficult to quantify and calculate. Social impact can range from inconvenience due to loss of power to Post Traumatic Stress Disorder, depression, and violence. Other social impacts include economic disruption, relocation, and fear. Researchers such as Stein and Preuss found that there is an unequal distribution of the impact with economically disadvantaged individuals feeling more of the effect (Stein and Preuss, 2010). This is a reasonable conclusion since economically disadvantaged people have fewer means to remove themselves from the immediate situation and less financial resources to recover from a catastrophe. While new technology related to forecasting a storm’s impact zone is beneficial, there still needs to be systems in place and precautions taken before landfall to help lessen the effects of the disaster.

The steps taken to minimize the effect of a disaster, prior to a disaster striking, are called mitigation techniques. Mitigation techniques can range from the construction of sea walls to the education of the population. Some of the most important decisions a community can make to protect themselves from hurricanes are to institute stricter building codes for storm prone areas. Before 1994, there was no unified building code for the United States. However, after such disasters as Hurricane Andrew in 1992 and the 1989 Loma Prieta Earthquake, a uniform building code was created. The non-profit organization, the International Code Council, was formed in 1994 with the mission to, “Provide the highest quality codes, standards, products and services for all concerned with the safety and performance of the built environment” (International Code Council). The building codes developed by the ICC result in a safer, sturdier building that can
withstand powerful disasters. However, since the ICC codes have only been in effect since 1994, buildings constructed before that date, still constitute a major risk. Additionally, mobile homes are not subject to the same stringent codes as permanent dwellings, so the risk is greater for those residents. Since building codes are updated regularly, new construction will continue to be safer.

In addition to stricter building codes, other physical mitigation techniques include the construction of sea walls and levees. One of the largest sea walls in the United States was built in Galveston following the 1900 storm. When completed, the wall was 17 feet high above low tide, 15 feet thick at the base, five feet thick at the top and was three and a half miles long. To further protect Galveston from storm flooding, the entire city was raised from just inches above sea level to upwards of 16 feet above the Gulf of Mexico. The higher city and sea wall were subjected to a storm surge three feet taller than that of the 1900 storm during a hurricane in August of 1915. Some flooding occurred in the center of the city but only six people inside the sea wall were killed, as compared to 10-12,000 in the 1900 storm (Texas State Historical Society). This is an example of the successful use of a physical mitigation technique.

The city of New Orleans, Louisiana depends on the use of levees and pumps to keep their city from flooding. Much of New Orleans is situated between two feet below sea level to around 16 feet above sea level. New Orleans is in close proximity to three main bodies of water: Lake Pontchartrain, the Mississippi River, and the Gulf of Mexico. For these reasons, any increase in water height can cause significant flooding. Natural levees produced by sediment from the Mississippi River enabled the colonization of the
city, but man-made levees were constructed soon after to help alleviate the severe flooding caused by heavy rains along the river. Early levees consisted of silt and organic clays found in the area. By the early 1990’s, the levee system in and around the city was built using rock and concrete. Also utilized today are extensive drainage canals and water pumping stations. These precautions combined were not enough to protect New Orleans from massive damage during Hurricane Katrina in August of 2005. During Katrina, several levees and floodwalls failed and the water pumps were not able to keep up with the intense flow from the increased storm surge. Experts believe that if the levee system had been updated and better maintained, there would have been less loss of life and property. However, a storm the size and scale of Katrina had not been seen in that region since the 1900 Galveston Storm, which was certainly not as well documented and studied as Katrina was in 2005. The impacts of Hurricane Katrina continue to be intensely scrutinized by engineers, scientists, and politicians and will result in to the creation of more effective mitigation techniques.

Another vital component of storm mitigation is education. If people living in tropical cyclone prone areas are better educated regarding the dangers of a storm and the evacuation procedures; then countless lives may be saved. Hundreds if not thousands of lives could have been saved in Galveston if the citizens had known that a massive storm was heading their way. Similarly, had residents of New Orleans and Mississippi been aware of the life threatening risk of Katrina, they may have heeded the warnings of government and emergency management officials and evacuated when ordered to do so.
Public servants in risk management positions also need education regarding the dangers of a storm in their jurisdiction. People in these positions need to work alongside of local political officials to make evacuation decisions during an emergency. During Hurricane Katrina, there was a great deal of miscommunication between local political officials and emergency management officials. Poor communication cost time, and ultimately lives, in the New Orleans area. Organizations such as the National Hurricane Center (NHC) provide outreach resources for scientists, teachers, government officials, and the public. The NHC is in direct contact with various scientific and emergency management officials through formal training and data sharing that helps them make the best decisions when it comes to safeguarding lives and property in the face of an oncoming tropical cyclone. The NHC holds an annual hurricane conference that highlights research regarding storms and mitigation techniques. The 2013 conference even held a seminar titled, “Hurricane Readiness for Coastal Community” (NHC). The NHC Outreach Program, as well as education programs developed by other organizations, is invaluable resources that contribute to mitigating the impact of tropical cyclones by increasing knowledge and raising awareness.

“Vulnerability” is a vital factor when determining the risk posed by a tropical cyclone. Vulnerability describes exactly what potential risks threaten an area. Hurricanes are associated with their destructive wind speeds. However, much of the damage and loss of life in an event is caused by flooding and storm surge. For this reason, variables relating to storm surge are closely examined in this project. These variables include the altitude of the affected area, the proximity of major population centers to the coast, and
the flash flooding history (water drainage ability). These variables, along with the use of the National Weather Service’s Sea, Lake, and Overland Surges from Hurricanes (SLOSH) or the US Navy’s Advanced Circulation (ADCIRC) models, will provide measurements for the risk in coastal areas to storm surge. These models examine the height of storm surge in an area based on shallow water equations for various storms of differing sizes and strength.

The “elements at risk” variable contains demographic information about residents as well as the types of industry and commercial businesses in an affected area. The demographic information is important because it presumes the types of housing construction based on the mean income of the residents, as well as the monetary value of possessions in the home that is at risk in the storm. Age is also significant in determining risk. During Hurricane Katrina, 1.2% of the people that did not evacuate were killed. Of the 829 individuals that perished in the storm, 65% were older than 65 while almost half were older than 75 (Greenberg, 2013). These statistics could stem from the fact that elderly individuals have less mobility and depend on others to evacuate. It could also mean that the elderly are less predisposed to leaving their lifelong residence for the unknown.

Another key component of the “elements at risk” variable is infrastructure. Infrastructure includes water, power, road and sewage systems. This is the most difficult portion of this project to quantify because of the broadness of each of these systems. Most of the research on critical infrastructure has been devoted to power systems. Data from the other three systems mentioned is severely lacking in terms of risk in a disaster.
(LaRocca and Guikema 2011). In order to develop a valid and reliable risk analysis model, the critical infrastructure networks will have to be studied and quantified.

The “resilience” variable describes how easily a community can cope with, and bounce back from, a tropical cyclone. Variables include the number of churches, hospitals, and organizations such as the YMCA and the American Red Cross. Also included are the percentages of the population that categorize themselves as religious, along with the voter rates. These variables help to paint a picture and enumerate the support system in place in a community. In times of high stress, a strong support system is vital in the recovery process (King 2010).

2.3 Project Area

Hurricanes can strike the United States anywhere between Texas and New England. This is a broad area and is beyond the scope of this project. In order to confine the study area, a frequency map provided by the National Hurricane Center was obtained. This map shows that the majority of the tropical cyclones that make landfall in the United States occur along the Central Gulf Coast, Southern Florida, and the Carolinas (NHC climate). However, over the last 10 years, only seven storms have made landfall as a major hurricane, that is hurricanes with categories of three or greater. All of these, with the exception of Jeanne (2004, Eastern Florida), hit the Gulf Coast. For this reason, the risk to the region between Cameron County, Texas and Dade County Florida is the focus of this project. The study region has a suitable mix of industry, tourism, and land ecosystems which make it interesting to evaluate how each of these factors affects risk.
2.4 Social Vulnerability

The bulk of this project assesses the social aspect of a natural disaster. It is important to note that not everybody reacts the same way when subjected to the stresses of a land-falling tropical cyclone. The science of social vulnerability is relatively new. This field began in the 1830’s in the United States and United Kingdom in an attempt to improve the quality of life for their citizens. By 1960, nations and organizations were developing comprehensive research plans in order to develop political policy. Agencies such as the United Nations and World Bank devote substantial resources to develop social indicators, and collecting relevant data on these indicators, to develop comparative assessments across the globe. (Dwyer, 2004). Before then, most researchers were only concerned with the financial and loss of life statistics resulting from natural disasters.

