Enhancing Natural Hazards and Vulnerability/Resilience Studies Using Social Theory and Spatial Statistics

A Dissertation
Presented in Partial Fulfillment of the Requirements for the
Degree of Doctorate of Philosophy
with a
Major in Geography
in the
College of Graduate Studies
University of Idaho
by
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May 2017

Authorization to Submit Dissertation

This dissertation of Courtney M. Thompson, submitted for the degree of Doctorate of Philosophy with a Major in Geography and titled “Enhancing Natural Hazards and Vulnerability/Resilience Studies Using Social Theory and Spatial Statistics," has been reviewed in final form. Permission, as indicated by the signatures and dates below, is now granted to submit final copies to the College of Graduate Studies for approval.

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Abstract

In order to reduce the impacts of natural disasters, research in Geography and the natural hazards sub-discipline have made efforts to understand the complex relationship between social systems and natural hazard and their associated impacts. These studies help agencies and communities better understand local hazards and their resulting impacts, which can help them develop and implement ways to mitigate natural hazards impacts and improve recovery potential. However, natural hazards research is often applied and has been criticized for lacking theoretical focus. Due to these limitations, this dissertation examines alternative theoretical foundations that can be used to develop a theoretical framework that utilizes social theory to explain existing patterns of vulnerability and resilience and how those influence overall recovery potential. Additionally, this dissertation presents enhanced methodologies for measuring vulnerability from and theoretically robust standpoint.

This research presents the INjecting Structuration into Resilience/Vulnerability STudies (INSeRT) conceptual framework and associated methodologies developed from a resilience theory, political ecology, and structuration theoretical perspective. This INSeRT framework addresses the impact of the social structuration of society, multi-scalar factors, risk perception, social capital and human-environment interactions on vulnerability by utilizing social theory foundations. Societies are structural, so the employment of a structural or hierarchical model based on structuration theory principles reliably represent processes occurring within the current social structure. This dissertation also provides a measureable link between social structure, risk perception and demographics from surveys and statistical analysis to provide information about how risk perception and structuration impact the way people react to or cope with hazard events at an individual level. This information can enhance existing vulnerability/resilience assessments to provide a holistic measure of vulnerability. The methods presented can also help explain why people live in risky areas and help communities develop ways to mitigate against policies or social processes that perpetuate these types of development patterns.

Acknowledgements

I would like to thank the members of my committee, Dr. Ray Dezzani, Dr. Steven Radil, Dr. Karen Humes and Dr. Todd Norton, for supporting my work for this dissertation. I would also like thank Dr. Ray Dezzani for his guidance and support during this process. I could not have finished this work without his help and encouragement, and I am very grateful for his patience in taking endless hours to support me with this research. I also want to thank Dr. Tim Frazier and individuals in Sarasota County who took time out of their busy schedules to discuss aspects of this research, which led to improvements in the overall product. I want to thank all of my friends for all of their help and support. Finally, I would like to thank my family and Thomas for being there for me during this process.

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Chapter 1 - Introduction and Literature Review

1.1 Introduction

Population increase in the developed world has resulted in an increased amount of infrastructure exposed to natural hazards (Adger 2006; Cutter et al. 2009; Frazier, Wood, and Yarnal 2010; Keller, DeVecchio, and Blodgett 2014). This pattern of development influences the frequency and intensity of natural disasters, as the number of people and societal assets exposed and vulnerable to disaster impacts increases. In coastal areas, consistent population growth fuels coastal community development, especially as economic growth focuses more on urban-based commerce and service sector employment (Keller, DeVecchio, and Blodgett 2014; Wisner et al. 2004). This trend of continual development in vulnerable areas along the coast creates increased exposure to both contemporary and future hazards (Frazier, Wood, and Yarnal 2010; Frazier et al. 2010; Frazier, Thompson, and Dezzani 2013).

To reduce societal losses from natural hazards and climate change, it is important for communities to lower their vulnerability and increase their resilience to these events (Adger et al. 2005; Rose 2007). Vulnerability and resilience often have variable definitions, depending on the context of the discipline. For this research, vulnerability is the potential for loss (Cutter 2003; Frazier, Thompson, and Dezzani 2014; Turner et al. 2003) and is a function of exposure, sensitivity, and adaptive capacity (Frazier, Thompson, and Dezzani 2014). Exposure describes the physical proximity of a community to a hazard (Cutter, Burton, and Emrich 2010; White 1945). Sensitivity is the degree to which a community is affected by a hazard, and adaptive capacity is the ability of a community to cope with and adapt to the effects of a natural disaster event (Birkmann 2006; Brooks 2003; Cutter 2003; Cutter et al. 2009; Frazier, Thompson, and Dezzani 2014; Füssel 2007; Gallopín 2006). Resilience describes the ability of a system to resist and recover from a hazard event, through the development of adaptive processes that are based on learning from the hazard event experience (adaptive capacity) (Adger 2000; Cutter, Burton, and Emrich 2010; Frazier, Thompson, et al. 2013; Kimhi and Shamai 2004; Rose 2007; Zhou 2010), as communities that return to a pre-existing state may not necessarily return to a resilient state. While several factors can influence resilience, reducing vulnerability is considered to be one possible way to increase resilience (Adger 2000; Cutter, Burton, and Emrich 2010; Frazier, Thompson, et al. 2013; Rose 2007). Later sections of this chapter discuss other definitions of vulnerability to provide support for the definitions applied to the terms vulnerability and resilience in this dissertation.

Understanding community vulnerability is important for resource management and effective disaster response (Boin and McConnell 2007; Pederson et al. 2006). Vulnerability and resilience assessments, mitigation, and adaptation can reduce the impacts of disaster events through proactive hazard mitigation planning (HMP) (Berke and Campanella 2006; Berke and Godschalk 2009; Burby 2006a; Burby et al. 2000; Frazier, Walker, et al. 2013; Godschalk, Brody, and Burby 2004; Godschalk 1999). However, human development and population distributions occur unequally across the landscape, which causes overall vulnerability to vary from place to place (Frazier, Thompson, and Dezzani 2013, 2014).

Spatial variability occurs because landscapes develop in different ways. The natural terrain influences development to a degree, often resulting in patterns that reflect constraints from the natural landscape. However, places also develop due to different values, cultures, beliefs and attitudes that people attribute to places (Chakraborty, Tobin, and Montz 2005; Knox and Marston 2013). This combination of factors shapes all places in different ways, meaning that each place, while it may share similarities with places close by, is unique to that location. The uniqueness of place, therefore, leads to spatially variability in both natural landscapes, population and distribution of social assets. Exposure to natural hazards is also spatially variable, as different natural hazards develop in very specific environmental conditions. The formation of natural hazards is constrained to certain areas that exhibit specific internal or external natural processes (i.e. earthquakes occurring along fault lines or hurricanes occurring over ocean areas with warm water sources) (Keller, DeVecchio, and Blodgett 2014). The extent of a hazard will vary both spatially and by hazard type, which will also cause the exposure of societal assets to vary.

HMP can facilitate the reduction of hazard impacts within a community; however, local governments often lack the necessary resources to implement mitigation or adaptation strategies in places with a large amount of exposed populations or societal assets (Frazier, Thompson, and Dezzani 2014; Frazier, Thompson, et al. 2013; Thompson and Frazier 2014). Therefore, understanding how vulnerability varies within a community can aid decision makers in implementing more effective HMP strategies that reduce vulnerability in higher-risk areas (Frazier, Walker, et al. 2013; Frazier, Thompson, and Dezzani 2014).

In order to identify areas of high hazard exposure or risk, communities typically conduct vulnerability assessments that provide decision makers with information about a community's vulnerability and resilience levels (Turner et al. 2003; Polsky, Neff, and Yarnal 2007; Thompson and Frazier 2014). This information is important for post-disaster recovery and estimation of potential losses, which aid decision makers in developing and implementing mitigation strategies targeted at lowering vulnerability, thereby increasing resilience (Cutter, Burton, and Emrich 2010; Frazier, Thompson, et al. 2013; Thompson and Frazier 2014).

Targeting mitigation allows agencies with limited resources to prioritize mitigation to areas with high vulnerability or exposure (Frazier, Walker, et al. 2013). However, even with the availability of mitigation and adaptation tools such as economic incentives and legislation, guiding or relocating development out of hazardous areas is difficult. These tools are only marginally effective for new and existing development due to competing interests in many communities (e.g. natural resources, tourism, amenities, etc.) that perpetuate development in exposed areas. Development and relocation limitations often occur as a result of differing levels of risk tolerance, risk perception and willingness to pay for certain mitigation strategies that may negatively impact the economic vitality of an area (Frewer 1999; Slovic 1987).

Risk perception describes how people objectively identify and measure risk based on information they have about the risk (Kasperson et al. 1988; Siegrist and Cvetkovich 2000; Slovic 1987), while risk tolerance describes the amount of risk they are willing to accept, even when they are aware it is unsafe. When people experience low risk perception, they often experience higher risk tolerance and are less likely to support mitigation to help minimize damage; when people experience high risk perception, their risk tolerance has been lowered and become more likely to demand mitigation policies or programs that help minimize hazards losses (Frewer 1999; Lazo, Kinnell, and Fisher 2000; Siegrist 2000; Sjöberg 1999; Wachinger et al. 2013; Lindell and Perry 2012). Perceived benefits of consequences of a hazard can also drive development and mitigation patterns (Ajzen 1991; Miller, Adame, and Moore 2013; Bubeck, Botzen, and Aerts 2012). However, the variability of natural hazards, culture, and beliefs also leads to spatially variable perceptions of risk, which can influence the potential success of implementing certain hazard mitigation strategies.

Vulnerability assessments also have several limitations that make them less effective for community-scale HMP. Global and national scale vulnerability assessments are beneficial in that they often use common datasets for their analysis (Polsky, Neff, and Yarnal 2007), which can make comparison between assessments easier. However, indicators that are standardized must be scale-independent in order to be comparable to other analyses (Polsky, Neff, and Yarnal 2007), which is problematic when data is gathered at different spatial scales. Additionally, vulnerability assessments conducted at the county level often result in assessments that generalize sub-county vulnerability and are less effective for sub-county level hazard mitigation (Frazier, Walker, et al. 2013). Scale is an important factor to consider when conducting vulnerability assessments as HMP occurs at a sub-county or community scale, not a county scale (Thompson and Frazier 2014). Vulnerability assessments conducted at the sub-county scale with scale-appropriate data are often more suitable for community level HMP.

Spatial dependency can also influence the reliability of vulnerability analyses for sub-county HMP because spatial relationships that hold true in a regional setting may not apply to smaller areas within that region. Previous work by Frazier, Wood, and Yarnal (2010) suggests that conducting hazard analysis at larger scales often does not provide sufficient information about processes occurring at the local level. Identifying spatial autocorrelation (which is the degree of dependency among observations in a geographic space) is important because those spatial patterns may not exist at differing scales of analysis. Spatial processes can inhibit the reliability of certain analytical types and physical hazard models devised for specific scales as these models often rely on spatial data that can violate statistical assumptions. The way that enumeration units for spatial data are defined can affect the model results, potentially leading to biased model conclusions (Arbia and Petrarca 2011; Burt, Barber, and Rigby 2009).

In addition to these methodological limitations, the theoretical foundations behind the structure of vulnerability assessments are often weak or non-existent. Theory is important for scientific studies because it provides a common framework for judging whether methods and resulting explanations from scientific analyses are consistent and reasonable for that discipline (Harvey 1969). The scientific method is a set of rules that scientists use to conduct hypothesis testing in a manner that is both falsifiable (there is a potential false outcome) and reproducible. Scientists use the scientific method to identify norms within a discipline, which help scientists determine whether a study's explanation is reasonable and follows normal scientific conventions. If theoretical norms do not exist, explanations from different studies within the context of the discipline cannot be compared or criticized with any real theoretical rigor (Harvey 1969).

Most studies on vulnerability quantification lack theoretical focus in terms of framework and methodology structure (Alexander 1997; Montz and Tobin 2011). Theory is critical for providing rigor in vulnerability research; research methods with weak theoretical foundations can lead to the development of indices or assessments that are incomparable due to inconsistent methods, model structure or indicator inclusion. These inconsistencies can cause comparisons of different modeling results to provide different or conflicting explanations of vulnerability patterns (Root and Emch 2011). This in turn can lead to less effective HMP that does not accurately target vulnerable areas.

Due to these limitations, more research is needed to develop enhanced, theoretically founded spatial modeling and vulnerability assessment techniques that measure hazard impacts and overall vulnerability at the community level. This dissertation addresses these challenges by examining the feasibility of incorporating theory from both geographic and general social theory into vulnerability and resilience research and developing conceptual frameworks and methods that more accurately measure community scale vulnerability.

This dissertation utilizes the following format. Chapter One provides an introduction and general literature review for the research problems and goals associated with addressing the major limitations that currently exist within the natural hazards field. This chapter includes a discussion of any major theories or methods that other chapters do not discuss in depth but are critical to the development of this research, and discusses the major goals and research questions for this dissertation.

Chapters Two, Three, and Four serve as standalone papers that address separate but related limitations associated with current vulnerability research. Chapter Two describes the development of the INSeRT theoretical framework that can be used to inject outside theory into natural hazards literature and vulnerability/resilience assessment methodologies. Chapter Three describes the development of a hierarchical model that uses theoretical foundations from Chapter Two as the basis for its model structure and implementation for use in advancing vulnerability/resilience quantification methods. Chapter Four discusses the methods for measuring the potential influence of risk perception and agency on overall vulnerability, how they are interdependent and potential methods for including them in the model framework developed in Chapter Three. Finally, Chapter Five provides a summary and conclusion of this research, as well as limitations and possible improvements moving forward. Because Chapters Two, Three, and Four are written as standalone articles, there may be some level of repetition from text in Chapter One within these chapters.

1.2 Theoretical Foundations and Paradigms in the Natural Hazards Field

Several paradigm shifts and theoretical foundations in vulnerability research on human-environment interactions have been established over time to examine and measure vulnerability from different perspectives. There are three main paradigm eras, each with different theoretical foundations associated with them: 1) the Acts of God Paradigm, 2) the Human Ecology Paradigm, and 3) the Structural Paradigm. In addition, a new paradigm that is slowly becoming associated with vulnerability studies is the Ecological Resilience/Resilience Theory.

1.2.1 Acts of God Paradigm

The earliest vulnerability paradigm, the Act of God Paradigm, describes natural disaster events as punishments handed out by a deity or higher being in order to discipline the human race for transgressions (White, Kates, and Burton 2001; Cuff and Goudie 2009). Under the 'Acts of God' perspective, people believed that they could do nothing to mitigate or minimize damage caused by natural events, so they simply rebuilt what they could or moved somewhere else to find new livelihoods. Another similar type of perspective is as the naturalist perspective, where all blame for hazard events is directed toward 'the violent forces of nature' or 'nature on the rampage' (Blaikie et al. 2004, p. 10). The 'Acts of God' perspective is heavily influenced by religious beliefs whereas the naturalist perspective focuses more on the power of nature, not the wrath of a deity or other religious figure that is a response to human behavior (White, Kates, and Burton 2001).

1.2.2 Human Ecology Paradigm

Human ecology is an interdisciplinary science that shifted away from the idea that natural disasters were 'Acts of God' and moved toward viewing disasters as social constructs (White, Kates, and Burton 2001). Gilbert White (1945, p. 2) in his dissertation stated that "Floods are 'acts of god", but flood losses are largely acts of man," meaning that while natural hazards are natural events that humans have no control over, they can and do behave in ways that increase exposure and vulnerability to natural hazard events (i.e. building in a floodplain). Hazards can be mitigated against and modified, but human behavior should also be adjusted to lower hazard exposure (White 1945; Eakin and Luers 2006). The Risk-Hazard theory/approach was developed by White (1945) during this paradigm and focuses on identifying environmental and natural hazards, determining their possible consequences and predicting when those hazards are more likely to occur (White 1945; Eakin and Luers 2006; Hufschmidt 2011; Thomas et al. 2013). The Risk-Hazard theory suggests that people create vulnerability practicing risky behavior, such as living in a floodplain or developing near landslide prone areas. Therefore, White (1945) believed that humans should learn to adjust to their environment instead of attempting to control it. This theory emphasized the need for people to modify their own behavior in a way that better allows them to adapt and cope with hazards (White 1945; White, Kates, and Burton 2001; Hufschmidt 2011).

While the Risk-Hazard theory remained the key driver to the dominant natural hazards paradigm for many years, it was limited in that it focuses solely on physical vulnerability and does not consider the role of social drivers on vulnerability (Eakin and Luers 2006; Thomas et al. 2013).

Due to this limitation, researchers introduced the structural paradigm as a way to incorporate the role of social processes into vulnerability assessments.

1.2.3 Structural Paradigm

As a response to the lack of focus on the role of social processes in vulnerability, theories and conceptual models such as political economy/ecology and the Social Vulnerability Index (SoVI) were developed in an attempt to address how social variables can cause differential levels of vulnerability within a population (Bogard 1988; Oliver-Smith 1996; Eakin and Luers 2006; Hufschmidt 2011). These theories or conceptual models try to determine the underlying processes that perpetuate those patterns of differential impact (Eakin and Luers 2006; Miller et al. 2010; Oliver-Smith 2009).

Political economy developed as a response to the Risk-Hazard approach as a way to examine how economic and political processes influence vulnerability (Eakin and Luers 2006). The main theme in political economy is that politics and economies are intertwined and affect access to resources (Eakin and Luers 2006). Political economy analyzes the allocation of resources (production, distribution, and consumption of services) based on politics (struggle for power) (Warf 1997; Sheppard 2011). The presence or absence of power can influence the allocation of resources between groups, which is why political economy is crucial to understanding how the relationship between politics and economies influence vulnerability (Warf 1997).

While political economy examines how social inequalities influence overall vulnerability, it does not examine the influence of variables at different scales and looks at vulnerability from a top-down approach. Political economy also does not consider nature to be an active agent in the social system (Goldman and Schurman 2000; Adams 2003). In response to these limitations, political ecology combines ecology and political economy concepts to examine social structure and how societies interact with their environment. Political ecology shares the political economy emphasis on the role of politics and socioeconomic variables on human-environment interactions, but it also places a greater focus on the role of physical processes on vulnerability and examines these interactions from a multiscalar perspective (Peterson 2000; Adams 2003). Political ecology also places an emphasis on multiscalar interactions and relationships between society and nature (Adger et al. 2001; Eakin and Luers 2006). This allows political ecology to examine both global and local influences on vulnerability within the same conceptual framework. While political ecology does have some benefits, it has received criticism because it does not provide an explanation of *how* certain social or environmental factors become causes of change (Eakin and Luers 2006;

Rangan and Kull 2009). However, political ecology can still help researchers illustrate how human activity, social structure and biophysical agents influence vulnerability.

The concept of power and agency that is integral to political economy and political ecology is described in greater detail in structuration theory. Structuration theory is a theoretical framework developed by Anthony Giddens that could be used in the natural hazards field to examine how power and agency affect vulnerability. Structuration theory defines social structure as roles and resources that actors use when interacting within society (Giddens 1984; Cozzens and Gieryn 1990). Different roles and resources provide different levels of power and agency, thereby affecting an individual's ability to act (Giddens 1984). Agency describes the capacity of an agent to act in the world and power must be exercised in order for an individual to 'act' in a way that 'makes a difference' or changes preexisting social conditions (Giddens 1984; Turner 1986). Power is not inherent, but is gathered by people with access to certain resources (Giddens 1984; Turner 1986). This means that both social structure (which is a result of repetitive human behavior) and human agency both influence social life (Giddens 1984; Turner 1986). Because power is necessary for agents to 'act,' power should also be a first-order consideration in the social sciences.

The main basis of structuration theory comes from the idea that the actions of the agents are forever developing or altering the social structure while simultaneously drawing on social structures (Giddens 1984; Cozzens and Gieryn 1990). This 'duality' of the system is based on the actors' implicit knowledge of social rules or regulations and using that knowledge to guide their behavior and create social structures (Giddens 1984). Structuration theory could be applied in the natural hazards field to model how differential levels of power and agency affect vulnerability in terms of how they create social structures that limit access to resources. Social vulnerability develops due to social inequalities that interfere with the access to resources (Bogard 1988; Morrow 1999; Goldman 2000; Eakin and Luers 2006), so structuration could help researchers identify those structures and processes that help to form and perpetuate them. Structural properties such as rules and resources are then used to describe the presence or absence of domination or power (Giddens 1984).

This distinction is important to structuration theory because *structure* symbolizes the order of rules and resources, whereas observable social behaviors or interactions (or development of social structure) are considered to be the *system* (Giddens 1984; Cozzens and Gieryn 1990). Structuration theory also examines similarities and differences in the social structure in terms of specific combinations of these rules or resources, which are grouped into four main categories. Together, these categories are called 'modalities of structuration,' and are considered to be the basic dimensions of social structure (Giddens 1984). Two of these categories represent types of rules (normative rules and interpretive schemes), while the others represent two types of resources (economic and political) (Table 1.1). Combinations of these rules and resources result in types of institutions, which allow social structure to be examined through the interplay of these types if institutions instead of conducting studies from a more 'one-sided' perspective (Cozzens and Gieryn 1990).

Table 1.1 – Modalities of Structuration Giddens

Rules	**Definition** (from Giddens (1984) & Cozzens and Gieryn (1990))
Normative rules	Specification of rights and obligations in particular instances
Interpretive schemes	Basis of process of signification (Production of meaning through organized languages (i.e. semantic codes & language))

Resources	**Definition** (from Giddens (1984) & Cozzens and Gieryn (1990)
Economic	"Allocative type" - represents access to material goods
Political	"Authoritative resources" - represent authorities that control the uses of resources; Ability to secure outcomes that are dependent upon the agency of others

1.2.4 Resilience Theory

An emerging paradigm used more frequently in the hazards literature is resilience theory. Resilience originated in the ecology field to characterize an ecosystem's ability to maintain itself or recover from perturbations to the system (Holling 1973; Cutter et al. 2008; Rose 2007; Deppisch and Hasibovic 2013). Natural hazards studies in particular use resilience to examine the ability of a community to recover from a disaster event. Resilience theory in the natural hazards field also has a large focus on adaptive capacity and highlights a necessity for adaptive capacity in both the biophysical and social systems (Adger 2000; Adger and Vincent 2005; Cutter et al. 2008). Resilience theory challenges traditional hazard mitigation policy notions in that it advocates more adaptable and sustainable mitigation decisions that may not fall within traditional change-resistant mitigation strategies (Eakin and Luers 2006; Folke 2006; Berkes 2007).

