Tropical Cyclone Risk and Social Vulnerability Amongst Small and Medium-Sized Cities Along the Gulf of Mexico in the United States

by

Miranda Rose Silano

A thesis submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Master of Science

Auburn, Alabama
August 5, 2023

Keywords: tropical cyclones, social vulnerability, natural hazard risk estimation, small and medium-sized cities, Geographic Information Systems, Gulf of Mexico coastal cities

Approved by

Chandana Mitra, Chair, Associate Professor, Department of Geosciences, Auburn University
Christopher Burton, Affiliate Professor, Department of Geosciences, Auburn University
Sweta Byahut, Associate Professor, Department of Political Sciences, Auburn University

Abstract

As climate change continues to warm the waters of the Gulf of Mexico in the United States, tropical cyclone intensity in the region may increase which will threaten vulnerable communities. The goals of this project include estimating the physical damage risk to small- and medium-sized cities, the socially vulnerable populations therein, and the relationship between physical risk and social vulnerability for these communities. Hazus, FEMA's risk-estimating tool, was used to determine the physical risk to each study site and showed higher risk areas were associated with severe winds. A principal component analysis was used on U.S. Census data to construct a social vulnerability index of each site. Spatial analyses determined that there were fewer areas of statistically significant correlations between risk and vulnerability than statistically significant areas, meaning vulnerability may not be as strong a determinant of risk. Studies on risk should include and explore other determinants beyond social vulnerability.

Acknowledgements

I'll start by thanking those on the academic front who helped me complete my thesis. First, I'd like to thank my advisor, Dr. Chandana Mitra, for her support throughout the two years it has taken me to do my thesis. She took a chance on me, and I am grateful for the opportunity. Secondly, I'd like to thank my committee members, Dr. Christopher Burton, and Dr. Sweta Byahut, for their support. If it weren't for Dr. Burton's Natural Hazard Risk and Disaster Resiliency course, I may not have learned about the topics and methodologies that helped shape my thesis. Thank you to Brandon Ryan, Syeda Nazifa Tasneem, Megha Shrestha, and Sukanya Dasgupta for their extra help, specifically when it came to learning methodologies and comprehending results. I'd like to thank all the friends that I have made while at Auburn University. I am grateful for our friendship and your support while I have worked on my thesis. I also have my friends from my time at the University of Florida and my hometown of Naples, Florida, who have helped me grow over several years of friendship and provided me with support, even if from hundreds (in two cases, thousands) of miles away. My boyfriend, Ed, deserves a shoutout as well as he has constantly reminded me that I am fully capable of completing a thesis and Master's degree. Thank you to my family for their reminders that anything is possible with hard work and drive. My family's experience with Hurricane Ian (discussed later in my thesis) also served as a driving source for me to examine the significance of tropical cyclone impacts. A special thanks to my mom, who graduated with her fourth (yes, 4th) Master's degree just before I graduated with mine, and who has served as an inspiration to me throughout my entire life and my educational journey. I would like to thank you – yes, you, the reader! I once heard that science is not over until it is communicated. You reading my thesis helps me fulfill this, and I hope you enjoy and learn from my thesis.

Table of Contents

Abstract …………………………………………………………………………………...…2

Acknowledgements…………………………………………………………………….................3

List of Tables……………………………………………………………………………...……7

List of Figures………………………………………………………………………….........8

List of Equations……………………………………………………………………….....11

List of Abbreviations………………………………………………………………………12

NSF Reporting Statement…………………………………………………………………..13

Chapter 1: Introduction to Thesis..…………………………………………………………14

1.1 Introduction.…………………………………………………………….............. 14

1.2 Background…………………………………………………………………………16

1.2.1 Tropical Cyclones ...……………………….……………………….................16

1.2.2 Vulnerability…….………………………………………………………………18

1.2.3 Risk Mitigation and Perception……………………………………….……………...20

1.3 Study Sites ……………………………..…………………………...……………...22

1.4 Research Objectives, Questions, and Hypotheses …………………………...………28

1.5 Significance…………………………………………………………….............30

1.6 Overview of Coming Chapters……………………………………………….……….32

Chapter 2: The Risk of Physical Damages by Tropical Cyclones……….…………………….… 33

2.1 Introduction……………………………………………………………...……….……33

2.2 Background…………………………………………………………………………... 34

2.2.1 Hazus………………………………………………………………………….34

2.3 Research Question, Hypothesis, and Objective……………………………………….35

2.4 Data…………………………………………………………………………………... 36

2.5 Methods…………………………………………………………………...............37

2.6 Results……………………………………………………………………………….. 39

2.7 Discussion………………………………………………………….....……… 47

Chapter 3: Social Vulnerability Amongst the Study Sites .....………………………………… 51

3.1 Introduction………………………………………………………………………….. 51

3.2 Background………………………………………………………………………….. 51

3.2.1 Social Vulnerability………………………………………………………… 51

3.2.2 Factors Impacting Social Vulnerability…………………………………........... 52

3.2.3 Principal Component Analysis……………………………………………….55

3.3 Research Question, Hypothesis, and Objective………………………………...........56

3.4 Data………………………………………………………………………………… 56

3.5 Methods………………………………………………………………………………57

3.6 Results……………………………………………………………………………..61

3.7 Discussion………………………………………………………………………... 67

Chapter 4: The Relationship Between Risk for Physical Damage and Social Vulnerability…..70

4.1 Introduction…………………………………………………………………………70

4.2 Background…………………………………………………………..………………70

4.2.1 Social Vulnerability's Influence on Risk for Physical Damage……...………...70

4.2.2 Bivariate Local Moran's I Spatial Statistic…………………………..……...72

4.3 Research Question, Hypothesis, and Objective…………………………………...73

4.4 Data…………………………………………………………………………..…….. 74

4.5 Methods……………………………………………………………...……….……...74

4.6 Results………………………………………………………………………………75

4.7 Discussion…………………………………………………...………………85

Chapter 5: Conclusions, Limitations, Future Directions, and Significance…...………………88

5.1 Conclusions……………………………………………………………………88

5.1.1 Question 1………………………………………………………...………88

5.1.2 Question 2……………………………………………………………...88

5.1.3 Question 3……………………………………………………………...89

5.2 Limitations…………………………………………………………….........89

5.2.1 Question 1……………………………………………………………...89

5.2.2 Question 2……………………………………………………………...91

5.2.3 Question 3……………………………………………………………...92

5.3 Future Directions………………………………………………………………92

5.3.1 Question 1…………………………………………………………..92

5.3.2 Question 2…………………………………………………………..93

5.3.3 Question 3…………………………………………………………..94

5.4 Significance…………………………………………………………………...95

References…………………………………………………………………………………98

List of Tables

Table 1.1 A table describing the population, location, area, state, and percent of the population from the county residing in the city for each of the five study site cities……………….........27

Table 2.1 A table of the highest and lowest wind speeds by hurricane category experienced within at least one Census tract for all five cities…………………………………………...46

Table 2.2 A table of the highest and lowest number of displaced households within at least one Census tract for all five cities……………………………………………………………….46

Table 2.3 A table of the highest percentage of no building damage and the highest percentage of building damage (calculated by subtracting the lowest percentage of buildings with no damage from 100) within at least one Census tract for all five cities……………………………........46

Table 2.4 A table of the highest total economic loss amount (in USD) and the lowest total economic loss amount (in USD) within at least one Census tract for all five cities…….…….46

Table 3.1 A table showing the KMO value, the number of components, and the socially vulnerable group that is responsible for most of the variance in PC1, by city………………..61

Table 3.2 A table showing the component number for each city and its corresponding eigenvalue, variance explained (as a percentage), and dominant socially vulnerable group. Results for the Component Group are drawn from the Rotated Component Matrix..62

Table 3.3 A table showing each city and how many Census tracts were included in the SVI, along with how many Census tracts fell within each SVI rating…………………………..…65

Table 3.4 A table displaying the mean values of each city for all six variables *as a percentage of what they make up of the total population of their city.* All values are rounded to the nearest whole number…………………………………………………………………...……….66

Table 4.1 The number of Census tracts in the four statistically significant groups and one not statistically significant group for each risk factor map for Brownsville, Texas…………………………………………………………………………………………..77

Table 4.2 The number of Census tracts in the four statistically significant groups and one not statistically significant group for each risk factor map for Lafayette, Louisiana……………..79

Table 4.3 The number of Census tracts in the four statistically significant groups and one not statistically significant group for each risk factor map for Mobile, Alabama………………...81

Table 4.4 The number of Census tracts in the four statistically significant groups and one not statistically significant group for each risk factor map for Cape Coral, Florida……………...84

List of Figures

Figure 1.1 A map of all five study sites along the United States Gulf of Mexico Coastline…………………………………………………………………………………..24

Figure 1.2 A map displaying Brownsville, Texas, and where Brownsville is in Texas……………………………………………………………………………….………...24

Figure 1.3 A map displaying Lafayette, Louisiana, and where Lafayette is in Louisiana...25

Figure 1.4 A map displaying Gulfport, Mississippi, and where Gulfport is in Mississippi……………………………………………………………………….............25

Figure 1.5 A map displaying Mobile, Alabama, and where Mobile is in Alabama………...26

Figure 1.6 A map displaying Cape Coral, Florida, and where Cape Coral is in Florida…………………………………………………………………………………..26

Figure 2.1 The wind speeds from a probable 100-year hurricane in Brownsville by Census tract and the storm track……………….…………………………………………………..40

Figure 2.2 The number of displaced households within Brownsville following a 100-year hurricane by Census tract…………………………………………...…………………..40

Figure 2.3 The expected percentage of buildings with no damage from a probable 100-year storm within Brownsville by Census tract…………………………………………..........40

Figure 2.4 The money that is lost in thousands of dollars, by Census tract, from a probable 100-year storm within Brownsville…………………………………………………….........40

Figure 2.5 The wind speed by category within a Census tract that is likely to be experienced by a probable hurricane in a 100-year scenario in Lafayette, along with the storm track………...41

Figure 2.6 The number of displaced households within a Census tract that would be caused by a probable 100-Year Storm to Lafayette……………………………………………………41

Figure 2.7 The expected amounts of buildings within a Census tract that would experience no damage from a probable 100-year storm within Lafayette…………………………..........41

Figure 2.8 The money that is lost in thousands of dollars, by Census tract, from a probable 100-year storm within Lafayette……………………………..…………………………...……41

Figure 2.9 The wind speed by category within a Census tract that is likely to be experienced by a probable hurricane in a 100-year scenario in Gulfport, along with the storm track ...………42

Figure 2.10 The number of displaced households that would be caused by a probable 100-year storm at the Census block level in Gulfport………………………………………………42

Figure 2.11 The expected amounts of buildings within a Census block that would experience no damage from a probable 100-year storm within Gulfport……………………………….......42

Figure 2.12 The financial loss in thousands of dollars, by Census block, from a probable 100-year storm within Gulfport………………………………………………………….......42

Figure 2.13 The expected wind speed by category is likely to be experienced by a probable hurricane in a 100-year scenario within a Census tract in Mobile, along with the storm track ……………………………….……………………………………………43

Figure 2.14 The number of displaced households within a Census tract that would be caused by a probable 100-year storm in Mobile…………………………………………………......43

Figure 2.15 The buildings within a Census tract that would experience no damage from a probable 100-year storm within Mobile…………………………………………………......44

Figure 2.16 The financial loss in thousands of dollars, by Census tract, from a probable 100-year storm within Mobile………………………………...…………………………………..44

Figure 2.17 The wind speeds from a probable 100-year storm by Census tract in Cape Coral, along with the storm track……………………………………………………45

Figure 2.18 The number of displaced households, by Census tract, following a 100-year hurricane, in Cape Coral……...……………………………………………………………45

Figure 2.19 The buildings that would experience no damage from a probable 100-year storm within a Census tract in Cape Coral……………………………………………………45

Figure 2.20 The financial loss in thousands of dollars from a probable 100-year storm by the Census tract in Cape Coral………………………………………………………….......45

Figure 3.1 The SVI created for Brownsville, Texas……………………………….......63

Figure 3.2 The SVI created for Lafayette, Louisiana……………………………………..63

Figure 3.3 The SVI created for Gulfport, Mississippi……………………………………64

Figure 3.4 The SVI created for Mobile, Alabama………………………………….......64

Figure 3.5 The SVI created for Cape Coral, Florida……………………………….......65

Figure 4.1 A cluster map generated by the Local Bivariate Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Displaced Households due to a tropical cyclone in Brownsville, Texas……………………………………………………76

Figure 4.2 A cluster map generated by the Local Bivariate Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and the Percentage of Buildings with No Damage due to a tropical cyclone in Brownsville, Texas………………………………..76

Figure 4.3 A cluster map generated by the Local Bivariate Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Total Financial Loss due to a tropical cyclone in Brownsville, Texas……………………………………………………77

Figure 4.4 A cluster map generated by the Local Bivariate Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Displaced Households due to a tropical cyclone in Lafayette, Louisiana……………………………...……………….......79

Figure 4.5 A cluster map generated by the Local Bivariate Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and the Percentage of Buildings with No Damage due to a tropical cyclone in Lafayette, Louisiana……………………….……..79

Figure 4.6 A cluster map generated by the Local Bivariate Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Total Financial Loss due to a tropical cyclone in Lafayette, Louisiana…………………………………..……………79

Figure 4.7 A cluster map generated by the Local Bivariate Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Displaced Households due to a tropical cyclone in Mobile, Alabama……………………………………………….…..81

Figure 4.8 A cluster map generated by the Local Bivariate Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and the Percentage of Buildings with No Damage due to a tropical cyclone in Mobile, Alabama………………………………..…81

Figure 4.9 A cluster map generated by the Local Bivariate Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Total Financial Loss due to a tropical cyclone for Mobile, Alabama……………………………………………………….81

Figure 4.10 A cluster map generated by the Local Bivariate Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Displaced Households due to a tropical cyclone in Cape Coral, Florida………………………………………………..83

Figure 4.11 A cluster map generated by the Local Bivariate Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and the Percentage of Buildings with No Damage due to a tropical cyclone in Cape Coral, Florida……………………...….........83

Figure 4.12 A cluster map generated by the Local Bivariate Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Total Financial Loss due to a tropical cyclone for Cape Coral, Florida……………………………………………………84

List of Equations

Equation 3.1 The equation used within Microsoft Excel to calculate the population percentage of each demographic group…………………………………………………………………58

Equation 3.2 The standard equation used when calculating a Z-score…………..…………...58

Equation 3.3 The equation used to calculate the SVI scores, where PC1 is the first principal component, and PCF is the final principal component. The number of principal components between PC1 and PCF varies by study site…………………………………………………59

Equation 4.1 The formula that was developed by FEMA to calculate risk for the National Risk Index…………………………………………………………………………………………...72

List of Abbreviations

AL	Alabama
EF	Enhanced Fujita
ESRI	Environmental Systems Research Institute
FEMA	Federal Emergency Management Agency
FL	Florida
GIS	Geographic Information Systems
IPUMS	Integrated Public Use Microdata Series
KMO	Kaiser-Meyer-Olkin
LA	Louisiana
MS	Mississippi
NCEI	National Centers for Environmental Information
NGHIS	National Historical Geographic Information System
NHC	National Hurricane Center
NOAA	National Oceanic and Atmospheric Administration
NOS	National Ocean Service
NRI	National Risk Index
PCA	Principal Component Analysis
PCF	Final Principal Component
PC1	First Principal Component/Principal Component 1
PC2	Second Principal Component/Principal Component 2
PC3	Third Principal Component/Principal Component 3
SPSS	Statistical Package for the Social Sciences
SVI	Social Vulnerability Index
TX	Texas
UCLA	University of California: Los Angeles
WMO	World Meteorological Organization

NSF Reporting Statement

This material is based upon work supported by the National Science Foundation under Grant Number (NSF Grant #1922687). Any opinions, findings, and conclusions, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

Chapter 1: Introduction to Thesis

1.1 Introduction

Tropical cyclones are well-known for being one of the most feared and destructive weather and climate hazards in the world. “Tropical cyclone” is an umbrella term that refers to an organized system of rotating thunderstorms with a low-pressure center that forms over warm ocean water (Roy and Kovordányi, 2012). Tropical cyclones include tropical depressions, tropical storms, and hurricanes; a categorization based on sustained wind speed (NHC, 2019; WMO, 2022). Tropical depressions have winds under 38 mph, and tropical storms have wind speeds between 39 mph and 73 mph (WMO, 2022). Once a storm has reached 74 mph, it is categorized as a hurricane: specifically, it is a Category 1 hurricane until wind speeds exceed 95 mph (NHC, 2019). Category 2 hurricanes have wind speeds between 96 mph and 110 mph. Category 3, 4, and 5 hurricanes are known as “Major Hurricanes” (NHC, 2022). A Category 3 hurricane has wind speeds between 111 mph and 129 mph (NHC, 2022). A Category 4 hurricane has wind speeds between 130 mph and 156 mph (NHC, 2019). A Category 5 hurricane must have winds that are at least 157 mph; being the deadliest storm category of the Atlantic Ocean tropical cyclones (NHC, 2019). Storms receive names once they have made it to at least tropical storm status (WMO, 2022). Threats such as storm surge, flooding, rip and storm tides, precipitation, damaging winds, landslides, and tornadoes can all be found within a tropical cyclone (WMO, 2022).

The Gulf of Mexico, which has been hit by countless tropical cyclones, is the fastest-growing coastline in terms of population in the United States, with a population increase of 26.1% between 2000 and 2017 (Cohen, 2020). The population moving to this area has varied demographics, and some of these demographics may be more susceptible to tropical cyclone damages. Socially vulnerable populations are social groups with the potential of loss based on the location of people and structures, how susceptible some individuals are, and their ability to prepare and recover based on demographic information (Cutter, 1996; Cutter et al., 2000; Yoon, 2012). These groups, such as the elderly or very young, disabled, not English proficient, lower income, varying ethnicities and races, and females, can be found living in the study sites for this project (US Census Bureau, 2020). This is important because the presence of these groups will affect the area's overall social vulnerability. Delineating the identified groups will be accomplished to better comprehend the vulnerability.

The financial burden that tropical cyclones bring to the Gulf of Mexico are substantial. Between 1980 and July 9, 2021, there have been 39 tropical cyclones to hit the Gulf of Mexico that have individually cost $1 billion (NCEI, 2021). Since 1980, hurricanes cost the Gulf of Mexico an average of $16.2 billion a year, and over the past four decades, have cost the Gulf of Mexico a total of $680.9 billion (NCEI, 2021). In recent years, the average number of billion-dollar weather and climate disasters in the United States has increased. In 2020 alone, 22 weather and climate disasters individually cost over $1 billion. Of these 22 extreme weather events, 7 were tropical cyclones (NOAA, 2021). Tropical cyclones are the most destructive weather and climate disasters historically in the United States, in terms of lives lost as they have been directly responsible for 6,697 deaths, the most deaths out of any weather and climate hazard (NOAA, 2021).

This thesis will explore what the risk from tropical cyclones is to five small and medium-sized coastal cities along the Gulf of Mexico in the United States. The study sites include Brownsville, Texas, Lafayette, Louisiana, Gulfport, Mississippi, Mobile, Alabama, and Cape

Coral, Florida. In addition to the physical risk, the social vulnerability of each study will be investigated by ranking each Census tract in the county, from “Very Low” to a “Very High” social vulnerability. Then, the risk and social vulnerability results are assessed for relationships, specifically if social vulnerability factors into the results of the risk analysis. The goal of this thesis is to take a deep dive into the understanding of the functions of risk and social vulnerability in overall risk assessments. The methodologies utilized in this thesis include Hazus, FEMA’s GIS-based risk-estimating program, constructing a social vulnerability index (SVI) designed from the results of a Principal Component Analysis (PCA), and the Bivariate Local Moran’s I spatial statistic test. The conclusions made from this thesis can be helpful for emergency managers, city and urban planners, disaster relief organizations, and policymakers by providing insight into where physical damage and socially vulnerable populations are located. This awareness will create a better outcome for recovery, mitigation, and preparedness planning and policies that will create more resilient coastal cities.

1.2 Background

1.2.1 Tropical Cyclones

Tropical cyclones require necessary conditions to go from normal thunderstorms to a complex system of thunderstorms. To form, tropical cyclones require warm ocean water (specifically at least about 80º Fahrenheit), low pressure over the ocean due to an atmospheric disturbance, at least 200 miles away from the Equator, and low wind shear so storms can form (NOAA, 2020; NOS, 2021; Roy and Kovordányi, 2012). Tropical cyclones often begin as tropical waves, and as these waves move over warmer water, they become capable of forming thunderstorms that help to fuel the storm and create lower pressure (NSO, 2021). In the Northern Hemisphere (including the Gulf of Mexico), tropical cyclones rotate counterclockwise (WMO, 2022). There is consensus across the scientific community that there is a relationship between tropical cyclone intensity and sea surface temperature (Holland and Bruyère, 2014; Mudd et al., 2014; Dinan, 2017) This is because sea surface temperature affects the intensity of tropical cyclones (NOAA, 2020; NOS, 2021). Recent models are supporting the idea that climate change will cause a spike in higher intensity tropical cyclones, such as fewer lower-category hurricanes, and more major hurricanes (Holland and Bruyère, 2014; Mudd et al., 2014; Dinan, 2017). This is due to an increase in tropical cyclone wind speeds related to rising sea surface temperatures (Holland Bruyère, 2014; Mudd et al., 2014). Additionally, hazards such as storm surge may increase due to climate change's effect on sea level and tropical-cyclone wind intensity (Neumann et al., 2015; Dinan, 2017). The factor of climate change's effect on storm surge can affect populations by increasing tropical cyclone costs, showing the need for climate change to be accounted for in future tropical cyclone risk research (Neumann et al., 2015).

Besides their population size, the study sites (Brownsville (TX), Lafayette (LA), Gulfport (MS), Mobile (AL), and Cape Coral (FL)) were also chosen based on the number of times these cities were in the pathway of a tropical cyclone. Since 1980, within a 31-mile radius around each city, there have been 2 hurricanes that hit Cape Coral, 4 hit Mobile, 5 hit Gulfport, 5 hit Lafayette, and 3 hit Brownsville (NOAA, 2021). These hurricanes include well-known storms such as Hurricanes Irma, Charley, Andrew, Katrina, and Ivan (NOAA, 2021). Hurricane-force winds can extend up to 100 miles across a storm, and tropical storm-force winds can be felt up to 300 miles from the eye of a tropical cyclone (URI, 2020). The strongest winds, those around the eye (the center of a storm where winds are at their weakest), can be felt up to 31 miles away from the edge of the tropical cyclone's eye (URI, 2020). Based on this, hurricane-force winds (winds 74+ mph) should be felt, at most, 31 miles away from the center of the storm. This is how a radius of 31 miles for each study site was decided upon (URI, 2020). This was done to calculate the maximum distance for hurricane-force wind destruction that each study site could have felt by a storm.

1.2.2. Social Vulnerability

Social vulnerability is not hard conceptually to grasp, but it has had a plethora of definitions throughout the years (Cutter, 1996). For this project, social vulnerability will be considered as the potential of loss based on the location of people and structures, how susceptible some individuals are, and their ability to prepare and recover based on demographic information (Cutter, 1996; Cutter et al., 2000; Yoon, 2012). In general, an area of high social vulnerability would be an area where there would be great loss due to too many susceptible people that were at a high exposure and would not be able to recover. An area of low social vulnerability would be at a location not as likely to be damaged by a specific hazard with a population that can adapt and recover from the hazard (Bergstrand et al., 2014). Some definitions of vulnerability, define it as being a function of exposure and sensitivity to a hazard, with exposure being who or what is susceptible to the hazard, and sensitivity being how damaging can the hazard be to those affected by the hazard (Cutter et al., 2008; Dunning, 2020). Exposure can come from areas such as geographic location (being located closer to areas exposed to hazards), issues within the government's framework, or a lack of effective planning. Sensitivity on the other hand can originate from a lack of proper insurance on physical assets. Different levels of exposure and sensitivity are necessary for comprehending how each study site will respond to a hazard (Dunning, 2020).

