# SPATIAL ADJUSTMENTS OF SOCIALLY VULNERABLE POPULATIONS IN GALVESTON COUNTY FOLLOWING HURRICANE IKE

A Thesis

by

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## ABSTRACT

The insistent threat of natural disasters has invoked a plethora of literature on the vulnerability of communities. Understanding the role socio-demographics play in disaster adjustment is becoming an increasingly important aspect for disaster adaptation. This thesis examines the spatial adjustments of socially vulnerable populations to the 2008 Hurricane Ike by estimating the effects of damage on the changes of socially vulnerable populations between 2000 and 2015. This is done in an effort to address the inequality in disaster impacts across vulnerable segments of the population. Block groups within Galveston County are used to quantitatively index the drivers of social vulnerability in order to analyze the correlation with inundation levels brought by Hurricane Ike. Furthermore, multivariate statistical models are used to understand household-level adjustments to different types of flood zones and inundation levels. Particular attention is given to the spatial error dependence and models are adjusted for spatial autocorrelation. Local Indicators of Spatial Autocorrelation (LISA) are also conducted to understand the spatial relationships between social vulnerability and damages. Overall, the results of regression models indicate that Socially Vulnerable populations have moved out of high damage areas. The LISA model also indicated a decrease in the clustering of social vulnerability in areas with high levels of inundation. These adjustments offer important insights into the recovery of Galveston County post Ike and can help inform disaster policy.

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# CHAPTER I

# INTRODUCTION

## 1.1 Introduction

Disasters, while commonly seen as external and arbitrary, bearing no mind to the social situation of race or class, are inadvertently spatial phenomena and are not spatially random. In fact, the social constructs which oppress populations are exceedingly relevant in the context of disasters, and the ability to adapt, withstand and recover from a disaster event is linked to social infrastructure (Elliott and Pais, 2006). Among disasters floods, including storm surge events, are some of the most persistent and costly (Brody et al., 2007). These events are expected to become more severe and frequent with climate change and the resultant sea level rise (IPCC, 2007).

The threat of more extreme and frequent floods and surge events are further exacerbated by growing populations on the coast. Living on the coast provides many benefits including access to jobs and resources, as well as quality lifestyle brought by water amenity. Not surprisingly, coastal regions are some of the fastest growing areas globally (Creel, 2003 ). Approximately 3 billion people live within 200 kilometers of a coastline, and that number is predicted to double by the year 2025, exposing a greater number of people to coastal hazards and disasters (Creel, 2003 ). Biophysical hazards become disasters when when they intersect with human lives and livelihood (Nakagawa and Shaw, 2004; Perry and Quarantelli 2005; Quarantelli, 1989; Quarantelli and Dynes 1977; Smith, 2006). However, the degree of impacts depends on various factors including socio-economic conditions of the region (Cutter, 1996) and its adaptive capacity to absorb persistent disturbances, such as Hurricanes, and retain vital economic and social structures (Adger et al., 2005; Holling, 1973; Walker, Holling, and Carpenter, 2004). While assets (e.g., homes and business) at risk can increase the potential for economic losses, the brunt of this loss is particularly felt by socially vulnerable populations because they may lack the resources to readily adapt (Brooks et al., 2005). Moreover, poor institutions (both the social and public) could further degrade the adaptive capacity (Wijkman and Timberlake, 1988.) Adaptive capacity refers to the action of a system to manage, cope or adjust to changing conditions, in this case hazards (Smit and Pilifosova, 2003)

Given preponderant scientific consensus that flooding is going to become more frequent and damaging, understanding the socio-economic drivers of vulnerability and adaptive capacity of vulnerable segments of population are critical and will help to identify the challenges of disaster adaptation and inform public policy pertinent to disaster management and planning.

### 1.2 Study area

Galveston County, which is located on the upper Texas Gulf Coast about 25 miles south of Houston, is a large metropolitan area encompassing the Galveston bay, East bay, and West Bay (Figure 1). It is bounded by Harris and Chambers counties to the North and Brazoria County to the West. To the East and South, it is bounded by The Gulf of Mexico. Fourteen cities make up the County, including:  Galveston, Dickinson, Bolivar, Clear Lake Shores, Kemah, La Marque, Bacliff, Jamaica Beach, Tiki Island, Bayou Vista, Santa Fe, Hitchcock and San Leon. The area is rich in architecture and history, and its citizens have a strong sense of place and are protective of its unique character and distinct identity (City of Galveston, 2009).  Unsurprisingly the majority of the economy is reliant on the various natural resources and the most prevalent industries in the area include: fishing, shipping via ports, petrochemical, and tourism (City of Galveston, 2009). Geographically the County is 874 square miles, and a large portion of Galveston County is Galveston island, a low lying micro tidal barrier island.

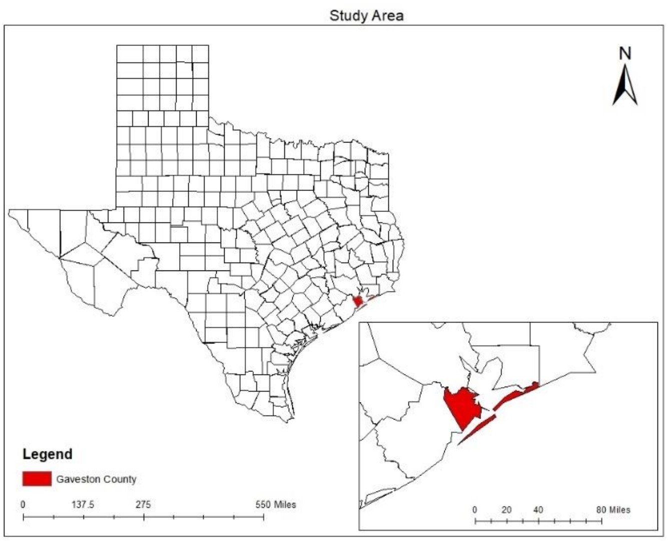


Figure 1: Galveston County

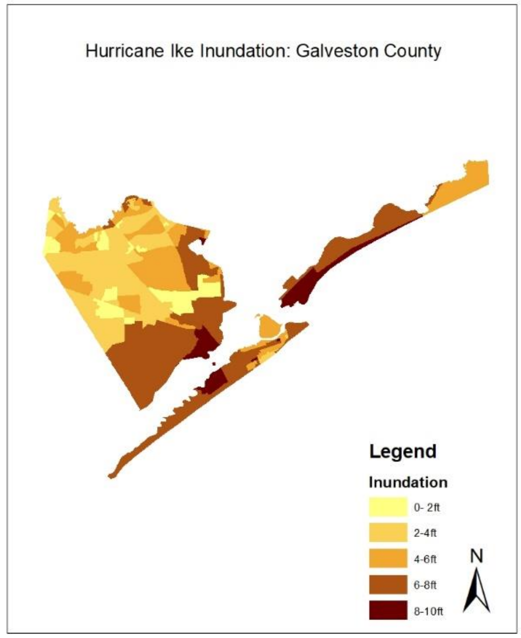


Figure 2 Hurricane Ike Inundation levels by block group

Despite the many benefits of coastal living there is a high risk for coastal storms in Galveston County. In fact, the South Eastern Gulf of Mexico is one of the most Hurricane and flood prone areas in the United States, and on average this area experiences a major Hurricane every 15 year (Roth, 2000). Galveston bay, which corresponds to the study area, experienced sixteen Hurricanes since 1850. Due to rising sea levels the National Oceanic and Atmospheric Administration (NOAA) predicts that the frequency of surge events in this region will increase dramatically and surge events could become as frequent 200 days a year with 80 to 100% attributed to higher tides (NOAA, 2018). While disasters could overwhelm communities, they also open up a window of opportunity in the recovery phase to rebuild more resilient (Holling, 2001). The seawall in Galveston island is a good illustration of a proactive public response to avoid future losses. The wall was built in response to the 1900 storm, the deadliest ever recorded Hurricane s in U.S. history, responsible for approximately 8000 fatalities. Along with the seawall, following Hurricane Carla in 1961, Texas City constructed a levee system to protect valuable industrial infrastructure. Despite mitigation efforts, this area continues to be overwhelmed by coastal storms and Hurricanes. In an effort to delineate effective policy recommendations for coastal resilience this thesis analyzes the second most recent Hurricane to cause storm surge in the area, Hurricane Ike. In September of 2008 Hurricane Ike, a category 2 storm, made landfall on the Texas coast causing 195 deaths and 29.6 billion dollars in damages (Hayden, 2010). However, waves and surge played the biggest role in damage for this storm (Kennedy et al., 2011). Hurricane Ike had surge levels comparable to a category 5 storm, causing most of Galveston County to be inundated, with the average inundation level of 3.54 feet, and the highest reaching 10 feet. Spatial distribution of depth is presented in Figure 2. Given size of its impacts, Hurricane Ike provides a natural experiment to analyze the changes in specific social conditions contributing to social vulnerability and post-disaster adjustment patterns. This will aid in policy recommendations for resilient recovery following surge events.

### 1.3 Research Purpose and Objectives

This study statistically examines the spatial distribution of socially vulnerable populations with relation to Hurricane Ike inundation levels in Galveston County. The 152 block groups[1] within the County are used to quantitatively analyze the correlation of social vulnerability with inundation levels. Inundation levels are used as a proxy to describe damage as there is no consistent data for damage across block groups. Multivariate statistical models are used to understand adjustment across the segments of socially vulnerable populations by flood zones and inundation levels.

Specifically, I address the following research question:

[1] Only block groups which were consistent between years 2000 and 2015 were used for comparison.

- What are spatial adjustment patterns to disasters across vulnerable segments of population, and how can the impact of persistent storm surge events to socially vulnerable populations be mitigated?

To address this research question, this thesis has several research objectives. First, I identify the factors that influence social vulnerability and household adjustments to disaster. Second, I construct a social vulnerability index for 2000 and 2015 and statistically examine their changes along with the changes of socio-demographic make-up of Galveston County across damaged block group over time. Third, I determine the changes in clustering of socially vulnerable populations across space between the years 2000 and 2015.

The following literature review section outlines the relevant literature. Next, the research methods section describes the data analysis process. The following section presents results, and the final section discusses the results relative to existing research and presents policy recommendations.

# CHAPTER II

# LITERATURE REVIEW

This section reviews the relevant literature and methodological approaches to understanding social vulnerability to disasters, household adjustments based on changes in concentrations, as well as addresses the issues of social isolation and benefits of social mixing for disaster resiliency.

## 2.1 Social Vulnerability

Situational exposure and biophysical risk are not necessarily the only underlying factors for being "vulnerable" to a disaster event: social factors also contribute to vulnerability. Broadly, vulnerability can better be described as the inability to cope with a situation without external help (Brooks, 2003). More specifically, vulnerability can be defined as the state that exists within a system before a hazard event and communities ability to cope with hazards once they occur (Pelling, 2006). Therefore, vulnerability exists within a system independently of external hazards (Pelling, 2006). Further, social vulnerability is the social components (i.e. income, age, etc.), which amplify the negative outcomes post hazard. The interaction between a vulnerable social system and hazard, biophysical or otherwise, produces outcomes which can be measured in terms of physical or economic loss (Brooks and Adger, 2003).

Moreover, vulnerability is not distributed equally across the population. Social dimensions which create inequalities in access to opportunities for certain groups and communities cause unequal exposure to risk and cannot simply be ignored in the context of natural disasters (Varley, 1994). Marginalized populations, or those with limited access to resources and political representation, are typically more susceptible to disaster as they have a lesser adaptive capacity (Daniels, Kettl, and Kunreuther, 2011; Smit and Pilifosova, 2003; Adger, 2003).