However, there are some challenges when describing the relationship between vulnerability and resilience because their definitions vary based on the perspective of the researcher and the context in different fields. In some cases both terms describe very different concepts, whereas in others they are very similar (Timmerman 1981). There are, however, some points of agreement throughout the literature on how vulnerability and resilience differ. In terms of the temporal aspects of vulnerability and resilience, vulnerability is typically seen as a pre-event and event attribute, whereas resilience is a post-disaster outcome or a continual dynamic process (Cutter 1996; Rose 2007; Cutter et al. 2008; Miller et al. 2010). Resilience is also seen as a more dynamic process, whereas vulnerability is often considered to be a static, pre-event state (Zhou et al. 2010).

Vulnerability and resilience also differ in their theoretical influences and origins. The concept of vulnerability developed from geophysical sciences, human ecology, political economy, and political ecology origins, and is influenced by both positivist and constructivist backgrounds. Resilience, however, originated in the natural and ecological sciences and takes on a positivist perspective (Holling 1973; Miller et al. 2010). Vulnerability studies are typically static in nature and focus more on responding to hazard events, rather than examining the ability of a system to persist or recover and adaptation strategies (resilience) (Miller et al. 2010).

Another major difference between vulnerability and resilience is how they are examined. Vulnerability is typically examined from an actor-based perspective. Indicators that are commonly examined are based on social, economic, infrastructure and political processes or attributes, such as values, knowledge, power and agency, access to resources, and social structure (Miller et al. 2010). Resilience is examined from a systems perspective and uses indicators such as biophysical variables, ecological thresholds, socio-ecological system relationships, and system feedback loops (Berkes 2007; Miller et al. 2010).

One of the most contested differences between vulnerability and resilience lies in how the two concepts are related. Several scholars, such as Adger et al. (2005), Folke (2006) and Berkes (2007) refer to vulnerability as the ‘flip side’ or antonym of resilience, whereas others such as Turner et al. (2003), (Cutter et al. 2008), and Wood, Burton, and Cutter (2010) (primarily in the hazards and climate change fields) view resilience as component of vulnerability (Gallopín 2006). This confusion leads to contention in the form of how adaptive capacity is defined. In some vulnerability studies, resilience is equivalent to adaptive capacity (Cutter, Boruff, and Shirley 2003; Turner et al. 2003), while in resilience theory, adaptive capacity is the major driving component for enhancing resilience (Berkes 2007). Adaptive capacity essentially serves as the linking concept between vulnerability and resilience in that it can reduce vulnerability and increase resilience (Engle 2011), but it should not be confused with resilience.

While different, both of these concepts are complimentary and could enhance the other so that the concept of resilience is more holistic. Therefore, this research uses the Adger et al. (2005), Folke (2006) and Berkes (2007) definition where vulnerability is considered the antonym of resilience. Therefore, lowering vulnerability serves as one method for increasing community resilience.

1.3 Primary Conceptual Frameworks in Natural Hazards Literature

Researchers in the natural hazards field developed several conceptual frameworks to enhance the use of theory in the natural hazards field. The first model, the Hazards of Place model (Figure 1.1), was developed by Cutter (1996) to provide a conceptual model that accounted for locally based vulnerability with parameters that change over time. The Hazards of Place model demonstrates how different elements that influence vulnerability interact with one another (Cutter 1996). The purpose of the Hazards of Place model is to integrate the influences of the biophysical and social vulnerability on a particular place by attaching them to a place-based model (Cutter 1996; Cutter, Mitchell, and Scott 2000). While the Hazards of Place model was supposedly developed using the risk/hazard and political ecology theoretical perspectives, it fails to examine root causes of social vulnerability (Cutter et al. 2009). The studies by Cutter (1996); (2003), primarily the Hazards of Place model, also do not explicitly demonstrate asymmetric power amongst actors, which is a key driver behind political ecology (Adams 2003).

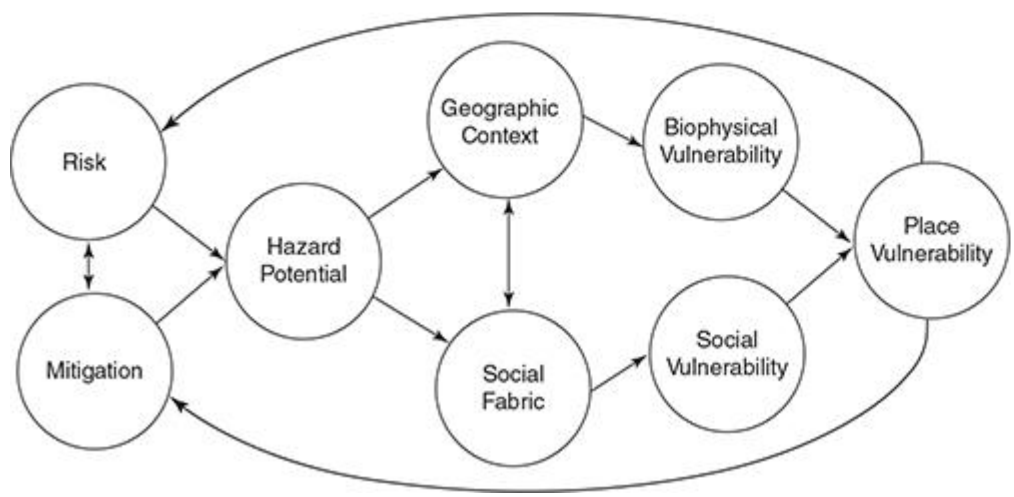

Figure 1.1 - Modified Hazards of Place Model of Vulnerability

Another conceptual model developed by Blaikie et al. (1994) was the Pressure and Release (PAR) model (Figure 1. 2), which is used to demonstrate how natural hazards affect vulnerable populations based on the following relationship:

$$DR = H \times V$$

where DR is disaster risk (probable level of loss), H is the hazard (form of loss-causing agent) and V is vulnerability (potential for loss) (Blaikie et al. 2004).

The PAR model assumes that a disaster occurs when two opposing forces intersect (a hazard event and pre-existing vulnerability), causing pressure to occur from both sides (Figure 1.2). In order to lower that pressure, or provide 'release,' vulnerability must be reduced. The PAR model focuses on how existing vulnerabilities cause exposure to certain hazards and become 'unsafe' so that actions can be taken to reduce those pressures (Cutter 1996; Turner et al. 2003; Blaikie et al. 2004).

The PAR model serves as a way to bridge the gap between human ecology and natural hazards theoretical perspectives and was one of the first models to synthesize the interaction between social and biophysical vulnerability (Adger 2006). According to Hufschmidt (2011), this model is considered one of the best conceptual frameworks for summarizing the structural perspective (i.e. political economy and ecology). However, the model does not take the role of human agency on access to resources into account (Pelling 1998). In addition, the PAR model does not provide a theoretical analysis of social and environmental interactions that serve as 'pressures' on the human-environment system (Blaikie et al. 1994; Turner et al. 2003).

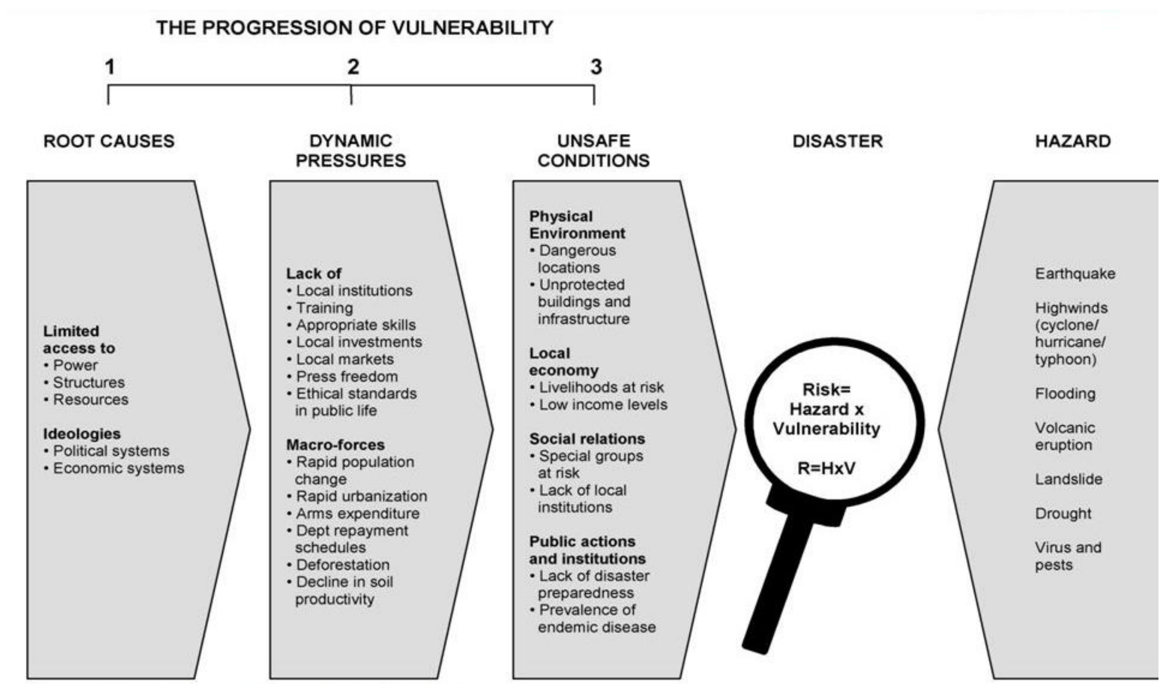

Figure 1.2 – Pressure and Release (PAR) Model (Blaikie et al. 2004)

Another common conceptual model used in the natural hazards field is the vulnerability framework developed by Turner et al. (2003) (Figure 1.3.). This model proposes a framework for vulnerability analyses using three major components: 1) linkages between human and biophysical processes, 2) stressors on the system, including natural hazards, and 3) the human–environment system, which includes exposure, sensitivity and resilience (Turner et al. 2003). This framework is technically a climate change framework that has been adopted by several researchers in the natural hazards field to assess vulnerability (Cutter, Boruff, and Shirley 2003; Wood, Burton, and Cutter 2010; Frazier, Thompson, and Dezzani 2014). While this framework claims to build on risk/hazard, political economy and political ecology theoretical principals, it fails to examine root causes of social vulnerability in a detailed manner. The generality of the framework makes the possibility of injecting theory into the human environment component plausible, but it is not strictly stated as being part of the framework development.

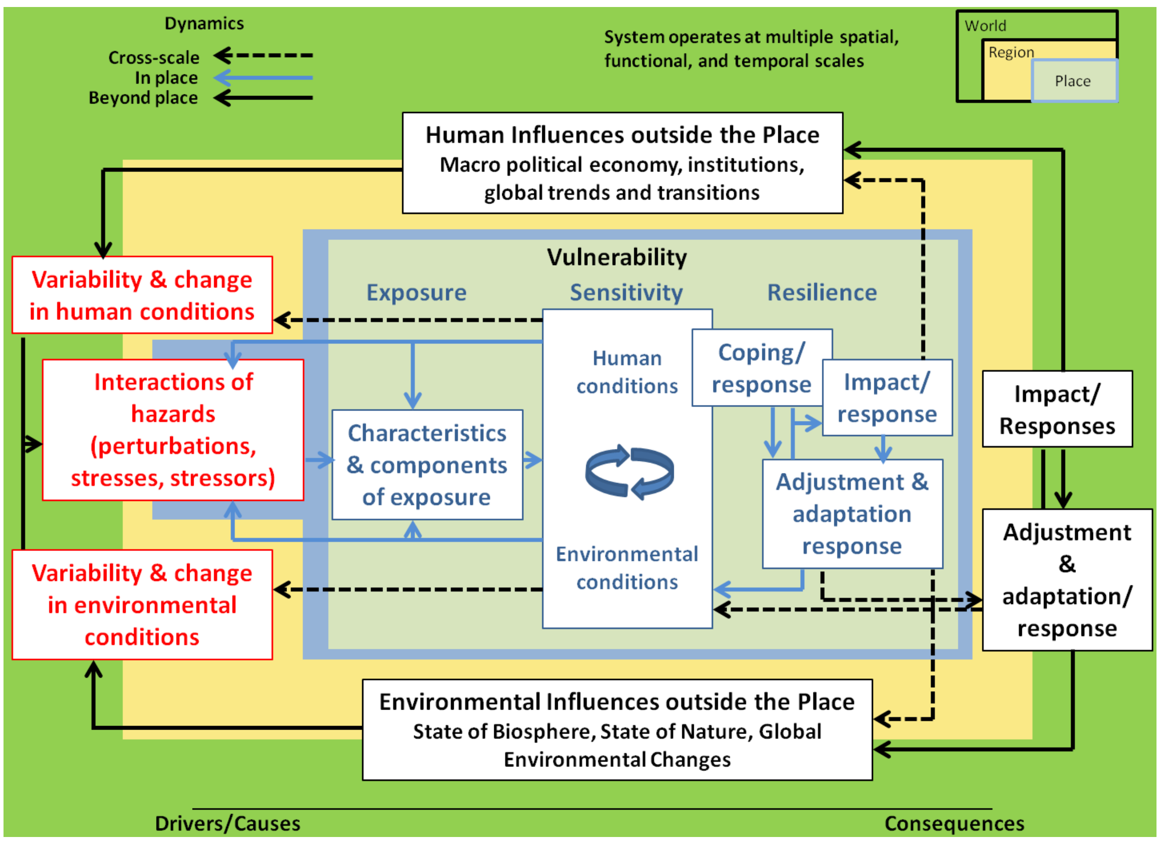

Figure 1.3 - Turner et al. (2003) Vulnerability Framework

The Social Vulnerability Index (SoVI) is a vulnerability index that was developed by Cutter, Boruff, and Shirley (2003) to assess and measure social vulnerability at the county scale using national vulnerability indicators. In order to develop the index, the SoVI conducts principal component analysis (PCA) on a list of traditional vulnerability indicators to identify statistically significant socioeconomic, demographic, and built environment variables that are empirically considered to have an influence on vulnerability (Cutter, Boruff, and Shirley 2003).

This index is capable of providing a relative vulnerability score for each county in the nation. However, while the SoVI defines vulnerability as a function of exposure, sensitivity and resilience, it does not incorporate the effects of exposure or resilience on overall vulnerability; it simply describes county-level sensitivity through several indicators (Cutter, Boruff, and Shirley 2003). In addition, the SoVI model uses the Hazards of Place model (Cutter 1996) as the foundation for measuring vulnerability, meaning that the SoVI still fails to examine root causes of social vulnerability (Cutter et al. 2009).

The Baseline Resilience Indicators for Communities (BRIC) model was developed by Cutter, Burton, and Emrich (2010) to create a resilience index that measures baseline resilience using indicators from five sub-dimensions: social, economic, institutional, infrastructure, and community capital. The structure and selection of indicators uses the Disaster Resilience of Place (DROP) model for its basis (Figure 1.4), a conceptual framework that attempts to model the relationship between vulnerability and resilience at the community level (Cutter et al. 2008; Cutter, Burton, and Emrich 2010). While the theoretical basis of the DROP model comes from resilience theory literature, it is never explicitly stated by Cutter et al. (2008) or Cutter, Burton, and Emrich (2010) that this theoretical framework drives these models.

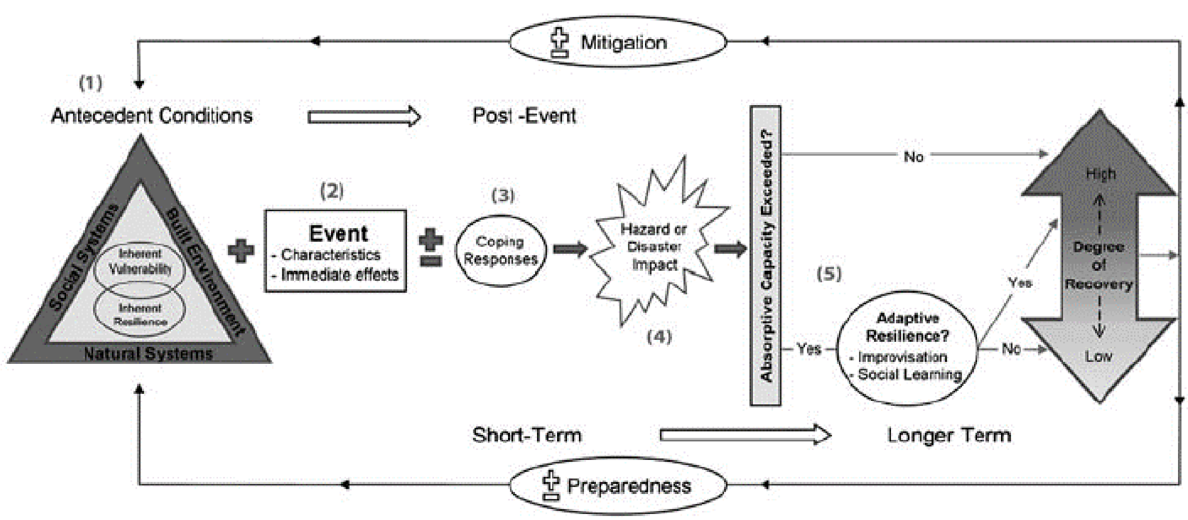

Figure 1.4 - Cutter et al. (2008) DROP model

The vulnerability scoping diagram (VSD) (Figure 1.5) was developed Polsky, Neff, and Yarnal (2007) as a way to conceptualize vulnerability from several perspectives. Due to the variation in vulnerability studies and definitions, Polsky, Neff, and Yarnal (2007) sought to develop an "all-embracing methodological approach" that could effectively be used across disciplines, even though it is developed from a climate change perspective. The main function of the VSD itself is to serve as a method for gathering and organizing information about the three components of vulnerability: exposure, sensitivity and adaptive capacity. The VSD then serves as step 5 in the ''Eight Steps'' methodological protocol developed by Schröter, Polsky, and Patt (2005) to characterize vulnerability holistically (Polsky, Neff, and Yarnal 2007). While the VSD could provide a standardized method for conducting vulnerability assessments, it is difficult to implement in reality due to data limitations, differentiating research goals and differing theoretical framings of vulnerability. The VSD has no theoretical framing itself; because other disciplines all have different theoretical foundations, this model essentially has no utility other than being an applied framework.

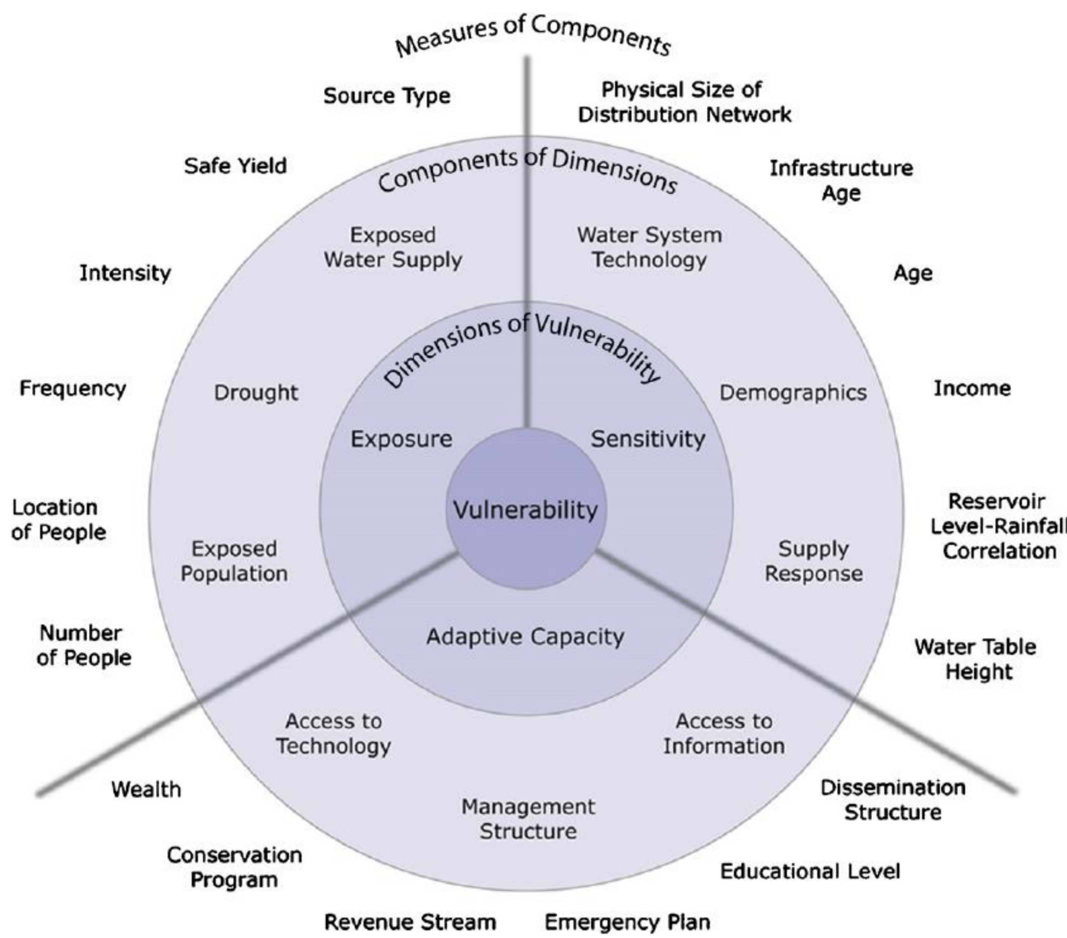

Figure 1.5 - Polsky, Neff, and Yarnal (2007) VSD model

1.3.1 Theoretical Limitations of Existing Frameworks

The presence of theory in the natural hazards field is often weakly applied. While the natural hazards field does employ some theoretical frameworks and conceptual models, these are often not sufficient for supplying the field with an adequate theoretical foundation or their presence in research is not explicitly stated. The natural hazards field has been criticized for the lack of theoretical focus because most natural hazards research is heavily applied (Alexander 1997; Montz and Tobin 2011). Despite the lack of theory in the natural hazards field, theory from other disciplines could be injected into natural hazards research in several ways. Theories like structuration theory, environmental justice, social justice and the behavioral response approach examine how underlying socioeconomic processes and social structures influence how people deal with and respond to disaster events (Bogard 1988; Oliver-Smith 1996; Goldman and Schurman 2000; Eakin and Luers 2006; Miller et al. 2010). These theories can also be used to examine how social variables (such as gender race, wealth, class, etc.) can cause differential levels of vulnerability within a population and try to determine the underlying processes that perpetuate those patterns of differential impact (Eakin and Luers 2006; Miller et al. 2010). Therefore, injecting these types of theories into the natural hazards field would provide more insight into how social processes perpetuate social inequalities and an unequal access to resources (de Oliveira Mendes 2009; Dezzani and Frazier 2015). The potential for integrating these theories into natural hazards literature is further discussed in Chapter Two.