To compute the impact of societal factors, many variables must be calculated. Each of these variables represents a separate segment of society and may range from age and race, to job status, and access to various forms of transportation. These variables are selected, combined, and quantified to form a “vulnerability index.” Several distinct vulnerability indices exist in the social science community today. These include the Climate Vulnerability Index, which discusses public vulnerabilities to the effects of climate change and the Histopathological Plaque Vulnerability Index, which is used in the medical field to discuss the vulnerabilities of homeless individuals in major cities (Vulnerability Index). For the purpose of this project, the Social Vulnerability Index or SoVI was utilized (SoVI). The SoVI provides a comprehensive look into some of the most important social indicators that affect populations in the path of a tropical cyclone.
The SoVI was created by the Hazards and Vulnerability Research Institute at the University of South Carolina in order to measure the social vulnerabilities of counties in the United States to environmental hazards. It examines not only the vulnerabilities before and during a disaster, but also how quickly a community can recover from a catastrophic event such as a tropical cyclone. Several applications of SoVI include, but are not limited to, usage in the California Disaster Management Plan, the Natural Hazards Risk Assessment for the state of California, and the Hurricane Wind Risk Assessment for Miami-Dade County, Florida. SoVI was chosen for this project because of the broad spectrum of data points it incorporate. Most of the data used for this index was extracted from the 2010 United States Census. The index uses 29 variables that are known to have the most significant effect on the social vulnerability in a disaster situation. A value may increase or decrease the social vulnerability in an area depending on the variable being explored. These 30 variables are divided into seven components, or social indicators, that explain 72% of the variance seen in the data. These seven social indicators are “race, class, poverty; wealth; elderly residents; Hispanic ethnicity; special needs individuals; Native American ethnicity; and service industry employment (SoVI).

**Race (Black), Class, Poverty**

According to the SoVI index, three groups are at greatest risk from a natural disaster. Those groups include African Americans, people living at a lower socio-economic class, and people living below the poverty level. These three factors explain 17.45% of the variance seen in the index calculations. This is number is easily seen when
considering more than 55% of African Americans live in the Southern United States according to the 2010 US Census. Similarly, 105 Southern counties reported an African American population of greater than 50%. Since this project’s main study area is located in this region, the percentage of African Americans living there will surely influence the results.

According to Cutter et al. “Race contributes to social vulnerability through the lack of access to resources, cultural differences, and the social, economic, and political marginalization that is often associated with racial disparities (Cutter et al., 2003).” A clear example of this marginalization occurred in New Orleans after Hurricane Katrina. While this was a disaster on an unprecedented scale, many cite the slow reaction time of federal and local governments, along with poor communication by those in positions of power, as main factors contributing to the tremendous loss of life suffered by the African American population. Some of these areas still have not recovered from the disaster.

Another factor presented by Cutter, is the unequal distribution of power in government positions. In times of disaster, the government is responsible for providing aid in the form of money, shelter, and even protection from the National Guard. At the time of this writing, there are 44 African Americans out of the 535 voting members in Congress. This percentage is low and demonstrates the disparity in the balance of racial power in politics. While Congress should be working in the best interests of all Americans, it is difficult not to question the aid distribution in times of crisis.

Along with the African American population, class level influences the variance of social vulnerability. The variable that has the highest correlation in the race, class,
poverty component is the percentage of female heads of household. The United States Census Bureau 2006 American Community survey stated that there were approximately 8,305,456 single mother homeowners living in the United States. This number is expected to rise. While there is a push for gender equality, it is apparent there is a separation between the social mobility of male and female-headed households. Statistics show that, “Women who are heads of households live in poverty at twice the rate of male heads of households (Enarson, 2007).” When this metric is combined with racial and ethnic factors, it is apparent that a clear risk is present for women that are heads of household in the study area. The correlation of the female head of household variable is .853 in the SoVI, which is the highest in the race, class, and poverty social indicator. The other variables that make up the class indicator are percent of families without a car, number of individuals with less than a 12\textsuperscript{th} grade education, and percent of children living in a married couple household. The percent of children in a married couple household variable is the only variable in this indicator that provides a negative correlation. This negative correlation shows that married families help to decrease the risk in a population.

Finally, poverty is the major indicator in social vulnerability. Poverty can encompass both the African American and class variables. As was discussed previously, a portion of the problems plaguing African Americans and female heads of households was the fact many are living below the poverty line. For an American family of four, the poverty line is an annual income below $23,500. In order to compute the poverty portion of the SoVI, the percentage of families living under the poverty line was determined. This
variable had a .766 correlation to the social indicator as a whole, which was second among the variables used.

**Wealth**

As can be expected, one of the leading indicators of social vulnerability is wealth. This is because higher degrees of wealth facilitate the purchase of insurance and involvement in social programs such as church groups or elite housing communities. However, wealth is a double-edged sword in the context of social vulnerability. While the wealthy have more means to prepare and recover from a disaster, they also have higher value possessions, so the elements at risk value are greater. The wealth category is comprised of elements such as median gross rent, percent of households that are classified as rich (having an annual income greater than $200,000), and median house value among others. These three variables provide for the largest component loading terms.

The median gross rent of a community is coupled with the median house values to provide information regarding property values in an area. These property values shed light on the wealth levels of a county. Obviously, wealthier individuals normally populate locations with high rent and home prices. The median gross rent and median property values have loadings of .790 and .852 respectively.

The percentage of households with incomes of greater than $200,000 annually also provides a strong correlation to wealth. The $200,000 thresholds one that should be modified in future iterations of the SoVI. The highest tax bracket for the 2012 fiscal year
for a married couple filing jointly started at $388,350. The $200,000 figure could be raised in future SoVI model runs to reflect the change in wealth among Americans, as well as changes to the inflation of the dollar.

Age (Elderly)

Age, as a social vulnerability characteristic, can be broken down into two specific aspects using the youth and elderly at the ends of the aging spectrum. On one hand, children under the age of five are unable to provide for themselves and require a great deal of care. On the other, elderly individuals also may struggle with caring for themselves because of sickness or other handicaps. The main difference between children and the elderly when discussing them in the context of social vulnerability is that children have one or two parents or caregivers that will protect and help them recover from a significant disaster. The elderly may no longer have anyone left to care for them. As was stated earlier, of the 829 fatalities during Hurricane Katrina, 65% were senior citizens and half of those were older than 75. These statistics show that the age is one of the most useful demographics in determining social vulnerability. Another important distinction between children and the elderly is life experience. It is very possible that a severe hurricane could be a child’s first traumatic life experience. They may not have dealt with a natural disaster before and will not have any idea how to react or what to do. Elderly persons that have lived in the same area for most of their lives will most likely have gone through a hurricane before. They will know what to look for and hopefully, when to evacuate. The danger rises when elderly individuals know when to leave, but do
not have the means to do so, or when complacency sets in because they have weathered previous storms.

The age component explains 12.98% of the variance and is comprised of elements such as median age, percentage receiving social security benefits, and percent of population less than five or greater than 65 years old. The median age variable has the highest loading value at .914.

**Ethnicity (Hispanic)**

The Hispanic population is experiencing some of the most rapid growth among ethnic demographics in the United States. According to the New York Daily News, by the year 2039, one in four Americans between the ages of 18 and 64 will be of Latin descent. Several factors contribute to risk experienced by the Hispanic population in the event of a tropical cyclone. As with any ethnic group, language barriers may exist, which can delay comprehension of warnings and evacuation notices. Today however, bilingual notices and instructions are common in most areas of the United States.