Social inequities construct the larger idea of social vulnerability. Social vulnerability has been described in a variety of ways but in the context of a disaster it has been defined as the susceptibility of marginalized groups risk for loss (Cutter, 2003). Researchers are in consensus about attributes of social vulnerability, including the lack of access to resources, limited access to political power, lack of social capital, poor building stock i.e. structural soundness and occupancy density, and age (Cutter, 1996; Cutter, 2003; Adger, 1999; Bohle, Downing, and Watts, 1994; Flanagan, 2011).

Of different age groups elderly and children are the most vulnerable groups in disaster events. The latter lack the ability to protect themselves because of lack of resources and information (Bohle et al.,1994; Flanagan, 2011; Cutter, 1996). While the former live on fixed incomes and may have health, problems effecting their cognitive and physical abilities to prepare and respond (Eidson et al. 1990; Schmidlin and King 1995; Morrow 1999; Peek-Asa et al. 2003; White et al. 2006; McGuire et al. 2007; Rosenkoetter et al. 2007; Flanagan, 2011).

Racial and Ethnic minorities in particular are challenged by natural calamities. Inequities for these groups are typically social, political, and economic, affecting their ability to prepare, cope, respond and recover from disaster (Flanagan, 2011; Elliot and Pais, 2006, Cutter et al., 2003). The consequence of these inequalities is especially evident in housing. These groups tend to live in housing which is usually more densely occupied, less structurally sound, and in areas which are more susceptible to hazard (Flanagan, 2011; Elliot and Pais, 2006; Cutter et al., 2003).

Finally, socioeconomic status affects both the hazard perception as well as the ability to prepare for (e.g. purchase hazard insurance, afford hazard-proof housing) and recover after a disaster (Fothergill, 2004; Flanagan, 2011; Elliot and Pais, 2006; Cutter et al., 2003).

In order to quantify the various drivers of social vulnerability, composite indices, which aggregate multiple proxy indicators of social vulnerability into a single index, are created. The techniques for creation of these indices vary greatly in normalization, aggregation, weighting and component retention. There are three ways in which social vulnerability can be quantified through the creation of indices: (1) a deductive approach; (2) an inductive approach; and (3) a hierarchical approach. The deductive approach selects a limited number of variables deductively to create and index based on prior knowledge (Yoon, 2012). In order to normalize the data for the deductive approach there are a few methods of linear aggregation techniques used. These include the z-score transformation method, maximum value transformation method, and the Min-Max rescaling transformation method. The z-score transformation method takes the summation of individual variables z-scores to create a composite social vulnerability score (For e.g., see Zahran et al., 2008). The second method is the maximum value transformation method which is the ratio of the value of variable (Xi) to the maximum value for the variable (Xmax) (For e.g., see Cutter et al., 2000, Wu et al., 2002, and Chakraborty et al., 2005). The third method used in the deductive approach is the Min-Max rescaling transformation. This method decomposes each variable into a range between zero and one by subtracting the minimum value (Xmin) and divides by the range of indicator values (Xmax) and subtracts the minimum value (Xmin) (For e.g., see Cutter et al., 2010, and Bernard 2007). The second way that social vulnerability can be indexed is the inductive approach. This approach differs as it is not limited in the number of variables selected (Yoon, 2012). Deductive approach variables are normalized using factor analysis or principal component analysis (PCA). PCA is an aggregation technique which transforms variables by reducing the dataset into a smaller set of inter-correlated components (For e.g., see Cutter et al., 2003, Boruff et al., 2005, Boruff and Cutter, 2010, Cutter and Finch 2008, and Rygel et al., 2006). The third method used to create social vulnerability indices is the hierarchical approach. This approach uses ten to twenty indicators which are separated into sub-indices (Tate 2012; Vincent 2004; Chakraborty et al. 2005; Hebb and Mortsch 2007; Flanagan et al. 2011; Mustafa et al. 2011). Hierarchical approach variables are typically normalized using the min max rescaling method or Factor analysis (Tate, 2012). For this study the inductive method is used and variables are normalized using PCA. This method is used because it is most commonly found in the literature and offers the greatest ability to compare indices between years (Cutter et al., 2008).

### 2.1.1 Mapping Social Vulnerability

Social vulnerability is a spatial phenomenon; therefore, the practical application of these indices is through the use of maps. The usage of mapping allows researchers and policy makers to geographically identify the areas that may be in need of special attention, which is exceedingly relevant in the context of disasters.  Current research maps social vulnerability at the block group level, the smallest level at which census data is collected. However, the approach of mapping at such a small spatial scale is not without limitation. The availability of social and economic measures needed to construct a social vulnerability index are not always readily available at the block group level as opposed to the data on census tract, or County level (Schmidtlein et al., 2008). However, the small spatial scale of block-groups offers the best representation of population needs for emergency managers and city planners. Several past studies have used block group level data to create social vulnerability indices (for e.g., see Van Zandt (2012) for Galveston County, TX, Rygel et al., (2006) for Hampton Roads, VA, Chakraborty et al., (2005) for Hillsborough County, FL.) While these studies use the block group level to analyze social vulnerability they to not look at the spatial adjustments of housholds temporally which is done in this Thesis.

## 2.2 Household Adjustments

The ways in which households respond to disasters largely depend on their entitlements and assets, financial capacity, access to political power, and social capital (Bohle, Downing, and

Watts, 1994; Cutter, 1996). The latter refers to the networking, cultural and societal norms, and trust within social and economic activities (Nakagawa and Shaw, 2004). Following disaster there is often large dislocations of populations, and so examining the adjustments and drivers of adjustment is important for delineating effective disaster recovery policy (Davlasheridze and Fan 2017; Coffman and Noy, 2011; Lynham, Noy, and Page 2017; Smith et al., 2006; Anttila-Hughes and Hsiang, 2013).

Extant research highlights a few adjustment options including moving out of harm's way, self-protection, and insurance (Smith et al. 2006; Davlasheridze and Fan 2017). While moving out of harm's way may be the best option, availability of resources represents impediment to mobility for many and in particular for those economically disadvantaged. However, empirical evidence also indicates that not everyone who possesses financial resources relocates. For example, wealthier people may choose to return back and rebuild because they can afford rebuilding. Importantly, they return because they are able to self-protect (e.g., retrofitting homes) and insure (Varley, 1994). Low income households are also suggested to remain in damaged areas because of lack of resources to relocate and depressed housing market post-disaster (Smith et al., 2006). The lack of resources also implies that this segment of population is less likely to retrofit, hazard-proof homes or self-insure.

Home maintenance is a costly endeavor and may be less important for some than more immediate needs. Hazard protection, such as retrofitting of homes by investing in Hurricane shutters, elevating homes, filling etc., are also expensive and may not be top priority for resource constrained. While self-insuring, which entails putting money to the side in the event of misfortune, is not an option for the resource constrained. Hence, it is expected dwellings for poor population to remain vulnerable to future hazard events. (Fothergill et al., 2004; Flanagan et al., 2011; Cutter et al., 2003)

Households adjustments are not only influenced by their own financial resources (e.g., income), but governmental assistance and other financial resources following disaster (Davlasheridze and Fan, 2017; Kousky et al., 2018). Research indicates that public disaster aid can create perverse incentives by dissuading private individuals from undertaking self-protection/self-insurance measures or purchasing private insurance in anticipation of disaster aid (Davlasheridze and Miao, *forthcoming*). Few recent studies empirically examine the effect public disaster aid has on the purchasing of private insurance. For example, Kousky et al., (2018) found that federal disaster grants given to individuals as housing and other needs assistance reduces flood insurance coverage. Davlasheridze and Miao (forthcoming) also examine this effect but focusing on Public Assistance (PA) programs of Federal Emergency Management Agency (FEMA), which targets community rehabilitation through post-disaster cleanup and infrastructure recovery. Their study suggests reduced insurance policies in response to increased PA program spending even though PA grants do not directly compensate individuals for their losses. Two possible explanation for such responses are discussed; one that PA signals federal disaster bail-out and may discourage private risk management in a similar manner as individual assistance does and second, public projects funded via PA grants could alter the risk perception of individuals (e.g., people may feel secure after large public investment in flood protection infrastructure). Public projects targeting infrastructure recovery can incentivize homeowners to stay in high risk areas and businesses to reopen (Kunreuther, 2001; Lewis and Nickerson,1989; Baade, Bauman, and Matheson, 2007; Kousky and Zeckhauser, 2006; Davlasheridze and Fan, 2017). However, public projects such as home buyouts, often initiated after a major disaster, which seek to permanently relocate housing away from hazardous areas force relocation, and can reduce hazard vulnerability (Binder et al., 2015).

While it is not recognized in research, social memory of communities, commonly referred to as shared experiences of social groups, also plays a role in how households respond to natural disasters (Tidball et al., 2010; Adger et al.,2005). The social memory of a community in a disaster-prone area is important because it helps people understand how to respond (evacuate or stay), cope (adjust to the situation before and after) and recover based on the lessons learned from past disturbances (Chamlee-Wright, 2013; Colten and Sumpter, 2008). These memories, when shared through social learning processes are important for the rebuilding and reorganization phase post-disaster (Olsson, Folke, and Berkes, 2004).

### 2.3 Public housing, social mixing and gentrification

Post disaster household adjustments can lead to further isolation of vulnerable groups. Socially vulnerable groups may be unequally exposed to displacement following disaster (Myers et al., 2011). In particular for Galveston County, one determinant of displacement may be the loss of public housing. Following Hurricane Ike, four public housing units on Galveston island were destroyed, causing 569 units to be demolished (Walters, 2018; Hamideh and Rongerude, 2018). In April of 2009 the city made plans for recovery, which included the rebuilding of all destroyed public housing, but as of 2015 less than half had been rebuilt. The stalling of rebuilding is ultimately linked to the negative push back by the community (Walters, 2018; Hamideh and Rongerude, 2018). Community push back is not uncommon with public housing projects for a variety of reasons (Rohe and Burby, 1988) Specifically, many scholars address systematic social isolation or the negative “neighborhood effect” commonly associated with American ghettos (Watt, 2017). By living in segregated neighborhoods residents are limited in their access to resources, ability to escape poverty, and job opportunities which can lead to higher crime rates (Rohe and Burby, 1988). This is specifically apparent for minorities for example living in the inner city (Sampson and Wilson, 1995). The effects of urban poverty and social isolation became hypervivid in the context of natural disasters in 2005 when Hurricane Katrina devastated New Orleans (Cutter et al., 2010). The underlying issues of urban poverty were exposed by news broadcasters as the cameras panned to the fetid living conditions of the poorest of the poor, trapped in homes and apartments as they had no means to evacuate (Jonkman et al., 2009)

The scenes in New Orleans following Hurricane Katrina displayed the devastating effects of urban poverty and the unequal exposures felt by income limited groups. However, urban poverty is not isolated to coastal regions, it is widespread throughout the Nation. Many social scientists agree that one of the leading causes of urban poverty is the spatial concentration of mono tenure estates (Watt, 2017; Gallie et al., 2010; Rankman and Quane, 2000). There has been a significant research and public focus on social mixing and revitalization policies, both urban and rural, to combat the issues of socially isolated housing, specifically the HOPE VI programs (Elliott et al., 2004). The HOPE VI program is federal program which focusses on replacing inner city public housing structures with integrated subsidized communities (Elliott et al., 2005; National Commission on Severely Distressed Public Housing, 1992). The idea is that the mixed tenure communities will give low income or marginalized groups better access to resources, political power, and greater ability to escape poverty through interaction with the middle class (National Commission on Severely Distressed Public Housing, 1992). However, the widespread demolition of public housing in an effort to revitalize urban areas has often lead to the replacement of tenure as opposed to tenure mixing, where low mono-tenure estates are consequently taken over by middle mono-tenure estates, as well as the displacement of low income populations (Popkin et al., 2007; Keene and Geronimus, 202011; Goetz2010; Byrne, 2003).