Several variables determine the social vulnerability of an area. These include the demographics of the areas, ages of the population, financial statuses, physical limitations, education levels, and technology and automotive availability, amongst others (Cutter et al., 2000; Yoon, 2012). Each variable can hold a different weight depending on what area of vulnerability is being examined. For example, some groups may have a harder time evacuating than recovering and vice versa. Someone who is over the age of 65 may have a physically hard time preparing for or evacuating, but if they are not in poverty, may have the money to recover. However, as will likely be seen later, no two variables are mutually exclusive, as an individual may have multiple variables factoring into their vulnerability. In coastal areas, policymakers and local governments understand how their areas are exposed and how sensitive they are critical in making their community less vulnerable to hazards. The response to the hazard is also critical in vulnerability since a community's ability to respond effectively to a hazard overall reduces the vulnerability of a population while increasing resiliency (Dunning, 2020).

Some drivers that impact social vulnerability to storms include race and ethnicity (black, Hispanic, Asian, Native), gender, language (English as a second language), age (the very young and the elderly), disability status and economic situations (poverty status), to name a few (Rufat et al., 2015). A lot of these drivers are not mutually exclusive. The level of income can affect one's ability to prepare for and recover from a tropical cyclone since it costs money to do that. A factor such as level of education is more likely to affect one's ability to prepare if the information is not presented understandably, but if they are able-bodied and physically capable, they may have an easier time recovering. Information such as age, ability, languages spoken, and education can be gathered by examining census data. (Tate, 2012). Identifying the major vulnerable groups in these cities and understanding why these groups are vulnerable can clarify the social damage that could have afflicted them.

1.2.3 Risk Mitigation and Perception

For this project, risk will be defined as the likelihood that a specific hazard is to occur in an area (Cutter, 1996). With this, the impact of the hazard and the source can also be factored in. Comprehending risk and combining mitigation techniques can create an overall hazard potential. Mitigation, for this project, will be defined as fortifying anticipated "weak spots" based on previous occurrences and supporting recovery to reduce the effects of a natural hazard (Adger et al, 2005; Cutter et al., 2008; Cutter et al., 1996; Dunning, 2020). Mitigation involves having a community that can recover from hazards but improves itself after the hazard. In theory, this can range from updating building codes to withstand the hazard or creating evacuation and recovery plans tailored to those living in that area. Being able to mitigate a hazard can also lower vulnerability by decreasing exposure and risk (Adger et al., 2005). Mitigation also creates an increase in resilience (Cutter et al., 2008). These concepts are important as mitigation is hypothesized to affect the physical and social damage that arises after tropical cyclone impacts.

As risk and mitigation can help us understand how a hazard is going to affect an area, understanding the hazard potential is key. While the hazard potential's main components are risk and mitigation, both of those are affected by other factors (Cutter, 1996). In this project, the biggest factors affecting hazard potential besides risk and mitigation will be geographic location and social vulnerability. Geographic location is important when discussing tropical cyclones, and the reason why is in the name: tropical. The threats of these storms in the United States are found within the southeastern United States. This means that people living in other areas of the country are less likely to be affected by tropical cyclones. The Gulf of Mexico was chosen as the location to get study sites because these study sites are geographically in the pathway of hurricanes, making the potential for hazards here higher than for other areas. Social vulnerability is important because if there is a high population of one or several socially vulnerable groups high in one area, even a low magnitude of a specific hazard can have drastic effects. On the opposite end, in areas where social vulnerability is lower, a higher magnitude of a specific hazard may be required to inflict the same damage as a low magnitude hazard in a socially vulnerable area.

Risk perception can factor into how vulnerable a population is, but it also affects resilience. Perceptions can vary based on the type of culture and society they were raised in, the hazard they are experiencing, the media source that provides their news for them, and their own experiences, and that a high-risk perception can lead to better perception of the hazard (Wachinger et al., 2013). Many people within a population who are moving directly on the coast may not have had much experience with tropical cyclones if any at all. The effects of experience on vulnerability work in two ways. The first is that the community is either new to the hazard, and over prepares and makes time to evacuate, or because they are new, they undermine the hazard since they haven't experienced it. The other end of this is that people who have experienced a severe hazard will over prepare or evacuate, but if they have only experienced a weak hazard, they are more likely to be underprepared or not evacuate (Wachinger et al., 2013; Rufat et al, 2015). In terms of tropical cyclones, a great example would be a population that has experienced a major hurricane (Category 3 and above) or a tropical storm or depression (both are below Category 1 as far as wind speed). Communities that have a higher risk perception or understand the severity of the hazard will likely have more mitigation strategies and awareness will be increased, and both can increase resilience by increasing adaptive capacity (Rufat et al., 2015; Turner II et al., 2003).

1.3 Study Sites

The preferred criteria for choosing the study sites for this research was a population between 100,000 to 500,000 people, which is referred to as a medium sized city. A city with a population under 100,000 people is considered a small sized city (Giffinger et al., 2007). Small and medium-sized cities were chosen as they are overlooked in studies that focus on the aftermath of Gulf of Mexico tropical cyclones. The chosen cities for study sites are Brownsville (Texas), Lafayette (Louisiana), Gulfport (Mississippi), Mobile (Alabama), and Cape Coral (Florida) (Figures 1.1, 1.2, 1.3, 1.4, 1.5, and 1.6). All the cities besides Gulfport are medium-sized cities; Gulfport is a small-sized city (Table 1.1) (US Census Bureau, 2020). Each city has been hit by at least one hurricane since 1980 (NOAA, 2021).

When going by population, the definition of a medium-sized city can vary by country and relative size. A rule of thumb can be that a medium-sized city is at least 10% of the largest city in the country; this demonstrates a medium-sized city on a country level (Roberts and Hohmann 2014). Another definition of a medium-sized city is global and requires a city to have a population of 100,000 – 500,000 people (Giffinger et al., 2007; Giffinger & Gudrun, 2010; Roberts and Hohmann., 2014). The largest city in the United States by population is New York City, with a population of 8,336,817 as of July 1, 2019 (US Census Bureau, 2021). 10% of New York City is 833,681; none of the Gulf of Mexico states have a city with a population over 833,681 closest to the Gulf of Mexico as of.

One detail is note is that the shapefile boundary that is designated for Gulfport also includes nearby cities such as Biloxi. The reason for this is due to the definition by the US Census Bureau for Urban Areas, as this shapefile layer from the US Census Bureau was what was used to define the cities. The definition of an urban area changed for the 2020 Census, a normal process following all decennial censuses. Key changes to the definition were the minimum population requirement changing to a minimum housing unit requirement, population density being replaced by housing unit density, and distinguishing between Urbanized Areas and Urban Clusters (Ratcliffe, 2022). The last change is the one that applies to the situation with Gulfport. Previously, Urbanized Areas and Urban Clusters were differentiated based on population size (50,000 people being the defining characteristic). The population of Biloxi is slightly under the previous 50,000 people threshold (49,449) (US Census Bureau, 2021). The population of Gulfport is larger than Biloxi (Table 1.1). This means that based on previous definitions, Gulfport and Biloxi would have different urban classifications. The reason for no longer distinguishing between Urbanized Areas and Urban Clusters is that the economic influence of an urban area has more significance than simply population alone (Ratcliffe, 2022). Gulfport has a larger population, and the effect that this has on the economy goes beyond the city boundaries of Gulfport and reaches nearby cities like Biloxi. The change in this definition provides the most likely explanation for the grouping of Gulfport with smaller cities such as Biloxi.

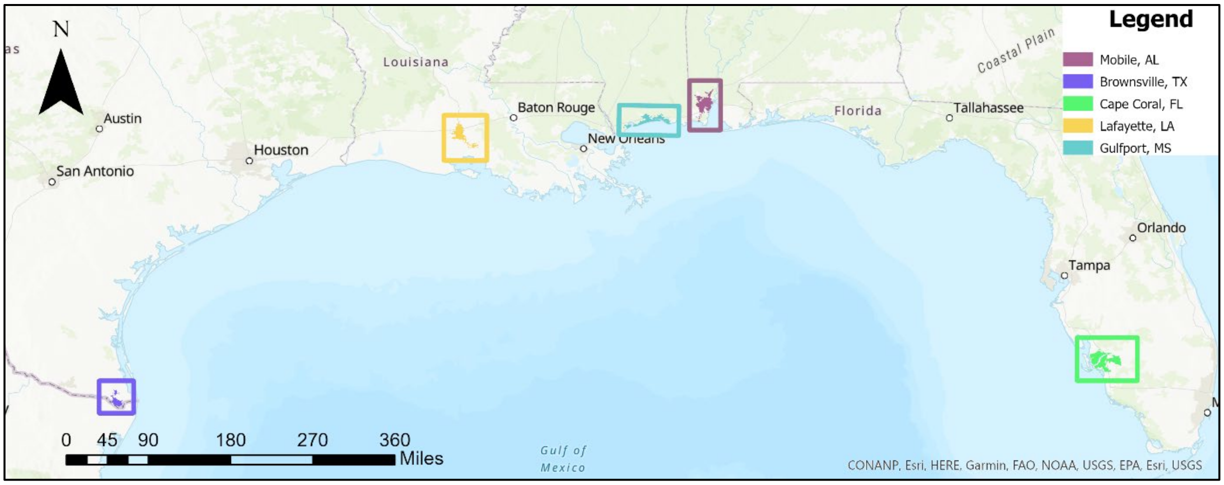


Figure 1.1: A map of all five study sites along the United States Gulf of Mexico coastline.

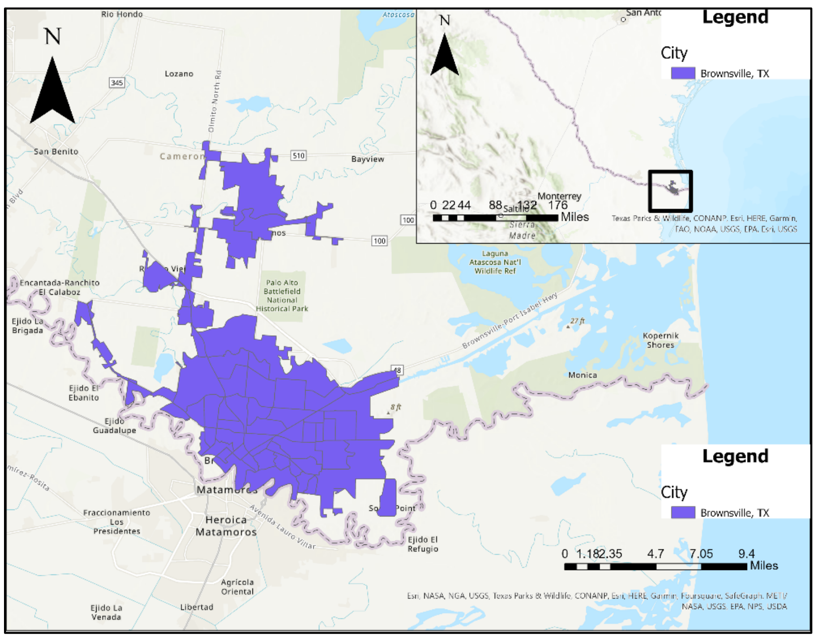


Figure 1.2: A map displaying Brownsville, Texas, and where Brownsville is in Texas.

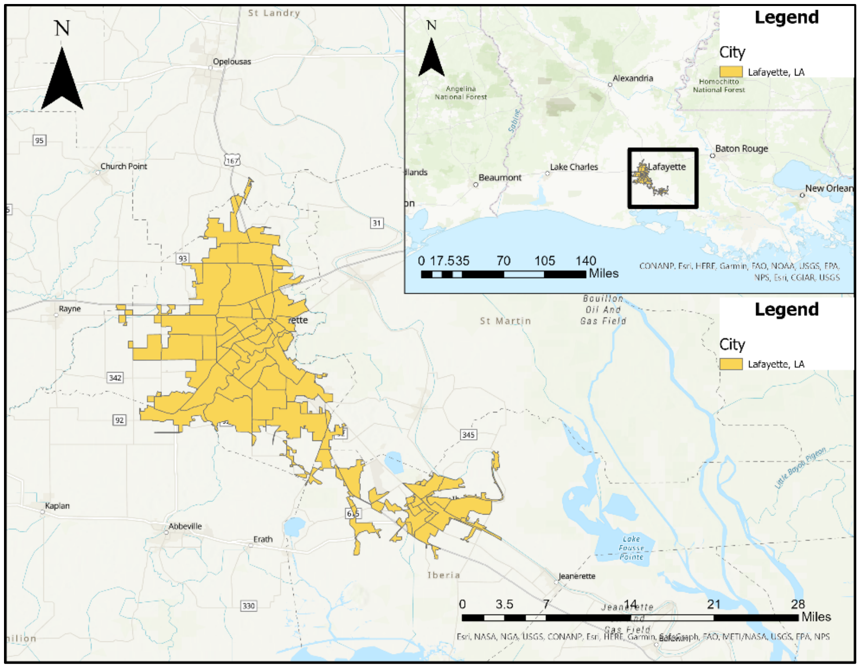


Figure 1.3: A map displaying Lafayette, Louisiana, and where Lafayette is in Louisiana.

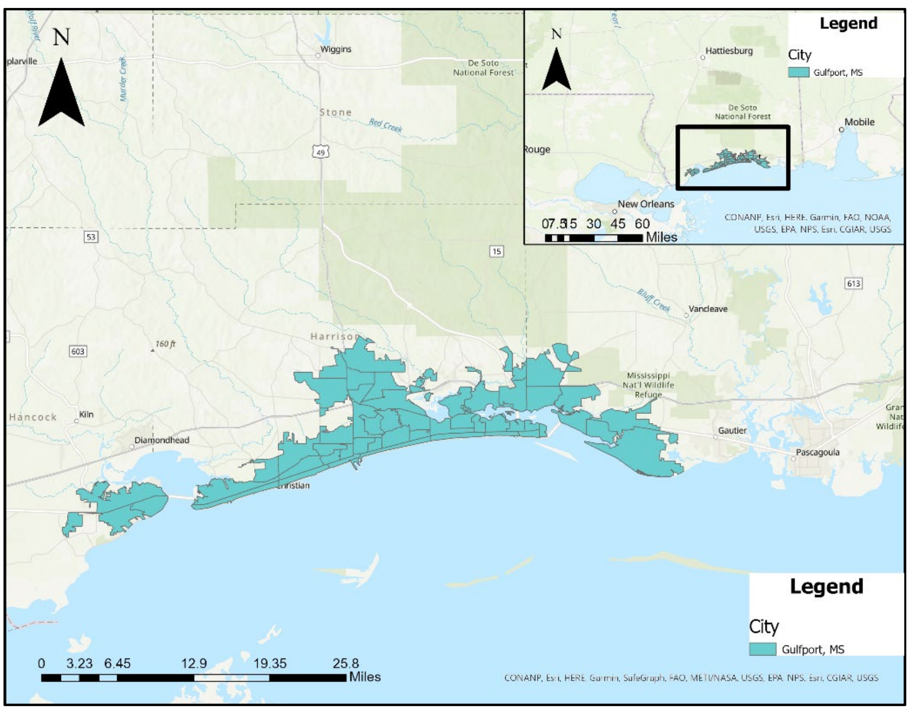


Figure 1.4: A map displaying Gulfport, Mississippi, and where Gulfport is in Mississippi.

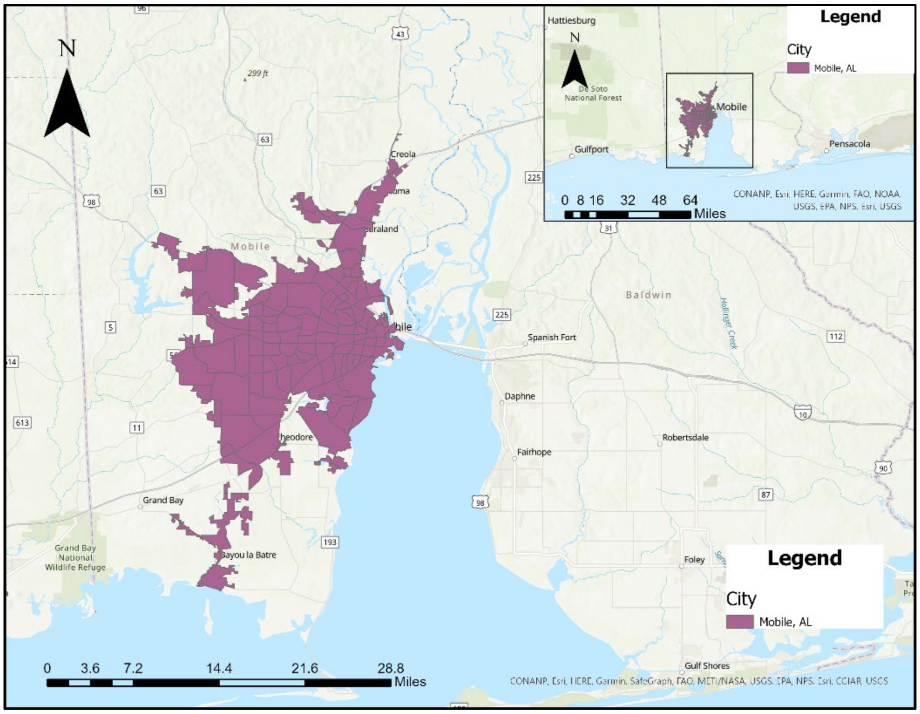


Figure 1.5: A map displaying Mobile, Alabama, and where Mobile is in Alabama.

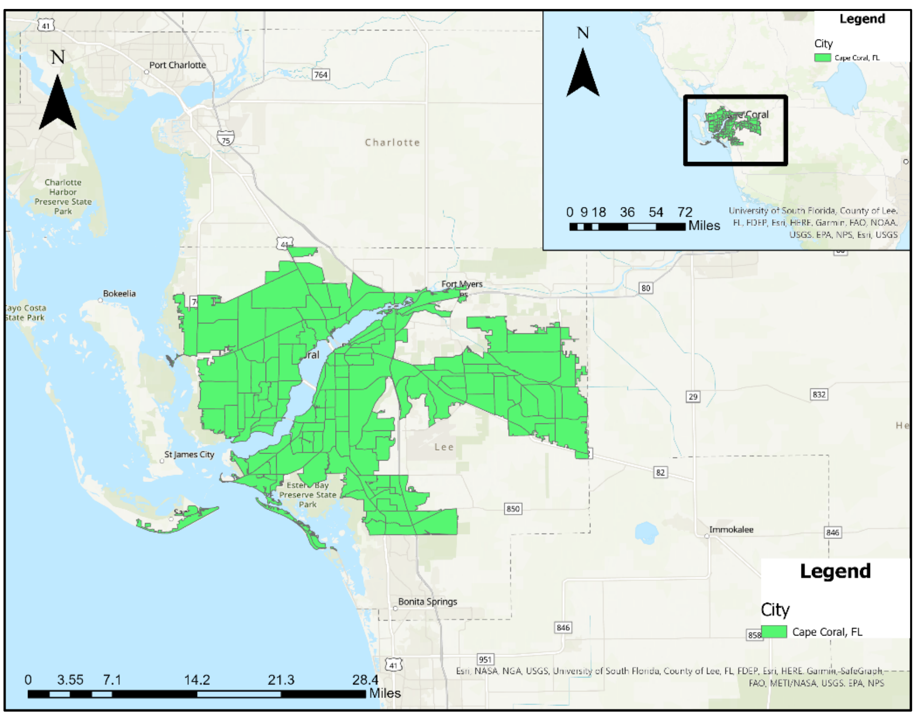


Figure 1.6: A map displaying Cape Coral, Florida, and where Cape Coral is in Florida.

City	Population	Location (Latitude, Longitude)	Area (Square Miles, Total)	State	Percent of the population in county living in this city	Hurricane Impacts since 1980 (center within a 31-mile radius)
Cape Coral	194,016	26.5629° N, - 81.9495° W	106	Florida	26%	2
Mobile	187,041	30.6954° N, - 88.0399° W	139	Alabama	45%	4
Gulfport	72,926	30.3674° N, - 89.0928° W	56	Mississippi	35%	5
Lafayette	121,374	30.2167° N, - 92.0333° W	269	Louisiana	50%	5
Brownsville	186,738	25.9017° N, - 97.4975° W	132	Texas	44%	3

Table 1.1: A table describing the population, location, area, state, and percent of the population from the county residing in the city for each of the five study site cities (NOAA, 2021; US Census Bureau, 2021; LatLong, 2022).

While large cities such as New Orleans, Miami, Pensacola, and Houston get attention from tropical cyclones, they are not the only cities in those states that are affected by tropical cyclones. People in those coastal communities are spread throughout the Gulf of Mexico states; whether it is 100,000 people or 1,000,000 people, there are still people living there. For this project, one medium-sized city from each of the Gulf of Mexico neighboring states that has experienced at least one hurricane since 1980 has been chosen. At times, these cities may be overlooked unless overwhelming damage is expected as the population is not large. Despite this, showing that they have been hit by tropical cyclones shows that they are at risk of tropical cyclones.

1.4 Research Questions, Objectives, and Hypotheses

As people continue to move to the Gulf of Mexico despite the threat of tropical cyclones, it is important to understand how people are at risk. There are three main questions this thesis will answer: *1) What is the potential for physical damage due to tropical cyclones to the five study sites? 2) What is the social vulnerability amongst the five study sites? 3) Are there any spatial relationships or correlations between tropical cyclone physical damage and social vulnerability at each study site?*

To answer the first research question, Hazus, a risk-estimating program developed by the Federal Emergency Management Agency (FEMA) that utilizes geographic information systems (GIS), will be used to map different types of physical damage, along with display varying wind speeds, amongst the study sites (FEMA, 2022). The objective is to show what areas of the study sites will be the most afflicted by tropical cyclones in terms of different physical damages. For this thesis, physical damage focuses on structural damage that affects the integrity of buildings and results in financial loss. It also includes damage to residential complexes (houses, apartments, mobile homes) that would require the use of shelters to house people. The extent of the physical damage from a probable tropical cyclone (a model run in Hazus to model a storm that has not happened yet according to the authors knowledge) will also be examined. The hypothesis for this question is that the areas on the wind speed map will correspond to areas of structural damage to buildings on the maps. For example, if there are higher wind speeds predicted in the northeastern part of a study site, then the most damage will be found in the northeastern part of the study site. Mitigation policies, along with terrain, ecological relationships, building types, and financial support for fortifying buildings before impact, factor into potential physical damage. Even if winds are strong, if policies, build structures, and ecological relationships are strong, terrain is favorable, and financial support is amble, physical damage can be lowered.

To answer the second research question, a Social Vulnerability Index (SVI) was created for all five study sites. SVI scores were calculated by running a Principal Component Analysis (PCA). A PCA is a statistical test that is used to determine components from a group of variables in a dataset that are causing variance in the dataset. A PCA is related to the construction of this thesis' SVI because it provides insight into which socially vulnerable group is contributing the most to a specific social vulnerability score. The objective is that the SVIs can be used to visualize areas of varying levels of social vulnerability. The PCA results for the SVIs can show which socially vulnerable groups may be responsible for the SVI scores in the study site. The hypothesis is that the degree of social vulnerability will vary spatially amongst all five study sites. However, of the variables, a different variable will be the main factor in the social vulnerability for the study sites.