The Federation for American Immigration Reform states that there are over 12 million illegal immigrants living in the United States. The majority of these illegal immigrants are of Hispanic descent. These residents may not have access to federal assistance programs such as Welfare, Social Security, and healthcare, thus making recovery more difficult. Additionally, illegal immigrants may have low paying jobs that cease to exist during, and immediately following, disasters.
The SoVI lists Hispanic ethnicity as the fourth highest risk group with 9.34 percent of the variance explained. The main variables that comprise the Hispanic ethnicity category are quantity of individuals without health care and Hispanic population with .728 and .687 loading values respectively.

**Special Needs**

The special needs category in the context of the SoVI describes those individuals that are housed in facilities designed to provide professional care due to sickness, injury, or age. The special needs category was first added to the SoVI for the 2010 Census model run. It provides a fresh dynamic look at risk. Those in the special needs category are not able to care for themselves. Most need full-time care and supervision and it is impossible for them to evacuate an area or sustain themselves without basic resources such as food, water, electricity, etc. The special needs category contains some of the most fragile portions of the population. However, the special needs population makes up a small portion of the overall makeup of a community. For this reason, special needs explain 6.73 percent of the variance with the major variables of proportion of those living in nursing homes, and hospitals per capita. While hospitals are a strong factor in providing care in the aftermath of a storm, they also house the sick, injured, and those that can otherwise not care for themselves and this becomes a problem during pre-storm preparations and during the evacuation process.
**Ethnicity (Native American)**-

Native Americans make up a very small portion of the population of the United States, and an even smaller portion of the study area. Texas has approximately 98,000 Native Americans living in the state, which is about .5 percent of the state’s population. However, Native American ethnicity still provides for the explanation of 4.94 percent of the variance in the SoVI. Native American’s possess a very strong culture and many wish to remain true to the past. For this reason, many still speak their native tribal languages at home and it is very rare for weather watches, warnings, or notices to be transmitted in Native dialects. The main variables that comprise the Native American ethnicity component are percent Native American, quantity of English as a second language population, and number of those without access to cars or other motorized transportation.

**Service Industry (Employment)**-

The final SoVI component is service industry employment. The majority of service industry jobs are low paying jobs. Examples of service industry jobs include waiters/waitresses, landscapers, housekeepers, etc. While there are exceptions, the service industry jobs used in SoVI represent low wealth populations. Many in these jobs do not require higher education and do not offer health and wellness benefits. These factors make personal mitigation techniques difficult, and extend recovery times after the storm has passed. Service industry employment explains 4.45 percent of the variance and is composed of one variable, quantity of individuals in a service industry.
In the context of a natural disaster such as a tropical cyclone, each of the components of the Race, Class, and Poverty social indicator increase the risk in a community. The race component is observed during the aftermath of the storm and the lack of support by federal government agencies. Those in lower classes may not have the money or modes of transportation to evacuate an oncoming storm. Individuals living below the poverty level do not have the means to use mitigation strategies such as boarding up windows or reinforcing their homes. In addition, people below the poverty level may not have the insurance needed to cover damages after the storm, making recovery a difficult task. Wealthier individuals are able to better prepare for a natural disaster and are able to recover faster because of their access to money, health coverage, and contingency plans. However, they may also face higher risk due to the value of their possessions. The elderly population may not be able to take care of themselves in the event of a natural disaster. They find difficulty in evacuating and in some cases will not have any family or friends to assist them. Hispanics are faced with language barrier issues as well as fear of deportation or other repercussions if discovered to be illegally residing in the country. Those classified as special needs are in care facilities such as hospitals and nursing homes and rely on others to survive a catastrophic event. Local officials must be cognizant of their needs when issuing notices and evacuations. Many of the Native American’s living in the United States choose to speak their own language and instructions from emergency management officials are not usually transmitted in these dialects. Finally, those in service industry jobs are disproportionately impacted because they work for low pay, often without health benefits, in positions that may not exist in the
aftermath of a major weather event. Combined, these factors explain over 74 percent of the variance associated with the SoVI. Viewing social risk from various perspectives is essential for developing the risk assessment model for this project and the SoVI index provides the data points needed.
Chapter 3

SCIENTIFIC OBJECTIVE AND METHODOLOGY

3.1 Introduction

Tropical cyclones have the potential to inflict devastating loss of life and property to those in their path. It is imperative to understand who is at greatest risk from these storms in order to better develop strategies for evacuation and asset protection. This project investigates the risk factors that play major roles in the outcome of regions before, during, and after a tropical storm event.

3.2 Data Set Selection

3.2.1 Vulnerability Index

To begin the process of developing a risk analysis model, the data that is incorporated into the model must be selected. Since this model focuses on socio-economic risk factors, a social risk index was selected first. As previously discussed, the index selected was the Social Vulnerability Index (SoVI) developed by researchers at the University of South Carolina. SoVI is an excellent choice as a social risk index because it is comprised of values that show the vulnerability, resilience, elements at risk, and
mitigation of a region. These values are paramount for determining the risk and the SoVI provides valid and reliable data for the model.

3.2.2 Computer Programing Language

The choosing of a computer programming language for this project was particularly important. The programming software had to support the computational capacity of the tasks being requested. The program also must have the capacity to handle a great deal of mathematical calculations and be compatible with other data sets utilized for the project. For these reasons, Matlab, developed by Mathworks Inc., was chosen as the modeling language. It possesses the capability to process countless computations and is compatible with other data sets. Mathworks provides technical support and help solutions on their webpage, which was also a consideration when choosing a programming language.

3.2.3 GIS Data

Since this project is concerned with how hurricanes interact with social and political regions (counties) of the United States, a great deal of Geographic Information Systems or GIS data was required. The data sets used in the project were either accessed from, or created using the ArcGIS software suite. The first data collected was that of the land mass of the United States. This narrowed the bounds for the maps created from the entire globe to the western hemisphere to make the maps easier to view and work with. The next set of data obtained was of the actual state boundaries in the United States.
Finally, data for the counties in the project area were input. This data set was created by selecting the specific counties desired from ArcGIS and saving the input. These GIS datasets were saved as shapefiles in the .shp format. This is a file format developed for use by ESRI, which is one of the largest producers of mapping software in the world and the creators of the ArcGIS software suite used in this project. The shapefiles work seamlessly with the Matlab Mapping Toolbox, which was purchased in order to complete this research. They provide polygon data with cell arrays of X and Y coordinates that act as longitude and latitude data. Matlab is able to read this and create a figure using the X and Y coordinate information.

### 3.2.4 Hurricane Data

Hurricane data from previous storms is imperative to developing a valid and reliable risk analysis model because information about the hazard greatly affects the impact. In order to remain consistent with the other data collected, hurricane GIS data in shapefile form was required. The National Hurricane Center (NHC) has a large archive of GIS data sets from previous storms and more data is added with every approaching tropical system. For the purposes of model development, Hurricane Isaac was chosen for the creation and testing of the model. Isaac was selected because of its path through the center of the project area. Isaac provided a good simulation of what a direct storm impact in the project area would look like. The ultimate goal of the project is for the model to be used in real time with approaching storms but that is not possible to show at this point.
because of the timing of this writing. The NHC will provide updated forecast data for an approaching storm as it becomes available.

After Isaac was selected, various archived datasets were uploaded to quantify the risk. First, the cone of uncertainty was input. This cone shows the potential area of the forecasted center of the storm as it moves. This piece of data is particularly important because it allows the model to focus on a specific part of the project area.