It is important, however, to note that gentrification does not solely occur based on urban policy. Natural and Disaster induced fluctuation in the housing markets can incentivize "outsiders" to take advantage of low cost housing as investment opportunities. Effectively changing the income stratification for the area which can lead to a "push out" effect for lower income residents as housing prices and taxes increase, and small businesses are replaced by big box stores. This is currently the challenge faced by Port Aransas, Texas, which was devastated by Hurricane Harvey in August of 2017. There has been a large influx of investors to this small coastal community threatening to change its identity, with many residents worried their town will soon become the "Florida Key's" of the Gulf (Crow, 2018). The influx of investors to coastal communities not only threatens to reshape community identity, it can degrade social memory of communities. Moreover, the stagnation in public housing recovery may significantly contribute to the long-term post Ike adjustments for Galveston County because of inadequate access to housing resources, and changes in tenure stratification due to investment opportunities post disaster.

Current research builds on past research; adopts a similar approach and examines adjustment patterns across socioeconomic groups in Galveston County and in response to Hurricane Ike. It further extends the existing research by incorporating clustering of socially vulnerable populations in space. Throughout, the maintained hypothesis is that socially vulnerable populations will be more geographically concentrated in high risk and high damage areas following a disaster incident because of inability to leave, inability to rebuild, opportunistic adjustments in housing markets, and partially due to potential perverse incentives associated with disaster assistance programs.

# CHAPTER III

# METHODOLOGY

### 3.1 Data Description

Data for this study came from various sources including American Community Survey of U.S. Census Bureau, Houston Galveston Area Council, The Harris County Flood Control District, and The Federal Emergency Management Agency (FEMA).

Socio-economic and demographic block group level data for Galveston County for the years 2000 and 2015 were drawn from the Census American Community Survey (U.S. Census Bureau; American Community Survey, 2000; 2015). The variables used included race and ethnicity, number of people below poverty level, female population , count female headed households, count of renters, count of owners, count of persons with no vehicle, count under 5 years old, count 65 and older, count of unemployed, number receiving social security income, and count without a high school diploma. These counts were converted into percentages and, the changes in percentages over the two periods were calculated. There were changes in block group lines from 2000 to 2015. Specifically, there were 211 block groups in 2000 and only 194 block groups in 2015. Only block groups that were matched between the two periods were considered for analysis.

Hurricane Ike inundation level data were obtained from The Harris County Flood Control District. The data were spatially joined with the Block group shapefile in order to display average inundation levels by block group. Five levels of inundation were created including (i) less than 2ft; (ii) 2-4ft; (iii) 4- 6ft; (iv) 6- 8ft; and (v) 8-10ft (Figure 2). Categorizing inundation at different levels is intended to capture the varying degrees of effects inundation on changes in socio-economic characteristics of households across block groups and over-time.

Flood zone areas were drawn from the FEMA (FEMA, 2017). Flood zone data was spatial joined with block group data in ArcGIS and the percentage areas for each flood zone class were calculated. For this research, three different flood risk zones were created: (i) A zones (ii) X zones and (ii) V zones. A zone represents areas with a 1% annual chance of flooding in the 100-year flood plain, V zones represent coastal areas in the 100-year flood plain with a 1% annual chance of flooding and coastal velocity hazard,  and X zone represents moderate to low risk areas outside of the 1% and 0.2% chance of annual flooding outside of the 500 year floodplain (FEMA, 2017). Flood zones in the model capture the already existing "objective" risk for flooding in the block group.

Count of various socio-economic and demographic indicators were converted into percentages. Tables 1 and 2 report their summary statistics corresponding to years 2000 and 2015 respectively. After creating percent's thirteen of the variables, percent under 5 out of the total population , percent 65 and older out of the total population, percent renter occupied out of total housing , percent owner occupied out of total housing,  percent in poverty out of total population, percent female headed household out of total population, percent unemployed out of total employed population, percent female out of total population, percent not white out of total population, percent with no high school diploma out of population 25 and older, percentage of mobile homes out of total housing, percent receiving social security out of total population, and percent with no vehicle out of total population (Table 1 and 2) are used to to conduct principal component analysis, discussed in the following section and create Social Vulnerability (SV) indices.

Lastly, The differences for the variables between the years 2000 and 2015 are taken (Table 3) in order to conduct regression analysis, which is discussed in subsection 3.4 below. In order for the social vulnerability indices to be compared between the two years they were transformed into z-scores. This approach for comparability follows the approach taken by Cutter and Finch 2007 in their paper *"Temporal and spatial changes in social vulnerability to natural hazards."* The difference between the transformed z-scores for SV indices was found for 2000 to 2015, these are the values for regression analysis, discussed below.

**Table 1: Summary statistics 2000**

| | Shares in 2000 | | | |
|---|---|---|---|---|
| Variable | Mean | Std.Dev | Min | Max |
| *Percent in poverty* | 26.731 | 16.389 | 0 | 86.769 |
| *Percent female headed household* | 44.109 | 18.355 | 0 | 94.659 |
| *Percent no vehicle* | 10.280 | 11.653 | 0 | 69.733 |
| *Percent unemployed* | 4.544 | 3.461 | 0 | 20.552 |
| *Percent owner* | 64.769 | 22.511 | 1.780 | 100 |
| *Percent receiving social security income* | 25.447 | 10.937 | 0 | 63.099 |
| *Percent renter* | 35.230 | 22.511 | 0 | 98.219 |
| *Percent of mobile homes* | 5.965 | 10.876 | 0 | 55.670 |
| *Percent not white* | 42.801 | 26.209 | 3.618 | 100 |
| *Percent 5 years and under* | 7.955 | 3.362 | 0 | 17.078 |
| *Percent 65 years and older* | 12.611 | 6.958 | 0 | 43.444 |
| *Percent female* | 51.332 | 4.680 | 27.298 | 65.119 |
| *Percent with less than a 12th grade education* | 23.176 | 13.152 | 0 | 62.205 |

## Table 2: Summary statistics 2015

| | Shares in 2015 | | | |
|---|---|---|---|---|
| Variable | Mean | Std.Dev | Min | Max |
| *Percent in poverty* | 20.124 | 14.761 | 0 | 78.626 |
| *Percent female headed household* | 15.096 | 11.081 | 0 | 57.209 |
| *Percent no vehicle* | 8.659 | 10.507 | 0 | 71.756 |
| *Percent unemployed* | 5.431 | 4.470 | 0 | 22.403 |
| *Percent owner* | 62.996 | 24.237 | 5.549 | 100 |
| *Percent receiving social security income* | 30.164 | 12.800 | 0 | 72.875 |
| *Percent renter* | 37.004 | 24.237 | 0 | 94.450 |
| *Percent of mobile homes* | 4.755 | 9.959 | 0 | 62.897 |
| *Percent not white* | 45.392 | 23.934 | 0 | 100 |
| *Percent 5 years and under* | 5.847 | 4.416 | 0 | 19.846 |
| *Percent 65 years and older* | 14.492 | 7.930 | 0 | 39.930 |
| *Percent female* | 51.012 | 6.383 | 22.227 | 68.845 |
| *Percent with less than a 12th grade education* | 15.676 | 11.495 | 0 | 51.726 |

## Table 3: Summary Statistics and descriptions of variable differences

| Variable | Description | Mean | Std.Dev | Min | Max |
|---|---|---|---|---|---|
| *Dpctyoung* | *The Difference in percent of the population 5 years and under from 2000 to 2015* | -1.83291 | 5.228121 | -17.07819 | 14.44945 |
| *Lpctyoung* | *The Lag in percent of the population 5 years and under from 2000 to 2015* | 7.661277 | 3.294458 | 0 | 17.07819 |
| *Dpctold* | *The Difference in percent of the population 65 and older from 2000 to 2015* | 1.656063 | 7.732376 | -14.09782 | 34.8163 |
| *Lpctold* | *The Lag in percent of the population 65 and older from 2000 to 2015* | 13.30119 | 6.805092 | 2.28321 | 43.44392 |
| *Dpercentren* | *The Difference in percent of renter occupied housing units from 2000 to 2015* | 2.978593 | 14.11201 | -32.65145 | 41.29247 |
| *Lpercentren* | *The Lag in percent of renter occupied housing units from 2000 to 2015* | 37.41027 | 22.2659 | 1.22449 | 89.47928 |
| *Dpctowner* | *The Difference in percent of owner occupied housing units from 2000 to 2015* | -2.978593 | 14.11201 | -41.29247 | 32.65146 |
| *Lpctowner* | *The Lag in percent of owner occupied housing units from 2000 to 2015* | 62.58973 | 22.2659 | 10.52072 | 98.77551 |
| *Dpctheadfemale* | *The Difference in percent of female headed households from 2000 to 2015* | -29.65245 | 17.33242 | -78.9632 | 9.99205 |
| *Lpctheadfemale* | *The Lag in percent of female headed households from 2000 to 2015* | 45.6382 | 16.71891 | 10.64815 | 84.39491 |
| *Dpctunemployed* | *The Difference in percent of the popuation that is unemployed from 2000 to 2015* | 1.096139 | 5.452442 | -20.55215 | 19.21534 |
| *Lpctunemployed* | *The Lag in percent of the popuation that is unemployed from 2000 to 2015* | 4.686873 | 3.486315 | 0 | 20.55215 |
| *Dpctfemale* | *The Difference in percent of female population from 2000 to 2015* | 0.3291956 | 7.350708 | -33.02339 | 20.7777 |
| *Lpctfemale* | *The Lag in percent of female population from 2000 to 2015* | 51.01873 | 4.718675 | 27.29821 | 59.93538 |
| *Dpctnotwhite* | *The Difference in percent of the population that is not White from 2000 to 2015* | 5.306354 | 18.01012 | -44.81467 | 53.08733 |
| *Lpctnotwhite* | *The Lag in percent of the population that is not White from 2000 to 2015* | 43.17182 | 26.20435 | 3.618421 | 100 |
| *Dpctpoverty* | *The Difference in percent of the population in poverty from 2000 to 2015* | -5.377944 | 13.60433 | -44.63659 | 38.80289 |
| *Lpctpoverty* | *The Lag in percent of the population in poverty from 2000 to 2015* | 27.69473 | 15.3168 | 1.354582 | 72.95598 |
| *Dpctunder12* | *The Difference in percent of the population with less than a highschool education from 2000 to 2015* | -5.837317 | 11.68792 | -39.52747 | 31.1288 |
| *Lpctunder12* | *The Lag in percent of the population with less than a highschool education from 2000 to 2015* | 23.08382 | 12.31185 | 0 | 54.00844 |
| *Dpctmobilehome* | *The Difference in percentage of mobile homes from 2000 to 2015* | -0.7214189 | 5.836099 | -20.23161 | 21.63763 |
| *Lpctmobile* | *The Lag in percentage of mobile homes from 2000 to 2015* | 5.833261 | 10.71807 | 0 | 53.62903 |
| *Dpctsocials* | *The Difference in percentage of the population receiving Social Security Benefits from 2000 to 2015* | 4.754415 | 12.35438 | -28.57691 | 44.22518 |
| *Lpctsocials* | *The Lag in percentage of the population receiving Social Security Benefits from 2000 to 2015* | 26.4096 | 10.92725 | 3.904382 | 63.09859 |
| *Dpctnovehicle* | *The Difference in percentage of the population without a vehicle from 2000 to 2015* | -0.7613047 | 9.887895 | -50.56689 | 34.17949 |
| *Lpctnovehicle* | *The Lag in percentage of the population without a vehicle from 2000 to 2015* | 10.60341 | 11.35327 | 0 | 62.55411 |
| *DSV* | *The Difference in Social Vulnerability from 2000 to 2015* | 0.0107883 | 0.6939685 | -2.312634 | 1.679574 |
| *LSV* | *The Lag in Social Vulnerability from 2000 to 2015* | 0.0542656 | 0.6678734 | -1.510437 | 2.160639 |

### 3.2 Principal Component Analysis

To construct social vulnerability indices, principal component analysis (PCA) was employed. PCA was developed by Karl Pearson in 1901 as a means to understand the relationships between independent variables in a least squared regression (Pearson, 1901). PCA is a rotation of the axis of original variables' coordinate system to new orthogonal axes, principal axes, where the new axes match with the directions of maximum variation within the initial dataset. The maximum variation of the projected points represents the first principal axis, or principal component. Successive principal axes, which are orthogonal to the previous ones and maximize the variation, are determined to find the components of independent variables which describe maximum variation (Campbell and Atchley, 1981). PCA extracts the dominant patterns within a data matrix to create a smaller set of uncorrelated components (figure 3).