1.4 Vulnerability Indicators and Their Limitations

One of the most important components of vulnerability/resilience conceptual frameworks is the use of indicators, which serve as data proxies for physical or social characteristics that can influence vulnerability. Disaster vulnerability is a social construct that develops based on unequal access to resources and power, settlement patterns and social order (Birkmann 2007; Cutter 2003; Morrow 1999). Therefore, developing models using data indicators that reflect these characteristics allows vulnerability analyses to provide a more complete assessment of individuals' access to resources, which is often considered a primary indicator of vulnerability (Cutter 2003; Morrow 1999).

As discussed previously, early vulnerability assessments often only examined physical vulnerability, which describes how proximal communities were to potential hazard impacts (exposure) (White 1945). These assessments identified biophysical hazards and potential levels of damage that might be incurred during a particular hazard event, but did not examine social processes that can exacerbate vulnerability and cause differential impacts to occur (Eakin and Luers 2006; White 1945). For this reason, more recent vulnerability studies focused on the inclusion of data that is representative of both physical and social vulnerability. Social vulnerability describes socioeconomic, demographic, infrastructure and physical characteristics that can influence a community's ability to respond to, cope with and recover from a hazard event (Bang 2008; Bergstrand et al. 2015; Blaikie et al. 2004; Cutter et al. 2009; Eakin and Luers 2006; Flanagan et al. 2011; Frazier, Thompson, and Dezzani 2014; Turner et al. 2003). Social vulnerability develops due to social inequalities that interfere with the access to resources and information, the ability to absorb the impacts of hazards and disasters without governmental interventions, housing choice and location, and the political marginalization of impoverished residents.

Populations that are consistently considered socially marginalized in the literature include the poor, women, racial and ethnic minorities, and those who are members of other disenfranchised groups (Cutter, Burton, and Emrich 2010; Morrow 2008). These groups are often more vulnerable to and slower to recover from disasters (Cutter, Burton, and Emrich 2010; Morrow 2008). For example, marginalized populations in underdeveloped countries often reside in poorly built housing in hazardous areas (i.e. in floodplains or along the coast) out of necessity due to lack of resources or other housing opportunities (Frazier, Thompson, and Dezzani 2013; Morrow 1999; Tierney 2006). Low-income individuals experience more difficulty during and after disaster events because they often do not have the resources to prepare for or recover from a disaster event or lack the transportation to evacuate (Cutter 2003; Fothergill and Peek 2004). In addition, those who are already unemployed might have further trouble seeking employment after disaster if they are forced to relocate or their current employing businesses are forced to close due to damage (Cutter 2003; Fothergill and Peek 2004; Tierney 2006). Variables that describe socioeconomic conditions are important for understanding the differential vulnerability a community might experience to a given hazard.

Socioeconomic factors also provide information about inequalities in the social structure that might increase or decrease an individual's vulnerability to hazards. Earlier studies on vulnerability assessments neglect the influences of socioeconomic factors on vulnerability because it is difficult to quantify indicators that are inherently qualitative in nature (Cutter 2003; Cutter, Burton, and Emrich 2010; Frazier, Thompson, and Dezzani 2014). Some studies attempt to quantify vulnerability through the creation of vulnerability and quantification models, assuming that all factors are weighted equally unless a method to specify otherwise is employed (Cutter, Boruff, and Shirley 2003; Fekete 2012; Gall 2007; Wood, Burton, and Cutter 2010). In response to these challenges, vulnerability indices were developed based on the above-mentioned conceptual frameworks in recent years to identify and measure vulnerability. Vulnerability indices are used for planning because they provide a tangible vulnerability score that can be used to guide hazard mitigation policies and planning (Jones and Andrey 2007; Tate 2012; Wood, Burton, and Cutter 2010). These indices measure total community vulnerability as well as the influence of certain physical and social factors on vulnerability at various jurisdictional and socio-political levels (Birkmann 2007; Cutter 2003; Cutter, Burton, and Emrich 2010; Jones and Andrey 2007; Tate 2012).

While the vulnerability indices and quantification methods discussed in section 1.3 utilize traditionally indicators of vulnerability that are representative of socioeconomic and physical characteristics of a community, they do have several limitations. Many existing vulnerability indices often neglect place-specific, spatial, and temporal vulnerability indicators in the selection process (Jones and Andrey 2007; Wood, Burton, and Cutter 2010). Incorporating locally derived factors is important, rather than relying solely on nationally collected data because of variable variation across a landscape (Fekete, Damm, and Birkmann 2010; Frazier, Thompson, and Dezzani 2014; Frazier et al. 2010; Wood, Burton, and Cutter 2010). Excluding local indicators, therefore, can hinder the effectiveness of sub-county hazard mitigation, potentially influencing community preparedness (Berke and Godschalk 2009; Burby 1999; Burby 2006b; Burby et al. 2000).

Existing vulnerability studies also commonly do not consider differential distribution of individual indicators within a study site (Frazier, Thompson, and Dezzani 2014; Jones and Andrey 2007; Wood et al. 2007). Vulnerability is unequally distributed across a county. Therefore, vulnerability determined using spatially homogenous indicators might not be accurate. Some studies have accounted for unequal distribution of vulnerability within a study area by using higher resolution indicator data (Wang and Yarnal 2012; Wood, Burton, and Cutter 2010). For example, Wood, Burton, and Cutter (2010) and Frazier, Thompson, and Dezzani (2014) examined sub-county vulnerability by using Census block-level data, while Wang and Yarnal (2012) measured vulnerability using Census block group-level data. This technique provides more information about vulnerability distributions at the sub-county scale and can lead to the creation of more accurate vulnerability assessments for local hazard mitigation (Frazier, Thompson, and Dezzani 2014, 2013). These studies, however, are limited in that they do not consider differential influence of individual indicators on vulnerability (Frazier, Thompson, and Dezzani 2014; Jones and Andrey 2007; Wood, Burton, and Cutter 2010). Assessing the differential influence of indicators helps determine where specific indicators that increase vulnerability are more prevalent (Frazier, Thompson, and Dezzani 2014; Wood, Burton, and Cutter 2010; Wu, Yarnal, and Fisher 2002).

Some studies have weighted vulnerability scores based on the percentage of explained variance for the indicator's encompassing factor but do not consider variable influences of individual indicators (Cutter, Boruff, and Shirley 2003; Wang and Yarnal 2012; Wood, Burton, and Cutter 2010). This technique provides an incomplete view of indicator influence on vulnerability because certain indicators may have a greater impact on the overall explained variance than others. Existing vulnerability studies also do not address the spatial distribution of indicators, particularly at the sub-county level (Frazier, Thompson, and Dezzani 2014; Jones and Andrey 2007; Wood, Burton, and Cutter 2010). Spatial autocorrelation describes the correlation of values in a variable over space and suggests a non-random distribution (Burt, Barber, and Rigby 2009). If spatial autocorrelation is present in a dataset, then it is possible that the distribution of variables no longer exhibits an independent and identically distributed (*i.i.d.*) distribution (Burt, Barber, and Rigby 2009). This violation can cause classical statistical techniques, such as principal component analysis (PCA) and factor analysis, to provide less reliable results (Burt, Barber, and Rigby 2009). Variables that are nearer to other variables will have a greater covariance. Therefore, a varimax rotation becomes ineffective for PCA because it does not mirror the spatial distribution of the data (Johnston 1978). Thus, conducting classical statistical tests without correcting for spatial effects in the data can provide unreliable results (Burt, Barber, and Rigby 2009).

Additionally, existing indices do not include non-traditional or external indicators that might influence vulnerability, such as risk perception, social structure and agency, federal funding sources, disaster relief funds and other outside agencies that aid communities during a hazard event. Aid programs might increase a community's overall resilience, but that information is not incorporated into current studies. This omission could occur because external indicators are often determined at a different scale than the sub-county level, making it difficult to incorporate them into sub-county vulnerability or resilience models. Vulnerability indices also do not consider the role of risk perception on vulnerability, which can influence how sensitive or adaptive people are during a hazard event.

Risk perception describes how people objectively identify and measure risk based on information they have about the risk and can be influenced by several factors, such as past experience with the hazard, indirect information about the risk, distrust in risk model outputs due to lack of knowledge, or lack of knowledge about the risk (Howe 2011; Kasperson et al. 1988; Sjöberg 1999; Wachinger et al. 2010). Previous studies have found that risk perception for certain hazards does influence evacuation behavior or mitigation strategy implementation (Barnett and Breakwell 2001; Bubeck, Botzen, and Aerts 2012; Frewer 1999; Matyas et al. 2011; Wachinger et al. 2013; Paton et al. 2008), but it is not always clear as to what specifically causes people to make those decisions (Peacock et al. 2005; Wachinger et al. 2013). While several past studies have demonstrated that there is a relationship between disaster risk perception and preparedness (Ainuddin et al. 2013; Frewer 1999; Sjöberg 1999), individual indicators of risk perception are not often included in vulnerability indices. For example, people with lowered risk perception may be less likely to implement hazard mitigation techniques, such as installing storm shutters on their houses, or evacuating before a possible storm event (Barnett and Breakwell 2001; Howe 2011; Matyas et al. 2011; Paton et al. 2008). If people are less likely to implement disaster preparedness strategies at the individual level, then community vulnerability could be increased, and vice versa. Therefore, understanding risk perception could provide more complete information about how people will react to a hazard event in terms of sensitivity and adaptive capacity.

Agency can also influence risk perception because of its influence on access to information. Different levels of agency affect what resources people can access, thereby affecting an individual's ability to act or cope with a hazard event (Giddens 1984). People identify and measure risk based on information they have about the risk. This information can come from a variety of sources and experiences (Slovic 1987; Kasperson et al. 1988), such as by social factors, direct experience, indirect information, or lack of general knowledge about the risk (Kasperson et al. 1988; Howe 2011). This is important to consider because mitigation strategies are often developed based on perceptions of the consequences of future risks, not what might actually occur. People make decisions based on knowledge they already have, but do not assume that they know all of the alternative options (Bang 2008; Barnett and Breakwell 2001; Fischhoff et al. 2009; Frewer 1999), which emphasizes how much risk perception and risk tolerance drives mitigation practices. Risk perception and agency can also interact with one another in that someone may have a heightened risk perception, but lack the agency or power to implement changes or mitigation. Neglecting these characteristics can result in vulnerability analyses that disregard the influence of risk perception and levels of agency on people's behavior concerning how they react to or cope with hazard events at both the individual and community level. Therefore, the inclusion of risk perception and power and agency within the community as individual indicators could provide a measure of community vulnerability from a more holistic social-structure perspective. These indicators are discussed in more detail in Chapter 4.

1.5 Quantitative Modeling Methods Associated with Vulnerability Assessments

The effectiveness of vulnerability assessments is also largely based on the statistical methods associated with the vulnerability analysis. Vulnerability is difficult to measure because vulnerability indicators are inherently qualitative in nature (Cutter 2003; de Oliveira Mendes 2009; Frazier, Thompson, and Dezzani 2014). Researchers have employed statistical methods, such as regression modeling, to develop vulnerability models or indices that provide quantitative vulnerability scores that can be used to guide hazard mitigation policies and planning (Jones and Andrey 2007; Tate 2012). Several different types of statistical approaches have been used to measure total community vulnerability as well as the influence of certain physical and social factors on vulnerability at various levels (Birkmann 2007; Cutter, Boruff, and Shirley 2003; Wood, Burton, and Cutter 2010). Common statistical approaches in the natural hazards field include principal components analysis, classical regression (OLS), simultaneous autoregressive (SAR) models and conditional autoregressive (CAR) models (Benson, Chamberlin, and Rhinehart 2005; Chakraborty 2011; Cutter, Burton, and Emrich 2010; Frazier, Thompson, and Dezzani 2014; Hsu and Su 2012; Mentzafou, Markogianni, and Dimitriou 2016; Poudyal et al. 2012; Ugarte, Ibáñez, and Militino 2005). However, all of these approaches have limitations for measuring community vulnerability. The limitations and applicability of these models for vulnerability assessments is further discussed in Chapter 3. However, this section provides statistical backgrounds on the modeling types themselves, such as their basic functions and associated equations.

1.5.1 Principal Components Analysis

One of the most prevalent statistical analyses used in the hazards research is principal component analysis (PCA). PCA is a form of exploratory factor analysis that is commonly used as a data-reduction technique. PCA is often employed studies for two main reasons: 1) it identifies groups of variables that are inter-correlated and 2) it reduces the number of variables in the analysis (Johnston 1978). PCA transforms multivariate data into a smaller number of independent linear combinations (principal components) that account for the majority of variance in the larger dataset (Dillon and Goldstein 1984). The first principal component will always account for the largest amount of variation in the dataset, and is first extracted using the following equation:

$$PC_{(1)} = w_{(1)1}X_1 + w_{(1)2}X_2 + \cdots + w_{(1)p}X_p$$

where $w_{(1)1}$, $w_{(1)2}\ldots w_{(1)p}$ represent weights that maximize the ratio of variance for $PC_{(1)}$ (Dillon and Goldstein 1984). The second principal component ($PC_{(2)}$) consists of a linear combination of variables not observed in the first component, but accounts for the next largest amount of remaining variation not explained by $PC_{(1)}$. Principal components $PC_{(2)}$ through $PC_{(m)}$ are calculated using the same equation below until the maximum amount of explained variance is calculated (Dillon and Goldstein 1984).

$$PC_{(m)} = w_{(m)1}X_1 + w_{(m)2}X_2 + \cdots + w_{(m)p}X_p$$

where $w_{(m)1}$, $w_{(m)2} \ldots w_{(m)p}$ represent weights that maximize the ration of variance for $PC_{(m)}$ (Dillon and Goldstein 1984). Once all principal components are calculated, the analysis also reveals which variables within the linear combinations exhibit the most influence on the factor within which it is grouped. This value is called the component loading, which describes how much of the variation of an original variable is explained by the factor in which it is grouped (Dillon and Goldstein 1984).

PCA is often used in hazards studies to determine significant and interrelated indicators of vulnerability, resilience, sensitivity or adaptive capacity for index or regression model development (Cutter, Boruff, and Shirley 2003; Frazier, Thompson, and Dezzani 2014; Wood, Burton, and Cutter 2010; Myers, Slack, and Singelmann 2008). In addition to providing these groups or components, the analysis also detects which indicators are more meaningful to the analysis and, therefore, helps to reduce the dataset to only those indicators that are most influential. A reduced dataset helps make analysis with large datasets more manageable and removes indicators that may not be pertinent. PCA can also identify variables with high multicollinearity. Multicollinearity occurs when two or more variables are highly correlated, which can bias or reduce the accuracy of statistical operations such as regression modeling (Johnston 1978; Dillon and Goldstein 1984).

1.5.2 Classical Regression and Ordinary Least Squares Estimation

Classical regression models seek to identify and explain statistical relationships between a dependent variable and explanatory variables. The simplest form of regression is the linear regression model, which can be determined using the following equation:

$$Y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$$

where β are the unknown parameters in the model and ε_i is the error term.

This initial equation symbolizes how a response variable, y, is dependent on one explanatory variable, x. β_0 is the y-intercept of the regression line, while β_1 represents the slope (Gelman and Hill 2007). This type of model is best used in situations where a response variable is explained by a single independent variable (Burt, Barber, and Rigby 2009). While the linear regression form is easy to compute, many regression processes are too complicated to be explained by one explanatory variable alone. In cases where the model must be modified to include multiple explanatory variables, the linear equation can be expanded to a multiple linear regression. This type of regression is described with the following equation (Burt, Barber, and Rigby 2009):

$$Y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 \ldots \beta_k x_k + \varepsilon_i$$

Multiple linear regression uses multiple explanatory variables to help predict the value of Y_i. This is done in cases where one explanatory variable is simply not enough information to predict the value of a response variable. Using a global warming example, CO_2 is most likely not the only influencing factor of global warming. In this case, several other factors, such as the amount of volatile organic compounds and ozone-destroying chemicals that exist within the atmosphere may also change the global climate. To determine the combined influence of all three factors, a multiple linear regression with three explanatory variables would be used (Burt, Barber, and Rigby 2009).

In order for classical linear regression to be used to make accurate statistical inferences about data, errors are *i.i.d.*, predictors exhibit no multicollinearity and the error terms have a normal distribution. When these assumptions are met, then basic estimation procedures can be used to determine the unknown parameters in the equation (Burt, Barber, and Rigby 2009; Gelman and Hill 2007). To estimate unknown parameters, different estimation types can be utilized depending on the distribution of the data and the estimation criteria. In the classical regression, the ordinary least squares (OLS) estimation technique is used to estimate the coefficient values for the unknown parameters so that the regression line is the best fit for the data (Burt, Barber, and Rigby 2009). OLS is described as minimizing the squared distance between observed and predicted dependent variables. OLS is appropriate when the model is linear, no linear dependence exists within regressors, and error terms exhibit exogeneity, are homoscedastic, have a normal distribution and no autocorrelation (Burt, Barber, and Rigby 2009). Additionally, OLS is applicable when the purpose of the model is to create a global regression (Burt et al., 2009). In the cases where spatial autocorrelation, nonstationarity or multicollinearity occurs, this model is not applicable. Another type of model that corrects for spatial relationships, such as GWR, spatial error or spatial lag models, should be considered in place of classical linear regression, and OLS estimation.

1.5.3 Generalized Least Squares Estimation

Like OLS, generalized least squares (GLS) can be used to estimate the coefficient values for the unknown parameters for a regression line. GLS can be used for linear and multiple linear regression models and functions in similar way as OLS. However, GLS does not assume that the error terms in a model are homoscedastic or that no correlation between observations exists. When these assumptions are violated, OLS can no longer be used, which is why GLS is often applied in those circumstances. GLS can be used in these situations because it develops a local regression model in which every value has its own variance. This method helps provide a more accurate model when the data is heteroscedastic or has correlated observations. The general form of GLS is as follows (Dezzani, 2012):

$$\hat{\beta} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}Y$$

where Ω can be replaced with σ if σ is known.

The GLS estimator adjusts observed variances through a weighting matrix, which permits a linear regression to be applied to the dataset. GLS does assume certain assumptions about the dataset that are very similar to OLS. This estimator will be consistent and unbiased if the model has the correct functional form (is linear), there is no linear dependence within the regressors in X, error terms have a conditional mean zero, there is no autocorrelation between observations, and error terms have a normal distribution.

GLS does not assume that the error terms are homoscedastic; however, the assumption of homoscedasticity is still necessary for classical regression models to be reliable. To correct for this assumption, GLS transforms the linear model, using the above equation, so that the assumption of homoscedasticity is satisfied. Because GLS allows for the effects of heteroscedasticity, it has the ability to create statistically reliable regression models for datasets that OLS cannot. As far as parameters for the GLS estimator, they are the same as those of OLS. GLS also provides for the best linear unbiased estimator under the Gauss-Markov theorem when spatial relationships are present and OLS becomes inadequate. In order to test for the goodness of fit for the line, R^2 values are still used for comparison in the GLS model.

1.5.4 Spatial error model (SAR)

Simultaneous Autoregressive Models (SAR) are regression models that account for spatial processes occurring within the data, which can be used to provide more reliable regression model results. The spatial error model is a SAR model that is used when the OLS assumption of uncorrelated error terms is violated because it adapts for spatial dependence in a regression. It should also be used when the residual term appears to be influenced by a spatial structure (Fotheringham and Rogerson 2009; Burt, Barber, and Rigby 2009). This model can be used in situations where significant spatial autocorrelation is present, but tests for spatial lag effects do not indicate that including those effects will improve the regression model. To do this, the spatial error model determines a weighting factor that accounts for the spatial dependence within the dataset. The spatial error model can be described using the following equations (Anselin 1996; Fotheringham and Rogerson 2009):

$$y = x\beta + \varepsilon$$

$$\varepsilon = \rho W\varepsilon + \xi$$

where ε is the error terms vector that has been spatially weighted using the weighting matrix (W), ξ is the vector of uncorrelated error terms and λ is the spatial error coefficient.

The spatial error model transforms the errors that are part of the influencing spatial process to an error term in the model. Researchers can test the OLS method to determine if the spatial error model would be more representative of the data, given the presence of spatial autocorrelation, using the OLS regression model with a weighting file in Geoda. Geoda uses six tests to determine spatial dependence in the model. The first is the Moran's I, which tests for spatial dependence in the residuals. If there is spatial dependence, the other tests can be used to determine which spatial model is the best representative for the data. In the case of the spatial error model, if the Lagrange multiplier for the LM (error) is statistically significant, and the LM (lag) is not, then the spatial error model is the better fit. The LM test tests for a missing spatially lagged dependent variable. If that variable is not present, then the spatial error model is used. If both tests are significant, the Robust LM (error) and Robust LM (lag) tests are used to determine which model is more appropriate. These tests test for error dependence if a spatially lagged dependent variable is possibly occurring. If the Robust LM (error) test is more significant, then it should be used as the model of choice for that regression model (Anselin 1996; Anselin 1999; Anselin, Gallo, and Jayet 2008).