To answer the third question, a local bivariate Moran's I spatial statistic was used to examine any relationship between the physical damage results from Question 1 and the social vulnerability results from Question 2. The objective is to determine if areas of high or low types of physical damage are associated with high or low social vulnerability scores. The hypothesis is that areas of higher physical damage will correspond to areas of higher social vulnerability scores and that areas of lower physical damage will correspond to areas of lower social vulnerability scores.

1.5 Significance

Despite the threat of tropical cyclones, people continue to move to the Gulf of Mexico coastline. This puts more lives and built systems at risk of damage from tropical cyclones. As of 2017, 29.1% of the United States population lives in a county lying directly along a coastline region (this includes the Atlantic, Pacific, and Gulf of Mexico coastlines) (Cohen, 2020). From this, 4.9% of the United States population lives in any US county that directly touches the Gulf of Mexico. Between 2000 and 2017, the Gulf of Mexico coastline counties overall experienced a 26.1% increase in population; this is faster than any other United States coastline, and even the average United States growth rate (United States Census, 2019).

As tropical cyclones move inland, flooding can become a large issue due to all the precipitation that falls and has nowhere to run off to. There is the probability that more than 4.9% of the United States population is affected by tropical cyclones that hit the Gulf of Mexico due to hazard such as inland flooding as hurricanes move over land. As the population continues to rise, more and more people are becoming susceptible to death from tropical cyclones, even if they are living inland. Tropical cyclones have been directly responsible for 6,697 deaths between

1980 and 2021, the most deaths out of any weather and climate hazard (NOAA Office of Coastal Management, 2021). As the population along the exposed and vulnerable parts of the Gulf of Mexico continues to increase, there is a possibility that the potential for loss of life from tropical cyclones to increase.

The main outcome of this research is the ability to better understand the risk of tropical cyclones to coastal cities along the Gulf of Mexico in the United States, and the threats that the current citizens of those cities will face when tropical cyclones make landfall. A more thorough understanding of tropical cyclones, the hazards they bring, and how people living in affected areas are likely to interact with these storms, can help improve community planning, policy making, and mitigation efforts. For example, if there is a risk of hazards from tropical cyclones in an area, research like this can help show the highest-risk regions. Then, city officials and planners can take a closer examination of these regions by seeing who is living there, if and why they are socially vulnerable, and how to reduce their vulnerability. The ability to recognize vulnerability and know how to combat it can help save lives, prepare them to get back on their feet after a disaster hits the area. Besides the social benefits, understanding tropical cyclone risk, comprehending the extent of physical damage (which research like this can help) can help save the economy. Knowing the types of buildings that are the most likely to be affected, and the areas that they are in, can help to improve building standards for those buildings, or any future structures in those areas. A combination of understanding vulnerability and physical damage and their joint functions in risk analysis can help make coastal cities more resilient and sustainable as they learn the coping mechanisms of tackling the hazards of tropical cyclones when they arise.

1.6 Overview of Upcoming Chapters

This thesis contains five main chapters, including this chapter. Chapter 2 will address the first research question, Chapter 3 will address the second research question, and Chapter 4 will address the third research question. Chapters 2, 3, and 4 will consist of a literature review, description of data, methods walkthrough, results, and discussion. Chapter 5 will be a conclusion chapter that summarizes the main conclusions of each research question, limitations of answering each question, future directions, and a brief reminder of the significance.

Chapter 2: The Risk of Physical Damages by Tropical Cyclones

2.1 Introduction

Due to its geographic location along the warm waters of the Gulf of Mexico, the surrounding Gulf of Mexico coastline, and its residents, are at the risk of impact from tropical cyclones (Liu and Fearn, 2000). Recently, Hurricane Ian impacted the southwestern coast of Florida as a Category 4 hurricane. It was a major hurricane that caused significant damage to the southwestern part of the state. This included severe storm surges, wind, tornadoes, and inland flooding that has already been responsible for claiming the lives of over 100 people (Salahieh and Andone, 2022). This is only one example of the devastation that these storms can cause along this coastline, and as climate change continues to increase the temperature of the ocean, these storms are only likely to increase in intensity (Holland and Bruyère, 2014).

The importance of this study is that the Gulf of Mexico coastline is, in terms of population, the fastest-growing coastline in the United States, and has been over the past 20 years (Cohen, 2019). With millions of people now calling the Gulf Coast home, this puts these people at risk for the devasting impacts a hurricane can bring. Being able to understand the consequences of storms based on their severity can help city planners, emergency managers, and local officials make more effective decisions when it comes to policy and planning on how to handle these storms. In addition to legislators making better decisions, it will also allow residents to make more informed decisions when the officials make announcements of a potential storm coming their way.

Hazus, a risk-estimating tool incorporating GIS developed by FEMA is the main methodology used in this thesis for estimating risk from physical damage of tropical cyclones, is one way to better comprehend the risks that a tropical cyclone is likely to face. Hazus can be helpful in the visualization aspect of hazard research and make it easier to communicate hazards to nonscientists and help reach a wider audience. The data that is provided by Hazus can help the groups mentioned above, and even homeowners, understand the type of risk and the damages that they are likely to receive when the hazard occurs.

2.2 Background

2.2.1 Hazus

Hazus is a risk-estimating tool developed by FEMA to allow a wide audience to model risk in a specific area of the United States. Hazards that Hazus estimates the risk for include hurricanes as well as floods, tsunamis, and earthquakes. It can be used by emergency managers, city planners, policymakers, or homeowners to help them identify their risks and the losses that they are likely to suffer. Produced data examines physical damage, social impacts, and economic losses (FEMA, 2022). Hazus can use ArcMap 10.8.1 to map certain information, and this information will be the focus of this thesis. Hazus can run a probabilistic and historical tropical cyclone scenario (FEMA, 2022). For the Hurricane Model, all damage in a probable scenario is modeled by likely damage from wind only, and not from other hazards associated with hurricanes. The hurricane model takes into consideration global, historical tropical cyclones to generate the most reliable wind models. Storm surge can be modeled when the Hurricane Model is combined with the Flood Model of Hazus. The storm surge model also looks at the financial effects of tropical cyclones on buildings as the wind model does.

Storm surge, while responsible for high amounts of deaths and financial costs from tropical cyclones, was not included in this thesis. Storm surge was excluded because it is easier to standardize impacts based on wind speed over storm surge, as wind speed is the only way tropical cyclones are categorized. Storm surge can vary between the same category storms, which is why tropical cyclones are not categorized by this hazard. This makes storm surge not as consistent as wind speeds amongst different category tropical cyclones. Additionally, storm surge data in Hazus are only available in Historical Scenarios, and this thesis did not examine historical scenarios.

In this project, Hazus was run on a probabilistic hurricane model. In a probabilistic scenario, a Monte Carlo approach is done to create a reliable statistical result for the model to run the parameters of radius to maximum winds, the translation speed, the distance of the closest approach, heading, and central pressure deficit. A single path line is created for the storm track, and winds are simulated at a constant speed until landfall is achieved. The track and model are created by using an axisymmetric balance model and incorporates historical storm tracks, humidity, and sea surface temperature. All of this is used to mimic the changes in intensity in a storm during its lifetime (Vickery et al., 2009). The physical damage analysis functions within Hazus have been an accomplishment for the program as it can determine losses that generally go beyond other models that attempt to do the same thing. This adds reliability to the model, especially since the damage can be broken down into building class and structure type (Schneider and Schauer, 2006).

2.3 Research Question, Hypothesis, and Objective

The research question that will be answered in this chapter is *"What is the risk for physical damage due to tropical cyclones to the five study sites?"* Hazus has been used to previously model potential physical damage from tropical cyclones (Schneider and Schauer, 2006). Having Hazus be more closely examined in the context of how it applies to the study sites, all of which are either of small or medium populations sizes, can help to show that it can be useful at any scale, no matter the size of the city and the population residing there. The hypothesis for this question is that the areas on the wind speed map will correspond to areas of damage on the maps. For example, if there are higher wind speeds predicted in the northeastern part of a hurricane, then the most damage will be found in the northeastern part of the study site. Areas of the highest wind speed may be observed in the northeastern portion of the storm track as this is, generally, where the strongest winds are in most Gulf of Mexico tropical cyclones (Liu and Fearn, 2000). The objective is that the visualization that will be provided from the geospatial data will help put into perspective the areas of highest risk for physical damage. It will also provide insight into the specific types of damage that will be generated.

2.4 Data

The data that was used within Hazus to create hurricane wind fields and estimates for structural damage are provided to the user upon download as they are stored in an internal Hazus database. The data that Hazus provided were from the US Census Bureau, the National Structure Inventory, and the US Army Corps of Engineers. The spatial resolution of the data came at the US Census tract level and was run for each tract within a county. All data came from the 2010 US Census.

The National Structure Inventory, US Census Bureau, and the US Army Corps of Engineers data was used in estimating the damage to the buildings based on the result of the storm models. The other data that were used in this project are from the FEMA Flood Map Service Center. State specific data was downloaded from the FEMA Flood Map Service Center for the states of Florida, Alabama, Mississippi, Louisiana, and Texas. This data was used in creating the study regions for each of the five cities. However, it must be downloaded at the state level, and then when in Hazus, it can be broken down into the Census tract level. To break it down to the city level, the city boundaries were downloaded from the US Census Bureau website to show Census tracts in each city.

2.5 Methodology

After the state data were downloaded from the FEMA Flood Map Service Center, and Hazus was installed, a study region was created within Hazus. The program prompts a region to be created and named. While data are at the Census tract level, the specific county that each city is in was selected when creating the region to make sure all Census tracts in the city were accounted for. Census tract units are included in the county region model. Next, the program asked for a hazard selection, and the "hurricane" option was selected.

Once a study region was opened, several maps were generated. These included maps for 10, 20, 50, 100, 200, 500, and 1,000-year storm event scenarios. For this thesis, the focus will be on 100-year storm scenarios. This is because a 100-year storm yielded more drastic results than the 10, 20, and 50-year storm scenarios when models were initially run in Hazus, but is more likely to occur than a 200, 500, or 1,000-year scenario (a 100-year storm has a 1% chance of occurring in any given year). Due to these reasons, the 100-year scenario served as a compromise between the severity of the storm along with the realistic probability of the storm occurring.

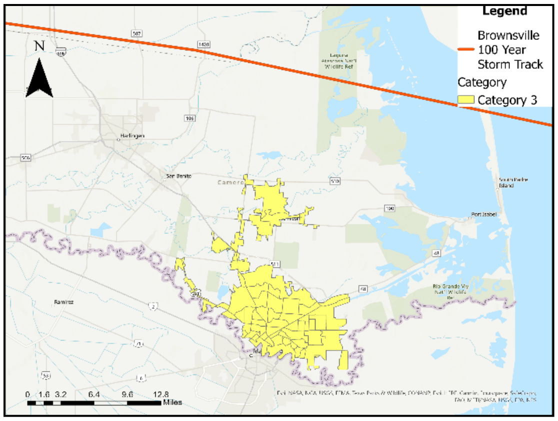
The preset symbology for these maps is wind speed, but not by any category. However, this was manually changed to reflect the proper hurricane category ranking instead of displaying regular wind speed values. Wind speeds were described as a category because they are the only way that hurricanes are categorized, and this gives more context to the wind speeds. The map is interactive; a polygon of a Census tract within a city can be clicked on, and information about the tract and the wind will appear. These were the maps of focus for this thesis as storm surge will not be run since the thesis only focuses on wind damage and Hazus cannot run probable storm surge data.

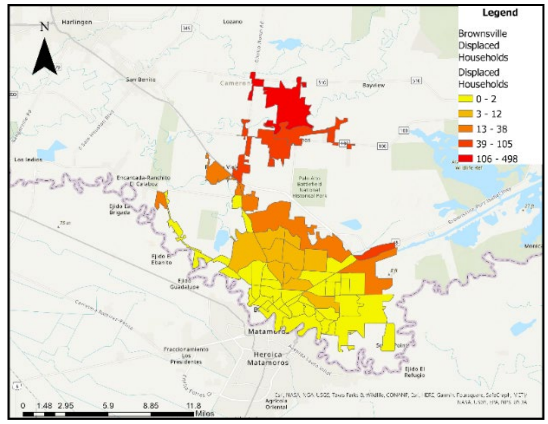
Under "Hazard," "Scenario" is selected, after which the Hurricane Scenario Management Wizard opens. Different options for Hurricane Scenarios were provided, and "Probabilistic" was selected, and on the next screen, the scenario was selected to be activated. A "Probabilistic" Scenario was selected over a "Historic" Scenario because this scenario focuses on storms that have already occurred and does not simulate potential ones (FEMA, 2018). Additionally, a "Determinist/User-Defined Storm Scenario" was not chosen for this thesis as these data must be provided by the user and should be provided by an expert and also only considers a single-risk scenario (FEMA, 2018). Once this is set, under the "Analysis" header, at the bottom, "Run" was selected so the model can run its results for the wind damage. Under the "Results" header, "Shelter" was selected, then from that, "Displaced Households," was selected and mapped by clicking the "Map" button from the popup that was generated. Under "Results," there was also an option for "General Building Stock," where "Building Damage States" was selected, and under that "by Building Type" was selected and mapped to show total damage from the scenario by the type of building (residential, business, etc.). "Building Economic Loss" is also under "General Building Stock," and "by Building Type" was used again to determine the total economic loss for the scenario and by the building type. For this thesis, instead of looking at the specific type of building, the total loss and damage from all building types were used. "100-Year Storm Track" was selected under "Results" to produce the most probable tropical cyclone track.

After each map was generated, to adhere to the city boundaries for each study site, the county maps were converted to city maps by using the "Clip" function in ArcGIS Pro 2.9. This left behind only the Census tracts that fit within the city boundaries. The Census tract boundaries provided by Hazus usually fit within the city boundaries provided by the US Census Bureau, but in rare cases, they may extend past the city's boundaries. If this does occur, then it will leave out data, but due to the unlikeliness of this happening, the clipping was done. To categorize the output data, the wind speed results were grouped manually into classes by hurricane category based on their wind speed. Displaced Households, No Damage (gathered from "Building Damage States" to show the percentage of buildings with no damage), and Total Loss (in Thousands of Dollars, calculated from "Building Economic Loss"), were broken naturally into five classes using the Natural Jenks methods.

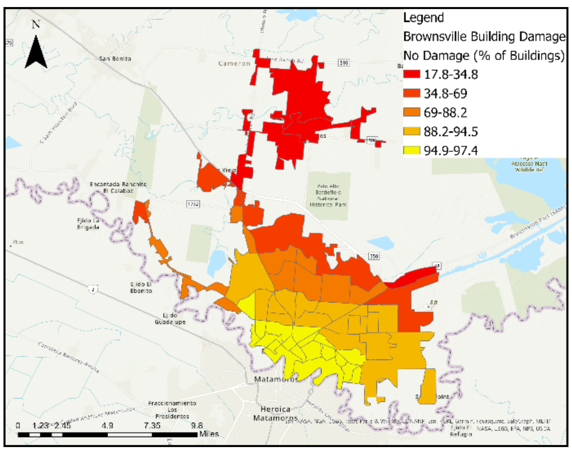
2.6 Results

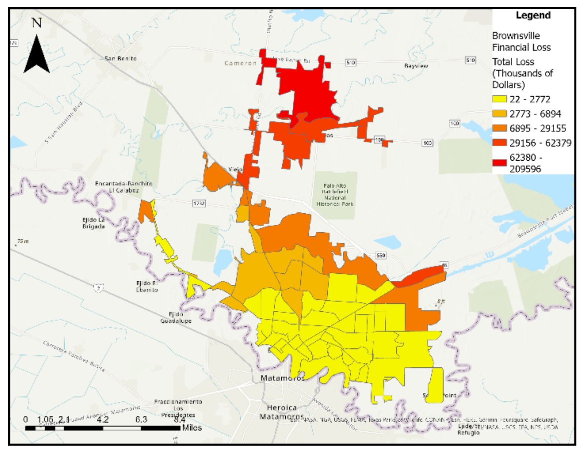
The number of displaced households is important because, from a planning perspective, it is imperative to grasp how many temporary shelters may be needed if there are a lot of displaced households. The number of buildings with no damage is useful because it may show that buildings in the area are more structurally sound than in areas with high building damage. The total building loss is important because cities will need to budget losses and this result allows them to plan in time.





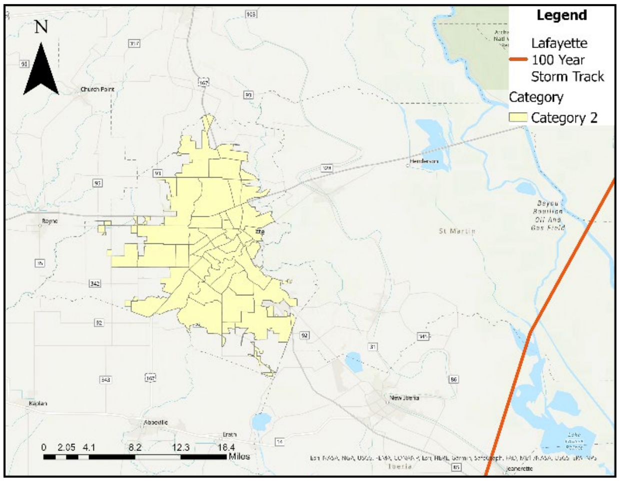
Figures 2.1 (left) and 2.2 (right): Figure 1 depicts wind speeds and track of a probable 100-year hurricane in Brownsville by Census tract. Figure 2 shows the number of displaced households within Brownsville following a 100-year hurricane by Census tract.

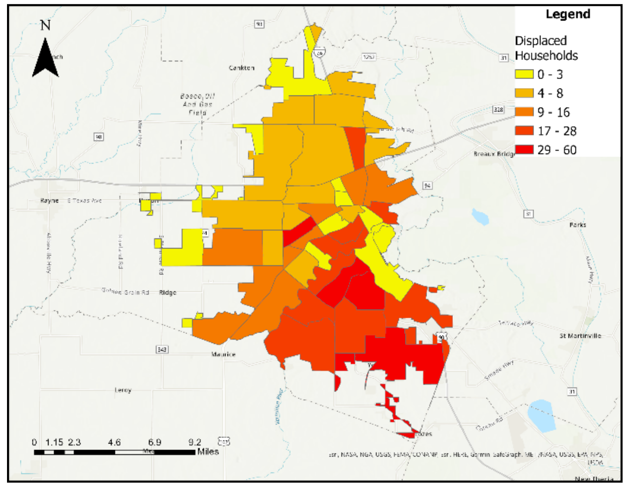




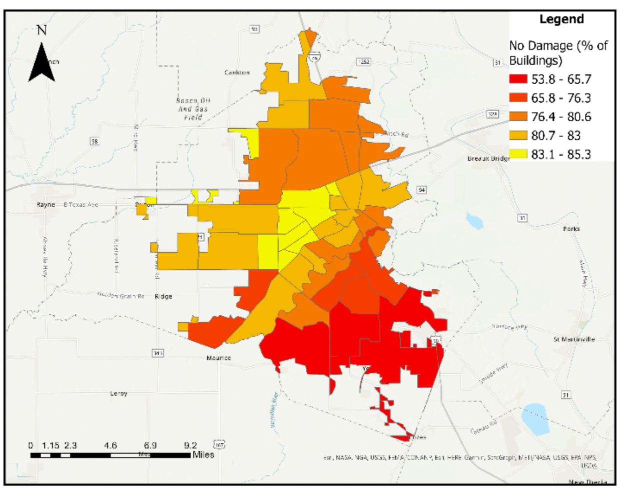
Figures 2.3 (left) and 2.4 (right): Figure 2.3 shows the expected percentage of buildings with no damage from a probable 100-year storm within Brownsville by Census tract. Figure 2.4 depicts how much money is lost in thousands of dollars, by Census tract, from a probable 100-year storm within Brownsville.

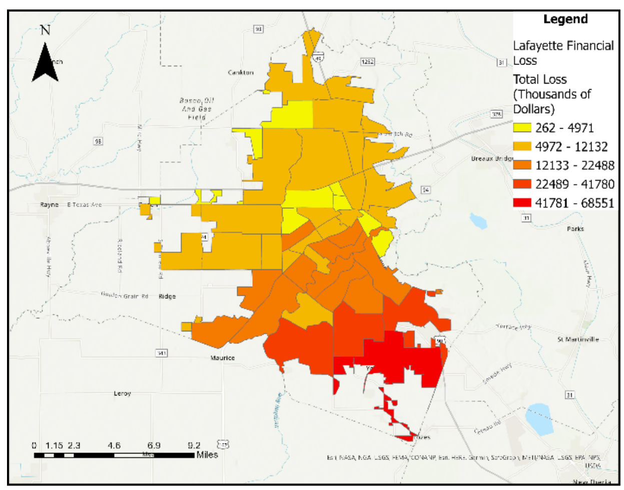
In a 100-Year Scenario for Brownsville, Texas, Hazus predicts that the highest and lowest wind speeds will be within the Category 3 range (Figure 2.1). The storm track moves in a western direction (Figure 2.1). The highest number of displaced households seen is 498 households (Figure 2.2). However, several Census tracts in Brownsville will not have any displaced households (Figure 2.2). The highest percentage of buildings that experienced no damage in a Census tract in this scenario was 97.4%, while the lowest percentage is 17.8% (Figure 2.3). This implies that the most heavily hit areas can expect up to 82.2% of all types of buildings to experience some form of damage from that tropical cyclone. For the amount in total building loss, some Census tracts will experience a loss of as little as $22,000, while others can experience a loss of up to $209,596,000 (Figure 2.4).





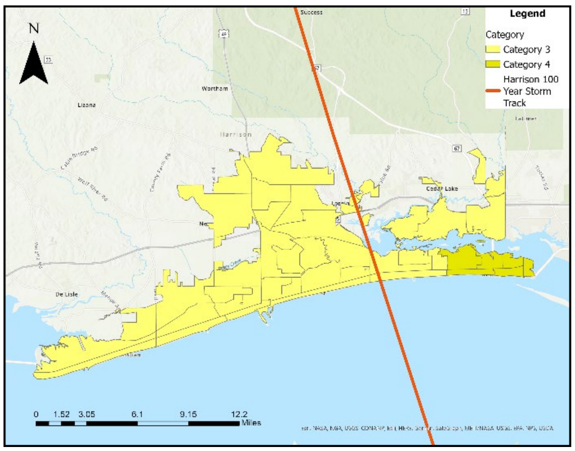
Figures 2.5 (left) and 2.6 (right): Figure 2.5 displays the wind speed by category within a Census tract and the storm track that is likely to be seen by a probable hurricane in a 100-year scenario in Lafayette. Figure 2.6 shows the number of displaced households within a Census tract that would be caused by a probable 100-Year Storm to Lafayette.