3.2.4 Storm Surge Data

The storm surge data used in the model was obtained from the NHC’s probabilistic storm surge archive. As with the other NHC data, the storm surge information was in shapefile format and loaded into Matlab. The NHC offered archived data in the form of probabilistic storm surge forecasts at various advisory times of the storm for surge heights ranging from greater than one to greater than 25 feet. To simplify the data, the greater than 5, 10, 15, and 20 feet data sets were used for this project. These data sets contained latitude and longitude data that formed polygons covering there area for each probability level. Each data set ranged in size based on the probability the respective heights will be reached. For example, for Hurricane Isaac, the greater than 5 feet storm surge probability featured 36 rows. Row 1 indicated the area where there was a 1% chance of having a higher than 5 foot storm surge while row 36 corresponded to the polygon covering an area with a 36% chance of greater than 5 foot surge. The probabilities are based on five Sea Lake and Overland Surges from Hurricanes (SLOSH) model runs. Each model run consists of a hypothetical storm with similar characteristics.
to the current storm being tested. “The set of hypothetical storms is created by permuting the hurricane’s position, size, and intensity based on past errors of the advisories (Taylor and Glahn).” The model runs have associated weights of 0.1, 0.2, 0.4, 0.2, and 0.1 for a given height. If runs one and two exceed the given height while the others do not, a probability of .3 or 30% is used. This surge data is an extremely vital piece of information for the model because it provides storm specific information. Since the surge data is forecasted by the NHC, it is unique to a given storm unlike the evacuation data, which is solely based on storm category, or SoVI values, which are constant depending on the county of choice.

3.2.5 Evacuation Data

The final piece of data used in the model was the evacuations times in each county based on worst-case scenario estimates. The HURREVAC program was developed to inform risk management professional when they need to make evacuation decisions (HURREVAC Support). It uses information based on several Hurricane Evacuation Studies completed by state disaster agencies to determine evacuation times for each county based on several factors. These factors include public response time, forecasted storm characteristics (storm surge, storm category, etc.), and tourist occupancy. For the purpose of this project, it was chosen to use the worst-case scenario evacuation times for each category storm. This worst-case called for slow public response times with high tourist occupancy. For a higher resolution model, it would be ideal to select response times and current tourist occupancy for a given storm but that is not
possible in the scope of this project. The final output of evacuation times include the
times, in hours, for each county in the project area for tropical storms and category 1-5
hurricanes.

3.2.6 Test Storms

Five test storms were used in the creation of the model; Ivan (2004), Katrina
(2005), Ike (2008), Ida (2009), and Isaac (2012). The NHC contains substantial archived
data from 2009 to present. However, due to disk space limitations and less than ideal
 technological deficiencies at the time, only the Ida and Isaac data sets contain the desired
amount of information. In order to obtain suitable model runs, some adjustments were
made in the model for the test storms before 2009. These adjustments are discussed
further in the methods section of this paper. While the data for the pre-2009 storms is not
perfect, that the relevance of these storms was important to validating the model and
therefore were included in the project.

3.2.6.1 Hurricane Ivan (2004)

Much like other tropical cyclones, Ivan developed from a tropical wave off the
African Coast on August 31, 2004. Strong convective activity could be viewed from the
satellite imagery as early as September 1 and the cyclone continued to strengthen into a
tropical storm on September 3. Ivan underwent rapid intensification (RI) where its central
pressure dropped by 39 mb in an 18-hour period to become a major hurricane. Ivan then
began a 24-hour weakening period followed by another period of RI. As Ivan reached the
Caribbean Sea, recon aircraft data showed a wind speed of 140 kts making Ivan a category 5 storm. It weakened to a category 4 storm as it brought heavy winds, rain, and storm surge to the island of Jamaica on September 11. Ivan continued its previous cycle of strengthening to a category 5 and then weakening back to a category 4. As the hurricane approached the United States, vertical shear increased and drier air was advected into the center of the storm. This caused a weakening to a category 3 storm as landfall was made on September 16 just west of Gulf Shores, Alabama.

Ivan was blamed for 25 deaths in the United States mostly from spawned tornados and storm surge. Fourteen of the deaths occurred in the state of Florida. In the aftermath of the storm, sections of roads including bridges were heavily damaged in Florida, and Alabama. Many beachfront homes were destroyed by the storm surge and resulting beach and soil erosion caused by Ivan. Some of the most damage occurred in Baldwin, Escambia, and Santa Rosa counties. Insurance companies report that insured losses topped $7.11 billion, while uninsured losses were estimated to total $14.2 billion.

3.2.6.2 Hurricane Katrina (2005)

Hurricane Katrina began as an interaction between the remnant of unnamed storm 10 and an upper level trough in the Eastern Caribbean near Puerto Rico on August 19, 2005. The convective storms that would later become Katrina moved westward towards Florida before becoming a tropical depression on August 23 near the Southern Bahamas. Deep convection developed in the evening of the 23rd and a circulatory center was viewed early on the 24th. Katrina achieved hurricane status on August 25th just east of Southern
Florida. The category 1 Katrina made landfall near Broward County on the 25\textsuperscript{th} of August just after reaching hurricane status. After traversing across Florida, Katrina entered the Gulf of Mexico on the 26\textsuperscript{th} and rapidly intensified (RI) to a category 3 storm on August 27\textsuperscript{th}. Katrina then turned northeast and underwent another, more powerful, RI period resulting in the storm achieving category 5 designation. Hurricane force winds extended 90 n miles from the center making this a massive storm in both strength and size. Katrina made a turn north and made landfall as a strong category 3 storm in Southeastern Louisiana on August 29\textsuperscript{th}.

The size and strength of hurricane Katrina had not been realized along the Gulf Coast since the Galveston hurricane of 1900. The NHC storm report described the results as, “The scope of human suffering inflicted by Hurricane Katrina in the United States has been greater than that of any hurricane to strike this country in several generations” (Knabb, 2005). While the total fatalities caused by Katrina is unknown, officials estimate the total is close to 1,830. Most of these fatalities were caused by the massive storm surge associated with the storm and the subsequent levy and dam failures in the city of New Orleans. Louisiana reports that most of the fatalities were of individuals greater than 60 years of age. Most of the damage to structures in hurricanes usually is the result of high storm surges and flooding. However, in Katrina, an increase in wind damage was seen in New Orleans and parts of Mississippi. The roof of the Louisiana Superdome was irreparably damaged along with homes destroyed with only foundations remaining in Mississippi. Hundreds of businesses, tourist destinations, oil facilities, and transportation centers were either damaged or destroyed and this extended the time to rebuild the area.
As of this writing, some areas of New Orleans and Louisiana have still not recovered from the storm and were simply abandoned. Uninsured, and insured loss estimates were calculated to be upwards of $108 billion, making Katrina the costliest hurricane in United States history.

3.2.6.3 Hurricane Ike (2008)

Originating from a tropical wave off the coast of Africa on August 28, 2008, Ike traversed across the Atlantic Ocean towards the Caribbean. Ike was surrounded by a great deal of dry air and was only able to form convective bands starting on September 3rd. A maximum intensity of 125 kts was reached on September 4th in the Western Atlantic Ocean after a period of RI. Ike struck the Turks and Caicos island chain on September 7th and continued to make landfall on Great Inagua Island in the Bahamas later that day. After brief weakening and strengthening periods, Ivan affected Cuba on September 9th and this interaction caused visible weakening of the storm. Ike lacked inner core convection but maintained a large wind field and this prevented rapid intensification. Ike, influenced by a subtropical ridge, turned north-northwest towards Eastern Texas. Ike made landfall as a strong category 2 storm on the north end of Galveston Island on September 13th.

Ike was blamed for 20 fatalities in the United States. Twelve of these deaths occurred in Galveston and Chambers Counties. These deaths correspond with the highest storm surges recorded in these counties. As of May 2010, 23 people are still listed as “missing” with 16 of these individuals from the Galveston area. Insurance offices estimate the insured and uninsured losses extend to $24.9 billion. These values place Ike
as the 3\textsuperscript{rd} costliest storm in history behind the previously discussed Katrina and Andrew (1992).

\textbf{3.2.6.4 Hurricane Ida (2009)}

Hurricane Ida organized after a poorly defined tropical wave interacted with a low pressure system over the Western Caribbean in November of 2009. Satellite imagery estimated that Ida became a tropical storm on November 4 off the coast of Nicaragua. Ida intensified into a category one hurricane the next day after experiencing warm waters and light shear conditions. As Ida moved north, it brought significant rain to Central America and the Yucatan Peninsula before entering the Gulf of Mexico early November 9. After weakening to tropical storm category, Ida reintensified once in the Gulf of Mexico but encountered cooler winds and stronger shear on its path towards the United States. Ida made landfall along the Alabama Coast on November 10 and quickly became extratropical in nature. Because of Ida’s large wind field and the curvature of the terrain, rising tide levels were experienced from Mississippi to Central Florida. The damaging effects of Ida were mostly seen in Central America where 80\% of the homes on the Nicaraguan Coast were damaged and 6,000 people were affected. In the United States, minimal damage was caused by the storm but there was one fatality along the Mississippi River.