To test the significance of the regression coefficients, the *z* statistic can be used from the model output. In order to test for the goodness of fit for the line, R^2 values are still used for comparison in the spatial error model. Another way to test the effectiveness of the spatial error model is to once again test the residuals for spatial autocorrelation. If the Moran's I for the residuals indicates that the residuals are not spatially correlated, then any spatial autocorrelation has been captured by the spatial error model (Burt, Barber, and Rigby 2009).

1.5.5 Spatial lag model (SAR) (MLE)

The spatial lag model is used when the assumptions that there is no spatial autocorrelation is violated. It is used to describe substantive spatial dependence and the strength of spatial interaction in a dataset. Unlike the spatial error model, the pure spatial lag model (or pure autoregressive model) does not have regressive components. It is simply a modeled, spatially lagged dependent variable that can be used to include the effects that neighboring dependent variables may have on the original dependent variable (Fotheringham and Rogerson 2009). The spatial lag model with no regressive components is simply:

$$Y = \rho WY + \varepsilon$$

where ε is the error term vector, WY is the spatially lagged dependent variable for the weights matrix, and ρ is the spatial coefficient (Fotheringham and Rogerson, 2009).
The SAR model is estimated using OLS, where the estimator is:

$$(\lambda)= (X_n'X_n)^{-1}X'_nS_n(\lambda)Y_n$$

Like the spatial error model, the SAR model assumes that the error terms are normally distributed, have a constant variance of 0 and are *i.i.d.* (Cliff and Ord 1981). Spatial autocorrelation should be tested for in the residuals to see if any spatial autocorrelation within the dataset has been accounted for in the spatial lag model (Cliff and Ord 1981). The spatial lag model is a global measure of spatial autocorrelation, and provides information about the overall spatial pattern within a dataset. Because there are no regressive components in the model, it simply determines "block effects" in the data, which is very similar to trend surface analysis. The SAR model can also be mixed with regressive components to rerate a spatial lag model with regressive components, which can be used to account for global spatial autocorrelation in a classical regression model. However, literature on the pure simultaneous autoregressive model is limited. Related literature often provides greater information about the spatial lag model with mixed regressive components, which is discussed in the next section.

1.5.6 Conditional Autoregressive Model (CAR)

Another spatial model sometimes utilized in hazards modeling is the conditional autoregressive (CAR) model. The CAR model, introduced by Besag (1974), is a type of Markov Random Field (MRF) model that specifies univariate conditions on each variable in order to identify global trends and local spatial autocorrelation present at both a local and global scale (Lichstein et al. 2002). A CAR model assumes that observations are conditional based on the values of neighboring observations and is defined by the following equation:

$$E\left(y_i \middle| all\ y_{j\neq i}\right) = \mu_i + \rho \sum_{j\neq i} w_{ij}(y_i - \mu_j)$$

where y_i is the expected value for a specific observation, μ_i is the expected value at *i*, *j* is all other locations, ρ is a spatial autocorrelation parameter that determines the size and nature of the spatial neighborhood effect, and w_{ij} is the spatial weights matrix (Lichstein et al. 2002).

Covariances in the CAR model are considered nonzero and they increase as locations *i* and *j* are in closer proximity. Spatial correlation is also based only on neighbor adjacency, not neighbors of neighbors (Lichstein et al. 2002; De Oliveira 2012; Lee and Mitchell 2013). CAR prior distributions are sometimes used in disease mapping studies that utilize Bayesian hierarchical models to account for spatial autocorrelation in the data (Lichstein et al. 2002; De Oliveira 2012; Lee and Mitchell 2013). CAR models are typically used to model spatial autocorrelation in a non-overlapping dataset, making them ineffective for modeling vulnerability using multiscalar, nested datasets. However, CAR models can be included in the second level of hierarchical models to correct for any spatial correlation in the data (Lee 2011, 2013).

1.5.7 Geographically Weighed Regression

One of the limitations of both the spatial error model and the spatial lag model is that they assume that spatial dependence in the data is uniform throughout the study region. This implies that there is some level of stationarity within the dataset. In the case where neither the spatial lag model nor the spatial error model adequately account for spatial processes such as nonstationarity or heterogeneity in the data, another regression model may need to be utilized. Geographically weighted regression (GWR) is a local statistic that accounts for non-stationarity and heterogeneity in a dataset, as well as any spatial dependence. Instead of using globally fixed regression coefficients, GWR allows them to vary from location to location (Fotheringham, Brundson, and Charlton 2002; Fotheringham and Rogerson 2009; O'Sullivan and Unwin 2010). GWR is described by the following equation:

$$Y_i = \beta_0(g) + \beta_1(g)\, x_1 + \beta_2(g)\, x_2 + \beta_3(g)\, x_3 + \beta_4(g)\, x_4 \ldots\ \beta_k(g)\, x_k + \varepsilon_i$$

where (g) represents the location at which estimates of the parameters are gathered.
The estimator for the parameters of the GWR then becomes:

$$\beta'(i) = (X^T W(i) X)^{-1} X^T W(i) Y$$

where W(i) is the weighting matrix and specific to each location.

This estimator is one of the GLS estimator types called the weighted least squares estimator. It allows for estimation to be conducted for each observation. The method of determining regression weights is extremely important because GWR uses the weighting matrix to create an estimator for each observation. Kernel estimation can be fixed or adaptive. Several approaches to determine the weighting matrix exist. Examples of fixed kernel weighting schemes are the Gaussian or biweight kernel functions. These methods are used to assign weights to all of the nearby observations for a given observation (Fotheringham, Brundson, and Charlton 2002; Fotheringham and Rogerson 2009; O'Sullivan and Unwin 2010). Adaptive weighting methods can also be used to create a different kernel that has a different bandwidth size at every location (Fotheringham and Rogerson 2009; Brunsdon and Comber 2015). The main concern when using kernel estimates is the bandwidth of the kernel because it does influence the results of the model. To determine which kernel bandwidth will produce the best results, several GWR models with various kernel bandwidths should be carried out. Some programs can automate this process, but it can be a tedious and complex undertaking (Fotheringham and Rogerson 2009; O'Sullivan and Unwin 2010).

The results of a GWR are different from those of the spatial lag and spatial error model in that a GWR does not provide a single statistic for the model. Each observation is assigned estimated regression coefficients that can be mapped to show how the relationship of each variable differs across the study region. Testing can then be done to determine if the variation of the regression coefficients is due to a spatial relationship within the landscape, or if the pattern is simply due to random sampling effects (Fotheringham and Rogerson 2009; O'Sullivan and Unwin 2010). No matter which weighting function decided upon, they are all susceptible to the degree of distance-decay. In order to determine which h value is the most optimal for the GWR model, the Corrected Akaike Information Criterion (AICc) can be used. The lower the AICc value, the better the model fit (Fotheringham and Rogerson 2009; Brunsdon and Comber 2015).

To test the significance of the regression coefficients, the *p*-value from the model output indicates which coefficients in the model are statistically significant. In order to test for the goodness of fit for the line, R^2 values are used for comparison in a GWR. While the GWR provides regression coefficients for every observation, an overall R^2 statistic is provided to determine the amount of explained variance in the model. The residuals should also be tested for spatial autocorrelation to determine whether or not spatial dependence has been accounted for. If the Moran’s I for the residuals indicates that the residuals are not spatially correlated, then any spatial autocorrelation has been captured by the GWR (Brunsdon and Comber 2015; Brunsdon, Fotheringham, and Charlton 1996; Fotheringham, Brundson, and Charlton 2002; Gollini et al. 2013; Lu et al. 2013).

While the GWR does correct for non-stationarity, it does not account for multiscalar variables. A semi-parametric GWR (S-GWR) model, however, does allow researchers to run GWRs using both local and global scales (Lu et al. 2013). This method allows variables that are global (stationary) to be treated and global coefficients, while other are treated as local (non-stationary) (Nakaya et al. 2009; Lu et al. 2013). The S-GWR model's form is written as (Lu et al. 2013):

$$y_i = \sum_{j=1,k_a} a_j x_{ij}(a) + \sum_{l=1,k_b} b_l(u_i, v_i) x_{il}(b) = i$$

where:

$[a_l,\ldots,a_{ka}] = k_a$ global coefficients

$[b_l(u_i,v_i)\ldots,b_{kb}(u_i,v_i)] = k_b$ local coefficients

$[x_{ij}(a), \ldots, x_{ika}(a)]$ = independent variables associated with global coefficients

and $[x_{il}(b), \ldots, x_{ikb}(a)]$ = independent variables associated with local coefficients

While the level of these variables may vary, the rate of spatial variation remains the same (Nakaya et al. 2009; Lu et al. 2013). The S-GWR could be useful for conducting multiscalar vulnerably assessments because it corrects for non-stationarity in the data and provides both global and local regression coefficients. However, there is a possibility that vulnerability indicators will exist at multiple scales (i.e. block, tract, municipality and county). If the global or local variables cannot be multiscalar, the S-GWR becomes less applicable for enhancing vulnerability assessments using multiscalar variables.

1.6 Vulnerability Assessments and Risk Perception Theory

While many studies utilize traditional statistical methods and vulnerability indicators to measure social vulnerability, access to information (which can be influenced by levels of agency) is often overlooked. This exemption is important for gathering a more complete measure of vulnerability because access to information is one of the main drivers of risk perception development, which drives risk reduction behaviors. Risk perceptions directly and indirectly affect hazard mitigation and adaptation behavior. People make subjective judgments about a risk from gathered information to develop their perceived risk (Frewer 1999). People typically develop mitigation and adaptation strategies for contemporary and future hazards using existing risk perceptions of the consequences of those risks, not what might actually occur (for which they have no basis).

These behaviors are traditionally associated with behaviors that fall under the theory of decision under uncertainty, where people make the best decision possible with the knowledge they have and within socioeconomic constraints. The theory of bounded rationality was originally developed by Herbert Simon to explain economic decision making behaviors (Kahneman 2003; Simon 1972), but can be applied to HMP as that is often limited by economic constraints. While the theory of decision under uncertainty identifies basic reasons why people make certain risk decisions, it does not identify specific factors that influence risk perception and risk tolerance, or their influence on mitigation implementation. In response, several risk perception theories have been developed to identify how different factors influence an individual's risk perception, to better understand how people form judgments about risks they face in everyday and how they act on those judgments.

1.6.1 Psychometric and Behavioral factors

Several early studies focused on the psychometric paradigm, which emphasizes that people develop risk perception through information about a risk as well as intuition or perceptions about the risk. For example, a person may read that a nuclear power plant in the present day is significantly safer than when the Three Mile Island or Chernobyl incidents occurred, but may still fear the prospect of nuclear power because they perceive nuclear plants having a certain level of dread (Siegrist, Keller, and Kiers 2005; Siegrist 2000; Sjöberg 1999; Slovic 1987). The goal of the psychometric paradigm is to determine why people perceive risks differently, and what specific factors cause that perception to differ based on familiarity with the hazard, severity of consequences and knowledge about the risk (Siegrist, Keller, and Kiers 2005).

The theory of planned behavior (TPB) states that a combination of consequences of an event or action, social value of the consequences and perceived ability to act influences an individual's decision to take certain actions (Shreve et al. 2016). Therefore, how people react to a hazard event is based on what possible consequences the hazard may have on the individual, the social value of their hazard response, and their ability to react to the hazard are what drive their risk perception (Ajzen 1991; Siegrist, Keller, and Kiers 2005; Ng and Rayner 2010). For example, if an individual feels they are unable to evacuate from a hurricane event on time or that the storm is not large enough to cause enough damage that would justify the expenses of evacuation, then that person is less likely to evacuate during a hurricane event.

1.6.2 Cultural and Ethnic Factors

Identifying how culture influences people and their behaviors, values and beliefs is a common theme in geographic and anthropological research. However, the perspective from which culture is examined can affect what "lens" is used to make observation about culture. For example, cultural geography examines culture in terms of how space, place and the environment influence culture and how culture shapes space, place and landscapes (Knox and Marston 2013). In anthropology, culture is often viewed as a cognitive system, a structural system or a symbolic system. When examining culture as a cognitive system, culture is considered to be a system of knowledge that is comprised of whatever information a person must know (i.e. language) to operate successfully within that culture (Keesing 1974). Structural systems consider culture as a system of shared symbols that are created from similar patterns of individual human thought (Keesing 1974; McGee 2003), whereas symbolic systems consider culture as a system of shared symbols and meanings that are shared in public between actors, not individual minds (Geertz 1973; Keesing 1974).

To describe how risk perceptions and associated behaviors are influenced by culture, was Douglas and Wildavsky (1983) developed the cultural theory of risk. The cultural theory of risk states that individuals develop risk perceptions based on cultural biases and social norms that influence how they acknowledge (or avoid) certain risks (Ng and Rayner 2010; Rayner 1992). Cultural theory argues that risk is socially constructed and is different from other risk perception theories because it takes place from an institutional, not individual perspective (similar to Geertz (1973)'s view of culture) (Steg and Sievers 2000). The institutional (or social) structure is the driving force behind risk perception and is developed from three main societal components: 1) social relationships; 2) cultural values and beliefs concerning societal views, risk perceptions, and biases toward environmental risks; and (c) preferred behavioral strategies used to deal with environmental risks (Steg and Sievers 2000). Therefore, if dangers exist, social institutions will identify and stress risks that help reinforce social order (Steg and Sievers 2000). An example of this type of risk perception comes in the form of Jewish dietary restrictions. Pigs, snakes, and shellfish are not a part of a kosher Jewish diet because these animals are considered unclean and abominations according to the Hebrew bible (Ng and Rayner 2010; Rayner 1992; Rippl 2002). Because these animals are given a negative connotation in the Jewish social order, they are emphasized as bad for Jewish health.

People's group membership, cultural values and prior experiences all affect how social groups view different risks. Two main features make up the basic structure of Cultural Theory: 1) individuals will associate societal risks with deviant behavior, or behavior that does not follow social norms, and 2) cultural norms and values are developed along two dimensions: *groups* and *grids*. A *group* describes the level of social incorporation of an individual, whereas a *grid* describes the type of social interaction that takes place in a *group* (Douglas 2013; Ng and Rayner 2010; Rayner 1992; Rippl 2002). For example, a high group would be one that has a large number of networks, closed social boundaries and many shared activities, and a high grid would require a large amount of discriminations (such as age, family ties, wealth, etc.) in order to gain access to certain social activities.

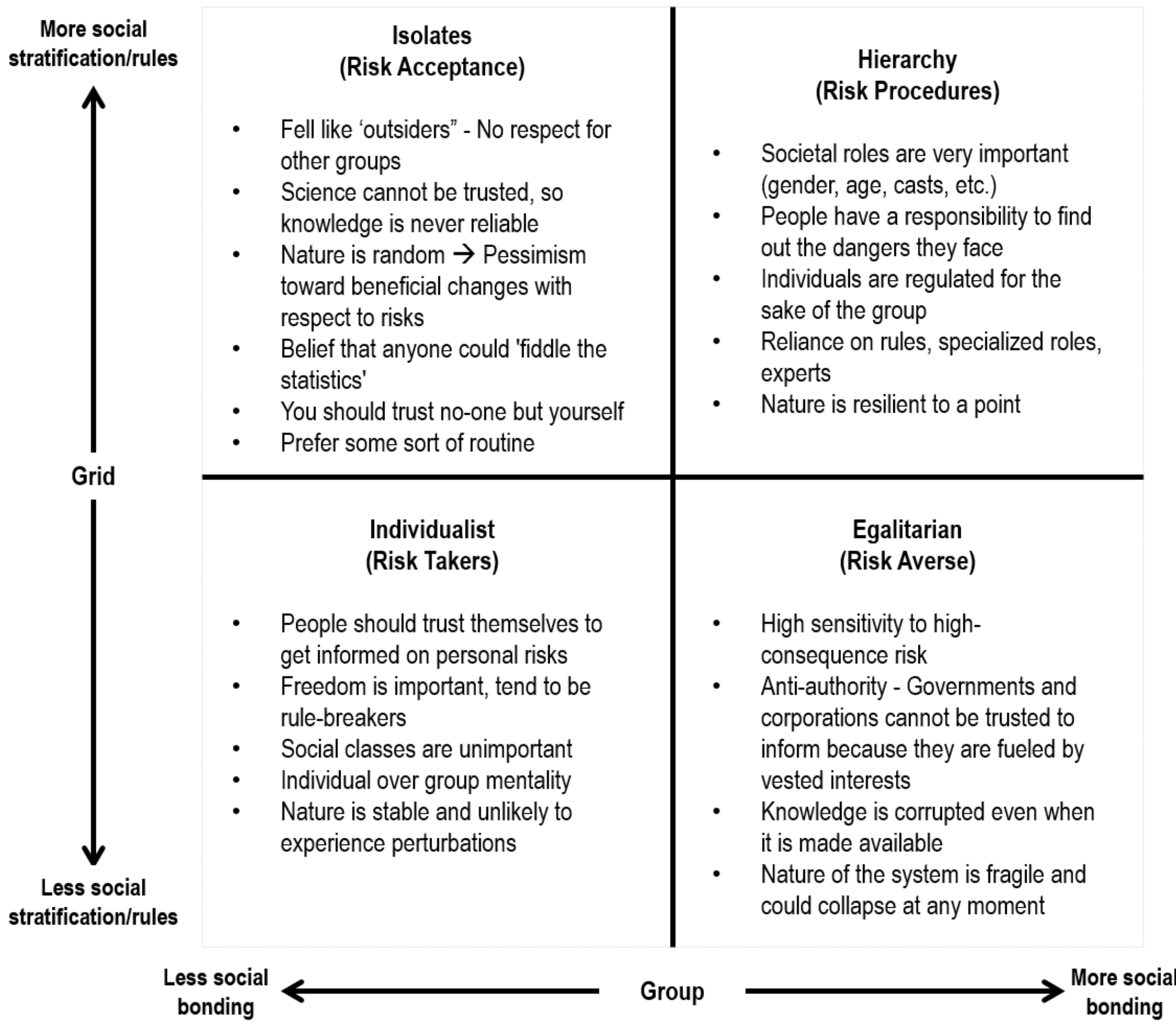

Figure 1.6 – Group/grip classifications for cultural theory

Based on this group/grip framework, people fall into one of four categories: Stratified Individuals (Low group/ High grid), Complex Groups/ Hierarchies (High group/ High grid), Competitive Individualists/Markets (Low group/High grid), and Egalitarian Groups (High group/ Low grid) (Rayner 1992; Rippl 2002; Kahan 2012). Figure 1.6 illustrates how certain values and beliefs are associated with different group/grid classifications and how those attributes might impact risk perception and behaviors (Douglas and Wildavsky 1983; Tansey and O'riordan 1999; Lazrus 2015; Tsohou, Karyda, and Kokolakis 2015).

1.6.3 Media and Social Amplification of Risk (SARF)

The Social Amplification of Risk framework explores how social interactions and values often influence how people perceive dangers or hazards. For example, if an individual's neighbors claim over and over again that they survived one hurricane with manageable damage and, therefore, they can manage the next, the individual or other neighbors may take their underestimation as fact and perceive that hazard as low risk (Kasperson et al. 2003; Kasperson and Kasperson 1996). Media, public opinion, and social values can also amplify risk. The American fear of switching to nuclear power is partially due to the disasters at Three Mile Island and Chernobyl. While nuclear energy plants now employ much safer conditions and safety precautions, Americans are much less inclined to allow the country to use nuclear power due to an increase perceived risk (Clark et al. 1998; Kasperson et al. 1988). When people experience low risk perception, they often experience higher risk tolerance and are less likely to support mitigation to help minimize damage; when people experience high risk perception, their risk tolerance has been lowered and therefore they become more likely to demand mitigation policies or programs that help minimize hazards losses (Clark et al. 1998; Kasperson et al. 2003; Kasperson and Kasperson 1996).

1.6.4 Vested Interest and Trust

The vested interest theory specifically looks at the relationship between an individual's attitude toward disaster preparedness and their behavior in preparing for a disaster event (Miller, Adame, and Moore 2013). Essentially, an individual will have certain attitudes towards hazard events, but they may or may not act or behave in a way that reflects that attitude. For example, a wealthy retiree that has a winter vacation home along the Florida coast (with insurance) is told that a hurricane is coming toward the area where his vacation home is in September. While his home may suffer damage, he is likely not going to be in the area at that time and therefore is unlikely to travel to that area to mitigate against possible damage that he will receive insurance payments to rebuild or repair. Vested interest theory asserts that certain components are necessary to predict whether an individual's attitude will result in behavioral expression of that attitude (Miller, Adame, and Moore 2013). Vested interest theory is based on five main components: 1) a person's stake in the outcomes of the disaster event, 2) salience, or the relative importance or prominence of an attitude toward a d disaster event, 3) the perceived certainty of potential consequences from a disaster event, which will influence an individual's attitude toward that hazard, 4) immediacy of the hazard event and its consequences, and 5) self-efficacy. If one of these components is not present, then the overall vestedness for the attitude, and therefore predictive behavior related to that attitude, will be reduced (Miller, Adame, and Moore 2013).

1.6.5 Situational Theory of Publics

The situational theory of publics asserts that the general public is not comprised of a singular type of public. Grunig (1983) describes publics as groups of distributed people that communicate in a similar manner about similar issues (Grunig 1983; Major 1999; Illia, Lurati, and Casalaz 2013). Different publics form in response to problems, and differ in how they interpret and organize to face said problem (Sriramesh, Moghan, and Kwok Wei 2007). Different problems will therefore cause populations to form different publics. For example, when people react to a disaster, the level of awareness about the disaster and the manner in which they respond will differ. This difference in reactions may result in the development of several publics (Grunig 1983). The situational theory of publics examines how individuals become aware of or identify possible risks and the extent to which they react to or mitigate those risks. This theory identifies and classifies individuals' level of awareness concerning a hazard or risk and determines the extent to which they react to that hazard or risk.