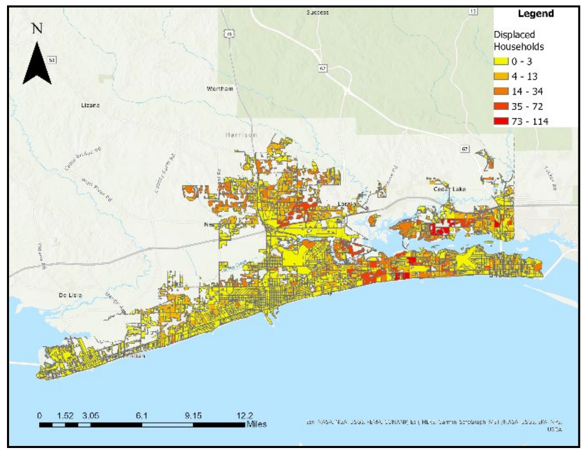




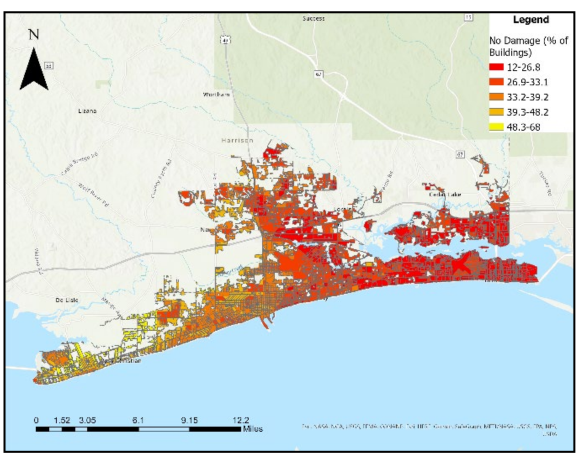
Figures 2.7 (left) and 2.8 (right): Figure 2.7 shows the expected amounts of buildings within a Census tract that would experience no damage from a probable 100-year storm within Lafayette. Figure 2.8 depicts how much money is lost in thousands of dollars, by Census tract, from a probable 100-year storm within Lafayette.

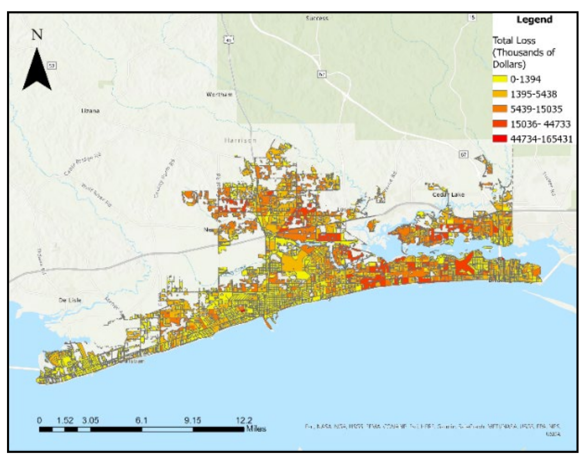
In a 100-Year Scenario for Lafayette, Louisiana, Hazus predicts that the highest and lowest wind speeds all fall within a Category 2 range (Figure 2.5). The storm track moves in a northeastern direction (Figure 2.5). For the same scenario, the highest number of displaced households seen is 60 households and the lowest is zero (Figure 2.6). Most of the Census tracts will experience little damage to their buildings (as many as 85.3% of buildings remain untouched), but some will have most of the buildings damaged to some capacity (Figure 2.7). For the amount in total building loss, some Census tracts will experience a loss of $262,000, while others can experience a loss of up to $68,551,000 (Figure 2.8).





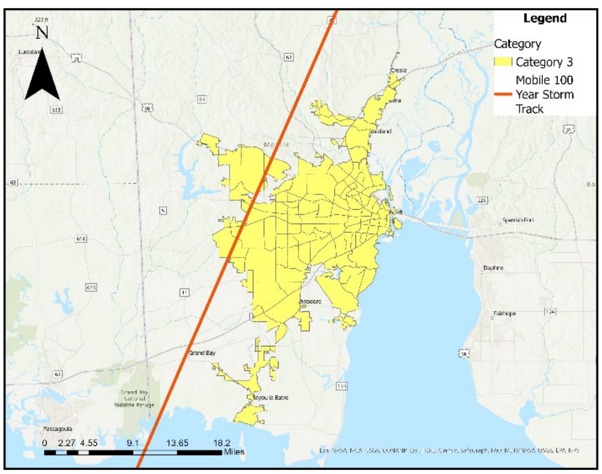
Figures 2.9 (left) and 2.10 (right): Figure 2.9 shows the wind speed by category within a Census tract and the storm track of a probable hurricane in a 100-year scenario in Gulfport. Figure 2.10 shows the number of displaced households that would be caused by a probable 100-year storm at the Census block level in Gulfport.

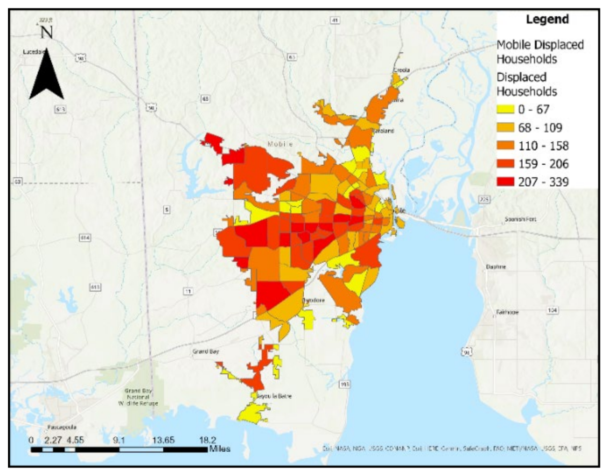




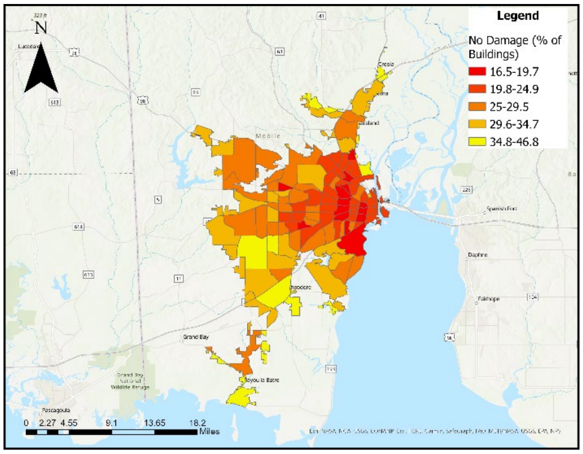
Figures 2.11 (left) and 2.12 (right): Figure 2.11 displays buildings within a Census block that would experience no damage from a probable 100-year storm within Gulfport. Figure 2.12 displays the financial loss in thousands of dollars, by Census block, from a probable 100-year storm within Gulfport.

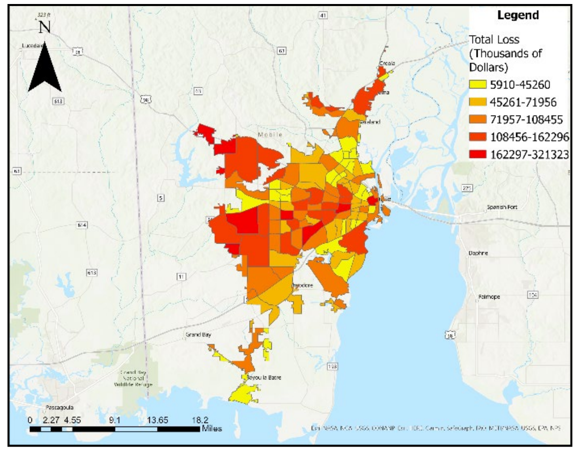
In a 100-Year Scenario for Gulfport, Mississippi, Hazus predicts that the highest wind speeds will fall within a Category 4 range, and the lowest in the Category 3 range (Figure 2.9). The storm track is seen moving in a northwestern direction. Much of the city can expect to feel Category 3-force winds (Figure 2.10). For the same scenario, the highest number of displaced households seen is 114 households, and the lowest number is zero households (Figure 2.10). Some areas within Gulfport will have as many as 68% of buildings not receiving any damage, while others will have only 12% of buildings not damaged (Figure 2.11). For the amount in total building loss, some Census tracts will experience no financial loss, while others can experience a loss of up to $165,431,000 (Figure 2.12).





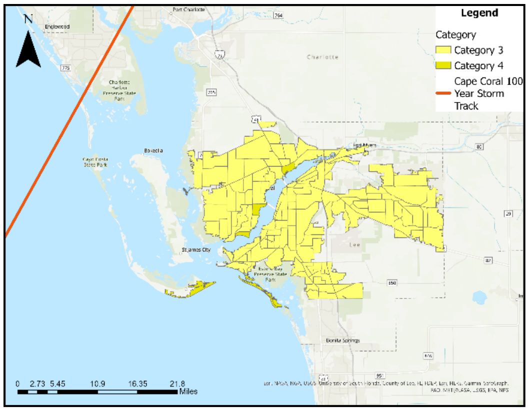
Figures 2.13 (left) and 2.14 (right): Figure 2.13 shows within a Census tract the expected wind speed by category likely to be experienced by a probable hurricane in a 100-year scenario in Mobile, along with the storm track. Figure 2.14 shows the number of displaced households within a Census tract that would be caused by a probable 100-year storm in Mobile.

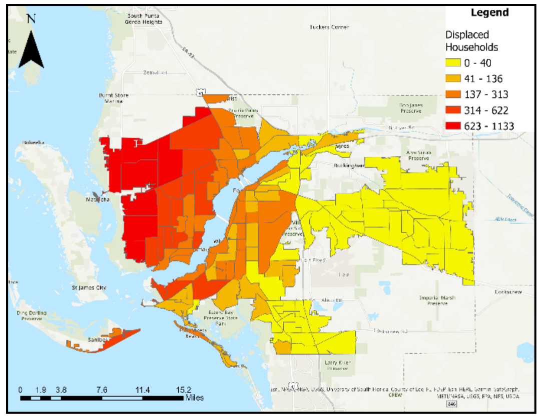




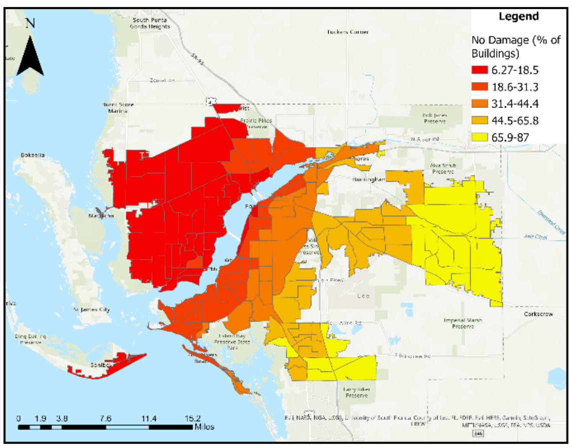
<u>Figures 2.15 (left) and 2.16 (right):</u> Figure 2.15 displays buildings within a Census tract that would experience no damage from a probable 100-year storm within Mobile. Figure 2.16 displays the loss in thousands of dollars, by Census tract, from a probable 100-year storm within Mobile.

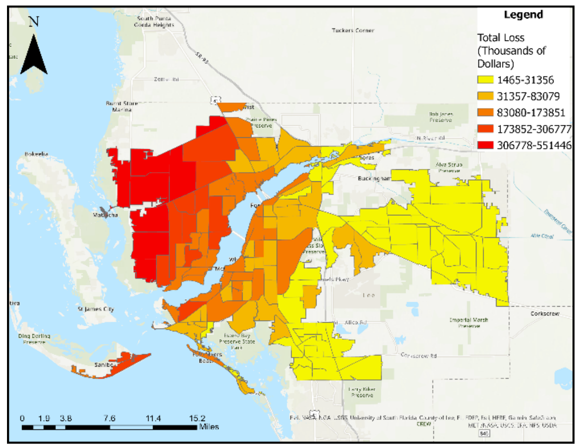
In a 100-Year Scenario for Mobile, Alabama, Hazus predicts that the highest and lowest wind speeds will be within the Category 3 range (Figure 2.13). The storm track moves in a northeastern direction (Figure 2.13). The highest number of displaced households seen is 339 households, and the lowest number is zero households (Figure 2.14). Some areas within Mobile will have 46.8% of buildings remain undamaged, while as few as 16.5% of buildings are undamaged (Figure 2.15). For the amount in total building loss, some Census tracts can experience a loss of $5,911,000, and others can experience a loss of up to $321,323,000 (Figure 2.16).





Figures 2.17 (left) and 2.18 (right): Figure 2.17 depicts wind speeds from a probable 100-year storm by Census tract and the storm track in Cape Coral. Figure 2.18 shows the number of displaced households, by Census tract, following a 100-year hurricane in Cape Coral.





Figures 2.19 (left) and 2.20 (right): Figure 2.19 displays buildings that would experience no damage from a probable 100-year storm within a Census tract in Cape Coral. Figure 2.20 displays the loss in thousands of dollars from a probable 100-year storm by the Census tract in Cape Coral.

In a 100-Year Scenario for Cape Coral, Florida, Hazus predicts that the highest wind speeds will fall within a Category 4 range, and the lowest in the Category 3 range (Figure 2.17). The storm track moves in a northeastern direction (Figure 2.17). Most of the city will experience Category 3-force winds (Figure 2.17). For the same scenario, the highest number of displaced households seen is 1,133 households, and the lowest number is zero households (Figure 2.18). In Cape Coral, some Census tracts have 87% of their buildings undamaged, while some Census tracts only have 6.27% of their buildings not damaged (Figure 2.19). Some Census tracts can expect a total building financial loss of up to $551,466,000, while the lowest amount of loss is $1,465,000 (Figure 2.20).

City	Highest Winds (Category)	Lowest Winds (Category)
Brownsville	3	3
Lafayette	2	2
Gulfport	4	3
Mobile	3	3
Cape Coral	4	3

Table 2.1: A table of the highest and lowest wind speeds by hurricane category experienced within at least one Census tract for all five cities.

City	Highest Households Displaced	Lowest Households Displaced
Brownsville	498	0
Lafayette	60	0
Gulfport	114	0
Mobile	339	0
Cape Coral	1,133	0

Table 2.2: A table of the highest and lowest number of displaced households within at least one Census tract for all five cities.

City	Highest Percentage of No Building Damage	Highest Percentage of Building Damage
Brownsville	97.4	82.2
Lafayette	85.3	46.2
Gulfport	68.0	12.0
Mobile	46.8	16.5
Cape Coral	87.0	6.27

Table 2.3: A table of the highest percentage of no building damage and the highest percentage of building damage (calculated by subtracting the lowest percentage of buildings with no damage from 100) within at least one Census tract for all five cities.

City	Highest Total Economic Loss (USD)	Lowest Total Economic Loss (USD)
Brownsville	209,596,000	22,000
Lafayette	68,551,000	262,000
Gulfport	165,431,000	0
Mobile	5,911,000	321,323,000
Cape Coral	551,466,000	1,465,000

Table 2.4: A table of the highest total economic loss amount (in USD) and the lowest total economic loss amount (in USD) within at least one Census tract for all five cities.

Based on the results, the highest wind speeds are seen at Category 4 in Gulfport and Cape Coral, and the lowest wind speeds are seen at Category 2 in Lafayette (Table 2.1). The highest number of displaced households is 1,133 in Cape Coral, and all cities experienced a displaced household rate as low as zero (Table 2.2). The highest percentage of buildings that experience no damage is in Brownsville at 97.4% and the lowest is in Mobile at 46.8% (Table 2.3). The highest percentage of buildings that experience some (minor to complete) damage is Brownsville at 82.2% and the lowest is Cape Coral at 6.27% (Table 2.3). The highest total economic loss seen is in Cape Coral with $551,466,000 and the lowest is seen in Gulfport with $0 in loss (Table 2.4).

2.7 Discussion

Hazus has several ways of estimating risk, especially in the hurricane model, that can benefit coastal cities. The study site cities (besides Lafayette) are expected to see Category 3-force winds, which is considered a major hurricane. This is important to note because this is when wind damage alone becomes extensive and can even lead to a higher loss of life (NOAA, 2020). Lafayette experiences the lowest wind speeds at a Category 2 level and is the only city that has wind speeds as low (and as high as Category 2). This may be because Lafayette lies slightly more inland than the other cities (which all directly touch the Gulf of Mexico). This could mean that the city is not as subjected to the full intensity of the probable hurricane as other study sites are.

In general, the location of the highest wind speeds appeared to line up with where the most damage in each of the three maps appeared. Even in areas where the highest and lowest wind speeds fall within the same hurricane category, the locations for the highest amount of damage, economic loss, and displaced households occur within the same geographic area. In Brownsville, the highest damage and impacts start in the north and progressively improve as you move south in the city. In Lafayette, the highest damage occurred in the south and southeastern part of the city. Generally, the eastern portion of Gulfport is estimated to experience more damage than the western part. Cape Coral follows a gradual progression of the most damage occurring in the west and then decreasing as you move from western to eastern Cape Coral. Mobile is the only city where the damage tends to be more random.

Another observation is the relationship between the storm track and the areas of the highest winds and the most damage. In Gulfport, the highest wind speeds were observed in the areas where the northeastern quadrant of the tropical cyclone would impact. This is the most prevalent in Gulfport since the windspeeds vary between Census tracts and the storm track's course goes right through Gulfport. In all the study sites besides Mobile, the most severe damage is observed where the proximity between the storm track and the damage is close. Mobile is an interesting case as the storm track does cross into the city's limits, but the wind speeds are uniform throughout the city (Category 3). Additionally, in Mobile, the damage is more haphazard when compared to most of the other study sites.

One factor that could attribute to the risk results from Hazus is the number and quality of structures in a Census tract. For example, if a group of Census tracts are all subjected to the same wind speeds, and the quality and number of buildings are the same, then the amount of damage should be consistent across all Census tracts. However, that is not what is observed here, especially in the case of Mobile. Therefore, a conclusion can be drawn that another factor must be going on to cause the results to vary amongst Census tracts when wind speeds remain consistent. Poorly structured buildings will be more susceptible to damage from a tropical cyclone. A Census tract with a high number of poorly built structures over a Census tract with a low quantity of weak buildings is more likely to experience more damage. Similarly, if all the buildings are of the same structural intensity, but one Census tract has more buildings than another, then the Census tract with more buildings is likely to experience more damage since there are, simply, more structures to be damaged. The results from this section show that areas of high damage tend to be in similar Census tracts within a city, no matter the type of damage, and the damage can be explained based on the wind speeds and storm track.

An observation related to Gulfport is that it is the only city that had Census block data instead of Census tract data for all maps but wind speed. The methodology for the creation of each study region for each study site was consistent (choosing the Census tract for all study sites), and the wind speeds were created at the Census tract level, not the Census block level. Speculation for the results of the wind speed map based on knowledge of hurricanes may be that the Flood Model data will not have an impact on the wind speed results but will affect the type of damage caused by a probable tropical cyclone. The reason why three of the four maps are shown at the Census block resolution is that Hazus provides results at the Census block level when both wind and flood hazard scenarios can be modeled (FEMA, 2021b). In the future, a further explanation into why the Hurricane Model defaults to Census block data even when Census tract data are automatically selected should be examined.

There are caveats that come with working with an estimation program such as Hazus. As the data is provided by the Census, there are inaccuracies that can arise from this and will influence the results of a Hazus output. Additionally, the data used in this thesis are from the 2010 Census Bureau, and the number of buildings, along with their structural integrity, will have evolved in the 13 years after these data were initially collected. The Hurricane Model (when not coupled with the Flood Model) has the finest spatial resolution set to Census tracts, and if the units could be finer, better results can be yielded. Also, with all models, there is no guarantee that the exact scenario for each study site modeled in this thesis will happen. These limitations will be discussed more in depth in Chapter 5, Section 5.2.1.

Chapter 3: Social Vulnerability Amongst the Study Sites

3.1 Introduction

There are specific socioeconomic and demographic groups within Gulf of Mexico communities affected by tropical cyclones that may struggle more with hurricane preparation and recovery more than others. Acknowledging who is socially vulnerable in a city can lead to a more resilient community. There is a known risk of tropical cyclone damage to those living along the Gulf of Mexico due to its geographic location, but the beautiful beaches and weather continue to attract people to become permanent residents of this coast. These residents come from a plethora of socioeconomic and demographic groups. Each will have their struggles depending on their socioeconomic and demographic statuses as this may impact their tropical cyclone preparation and recovery efforts. For this thesis, six socially vulnerable groups were identified and were used in a Principal Component Analysis to reduce the number of variables and determine statistically significance socially vulnerable groups. Research like this helps to bridge the gap between the academic world and the "real" world and allows for the application of science on a broader scale that can create a positive impact on people's lives.

3.2 Background

3.2.1 Social Vulnerability

In this thesis, social vulnerability is defined as a compounder of loss based on the susceptibility of a socioeconomic or demographic group when evacuating, preparing, or recovering from a tropical cyclone. There is no one group alone that is more susceptible than another as each group has unique reasons for being vulnerable. These can range from being in a weak financial situation to not having a car or being physically unable to act (Cutter et al., 2000;

Yoon, 2012). The vulnerabilities of these groups can also be compounded by uninsured assets, weak planning, outdated building codes, poor funding, lack of support through public assistance programs, and lack of communication and enforcement (Dunning, 2020). The overall grouping of the socially vulnerable groups chosen for this thesis include age, gender, race, ethnicity, education, language proficiency, poverty status, and disability status.

3.2.2 Factors Impacting Social Vulnerability

Age, specifically under the age of five (young) and over the age of 65 (elderly), are important because people of these ages may rely on the help of others to take proper care of themselves (Bergstrand et al., 2014; Cutter et al., 2000; Rufat et al., 2015). For example, a young person, such as an infant, relies on their parents or other caregivers to do everything for them, and requires special supplies such as diapers. This is unanimous across those of a young age. An elderly person can find themselves in a similar situation, which is why some people end up with home health care or in nursing homes. However, not everyone who is considered elderly needs assistance or special supplies, although as their age increases from 65, these needs become more common (Bergstrand et al., 2014; Cutter et al., 2000; Rufat et al., 2015).

Females in natural hazards and disasters have experienced a higher loss of property in value, and, if mothers, may have issues accessing childcare after the natural hazard's impact (Bergstrand et al., 2014; Yoon, 2012). Again, depending on the level of disability, those that are not able-bodied may not be able to physically prepare themselves or their assets (like homes and cars) to withstand the damage of a hurricane. They may need help in doing this or may require technological assistance (a charged glucometer for diabetics) that relies on electricity at some level for functioning. Electricity will almost certainly go out in a hurricane, requiring these people to have some form of nonelectric backup, but not everyone may be able to afford this.

Some shelters may not be prepared to deal with the physically disabled, such as those in wheelchairs (Bergstrand et al., 2014; Cutter et al., 2000; Rufat et al., 2015). Language barriers can exist in communities where a significant portion of the population consists of immigrants, especially those who recently moved to the United States. In most communities across the United States, English is the dominant language. Some may assume that all community members of this city are proficient in English, but this is not always the case. These citizens will then become reliant on those who speak English, and even then, it is assumed that the English speakers will properly provide the correct information (Rufat et al., 2015).

In every community, there will be a percentage of the population that, unfortunately, live in poverty. Here, it is likely that the financial resources to prepare, evacuate, and recover from a hurricane are not much. These people may be physically able to act but lack the financial resources to do so. They may not be able to afford cars, making them reliant on others to evacuate. They are not able to afford flood insurance in their homes (in homes with poor infrastructure if they cannot afford proper housing). Although they may be able to physically place window protection on their window, they may not be able to afford hurricane shutters. Evacuation is also harder in these areas if the area has a high population density, and the roads in those areas may not be capable of handling a large-scale evacuation (Cutter et al., 2000; Rufat et al., 2015).