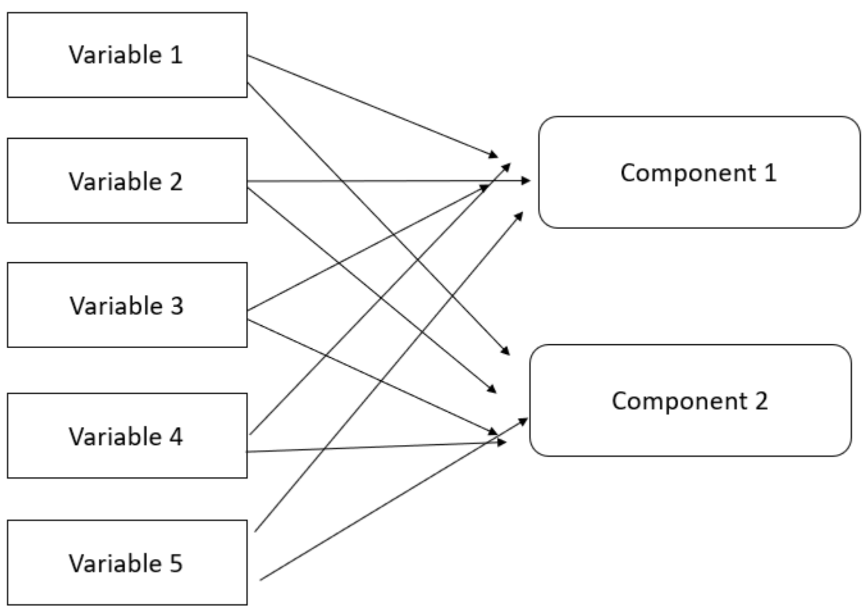


Figure 3 Diagram for Principal component analysis

For this study, in order to retain the most influential components which described most of the variance within the data, the components were retained based on the Kaiser criterion, i.e. components for which eigenvalues were greater than or equal to 1.

**3.3 Construction of SV**

The variables used in the construction of the Social Vulnerability index (SV) included block group level percentages for female population, female headed households, renters, owner, population with no vehicle, population under 5 years old, and population 65 and older, population unemployed, population receiving social security income, and percent with less than high school degree. Once the components were identified using PCA for each year the unweighted average of the components was taken to create SV index where each factor was assumed to have the same contribution to the block group's overall social vulnerability, with positive values of SV indicating higher levels and negative values indicating lower levels of social vulnerability, respectively.

**3.4 OLS Model**

The regression analysis was used in order to examine the effects of Hurricane Ike on the changes in socio-economic and demographic makeup of the block groups. To understand this effect the regression model was specified in equation (1) that follows:

$$y_{j,2015}^{k}-y_{j,2000}^{k} = \beta_0 + \beta_1\left(y_{j,2000}^{k}\right) + \beta_2 Risk_j + \sum_{j=1}^{5}\gamma_j D_j + e \quad (1)$$

Where $y_{j,t}^{k}$ represents the proportion of households (or people) of type k in the census block j in time period t (t corresponds to 2000 and 2015 years). Household type k includes percent of people under 5 years, percent 65 and older, percent renter occupied units, percent owner occupied, percent of people in poverty, percent female headed household, percent unemployed, percent female population, percent non-white, percent with less than high school diploma, percentage of mobile homes, percent people receiving social security, and percent of people with no vehicle. We also estimate the model in which $y^k_{j,t}$ corresponds to SV index for block group j at time t. Where $D_j$ is the vector for five inundation levels capturing varying degree of impacts of Hurricane Ike, where the omitted category is level one inundation (i.e., less than 2 feet). It is expected that with increasing level of inundation the SV will increase. Last, Risk is the variable that captures inherent risk of flooding, represented by the two types of flood zones (A and V). The moderate and no flood risk zones are omitted levels. e is the error term assumed to be normally distributed.

### 3.5 Simple OLS vs. Spatial Model

Spatial autocorrelation within a set of variables can threaten the validity of OLS regression models. The presence of spatial error indicates that the error term across different spatial units are spatially correlated, violating the assumption of uncorrelated errors. If there is spatial lag in the model the dependent variable y in blockgroup i is affected by the independent variables in both block groups *i* and *j*, and again the assumption of uncorrelated errors is violated. In such instances, a spatial autoregressive model is used to account for the autocorrelation in either the error or the lag of the dependent variable.

In order to test for spatial autocorrelation spatial diagnostics were conducted based on the Lagrange Multiplier test. The two different models, one for lag dependent variable and one for error spatial correlation were estimated. The spatial model that accounts for spatial lag dependency is specified by equation (2) and the model for spatial error is specified as equation (3) as follows:

$$y^k_{j,2015}\text{-}y^k_{j,2000} = \beta_0 + \rho W y + \beta_1\left(y^k_{j,2000}\right) + \beta_2 Risk_j + \beta_3 D_j + \mu \quad (2)$$

$$y^k_{j,2015}\text{-}y^k_{j,2000} = \beta_0 + \beta_1\left(y^k_{j,2000}\right) + \beta_2 Risk_j + \beta_3 D_j + \varepsilon \quad (3)$$

$$\varepsilon = \lambda W \varepsilon + \mu$$

In equation (2) W $y_{j,t}^{k}$represents the dependent variable as described in sub-section 3.4.1 and houshold type k represents the independent variables described in subsection 3.4.1. Where $Wy$ is the spatially- lagged y's (i.e. $y_{2015}^{k}$-$y_{2000}^{k}$) and W corresponds to spatial weights matrix. $\rho$ is the coefficient associated with the spatial lag variable.

In equation (3) $\varepsilon$ corresponds to a spatially weighted error term, where $\lambda$ is the autoregressive coefficient, $W\varepsilon$ is the spatial lag for the errors, and μ is another error term.

**3.6 Spatial Autocorrelation**

In order to make more robust assumptions about the spatial concentrations of socially vulnerable populations a bivariate Local Indicator of Spatial Autocorrelation (LISA) was used. The LISA method was developed by Luc Anselin in 1995 as the means to understand the significance of clustering of similar values in a location surrounding a particular observation and at what extent there is correlation (Anselin, 1995). Broadly, the LISA is used here to find the similarity and significance of SV in a spatial location with inundation at a neighboring location.

A bivariate LISA specified by equation (4) was used to analyze the spatial autocorrelation between Social Vulnerability (SV) and average Hurricane Ike inundation levels

$$I_l = z_{x_i} \sum_{J=1 J\neq i}^{N} w_{ij} z_{yj} \quad (4)$$

Where, $I_l$ is the local Moran's I, and x and y are two variables of interest measured as the average inundation (rather than levels of inundation) and social vulnerability at neighborhood i and j, respectively. Similarly, $z_x$ and $z_y$ represent the standardized z-scores for variables SV and inundation, respectively. The term $w_{ij}$ is the weight matrix corresponding to the distance weights from block group *i* centroid to the 1st order neighboring block group block group j centroids. LISA and weight matrices were created in GeoDa.

This analysis used 99 permutations and a first order Queen's contiguity matrix, where $w_{ij}$ corresponds the distance weight between location i and location j. Spatial autocorrelation was run for years 2000 and 2015 separately in order to identify statistically significant hotspots of correlation with average inundation at different time periods.

CHAPTER IV

RESULTS

### 4.1 Principal Component Analysis

Through the conduction of principal component analysis, the thirteen variables were condensed into sets of uncorrelated components. For the year 2000 four components were retained based on the Kaiser retention method, with eigenvalues greater than one (figure 4). The components were given general names to describe them, although more individual variables were loaded onto these components (Table 4). Overall the four components described 63% of the variation. For the year 2015 six components with eigenvalues greater than one were retained (figure 5). The naming of these components differed from the year 2000 as the loadings on the components were not the same (Table 5). Overall the six retained components described 70.5% of the variation in the year 2015.

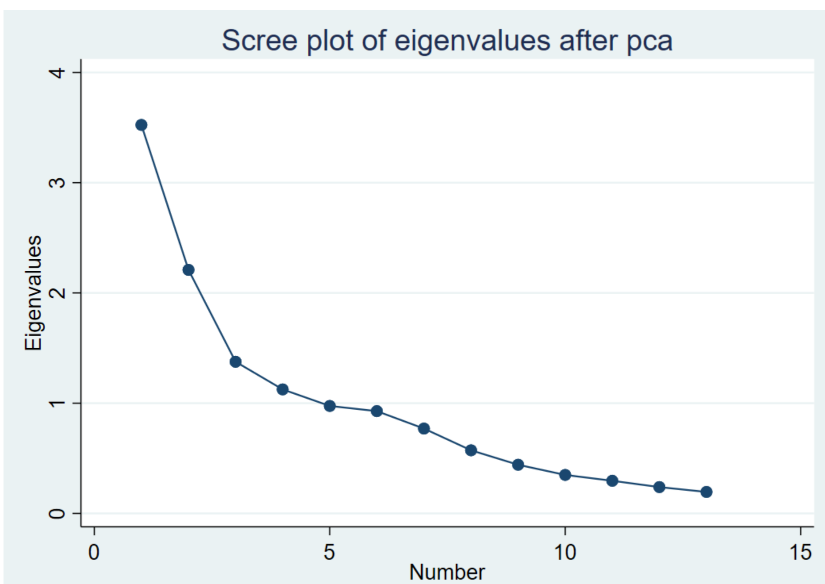

Figure 4 Eigenvalues for the year 2000 components

**Table 4: 2000 Variable loadings**

| *FACTOR* | *PERCENT VARIANCE EXPLAINED* | *DOMINANT VARIABLE* |
|---|---|---|
| **MARGINALIZED POPULATION** | 27.1 | Percent Not White |
| **DEPENDENT POPULATION** | 16.99 | Percent 65 and older |
| **POPULATION WITH LIMITED EDUCATION** | 10.58 | Percent under a 12th grade education |
| **POPULATION WITH LIMITED MOBILITY** | 8.65 | Percent no Vehicle |