Grunig and Hunt (1984) described four distinct types of publics that form based on their level of awareness about the problem and the perceived ability to resolve the problem (constraint recognition) (Major 1999; Sriramesh, Moghan, and Kwok Wei 2007). The four types of publics are: 1) *Latent* publics, which describe people that face a similar issue, but do not recognize the problem, 2) *Aware* publics, which are formed when people become aware of the problem, 3) *Active* publics, which develop when people organize to address the problem and form solutions and 4) *Nonpublic*, which are formed by people who do not face the problem (Major 1999; Sriramesh, Moghan, and Kwok Wei 2007; Grunig and Hunt 1984). The definitions of the publics, however, can be modified to represent different issues. For example, Major (1999) described the four publics in terms of earthquake risk. People with high problem recognition and low constraint recognition recognize earthquake risk and feel they can do something to mitigate earthquake impacts, whereas people with low problem recognition and low constraint recognition does not often think about earthquake risk, but they feel that they could mitigate against earthquake risks. The level of problem recognition is different, but the perceived ability to act is the same in these two publics (Major 1999).

This theory was developed to determine why certain individuals take an active or passive role in response to a problem or issue. People are described as passive or active based on three independent variables and two dependent variables: problem recognition (independent), constraint recognition (independent), level of involvement (independent), information seeking (dependent) and information processing (dependent) (Hamilton 1992; Illia, Lurati, and Casalaz 2013). These factors vary depending on the type of 'public'. For example, latent publics are more likely to be passive in information seeking and processing, while active publics are more likely to actively seek information (Sriramesh, Moghan, and Kwok Wei 2007). Several studies have also demonstrated that certain demographic variables such as age, gender, or education can also influence how people fall into certain publics (Hamilton 1992; Major 1999; Illia, Lurati, and Casalaz 2013). This information could be used to determine if certain groups are more of less active during hazard situations, and how that could affect their overall response to risk situations. STP helps decision makers identify which segments of the public are more active. This information can be used to develop more cost-effective communication campaigns that reach information seeking and processing publics more efficiently, while still addressing some of the publics who take more passive roles (Grunig 2009; Kim and Grunig 2011).

1.6.6 Mental Models

The mental models approach is commonly used in risk communication to assess how people understand and process information. They represent an individual's general cognitive structure that is developed based on experiences, perceptions and understanding of reality (Jones et al. 2011). Individuals' decisions are then guided or based on mental models they have for particular issues or subjects (Doyle and Ford 1998; Coles et al. 2011). The concept of mental models was first introduced by Kenneth Craik, a philosopher and psychologist, who described them as 'small scale models' of reality (Doyle and Ford 1998; Westbrook 2006).

Mental models are developed by humans to represent reality, but their perception is not necessarily accurate (Besnard, Greathead, and Baxter 2004). How people receive, process and interpret information influences how their mental model develops (Doyle and Ford 1998). While this may mean that mental models do not accurately represent reality, they do represent how people *perceive* reality to be (Doyle and Ford 1998), which can represent how system processes are perceived and how that perception influences human behavior (Lane 1999). This relates to structuration theory in that it argues that humans both shape and are shaped by social structure (Giddens 1984; Lane 1999). Through this 'duality' values and belief based on the social structure are internalized then externalized through behaviors, which further perpetuates the social structure (Lane 1999). This means, essentially, that social structure does help shape an individual's mental model in some form, and acting on those models maintains the social structure (Giddens 1984; Lane

1999). Therefore, understanding an individual mental model for a specific event or object could provide insight about both the social structure that helped form the model and how that influences the individual's behavior.

Because there are imperfections in mental models, some studies have also used them to identify differences or gaps in attitudes, beliefs, information or knowledge between lay people and experts (Kolkman, Kok, and Van der Veen 2005; Sheppard, Janoske, and Liu 2012). This information is important in terms of disaster planning and decision making because neglecting to incorporate local knowledge into disaster planning can result in less effective solutions to problems, plans that do not address local priorities or results that are non-specific to the community (Coles et al. 2011; Kolkman, Kok, and Van der Veen 2005). By addressing these information gaps, decision makers can develop planning strategies that better fit local needs (Kolkman, Kok, and Van der Veen 2005).

1.7 Study Area

This research uses Sarasota County, Florida, as a case study. Sarasota County, Florida is located on the west coast of the Florida peninsula (Figure 1.7) and has approximately 35 miles of shoreline and a low average elevation (~42 ft.). These physical characteristics make the county susceptible to coastal hazard inundation impacts, such as inland precipitation flooding and storm surge inundation, with ~45% of the county falling within the 100-year floodplain (Sarasota County Department of Planning 2016).

The county has also experienced significant population growth within the last decade, experiencing approximately 16% population increase from 2000 to 2010 (Bureau 2010) and is highly developed along the coast due to the Urban Service Area (USA) delineation. The USA describes the general area along the coast that Sarasota County has prioritized in terms of urban services (i.e. central water and sewer utilities, master stormwater management systems, neighborhood parks, and street facilities, etc.) (Sarasota County Department of Planning 2016). Future development will likely continue to increase along the coast due to the location of Interstate Highway 75 and the urban service boundary, leading to increased societal exposure and vulnerability to coastal inundation hazards (Sarasota County 2015).

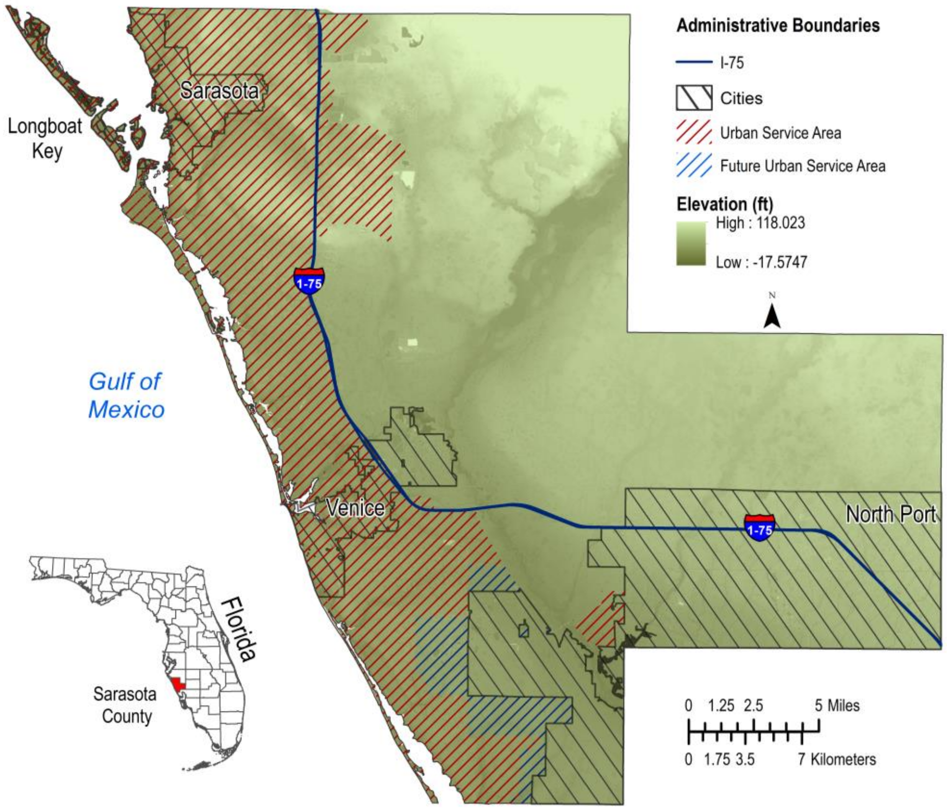

Figure 1.7 - Sarasota County, Florida

1.8 Research Questions and Goals

In response to the challenges discussed in the above sections, my dissertation research seeks to develop new conceptual frameworks and quantitative models that can better assist stakeholders in targeting hazard mitigation to highly vulnerable areas. Additionally, my dissertation advances the natural hazards literature, which is typically applied in nature, by examining social vulnerability from a political economy, social theory and resilience theory perspective. My dissertation advances the literature by grounding my research in resilience theory, social theory and political ecology through analysis of how social conditions, social structure, and risk perception influence vulnerability and resilience at the community level.

To accomplish this goal, I developed a vulnerability/resilience quantification method that is structured on political ecology and structuration theory through the use of multiscalar traditional, external and non-traditional vulnerability indicators. A sub-goal is to determine how risk perception and agency influence overall vulnerability. These goals will help me determine if including multiscalar, sub-county vulnerability analysis, and risk perception and external indicators will provide more accurate information for vulnerability assessments that are more effective for developing and implementing mitigation strategies at the sub-county scale. Research of this type is critical for guiding mitigation and adaption planning in toward higher vulnerability areas and underlying social processes in order to decrease overall vulnerability and increase resilience.

Based on my goals and objectives this research addresses the following questions:

1. What social theories can be “injected” into current natural hazards and vulnerability literature to enhance the explanatory value of these types of assessments?
    i. In what ways can existing general social theory supplement current natural hazards theory in a way that helps to explain how vulnerability develops from a social structure perspective, not just a vulnerability indicator perspective?
    ii. What kind of theories can be used to guide conceptual framework development that bases any quantitative methodologies on theoretical foundations?
    iii. How do individuals respond to structural constraints that exist within the human-environment system?

2. Is it possible to create a vulnerability quantification methodology that more accurately measures overall community vulnerability in a more theoretically robust manner using multiscalar, spatially explicit vulnerability indicators for Sarasota County?
    i. What are the existing place-specific vulnerability indicators within Sarasota County, FL and which ones have the greatest influence on vulnerability?
    ii. How do spatial effects influence regression modeling results when compared to traditional, classical regression techniques?
    iii. How can multiscalar indicators be included in the model without downscaling or aggregating data to a single scale?

3. How can the influence of risk perception and structuration on vulnerability be quantitatively examined?
    i. Are risk perception, structuration and traditional vulnerability indicators (i.e. demographic data) interdependent?
    ii. In what ways do risk perception and structuration influence risk reduction behaviors?

iii. Can risk perception and structuration indicators be measured in a way that they can be aggregated to a specific scale and used in a multiscalar vulnerability assessment that measures overall community vulnerability and resilience?

Chapter 2 – Opportunities for Injecting Social Theory into Natural Hazards and Vulnerability/Resilience Studies

2.1 Introduction

Worldwide population has grown from ~2.5 billion people in 1950 to ~7.3 billion people in 2015 (Chakraborty 2011), resulting in increased developed infrastructure in areas exposed to natural hazards (Clason and Dormody 1994). This can influence the frequency and intensity of natural disasters, as a larger number of people and infrastructure are exposed to natural hazard impacts. To reduce natural disasters impacts, research in Geography and the natural hazards sub-discipline have made efforts to understand the complex relationship between social systems and natural hazards. These studies help agencies and communities better understand local hazards and related impacts. Such information can help decision makers develop and implement mitigation plans and policies that reduces natural hazard impacts and improves recovery potential. However, these scientific studies often lack theoretical focus and the model structure do not reflect theoretical foundations in vulnerability literature (Alexander 1997; Montz and Tobin 2011). This is problematic because theory is critical to scientific research as it provides necessary rigor for research methods within a discipline. If applied methods are not based in theoretical foundations, inconsistency in modeling methods or indicator development can occur. It may also become difficult to assess results, provide explanations and develop policy without appropriate expressions of theory (Root and Emch 2011). Poor theoretical development and the concomitant inconsistencies in interpretation and explanation can make comparison of model accuracy difficult and may contribute to misunderstandings concerning model development and potential benefits.

Many models in natural hazards are based on sets of indicators that are traditionally thought to influence vulnerability and resilience (Morrow 1999; Cutter 2003; Jones and Andrey 2007). Previous qualitative research with theoretical foundations in political economy and political ecology has identified general indicators of vulnerability. However, many natural hazards studies have variable definitions of vulnerability and resilience, which affects how certain indicators are utilized in quantitative models. The lack of a common definition results in studies that vary in terms of chosen indicators and the justification of their use in vulnerability and resilience indices, making comparing models difficult. Another limitation in the natural hazards literature is that studies that do cite theoretical foundations of vulnerability or resilience often do not explicitly apply those foundations in research methods (Zou and Thomalla 2008; Miller et al. 2010). One recent example of studies furthering theoretical perspectives in risk and vulnerability literature using outside theories is Schröter, Polsky, and Patt (2005), which uses urban fragmentation theory to provide alternative methods for measuring urban vulnerability from a socio-ecological perspective. Based on the lack of theory in natural hazards, there is a need for additional research on developing frameworks or methods for enhancing theoretical bases in natural hazards studies.

To address theoretical limitations in natural hazards literature, this research examines the feasibility of incorporating theory from outside geography into natural hazards research. Conceptual frameworks developed in resilience theory could help further develop adaptive capacity indicators that identify how social and environmental systems interact and adapt to hazards (Adger 2000; Peterson 2000; Folke 2006; Berkes 2007; Miller et al. 2010). Structuration theory and political ecology have previously been applied in a geographic context (Corrado and Fingleton 2011; Chen and Truong 2012) and can provide a theoretical basis for identifying individual factors within the social system and determine how they perpetuate certain social processes that lead to uneven geographic distribution of social vulnerability (Giddens 1984; Blaikie and Brookfield 1987; Cozzens and Gieryn 1990; Pelling 1999; Turner et al. 2003). In terms of methodological rigor, hierarchical models and spatial statistics may better represent processes occurring within the current social structure, as society is segmented and hierarchical (Cozzens and Gieryn 1990; Giddens 1984; Schelling 1971).

This paper presents a framework that addresses the impact of the social structuration of society, multi-scalar factors, risk perception, social capital and human-environment interactions on vulnerability by utilizing structuration theory, risk perception and political ecology as its major theoretical foundations. The impact of natural events on a community is usually determined by everyday patterns of social interaction, social organization and access to resources. Social structures can lead to discrimination against marginalized populations, which can also increase vulnerability at several scales. Therefore, this research proposes the **IN**jecting **S**ocial Theory into **R**esilience/Vulnerability S**T**udies (INSeRT) conceptual framework that incorporates structuration and political ecology into the natural hazards literature to serve as the theoretical basis for identifying individual factors that comprise the social system and how they perpetuate certain social processes that lead to the uneven distribution of social vulnerability.

2.2 Natural Hazards Paradigms

Vulnerability research on human-environment interactions has undergone several paradigm shifts that attempt to measure social and physical vulnerability from different, but closely related, perspectives. Gilbert White's risk-hazard approach focused on identifying environmental and natural hazards, their possible consequences and determination of when those hazards are likely to occur (White 1945). His ideas challenged the naturalist and 'Acts of God' views by arguing that natural hazards are naturally occurring processes, yes, but people are the ones who choose to develop or live in hazardous areas (White 1945; White, Kates, and Burton 2001). While this theory identifies the biophysical hazard and determines the level of damage that might be incurred during a particular hazard event, it does not examine underlying social processes that can increase vulnerability and cause differential impacts (White 1945; Eakin and Luers 2006).

As a response to the lack of focus on social process on vulnerability, several theories such as political economy/ecology, environmental justice, and social justice were developed to examine how underlying socioeconomic processes and social structures influence how people respond to disaster events (Bogard 1988; Oliver-Smith 1996; Goldman and Schurman 2000; Eakin and Luers 2006; Miller et al. 2010; Hufschmidt 2011). These theories or conceptual models examine social variables (such as gender, race, wealth, class, etc.) and underlying processes that perpetuate patterns of differential vulnerability and hazard impact (Oliver-Smith 1996; Goldman and Schurman 2000; Eakin and Luers 2006). Political economy, developed as a response to the Risk-Hazard approach, sought to examine how economic and political processes influence vulnerability (Eakin and Luers 2006). Political economy argues that politics and economies are intertwined and analyzes how politics (struggle for power) affect the allocation of resources (production, distribution, and consumption of services) (Warf 1997; Eakin and Luers 2006; Sheppard 2011). The presence or absence of power can influence the allocation of resources between groups, which is why political economy is crucial to understanding how the relationship between politics and economies influence vulnerability (Warf 1997).

While political economy examines how social inequalities influence overall vulnerability, it does not examine the influence of variables at different scales and looks at vulnerability from a top-down approach (Goldman and Schurman 2000; Adams 2003). Political ecology addresses these limitations by combining ecology and political economy concepts to examine social structures and how societies interact with their environment. Political ecology shares the political economy emphasis on the role of politics and socioeconomic variables on human-environment interactions, but it also places a greater focus on the role of physical processes on vulnerability (Peterson 2000; Adams 2003). Political ecology also places an emphasis on multiscalar interactions and relationships between society and nature (Adger et al. 2001; Eakin and Luers 2006). Blaikie and Brookfield (1987) developed a definition of regional political ecology as a way to examine how different scales and hierarchies within society and the environment interacted or influenced each other over time. Their 'chain of explanation' concept incorporates politics into human ecology as a way to address how access and control of resources is influenced by social and environmental change (Blaikie and Brookfield 1987; Rangan and Kull 2009). This concept has received some criticism, however, because some believe it does not provide an explanation of how certain social or environmental factors become causes of change and it views space as a container (Blaikie and Brookfield 1987; Rangan and Kull 2009; Peet 1998). Some scientists have taken an alternative approach though 'integrated analysis' and 'cross-scale lineages.' Zimmerer and Bassett (2003) were critical of the 'chain of explanation', arguing that space should be considered as a place in which social processes occurred, but also as a dynamic product of existing and changing social relationships. Space is created and shaped by social processes that occur within it, which is not something the 'chain of explanation' takes into account. For example, the 'chain of explanation' has been used to examine how colonialism and state-level interventions into localize economies have influenced famine in Nigeria, from a broad scalar perspective (Zimmerer and Bassett 2003). However, state and rural/local scales are still essentially social constructed containers of space, and do not necessarily consider the effect of ecological scales on famine (Zimmerer and Bassett 2003). Therefore, socially and ecologically developed scales should be considered in political ecology analyses (Zimmerer and Bassett 2003). Overall, political ecology can illustrate how human activity, social structures and biophysical agency influence the physical landscape and social relations. While political ecology does have some benefits, it has received criticism because it does not provide an explanation of how certain social or environmental factors become causes of change (Eakin and Luers 2006; Rangan and Kull 2009).

These social theoretical frameworks try to identify existing social processes that may influence vulnerability, but they do not address biophysical or ecological changes that may result from a disaster event and they do not examine indicators from a systems perspective (Eakin and Luers 2006; Miller et al. 2010). The social system is influenced by the biophysical system and vice versa due to a series of feedback loops and interactions between the two systems (Deppisch and Hasibovic 2013). Recent studies, such as Thompson and Frazier (2014) and Thompson, Frazier, and Vachon (2016) have begun to focus on the applicability of social-ecological systems (SES) frameworks for resilience studies. Examining resilience from an SES perspective is beneficial because social and biophysical systems are interdependent (Sullivan and Artino 2013). Even if only one system is directly affected by a hazard (i.e. biophysical or social), feedback loops and interdependencies between the systems may be impacted, causing some level of disturbance in the other system (Folke 2006; Deppisch and Hasibovic 2013; Thompson, Frazier, and Vachon 2016; Sullivan and Artino 2013).

However, many political ecology/political economy studies often only examine the social aspect of vulnerability and fail to include the influence of biophysical exposure on overall system vulnerability and resilience. Political economy and ecology research does not examine the influence of exposure on overall vulnerability and provides inaccurate information as to how disturbances in each system influence the other. The concept of resilience originally developed from an ecological perspective as a way to characterize an ecosystem's ability to maintain itself or recover from disturbance (Holling 1973; Berkes 2007; Rose 2007; Cutter et al. 2008). Researchers in the human-environment field use resilience to determine social and environmental changes across a landscape, where humans are not viewed as the only affected species (Chapin et al. 2004; Eakin and Luers 2006). Natural hazards studies in particular use resilience as a way to examine the ability of a community to recover from a disaster event from a systems, not individual, perspective. Therefore, examining the vulnerability of both systems is important because it provides a holistic view of how disturbances in either system impact the other.

Resilience theory in the natural hazards field also has a large focus on adaptive capacity and highlights a necessity for adaptive capacity in both the biophysical and social systems (Adger et al. 2005). This theory challenges traditional hazard mitigation policy notions in that it advocates adaptable and sustainable mitigation decisions that may not fall within traditional change-resistant mitigation strategies (Eakin and Luers 2006; Folke 2006; Berkes 2007). Resilience theory encourages systems to develop adaptable ways to deal with disturbances in the systems rather than simply trying to resist or control change (Berkes 2007).

2.3 Overview of Existing Vulnerability Frameworks

The natural hazards field has several conceptual frameworks that were developed to enhance the use of theory. This section provides an overview of pivotal models in the natural hazards field, but is by no means an exhaustive list. These models are, however, the main basis for most vulnerability research being conducted today. One of the first conceptual models developed in the natural hazards field was the Hazards of Place model developed by Cutter (1996). The Hazards of Place model is a conceptual model that accounts for locally based vulnerability with parameters that change over time. The Hazards of Place model uses the risk/hazard and political ecology theoretical perspectives to demonstrate how different elements that influence vulnerability interact with one another from a fairly simplistic perspective (Cutter 1996; Cutter et al. 2009). The purpose of the Hazards of Place model is to integrate the influences of the biophysical and social vulnerability on a particular place by attaching them to a place-based model (Cutter 1996; Cutter, Mitchell, and Scott 2000).

Another conceptual model developed by Blaikie et al. (1994) was the Pressure and Release (PAR) model, which is used to demonstrate how natural hazards affect vulnerable populations. According to Hufschmidt (2011), the PAR model is considered one of the best conceptual frameworks for summarizing the structural perspective (i.e. political economy and ecology). The PAR model assumes that a disaster occurs when two opposing forces (a hazard event and pre-existing vulnerability) intersect, causing pressure to occur from both sides. In order to lower that pressure, or provide 'release,' vulnerability must be reduced. The PAR model focuses on how existing vulnerabilities cause exposure to certain hazards to become 'unsafe' so that actions can be taken to reduce those pressures (Cutter 1996; Turner et al. 2003; Blaikie et al. 2004). The PAR model serves as a way to bridge the gap between human ecology and natural hazards theoretical perspectives and was one of the first models to synthesize the interaction between social and biophysical vulnerability (Adger 2006).