Race and ethnicity (specifically Hispanic/Latino groups for this research) factor into vulnerability in different ways. For Census data related to races, the United States Census Bureau follows the requirement of the United States Office of Management and Budget of requiring at least five races: white/Caucasian, black/African American, American Indian, or Alaska Native, Asian, and Native Hawaiian or Other Pacific Islander. The Census Bureau adds Two or More

Races and Other Races as additional options. While these race groups include people of multiple heritages, Hispanic, Latino, or Spanish can be of any race (U.S. Census Bureau, "Race"). This is because, by definition, being Hispanic, Latino, or Spanish are considered ethnic groups. Ethnicity is defined as how a person identifies based on experiences and cultural and traditional practices (Merriam-Webster Dictionary, 2023). This differs from race because race focuses more on physical characteristics while ethnicity focuses on cultural characteristics (Merriam-Webster Dictionary, 2023). One can be a part of one or more race groups while also being in an ethnic group, but not everyone identifies with being in an ethnic group. For example, one can identify of being of the Asian race and the Hispanic/Latino/Spanish ethnic group.

Economic, immigration, and educational variances amongst different racial and ethnic groups can make individuals within these groups socially vulnerable. While overall poverty levels amongst different racial groups have declined over recent decades, most other races and the Hispanic ethnic group still experience higher rates of poverty when compared to the white race (Creamer, 2020). Another factor that related to how race and ethnicity influence vulnerability relates to immigration status. Approximately one million immigrants from all over the world move to the United States each year, with the United States housing about one-fifth of the world's immigrant population. This makes the United States the country with the highest population of immigrants in the world (Budiman, 2020). As discussed previously, language proficiency can make someone socially vulnerable if they are not proficient in the dominant language. Despite the United States not having an official language, English is the most dominant language, with 78% of the population speaking only English at home (Deshmukh, 2021). Not all immigrants migrate from a country where English is the dominant language or taught in school. In 2018, 53% of immigrants were identified as proficient English speakers, and the most spoken language by immigrants that is not English is Spanish (Budiman, 2020). Races of immigrants tend to vary. Amongst some of the racial groups previously listed, 27% are Asian, 22% are two or more races, 21% are white, 20% are another race, and 9% are Black (Ward and Batalova, 2023). Amongst these immigrants, 44% of immigrants to the United States identify as Hispanic or Latino (Ward and Batalova, 2023).

3.2.3. Principal Component Analysis

A Principal Component Analysis (PCA) is a statistical method used to reduce the data within large datasets but maintaining the variability and relationships amongst the data (Bucherie et al., 2022; Jolliffe and Cadima, 2016). It creates a fewer mount of variables to more accurately account for variability amongst all variables in large datasets (Aksha et al., 2019; Bucherie et al., 2022; Rabby et al., 2019). These components will also help to further explain which variables are responsible for the most variance that influences the SVI scores, specifically the first principal component (PC1) (Bucherie et al., 2022; Rabby et al., 2019). Whichever socially vulnerable group appears to have the highest correlation value in PC1 will be considered the “driving” socially vulnerable group as this group explains most of the variance in PC1.

For the results of a PCA to be considered statistically significant, it is recommended that the value from the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (or, in this thesis, simply referred to as the KMO value), is ≥ 0.5 as this is the minimum KMO value for statistical significance (Analysis Inn, 2020). Another important test to acknowledge when conducting a PCA are the results of Bartlett’s Test of Sphericity, which provides insight on if your variables are related enough to conduct a successful PCA (Analysis Inn, 2020). A statistical significance of < 0.05 for the Bartlett’s Test of Sphericity was desired (Analysis Inn, 2020). An eigenvalue of at least 1 was considered when examining the principal components produced from the PCA.

Specifically, the PC1 of each study site should have the highest eigenvalue as it accounts for most of the variance in the dataset (Aksha et al., 2019; Bucherie et al., 2022; Dintwa et al., 2019; Rabby et al., 2019; Spielman et al., 2020). This was insured by implementing the Kaiser criterion for the PCA.

3.3 Research Question, Hypothesis, and Objective

The research question that this chapter will answer is "What is the social vulnerability amongst the five study sites?" Six variable groups (females, age, race, poverty, language, and disability) were created, with some groups being a combination of individual demographic groups to form a larger variable group. These groups were identified as having the largest influence on all the study site's social vulnerability. The hypothesis is that the degree of social vulnerability will vary spatially amongst all five study sites. However, of the six variables, a different variable will be the main factor in the social vulnerability for the study sites due to the demographic makeup being different for each study site. PC1 should have the highest eigenvalue of all components and make up much of the variance observed. All principal components should have an eigenvalue >1. The main objective of answering this question is to visualize through GIS and statistical methods the locations of different levels of social vulnerability amongst the study sites and compare the driving factors of each study site.

3.4 Data

All Census data and shapefiles used for the composition of the Social Vulnerability Index (SVI) were downloaded from the National Historical Geographic Information System (NHGIS) from the Integrated Public Use Microdata Series (IPUMS) (Manson et al., 2022). Data was downloaded from the 2016-2020 Census (Manson et al., 2022). Data was downloaded from

NHGIS as the Census data and the shapefiles contained a GISJOIN Key, which allowed for the data to be joined as a table to the shapefiles in ArcGIS Pro. All data was downloaded at the Census tract level.

Once all Census data were downloaded, the socially vulnerable groups were decided for the study. In total, 16 socially vulnerable groups were identified based on demographics and socioeconomic statuses. The groups were determined based on groups previously selected for other studies that focus on social vulnerability and the construction of SVIs, along for the reasons stated in Section 3.2.2 of this chapter (Bergstrand et al., 2014; Cutter et al., 2000; Rufat et al., 2015; Yoon, 2012). These 16 groups are females, Black, Asian, Native (including Native Americans, Native Alaskans, Native Hawaiians, and Pacific Islanders), Hispanic/Latino, other races, two or more races (including two or more races, two races including some other race, two races excluding some other race, and three or more races), limited English speaking households (with the dominant languages being Spanish, other Indo/European, Asian and Pacific Islands, and other), under five years of age, over 65 years of age, disabled, and living below poverty. Census tract data for these groups by the county in which one of the five study sites resided was used in the analysis.

3.5 Methods

After the 16 socially vulnerable groups were selected, the data for each group were gathered at the Census tract level by the county that the study city resides in. The socially vulnerable populations were then all calculated to represent the percentage of the population that they represented. This was done to ensure that all the data are comparable and completed in Microsoft Excel (Equation 1). After this was completed, the data were uploaded into the Statistical Package for the Social Sciences (SPSS), and Descriptive Statistics were performed to convert the new values to z-scores, along with provided data on the minimum, maximum, mean, and standard deviation of each variable. When running these descriptive statistics, any variable that had a minimum, maximum, mean, and standard deviation of zero was eliminated and not converted to a Z-score to be used in the analysis as it meant that the Census tract had a population of zero. Z-scores were calculated to ensure that there was even standardization amongst the variables (Equation 2). A z-score ensures normal distribution and allows for results to be evenly compared to and used in a Principal Component Analysis (Glen, S. "Z-Score: Definition, Formula, and Calculation"). Minimums, maximums, means, standard deviations, and z-scores were computed in SPSS by selecting the "Analyze," selecting "Descriptive Statistics" from the options, choosing which variables to calculate this information for, and then clicking "Save standardized values as variables."

$$\text{Population Percentage} = \left(\frac{\text{Population within Demographic}}{\text{Total Population}}\right) \text{x } 100$$

Equation 3.1: The equation used within Microsoft Excel to calculate the population percentage of each demographic group.

$$\text{Z-Score} = \frac{(\text{Individual Value x Mean of Demographic})}{\text{Standard Deviation of Demographic}}$$

Equation 3.2: The standard equation used when calculating a Z-score.

A PCA was used to calculate the SVI score for each Census tract. The PCA was calculated in SPSS by selecting the "Analyze Header," then "Dimension Reduction," and finally "Factor." The z-scores of the variables that needed to be included for all Census tracts in the

PCA were selected. “Initial Solution,” “Significance Levels,” and “KMO and Barlett’s Test of Sphericity” were selected from “Descriptives.” “Varimax,” “Rotated Solution,” “Loading Plots,” and a maximum iteration of 100 were selected from “Rotation.” “Save as Variables” and “Regression” were selected from “Factor Scores.” Finally, under “Options,” “Replaced Missing Values with Mean” was selected. This process resulted in the values for each Principal Component to be generated by Census tract. Then, to calculate the SVI score for each Census tract, the Principal Component values for all Principal Components were added together by selecting the “Transform” header, and “Compute Variables” was selected from the options provided (Equation 3). All groups were added instead of some being subtracted as all the variable groups contributed to social vulnerability instead of reducing it.

$$SVI = PC1 + \ldots + PCF$$

Equation 3.3: The equation used to calculate the SVI scores, where PC1 is the first principal component, and PCF is the final principal component. The number of principal components between PC1 and PCF varies by study site.

To yield results that fell above the ≥ 0.5 KMO value, from the original socially vulnerable group, some were combined to result in six variables. The six variables were females, limited English speaking household (including the four language groups previously identified), age (under 5 years old and over 65 years old), race/ethnicity (Black, Asian, Native, Hispanic/Latino, other races, and two or more races), disability, and poverty. While these groups are all different, they are grouped together based on similarity and different combinations within the groups were attempted to yield the needed KMO value. After several attempts of different combinations, these six groups provided the needed KMO value while still having different groups represented amongst the data. While calculating the KMO value for Brownsville, limited

English speaking households that identified as speaking a language that was not Spanish, Indo/European, nor Asian or Pacific Islands-based were removed as all the values for this group were zero, and this resulted in Brownsville having an unacceptable KMO value. After this group was removed, the KMO value moved into the acceptable threshold. Additionally, a change in these variables altered the significance value for Bartlett's Test of Sphericity, placing all significance values below the 0.05 threshold. Components that yielded an eigenvalue >1 were considered in this thesis. Additionally, the variance explained by each component that produced an eigenvalue >1 was examined to make sure that PC1 explained the highest percentage of the variance observed.

To construct the SVI map, the SVI scores and the corresponding GISJOIN codes for all the Census tracts were copied and pasted into a Microsoft Excel spreadsheet. From there, the shapefiles for the Census tracts and the table containing the SVI scores and GISJOIN codes were uploaded into ArcGIS Pro 3.1. Then, by clicking on the shapefile, "Joins and Relates" was selected, and "Add Join" was chosen from the options. The "Input Table" was the shapefile, the "Join Table" was the Microsoft Excel spreadsheet, and the "Input Join Field" and "Join Table Field" were the GISJOIN codes. From here, under "Symbology," "Primary Symbology" was changed to "Graduated Colors." The SVI scores (labeled as "SVI" in the maps) were selected as the "Field," and "Natural Jenks" was selected as the "Method" because it creates ranges for classes based on groups already naturally in the data (ESRI, "Data classification methods"). Five classes for each SVI were used to represent the following levels of social vulnerability: "Very Low," "Low," "Moderate," "High," and "Very High."

3.6 Results

Results from the PCA analysis were examined for statistical significance (≥ 0.5 KMO value) before the SVI scores were calculated and mapped. Once the PCA met the statistical significance threshold, the SVI scores for each Census tract were created. These scores were then uploaded to ArcGIS Pro 3.1 and used as the main symbology for determining each socially vulnerable ranking.

City	KMO Value	Components	PC1 Group
Brownsville	0.548	2	Race
Lafayette	0.521	2	Disabled
Gulfport	0.581	3	Age
Mobile	0.534	2	Race
Cape Coral	0.653	2	Race

Table 3.1: A table showing the KMO value, the number of components generated in the PCA, and the socially vulnerable group that is responsible for most of the variance in PC1, by city.

Based on the results of the PCA, Cape Coral had the highest KMO value, and Lafayette had the lowest (Table 3.1). All KMO values fall above the significance threshold of 0.5 (Table 3.1). All the cities besides Gulfport had 2 components, while Gulfport had 3 (Table 3.1). Female, Race, Age, and Disabled were the variable groups that were the driving variables in PC1, and they explain where most of the variance in the data comes from (Table 3.1). For the variables in PC1, Race (3/5) was the most frequently observed socially vulnerable group, while Disabled (1/5) and Age (1/5) had the lowest observed frequency.

City	Component	Eigenvalue	Variance Explained (%)	Component Group
Brownsville	1	1.962	32.705	Race
Brownsville	2	1.313	21.888	Age
Lafayette	1	2.024	33.729	Disabled
Lafayette	2	1.267	21.109	Race
Gulfport	1	1.928	32.141	Age
Gulfport	2	1.461	24.355	Race
Gulfport	3	1.004	16.740	Language
Mobile	1	1.767	29.450	Race
Mobile	2	1.327	22.114	Age
Cape Coral	1	2.460	40.992	Race
Cape Coral	2	1.573	26.212	Disabled

Table 3.2: A table showing the component number for each city and its corresponding eigenvalue, variance explained (as a percentage), and dominant socially vulnerable group. Results for the Component Group are drawn from the Rotated Component Matrix.

The observed groups having the strongest influence on PC1 in all cities were Race (Brownsville, Mobile, and Cape Coral), Disabled (Lafayette), and Age (Gulfport), with all PC1s having the highest eigenvalue and percentage of variance explained for each city (Table 3.1, Table 3.2). The groups observed for Principal Component 2 (PC2) were Age (Brownsville and Mobile), Race (Lafayette and Gulfport), and Disabled (Cape Coral), with all PC2s having a eigenvalue over 1 (Table 3.2). Gulfport is the only city to have three components, and Principal Component 3's (PC3) group is language, and also has a eigenvalue over one (although it barely meets the threshold) (Table 3.2). Brownsville's components explained 54.593% of the variance in the data (Table 3.2). Lafayette's components explained 54.838% of the variance in the data (Table 3.2). Gulfport's components explained 74.236% of the variance in the data (Table 3.2). Mobile's components explained 51.564% of the variance in the data (Table 3.2). Cape Coral's components explained 67.204% of the variance in the data (Table 3.2). Cape Coral's PC1 had the highest eigenvalue and percentage of variance explained, while Mobile's PC1 had the lowest eigenvalue and percentage of variance explained (Table 3.2).

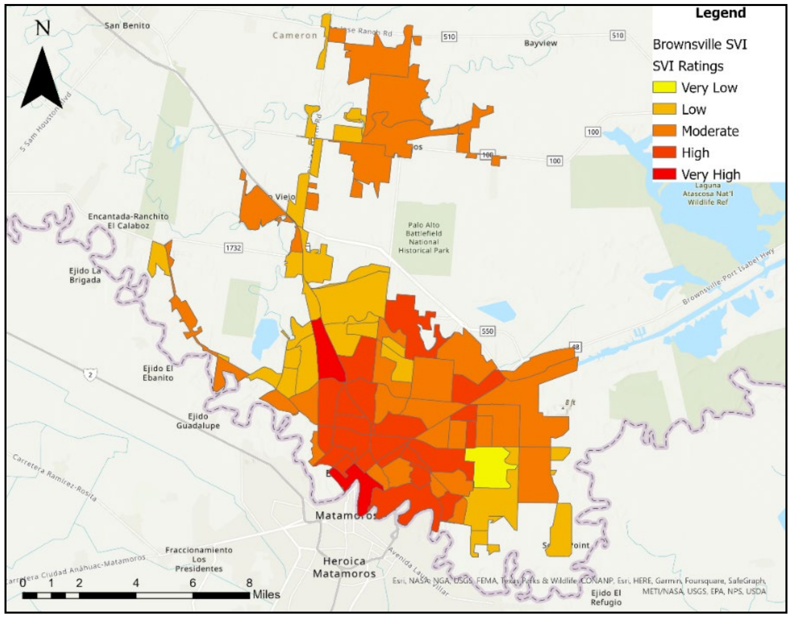


Figure 3.1: The SVI created for Brownsville, Texas.

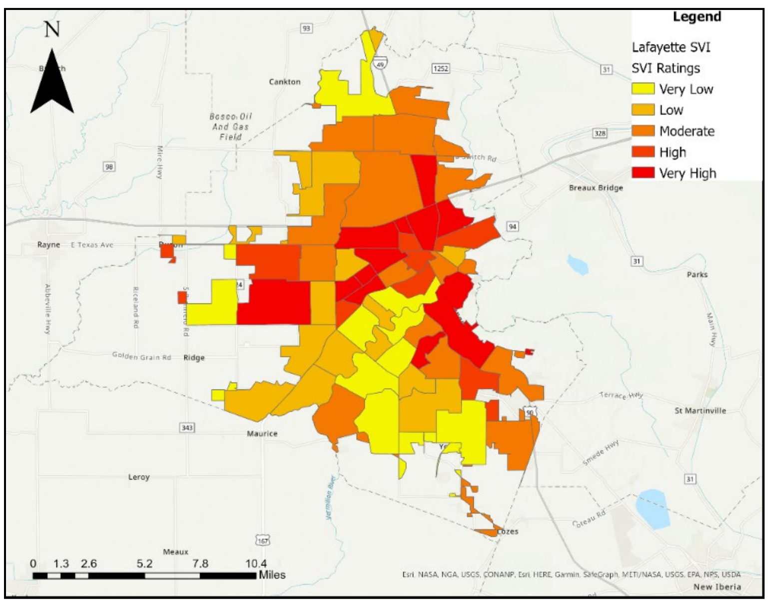
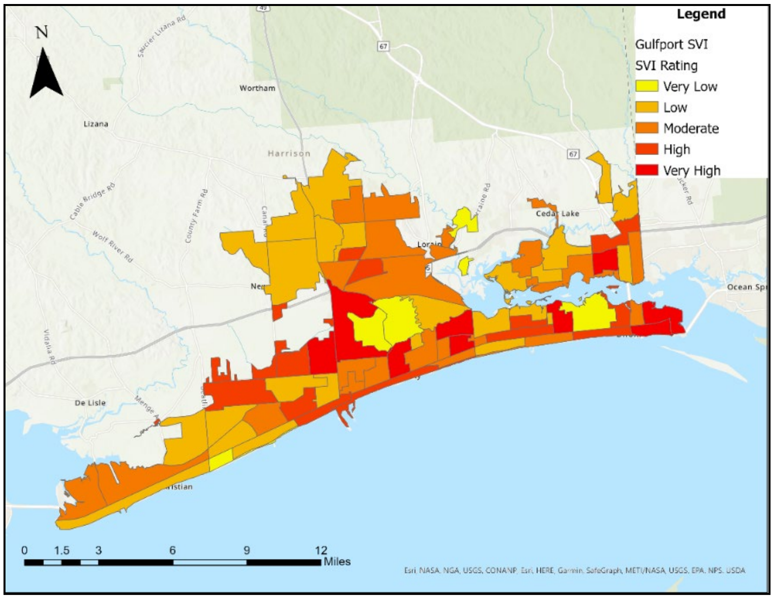
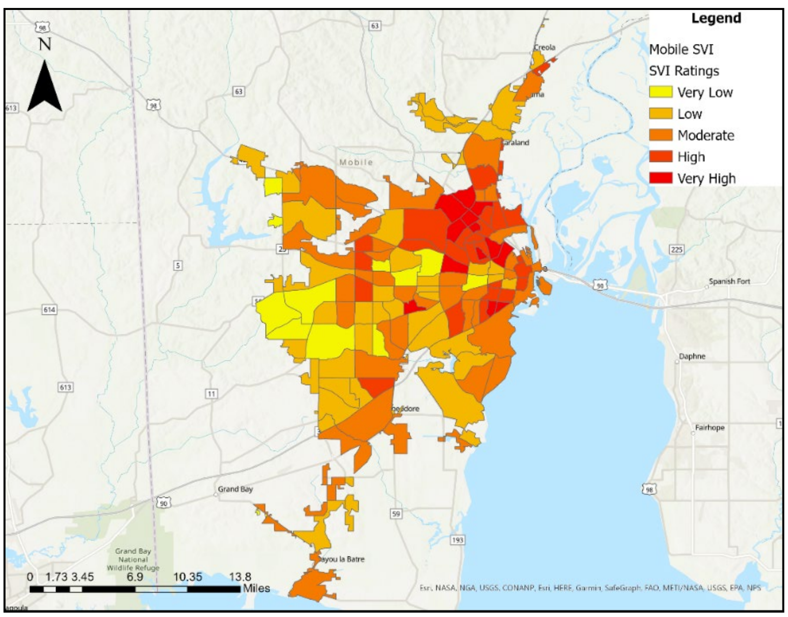


Figure 3.2: The SVI created for Lafayette, Louisiana.



<u>Figure 3.3:</u> The SVI created for Gulfport, Mississippi.



<u>Figure 3.4:</u> The SVI created for Mobile, Alabama.

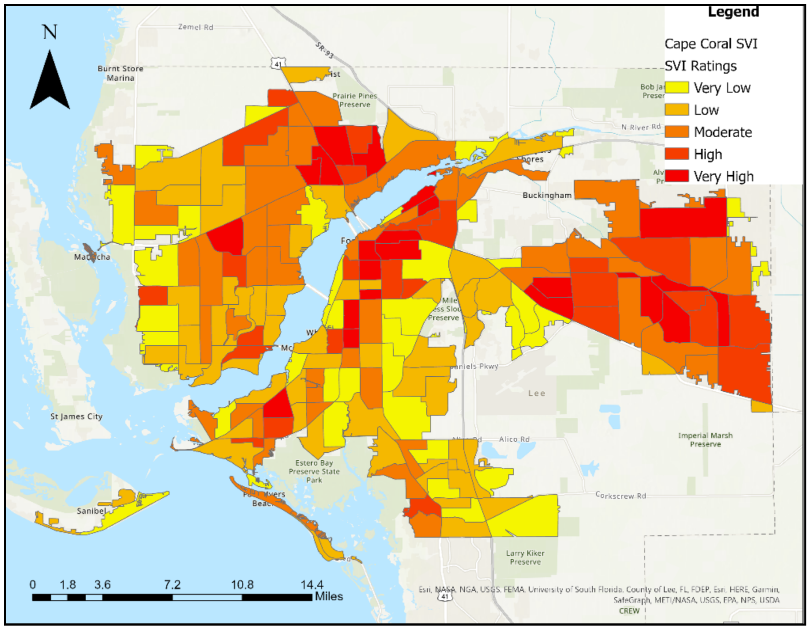


Figure 3.5: The SVI created for Cape Coral, Florida.

City	Sample Size	Very Low	Low	Moderate	High	Very High
Brownsville	67	1	16	26	22	2
Lafayette	58	10	13	15	8	12
Gulfport	75	7	24	21	14	9
Mobile	126	11	38	40	24	13
Cape Coral	199	40	60	52	25	22

Table 3.3: A table showing each city and how many Census tracts were included in the SVI, along with how many Census tracts fell within each SVI rating.

The sample size column in Table 3.3 represents the number of Census tracts used to create the SVI. For Brownsville, most Census tracts are within the "Moderate" SVI rating, with 39% of all Census tracts measuring in this rating (Table 3.3, Figure 3.1). For Lafayette, most Census tracts are within the "Moderate" SVI rating, with 26% of all Census tracts measuring in this range (Table 3.3, Figure 3.2). For Gulfport, most Census tracts are within the "Low" SVI rating, with 32% of all Census tracts measuring in this range (Table 3.3, Figure 3.3). For Mobile, most Census tracts are within the "Moderate" SVI rating, with 32% of all Census tracts measuring in this range (Table 3.3, Figure 3.4). For Cape Coral, most Census tracts are within the "Low" SVI rating, with 30% of all Census tracts measuring in this range (Table 3.3, Figure 3.5). Proportional to the size of the city, Brownsville is the city with the lowest amount of the "Very Low" socially vulnerable composition and Mobile had the highest (Table 3.3, Figures 3.1 and 3.4). Lafayette has the highest amount of the "Very High" socially vulnerable composition proportional to its city size, and Brownsville has the lowest amount (Table 3.3, Figures 3.1 and 3.2).