While these storms may not be the strongest, they provide good sample data in which to test the model. Isaac had a major impact on New Orleans, which is the largest city in the project area, while Ida showed the risk caused by increased storm surge on the
Florida Gulf Coast. The aftermath of these storms along with the model analysis will be discussed further in the results section of this paper.

**3.2.6.5 Hurricane Isaac (2012)**

Isaac developed from a tropical wave into a tropical storm on August 21, 2012 625 n miles east of the Lesser Antilles. It remained a tropical storm for days while bringing heavy rains and surf to Haiti, the Dominican Republic, and Cuba. It entered the Gulf of Mexico on August 27 after causing increased winds and downpours in the Florida Keyes and Central Florida. Once over the warm gulf waters, Isaac began to strengthen and achieved category one status on August 28. As it approached the Louisiana Coast, it interacted with a mid-level blocking ridge that significantly slowed the pace of Isaac. This slower speed caused increased wind, surge, and rain along the Louisiana Coast. Isaac finally made landfall on August 29 just to the east of the Mississippi River.

During this landfall, inundation levels were extremely high for some counties. These include, St. John the Baptist and St. Charles Parish at 1-3 feet inundation, Jefferson and Tangipahoa Parish at 3-6 feet inundation, Orleans and St. Tammany Parish at 4-8 feet inundation, St. Bernard Parish at 8-12 feet inundation and Plaquemines Parish at a staggering 10-17 feet inundation level. Hancock and Harrison Counties in Alabama recorded a 5-9 foot inundation level, while counties as far east as the Florida Panhandle saw a ~3.5 foot rise in sea level due to Isaac. Five deaths in the United States were attributed to Isaac while the total U.S cost after adjusting for uninsured losses exceeded $2.3 billion.
3.3 Methods

After selecting the modeling program, data, and storms the computer model was created. The first step was to insert the data into Matlab. This was done by using Matlab’s shaperead function that forms matrices from the shapefile data. This was completed for the state (Figure 3.1), county (Figure 3.2), cone of uncertainty (Figure 3.3), and 5, 10, 15, and 20 foot storm surge data (Figure 3.4). The SoVI data was then entered manually into the program because a tabular output was not offered by the index researchers. Similarly, since the shapefile data only included geolocation data, the county names and states were not present. These values were manually written into the code from an ArcGIS spreadsheet.

After the data for the project was accepted by Matlab in a suitable format, the model generation could begin. The first step was to determine which counties were in the cone of uncertainty forecast provided by the NHC. To do this, the inpolygon function was used. This function asks for geolocation data of polygons and determines if a given point is inside said polygon. In this case, a central point was chosen for each county and compared to the cone polygon. If this point was located in the cone of uncertainty, Matlab would recognize that the county was in the cone. The cone of uncertainty data was not available for the pre-2009 storms so for the purpose of creating a model test simulation, the affected counties for these storms were input manually.

The next step was to determine the category of a current, simulated storm. Since the model is not connected through the internet for real time updates, the model is dependent on this piece of information from user input. At this stage in the model, the
user is required to select a current category of the storm between one and five. If the system is classified as a tropical storm, the user is instructed to use 0.5. The storm category data is used by this model to examine the risk from wind speeds and unlike storm surge, this is a much more localized quantity. For this reason, the category data only directly increases risk for those counties within the cone of uncertainty.

Once the counties within the cone are determined, the evacuation times provided by the HURREVAC Program are added to the model. These times are based on the category of the approaching storm so the user input determines which times to use. The evacuation times do not distinguish between a tropical storm and category one hurricane so the times for each are identical.

The most difficult portion of the model creation was the utilization of the storm surge data. Like the cone of uncertainty, the program needed to distinguish what parts of the storm surge data was in each county. However, the surge data was much more complex because it contained polygon data that acted as contours. It was not possible to simple select a point in each probability layer to see if it was inside a county. These probability layers could be as long as several counties so if only one point was selected there is a large possibility data would be missed. In order to solve this, a series of loops were used to from the data into individual points. Each of these thousands of individual points were compared to the dimensions of each of the county polygons using the inpolygon function.

The output for each surge level was an array of zero’s and ones with the rows pertaining to the probability of the surge event occurring and the columns pertaining to
each point. Next, the x, y data was collected for each of the points referred to by the various ones in the array. This x and y data was combined with the county dimensions to determine what the max probability of surge was in each county. The worst case scenario was used for this project in order to keep the data manageable. For example, if a county had 3%, 8%, and 14% probability contours then the 14% probability was used for the county. Similarly, when compared with the 5, 10, 15, and 20 foot surge data sets, the worst case scenario was used. If there was 20 foot surge contours forecasted for a county then the 20 foot surge probability was used for the county. If there was no 20 foot surge contours in a county, the highest probability 15 foot surge values for the county were used and so on. To get the risk value associated with the storm surge, the greatest height was multiplied by the highest probability. For example, a county with a 20 foot storm surge forecast and the highest probability of 3%, the risk would equate to (20 feet * .03) giving a risk value of 0.6. As discussed earlier, the storms that pre-date 2009 did not have some of the information contained in post-2009 data sets. The majority of this data was surge values. The post-2009 storms contained data for probabilities >1 foot to >20 feet. The pre-2009 data sets only included probabilities for surges >1 foot to >10 feet. This information is taken into account when discussing the validity of the results for these storms.

In order to receive an accurate risk value, the variables must be normalized to prevent one from having a greater effect than others. To do this, the standard score for the evacuation times, SoVI, and storm surge values were used. This score was determined by taking the subtracting the mean of each variable from each value and dividing by the
variables standard deviation. This process prevents the much higher evacuation time data from significantly skewing the results. In order to normalize the category data, a different technique must be used because the data is not normally distributed. To normalize the category data, the category was simply divided by 2 in order to lessen the wind speed risk related to the storm to a more realistic value.

Once the variables were normalized, the risk analysis could be performed. The risk equation used in the project is a simple additive function of the SoVI, evacuation times, storm surge, and storm category risks. After this function was performed, the data was plotted using a custom color map developed in Matlab. This color map allows the results to be easily identified on the county map.
Figure 3.1: Generation of the Gulf States used in the project area.
Figure 3.2: Generation of the counties used for the project area.
Figure 3.3: Generation of the cone of uncertainty for Hurricane Isaac
Figure 3.4: Generation of the 10 foot probabilistic storm surge data for Hurricane Isaac
Chapter 4

RESULTS

4.1 Hurricane Ivan (2004)

Hurricane Ivan made landfall along the Gulf Coast of Mississippi. Since the model is a point in time model, meaning it assesses that risk at a specific time period, a specific data set from the NHC was used. To obtain a better understanding of how the model results change with time, three separate advisory times were used. The storm surge data, as well as the user input cone of uncertainty data each correspond with the parameters of the storm at advisory 48. Data was taken for this advisory on September 14 at 4 AM Central time when the maximum sustained wind speeds extended to 160 mph. This wind speed gave Ivan category 5 distinction. At this time, the storm was well off the United States coast and had a widespread cone of uncertainty reaching from Southeast Louisiana to the Florida mainland. When the risk analysis model was run, Franklin County, Florida had the highest risk at 6.0275 followed by Hancock, Harrison, and Jackson Counties in Mississippi at 5.4410, 5.3951, 4.8027 respectively (Figure 4.1). Franklin County, Florida had the highest risk for several reasons. The SoVI value was the highest for any of the affected counties at 4.7173. The evacuation time for this county
was also extremely high at 70 hours. The surge risk was not much of a factor for Franklin County with an added risk of only 0.5. The high risk Mississippi counties were influenced primarily from the surge risk of 1.8 for Hancock and Harrison Counties and 1.7 for Jackson County. The SoVI values were negative for these counties and diminished the risk while the evacuation times were relatively high at 56 hours for each of these counties.