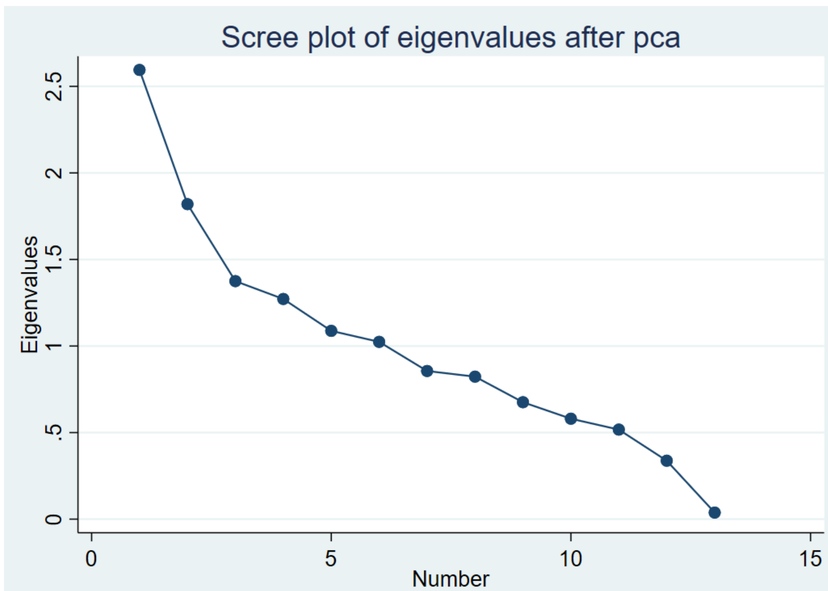


Figure 5 Eigenvalues for the year 2015 components

**Table 5: 2015 Variable Loadings**

| *FACTOR* | *PERCENT VARIANCE EXPLAINED* | *DOMINANT VARIABLE* |
|---|---|---|
| **POPULTION IN DENSELY OCCUPIED HOUSING** | 19.96 | Percent renter |
| **DEPENDENT POPULATION** | 14 | Percent 65 and older |
| **POPULATION IN LESS STRUCTURALLY SOUND HOUSING** | 10.58 | Percent mobile homes |
| **MARGINALIZED POPULATION** | 9.78 | Percent Female |
| **POPULATION WITH DEPENDENTS** | 8.37 | Percent Female Headed Household |
| **POPULATION WITH LIMITED FINANCIAL STABILITY** | 7.88 | Percent Unemployed |

### 4.2 Social Vulnerability Index

Components were aggregated for both years by averaging in order to create a composite index which captures social vulnerability. The resulting index for the year 2000 ranged from -1.51 to 2.16 with positive values being more vulnerable block groups and negative values indicating less vulnerable block groups (Table 6) The resulting index for the year 2015 ranged from -1.08 to 1.35 with the positive block groups being less vulnerable and the negative block groups being more vulnerable (Table 6)

**Table 6: Summary statistics for SV**

| Variable | Std.Dev | Mean | Min | Max |
|---|---|---|---|---|
| *2000 SV* | 0.6679 | 0.0543 | -1.5104 | 2.1606 |
| *2015 SV* | 0.4821 | 0.065 | -1.0818 | 1.3462 |

### 4.3 Spatial Autocorrelation Tests

The results for the autoregressive testing indicated that there were six models which violated OLS assumptions (Table 7). Five of the models had autocorrelation in the lag of the dependent variable, those included and were corrected based on equation (2) and one model with autocorrelation in the error term, which were corrected based on equation (3).

## Table 7: Autocorrelation Tests

| | *LM Value* | *Probability* |
|---|---|---|
| **Dpctyoung** | | |
| *LM LAG* | *3.318* | *0.069** |
| *LM ERROR* | *2.244* | *0.134* |
| **Dpctold** | | |
| *LM LAG* | *0.569* | *0.451* |
| *LM ERROR* | *0.162* | *0.687* |
| **Dpctrenter** | | |
| *LM LAG* | *4.088* | *0.043*** |
| *LM ERROR* | *2.212* | *0.137* |
| **Dpctowner** | | |
| *LM LAG* | *4.088* | *0.043*** |
| *LM ERROR* | *2.212* | *0.137* |
| **Dpctheadfemale** | | |
| *LM LAG* | *0.062* | *0.804* |
| *LM ERROR* | *4.933* | *0.026*** |
| **Dpctnotwhite** | | |
| *LM LAG* | *0.005* | *0.942* |
| *LM ERROR* | *1.754* | *0.185* |
| **Dpctpoverty** | | |
| *LM LAG* | *3.741* | *0.053** |
| *LM ERROR* | *0.169* | *0.681* |
| **Dpctunder12** | | |
| *LM LAG* | *0.05* | *0.824* |
| *LM ERROR* | *2.021* | *0.155* |
| **Dpctmobilehome** | | |
| *LM LAG* | *0.723* | *0.395* |
| *LM ERROR* | *0.016* | *0.9* |
| **Dpctsocials** | | |
| *LM LAG* | *1.346* | *0.246* |
| *LM ERROR* | *0.717* | *0.397* |
| **Dpctnovehicle** | | |
| *LM LAG* | *3.19* | *0.074** |
| *LM ERROR* | *0.059* | *0.808* |
| **Dpctfemale** | | |
| *LM LAG* | *2.312* | *0.128* |
| *LM ERROR* | *0.997* | *0.318* |
| **Dpctunemployed** | | |
| *LM LAG* | *0.342* | *0.559* |
| *LM ERROR* | *0.003* | *0.956* |
| **Dsv** | | |
| *LM LAG* | *2.061* | *0.151* |
| *LM ERROR* | *0* | *0.985* |

### 4.4 Regressions

The results for regressions are presented first as Tables 6 through 10 from models defined in equation (1), and equation (2) and (3); column headings indicate the change in the dependent variable from 2000 to 2015. Table 8 reports regression coefficients for the difference in SV model. The results reveal that social vulnerability decrease in a statistically significant manner in inundation level 3, 4 and 5 relative to level 1 and no significant change was observed in block groups falling under inundation level 2 relative to level 1. The results also show a statistically significant increase of socially vulnerability in A-zones, relative to X-zones.

These results are contradictory to the hypothesis but may elude to a longer adjustment time period or may be influenced by unobservable factors. Further investigation into the drivers of social vulnerability are presented in Tables 9 - 12.

**Table 8: Regression Coefficients for SV**

| | *Difference of social Vulnerability indices (z-scores)* |
|---|---|
| *Lag of Social Vulnerability* | -0.548*** |
| | (0.080) |
| *Percent A-zone* | 0.009*** |
| | (0.004) |
| *Percent V-zone* | 0.005 |
| | (0.006) |
| *Inundation zone 2* | -0.216 |
| | (0.207) |
| *Inundation zone 3* | -0.810*** |
| | (0.305) |
| *Inundation zone 4* | -0.983** |
| | (0.391) |
| *Inundation zone 5* | -1.111** |
| | (0.520) |
| $R^2$ | 0.270 |
| *N* | 152 |

* $p$<0.1; ** $p$<0.05; *** $p$<0.01

Standard errors in parenthesis. Column headings correspond to the dependent variable used in the estimation and represents the change between 2015 and 2000

To understand what has contributed to a decline in social vulnerability regression coefficients from the models in which dependent variable corresponds to changes in various housing levels are analyzed. The results are presented in Table 9, and reveal that the percentage of renter occupied housing units decreased in a statistically significant way in inundation level 3 (i.e. indundation 4-6ft) areas, relative to inundation level 1. The results for the difference in percentage of mobile homes show a statistically significant increase in inundation level 3 areas relative to inundation level 1. There are no statistically significant changes in flood zones.

**Table 9: Regression Coefficients for Housing**

| | *Percent Renter* | *Spatial lag (Percent Renter)* | *Percent Owner* | *Spatial lag (Percent Owner)* | *Percent Mobile homes* | *Spatial error (Percent Mobile homes)* |
|---|---|---|---|---|---|---|
| *A-zone* | 0.048 | 0.049 | -0.048 | -0.049 | -0.034 | -0.034 |
| | (0.057) | (0.92) | (0.84) | (0.92) | (1.49) | (1.52) |
| *V-zone* | -0.039 | -0.039 | 0.039 | 0.039 | 0.023 | 0.023 |
| | (0.088) | (0.47) | (0.44) | (0.47) | (0.66) | (0.67) |
| *Inundation cat 2* | -3.247 | -5.238* | 3.247 | 5.238* | -0.451 | -0.490 |
| | (3.205) | (1.70) | (1.01) | (1.70) | (0.34) | (0.37) |
| *Inundation cat 3* | -7.207 | -9.698** | 7.207 | 9.698** | 3.260* | 3.263* |
| | (4.831) | (2.10) | (1.49) | (2.10) | (1.67) | (1.71) |
| *Inundation cat 4* | -2.468 | -4.130 | 2.468 | 4.130 | 2.708 | 2.705 |
| | (6.095) | (0.72) | (0.40) | (0.72) | (1.10) | (1.13) |
| *Inundation cat 5* | -2.803 | -4.518 | 2.803 | 4.518 | -0.100 | -0.115 |
| | (8.051) | (0.60) | (0.35) | (0.60) | (0.03) | (0.04) |
| *Lag Percent Renter* | -0.161*** (0.056) | -0.162*** (3.09) | | | | |
| *Lag Percent Owner* | | | -0.161*** (2.85) | -0.162*** (3.09) | | |
| *Lag Percent Mobile Homes* | | | | | -0.155*** (3.52) | -0.160*** (3.15) |
| $R^2$ | 0.08 | 0.073 | 0.073 | 0.08 | 0.14 | 0.12 |
| N | 152 | 152 | 152 | 152 | 152 | 152 |

* *p*<0.1; ** *p*<0.05; *** *p*<0.01

Standard errors in parenthesis. Column headings correspond to the dependent variable used in the estimation and represents the change between 2015 and 2000

Results presented in Table 10 show the adjustments of populations by income level. Significant declines, indicated by negative and statistically significant coefficients associated with inundation levels 2, 3,4, and 5 are found for percent receiving social security benefits, relative to inundation level 1. Results also reveal a statistically significant decrease in percent unemployed for inundation level 3 relative to level 1. Damage coefficients for percent poverty show a statistically significant decrease in inundation levels 2 and 3 relative to level 1. Overall the income factors: Percent Receiving Social Security, Percent Unemployed, and Percent in Poverty, which drive social vulnerability are seen to decline in moderately damaged areas post Hurricane Ike. There is also a statistically significant increase in the population in poverty for A-zones, relative to X-zones. For flood- zone areas there is a statistically significant increase in V-zones, relative to X-zones for the population receiving social security.

**Table 10: Regression Coefficients for Income**

| | *Percent receiving Social security* | *Percent unemployed* | *Percent Poverty* | *Spatial Lag (Percent Poverty)* |
|---|---|---|---|---|
| *A-zone* | 0.050 | 0.024 | 0.101** | 0.088** |
| | (0.044) | (1.30) | (2.11) | (1.97) |
| *V-zone* | 0.215*** | -0.027 | -0.060 | -0.076 |
| | (0.073) | (0.91) | (0.81) | (1.10) |
| *Inundation cat 2* | -5.247** | -1.186 | -4.808* | -5.646** |
| | (2.635) | (1.10) | (1.73) | (2.17) |
| *Inundation cat 3* | -7.801** | -3.223** | -9.142** | -9.314** |
| | (3.899) | (1.99) | (2.23) | (2.44) |
| *Inundation cat 4* | -10.784** | -2.346 | -6.735 | -6.629 |
| | (4.977) | (1.14) | (1.30) | (1.37) |
| *Inundation cat 5* | -13.141** | -3.407 | -2.111 | -2.356 |
| | (6.547) | (1.27) | (0.31) | (0.37) |
| *Lag Percent Social security* | -0.589*** | | | |
| | (0.089) | | | |
| *Lag Percent unemployed* | | -0.850*** | | |
| | | (7.55) | | |
| *Lag Percent Poverty* | | | -0.453*** | -0.468*** |
| | | | (6.80) | (7.52) |
| R2 | 0.24 | 0.31 | 0.29 | 0.27 |
| N | 152 | 152 | 152 | 152 |

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

Standard errors in parenthesis. Column headings correspond to the dependent variable used in the estimation and represents the change between 2015 and 2000

Table 11 reports regression coefficients based on age factors. There is not statistically significant change for populations 65 and older in any of the inundation levels. However, results reveal a statistically significant decrease for populations 5 and under in inundation levels 3 and 4 relative to level 1. Moreover, there is also an increase in the population 65 and over for V-zones, relative to X-zones, which is also supported by the increased population receiving social security income in these zones.