City	Mean Age*	Mean Race**	Mean Language***	Mean Disabled	Mean Poverty	Mean Female
Brownsville	24	23****	5 *****	12	26	50
Lafayette	20	39	2	12	17	52
Gulfport	17	42	2	16	18	50
Mobile	23	52	1	14	20	53
Cape Coral	37	37	4	14	11	51

Table 3.4: A table displaying the mean values of each city for all six variables *as a percentage of what they make up of the total population of their city.* All values are rounded to the nearest whole number.

*Consists of the total for both those under the age of five years old and those over the age of 65 years old used to compose the Age variable.

** Consists of the total for the Black, Asian, Native, two or more races, other races, and Hispanic/Latino groups used to compose the Race variable.

*** Consists of the total for the Spanish, Indo/European, Asian and Pacific Islands, and other, languages in a limited English-speaking household group that was used to compose the Language variable.

**** Since the population of Hispanic/Latinos in Brownsville is larger when compared to the other study sites, it is split up in this figure as a combination of both races and ethnicity put the mean percentage for race over 100%. Therefore, the value in this table only reflects the race groups and not the ethnic group.

***** All previously mentioned language groups besides the "other" language group are included in this calculation.

Cape Coral has the highest percentage of their population consisting of people over the age of 65 or under the age of five when compared to the other cities, and Gulfport has the lowest (Table 3.4). Mobile has the highest percentage of their population being made up by Race variable (which includes five race groups and one ethnic group), with Brownsville having the lowest (Table 3.4). However, it is important to note that Brownsville has a significantly high population of Hispanic/Latino identifying population members, which put the percentage of the population falling into the Race group over 100%. For this reason, it is the only city that had Hispanics/Latinos removed from the race calculation, and the percentage in Table 4 represents only race groups. Brownsville has the highest percentage of their population living in a limited-English speaking household, while Mobile has the lowest (Table 3.4). Gulfport has the highest percentage of their population identifying as disabled, while Brownsville and Lafayette have the lowest (Table 3.4). Brownsville has the highest percentage of their population living at or below the poverty line, and Cape Coral has the lowest percentage (Table 3.4). Mobile has the highest percentage of their population identifying as female, while Brownsville and Gulfport have the lowest (Table 3.4).

3.7 Discussion

The KMO values for each study site, while still considered statistically significant, are low, being closer to 0.5 (the minimum) than 1. It is ideal that the KMO be closer to 1 than to 0.5 to enhance the statistical significance and reliability of the results (UCLA: Statistical Consulting Group, 2021). One reason that the KMO values can be low has to do with the number of variables used in tandem with the sample size (the number of Census tracts within each city). The highest KMO value was produced for Cape Coral, which had the highest sample size, and the lowest KMO value was produced for Lafayette, which had the lowest sample size (Tables 1 and 3). Variable groups were combined and separated to produce the most successful KMO values. While the separation of components within a group or additions of other demographic/socioeconomic populations may have increased the KMO value, there was a desire to keep uniformity amongst the variable groups used in this thesis. This resulted in only this combination of demographic groups into different variables that yielded a KMO value >0.5 at all five study sites. Additionally, PC1 and PC2 explained the most variance in Cape Coral over the

PC1s and PC2s in all study sites (Gulfport is excluded as it had three PCs, and having more PCs results in more variances being explained) (Table 3.2). As with any statistical test, the larger the sample size, the more robust and reliable the results are. For this thesis, the sample size and variable ratio affected the KMO value along with the percentage of variance explained by the principal components. The number of principal components does not appear to be directly influenced by the sample size as all cities except Gulfport had two principal components (and Gulfport had three).

The percentage of the population made up of a specific demographic/socioeconomic group appears to have mixed influences on explaining the variances on the data. The only study sites where the PC1s were the same as the highest mean makeup of that group in relation to the other study sites was Mobile with the Race group (Tables 3.1, 3.2, and 3.4). No PC2s correlated to the percentage of that socially vulnerable group's composition in a study site in relation to the other study sites (Tables 3.2 and 3.4). This also holds true for Gulfport's PC3 (Tables 3.2 and 3.4). From the opposite perspective, Gulfport, Mobile, and Cape Coral had the lowest makeup of the Age and Females, Language, and Poverty group compositions when compared to the other study sites (Table 3.4). None of these groups appeared as a principal component in their city's PCA results (Table 3.2). An observation that can be drawn from this is that a high presence of a socially vulnerable group may not result in it being a component, but a low presence of a socially vulnerable group may result in that group not being a component. This can be observed in Brownsville, Gulfport, Mobile, and Cape Coral. Respectively, each had the lowest percentage of the population being classified into the disabled, females, language, and poverty groups, and these groups were not a main component of each city's principal components. To counter the previous statement, Lafayette has the lowest composition of its population identifying as disabled compared to the other study sites, but the disabled population is the most prevalent socially vulnerable group in PC1 (Tables 3.2 and 3.4). Therefore, a low presence of a socially vulnerable group in a population does not mean that it has a low influence on its social vulnerability.

From the SVI rankings, all study sites had more “Very Low” ranking Census tracts than “Very High” Census tracts (Figures 3.1 - 3.5). Along with this, all cities had most of their Census tracts fall into either the “Moderate” or “Low” rankings. These are both promising results as a lower social vulnerability ranking is better regarding community resiliency as higher social vulnerability rankings. The spatial disbursement based only on the SVIs appears to be at random amongst all study sites (Figures 3.1 - 3.5). However, this perception may change based on the results of Question 3, which will be examined in Chapter 4. The PCA results, once statistical significance was achieved, were used to visualize areas of varying degrees of social vulnerability, along with provide insight into which of the six socially vulnerable groups contributed the most to the SVI score of each Census tract.

Chapter 4: The Relationship Between Risk for Physical Damage and Social Vulnerability

4.1 Introduction

As discussed in previous chapters, social vulnerability affects the ability for a population to prepare for and recover from a tropical cyclone. Knowing if someone will need to relocate to a shelter, their building is likely to be damaged, and the expected financial damage will influence how someone prepares for a tropical cyclone and helps them know what to do to successfully recover. The Hazus maps created in Chapter 2 incorporate Census data, but Hazus is not aimed at specifically incorporating social vulnerability into its calculations. Similarly, as seen in Chapter 3, the SVIs for the study sites were constructed independently of the information provided by the Hazus maps. This chapter aims to look and see if there are any spatial relationships, such as spatial autocorrelation, between areas of high risk, low risk, high social vulnerability, and low social vulnerability.

4.2 Background

4.2.1 Social Vulnerability's Influence on Risk for Physical Damage

It has long been thought that risk may not be influenced solely by physical components like geographic location, but that social vulnerability may influence this. Lower social vulnerability scores imply that the population may not struggle as much in tropical cyclone preparation and recovery when compared to higher social vulnerability scores. Social vulnerability can describe how people interact with their environment, making it important when looking at the risk of a natural hazard like tropical cyclones as it can also reveal social problems in a particular area (Singh et al., 2014). All but one of the Hazus maps from Chapter 2 relate to some form of infrastructure damage. The quality of a structure can be affected by who is living in those areas and the integrity of infrastructure can affect the ability to prepare for and recover from a tropical cyclone (Chakraborty et al., 2005; Singh et al., 2014). Understanding the influence of social vulnerability on risk may be the key to creating resilient communities that can be impacted by tropical cyclones (Bergstrand et al., 2015; Singh et al., 2014; Spielman et al., 2020). It has also been theorized that social vulnerability can change between different geographic locations depending on the demographic makeup of the socially vulnerable group in that area (Spielman et al., 2020). Regardless of the socially vulnerable makeup, areas of high risk from physical damage should still be given great consideration as damage can be expected (Chakraborty et al., 2005). In the case of tropical cyclones, areas that are closer to the coastline are at a higher physical risk from tropical cyclone impacts. Areas of high social vulnerability and high risk for physical damage should be given top priority, making identifying their location critical in mitigation planning.

The National Risk Index (NRI), designed by FEMA, was developed to look at the risk of many different natural hazards at the Census tract and county level in the United States. Unlike traditional risk maps, the goal of the NRI was to include other potential components that may affect risk (Zuzak et al., 2022). One of these components to be included was social vulnerability as little attempts have been made to include social vulnerability in previous risk assessments (Zuzak et al., 2022). Social vulnerability is identified as being a component that increases risk, explaining how it fits into the NRI's risk equation (Equation 1). While the NRI's equation for risk is not used in this thesis, it is important to note as it shows that social vulnerability is now an identifiable influence on risk from a federal emergency management standpoint.

$$\text{Risk} = \frac{\text{Expected Annual Loss x Social Vulnerability}}{\text{Community Resilience}}$$

Equation 4.1: The formula that was developed by FEMA to calculate risk for the National Risk Index (Zuzak et al., 2022).

4.2.2 Bivariate Local Moran's I Spatial Statistic

In 1969, Tobler's First Law of Geography was coined by Waldo Tobler, who stated that "everything is related to everything else, but near things are more related than distant things" (GISGeography, 2022). Essentially, objects or places that are closer in geographic proximity to each other will exhibit more similar attributes. Places or objects that are farther in geographic proximity will share fewer common attributes. This is the basis for the concept of spatial autocorrelation, which describes the intensity and linearity of spatial patterns and relationships between a variable with itself while considering the feature's value and locations at the same time (Dubé and Legros, 2014; ESRI). Simply, spatial autocorrelation describes if features are randomly dispersed or if there is a pattern to their dispersal.

Moran's I is a spatial statistical test that will describe the amount of spatial autocorrelation observed between a variable and its statistical significance (Dubé and Legros, 2014; ESRI; GISGeography, 2022; Lee, 2001). Moran's I can be used at a global or local level. Global Moran's I looks at the overall spatial autocorrelation, while Local Moran's I compares the local spatial autocorrelation to the global autocorrelation as it focuses on near neighbors (Dubé and Legros, 2014; ESRI). Local Moran's I was chosen over Global Moran's I as it provides a way to better identify patterns of varying values (Dubé and Legros, 2014; Lee, 2001). Local Moran's I produce four groupings: High-High, Low-Low, High-Low, and Low-High.

High-High and Low-Low are considered spatial clusters and imply a (positive) high degree of spatial autocorrelation. High-Low and Low-High are considered spatial outliers and imply that there is (negative) little to no spatial autocorrelation (Dubé and Legros, 2014). All four are considered to have statistical significance; features that are not statistically significant are labeled as so.

For this thesis, a Bivariate Local Moran's I analysis is used to examine the spatial autocorrelation between the Hazus maps and the SVIs. Bivariate Local Moran's I examines the statistical relationship between two nearby features and demonstrates spatial autocorrelation between both variables (Livings and Wu, 2020; Lee, 2001). A Weights Matrix must be computed, and the contiguity method was used as it works well for polygon data (which the Census tracts are) that are located near each other. There are two options for contiguity: Queen's case and Rook's case (Livings and Wu, 2020). Like the chess pieces that are their namesakes, each case uses a different way of defining near neighbors. The Queen's case allows for neighbors to be defined by features sharing a side and corner, while the Rook's case defines neighbors as features sharing only a common side (Livings and Wu, 2020). To incorporate more data, Queen's contiguity was chosen. The Bivariate Local Moran's I requires the identification of an X (independent or explanatory) variable and a Y (the dependent) variable. SVI is selected as the X variable because SVI is not influenced by physical risk. The Hazus map risk factor is assigned as the Y variable as it should be influenced by the SVI value.

4.3 Research Question, Hypothesis, and Objective

The research question that will be answered in this chapter is *"Are there any spatial relationships between the risk of tropical cyclone physical damage and social vulnerability at each study site?"* One hypothesis is that areas of higher risk for different physical damages will correspond to areas of high social vulnerability, while areas of lower risk for different physical damages will correspond to areas of low social vulnerability. Another hypothesis is that there will be more areas of high damage-high vulnerability and low damage-low vulnerability over areas of high damage-low vulnerability and low damage-high vulnerability. The objective is that the Bivariate Local Moran's I spatial statistic will map and count areas where the four relationships between damage and vulnerability above appear in each city.

4.4 Data

The data that are used in this chapter are the same sources used in Chapters 2 and 3 as the maps created to answer this question are based on the maps from Chapters 2 and 3. These data sources include the US Census Bureau, the National Structure Inventory, and the US Army Corps of Engineers.

4.5 Methodology

Similar to what was done for Question 2 (in Chapter 3), the Hazus maps and the SVI maps must be linked by a unique identifier. For the maps in this chapter, the linking unique identifier is going to be the Census tract numbers, or "Tract_1" in the data files. In ArcGIS Pro, the spreadsheet with the SVI data was joined to three of the four generated Hazus maps for Question 1 (Chapter 2) for each study site. These three maps were for Displaced Households, Percentage of Buildings with No Damage, and Total Loss. The windspeeds map was left out as the windspeeds from a tropical cyclone are not influenced by social vulnerability, whereas the other maps' outcomes may be affected by social vulnerability. Once this join was complete, the shapefile was saved with the updated corresponding SVI information. Then, that shapefile is uploaded into GeoDa (Anselin, 2020b). Under "Tools," "Weights" is selected, which is necessary for a Bivariate Local Moran's I test to run. "Create" was selected, and from the options that appear, "Tract_1" was selected as the ID variable, and "Queen" was selected for Contiguity. Queen was selected over Rook because the Queen will include more neighbors in the analysis and will help provide the best results in the case of any inaccuracies in the dataset (Anselin, 2020a). All other values remain untouched. After this weight file was created and saved, under "Space," "Bivariate Local Moran's I" was selected. "SVI" is selected as "X" and the Hazus variable is selected as "Y." A "Cluster Map" was selected to be created, as these maps represent the clusters for High-High (high social vulnerability-high risk), High-Low (high social vulnerability-low risk), Low-Low (low social vulnerability-low risk), Low-High (low social vulnerability-high risk) and Not Significant (not statistically significant). Due to a difference in spatial resolution between the SVI and the Hazus maps used for Gulfport, Mississippi, this methodology was not able to be done for this study site (refer to Section 2.7 for more information). However, this methodology was completed in the other four study sites.

4.6 Results

After the Bivariate Local Moran's I analysis was completed, cluster maps were produced to visualize areas of statistically-significant clusters or outliers, and areas of no statistical significance. Areas were visualized by each Census tract unit within the city.

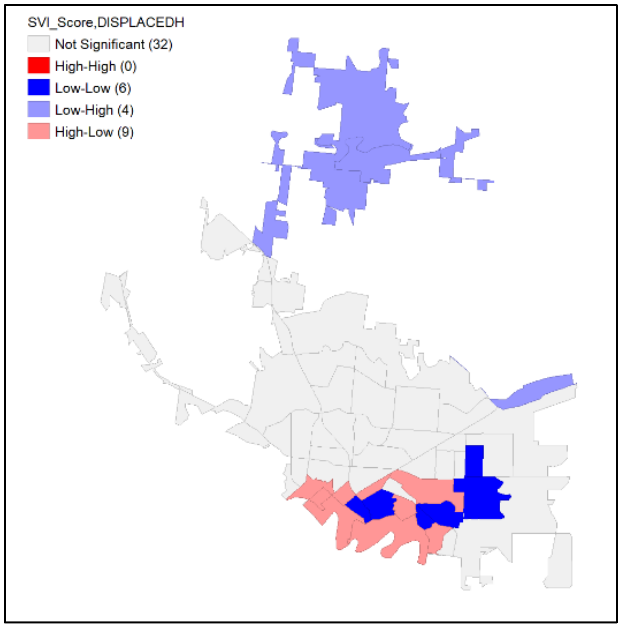


Figure 4.1: A cluster map generated by the Bivariate Local Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Displaced Households due to a tropical cyclone in Brownsville, Texas.

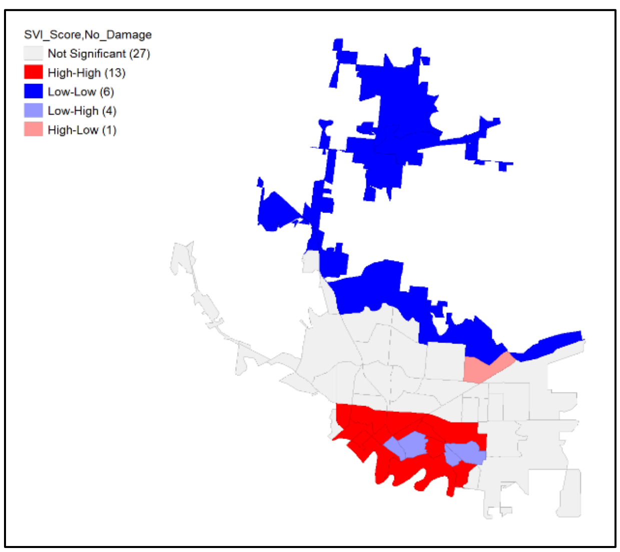


Figure 4.2: A cluster map generated by the Bivariate Local Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and the Percentage of Buildings with No Damage due to a tropical cyclone in Brownsville, Texas.

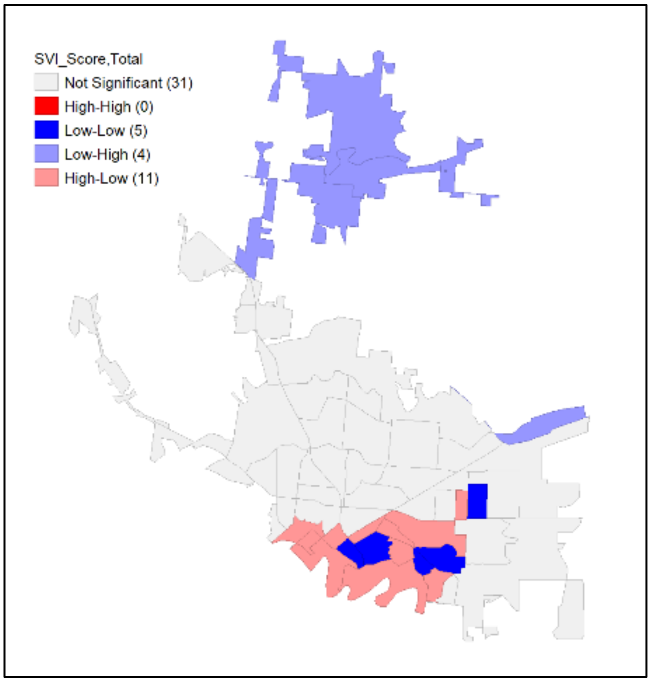
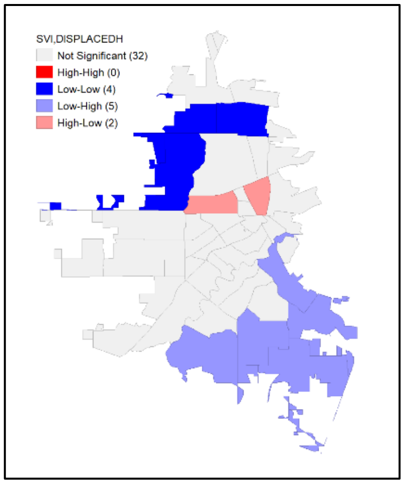


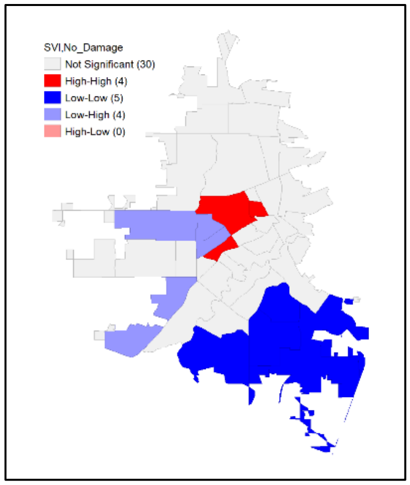
Figure 4.3: A cluster map generated by the Bivariate Local Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Total Financial Loss due to a tropical cyclone in Brownsville, Texas.

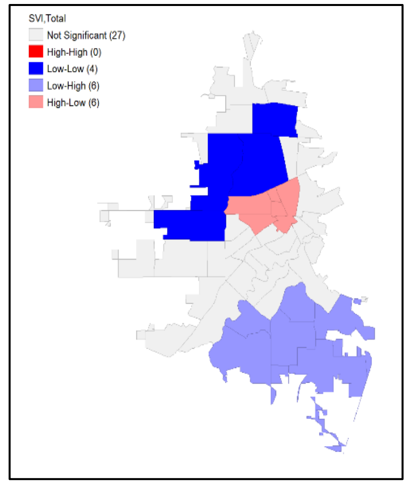
Risk Factor	High-High	Low-Low	Low-High	High-Low	Not Significant
Displaced Households	0	6	4	9	32
% of Buildings with No Damage	13	6	4	1	27
Total Financial Loss	0	5	4	11	31

Table 4.1: The number of Census tracts in the four statistically significant groups and one not statistically significant group for each risk factor map for Brownsville, Texas.

Three cluster maps were created for Brownsville, Texas for three of the four Hazus maps created in Chapter 2, with each map examining the relationship between the SVI score and the specific risk factors. For Displaced Households, the most prominent cluster or outlier, besides Not Significant, was the High-Low outlier (17.6% of all Displaced Household Census tracts) (Figure 4.1, Table 4.1). For the Percentage of Buildings with No Damage, the most prominent cluster or outlier, besides Not Significant, was the High-High cluster (25.5% of all Percentage of Buildings with No Damage Census tracts) (Figure 4.2, Table 4.1). For the Total Financial Loss, the most prominent cluster or outlier, besides Not Significant, is the High-Low outlier (21.6% of all Total Financial Loss Census tracts) (Figure 4.3, Table 4.1). The cluster or outlier amongst all three risk factors that had the most Census tracts is Not Significant (Table 4.1 top-to-bottom risk factors, 62.7%, 52.9%, and 60.8% for each risk factor, respectively), and the clusters or outliers amongst all three risk factors that had the least Census tracts are Low-High (7.8% for Percentage of Buildings with No Damage) and High-High (0.0% for Displaced Households and Total Financial Loss) (Table 4.1). Percentage of Buildings with No Damage had the most High-High clusters (100% of all High-High cluster Census tracts), Displaced Households and Percentage of Buildings with No Damage had the most Low-Low clusters (70.6% of all Low-Low cluster Census tracts), all three risk factors had the same amount of Low-High outliers (100% total of all Low-High cluster Census tracts), and Total Financial Loss had the most High-Low outliers(52.4% of all High-Low outlier Census tracts) (Table 4.1). Displaced Households had the most Not Significant outliers (35.6% of all Not Significant Census tracts), and Percentage of Buildings with No Damage had the least amount of Not Significant outliers (30.0% of all Not Significant Census tracts) (Table 4.1).