The next data set coincided with the surge and category of Ivan at the time of advisory 51, which occurred at 10 pm local time on September 14th. At this time, Ivan was a category 4 storm with sustained winds upwards of 140 mph. After running the risk analysis model for the advisory 51 data, Harrison, Hancock, and Jackson Counties in Mississippi had the highest risk values at 5.1607, 4.9137, and 4.4579 respectively (Figure 4.2). Each of these counties had high storm surge values ranging from 31% to 28% for >10 foot surge. Okaloosa County, Florida had a risk value of 3.8743 while Mobile County, Alabama was shown to be the 5th most at risk county with a value of 3.7820. Each of the five riskiest counties had SoVI values less than 0. The diminished risk associated with advisory 51 when compared with advisory 48 occurs because of the change of strength from a category 5 to category 4 storm. This change decreases the category risk as well as the evacuation times.

Finally, data for advisory 52 was utilized. Ivan was much closer to the Louisiana/Mississippi Gulf Coast and had sustained winds of 140 mph, which indicates a strong category 4 storm. A category 4 storm this close to the coast should provide high risk values because of the increased certainty of the location of the land fall as well as
more accurate storm surge probabilities. The increase in accuracy of these variables has narrowed down the counties with the highest risk to those in Mississippi and Alabama. All five of the Mississippi/Alabama counties have the highest risk values ranging from 5.4772 in Harrison County, Mississippi to 3.7822 in Baldwin County, Alabama (Figure 4.3). The SoVI values for these counties were below 0 so they had a negative effect on the risk. Surge values were extremely high with that risk ranging from 2.5 to 2.2. This shows that in the case of Ivan, storm surge values provided for most of the risk seen using this model. The evacuation times ranged from 56 hours to 42 hours and these added from 1.2202 to 0.4789 risk units depending on the given county.

The risk values for Hurricane Ivan show that the model is better able to estimate the risk as storms approach the coast. This is because much of the model is created off predictions from the National Hurricane Center. As these predictions become more accurate, so does the accuracy of the risk analysis model. In reality, Ivan took a slight turn to the East and this saved Mississippi from taking the brunt of the storm. Most of the damage was seen in Alabama and Escambia County in Florida. In the aftermath of the storm, agencies like FEMA and other government organizations stepped in and helped with the recovery effort. Escambia County administrators stopped most public projects in order to better facilitate recovery efforts. This helped to reduce recovery time and start to get the community back to normal. The lower risk SoVI values help to show the decreased recovery time in this county because of the lack high risk social factors.

4.2 Hurricane Katrina (2005)
The first advisory used for Katrina was 19 taken on August 27 at 10 PM Central Time. At this time, Katrina was listed as a category 3 storm with maximum sustained winds of 115 mph. It was located in the center of the Gulf of Mexico to the Southeast of the Louisiana Coast. As a category 3 storm, the risk values seen after the model runs are considerably less than those seen in the early model runs for the more powerful Ivan.

Hancock and Harrison Counties in Mississippi have the highest risk values at 3.6541 and 3.4283 followed by Orleans Parish in Louisiana at 3.3757 and Franklin and Jefferson counties in Florida at 3.1088 and 2.9052 (Figure 4.4). As with Ivan, Hancock and Harrison Counties are most influenced by high storm surge values ranging from 2.1458 to 1.9659 after normalization. Low SoVI values contributed to a decrease in risk for these two counties while evacuation times added slightly to the risk. Orleans Parish was also greatly affected by storm surge with 2.2658 units being added to the total risk. However, unlike the Mississippi counties, Orleans Parish had a higher SoVI value that added .4406 units. Low evacuation times of 12.5 hours contributed to a 0.8307 decrease in risk. It is interesting to see the outliers of Franklin and Jefferson Counties in Florida having high risk values. These counties have lower surge values but extremely high evacuation times and SoVI values.

Data taken for hurricane Katrina was from datasets related to advisory 23 from the morning of September 28, 2005. At this point, Katrina had a sustained wind speed of 150 kts, which signifies a category 5 storm. For this reason, risk values seen for the analysis model runs of Katrina are some of the highest seen in this simulation. Hancock County, Mississippi was shown to have the highest risk value at 5.5192 followed by
Harrison County, Mississippi at 5.1838 and Plaquemines Parish, Louisiana at 4.4374. Orleans Parish, Louisiana had the 5th highest risk value at 4.2069 (Figure 4.5). The primary causes for high risk values in Hancock County were that of extremely high storm surges and long evacuation times combined with a direct strike from the storm. Storm surge probabilities for Hancock County reached as high as 44% for a 10-foot storm surge. This is only exceeded by a 47% 10-foot storm surge in Plaquemines Parish. These storm surge risk estimates would most likely be even higher with the >15 and >20 probabilities included as well. Each of the counties with the highest risk values possessed evacuation times greater than 50 hours. The danger of a category 5 storm approaching the coast has the potential to cause mass evacuations thus clogging the roads and making evacuation times longer. The three Mississippi Counties (all in the top 5 counties with the highest risk), do not have a major south to north thoroughfare. Interstate 10 runs through all three counties but is an east to west artery. Since these counties are located at the center of the impact zone, counties to their east and west will also be evacuating making Interstate 10 very difficult to use. The five counties with the highest total risk consisted of relatively low SoVI values. These values ranged from -3.5507 in Plaquemines Parish to .9216 in Orleans parish and decreased the risk by a range of 1.4315 to 0.3643.

The advisory used for Katrina was advisory 25 and occurred on August 28 at 10 PM Central Time when the storm was just south of the Louisiana Coast. Maximum sustained wind speeds were recorded at 160 mph indicating that Katrina remained a category 5 storm. It is very rare to have a category 5 hurricane this close to the Gulf Coast so Katrina gives the risk analysis model a great baseline for a worst case scenario.
storm. Once again, Hancock and Harrison Counties were most at risk with 5.3374 and 5.1269 risk units respectively. Storm surge values were still incredibly high and added 2.4206 and 2.2559 risk units to the overall risk. Relatively high evacuation times added .7812 risk units and low SoVI values contributed to a 0.3643 and 0.4102 unit decrease in the total risk. In advisory 25, Orleans Parish had the 3rd highest risk at 4.2618 units particularly due to increased storm surge estimates from advisory 23 to 25 (Figure 4.6). The new storm surge values added 2.2230 units to the total risk while lower evacuation times contribute to a 0.9017 unit decrease and SoVI values add 0.4406 units to the total. The high evacuation times and highest storm surge values of the data set contribute to the fourth highest risk rating of Plaquemines Parish. The risk is less than the other counties/parishes discussed because low SoVI values decrease the risk by a factor of 1.4315 units.

The risk analysis performed on the three advisories associated with hurricane Katrina provided values that closely mimicked the real life events. Much of the damage was concentrated in Eastern Louisiana and Mississippi. However, it is impossible for the model to completely represent the events the occurred in the city of New Orleans. None of the data sets used in the model could anticipate the mass levy failures and subsequent catastrophic flooding that occurred in the city. Also, with only the >5 foot and >10 foot storm surge values available, the model may underestimate the actual storm surge amounts that occurred along the Louisiana and Mississippi Coasts. For these reasons, risk values could have been even higher than what is represented in the model output.
4.3 Hurricane Ike (2008)

The first available data for Ike occurred with advisory 41 on September 11, when the storm was well off the Texas Coast in the South Central Gulf of Mexico. Ike was listed as a category 2 storm with maximum sustained winds of 100 mph. The model reflected the lower strength of the storm as compared with that of Ivan and Katrina. After the model was run, it was discovered that two outlying counties had some of the highest risk. The cone projected Ike to strike the central of Eastern Texas Coast but Franklin and Jefferson counties in Florida had some of the highest risk. This is because of the combination of high SoVI values and evacuation times. The model is set so that risk is calculated only in counties where the NHC has issued increased storm surge values. In the case of Ike, a small storm surge was projected for these counties in Florida and that is what caused increased risk to be recorded for these counties. Since Ike did not immediately impact the Florida area, these counties will be disregarded and treated as outliers. Counties under the immediate effect of Ike with the highest risk were all located in Texas. Jefferson, Galveston, and Jackson Counties were most at risk with values ranging from 2.6223 to 2.3814 (Figure 4.7). High storm surge values added between 1 and 2.7 risk units to the overall risk and this is where most of the risk was experienced. Higher risk SoVI values added slightly to the total risk while low evacuation times decreased the risk in these counties.