Another common conceptual model used in the natural hazards field is the vulnerability framework developed by Turner et al. (2003). This model proposes a framework for vulnerability analyses using three major components: 1) linkages between human and biophysical processes 2) stressors on the system, including natural hazards, and 3) the human–environment system, which includes exposure, sensitivity and resilience (Turner et al. 2003). This framework is technically a climate change framework that has been adopted by several researchers in the natural hazards field to assess vulnerability (Cutter, Boruff, and Shirley 2003; Wood, Burton, and Cutter 2010; Frazier, Thompson, and Dezzani 2014).

The Social Vulnerability Index (SoVI) is a vulnerability index that was developed by Cutter, Boruff, and Shirley (2003) to assess and measure social vulnerability at the county scale using national vulnerability indicators. The SoVI model uses the Hazards of Place model (Cutter 1996) as the foundation for measuring vulnerability, meaning that the SoVI is based on political ecology risk/hazard theoretical perspectives (Cutter et al. 2009). In order to develop the index, the SoVI conducts principal component analysis (PCA) on a list of traditional vulnerability indicators to identify statistically significant socioeconomic, demographic, and built environment variables that are empirically considered to have an influence on vulnerability (Cutter, Boruff, and Shirley 2003). This index is capable of providing a relative vulnerability score for each county in the nation, at the county scale.

The vulnerability scoping diagram (VSD) was developed by Polsky, Neff, and Yarnal (2007) as a way to conceptualize vulnerability from several perspectives. Due to the variation in vulnerability studies and definitions, Polsky, Neff, and Yarnal (2007) sought to develop an "all-embracing methodological approach" that can effectively be used across disciplines, even though it is developed from a climate change perspective. The main function of the VSD itself is to serve as a method for gathering and organizing information about the three components of vulnerability: exposure, sensitivity and adaptive capacity. The VSD then serves as step 5 in the ''Eight Steps'' methodological protocol developed by Cakmak and Burnett (2003) to characterize vulnerability holistically (Polsky, Neff, and Yarnal 2007). The VSD attempts to provide an interdisciplinary standardized vulnerability assessments methodology, but other disciplines have different theoretical foundations and definitions of vulnerability, causing the VSD framework to have no set real theoretical framing.

As a response to limitations in current natural hazards literature, previous research by Frazier, Thompson, and Dezzani (2014) undertook the challenge of overcoming these limitations in vulnerability and resilience research by developing a Spatially Explicit Resilience and Vulnerability (SERV) model. The SERV model better determines community scale vulnerability and resilience using differentially weighted place-specific, spatial, and temporal vulnerability indicators. The SERV model is the first vulnerability and resilience assessment tool that considers all three components of vulnerability (exposure, sensitivity, and adaptive capacity) when calculating community vulnerability and resilience scores. SERV uses local data (sub-county level data), thus allowing for the targeting of mitigation and adaptation at the sub-county spatial scale. The SERV model employs the Hazards of Place model (Cutter 1996), the Turner et al. (2003) model and political economy and ecology (Eakin and Luers 2006) as the theoretical foundation for measuring vulnerability using place weighted place-specific, spatial, and multiscalar vulnerability indicators.

2.3.1 Theoretical and Methodological Limitations of Existing Vulnerability Frameworks

While these conceptual models are based on theory, there is a disparity between cited theoretical foundations in research and applied methods. This disconnect is evident in the theoretical foundations and applied methods in existing natural hazards conceptual models. For example, the Hazards of Place model cited the risk/hazard theory and political ecology as its theoretical foundation, but it fails to examine root causes of social vulnerability (Cutter et al. 2009). Cutter (1996) and Cutter (2003) also do not explicitly demonstrate asymmetric power amongst actors, which is a key driver behind political ecology (Adams 2003). The PAR model also demonstrates the disparity between its theoretical foundations and applied methods. While the PAR model summarizes the structural perspective, the model does not take the role of human agency on access to resources into account (Pelling 1998). In addition, the PAR model does not provide a theoretical analysis of social and environmental interactions that serve as 'pressures' on the human-environment system (Blaikie et al. 1994; Turner et al. 2003).

The vulnerability framework developed by Turner et al. (2003) attempted to address these limitations of previous models by examining vulnerability from a holistic perspective. However, the framework is difficult to test empirically due to the complexity of the framework. This framework also claims to build on risk/hazard, political economy and political ecology theoretical principals (Turner et al. 2003), but it fails to examine root causes of social vulnerability in a detailed manner. The generality of the framework makes the possibility of integrating components of social theory into the human environment component plausible, but it is not strictly stated as being part of the framework development. The VSD model suffers similar issues in that it could provide a standardized method for conducting vulnerability assessments, but it has no real theoretical framing and serves simply as an applied framework due to data limitations, differentiating research goals and differing theoretical framings of vulnerability.

The SoVI model also demonstrates limitations to its theoretical background. The SoVI utilizes the Turner et al. (2003) conceptual framework definition of vulnerability as a function of exposure, sensitivity and resilience, and uses the Hazards of Place model (Cutter 1996) as the foundation for measuring vulnerability. Therefore, like models it bases its theoretical foundations on, SoVI fails to examine root causes of social vulnerability indicators (Cutter et al. 2009) and does not incorporate the effects of exposure or resilience on overall vulnerability; it simply describes county level sensitivity through sensitivity indicators (Cutter, Boruff, and Shirley 2003).

Some studies have conducted meta-analyses on vulnerability studies to determine the level of theoretical coherence in the natural hazards field. The results demonstrate that the gap between cited theoretical foundations in research and applied methods goes beyond the mentioned studies or conceptual frameworks. Zou and Thomalla (2008) demonstrated through their meta-analysis of social vulnerability to coastal hazards in South and Southeast Asia that the majority of vulnerability studies do not refer to particular theoretical or conceptual frameworks for their assessments (about 86%). While some studies address a theoretical framework, no study in the meta-analysis actually utilized the identified framework or conceptual model in the vulnerability analysis (Zou and Thomalla 2008; Miller et al. 2010). Other meta-analyses further emphasized this disconnect in studies where the theoretical foundations of vulnerability are mentioned, but not applied (Zou and Thomalla 2008; Miller et al. 2010).

Many vulnerability assessments often neglect the influences socioeconomic factors have on vulnerability because it is often difficult to quantify indicators that are qualitative in nature (Cutter 2003; Cutter et al. 2008; Cutter, Burton, and Emrich 2010). Due to this challenge, studies in the natural hazards literature developed vulnerability indices as quantification methods that provide vulnerability scores that can help guide hazard mitigation planning and policies (Jones and Andrey 2007; Wood, Burton, and Cutter 2010; Tate 2012).

Several vulnerability models are said to be based on political ecology, but some limitations to the models suggest these foundations are mentioned in the research methods and not necessarily applied. Political ecology emphasizes the importance of multiscalar interactions and relationships between society and nature (Adger et al. 2001; Eakin and Luers 2006). However, many vulnerability studies do not include multiscalar indicators (Gotway and Young 2002; Arbia and Petrarca 2011; Frazier, Thompson, and Dezzani 2013, 2014). Indicators that are not multiscalar do not account for these relationships and indicators developed for one scale may not necessarily be applicable to other scales (Jones and Andrey 2007). Existing models also do not include external indicators that might influence vulnerability, such as federal funding sources, disaster relief funds and other outside agencies that aid communities during a hazard event. These types of aid programs might increase a community's overall resilience, but that information is not typically incorporated into current studies.

Existing vulnerability models often also neglect place-specific, spatial, and temporal vulnerability indicators (Jones and Andrey 2007; Wood, Burton, and Cutter 2010). These indicators reflect unique characteristics of the place, socioeconomic and biophysical factors, as well as spatial dependencies based on relationships or linkages with other places (Burby 1999; Füssel 2007; Cutter et al. 2008; Godschalk 2003). Some studies have accounted for unequal distribution of vulnerability within a study area by using higher resolution indicator data (Wood, Burton, and Cutter 2010; Wang and Yarnal 2012), but they do not weight the influence of individual indicators on vulnerability. Indicators are spatially explicit, so they will have differential impacts on vulnerability (Frazier, Thompson, and Dezzani 2014; Frazier, Thompson, et al. 2013). Therefore, assessing differential influence of indicators can identify areas where specific vulnerability indicators are prevalent (Frazier, Thompson, and Dezzani 2014; Frazier, Thompson, et al. 2013; Wood, Burton, and Cutter 2010).

In addition, many vulnerability models do not model the effects of exposure, sensitivity, and adaptive capacity in conjunction with one another. Existing vulnerability indices predominately conduct an exposure or sensitivity analysis for vulnerability assessments (Cutter 2003). The influence of adaptive capacity on vulnerability is rarely incorporated into vulnerability assessments (often through the inclusion of a few indicators within a sensitivity index) or is completely disregarded (Frazier, Thompson, and Dezzani 2014; Wood, Burton, and Cutter 2010). The direct impact of adaptive capacity on vulnerability is that it reduces social vulnerability (Adger et al. 2004). While several adaptive capacity indices exist, many studies do not use them in conjunction with vulnerability indices that also describe socioeconomic exposure and sensitivity (Engle 2011; Gupta et al. 2010; Nelson et al. 2010). Vulnerability assessments that do not examine the effects of all three components can potentially provide incomplete appraisals of vulnerability (Brooks 2003; Frazier, Thompson, and Dezzani 2014; Füssel 2007). Therefore, vulnerability assessments are often incomplete, and do not provide a full representation of community vulnerability.

2.4 Opportunities for Injecting Social Theory into Natural Hazards Literature

Existing conceptual models do try to incorporate theory into the natural hazards field, but still have several theoretical limitations. Despite the lack of theory (or application of theory) in natural hazards methodologies, theory from other disciplines could be integrated into natural hazards research to further develop the theoretical foundation of the discipline. Political economy and political ecology can be more explicitly used to inject theory into vulnerability studies. These theories approach key vulnerability indicators by examining underlying socioeconomic processes and social structures that influence how people deal with and respond to disaster events (Bogard 1988; Oliver-Smith 1996; Goldman and Schurman 2000; Eakin and Luers 2006; Miller et al. 2010). Political economy is typically used in the natural hazards discipline as a theoretical support when identifying certain socio-political, economic and cultural indicators of vulnerability that help to explain social inequalities (Eakin and Luers 2006). Political economy could help researchers identify non-physical factors that contribute to vulnerability and provide a more complete understanding of social processes that lead to uneven distribution of social vulnerability. Political economy can also be used to examine how historical land-use processes, existing resource distribution and access, and historical power dynamics reinforce marginalization patterns that influence vulnerability (Warf 1997; Eakin and Luers 2006).

Political ecology foundations applied to methods could pick up where political economy ends by addressing nature as an agent and examining the influence of scale in indicator behavior. Political economy uses a top-down approach whereas political ecology examines vulnerability from a bottom–up (local to global) perspective, which is better suited for effective community mitigation (Rangan and Kull 2009). Political ecology also provides a framework that can examine the relationships between society and nature from a multiscalar perspective (Adger et al. 2001; Eakin and Luers 2006). This would allow natural hazards researchers to consider both global and local influences on vulnerability within the same conceptual framework. Multiscalar indicators are important to consider because vulnerability varies spatially and indicators of vulnerability exist and interact at several scales (i.e. federal aid, household income, etc.) (Füssel 2007). Blaikie and Brookfield (1987) developed a definition of regional political ecology that examines how different scales and hierarchies within the social structure and the environment interact or influence each other over time (Blaikie and Brookfield 1987; Rangan and Kull 2009). Utilizing political ecology in the natural hazards field would, therefore, allow researchers to better understand how social interaction and social organization processes occurring across several spatial scales influence vulnerability. Basing future naturals hazards research on these types of theoretical frameworks can help researchers further investigate why people live in risky areas and help develop ways to mitigate against policies or social processes that perpetuate these types of development patterns (Goldman and Schurman 2000).

Several social theories that have been developed in sociology and psychology may also be applied in vulnerability studies, such as social theory, social justice or environmental justice. Social theory describes theories that identify underlying social processes that increase vulnerability to hazards (Bogard 1988; Klein, Nicholls, and Thomalla 2003). While social theory is technically present in natural hazards literature (i.e. vulnerability indicator selection), it is not explicitly stated as such or it is not acknowledged by researchers. For example, Morrow (1999), Fothergill and Peek (2004), and Cutter, Boruff, and Shirley (2003) employ aspects of political economy/ecology, environmental justice, social justice and structuration (access to resources, power, agency, political influence, etc.) in vulnerability indicators selection, but poorly acknowledge those theoretical frameworks. These theories may also examine how social variables (such as gender race, wealth, class, etc.) can cause differential levels of vulnerability and can help provide insight as to underlying processes that perpetuate those patterns of differential impact (Eakin and Luers 2006; Miller et al. 2010; Oliver-Smith 2005). Therefore, injecting these types of theories into the natural hazards field would provide additional insight into how social processes perpetuate social inequalities and an unequal access to resources.

Structuration theory is a sociology-based theoretical framework developed by Giddens (1984) that could be used to further include social theory foundations in vulnerability studies due to its examination of power and agency. Structuration theory defines social structures as roles and resources that actors use when interacting within society (Giddens 1984; Cozzens and Gieryn 1990). Different roles and resources provide different levels of power and agency, affecting an individual's ability to act (Giddens 1984). Agency describes the capacity of an agent to act in the world and power must be exercised in order for an individual to 'act' in a way that 'makes a difference' (Giddens 1984; Turner 1986). Power is not inherent but is gathered by people with access to certain resources (Giddens 1984; Turner 1986). This means that social structures (which is a result of repetitive human behavior) and human agency both influence social life (Giddens 1984; Turner 1986). Because power is necessary for agents to 'act,' power should also be a first-order consideration in the social sciences.

The main basis of structuration theory is derived from the idea that the actions of the agents are continuously developing or altering social structures while simultaneously drawing on existing social structures (Giddens 1984; Cozzens and Gieryn 1990). The system's 'duality' is based on the actors' implicit knowledge of social rules/regulations and using that knowledge to guide their behavior. Structural properties such as rules and resources are then used in conjunction to represent the presence or absence of domination or power (Giddens 1984). This distinction is important to structuration theory because *structure* symbolizes the order of rules and resources, whereas observable social behaviors or interactions (or development of social structure) are considered to be the *system* (Giddens 1984; Cozzens and Gieryn 1990). Combinations of these rules and resources result in types of institutions, which allow social structures to be examined through the interplay of these types of institutions instead of conducting studies from a 'one-sided' perspective (Cozzens and Gieryn 1990). Scale is associated with structures and the system in that different resources and different rules are available at different levels of interaction. Hierarchy theory argues that systems order themselves into a set of processes and structures that exist at different spatial levels (Birkmann 2007; Fekete, Damm, and Birkmann 2010; Jonas 2006; Marston, Jones, and Woodward 2005).

Structuration theory could be used in the natural hazards field to model how differential levels of power and agency affect vulnerability in terms of how they create social structures that limit access to resources and help identify how social structures and processes that help perpetuate patterns of power and agency create differential access to resources and vulnerability. Scale for this research relates the spatial levels of organization within which different structures and interactions occur, especially as they relate to institutional levels that may constrain a person's or agency's ability to implement disaster reduction techniques. Structuration could also be used to also examine how structure and agency influence vestedness or inhibitions toward mitigation strategy development and implementation. Oftentimes, the people that are most affected by hazards are typically those with the least agency. Therefore, they often have or feel they have less power to enact or influence hazard mitigation planning or policy.

Risk perception can also influence risk tolerance, which can impact development patterns and mitigation strategy implementation. When people are faced with a threat, they evaluate how the threat concerns them and then whether they feel they can do anything about the threat (Miller, Adame, and Moore 2013). A person's sense of place can also influence risk perception. Place attachment can cause people to become unwilling to relocate during a hazard event (Oliver-Smith 1996; Miller, Adame, and Moore 2013). If forced to resettle elsewhere post-disaster, people can be traumatized by the loss of their sense of place (Oliver-Smith 1996). Previous studies have also found that risk perception can influence evacuation behavior and mitigation strategy implementation (Barnett and Breakwell 2001; Frewer 1999; Matyas et al. 2011; Paton et al. 2008; Sjöberg 1999), which, in turn, can influence vulnerability. However, many studies do not address how risk perception affects vulnerability from a multiscalar level.

2.5 The INSeRT Framework

In response to current gaps in the natural hazards theory, this research presents the **IN**jecting **S**tructuration into **R**esilience/Vulnerability S**T**udies (INSeRT) conceptual framework developed from a resilience theory, political ecology, and structuration theoretical perspective. The basis for the INSeRT framework comes from the need to supplement existing natural hazards theory with greater theoretical foundations. Of the aforementioned theories, structuration theory and political ecology are the most appropriate for measuring vulnerability from a perspective that accounts for institutional hierarchies within society and includes multiscalar vulnerability indicator data. The impact of natural events on a community is usually determined by everyday patterns of social interaction, social organization and access to resources (Morrow 1999). Social structures systematically discriminate against marginalized populations, which increases vulnerability at several scales (Ugarte, Ibáñez, and Militino 2005; Morrow 2008). The impact of natural events on a community is usually determined by everyday patterns of social interaction, social organization and access to resources (Morrow 1999). Therefore, a framework that considers the social structuration of society, the influence of multi-scalar factors and human-environment interaction would be useful for determine social vulnerability to natural hazards.

Structuration theory and political ecology serve as the theoretical basis for identifying individual factors that comprise the social system and how they perpetuate certain social processes that lead to uneven distribution of social vulnerability (Giddens 1984; Turner 1986; Blaikie and Brookfield 1987; Cozzens and Gieryn 1990; Pelling 1999). Society is inherently structural, so the employment of a structural or hierarchical model based on structuration theory principles better represents processes occurring within the current social structure (Giddens 1984; Cozzens and Gieryn 1990). Structuration theory can also illustrate how differential levels of power and agency affect vulnerability in terms of how they create social structures that limit access to resources (Giddens 1984; Turner 1986; Blaikie and Brookfield 1987; Cozzens and Gieryn 1990; Pelling 1999). Conceptual frameworks developed in resilience theory serve as the theoretical foundation for the development of adaptive capacity indicators that identify how social and environmental systems interact and measure the adaptive capacity of both systems to coastal hazards (Adger 2000; Peterson 2000; Folke 2006; Berkes 2007; Miller et al. 2010). This information can be used to identify areas with greater vulnerability, which can help guide mitigation and adaptation planning in targeting those processes to reduce their influence on overall vulnerability. Finally, political ecology serves as the theoretical basis for identifying individual factors that comprise the social system from a multiscalar perspective.

The proposed framework uses internal and external vulnerability indicators to holistically measure community vulnerability from a systems perspective. The framework incorporates non-traditional, external and site-specific indicators and can be altered to reflect how vulnerability affects the system from both a community and system perspective. Vulnerability indicators can also be identified through past literature and stakeholder engagement. The INSeRT framework incorporates the three components of vulnerability (exposure, sensitivity and adaptive capacity) by including related indicators in system-based components in a hierarchical model.

2.5.1 Framework Structure and Components

Society is hierarchical and segregated in space because socials structures impose different 'constraints' that have hierarchical levels of freedom (Schelling 1971). Society is segregated in that vulnerability indicators are variably spatially distributed, such as having high income neighborhoods adjacent to lower income areas, while hierarchy implies there is interaction between variable levels (and potentially scales) of the social system (Schelling 1971). There is an asymmetric level of power between different administrative levels (scales), resulting in differential levels of agency in different structures (Giddens 1984; Warren 2005).

Scale, as used in this study, differs somewhat from the ongoing debates concerning scale in human geography (Jonas 2006; Marston, Jones, and Woodward 2005; Moore 2008). Human geographers often perceive scale as a socially constructed artifact of observation for convenience of measurement, making it an arbitrary characteristic. However, governments and public agencies create and use such constructs for sound statistical and planning reasons. For example, counties and cities are usually divided into planning districts, so as to address community-level issues unique to those districts that can then be integrated to a larger-scale hazard mitigation plan.

Therefore, while units such as census blocks may be "constructed" objects used as primary units of analysis, they can be employed to establish variational measurements at two or more levels of resolution. Planners and managers of urban space employ these units of analysis as instruments for the analysis and augmentation of the built space. Without loss of generality, resolution and scale may be used interchangeably in this study. Scale can be used to define resolution aspects of a process (Cressie 1991). Variation of measurements of a process across two or more levels of resolution (i.e., scale) may provide support for a deeper understanding of the spatial response of the process (Cressie 1991).

Based on these assumptions, this research proposes modeling these relationships with a multilevel regression model that determines vulnerability based on a series of multiscalar indicators that describe different components of vulnerability in the human-environment system.

The INSeRT model assumes that that society is hierarchical (Cozzens and Gieryn 1990; Giddens 1984; Schelling 1971); therefore, a structural or hierarchical model would better represent processes occurring within the current social structure. Hierarchical models (also known as multilevel models) are statistical models whose parameters (i.e. indicators) vary at more than one level (or in this case, scale) (Banerjee, Carlin, and Gelfand 2004; Gelman and Hill 2007). Each level of the model is allowed to have its own predictors, which can differ (the scale can go from group level to individual or vice-versa), so the model results should represent the level (or administrative spatial scale) that the analysis is focused on (Banerjee, Carlin, and Gelfand 2004; Gelman and Hill 2007).

Hierarchical modeling allows vulnerability indicators to be multiscalar, meaning data inputs can differ by scale (i.e. group level to individual or vice-versa) without having to be aggregated to a single scale. This model structure preserves the integrity of original datasets that are often used in vulnerability modeling but are gathered at different spatial scales (i.e. census data at the block, block group, tract or county scales). Additionally, the multiscalar aspect of the model can also determine general system interaction, social interaction, social organization processes that occur across and between several spatial scales, something that analyses conducted at a single scale cannot measure. Figure 2.1 demonstrates the structure of the INSeRT framework and describes the different types of variables that are considered indicators of vulnerability and the scale at which they are gathered.