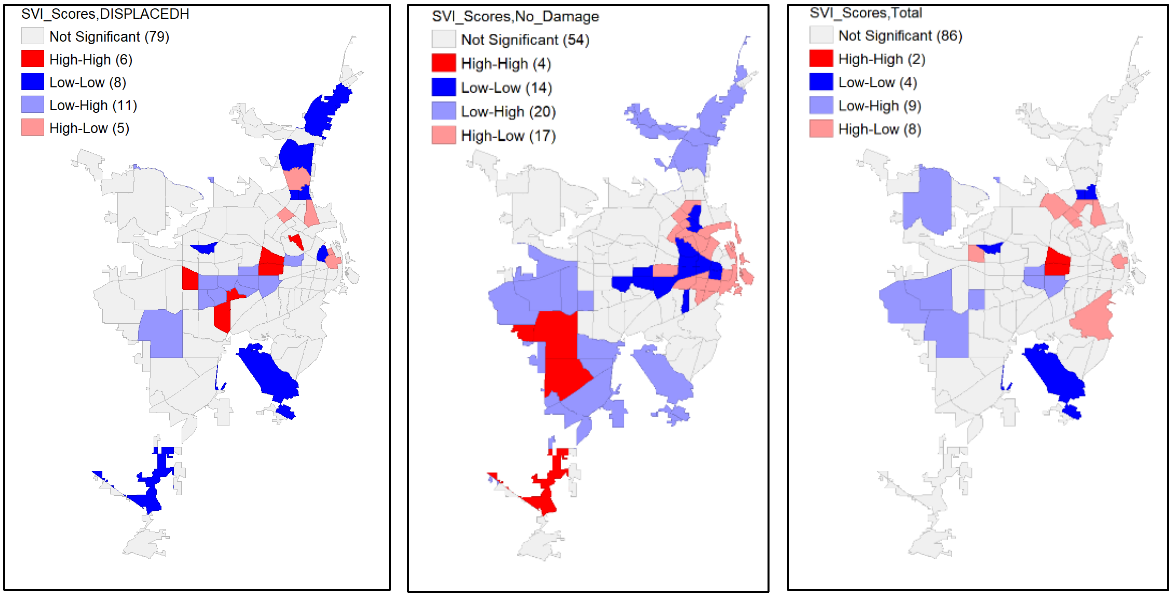


Figures 4.4 (left), 4.5 (middle), and 4.6 (right): Figure 4.4 is a cluster map generated by the Bivariate Local Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Displaced Households due to a tropical cyclone in Lafayette, Louisiana. Figure 4.5 is a cluster map generated by the Bivariate Local Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and the Percentage of Buildings with No Damage due to a tropical cyclone in Lafayette, Louisiana. Figure 4.6 is a cluster map generated by the Bivariate Local Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Total Financial Loss due to a tropical cyclone in Lafayette, Louisiana.

Risk Factor	High-High	Low-Low	Low-High	High-Low	Not Significant
Displaced Households	0	4	5	2	32
% of Buildings with No Damage	4	5	4	0	30
Total Financial Loss	0	4	6	6	27

Table 4.2: The number of Census tracts in the four statistically significant groups and one not statistically significant group for each risk factor map for Lafayette, Louisiana.

Three cluster maps were created for Lafayette, Louisiana for three of the four Hazus maps created in Chapter 2, with each map examining the relationship between the SVI score and the specific risk factors. For Displaced Households, the most prominent cluster or outlier, besides Not Significant, was the Low-High outlier (18.6% of all Displaced Household Census tracts) (Figure 4.4, Table 4.2). For the Percentage of Buildings with No Damage, the most prominent cluster or outlier, besides Not Significant, was the Low-Low cluster (11.6% of all Percentage of Buildings with No Damage Census tracts) (Figure 4.5, Table 4.2). For the Total Financial Loss, the most prominent clusters or outliers, besides Not Significant, are the Low-High and High-Low outliers combined (27.9% of all Total Financial Loss Census tracts) (Figure 4.6, Table 4.2). The cluster or outlier amongst all three risk factors that had the most Census tracts is Not Significant (Table 2 top-to-bottom risk factors, 74.4%, 69.8%, and 62.8% for each risk factor, respectively), and the clusters or outliers amongst all three risk factors that had the least Census tracts are High-High (0.0% for Displaced Households and Total Financial Loss) and High-Low (0.0% for Percentage of Buildings with No Damage) (Table 4.2). Percentage of Buildings with No Damage had the most High-High clusters (100% of all High-High cluster Census tracts), Displaced Households and Total Financial Loss had the most Low-Low clusters (total 61.5% of all Low-Low cluster Census tracts), Total Financial Loss had the most Low-High outliers (40.0% of all Low-High cluster Census tracts), and Total Financial Loss had the most High-Low outliers (75.0% of all High-Low cluster Census tracts) (Table 4.2). Displaced Households had the most Not Significant outliers (36.0% of all Not Significant Census tracts), and Total Financial Loss had the least amount of Not Significant outliers (30.3% of all Not Significant Census tracts) (Table 4.2).



Figures 4.7 (left), 4.8 (middle), and 4.9 (right): Figure 4.7 is a cluster map generated by the Bivariate Local Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Displaced Households due to a tropical cyclone in Mobile, Alabama. Figure 4.8 is a cluster map generated by the Bivariate Local Moran's I spatial statistic to show the relationship between Social Vulnerability and the Percentage of Buildings with No Damage due to a tropical cyclone in Mobile, Alabama. Figure 4.9 is a cluster map generated by the Bivariate Local Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Total Financial Loss due to a tropical cyclone for Mobile, Alabama.

Risk Factor	High-High	Low-Low	Low-High	High-Low	Not Significant
Displaced Households	6	8	11	5	79
% of Buildings with No Damage	4	14	20	17	54
Total Financial Loss	2	4	9	8	86

Table 4.3: The number of Census tracts in the four statistically significant groups and one not statistically significant group for each risk factor map for Mobile, Alabama.

Three cluster maps were created for Mobile, Alabama for three of the four Hazus maps created in Chapter 2, with each map examining the relationship between the SVI score and the specific risk factors. For Displaced Households, the most prominent cluster or outlier, besides Not Significant, was the Low-High outlier (10.1% of all Displaced Households Census tracts)

(Figure 4.7, Table 4.3). For the Percentage of Buildings with No Damage, the most prominent cluster or outlier, besides Not Significant, was the Low-High outlier (18.3% of all Percentage of Buildings with No Damage Census tracts) (Figure 4.8, Table 4.3). For the Total Financial Loss, the most prominent cluster or outlier, besides Not Significant, is the Low-High outlier (8.3% of all Total Financial Loss Census tracts) (Figure 4.9, Table 4.3). Based on percentages, the cluster or outlier amongst all three risk factors that had the most Census tracts is Not Significant (Table 4.3 top-to-bottom risk factors, 72.5%, 49.5%, and 78.9% for each risk factor, respectively), and the cluster or outlier amongst all three risk factors that had the least Census tracts is High-High (5.5% for Displaced Households and 1.8% for Total Financial Loss) (Table 4.3). Displaced Households had the most High-High clusters (50.0% of all High-High cluster Census tracts), Percentage of Buildings with No Damage had the most Low-Low clusters (53.8% of all Low-Low cluster Census tracts), Percentage of Buildings with No Damage had the most Low-High outliers (50.0% of all Low-High cluster Census tracts), and Percentage of Buildings with No Damage had the most High-Low outliers (56.7% of all High-Low cluster Census tracts) (Table 4.3). Total Financial Loss had the most Not Significant outliers (39.2% of all Not Significant cluster Census tracts), and Percentage of Buildings with No Damage had the least amount of Not Significant outliers (24.6% of all Not Significant cluster Census tracts) (Table 4.3).

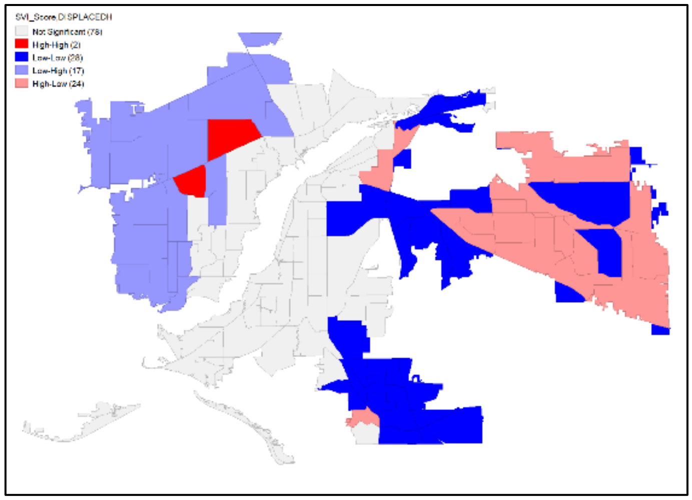


Figure 4.10: A cluster map generated by the Bivariate Local Moran’s I spatial statistic that demonstrates the relationship between Social Vulnerability and Displaced Households due to a tropical cyclone in Cape Coral, Florida.

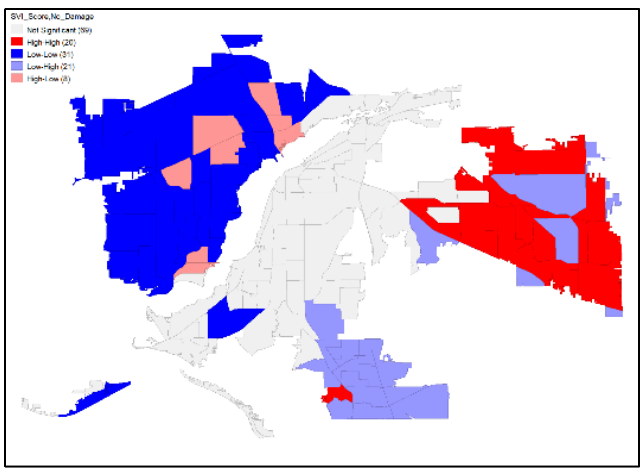


Figure 4.11: A cluster map generated by the Bivariate Local Moran’s I spatial statistic that demonstrates the relationship between Social Vulnerability and the Percentage of Buildings with No Damage due to a tropical cyclone in Cape Coral, Florida.

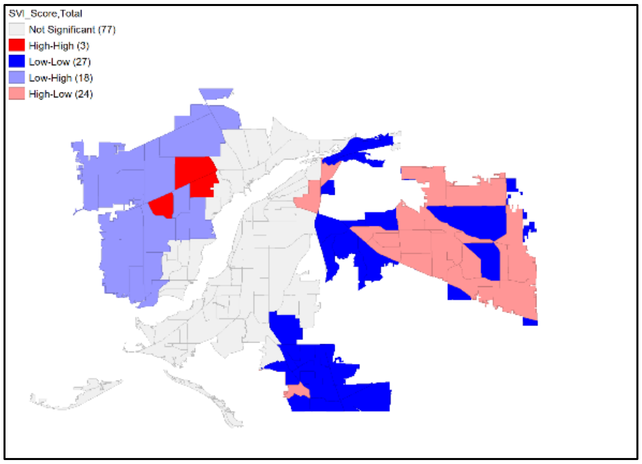


Figure 4.12: A cluster map generated by the Local Bivariate Moran's I spatial statistic that demonstrates the relationship between Social Vulnerability and Total Financial Loss due to a tropical cyclone for Cape Coral, Florida.

Risk Factor	High-High	Low-Low	Low-High	High-Low	Not Significant
Displaced Households	2	28	17	24	78
% of Buildings with No Damage	20	31	21	8	89
Total Financial Loss	3	27	18	24	77

Table 4.4: The number of Census tracts in the four statistically significant groups and one not statistically significant group for each risk factor map for Cape Coral, Florida.

Three cluster maps were created for Cape Coral, Florida for three of the four Hazus maps created in Chapter 2, with each map examining the relationship between the SVI score and the specific risk factors. For Displaced Households, the most prominent cluster or outlier, besides Not Significant, was the Low-Low cluster (17.5% of all Displaced Household Census tracts) (Figure 4.10, Table 4.4). For the Percentage of Buildings with No Damage, the most prominent cluster or outlier, besides Not Significant, was the Low-Low cluster (19.3% of all Percentage of Buildings with No Damage Census tracts) (Figure 4.11, Table 4.4). For the Total Financial Loss, the most prominent cluster or outlier, besides Not Significant, is the Low-Low cluster (16.9% of all Total Financial Loss Census tracts) (Figure 4.12, Table 4.4). Based on percentages, the cluster or outlier amongst all three risk factors that had the most Census tracts is Not Significant (Table 4.4 top-to-bottom risk factors, 48.8%, 55.6%, and 48.1% for each risk factor, respectively), and the cluster or outlier amongst all three risk factors that had the least Census tracts is High-High (Table 4.4 top-to-bottom risk factors, 0.01%, 12.5%, and 0.01% for each risk factor, respectively) (Table 4.4). Percentage of Buildings with No Damage had the most High-High clusters (80% of all High-High cluster Census tracts), Percentage of Buildings with No Damage had the most Low-Low clusters (36.0% of all Low-Low cluster Census tracts), Percentage of Buildings with No Damage had the most Low-High outliers (37.5% of all Low-High cluster Census tracts), and Displaced Households and Total Financial Loss had the most High-Low outliers (42.9% individually, or 85.7% total of all High-Low cluster Census tracts (Table 4.4). Percentage of Buildings with No Damage had the most Not Significant outliers (36.5% of all Not Significant cluster Census tracts), and Displaced Households had the least amount of Not Significant outliers (31.6% of all Not Significant cluster Census tracts) (Table 4.4).

4.7 Discussion

When looking at the maps, it is evident that certain cluster groups are favoring being spatially near another outlier group over the others. Specifically, High-High clusters are seen occurring near Low-High outliers, and Low-Low clusters and High-Low outliers are observed being near each other. This is a distinct feature visible on almost every map at all the study sites, regardless of what the specific damage or risk was. High-High clusters and Low-High outliers are related as there is a high risk for physical damage in the Census tracts in these clusters and outliers. Conversely, Low-Low clusters and High-Low outliers are similar in the sense that the risk for that specific type of damage or loss is low. This may suggest that the areas where the four cluster and outlier groups are broken up into these two smaller groups, a High Risk and a Low Risk group, based on their geographic proximity to one another are areas of either higher or lower risk for physical damage or loss, regardless of social vulnerability. This supports Tobler's First Law of Geography as spatial autocorrelation is observed since the High Risk and Low Risk group are composed of clusters and outliers that are more related to each other than the clusters in the other group.

When assessing whether a specific physical risk is more prevalent in one cluster than the other, some risks are common across all four study sites. The Percentage of Buildings with No Damage dominates the High-High cluster in all study sites besides Mobile; in Brownsville and Lafayette, it is the only risk that is in this cluster. In Mobile, The Percentage of Buildings with No Damage has more Census tracts in a cluster than the other two risk factors. The Percentage of Buildings with No Damage has a quite different prevalence across the High-Low outliers for every study site, as it is only the dominant risk factor in this cluster or outlier for Mobile. Except for Mobile, the Low-High outliers are mostly evenly distributed between all three risk factor groups.

The Percentage of Buildings with No Damage is the most prevalent (besides a tie with Displaced Households in Brownsville) risk factor in the Low-Low cluster, as well as the High-High cluster (excluding Mobile). This may mean that, when about the integrity of infrastructure, social vulnerability may influence how likely a building is to be damaged. This may hold in some cases as socially vulnerable populations who are struggling financially may only be able to afford to live in older, weaker buildings. Additionally, they may not have the money to recover if the building they reside in is destroyed in a storm. For resilient community purposes, the number of displaced households and the total financial needs to be kept as minimal as possible. On the other hand, it is good to have a high number of Census tracts in the High-High cluster or Low-High outlier for the Percentage of Buildings with No Damage, as a high number in this risk factor implies resiliency as fewer buildings are sustaining damage. This may explain why the High Risk and Low Risk groups, when looking at it from the Percentage of Buildings with No Damage risk perspective, are experiencing clustering. Wealthier areas typically have stronger infrastructure and are the home to affluent community members who are less socially vulnerable. These areas of lower social vulnerability are more likely to be focused in one location instead of several smaller or more randomly dispersed clusters.

Chapter 5: Conclusions, Limitations, Future Directions, and Significance

5.1 Conclusions

5.1.1 Question 1

When estimating risk, this thesis shows that it is important to pay attention to the locations of the strongest winds in a hurricane as this can be an indicator of where the most damage will occur. The highest category windspeeds modeled was at the Category 4 level (Gulfport and Cape Coral), and the lowest category was modeled at the Category 2 level (Lafayette). Cape Coral had the highest amount of potentially displaced households, which can mean that Cape Coral, of all the study sites, should plan for needing more storm shelter, and potentially evacuation routes, s in the event of a tropical cyclone. Mobile will experience the lowest percentage of buildings that receive no damage (46.8%) of all the study sites. This can imply that the Mobile building codes and standards may need to be updated and increased and that more shelters may need to be in place if more buildings are likely to be damaged. Cape Coral is most likely to experience the highest total economic loss ($551,466,000), and this should inspire planners and emergency managers to budget accordingly. The geospatial component of Hazus is particularly of use as it shows the exact location where damage is likely to occur.

5.1.2 Question 2

Six socially vulnerable groups were used to run a PCA that was used to create an SVI. Sample size appeared to influence the KMO. The dominant demographic/socioeconomic group for a study site was not always the group that was having the heaviest influence on the SVI results. The most common socially vulnerable group explaining the variance in PC1 was "race", which was the group for the PC1 in three study sites (Brownsville, Cape Coral, and Mobile). Gulfport was the only city to have three principal components (age, race, and language). Females and Poverty were the only groups that did not appear as the group explaining the variance in any principal component for any study site. In almost all the study sites, the least prevalent socially vulnerable group was not a group that had a heavy influence on the SVI values. For all the study sites, most of the Census tracts fall into the "Moderate" or "Low" SVI rating. Brownsville is the city with the lowest amount of "Very Low" socially vulnerable tract ratings, and Mobile had the highest amount, for their sample size. Lafayette has the highest amount of "Very High" socially vulnerable tract ratings, and Brownsville had the lowest amount, for their sample size.

5.1.3 Question 3

Spatial autocorrelation was observed when the Bivariate Local Moran's I spatial statistical test was used to see if areas of similar social vulnerability or risk levels would appear to be next to each other. Some risk factors, such as the Percentage of Buildings with No Damage, made up large portions of varying clusters across all study sites; in this case, it was the High-High cluster. There is a great variance in how much each of the three risk factors composed of the High-Low outliers throughout all four study sites where this test was computed for. Apart from Cape Coral, the High-High and Low-Low clusters for each of the three risk factors had a smaller number of Census tracts when compared to the other outliers.

5.2 Limitations

5.2.1 Question 1

The building data used is from the 2010 Census and has not been updated to have 2020 Census information. While this does not apply to all the data needed or used in the predictions, it is important since Census data supply some of the information regarding buildings, shelters, and total losses. However, the data is still reliable as it has a real basis but would need to be updated with the 2020 data to provide a more up-to-date risk estimate. There is a way to input user-generated data, which would require traveling to each study site to evaluate buildings and conduct interviews and surveys, but that was not possible for this thesis given time and money constraints. The user-generated data would have allowed for a more advanced level analysis that would have yielded more accurate results, but due to this constraint, the analysis was done at the basic (Level 1) level (FEMA, 2022).

Hazus functions at different resolutions of spatial data, and in this thesis, it is used at the Census tract level as this was the smallest spatial unit available for Hazus' Hurricane Model. Other Hazus models work at a smaller spatial level, such as at the Census block level. The finer the spatial resolution is, the more accurate the results are as it creates a larger sample size for the model to utilize. Despite this, the Census tracts will still yield usable and informative results as the data are directly input for that level, and there are multiple Census tracts featured at each study site. The issues with conflicting data between the Hurricane and Flood Models of Hazus may be why some results for Gulfport, Mississippi are automatically generated at the Census block level even when the Census tract level is selected.

Since Hazus is a model, it is always important to examine the information generated with caution. Hazus relies on the data it is provided along with the equation designed to give the most accurate predictions. Albeit it is used by risk-estimating practitioners around the United States, it has its flaws as with any model. There is no guarantee that what is seen in these 100-year scenarios for each city is certainly going to happen exactly as predicted. The benefit of models, however, is that they are constantly evolving as new data are gathered and equations are improved upon. All model and estimating program designers create their programs based on the most accurate information at the time. Hazus has been updated several times since it originally came out years ago, showing that the Hazus creators are dedicated to making sure it produces the most accurate information possible.

5.2.2 Question 2

A problem with Census data is that it is self-reported, and the data may not be accurate or complete as not all parts of the Census are required to be filled out. This affects the SVI results as it may not provide accurate insight into the population residing in each of the study sites. Additionally, there may be temporary residents in each study site that permanently reside elsewhere, even if they spend half of the year or more in the study site. If they spend much of the year in the study site but declare residency elsewhere, then they are not accounted for by the Census in that study site. This can cause issues with the results as they do not paint a picture of what the population appears to be for most of the year. This is likely as some people who declare residency in northern states go to the Gulf of Mexico states in the winter since the weather is warmer there.

Another way that social vulnerability of an area is affected is the number of tourists visiting the cities throughout the year. The Gulf of Mexico is a popular tourist destination, and there is no way to account for tourists in the Census data. This is of importance because tropical cyclones occur in the Gulf of Mexico during the summer and fall months, which tends to be when vacationers are prevalent in the study sites. A study site may experience a high number of vacationers that fall within socially vulnerable populations at the landfall of a tropical cyclone.

5.2.3 Question 3

The limitations presented in answering Questions 1 and 2 are limitations to this question as the results of those outputs were used to answer Question 3. Inaccuracies or incompleteness amongst the data will affect the results of the analysis done to answer this question. In this case, the question could not be answered for Gulfport, Mississippi, since the Hazus maps were generated at the Census block level, while the SVI was created at the Census tract level. Due to this difference, examining the influences of SVI on the different Hazus factors was impossible. Additionally, more statistically significant results may have been identified for the other study sites if the spatial resolution was increased (go to Census block instead of Census tract). However, this is impossible for the Hurricane Model of Hazus as it only goes down to the Census tract spatial resolution.

5.3 Future Directions

5.3.1 Question 1

Expanding the specific results that are produced within Hazus to incorporate all possible results would be a strong place to take this project in the future. Many options exist for looking at building losses (both economically and structurally), debris types and amounts, shelter requirements, and numerous more. Being able to examine all the outputs that Hazus has to offer can be beneficial to a scientific study, along with a general user who wants to learn more about the risk in their area. It would also provide a wider understanding of the risk to each of the study sites and would help in pinpointing where areas of future focus should be.

If capable, being able to do a more advanced study by inputting user-gathered information instead of the nationalized data that are pre-uploaded into Hazus can produce a more accurate and advanced study. This does not negate the use of the work done in this thesis, but user-generated data are more up-to-date and location-specific, and as previously discussed, the data in Hazus used for this thesis are from the 2010 US Census. In the future, if the Hazus Hurricane Model can work at a smaller spatial unit, then this study could be recreated at that smaller spatial unit and produce more accurate results. On this note, answers on why a default to the Hazus Hurricane Model is Census blocks over Census tracts in some cases can be further investigated.

Additionally, if storm surge data could be incorporated into a risk-estimation model, then the results of the model may change as storm surge will contribute in varying amounts to the damage. Storm surge data are not included in this model as Hazus only incorporates storm surge data in the historical model and not the probabilistic model. Tropical cyclones also bring other hazards beyond storm surge and wind including tornadoes and inland flooding from extensive rainfall. None of these data are currently incorporated into Hazus, and could, therefore, not be included in these results. If a model could be run that estimates the damage from all these hazards, then the results of the model can be more accurate.