The second data set for Ike occurred with advisory 45 at 4 AM Central Time on September 12. Ike was listed as a category 2 storm with wind in excess of 105 mph. The risk analysis model is able to greatly narrow down the high risk zone as compared with
the data from advisory 41. Jefferson, Galveston, and Chambers Counties in Texas have
the highest risk associated with Ike at this time. The total risk values are much lower than
other storms with totals of between 2.5526 and 2.0977 for the three riskiest counties
(Figure 4.8). This is because low SoVI values either add very small amount of risk or
help to decrease the risk of a county. Low evacuation times also decrease the risk. This
leaves most of the risk seen from Ike to be generated by the wind speed (category) and
the storm surge. The storm surge estimates added between 2.5662 and 2.4446 risk units
to these counties.

The final data set used for Hurricane Ike that corresponded to advisory 47 that
took place on 4 pm on September 12, 2008. At this point in time Ike was listed as a
strong category 2 storm with maximum sustained winds around 105 mph. The counties
with the highest risk are mostly in Texas and Louisiana. Jefferson, Galveston, Chambers,
and Willacy counties in Texas produced risk values of 2.6103, 2.3423, 2.0741, and
1.6368 with Cameron County, Louisiana producing a risk value of 1.5525 (Figure 4.9).
There is a wide range of SoVI values in this area of the Gulf Coast and the counties have
values ranging from -4.1934 in Chambers County, Texas, to 7.7064 in Willacy, Texas.
These SoVI values add between 3.2808 and 0.1 risk units to the total. The evacuation
times are also much lower than those seen in Mississippi with the greatest time of 21
hours occurring in Chambers, Texas which coincided with a 0.2726 total risk increase.

The aftermath of Hurricane Ike saw widespread damage in the Galveston, Texas
area. The risk model captured this as Galveston County was one of the counties with the
highest risk. However, the risk values were not as high as those for Katrina and Ivan
because of the lower SoVI values as well as low evacuation times. Hurricanes in this portion of the Gulf Coast are more common and for this reason, people are able to better handle evacuations in an orderly fashion and they know the preparations to take in the face of an oncoming storm to make recovery easier after the storm passes.

4.4 Hurricane/Tropical Storm Ida (2009)

Ida is a much weaker storm but allows for the use of the \(<15 \text{ and } <20\) foot surge data if such areas exist, the cone of uncertainty calculations, as well as examine risk of smaller tropical cyclones near the Florida Panhandle. The first data set for Ida was taken for advisory 20 on November 20 with category 2 strength wind speeds of 100 mph recorded. Ida was located just east of the Yucatan Peninsula with a northerly path. Risk values were considerably high due to the fact the forecasted path of Ida took the storm into the East Coast of Florida. Franklin, Citrus, Dixie, and Escambia Counties in Florida had the highest risk values. They ranged from 4.2209 to 3.7839 units respectively (Figure 4.10). The abnormality seen in the riskiest county of Franklin showed that storm surge actually had a negative correlation to the total risk. Most of the risk in this county come from high evacuation times as well as high SoVI values. The other counties had relatively high increased risk from storm surge as well as SoVI values, with a slight increase in risk from evacuation times.

Advisory 22 was issued on November 9 at 3 AM Central Time with category 1 strength wind speeds of 90 mph. Ida had moved north and is directly south of the Mississippi/Alabama state line. The track of the storm still predicts Ida will take a sharp easterly turn very close to landfall. For this reason, the Florida counties are still the most
at risk. Franklin, Jefferson, Taylor and Levy Counties have risk values ranging from 4.7002 to 3.5619 (Figure 4.11). Each of these counties is affected by higher than average storm surge, evacuation times, and SoVI values. The greatest predictor of risk for Franklin County is the SoVI while the other counties are most affected by storm surge.

The final data was taken at the time of advisory 24 on November 9, 2009 when maximum sustained wind speeds of 70 mph were present. This placed Ida as a tropical storm strength system. As the storm traveled closer to the coast, the risk for the land falling counties in Alabama increased. Baldwin and Mobile Counties in Alabama had the highest risk values at 4.2936 and 3.2309 (Figure 4.12). These risk are most affected by storm surge, which adds 3.8673 and 2.4957 risk units to the total. Low SoVI values help to decrease the risks while long evacuation times increase risk for each county by a factor of 1.1505. The Florida counties have decreased surge risk because of the weakening of the storm but are still prevalent as some of the riskiest counties.

Ida brought widespread flooding to the Gulf Coast. Because of its size and odd path, most of the damage came from flooding caused by rainfall and storm surge. Since this was a weak storm, the winds did not play as much of a factor as with the other storms examined in the project. The geography of the Florida Coast caused high storm surge prediction probabilities as well as inflated evacuation times. The evacuation times for the Florida counties are for a worst case scenario and may overestimate the risk, especially for a weaker storm, such as Ida, in which most people will try and ride out the storm in their homes.
4.5 Hurricane Isaac (2012)

Viable Isaac data began with advisory 28 on August 27 at 10 PM Central Time with 70 mph tropical storm force winds. The projected path takes Isaac through the city of New Orleans. The riskiest counties for this advisory were Hancock in Mississippi, Franklin in Florida and Orleans in Louisiana. Hancock County, Mississippi and Orleans Parish, Louisiana showed an extremely large surge risk of 2.9149 and 2.3306 risk units (Figure 4.13). The SoVI helped to diminish the risk while evacuation times added slightly in Hancock County and decreased risk in Orleans Parish. As discussed earlier, the SoVI for Franklin County, Florida contributed most to the total risk with 2.0295 units. Evacuation time added 1 risk unit while storm surge was less than the norm.

The next set of Isaac data was taken for advisory 30 at 4 AM Central Time on August 29. The wind speeds remained tropical storm strength at 70 mph. Drastic differences in risk values are realized for advisory 30. Hancock County, Mississippi remains the county most at risk from Isaac at 3.4050 risk units while Baldwin County, Alabama and Plaquemines Parish, Louisiana have risk values of 1.4284 and 1.2628 respectively (Figure 4.14). These new values stem from a change in the surge risk. Plaquemines now has a much higher surge risk addition of 3.0145 units but its SoVI values help to diminish the risk considerably. Hancock County still has a high storm surge and low SoVI while Baldwin County has high storm surge, high evacuation time, but low SoVI values. Because of the proximity of the storm to the coast and the available data, only two data sets were useful to determine the risk of Isaac.
Hurricane Isaac left approximately 50,000 homes damaged mostly in Plaquemines and Orleans Parishes. This is consistent with the results of the model output. Isaac was a very slow moving storm so the combination of increased wind speeds and long periods of rain along with increased storm surge contributed to most of the damage. According the Louisiana Damage Authority, Isaac caused about one third the damage of Katrina and this is substantiated in the risk values.
Figure 4.1 Hurricane Ivan risk at advisory 48
Figure 4.2 Hurricane Ivan risk at advisory 51
Figure 4.3 Hurricane Ivan risk at advisory 52
Figure 4.4 Hurricane Katrina risk at advisory 19
Figure 4.5 Hurricane Katrina risk at advisory 23
Figure 4.6 Hurricane Katrina risk at advisory 25
Figure 4.7 Hurricane Ike risk at advisory 41
Figure 4.8 Hurricane Ike risk at advisory 45
Figure 4.9 Hurricane Ike risk at advisory 47
Figure 4.10 Hurricane Ida risk at advisory 20
Figure 4.11 Hurricane Ida risk at advisory 22
Figure 4.12 Hurricane Ida risk at advisory 24
Figure 4.13 Hurricane Isaac risk at advisory 28
Figure 4.14 Hurricane Isaac risk at advisory 30
5.1 Conclusions