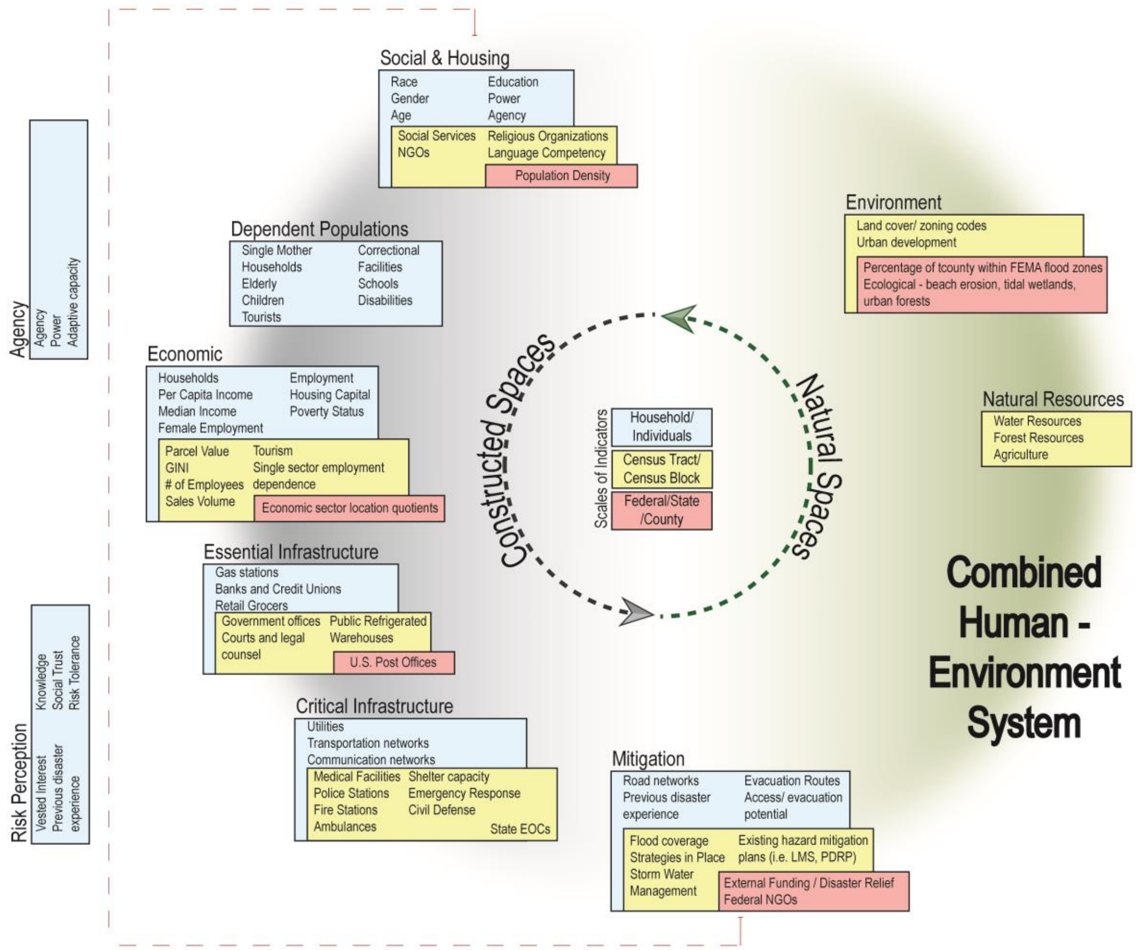

Figure 2.1 - Indicators by scales of measurement in INSeRT Framework

As seen in Figure 1, each level of the model is comprised of several indicators that have been identified by qualitative research as traditional causes of vulnerability. These indicators re based on previous research, which suggest that while identifying the number of total residents within the hazard zone is important, demographic characteristics can also affect an individual's vulnerability to a hazard event (Morrow 1999; Cutter 2003). Sociodemographic indicators include variables that impact social class, such as age, gender, race, education, social capital, or political agency, dependent populations (i.e. elderly or young children), economic variables that may influence social class and agency (i.e. household income or employment rates), and infrastructure components like major facilities that help keep the health, safety, and economy of the population intact. Vulnerability indicators occurring in natural spaces include existing mitigation measures, other institutional indicators that increase the recovery and adaptive capacity of the community, natural resources that are part of the environment and economy, land cover types, zoning codes, and natural ecological aspects of the environment that reduce the impacts of hazards (i.e. mangroves and wetlands help reduce storm surge impacts) (Wood et al. 2007; Cutter, Burton, and Emrich 2010; Frazier, Thompson, et al. 2013).

The blue boxes in Figure 1 represent variables that are typically gathered at a smaller scale, but are often aggregated to a larger, generalized scale, such as Census tracts or counties. When data aggregation occurs, the modifiable areal unit map problem (MAUP) can be introduced, as the scale of generalization may mask local data variation. This can lead to decision-making based on more generalized information, which can lead to oversight of existing local issues, especially in terms of hazard migration at a local scale.

The hierarchical aspect of the INSeRT framework allows multiscalar indicators to be included in the same regression analysis (such as variable census data levels and county level data sources) without lowering data integrity, something that is often lacking in many vulnerability studies (Frazier, Wood, and Yarnal 2009; Wood and Soulard 2009; Banerjee, Carlin, and Gelfand 2004; Gelman and Hill 2007). If this type of framework were applied to other vulnerability frameworks (i.e. the PAR, SoVI or other models) (Blaikie et al. 2004; Cutter, Boruff, and Shirley 2003; Schröter, Polsky, and Patt 2005; Polsky, Neff, and Yarnal 2007), the model results would provide detailed and localized information about how vulnerability differs at a sub-county or local scale. The INSeRT framework also permits the inclusion of non-traditional indictors, such as risk perception and measures of structures and agency, which heavily influence human behavior in the face of hazard events (Bang 2008; Kasperson and Kasperson 1996; Slovic 1987). These indicators can influence how people react to or cope with hazard events at both the individual and community level, but are difficult to quantify because they often gathered using qualitative measures and sampling schemes are developed at a single scale. The INSeRT model is multiscalar and can account for variation between datasets that are aggregated to different spatial scales (i.e. census block data versus county data), making the inclusion of these non-traditional indicators feasible for future vulnerability/resilience assessments. The INSeRT model would also better represent the level of influence variables have on vulnerability and how they interact with variables at different spatial scales.

This enhanced framework would allow indicators or variables from different scales to be applied to the same regression model, such as variable Census data levels and external data (Banerjee, Carlin, and Gelfand 2004; Gelman and Hill 2007). Including these types of indicators provides information that is not normally collected at the block level, but can still influence sensitivity or adaptive capacity within a given community. The INSeRT model also provides a systems-based approach that demonstrates how both the built/human and natural environment are impacted by risk and can be used to better determine overall human-environment systems failure. This information helps decision makers identify areas with greater vulnerability that are often lost in the data generalization, which can help guide mitigation and adaption planning in targeting those processes to reduce their influence on overall vulnerability.

2.6 Conclusion and Future Research Considerations

In natural hazards studies, developing a better understanding of the complex relationship between social systems and natural hazard impacts is important for developing strategies that help mitigate impacts and improve recovery potential. However, natural hazards studies are often applied and lack theoretical focus or mention theories as afterthoughts (Alexander 1997; Montz and Tobin 2011). Conducting research based on theoretical foundations is critical to maintaining rigor in research and ensuring that results across studies are comparable. Measuring and comparing model effectiveness is difficult if different methods are not developed with theoretical commonalities. Therefore, more theoretical basis in natural hazards studies and applied modeling methods is needed.

Due to these limitations in natural hazards research, this paper examines alternative theoretical foundations that can be used to develop a theoretical framework that utilizes social theory to better explain existing patterns of vulnerability and resilience and how those influence overall recovery potential. This research presents the INSeRT conceptual framework developed from a resilience theory, political ecology, and structuration theoretical perspective. The INSeRT framework can help explain why people live in risky areas and helps develop ways to mitigate against policies or social processes that perpetuate these types of development patterns (Goldman and Schurman 2000). Society is inherently structural, so the employment of a structural or hierarchical model based on structuration theory principles reliably represent processes occurring within the current social structures (Giddens 1984; Cozzens and Gieryn 1990).

While multilevel models allow this framework to incorporate multiscalar indicators of vulnerability, one major limitation needs to be addressed to make this framework relevant to real life applications. Traditional hierarchical models do not address spatial processes that violate classical statistical assumptions, but multilevel models can be modified to account for spatial processes (Banerjee, Carlin, and Gelfand 2004; Burt, Barber, and Rigby 2009). Future research using this framework will address these limitations to include the effect of spatial processes on statistical vulnerability and resilience modeling.

Future work using this framework also requires a quantification method for risk perception and agency as individual indicator components. However, these two components are difficult to measure with existing data sources because qualitative measures (i.e. surveys and focus groups) are used to gather relevant indicator information. The proposed framework describes socioeconomic vulnerability and resilience from a systems perspective, and risk perception and levels of agency can influence how people react to or cope with hazard events at both the individual and community level. Social vulnerability develops due to social inequalities that interfere with the access to resources and information, the ability to absorb the impacts of hazards and disasters without governmental interventions, housing choice and location, and the political marginalization of impoverished residents (Bogard 1988; Fothergill, Maestas, and Darlington 1999; Morrow 1999; Goldman and A. 2000; Eakin and Luers 2006). Agency is important to consider in vulnerability quantification because different levels of agency affect what resources people can access, thereby affecting an individual's ability to act or cope with a hazard event (Giddens 1984).

Agency is also related to the impact of risk perception on vulnerability. The way that people identify and measure risk based on information they have about the risk can come from a variety of sources and experiences (Slovic 1987; Kasperson et al. 1988), such as by social factors, direct experience with the hazard, indirect information about risk events, distrust in risk model outputs due to lack of knowledge, or lack of general knowledge about the risk (Kasperson et al. 1988; Howe 2011). Mitigation strategies for future hazards are often developed through perceptions of the consequences of future risks, not what might actually occur. People make decisions with the knowledge they have but do not assume that they know all of the alternative options (Bang 2008; Barnett and Breakwell 2001; Fischhoff et al. 2009; Frewer 1999), which emphasizes how much risk perception and risk tolerance drives mitigation practices. Risk perception and agency are also interconnected in that while some people may have heightened risk perception, they may not have the agency to implement changes or mitigation that can potentially help them decrease vulnerability.

Future research using the INSeRT framework will address the spatial modeling limitations of existing statistical models by including the effect of spatial processes in a hierarchical model. Applications of the INSeRT model will also focus on incorporating risk perception and agency indicators within the community as separate components in a hierarchical model through a mix of qualitative and quantitative methods. Future work will result in a model that can provide a measure of community recovery potential from a holistic social-structure perspective, based on existing vulnerability and resilience levels.

Chapter 3 – Hierarchical Modeling of Social Vulnerability

3.1 Introduction

Disasters result from an intersection of natural hazards and human environments (Cutter 2003; de Oliveira Mendes 2009; Frazier, Thompson, and Dezzani 2014; Morrow 2008). While natural hazards often cannot be controlled, disaster impacts can be managed and reduced using hazard mitigation planning (HMP). It is not possible to mitigate everywhere within the community when large numbers of societal assets are exposed to a hazard; therefore, targeting mitigation allows agencies with limited resources to mitigate in areas where hazard impacts are highest (Frazier, Thompson, and Dezzani 2014; Frazier, Thompson, et al. 2013). In order to target mitigation effectively, it is important to understand where exposure and vulnerability are highest within a community.

Disaster vulnerability is a social construct that develops based on unequal access to resources and power, settlement patterns and social order (Birkmann 2007; Cutter 2003; Morrow 1999). Vulnerability is generally described as a potential for loss and is influenced by both social (sociodemographic) and physical (natural exposure) characteristics (Cutter, Boruff, and Shirley 2003; Frazier, Thompson, and Dezzani 2014; Turner et al. 2003). The impact of natural events on a community is usually determined by everyday patterns of social interaction, social organization and access to resources (Morrow 1999). Physical vulnerability determines where a hazard is likely to occur, meaning that exposure can vary depending on the magnitude and intensity of the hazard (Cutter, Boruff, and Shirley 2003; Hufschmidt 2011; Wood, Burton, and Cutter 2010). Social vulnerability develops due to unequal access to resources and power, settlement patterns and social order (Morrow 1999). Social structures can discriminate against marginalized populations as they often lack the agency to exert power to access resources at different institutional levels, which can also increase vulnerability at several scales (Ugarte, Ibáñez, and Militino 2005). Physical and social vulnerability factors also interact with one another, as the physical landscape can drive where certain development occurs (Cutter and Emrich 2006; Cutter 1996; Thompson and Frazier 2014).

Recognizing existing vulnerability can aid decision makers in understanding what actions may help lower vulnerability, and in turn, increase resilience. Resilience is generally described as the ability of a system to resist and recover from a hazard event, through the development of adaptive processes that are based on learning from the hazard event experience (adaptive capacity) (Adger 2000; Adger et al. 2005; Gallopín 2006; Kimhi and Shamai 2004; Rose 2007; Zhou 2010) . While several factors can influence resilience, reducing vulnerability is considered to be one possible way to increase resilience vulnerability (Adger et al. 2005; Berkes 2007; Folke 2006; Folke et al. 2010). Despite the benefits of employing mitigation and adaptation tools such as economic incentives and legislation that can help reduce overall vulnerability, it is difficult to guide or relocate development out of the hazardous areas due to competing interests (Frazier, Walker, et al. 2013; Frazier, Wood, and Yarnal 2010). As the relocation of structures is typically an infeasible HMP option, it is important for communities to lower their vulnerability and increase resilience through other methods, such as targeting and reducing the influence of specific vulnerability indicators.

Decision makers often conduct vulnerability assessments to identify sources of vulnerability. Vulnerability assessments illustrate what areas in a community are most vulnerable and allows agencies with limited resources to mitigate areas where hazards impacts are highest (Frazier, Thompson, and Dezzani 2014; Frazier, Thompson, et al. 2013), which is important for post-disaster recovery (Tierney and Oliver-Smith 2012; Reid 2013). Vulnerability is typically measured through quantitative frameworks that provide vulnerability scores that can be used to guide hazard mitigation policies and planning (Jones and Andrey 2007; Tate 2012). Proactive HMP that utilizes vulnerability and resilience assessments to help reduce disaster impacts (Frazier, Thompson, and Dezzani 2014; Berke and Godschalk 2009; Burby 2006a; Burby et al. 2000).

Early vulnerability assessments examined physical vulnerability, which describes how proximal communities were to potential hazard impacts (exposure) (White 1945), but did not examine social processes that can exacerbate vulnerability and cause differential impacts to occur (Eakin and Luers 2006; White 1945). For this reason, more recent vulnerability studies focused on the inclusion of data that is representative of both physical and social vulnerability. Socioeconomic factors provide information about inequalities in the social structure that might increase or decrease an individual’s vulnerability to hazards.

Earlier studies on vulnerability assessments neglect the influences of socioeconomic factors on vulnerability because it is difficult to quantify indicators that are inherently qualitative in nature (Cutter 2003; Cutter, Burton, and Emrich 2010; Frazier, Thompson, and Dezzani 2014). Some studies quantify vulnerability using vulnerability indices, which provide a tangible vulnerability score that can be used to guide hazard mitigation policies and planning (Jones and Andrey 2007; Tate 2012; Wood, Burton, and Cutter 2010). These indices measure total community vulnerability, as well as the influence of physical and social factors on overall vulnerability (Birkmann 2007; Cutter 2003; Cutter, Burton, and Emrich 2010; Jones and Andrey 2007; Tate 2012).

Existing vulnerability assessments, however, have several limitations that make them less applicable for sub-county HMP and are not as sophisticated in terms of their statistical modeling methods. Many vulnerability assessments are conducted at the county level, resulting in assessments that generalize local vulnerability and are less effective for community level HMP (Frazier, Thompson, et al. 2013; Frazier, Wood, and Yarnal 2010). Previous work suggests that conducting hazard analysis at larger spatial scales often does not provide sufficient information about processes occurring at the local level (Tiefelsdorf and Griffith 2007; Ostrom 2009; Frazier et al. 2010). Current vulnerability assessments also neglect place and scale specific indicators, do not weight indicators differentially based on their influence on vulnerability and do not examine the effects of spatial patterns (i.e. spatial autocorrelation) on classical statistical techniques (Cutter, Boruff, and Shirley 2003; Fekete 2012; Fotheringham and Rogerson 2009; Frazier, Thompson, and Dezzani 2014, 2013). It is important to incorporate locally derived factors, rather than relying solely on nationally collected data because vulnerability varies spatially (Fekete, Damm, and Birkmann 2010; Frazier, Thompson, and Dezzani 2014; Frazier et al. 2010; Wood, Burton, and Cutter 2010). Excluding local indicators, therefore, can hinder the effectiveness of sub-county hazard mitigation, potentially influencing community preparedness (Berke and Godschalk 2009; Burby 1999; Burby 2006b; Burby et al. 2000).

Many vulnerability assessments are also conducted at a specific scale, meaning that any indicators used are either aggregated to a more generalized scale of analysis or downscaled, both of which can introduce issues based on the modifiable areal unit problem (MAUP) or the ecological fallacy (Burt, Barber, and Rigby 2009; Tiefelsdorf and Griffith 2007; Ostrom 2009). Vulnerability is heterogeneous across landscapes and socioeconomic variables gathered at different spatial scales are often interdependent (Tiefelsdorf and Griffith 2007; Ostrom 2009). The scale of analysis can affect the utility and reliability of vulnerability assessment estimations for different levels of hazard management and policy implementation. Vulnerability assessments conducted at one scale can provide information about how vulnerability differs at that particular spatial scale, but the results may not necessarily be representative of indicators that were aggregated to different scales (Frazier, Thompson, and Dezzani 2014). These types of assessments also only use indicators that are gathered or aggregated to a single scale, which is problematic when smaller-scale indicators are interdependent of larger-scale factors. For example, census tracts income and employment data is often related to census block demographic data, but when these variables are aggregated or downscaled to one level or the other, information about the relationships between variables at different administrative units is lost. Vulnerability assessments that account for multiscalar variables, spatial effects in the data and between-scale interactions between indicators can provide more accurate information about sub-county vulnerability.

Another limitation of existing vulnerability assessments is that some vulnerability quantification methods are not structured in ways that reflect their theoretical foundations, such as the risk/hazard theory, political economy, and political ecology. These theories examine how natural hazards impacts in a community are determined by everyday patterns of social interaction, social organization and unequal access to resources (Warf 1997; Eakin and Luers 2006; Sheppard 2011), and often drive indicator development in frameworks such as the SoVI, VSD, or SVI (Cutter, Boruff, and Shirley 2003; Hahn, Riederer, and Foster 2009; Tate 2012; Vincent 2004; Flanagan et al. 2011; Polsky, Neff, and Yarnal 2007).

Several studies often employ OLS as a preliminary tool for determining significant variables for regression modeling, testing for spatial process that may negate classical regression analysis, or identifying variables with multicollinearity (Benson, Chamberlin, and Rhinehart 2005; Burt, Barber, and Rigby 2009; Chatterjee and Simonoff 2013; Thompson and Frazier 2014). However, the quantification methods behind these indices do not reflect the multiscalar emphasis of political ecology, as indicators are aggregated to the same scale. These indices also utilize classical statistical methods like principal component analysis or regression modeling to measure total community vulnerability, as well as the influence of certain physical and social factors on vulnerability at various jurisdictional and socio-political levels (Birkmann 2007; Cutter, Boruff, and Shirley 2003; Wood, Burton, and Cutter 2010). However, these methods neglect spatial effects or interactions occurring between indicators occurring at different scales. Society is segregated and hierarchical, making scale a crucial consideration for accounting for interactions between multiscalar variables (Cozzens and Gieryn 1990; Giddens 1984; Schelling 1971; Subramanian, Duncan, and Jones 2001). Scale and spatial processes can inhibit the reliability of certain analytical types and physical hazard models devised for specific scales, resulting in biased conclusions based on the way areal units or scale of analysis are defined (Arbia and Petrarca 2011; Burt, Barber, and Rigby 2009).

For these reasons, examining the impact of the social structuration of society, multi-scalar factors and human-environment interactions on vulnerability is useful for determining social vulnerability to natural hazards. To address these limitations, this research presents a vulnerability assessment methodology that examines the impact of spatially-explicitly and multi-scalar socioeconomic and physical factors on vulnerability using structuration theory and political ecology, as the major theoretical foundations. This study employs a multilevel regression model with spatial components was utilized to measure vulnerability based on multiscalar indicators that describe different components of the human-environment system to quantify vulnerability/resilience using these theoretical perspectives. Structuration theory and political ecology provide a theoretical basis for identifying individual factors that comprise the social system and help determine how they perpetuate certain social processes that lead to uneven distribution of social vulnerability (Giddens 1984; Blaikie and Brookfield 1987; Cozzens and Gieryn 1990; Pelling 1999; Turner et al. 2003).

This study also utilizes scale in a manner that differs from definitions that have been offered in the ongoing debates concerning scale in human geography (Fekete, Damm, and Birkmann 2010; Jonas 2006; Marston, Jones, and Woodward 2005). Many human geographers perceive scale as a socially constructed artifact used for measurement. (MacKinnon 2011; Moore 2008)While these artifacts are essentially arbitrary, governments and public agencies create and use such constructs for statistical and planning purposes (MacKinnon 2011). Administrative units such as census blocks may be “constructed”, but they are still used by hazard mitigation planners as instruments for the analysis and augmentation of the built space, thereby making these units “real” (Barnes and Hannah 2001). For example, counties and cities are usually divided into planning districts, so that community-level issues unique to those districts can be integrated into larger-scale hazard mitigation plans. Census tracts and blocks are designed to minimize internal socio-economic variation for relatively fixed sample sizes (Census 1994), making them useful for community level planning, as different “but similar” blocks can then be compared against one another. Additionally, governments and public agencies use statistical scales to define the scale or resolution of a statistical analysis, which helps them create vulnerability assessments whose results are used as a viable basis for comparison of exposure or vulnerability across administrative units (i.e. counties, census tracts, etc.) (Census 1994).