5.3.2 Question 2

If possible, the ability to gather additional Census data, whether this is through surveys or another method, would yield more accurate SVI scores and create a better SVI. However, time and money constraints, along with participation, can pose problems for this occurring. Results can be improved upon by using a smaller spatial unit, such as a Census block or Census block group, as this creates a greater sample size that would allow for more variables to be included in a PCA-based SVI. Although this change can enhance the results of an SVI, it comes with its challenges as data may not be as evenly disbursed at this level, and some assumptions would be necessary. There are other methodologies besides conducting a PCA that can be used to construct an SVI, and choosing a different methodology may either confirm the results in this thesis or yield conflicting results. Another option to consider is adding information about residents who are in the study site for more than six months of the year, but still claim residency in another state. This information would provide a different perspective as it may portray a more accurate image of social vulnerability for most of the year. If data could be gathered monthly, specifically for June through November, this would prove to be beneficial when examining tropical cyclone social vulnerability. Hurricane Season is during these months in the Gulf of Mexico, and accounting for all potential residents during this period would help when considering the socially vulnerable populations exposed to tropical cyclones. A survey of the tourists visiting each study site can be helpful as well.

Something that was not a particular problem for this thesis, but could be improved on, is increasing the statistical significance of the PCA results by increasing the KMO value. One way to do this would be to increase the sample (spatial unit) quantity and leave the variables (the socially vulnerable groups) the same. Additionally, if the sample size is increased, the variables can be diversified (dividing amongst languages, races, ages, etc.) or even add other socially vulnerable groups such as those that lack certain educational levels, access to cars or the internet. Groups like these were not included in this thesis as, in some cases, it lowered the KMO below the 0.5 threshold. The higher the KMO value, the more reliable the PCA results will be, creating a more reliable SVI.

5.3.3 Question 3

While this thesis only focuses on one type of spatial statistic and concept, other spatial statistics can be performed on the data. Moran's I, while used in this thesis at the local level, can also be done at a global level. Both the local Moran's I and the global Moran's I test for spatial autocorrelation and spatial relationships amongst a dataset. This might produce different results that can be built on the information gathered from this thesis. A future project could add to the results for this question by examining the relationship between several variables, including ones that were not able to be used in this study. Working at a smaller spatial resolution can provide more insight into the specifics of the relationships observed in these results. In future versions of Hazus's Hurricane Model, modeling at the Census block level may be possible for all study sites used in this thesis. This could potentially create a more accurate representation of the relationship between the Hazus variables and the SVI results as a finer spatial resolution can create better results, and this may turn some areas that were deemed as not being statistically significant into being statistically significant.

The most prevalent cluster or outlier at all study sites for this question was the 'Not Significant' outlier. The high number of Census tracts in this outlier did not diminish the results of this question, but if this question were to be re-examined, more Census tracts in a cluster of significance over an outlier of no significance would be beneficial. More significant Census tracts can create a better image of the extent of the spatial autocorrelation in each study site. To reiterate this idea, increasing the number of spatial units, whether it be by working at a smaller spatial resolution or by creating a large site, may be beneficial in further attempts to answer this question. Additionally, incorporating flood and storm surge data, amongst other tropical cyclone-related hazards, may change the number of significant clustering.

5.4 Significance

On September 28, 2023, Hurricane Ian made landfall in southwestern Florida as a Category 4 hurricane (Bucci et al., 2023). Cape Coral, like most of southwestern Florida, was severely affected by Hurricane Ian. In Cape Coral, sustained windspeeds of Category 1 strength were measured, but there was instrumental failure near the areas of where the eyewall made landfall, and maximum sustained winds are estimated to be at least Category 4 in strength (Bucci et al., 2023). A storm surge of six to nine feet was observed in the Cape Coral area. In nearby areas of southwestern Florida, a storm surge height of 15 feet was observed (Bucci et al., 2023). In Florida alone, rainfall up to 26.95 inches and an EF-2 tornado were recorded (Bucci et al., 2023). 156 lives were claimed by Hurricane Ian; 66 deaths were direct. All the direct deaths occurred in Florida, and 36 of the 41 storm surge-related direct deaths occurred in Lee County, the county that Cape Coral resides in (Bucci et al., 2023). $109.5 billion in damages occurred in Florida alone, making it the costliest tropical cyclone in Florida's history. The total financial cost of Hurricane Ian in the United States, around $112.9 billion, makes Hurricane Ian the third costliest tropical cyclone in United States history (Bucci et al., 2023). 52,514 buildings sustained damage in Lee County, and approximately 3.28 million people in Florida lost power (Bucci et al., 2023).

While Cape Coral is only one of five study sites in this thesis, it shows that these study sites are at significant risk for severe impacts from tropical cyclones. Cape Coral was chosen before Hurricane Ian made an impact, but it was chosen because it was susceptible to impacts from tropical cyclones. The landfall of Hurricane Ian near Cape Coral shows the validity of the study site being chosen, and how realistic the situations dealt with in this thesis are. Cape Coral is a medium-sized city that directly touches the Gulf of Mexico. It has been impacted by other hurricanes besides Ian, and, unfortunately, will likely be impacted in the future. Tragedy may have struck this study site, but with it comes valuable information that can create more resilient communities. The work done in this thesis involves modeling and predicting, but these results have implications that go beyond the realm of furthering scientific knowledge to broaden our scientific understanding. The methods of this thesis can be applied to other cities, especially small and medium-sized cities, that are at risk for impact from tropical cyclones. Understanding what the risks from tropical cyclones are, the socially vulnerable populations living in susceptible geographic locations, and how social vulnerability influences risk, are critical to saving the lives and assets of the United States Gulf of Mexico residents.

References

Aksha, S. K., Juran, L., Resler, L. M., and Zhang, Y. (2018). An Analysis of Social Vulnerability to Natural Hazards in Nepal Using a Modified Social Vulnerability Index. *International Journal of Disaster Risk Science, 10,* 103-116. https://doi.org/10.1007/s13753-018-0192-7

Amini, M., & Memari, A.M. (2020). Review of literature on performance of coastal residential buildings under hurricane conditions and lessons learned. *Journal of Performance of Constructed Facilities*, *34*(6). https://ascelibrary.org/doi/pdf/10.1061/%28ASCE%29CF.1943-5509.0001509?casa_token=tldqb5u96fYAAAAA:NG5qII72Szl5T0tXhQK24W1aV96EC-qeUXmtrChJxXLPfmuDYepo8dW9mbEpSmPDDjWgmLls7A

Analysis Inn. (2020). KMO and Bartlett's test of sphericity. https://www.analysisinn.com/post/kmo-and-bartlett-s-test-of-sphericity/

Anselin, L. (2020a). Contiguity-Based Spatial Weights. *GeoDa: An Introduction to Spatial Data Science.* https://geodacenter.github.io/workbook/4a_contig_weights/lab4a.html#:~:text=The%20difference%20between%20the%20rook,queen%20criterion%20will%20yield%20eight

Anselin, L. (2020b). Multivariate Local Spatial Autocorrelation. *GeoDa: An Introduction to Spatial Data Science.* https://geodacenter.github.io/workbook/6c_local_multi/lab6c.html#implementation-1

Bergstrand, K., Mayer, B., Brumback, B., & Zhang, Y. (2014). Assessing the relationship between social vulnerability and community resilience to hazards. *Social Indicators Research, 122(*2), 391-409. https://doi.org/10.1007/s11205-014-0698-3

Bucci, L., Alaka, L., Hagen, A., Delgado, S., and Beven, J. (2023). Hurricane Ian (AL092022). *National Hurricane Center Tropical Cyclone Report.* The National Oceanic and Atmospheric Administration and the National Weather Service. https://www.nhc.noaa.gov/data/tcr/AL092022_Ian.pdf

Bucherie, A., Hultquist, C., Adamo, S., Neely, C., Ayala, F., Bazo, J., and Kruczkiewicz, A. (2022). *International Journal of Disaster Risk Reduction, 73* (102897). https://doi.org/10.1016/j.ijdrr.2022.102897

Budiman, A. (2020). Key findings about U.S. immigrants. Pew Research Center. https://www.pewresearch.org/short-reads/2020/08/20/key-findings-about-u-s-immigrants/

Chakraborty, J., Tobin, G.A., and Montz, B.E. (2005). Population Evacuation: Assessing Spatial Vulnerability in Geophysical Risk and Social Vulnerability to Natural Hazards. *Natural Hazards Review, 6*(1), 23-33. https://ascelibrary.org/doi/10.1061/%28ASCE%291527-6988%282005%296%3A1%2823%29

Cohen, D. (2019). About 60.2M Live in Areas Most Vulnerable to Hurricanes. US Census Bureau. https://www.census.gov/library/stories/2019/07/millions-of-americans-live-coastline-regions.html

Cohen, D. (2020, August 18). *94.7M Americans Live in Coastline Regions*. The United States Census Bureau. https://www.census.gov/library/stories/2019/07/millions-of-americans-live-coastline-regions.html

Creamer, J. (2020). Inequalities Persist Despite Decline in Poverty For All Major Race and Hispanic Origin Groups. U.S. Census Bureau. https://www.census.gov/library/stories/2020/09/poverty-rates-for-blacks-and-hispanics-reached-historic-lows-in-2019.html

Cutter, S. L. (1996). Vulnerability to environmental hazards. *Progress in Human Geography, 20(4),* 529-539. https://doi.org/10.1177/030913259602000407

Cutter, S. L., Mitchell, J. T., & Scott, M. S. (2000). Revealing the vulnerability of people and places: A case study of Georgetown County, South Carolina. *Annals of the association of American Geographers*, *90*(4), 713-737. https://doi.org/10.1111/0004-5608.00219

Cutter, S.L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008) A place-based model for understanding community resilience to natural disasters. *Global Environmental Change, 18* (4), 598-606. https://doi.org/10.1016/j.gloenvcha.2008.07.013

Deshmukh, A. (2021). Besides English and Spanish, which language do you think is the most commonly spoken in the U.S.? World Economic Forum. https://www.weforum.org/agenda/2021/12/spoken-language-united-states-america-english-spanish-mandarin/

Dinan, T. (2014). Projected Increase in Hurricane Damage in the United States: The Role of Climate Change and Coastal Development. *Ecological Economics, 138,* 186-198. https://www.sciencedirect.com/science/article/pii/S0921800916309752?casa_token=cItP0dVqW_EAAAAA:kazVKUhKQq5sa520fMH64PeHgoQw_rc93DS6GuJOX2OYGijJmWJWiVB48b-dtpmsH8OhUD7yXw

Dintwa, K.F., Letamo, G., and Navaneetham, K. (2019). Measuring social vulnerability to natural hazards at the district level in Botswana. *Jàmbá: Journal of Disaster Risk Studies, 11*(1), a447. https://doi.org/10.4102/jamba.v11i1.447

Dunning, K.H. (2020). Building resilience to natural hazards through coastal governance: a case study of Hurricane Harvey recovery in Gulf of Mexico communities. *Ecological Economics, 176*, 106759. https://doi.org/10.1016/j.ecolecon.2020.106759

Eiser, J. R., Bostrom, A., Burton, I., Johnston, D. M., McClure, J., Paton, D., van der Pligt, J., & White, M. P. (2012). Risk interpretation and action: A conceptual framework for responses to natural hazards. *International Journal of Disaster Risk Reduction, 1,* 5-16. https://www.sciencedirect.com/science/article/pii/S2212420912000040

ESRI. Data classification methods. ArcGIS Pro. https://pro.arcgis.com/en/pro-app/2.9/help/mapping/layer-properties/data-classification-methods.htm

Federal Emergency Management Agency. (2022). What is Hazus? https://www.fema.gov/flood-maps/tools-resources/flood-map-products/hazus/about

Federal Emergency Management Agency. (2021a). *Hazus*. FEMA.Gov. https://www.fema.gov/flood-maps/products-tools/hazus

Federal Emergency Management Agency. (2021b). Hazus Hurricane Model Technical Manual. https://www.fema.gov/sites/default/files/documents/fema_hazus-hurricane-technical-manual-4.2.3_0.pdf

Federal Emergency Management Agency. (2021c). Hazus Inventory Technical Manual. https://www.fema.gov/sites/default/files/documents/fema_hazus-inventory-technical-manual-4.2.3.pdf

Federal Emergency Management Agency. (2018). Hazus Hurricane Model User Guidance. https://www.fema.gov/sites/default/files/2020-09/fema_hazus_hurricane_user-guidance_4.2.pdf

Giffinger, R., Fertner, C., Kramar, H., & Meijers, E. (2007). City-ranking of European medium-sized cities. *Cent. Reg. Sci. Vienna UT, 9*(1), 1-12. https://www.researchgate.net/profile/Christian-Fertner-2/publication/313716484_City-ranking_of_European_medium-sized_cities/links/5993fa1aa6fdccaded20c53b/City-ranking-of-European-medium-sized-cities.pdf

Giffinger, R., & Haindlmaier, G. (2010). Smart cities ranking: an effective instrument for the positioning of cities? *Architecture, City, and Environment, 4(*12), 7-25. https://upcommons.upc.edu/handle/2099/8550

GISGeography. (2022). What is Tobler's First Law of Geography? https://gisgeography.com/tobler-first-law-of-geography/

Glen, S. Z-Score: Definition, Formula and Calculation. StatisticsHowTo.com: Elementary Statistics for the rest of us! https://www.statisticshowto.com/probability-and-statistics/z-score/

Holland, G., & Bruyère C. L. (2014). Recent intense hurricane response to global climate change. *Climate Dynamics, 42,* 617-627. https://link.springer.com/article/10.1007/s00382-013-1713-0

Jolliffe, I.T., and Cadima, J. (2016). Principal component analysis: a review and recent developments. *Philosophical Transactions of the Royal Society A.37420150202* https://doi.org/10.1098/rsta.2015.0202

Koks, E.E., Jongman, B., Husby, T.G., & Botzen, W. J. W. (2014). Combining hazard, exposure and social vulnerability to provide lessons for flood risk management. *Environmental Science and Policy, 47,* 42-52. https://www.sciencedirect.com/science/article/pii/S1462901114002056?casa_token=OTtBZdVbF0AAAAA:J3mITsDagxwdBqe7H6H1PEdcJc01xCbcVvIK6Qvg4KpkI76gkdlOlGXWcXFuByVUsjAGtxbDuw

LatLong.net. (2022). Cities in United States. https://www.latlong.net/

Liu, K., and Fearn, M.L. (2000). Holocene History of Catastrophic Hurricane Landfalls along the Gulf of Mexico Coast Reconstructed from Coastal Lake and Marsh Sediments. *Current stresses and potential vulnerabilities: Implications of global change for the Gulf Coast region of the United States, 223,* 38-47. https://www.researchgate.net/profile/Kam-Biu-Liu/publication/268357390_Holocene_History_of_Catastrophic_Hurricane_Landfalls_along_the_Gulf_of_Mexico_Coast_Reconstructed_from_Coastal_Lake_and_Marsh_Sediments/links/54f372bb0cf299c8d9e50b28/Holocene-History-of-Catastrophic-Hurricane-Landfalls-along-the-Gulf-of-Mexico-Coast-Reconstructed-from-Coastal-Lake-and-Marsh-Sediments.pdf

Manson, S., Schroeder, J., Riper, D.V., Kugler, T., and Ruggles, S. (2022). IPUMS National Historical Geographic Information System: Version 17.0. *IPUMS.* http://doi.org/10.18128/D050.V17.0

Merriam-Webster Dictionary. (2023). The Difference between 'Race' and 'Ethnicity,' https://www.merriam-webster.com/words-at-play/difference-between-race-and-ethnicity

Mudd, L., Wang, Y., Letchford, C., & Rosowsky, D. (2014). Assessing Climate Change Impact on the U.S. East Coast Hurricane Hazard: Temperature, Frequency, and Track. *Natural Hazards Review, 15*(3) https://doi.org/10.1061/(ASCE)NH.1527-6996.0000128

National Hurricane Center. (2019). Saffir-Simpson Hurricane Scale.

https://www.weather.gov/mfl/saffirsimpson#:~:text=The%20Saffir%2DSimpson%20Hurricane%20Wind,loss%20of%20life%20and%20damage.

National Oceanic and Atmospheric Administration. (2021). Historical Hurricane Tracks.

https://coast.noaa.gov/hurricanes/#map=4/32/-80

Neumann, J. E., Emanuel, K., Ravela, S., Ludwig, L., Kirshen, P., Bosma, K., & Martinich, J. (2015). Joint effects of storm surge and sea-level rise on US Coasts: new economic estimates of impacts, adaptation, and benefits of mitigation policy. *Climate Change, 129*, 337-349

https://link.springer.com/article/10.1007/s10584-014-1304-z

NOAA. (2020). Hurricanes.

https://www.noaa.gov/education/resource-collections/weather-atmosphere/hurricanes#:~:text=Tropical%20cyclones%20are%20classified%20by%20their%20maximum%20wind%20speed.&text=Major%20hurricanes%20have%20winds%20of,with%20gusts%20of%20200%20mph

NOAA Office of Coastal Management. (2021). Hurricane Costs.

https://coast.noaa.gov/states/fast-facts/hurricane-costs.html

NOAA National Centers for Environmental Information (NCEI). (2021). U.S. Billion-Dollar Weather and Climate Disasters.

https://www.ncdc.noaa.gov/billions/

National Ocean Service. (2021). How do hurricanes form?

https://oceanservice.noaa.gov/facts/how-hurricanes-form.html

National Ocean Service. (2021). What is a hurricane? National Oceanic and Atmospheric Administration.

https://oceanservice.noaa.gov/facts/hurricane.html

Rabby, Y.W., Hossain, M.B., and Hasan, M.U. (2019). Social vulnerability in the coastal region of Bangladesh: An investigation of social vulnerability index and scalar change effects. *International Journal of Disaster Risk Reduction, 41* (2019, 101329). https://doi.org/10.1016/j.ijdrr.2019.101329

Ratcliffe, M. (2022). Redefining Urban Areas following the 2020 Census. United States Census Bureau. https://www.census.gov/newsroom/blogs/random-samplings/2022/12/redefining-urban-areas-following-2020-census.html

Roberts, B. & Hohmann, R. P. (2014). The Systems of Secondary Cities: The neglected drivers of urbanizing economics. *Cities Alliance CIVIS, 7.* https://www.academia.edu/7301062/The_systems_of_secondary_cities_The_neglected_drivers_of_urbanising_economies

Rodgers III, J. C. & Murrah, A.W. (2009). The Impact of Hurricane Katrina on the Coastal Vegetation of the Weeks Bay Reserve, Alabama from NDVI Data. *Estuaries and Coasts,* 32, 496-507, DOI: 10.1007/s12237-009-9138-z

Roy, C., & Kovordányi, R. (2012). Tropical cyclone track forecasting techniques – A review. *Atmospheric Research, 104-105,* 40-69. https://doi.org/10.1016/j.atmosres.2011.09.012

Rufat, S., Tate, E., Burton, C.G., & Maroof, A. S. (2015). Social vulnerability to floods: Review of case studies and implications for measurement. *International Journal of Disaster Risk Reduction, 14, 470-486.* http://dx.doi.org/10.1016/j.ijdrr.2015.09.013

Salaheih, N., & Andone, D. (2022). Death toll from Hurricane Ian surpasses 100 as the search for survivors continues in Florida. CNN. https://www.cnn.com/2022/10/03/us/hurricane-ian-florida-recovery-monday/index.html

Schneider, P. J., & Schauer, B. A. (2006). HAZUS – Its Development and Its Future. *Natural*

Hazards Review, 7(2), 40-44.
https://www.researchgate.net/profile/Philip-Schneider/publication/248880484_HAZUS-its_development_and_its_future/links/54ac62f20cf23c69a2b7c6b0/HAZUS-its-development-and-its-future.pdf

deSherbinin, A., Bukvic, A., Rohat, G., Gall, M., McCusker, B., Preston, B., Apotsos, A., Fish, C., Kienberger, S., Muhonda, P., Wilhelmi, O., Macharia, D., Shubert, W., Sliuzas, R., Tomaszewski, B., & Zhang, S. (2019). Climate vulnerability mapping: A systematic review and future prospects. *Wiley Interdisciplinary Reviews: Climate Change, 10(*5), e600.
https://doi.org/10.1002/wcc.600

Singh, S. R., Eghdami, M. R., and Singh, S. (2014). The Concept of Social Vulnerability: A Review from Disasters Perspectives. *International Journal of Interdisciplinary and Multidisciplinary Studies (IJIMS), 1*(6), 71-82.
https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=f6bd4afdfab5f57d0fbc1d62675b03cf3abdc5e7

Spielman, S.E., Tuccillo, J., Folch, D.C., Schweikert, A., Davies, R., Wood, N., and Tate, E. (2020). Evaluating social vulnerability indicators: criteria and their application to the Social Vulnerability Index. *Natural Hazards, 100,* 417-436.
https://doi.org/10.1007/s11069-019-03820-z

Tate, E. (2012). Social vulnerability indices: a comparative assessment using uncertainty and sensitivity analysis. *Natural Hazards, 63,* 325-347. DOI: 10.1007/s11069-012-0152-2

Turner II, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Eckley, Kasperson, J. X., Luers, A., Martello, M. L., Polsky, C., Pulsipher, A., & Schiller, A. (2003). A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences of the United States of America, 100*(14), 8074-8079.
www.pnas.org_cgi_doi_10.1073_pnas.1231335100

UCLA: Statistical Consulting Group. (2021). Principal Components Analysis and SPSS Annotated Output. UCLA Advanced Research Computing: Statistical Methods and Data

Analytics.
https://stats.oarc.ucla.edu/spss/output/principal_components/

University of Rhode Island. (2020). Hurricane Structure. Hurricanes: Science and Society.
http://www.hurricanescience.org/science/science/hurricanestructure/

US Census Bureau. (2021). Data. *United States Census Bureau.*
https://www.census.gov/data.html

U.S. Census Bureau. "Race." *United States Census Bureau.*
https://www.census.gov/quickfacts/fact/note/US/RHI625221#:~:text=OMB%20requires%20five%20minimum%20categories,sixth%20category%20%2D%20Some%20Other%20Race

Vickery, P. J., Masters, F. J., Powell, M. D., and Wadhera, D. (2009). Hurricane hazard modeling: The past, present, and future. *Journal of Wind Engineering and Industrial Aerodynamics, 97*(7-8), 392-405.

Wachinger, G., Renn, O., Begg, C., & Kuhlicke, C. (2013). The Risk Perception Paradox – Implications for Governance and Communication of Natural Hazards. *Risk Analysis, 33*(6), 2191-2206.
https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1539-6924.2012.01942.x

Ward, N., and Batalova, J. (2023). Frequently Requested Statistics on Immigrants and Immigration in the United States. Migration Policy Institute.
https://www.migrationpolicy.org/article/frequently-requested-statistics-immigrants-and-immigration-united-states#demographic-educational-linguistic

World Meteorological Organization (WMO). (2022). Tropical Cyclones.
https://public.wmo.int/en/our-mandate/focus-areas/natural-hazards-and-disaster-risk-reduction/tropical-cyclones

Yoon, D.K. (2012). Assessment of social vulnerability to natural disasters: a comparative study. *Natural Hazards, 63,* 823-843.
https://doi.org/10.1007/s11069-012-0189-2

Zuzak, C., Mowrer, M., Goodenough, E., Burns, J., Ranalli, N., and Rozelle, J. (2022). The national risk index: establishing a nationwide baseline for natural hazard risk in the US. *Natural Hazards, 114,* 2331–2355. https://link.springer.com/article/10.1007/s11069-022-05474-w