The purpose of this project was to develop a risk analysis model using a combination of socio-economic values and tropical storm information. This model was developed using the MATLAB programming language in combination with GIS data. After the completion of the model, it was run for three advisories for five separate storms. These model runs were designed to show the change in risk as the storm progressed towards land and the NHC storm data continued to change. Evaluation of the results of the model, indicate that the model provides accurate information that will assist individuals living in affected areas and emergency management officials to better plan for an approaching hurricane. The most interesting information in terms of model output was that each of the variables played an important role in determining the risk. For example, the SoVI values for Franklin County, Florida during hurricane Ida provided for the highest increase in risk, while other counties were mostly affected by Ida’s increased storm surge. The main cause of the increased SoVI risk of Franklin County is that it is sparsely populated with minimal emergency services. Franklin County consists primarily
of a swamp and wetland used for recreational activities. Much of the risk of the Alabama and Mississippi counties stems from storm surge, but also long evacuation times. The main thoroughfare running through these coastal counties is United States Interstate 10. This interstate is an East/West road and if the county is at the center of a hurricanes path, the road becomes congested and it is difficult to evacuate. While the counties do have North/South state routes, these a made up of smaller roads that crowd easily and make evacuations difficult. Some counties along the Florida Coast also have large evacuation times because of the peninsular shape of the state. If a large storm approaches Florida, scores of people will try to evacuate on the few roads leading to more northern states.

As the storm tracked closer to the coast, the model became increasingly accurate. This is because the National Hurricane Center could provide better track and storm surge estimates. A great deal of research is being conducted in order to better predict tropical storm track and strength. As research advances the accuracy of these measurements, the accuracy of this project’s model will also improve. However, since no risk analysis model is perfect, new information and data inputs will also help to increase the model accuracy.

Finally, the counties towards the western part of the project area see considerably less risk than those in the central and eastern portions. This is because of geography as well as preparedness. The counties in Texas saw considerably less storm surge because of barrier islands protecting the mainland as well as mitigation techniques such as the sea wall in Galveston. Some counties in Mississippi, Alabama, and Florida do not have the natural protection of barrier islands and the geography of the land is much more
conducive to higher storm surges. Texas also has a long history of major hurricane activity. This gives those residents and emergency management officials a better understanding of the hazard being faced and this increased knowledge can be seen in decreased evacuation times for these counties.

5.2 Future Work

The only way to have a perfect risk analysis model is to have data that represents every facet of the hazard and the affected area. One piece of the project that could be reevaluated in future projects is the social vulnerability index. The SoVI used in this project placed an emphasis on the population of an area. For example, the city of New Orleans, Louisiana had a much lower SoVI risk than the sparsely populated county of Willacy, Texas. This is based on the fact that New Orleans has more services such as hospitals, and wellness facilities. However, in the case of a strong tropical storm, New Orleans has many more elements at risk than would be present in Willacy, Texas. For a future research project, a hurricane specific social risk index could be developed. This index could take variables such as building types, hurricane mitigation in architecture, asset proximity to the coast, and hurricane specific wellness organizations. The SoVI is a great start for a hurricane risk analysis model, but a hurricane specific risk index could provide even better data.

Another piece of information that would be useful for future projects is utilities information. A major factor in an area’s recovery time is how quickly power, water, and sewer services are repaired and functioning normally for a community. This information
is not readily available to the general public because of terrorist fears as well as difficulty in mapping these systems. Attempts were made to obtain power grid information for this project but a data set with the needed GIS information cost upwards of $800 per state. This was cost prohibitive for a thesis project but could be incorporated into future, funded projects. Obtaining utilities information is vital to determining recovery time and thus the overall storm risk.
REFERENCES


Freimarck, George. "EQECAT Licenses Data Products, Insured Exposure Database and Insured Loss Data Base." Message to the author. 27 June 2013. E-mail.


Needham, Hal. "SURGEDat." Message to the author. 15 June 2013. E-mail.


<http://web.mst.edu/~rogersda/levees/Historic%20background%20on%20the%20New%20Orleans%20Levee%20system%20Chapter%204.pdf>.


<http://www.louisianafolklife.org/LT/Articles_Essays/Lfmmoral.html>.


<http://water.epa.gov/infrastructure/watersecurity/emergencyinfo/pre-hurricane.cfm>.


Appendix A

STORM CONE OF UNCERTAINTIES

Figure A.1 Hurricane Ivan cone advisory 48
Figure A.2 Hurricane Ivan cone advisory 51

Figure A.3 Hurricane Ivan cone advisory 52
Figure A.4 Hurricane Katrina cone advisory 19

Figure A.5 Hurricane Katrina cone advisory 23
Figure A.6 Hurricane Katrina cone advisory 25

Figure A.7 Hurricane Ike cone advisory 41
Figure A.8 Hurricane Ike cone advisory 45

Figure A.9 Hurricane Ike cone advisory 47
Figure A.10 Hurricane Ida cone advisory 20

Figure A.11 Hurricane Ida cone advisory 22
Figure A.12 Tropical Storm Ida cone advisory 24

Figure A.13 Tropical Storm Isaac cone advisory 28
Figure A.14 Tropical Storm Isaac cone advisory 30
Appendix B

SoVI VARIABLES

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>DESCRIPTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>QASIAN</td>
<td>Percent Asian</td>
</tr>
<tr>
<td>QBLACK</td>
<td>Percent Black</td>
</tr>
<tr>
<td>QHISP</td>
<td>Percent Hispanic</td>
</tr>
<tr>
<td>QNATAM</td>
<td>Percent Native American</td>
</tr>
<tr>
<td>QAGEDEP†</td>
<td>Percent of Population Under 5 Years or 65 and Over</td>
</tr>
<tr>
<td>OFAM†</td>
<td>Percent of Children Living in Married Couple Families</td>
</tr>
<tr>
<td>MEDAGE</td>
<td>Median Age</td>
</tr>
<tr>
<td>QSSBEN</td>
<td>Percent of Households Receiving Social Security</td>
</tr>
<tr>
<td>QPOVTY</td>
<td>Percent Poverty</td>
</tr>
<tr>
<td>QRIC200K†</td>
<td>Percent of Households Earning Greater Than $200,000 Annually</td>
</tr>
<tr>
<td>PERCAP</td>
<td>Per Capita Income</td>
</tr>
<tr>
<td>QESL†</td>
<td>Percent Speaking English as a Second Language with Limited English Proficiency</td>
</tr>
<tr>
<td>QFEMALE</td>
<td>Percent Female</td>
</tr>
<tr>
<td>QFH</td>
<td>Percent Female Headed Households</td>
</tr>
<tr>
<td>QNRRES</td>
<td>Percent of Population Living in Nursing and Skilled-Nursing Facilities</td>
</tr>
<tr>
<td>HOSPTPC</td>
<td>Hospitals Per Capita (County Level ONLY)</td>
</tr>
<tr>
<td>QNOHLT†</td>
<td>Percent of Population Without Health Insurance (County Level ONLY)</td>
</tr>
<tr>
<td>QED12LES</td>
<td>Percent with Less Than 12th Grade Education</td>
</tr>
<tr>
<td>QCVLUN</td>
<td>Percent Civilian Unemployment</td>
</tr>
<tr>
<td>PPLUNIT</td>
<td>People Per Unit</td>
</tr>
<tr>
<td>QRENTER</td>
<td>Percent Renters</td>
</tr>
<tr>
<td>MDHSEVAL†</td>
<td>Median House Value</td>
</tr>
<tr>
<td>MDGRENT†</td>
<td>Median Gross Rent</td>
</tr>
<tr>
<td>QMOHO</td>
<td>Percent Mobile Homes</td>
</tr>
<tr>
<td>QEXTCT</td>
<td>Percent Employment in Extractive Industries</td>
</tr>
<tr>
<td>QSERV</td>
<td>Percent Employment in Service Industry</td>
</tr>
<tr>
<td>QFEMLRB</td>
<td>Percent Female Participation in Labor Force</td>
</tr>
<tr>
<td>QNOAUTO†</td>
<td>Percent of Housing Units with No Car</td>
</tr>
<tr>
<td>QUNOCCHU</td>
<td>Percent Unoccupied Housing Units</td>
</tr>
</tbody>
</table>

Table B. 1 SoVI Variables