**Table 11: Regression Coefficients for Age**

| | *Percent 65 and older* | *Percent 5 or less* | *Spatial Lag (Percent 5 or less)* |
|---|---|---|---|
| *A-zone* | 0.026 | 0.016 | 0.014 |
| | (0.028) | (0.91) | (0.86) |
| *V-zone* | 0.136*** | -0.005 | 0.003 |
| | (0.046) | (0.16) | (0.10) |
| *Inundation cat 2* | -0.674 | -0.184 | -0.412 |
| | (1.665) | (0.18) | (0.42) |
| *Inundation cat 3* | -1.126 | -2.572* | -2.960** |
| | (2.488) | (1.66) | (2.02) |
| *Inundation cat 4* | -2.204 | -3.922** | -4.386** |
| | (3.166) | (1.99) | (2.36) |
| *Inundation cat 5* | -6.077 | -2.308 | -2.863 |
| | (4.131) | (0.90) | (1.18) |
| *Lag Percent 65 and older* | -0.518***<br>(0.089) | | |
| *Lag Percent 5 or less* | | -0.842***<br>(7.30) | -0.791***<br>(7.18) |
| R2 | 0.21 | 0.31 | 0.30 |
| N | 152 | 152 | 152 |

* $p$<0.1; ** $p$<0.05; *** $p$<0.01

Standard errors in parenthesis. Column headings correspond to the dependent variable used in the estimation and represents the change between 2015 and 2000

In Table 12 the results for marginalized populations are reported. Results indicate that the percentage of the female population decreased in a statistically significant manner for inundation levels 3 and 4, relative to inundation level 1. Results also reveal that the percentage of not white population decreased in inundation levels 2 and 3 relative to level one. Similarly, the results for the percent of female headed households also decreased in a statistically significant manner for inundation levels 2 and 3 relative to level 1. However, there is no significant change for the percentage of the population with no vehicle for any of the inundation levels examined.

**Table 12: Regression Coefficients for Marginalized populations**

| | *Percent Female* | *Percent not white* | *Percent less than 12th grade* | *Percent no vehicle* | *Spatial Lag (Percent no Vehicle)* | *Percent Female headed household* | *Spatial Error (Percent Female headed household)* |
|---|---|---|---|---|---|---|---|
| *A-zone* | 0.031 | 0.063 | 0.042 | 0.057 | 0.048 | 0.037 | 0.037 |
| | (0.026) | (0.97) | (1.08) | (1.62) | (1.49) | (0.81) | (0.83) |
| *V-zone* | 0.079* | -0.185* | -0.073 | -0.064 | -0.080 | -0.106 | -0.105 |
| | (0.041) | (1.87) | (1.19) | (1.17) | (1.59) | (1.55) | (1.56) |
| *Inundation cat 2* | -0.315 | -6.336* | -0.907 | 1.058 | 1.255 | -4.966* | -4.594* |
| | (1.499) | (1.67) | (0.40) | (0.53) | (0.68) | (1.93) | (1.66) |
| *Inundation cat 3* | -1.866 | -11.666** | -5.270 | -2.551 | -2.179 | -6.969* | -6.443* |
| | (2.252) | (2.07) | (1.56) | (0.85) | (0.79) | (1.80) | (1.65) |
| *Inundation cat 4* | -6.253** | -10.179 | -3.481 | -1.790 | -1.016 | -7.636 | -7.123 |
| | (2.851) | (1.43) | (0.82) | (0.47) | (0.29) | (1.56) | (1.50) |
| *Inundation cat 5* | -7.469* | -7.394 | 5.715 | -1.834 | -1.174 | -5.196 | -4.596 |
| | (3.783) | (0.79) | (1.02) | (0.37) | (0.25) | (0.79) | (0.73) |
| *Lag Percent Female* | -0.782*** | | | | | | |
| | (0.116) | | | | | | |
| *Lag Percent not white* | | -0.379*** | | | | | |
| | | (6.88) | | | | | |
| *Lag Percent less than 12th grade* | | | -0.495*** | | | | |
| | | | (7.54) | | | | |
| *Lag Percent no vehicle* | | | | -0.458*** | -0.440*** | | |
| | | | | (7.01) | (7.28) | | |
| *Lag Percent Female headed household* | | | | | | -0.836*** | -0.853*** |
| | | | | | | (14.50) | (14.34) |
| $R^2$ | 0.26 | 0.28 | 0.35 | 0.28 | 0.26 | 0.62 | 0.60 |
| *N* | 152 | 152 | 152 | 152 | 152 | 152 | 152 |

* $p$<0.1; ** $p$<0.05; *** $p$<0.01

Standard errors in parenthesis. Column headings correspond to the dependent variable used in the estimation and represents the change between 2015 and 2000

### 4.5 LISA

In an effort to further explore the relationship between inundation and SV the LISA method was used. Results for the LISA indicate that for the year 2000 17 block groups had high values of vulnerability near high values of inundation, 11 block groups had low values of vulnerability near low values of inundation, 19 block groups had low values of vulnerability near high values of inundation, and 16 block groups had high values of vulnerability near now values of inundation (figure 7).

For the year 2015, 16 block groups had high values of vulnerability near high values of inundation, 10 block groups had low values of vulnerability near low levels of inundation, 18 block groups had low values of vulnerability near high values of inundation and 16 block groups had high values of vulnerability near low values of inundation (figure 8). The comparisons between the years is represented in figure 6.

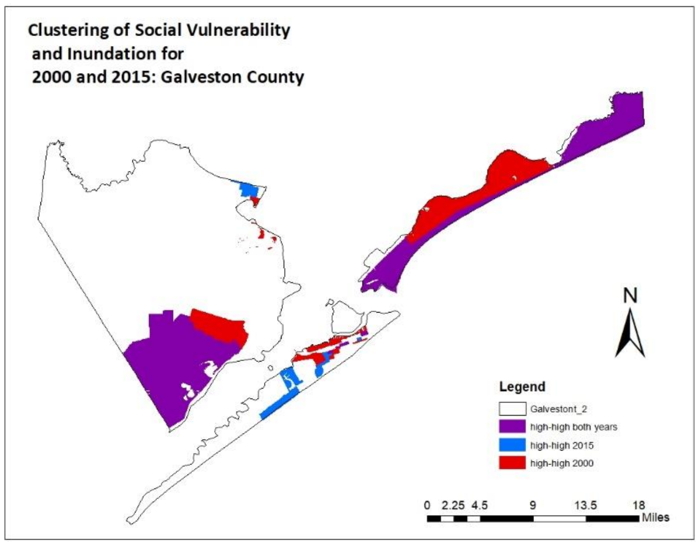


Figure 6 Clustering of SV with Inundation for 2000 and 2015

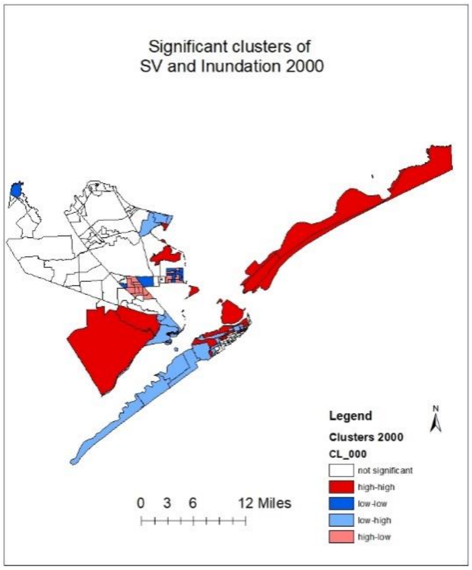


Figure 7 Clustering of SV and inundation 2000

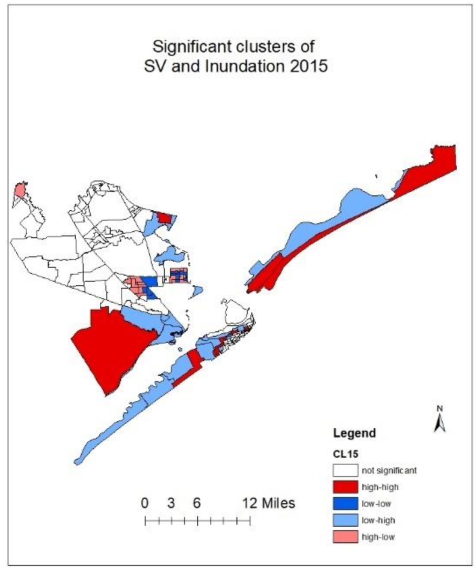


Figure 8 Clustering of SV and inundation 2015

CHAPTER V

# DISCUSSION AND CONCLUSIONS

The objective of this study was to identify spatial and temporal adjustment patterns to disasters across vulnerable segments of population. Findings in this paper offer important insights into the adjustments of socially vulnerable populations in Galveston County following Hurricane Ike in 2008. Overall, the results reveal a statistically significant decrease in both the indexed components of social vulnerability and the individual drivers of it in hazard-vulnerable block groups. The results for LISA compliment the regression results and confirms that the clustering of social vulnerability with inundation has decreased from 2000 to 2015. These results seem to contradict past studies which indicate that adjustments tend to be heterogeneous across income classes; low income populations tend to stay in high damage areas, middle income households move out of harm's way, and high-income households rebuild and insure (Smith et al., 2006; Davlasheridze and Fan, 2017). This study did not find that the drivers of social vulnerability, or the indexed components behaved in a similar fashion to those in New Orleans following Hurricane Katrina (Davlasheridze and Fan, 2017), or Miami-Dade following Hurricane Andrew (Smith et al., 2006). While it may be impetuous to expect similar results for very different geographic areas, with differing social makeup and scales of impact, searching for redundancy in disaster adjustments can aid in policy creation.

As mentioned, this study is limited by spatial scale, block groups within a single County, which may not capture the overall County to County migratory effect following Hurricane Ike. While multiple studies have shown that adjustments at a small scale are heterogeneous based on income, studies at larger scales, i.e. County to County migrations reveal that drivers of social vulnerability, specifically racial minorities, poor, less educated, and female headed households are disproportionally subject to larger scale displacement (Morrow-Jones, 1991; Belcher and Bates, 1983; Fordham 1999; Haas et al., 1977; Myers et al., 2011).

Furthermore, the loss of social and economic infrastructure, especially the temporary loss of tourism-based jobs may have prompted groups to take advantage of job opportunities elsewhere. Regardless of low housing costs post disaster, if there are lessened job opportunities following disaster there is little motivation for people to live in those areas. The overall trend in decrease in high inundation zones could be merely a snap shot of a much larger scale adjustment following Hurricane  Ike in 2008.

Another likely explanation of overall decrease in vulnerability may be the combination of the loss of public housing on Galveston island, and the changes in housing tenure due to coastal gentrification from investors. However, the exploration of these causalities is at present not possible with current Census data. Because the recovery of public housing has not yet been completed it is not possible to conclude whether this loss of housing has drastically affected the long-term post disaster composition of Galveston County. However, a recent study done in Galveston County shows that there is in fact a change in demographic and socioeconomic composition due to the changes in public housing (Hamideh and Rongerude, 2018).  Further study is warranted once the public housing has been fully recovered and enough time has passed to explore long-term adjustments to housing recovery.

While the decline in overall social vulnerability is indicative of resilient recovery, such major changes can also be indicative of an overall change of a community identity. The loss of populations with long established roots in coastal communities, means the social memory of these groups may also be lost.  Persons with multiple disaster experiences are essential for community information transfer, i.e. word of mouth on hazardous areas, evacuation and preparation knowledge. However, revitalization can also mean greater resilience. With the large influx of money going into properties, businesses, etc. the people living in the community will have greater means and better access to political powers. Moreover, it is at present uncertain what effect these changes will have for future resilience and more research on these changes is necessary to make such substantial claims.

This study makes significant contributions to existing literature by integrating the usage of a social vulnerability index and building upon the various methodological approaches to the hazard of place model developed by Cutter et al. (2003). Utilizing the social vulnerability model to examine the adjustment of populations provides a link between the bodies of work on social vulnerability and household adjustments to disasters. Further, another important contribution is the consideration of spatial effects. Because adjustments post disaster are a spatial phenomenon accommodating for the spatial effects and spatial dependence allows for more robust statistical modeling. Along with accounting for the spatial effects this study examines spatially driven correlations as a means to analyze post disaster adjustment. Theoretically, this is an important contribution as the adjustments of populations are spatially motivated and occur on a geographic scale.

Communities are extremely complex social systems, especially in disaster events, and the quantitative measures for social vulnerability and methodological approaches for assessing adjustments are not without limitation. Further research should be undertaken in order to understand the many motivators of adjustments, and limitations for composite measures of social vulnerability.

Taking advantage of location specific sources of resilience, social capital, and social integration can lessen vulnerabilities to disaster. Specifically, racial integration and revitalization projects which focus on heterogeneity in housing tenure can help to mitigate place- based social exclusion, increase community capital and decrease vulnerability to disaster events. The current reconstruction of public housing has had a large focus on social mixing which is a beneficial step towards resiliency. In the face of threatened risk due to rising sea levels more complex understanding of social motivations for adjustment and vulnerability should be explored and will be an important extension of the current study.

REFERENCES

Adger, W. N. (1999). Social Vulnerability to Climate Change and Extremes in Coastal Vietnam. World Development,27(2), 249-269. doi:10.1016/s0305-750x (98)00136-3

Adger, W. N. (2003). Social Aspects of Adaptive Capacity. In Climate Change, Adaptive Capacity and Development (pp. 29-49). London: Imperial College Press.

Adger, W. N., Hughes, T. P., Folke, C., Carpenter, S. R., and Rockstrom, J. (2005). Social-Ecological Resilience to Coastal Disasters. Science,309(5737), 1036-1039. doi:10.1126/science.1112122

Alice Fothergill, a. L. (2004). Poverty and disaster in the United States. Natural Hazards , 89-110.

Anttila-Hughes, J. K., and Hsiang, S. M. (2013). Destruction, Disinvestment, and Death: Economic and Human Losses Following Environmental Disaster. SSRN Electronic Journal. doi:10.2139/ssrn.2220501

Anselin, L. (1995). Local Indicators of Spatial Association - LISA. Geographical Analysis,27(2), 93-115. doi:https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Baade, R. A., Baumann, R., and Matheson, V. (2007). Estimating the Economic Impact of Natural and Social Disasters, with an Application to Hurricane Katrina. Urban Studies,44(11), 2061-2076. doi:10.1080/00420980701518917

Barrow, C. (2006). Environmental Management for Sustainable Development. New York : Routledge.

Belcher, J. C., & Bates, F. L. (1983). Aftermath of natural disasters: Coping through residential mobility. Disasters,7(2), 118-128. doi:10.1111/j.1467-7717.1983.tb00805.x

Binder, S. B., Baker, C. K., and Barile, J. P. (2015). Rebuild or Relocate? Resilience and Postdisaster Decision-Making After Hurricane  Sandy. American Journal of Community Psychology,56(1-2), 180-196. doi:10.1007/s10464-015-9727-x

Bohle, H. G., Downing, T. E., and Watts, M. J. (1994). Climate change and social vulnerability. Global Environmental Change,4(1), 37-48. doi:10.1016/0959-3780(94)90020-5

Boruff, B. J., & Cutter, S. L. (2010). The Environmental Vulnerability Of Caribbean Island Nations*. Geographical Review,97(1), 24-45. doi:10.1111/j.1931-0846.2007.tb00278.x

Brody, S. D., Zahran, S., Maghelal, P., Grover, H., & Highfield, W. E. (2007). The Rising Costs of Floods: Examining the Impact of Planning and Development Decisions on Property Damage in Florida. Journal of the American Planning Association,73(3), 330-345. doi:10.1080/01944360708977981

Brooks, W.N., Adger, Country level risk measures of climate-related natural disasters and implications for adaptation to climate change, Tyndall Centre Working Paper 26, Tyndall Centre for Climate Change Research, Norwich, 2003, 26 p

Brooks, N., Adger, W. N., & Kelly, P. M. (2005). The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. Global Environmental Change,15(2), 151-163. doi:10.1016/j.gloenvcha.2004.12.006

Byrne, J.P. (2003) Two cheers for gentrification. Howard Law Journal 46.3, 405–32.

Campbell, N. A., and Atchley, W. R. (1981). The Geometry of Canonical Variate Analysis. Systematic Biology,30(3), 268-280. doi:10.1093/sysbio/30.3.268

Chakraborty J, Tobin GA, Montz BE (2005) Population evacuation: assessing spatial variability in geophysical risk and social vulnerability to natural hazards. Nat Hazards Rev 6(1):23–33

Chamlee-Wright, E. (2013). The Cultural and Political Economy of Recovery: Social Learning in a post-disaster environment. London: Routledge.

Coffman, M., and Noy, I. (2011). Hurricane  Iniki: Measuring the long-term economic impact of a natural disaster using synthetic control. Environment and Development Economics,17(02), 187-205. doi:10.1017/s1355770x11000350

Colten, C. E., and Sumpter, A. R. (2008). Social memory and resilience in New Orleans. Natural Hazards,48(3), 355-364. doi:10.1007/s11069-008-9267-x

Creel, L. (2003 ). Ripple Effects: Population and Coastal Regions . Washington, DC : Population Reference Bureau .

Crow, K. (2018). As Port Aransas rebuilds after Hurricane  Harvey what will this coastal town become? Corpus Christi Caller-Times. Retrieved from https://www.caller.com/story/news/local/2018/05/01/port-aransas-rebuilds-after-Hurricane -harvey-what-coastal-texas-town-become/420334002/

Cutter, S. L., Burton, C. G., & Emrich, C. T. (2010). Disaster Resilience Indicators for Benchmarking Baseline Conditions. Journal of Homeland Security and Emergency Management,7(1). doi:10.2202/1547-7355.1732

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. doi:10.1111/0004-5608.00219

Cutter, S. L. (2003). Social Vulnerability to Environmental. Social Science Quarterly , 242-262.

Cutter, S. L., & Finch, C. (2008). Temporal and spatial changes in social vulnerability to natural hazards. Proceedings of the National Academy of Sciences,105(7), 2301-2306.

Cutter, S. L., Emrich, C. T., Mitchell, J. T., Boruff, B. J., Gall, M., Schmidtlein, M. C., . . . Melton, G. (2006). The Long Road Home: Race, Class, and Recovery from Hurricane

Katrina. Environment: Science and Policy for Sustainable Development,48(2), 8-20. doi:10.3200/envt.48.2.8-20

Cutter, S. L. (1996). Vulnerability to Environmental Hazards. Progress in Human Geography,20(4), 529-539.

Daniels, R. J., Kettl, D. F., and Kunreuther, H. (2011). On Risk and Disaster Lessons from Hurricane Katrina. Philadelphia: University of Pennsylvania Press.

Davlasheridze, M ., Q. M (Forthcoming). Does Governmental Assistance Affect Private Decisions to Insure . Full Stop Working Paper .

Davlasheridze, M., Fan, Q. (2017) Household Adjustments to Hurricane Katrina. Journal of Southern Regional Science Association,47, 93-112

Eidson, M.; J.A. Lybarger; J.E. Parsons; J.N. MacCormack; J.I. Freeman. 1990. Risk Factors for Tornado Injuries. International Journal of Epidemiology 19(4):1051–1056.

Elliott, J. R., Gotham, K. F., & Milligan, M. J. (2004). Framing the Urban: Struggles Over HOPE VI and New Urbanism in a Historic City. City and Community,3(4), 373-394. doi:10.1111/j.1535-6841.2004.00093.x

Elliott, J. R., and Pais, J. (2006). Race, class, and Hurricane Katrina: Social differences in human responses to disaster. Social Science Research,35(2), 295-321. doi: 10.1016/j.ssresearch.2006.02.003

Emerson, M. O., Bratter, J., Howell, J., Jeanty, P. W., & Cline, M. (n.d.). Houston Region Grows More Racially/Ethnically Diverse, With Small Declines in Segregation. A Joint Report Analyzing Census Data from 1990, 2000, and 2010(Rep.).

FEMA. (2017, April ). National Flood Hazard Layer . Retrieved from fema.gov: https://www.fema.gov/national-flood-hazard-layer-nfhl

Flanagan, B. E., Gregory, E. W., Hallisey, E. J., Heitgerd, J. L., & Lewis, B. (2011). A Social Vulnerability Index for Disaster Management. Journal of Homeland Security and Emergency Management,8(1). doi:10.2202/1547-7355.1792

Fordham, M. H. (1999). The intersection of gender and social class in disaster: Balancing resilience and vulnerability. International Journal of Mass Emergencies and Disasters, 17, 15–36.

Fothergill, A., & Peek, L. A. (2004). Poverty and Disasters in the United States: A Review of Recent Sociological Findings. Natural Hazards,32(1), 89-110. doi:10.1023/b:nhaz.0000026792.76181.d9

Gallie, D., Paugam, S., & Jacobs, S. (2003). Unemployment, Poverty And Social Isolation: Is there a vicious circle of social exclusion? European Societies,5(1), 1-32. doi:10.1080/1461669032000057668

Gideon Bolt, D. P. (2010). Housing Policy, (De)segregation and social mixing: An International Perspective . Housing Studies , 129-136.

Goetz, E. G. (2010). Better Neighborhoods, Better Outcomes? Explaining Relocation Outcomes in Hope VI. SSRN Electronic Journal. doi:10.2139/ssrn.1585369

Gotham, Kevin F. and Richard Campanella. (2011) "Coupled Vulnerability and Resilience: The Dynamics of Cross-Scale Interactions in Post-Katrina New Orleans," Ecology and Society, 16, 12.

Haas, E., Kates, R. W., & Bowden, M. J. (1977). Reconstruction following disaster. Cambridge, MA: MIT.

Hamideh, S., & Rongerude, J. (2018). Social vulnerability and participation in disaster recovery decisions: Public housing in Galveston after Hurricane  Ike. Natural Hazards. doi:10.1007/s11069-018-3371-3

Hayden, R. E. (2010). Storm Surge and “Certain Death”: Interviews with Texas Coastal Residents following Hurricane Ike. American Meteorological Survey .

Hebb A, Mortsch L (2007) Floods: mapping vulnerability in the upper Thames Watershed under a changing climate. University of Waterloo, Project Report XI, pp 1–53

Holling, C. S. (1973). Resilience and Stability of Ecological Systems. Annual Review of Ecology and Systematics,4(1), 1-23. doi:10.1146/annurev.es.04.110173.000245

Holling, C. S. (2001). Understanding the Complexity of Economic, Ecological, and Social Systems. Ecosystems,309-405. doi:10.1007ls10021-001-0101-5

Houston-Galveston Area Council . (2017, April ). GIS Datasets . Retrieved from h-gac.com: http://www.h-gac.com/rds/gis-data/gis-datasets.aspx

https://www.ipcc.ch/publications_and_data/ar4/wg1/en/spmsspm-projections-of.html.

IPCC, 2007: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Jonkman, S. N., Maaskant, B., Boyd, E., & Levitan, M. L. (2009). Loss of Life Caused by the Flooding of New Orleans After Hurricane Katrina: Analysis of the Relationship Between Flood Characteristics and Mortality. Risk Analysis,29(5), 676-698. doi:10.1111/j.1539-6924.2008.01190.x

Keene, D. E., & Geronimus, A. T. (2011). “Weathering” HOPE VI: The Importance of Evaluating the Population Health Impact of Public Housing Demolition and Displacement. Journal of Urban Health,88(3), 417-435. doi:10.1007/s11524-011-9582-5

Kennedy, A., Rogers, S., Sallenger, A., Gravois, U., Zachry, B., Dosa, M., and Zarama, F. (2011). Building Destruction from Waves and Surge on the Bolivar Peninsula during Hurricane Ike. Journal of Waterway, Port, Coastal, and Ocean Engineering,137(3), 132-141. doi:10.1061/(asce)ww.1943-5460.0000061

Kousky, C., Luttmer, E. F., and Zeckhauser, R. (2006). Private Investment and Government Protection. Journal of Risk and Uncertainty. doi:10.3386/w12255

Kousky, C., Michel-Kerjan, E. O., and Raschky, P. A. (2018). Does federal disaster assistance crowd out flood insurance? Journal of Environmental Economics and Management,87, 150-164. doi: 10.1016/j.jeem.2017.05.010

Kunreuther, H. (2001). Mitigation and Financial Risk Management for Natural Hazards. Geneva Papers on Risk and Insurance - Issues and Practice,26(2), 277-296. doi:10.1111/1468-0440.00113

Kunreuther, H., and A. Rose. 2004. Introduction. The Economics of Natural Hazards Volume I. H. Kunreuther and A. Rose. Cheltenham, UK, Edward Elgar Publishing, Inc.: xiii–xxxv.

Lewis, T., and Nickerson, D. (1989). Self-insurance against natural disasters. Journal of Environmental Economics and Management,16(3), 209-223. doi:10.1016/0095-0696(89)90010-7

Lynham, J., Noy, I., and Page, J. (2017). The 1960 Tsunami in Hawaii: Long-Term Consequences of a Coastal Disaster. World Development,94, 106-118. doi: 10.1016/j.worlddev.2016.12.043

Morrow, B.H. 1999. Identifying and Mapping Community Vulnerability. Disasters 23(1)1–18.

Morrow-Jones, H. A., & Morrow-Jones, C. R. (1991). Mobility Due to Natural Disaster: Theoretical Considerations and Preliminary Analyses. Disasters,15(2), 126-132. doi:10.1111/j.1467-7717. 1991.tb00441.x

Mustafa D, Ahmed S, Saroch E, Bell H (2011) Pinning down vulnerability: from narratives to numbers. Disasters 35(1):62–86

Myers, C. A., Slack, T., and Singelmann, J. (2008). Social vulnerability and migration in the wake of disaster: The case of Hurricane s Katrina and Rita. Population and Environment,29(6), 271-291. doi:10.1007/s11111-008-0072-y

Nakagawa, Y., and Shaw, R. (2004). Social Capital: A Missing Link to Disaster Recovery. International Journal of Mass Emergencies and Disasters,22(1), 5-34.

Nance, Earthea, Kevin Gotham, Richard Campanella, Josh Lewis, Farrah Gafford, and Mallikharjuna Avula. (2011) "Reconsidering the New Normal: Vulnerability and Resilience in Post-Katrina New Orleans," Global Horizons: The Journal of Global Policy and Resilience, 4, 54–68.

NOAA. (2018). Patterns and Projections of High Tide Flooding Along the U.S. Coastline Using A Common Impact Threshold (Tech. No. NOS CO-OPS 086). Silver Spring, MD.

Olsson, P., Folke, C., and Berkes, F. (2004). Adaptive Comanagement for Building Resilience in Social? Ecological Systems. Environmental Management,34(1). doi:10.1007/s00267-003-0101-7

Paul Watt, P. S. (2017). Social Housing and Urban Renwal: A Cross National Perspective . Emerald Publishing Limited.

Peacock, W. G., Grover, H., Mayunga, J., Van Zandt, S., Brody, S. D., & Kim, H. J. (n.d.). The Status and Trends of Population Social Vulnerability along the Texas Coast with special attention to the Coastal Management Zone and Hurricane  Ike: The coastal Planning Atlas and Social Vulnerability Mapping Tools(Rep.).

Pearson, K. (1901). LIII. On lines and planes of closest fit to systems of points in space. The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science,2(11), 559-572. doi:10.1080/14786440109462720

Peek-Asa, C.; M. Ramirez; H. Seligson; K. Shoaf. 2003. Seismic, Structural, and Individual Factors Associated with Earthquake Related Injury. Injury Prevention 9(1):62–66.

Pelling, M. (2006). Natural disasters and development in a globalizing world. New Fetter Lane, London: Routledge.

Perry, C. A. (2000). Significant Floods in the United States During the 20th Century USGS Measures a Century of Floods, USGS Fact Sheet 024–00, U. S. Geological Society.

Popkin, S. J., Levy, D. K., & Buron, L. (2009). Has Hope Vi Transformed Residents Lives? New Evidence From The Hope Vi Panel Study. Housing Studies,24(4), 477-502. doi:10.1080/02673030902938371

Rankin, B. H., & Quane, J. M. (2000). Neighborhood Poverty and the Social Isolation of Inner-City African American Families. Social Forces,79(1), 139-164. doi:10.1093/sf/79.1.13

Rohe, W. M., & Burby, R. J. (1988). Fear of Crime in Public Housing. Environment and Behavior,20(6), 700-720. doi:https://doi.org/10.1177/0013916588206003

Rosenkoetter, M.M.; E.K. Covan; B.K. Cobb; S. Bunting; M. Weinrich. 2007. Perceptions of Older Adults Regarding Evacuation in the Event of a Natural Disaster. Public Health Nursing 24(2):160–168.

Roth, D., 2000, Texas Hurricane  history: http://www .srh.noaa.gov/lch/research/txhur.php (September 2009).

Rygel, L., O’Sullivan, D., & Yarnal, B. (2006). A Method for Constructing a Social Vulnerability Index: An Application to Hurricane  Storm Surges in a Developed Country.

Mitigation and Adaptation Strategies for Global Change,11(3), 741-764. doi:10.1007/s11027-006-0265-

Sampson, R. J., & Wilson, W. J. (2013). Toward a Theory of Race, Crime, and Urban Inequality. In Race, Crime, and Justice(pp. 177-188). Routledge.

Schmidlin, T.W. and P.S. King. 1995. Risk Factors for Death in the 27 March 1994 Georgia and Alabama Tornadoes. Disasters: The Journal of Disaster Studies and Management 19:170–177.

Schmidtlein, M. C., Deutsch, R. C., Piegorsch, W. W., and Cutter, S. L. (2008). A Sensitivity Analysis of the Social Vulnerability Index. Risk Analysis,28(4), 1099-1114. doi:10.1111/j.1539-6924.2008. 01072.x

Shannon Van Zandt, W. G. (2012). Mapping social vulnerability to enhance housing and neighborhood resilience. Housing Policy Debate, 29-55.

Smit, B., and Pilifosova, O. (2003). From Adaptation to Adaptive Capacity and Vulnerability Reduction. Climate Change, Adaptive Capacity and Development,9-28. doi:10.1142/9781860945816_0002

Smith, K. V., Carbone, J. C., Pope, J. C., Hallstrom, D. G., and Darden, M. E. (2006). Adjusting to natural disasters. Journal of Risk and Uncertainty,33(1-2), 37-54. doi:10.1007/s11166-006-0170

Tate, E. (2012). Social vulnerability indices: a comparative assessment using uncertainty and sensitivity analysis. Natural Hazards , 325-347.

Tidball, K. G., Krasny, M. E., Svendsen, E., and Campbell, L. (2010). Stewardship, learning, and memory in disaster resilience. Environmental Education Research,16(5-6), 591-609. doi:10.1080/13504622.2010.505437

United States, National Commission on Severely Distressed Public Housing. (1992). The Final Report of the National Commission on Severely Distressed Public Housing. Washington, D.C.

U.S. Census Bureau; American Community Survey, 2000 American Community Survey 5-year estimates, Tables: h045; h007; p062; p008; h032; p013; p052; h019; p043; p037; p007; generated by Emily Fucile Sanchez; Using American Fact Finder <http://factfinder.census.gov>.

U.S. Census Bureau; American Community Survey, 2015 American Community Survey 5-year estimates, Tables: b25044; b25003; b19055; b01001; b25032; b01002; b19001; b11001; b23025; b15002; b03002; generated by Emily Fucile Sanchez; Using American Fact Finder <http://factfinder.census.gov>.

Varley, A. (1994). Disasters, development and environment. Chichester: J. Wiley.

Vincent K (2004) Creating an index of social vulnerability to climate change in Africa. Working paper 56. London: Tyndall Centre for Climate Change Research

Walker, B., Holling, C. S., Carpenter, S. R., and Kinzig, A. P. (2004). Resilience, Adaptability and Transformability in Social-ecological Systems. Ecology and Society,9(2). doi:10.5751/es-00650-090205

Walters, E. (2018, April 16). "It’s our form of apartheid": How Galveston stalled public housing reconstruction in the 10 years after Ike. The Texas Tribune. Retrieved from https://www.texastribune.org/2018/04/16/galveston-public-affordable-housing-Hurricane-ike/

Walters Peacock, S. V. (2015). Inequities in Long-Term Housing Recovery After Disasters. Journal of The American Planning Association, 356-371.

White, G.W.; M.H. Fox; C. Rooney; A. Cahill. 2006. Assessing the Impact of Hurricane  Katrina on Persons with Disabilities: Interim Report. Lawrence, Kansas: Research and Training Center on Independent Living, University of Kansas

Wijkman, A., and Timberlake, L. (1988). Natural disasters: Acts of God or acts of man? Philadelphia, PA: New Society.

Wu, S., Yarnal, B., & Fisher, A. (2002). Vulnerability of coastal communities to sea-level rise: A case study of Cape May County, New Jersey, USA. Climate Research,22, 255-270. doi:10.3354/cr022255

Yoon, D. (2012). Assesment of social vulnerability to natural disasters: a comparitive study. Natural Hazards , 823-843.

Zahran, S., Brody, S. D., Peacock, W. G., Vedlitz, A., & Grover, H. (2008). Social vulnerability and the natural and built environment: A model of flood casualties in Texas. Disasters,32(4), 537-560. doi:10.1111/j.1467-7717.2008.01054.x