Scale, in this study, is used to define resolution aspects of a process (Cressie 1991), as the variation of measurements of a vulnerability across two or more levels of resolution (i.e., spatial scale) can provide support for a deeper understanding of the spatial response of vulnerability. This study employs a multilevel regression model with spatial components was utilized to measure vulnerability based on multiscalar indicators that describe different components of the human-environment system to quantify vulnerability/resilience using these theoretical perspectives. Structuration theory and political ecology provide a theoretical basis for identifying individual factors that comprise the social system and help determine how they perpetuate certain social processes that lead to uneven distribution of social vulnerability (Giddens 1984; Blaikie and Brookfield 1987; Cozzens and Gieryn 1990; Pelling 1999; Turner et al. 2003). While this framework may imply a hierarchy of information, a single function defining the linkage of variability behaviors across scale (i.e., resolution orders), provides a concise description of the spatial behavior of the vulnerability in Sarasota County, Florida as a case study.

3.2 Literature Review of Existing Vulnerability Quantification Methods

Vulnerability is often difficult to measure because vulnerability indicators are qualitative in nature (Cutter, Burton, and Emrich 2010; Frazier, Thompson, and Dezzani 2014; Frazier, Thompson, et al. 2013), leading to the development of socioeconomic vulnerability indicators that serve as data proxies for qualitative social characteristics. Socioeconomic factors in vulnerability analyses provide a more complete assessment of individuals' access to resources, which is often considered a primary indicator of vulnerability (Cutter, Boruff, and Shirley 2003; Fothergill and Peek 2004; Morrow 1999). Socioeconomic factors also provide information about inequalities in the social structure that might increase or decrease an individual's vulnerability to hazards. Several theories, such as political economy/ecology, environmental justice, social justice and the behavioral response approach are used to identify social variables that can cause differential levels of vulnerability within a population (Eakin and Luers 2006; Miller et al. 2010; Oliver-Smith 1996; Oliver-Smith et al. 2012). However, while theory has been used to identify certain socioeconomic variables, current studies do not use the same socioeconomic information to examine underlying social processes that perpetuate certain social conditions.

3.2.1 Traditional Measures of Vulnerability/Resilience Using Indicators/Data Proxies

The methods through which socioeconomic data proxies are gathered and formatted for use in vulnerability indices also do not necessary reflect their theoretical basis. Many vulnerability models use place-specific and spatial vulnerability indicators (Jones and Andrey 2007; Wood, Burton, and Cutter 2010; Birkmann et al. 2013), that reflect unique socioeconomic and biophysical characteristics of a place (Burby 1999; Cutter et al. 2008; Füssel 2007; Godschalk 2003). These indicators are important for capturing spatially explicit vulnerability for specific areas because they capture the unequal distribution of vulnerability indicators across an area. Some studies account for unequal distribution of vulnerability by using higher resolution indicator data (Wood, Burton, and Cutter 2010; Wang and Yarnal 2012), but the level of influence of individual indicators on vulnerability is not examined (Frazier, Thompson, and Dezzani 2013, 2014; Frazier, Thompson, et al. 2013).

Other vulnerability studies do not include multiscalar indicators (Gotway and Young 2002; Arbia and Petrarca 2011; Frazier, Thompson, and Dezzani 2013, 2014), which is a key driver behind political ecology. Political ecology examines multiscalar interactions and relationships between social (Adger et al. 2001; Eakin and Luers 2006) and physical processes (Peterson 2000; Adams 2003) on vulnerability. Society is hierarchical in that social structures impose different 'constraints' that have hierarchical levels of freedom to engage in specific types of behaviors (i.e. choosing to implement risk reducing mitigation on their home, but being unable to get necessary county zoning permits). There is an asymmetric level of power between different levels, resulting in differential levels of agency operating in and through the hierarchical structure (Giddens 1984; Warren 2005). Multiscalar indicators may be interdependent, such as socioeconomic variables that are related, but aggregated at different scales (i.e. census block demographic data is related to census block group economic data). Multiscalar indicators are also important to consider because indicators that exist or develop at one scale and may not necessarily be applicable to other scales (Jones and Andrey 2007; Subramanian, Duncan, and Jones 2001). Neglecting multiscalar indicators, therefore, causes quantitative models to overlook scalar interactions that are key to understanding how vulnerability develops within a social hierarchy.

3.2.2 Traditional Quantitative Methods

Vulnerability researcher often attempts to measure social and physical vulnerability using statistical methods, such as regression modeling, to develop vulnerability models or indices that provide quantitative vulnerability scores that can be used to guide hazard mitigation policies and planning (Jones and Andrey 2007; Tate 2012). These methods measure total community vulnerability as well as the influence of certain physical and social factors on vulnerability at various jurisdictional and socio-political levels (Birkmann 2007; Cutter, Boruff, and Shirley 2003; Wood, Burton, and Cutter 2010).

One of the most prevalent statistical analyses used in the hazards research is principal component analysis (PCA). Hazards researchers often use PCA to determine significant and interrelated indicators of vulnerability, resilience, sensitivity or adaptive capacity for index or regression model development (Cutter, Boruff, and Shirley 2003; Frazier, Thompson, and Dezzani 2014; Wood, Burton, and Cutter 2010; Myers, Slack, and Singelmann 2008). While several variables have been identified as indicators or data proxies of vulnerability (i.e. race, age, sex, female-headed households, high tourism areas, and economic vitality) (Fothergill, Maestas, and Darlington 1999; Morrow 1999), indicators are often place-specific, meaning that some traditional indicators may be significant in one area, but not in another area (Wood, Burton, and Cutter 2010; Frazier, Thompson, et al. 2013; Frazier, Thompson, and Dezzani 2014). PCA can be used to identify place-specific vulnerability indicators and help weight indicators by their overall influence in vulnerability (Cutter, Boruff, and Shirley 2003; Wood, Burton, and Cutter 2010; Frazier, Thompson, and Dezzani 2014).

While PCA modeling can identify vulnerability indicators of interest for a given area, it is not applicable for predictive purposes. In order to model relationships between vulnerability indicators and their impact on overall vulnerability, regression modeling is more appropriate, as multiple regression examines the relationship between the dependent and independent variables. PCA serves more as a data reduction technique that identifies covariance relationships between indicator variables without indicating how much indicators interact with one another to influence a dependent variable. Therefore, to quantify the interaction between indicators and their influence on vulnerability, researchers employ regression modeling like classical linear regression.

Some existing studies employ classical regression models using ordinary least squares estimation (OLS) for preliminary data exploration OLS regression models seek to identify and explain statistical relationships between a dependent variable and explanatory variables (Benson, Chamberlin, and Rhinehart 2005; Burt, Barber, and Rigby 2009; Chatterjee and Simonoff 2013). OLS can serve as a tool for determining significant variables for more complex regression modeling, testing for spatial process that may negate classical regression analysis, or identifying variables with multicollinearity (Benson, Chamberlin, and Rhinehart 2005; Burt, Barber, and Rigby 2009; Chatterjee and Simonoff 2013).

While PCA and OLS methods are commonly used for disaster modeling, neither of these statistical methods take spatial effects like spatial autocorrelation or non-stationarity into account (Burt, Barber, and Rigby 2009). Demographic and socioeconomic data often exhibits spatial dependency and non-stationary, as development typically occurs in a systematic, not random, fashion (White and University of 1945) (White and University of 1945). These datasets, therefore, often exhibit some form of spatial autocorrelation, anisotropy or non-stationarity that violate classical OLS assumptions. Modeling vulnerability using demographic and socioeconomic variables with spatial statistical methods, therefore, provides more reliable vulnerability estimations (Burt, Barber, and Rigby 2009). To account for spatial effects, some researchers employ a combination of classical OLS regression and Simultaneous Autoregressive Models (SAR). SAR models can provide a more reliable regression model that takes spatial processes into account (Burt, Barber, and Rigby 2009).

Classical multiple regression using OLS estimation is defined using the following equation:

$$Y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 \ldots \beta_k x_k + \varepsilon_i$$

where β are the unknown parameters in the model and ε_i is the error term.

This equation symbolizes how a response variable, Y, is dependent on the explanatory variables, x. β_0 is the y-intercept of the regression line, while β_x represents the slope. However, in order for classical linear regression to be used to make accurate statistical inferences about data, the errors must be *i.i.d.*, predictors exhibit no multicollinearity and the error terms have a normal distribution. Spatial data often violates these assumptions, so many studies utilize OLS as a preliminary tool for testing for spatial processes that may negate classical regression analysis to determine what SAR model best fits the structure of the data (Benson, Chamberlin, and Rhinehart 2005; Burt, Barber, and Rigby 2009; Chatterjee and Simonoff 2013; Thompson and Frazier 2014).

Once OLS estimation or PCA analysis have been used to develop significant variables, other spatial models, such as spatial lag or spatial error are used to account for existing spatial autocorrelation in the data. Certain spatial models address very specific spatial effects within the data, such as spatial autocorrelation or non-stationarity. Therefore, determining what spatial effects are present in the data allows researchers to choose the most appropriate SAR model for the data.

The spatial error model is a type of SAR model that can address the presence of spatial processes in data. The spatial error model can be used when OLS assumptions of uncorrelated error terms are violated or when the residual term appears to be influenced by a spatial structure in the data (Fotheringham and Rogerson 2009; Burt, Barber, and Rigby 2009). The spatial error model can be described using the following equations:

$$y = x\beta + \varepsilon$$

$$\varepsilon = \rho W\varepsilon + \xi$$

where ε is the error terms vector that has been spatially weighted using the weighting matrix (W), ξ is the vector of uncorrelated error terms and λ is the spatial error coefficient. This model can be used in situations where significant spatial autocorrelation is present, but tests for spatial lag effects do not indicate that including those effects will improve the regression model. The spatial error model transforms the errors that are part of the influencing spatial process to an error term in the model. The spatial error model is typically focused on correcting for bias from autocorrelation found in spatial data (Anselin 2003).

Like the spatial error model, the spatial lag model assumes that the error terms are normally distributed and are *i.i.d.* (Cliff and Ord 1981). The spatial lag model with no regressive components is simply:

$$Y = \rho WY + \varepsilon$$

where ε is the error terms vector, WY is the spatially lagged dependent variable for the weights matrix, and ρ is the spatial coefficient.

However, the spatial lag model is used when the assumption that there is no spatial autocorrelation is also violated. It describes substantive spatial dependence and the strength of spatial interaction in a dataset. Unlike the spatial error model, the pure spatial lag model does not have regressive components. The spatial lag model is a global measure of spatial autocorrelation, and provides information about the overall spatial pattern within a dataset (Fotheringham and Rogerson 2009). Because there are no regressive components in the model, it simply determines “block effects” in the data, which is similar to trend surface analysis. This type of model could potentially provide a continuous vulnerability trend surface of, indicating “hot spots” where socioeconomic indicators likely to cause increased vulnerability across a study area (Brunsdon and Comber 2015; Burt, Barber, and Rigby 2009). A limitation of the spatial lag model for hazards analysis, however, is that it assumes some dependency exists between the levels of the dependent variable (i.e. vulnerability at one location is affected by income at another location) (Burt, Barber, and Rigby 2009). Because vulnerability varies based on the differential distribution of exposure and socioeconomic indicators that are often interdependent, the spatial lag is not applicable for examining overall, relative vulnerability.

One of the limitations of both the spatial error model and the spatial lag model is that they assume that spatial dependence in the data is uniform throughout the study region (stationary). In cases where neither the spatial lag model nor the spatial error model adequately account for spatial processes such as nonstationarity or heterogeneity in the data, geographically weighted regression (GWR) can be utilized. GWR is described by the following equation:

$$Y_i = \beta_0(g) + \beta_1(g)\, x_1 + \beta_2(g)\, x_2 + \beta_3(g)\, x_3 + \beta_4(g)\, x_4 \ldots\ \beta_k(g)\, x_k + \varepsilon_i$$

where (g) represents the location at which estimates of the parameters are gathered. GWR is a local statistic that accounts for non-stationarity and heterogeneity in a dataset, as well as any spatial dependence.

Instead of using globally fixed regression coefficients, GWR allows them to vary from location to location (Fotheringham, Brundson, and Charlton 2002; Fotheringham and Rogerson 2009; O'Sullivan and Unwin 2010). The method of determining regression weights is extremely important because GWR uses the weighting matrix to create an estimator for each observation. Kernel estimation can be fixed or adaptive. Examples of fixed kernel weighting schemes are the Gaussian or biweight kernel functions. These methods are used to assign weights to all of the nearby observations for a given observation (Fotheringham, Brundson, and Charlton 2002; Fotheringham and Rogerson 2009; O'Sullivan and Unwin 2010).

While the GWR does correct for non-stationarity, it does not account for multiscalar variables. A semi-parametric GWR (S-GWR) model, however, does allow researchers to run GWRs using both local and global scales (Lu et al. 2013). This method allows variables that are global (stationary) to be treated and global coefficients, while other are treated as local (non-stationary) (Nakaya et al. 2009; Lu et al. 2013). The S-GWR model's form is written as (Lu et al. 2013):

$$y_i = \sum_{j=1,k_a} a_j x_{ij}(a) + \sum_{l=1,k_b} b_l(u_i, v_i) x_{il}(b) = i$$

where:

$[a_l, \ldots, a_{ka}] = k_a$ or global coefficients;

$[b_l(u_i,v_i) \ldots, b_{kb}(u_i,v_i)] = k_b$ or local coefficients;

$[x_{ij}(a), \ldots, x_{ika}(a)]$ = independent variables associated with global coefficients;

and $[x_{il}(b), \ldots, x_{ikb}(a)]$ = independent variables associated with local coefficients.

While the level of these variables may vary, the rate of spatial variation remains the same (Nakaya et al. 2009; Lu et al. 2013).

Some researchers in the natural hazards field utilize SAR and GWR models (Benson, Chamberlin, and Rhinehart 2005; Chakraborty 2011; Hsu and Su 2012; Lichstein et al. 2002; Mentzafou, Markogianni, and Dimitriou 2016; Samson et al. 2011; Thompson and Frazier 2014), but spatial modeling is still not the predominately employed statistical technique in the hazards literature. Few studies utilized one type of spatial model, whereas Benson, Chamberlin, and Rhinehart (2005) is one of the few studies to conduct both a spatial lag and spatial error model, in conjunction with a GWR model, to try to determine poverty prevalence. Their results indicated that the GWR had greater explanatory power due to the local nature of GWR models (Benson, Chamberlin, and Rhinehart 2005). Jankowska, Weeks, and Engstrom (2011) considered using SAR models to examine the vulnerability of people to poverty, but initial OLS results indicated that non-stationarity was present in the data, making the GWR model the more appropriate spatial model. Other studies mention utilizing OLS to determine the most appropriate spatial model, but GWR is commonly deemed the most appropriate model due to the presence of nonstationarity in several datasets (Schmidtlein, Finch, and Cutter 2008; Salvati et al. 2011; Poudyal et al. 2012; Thompson and Frazier 2014).

While the GWR and semi-parametric GWR model is useful for local regression modeling, there are some limitations to the analyses. Recent studies have demonstrated that GWR and SAR models with a presence of collinearity between covariates can produce inaccurate results (Finley 2011; Wheeler and Tiefelsdorf 2005; Wheeler and Calder 2007). This issue can result in a limited ability to use GWR results to make inferences on regression coefficients (Wheeler and Calder 2007), which researchers use to determine how different indicators influence overall hazard risk or vulnerability. The semi-parametric GWR is also limited in that the model can only provide local and global model estimations, meaning that the data inputs still have to be aggregated or downscaled to a single spatial scale (local predictors). One of the predictors may occur across the study area as a global predictor, but the analysis occurs at a single, local scale. This means that the resulting model does not show variation across scales This is problematic when different vulnerability indicators occurs at several scales (i.e. census block, census block group and county), and makes the S-GWR ineffective for modeling vulnerability using multiscalar variables.

Due to these limitations, other, more advanced forms of spatial modeling are sometimes used in hazard studies, but these are few a far between. The Conditional Autoregressive (CAR) model, introduced by Besag (1974), is a type of Markov Random Field (MRF) model that specifies univariate conditions on each variable in order to identify global trends and local spatial autocorrelation present at both a local and global scale (Lichstein et al. 2002). CAR models are typically used to model spatial autocorrelation in a non-overlapping dataset and are often utilized in the second level of hierarchical models to account for spatial correlation in the data (Abell 1993). CAR models are not often utilized in examining hazards or hazard impacts, but some studies like Lichstein et al. (2002) and Salvati et al. (2011) have explored the spatial autocorrelation of ecological habitats and species and vulnerability of land degradation. Other studies, such as Sain and Cressie (2007) and Ugarte, Ibáñez, and Militino (2005), utilize CAR modeling to examine the presence of spatial autocorrelation in disease incidence or risk. While this information is useful in terms of hot spot or cluster detection, it does not necessarily provide information about the level of risk itself.

Another regression model that is used in some risk and vulnerability studies is hierarchical regression modeling. Hierarchical (multilevel) models are statistical regression models whose parameters vary at more than one level (Banerjee, Carlin, and Gelfand 2004; Gelman and Hill 2007). Multilevel models are often used for regression models with large amounts of coefficients that are individually modeled or as regression models with coefficients that vary by groups existing within some type of hierarchical structure (i.e. different spatial scales versus number of individuals in schools) (Corrado and Fingleton 2011; Finch, Bolin, and Kelley 2014; Gelman and Hill 2007; O'Connell and McCoach 2008). Multilevel models follow something similar to a two-step model but both steps are conducted simultaneously. In any of these models, each level of the model (in this case differencing resolution aspects of a process) is allowed to have its own predictors. The levels of the model can differ (the scale can go from group-level to individual or vice-versa), so the model results should represent the level (or spatial scale) on which the analysis is focused. Hierarchical models require several additional assumptions than OLS regression because each level of the model serves as its own regression, with its own set of assumptions (Gelman and Hill 2007). In addition to the model levels, the type of regression model (i.e. linear versus generalized) and the nature of the indicator variables (i.e. how levels are defined) are something to consider (Banerjee, Carlin, and Gelfand 2004; Gelman and Hill 2007; O'Connell and McCoach 2008).

Another major consideration for multilevel modeling concerns the model structure and random versus fixed effects. Multilevel models follow three basic model structures: 1) varying intercept model, 2) varying slope model, 3) varying intercepts and slope models. Varying intercept models use group level variables as regression predictors, thereby predicting the dependent variable using an intercept that varies across groups. Varying slopes models allow the slope of individual predictors to vary by group, which can identify interactions between group indicators and an individual-level predictors. A model with varying intercepts and slope model allows both the intercepts and slopes to vary, demonstrating where variable interactions between the individual-level predictors and the group indicators occur (Gelman and Hill, 2007). Of the three model types, the varying intercepts and slopes model is the most realistic and, therefore, the most complex.

In terms of the types of predictors used in the model, there is a distinction between random versus fixed variables, effects and coefficients. Random and fixed *variables* serve as the actual predictor variables in a multilevel model. Random variables are those that represent a sample of a population (i.e. subset of census tracts) whereas fixed variables are assumed to be measured without error (i.e. all census tracts) (Gelman and Hill 2007; Newsom 2006). Random and fixed regression *effects* are often used to describe the variable coefficients in multilevel models (Gelman and Hill 2007; Newsom 2006). Fixed effects are constant across individuals, whereas random effects vary. For example, intercepts in a varying-intercepts model are considered random effects if they randomly vary across groups (Bell, Ene, and Schoeneberger 2013; Ene et al. 2015). Fixed effects assume that a coefficient is non-variant across groups, indicating that the between-group variance is zero (Ene et al. 2015; Gelman and Hill 2007; Newsom 2006). Because levels within multilevel models can be both fixed (i.e. level-2 groups variables are considered fixed) and random (i.e. level-1 predictors vary across groups and individuals), they are often considered mixed models (Garson 2012; Gelman and Hill 2007).

Hierarchical models also allow model levels to differ by scale (i.e. group level to individual or vice-versa), which helps account for social interaction, social organization processes that occur across several spatial scales. This also allows both global and local influences on vulnerability to be considered within the same conceptual framework, something that is lacking in many vulnerability studies (Frazier, Wood, and Yarnal 2009; Wood and Soulard 2009; Frazier, Thompson, et al. 2013). Hierarchical models can also be used to realign spatial datasets or help to correct for the modifiable areal unit problem (MAUP) in aggregated data commonly used in vulnerability studies. This information could provide more accurate information about how vulnerability indicators interact with each other within a social system (Banerjee, Carlin, and Gelfand 2004).

Given the lack of advanced statistical modeling in the natural hazards field and limitations in spatial modeling used in current studies, statistical methods that better represent vulnerability data structures and social systems are necessary for developing better vulnerability quantification methods for planning and guiding hazard mitigation. Hierarchical modeling with spatial components, therefore, would allow researchers to measure vulnerability using variables of different scales, without lowering the integrity of the model due to data aggregation (Banerjee, Carlin, and Gelfand 2004; Gelman and Hill 2007; O'Connell and McCoach 2008; Subramanian, Duncan, and Jones 2001). This type of model better represents the structure of theoretical frameworks used for indicator development (i.e. political ecology or structuration), thereby tying modeling methods directly to conceptual frameworks.

Despite the applicability of hierarchical models for measuring systems vulnerability using multiscalar indicators, most risk/vulnerability studies employing this method often pertain to ecological vulnerability, social groups or disease (Ashtakala and Eno 1996; Banerjee, Carlin, and Gelfand 2004; Aldoory, Kim, and Tindall 2010). Some studies have used hierarchical models to examine disaster reliefs goods distribution, critical infrastructure risk to attacks, and disaster and risk management decision making (Bagheri, Verma, and Verter 2014; Arbuckle, Randle, and Wilson 1991). These methods, however, do not examine vulnerability from a structured social perspective and few use hierarchical modeling the natural hazards field.

3.3 Methods

In order to quantify vulnerability using a methodological framework that better represents theoretical foundations of vulnerability/resilience, this research presents a hierarchical regression model that measures vulnerability using multiscalar indicators that describe different components of the human-environment system. This research assumes that society is both hierarchical and segmented (Cozzens and Gieryn 1990; Giddens 1984). Therefore, measuring overall system vulnerability/reliance using a hierarchical model that accounts for multiscalar variable interaction will better represent processes occurring within the current social structure. The methods sections detail the model building process used to determine the appropriateness of hierarchical models for multiscalar vulnerability/resilience analysis, using Sarasota County, FL, as a case study.

3.3.1 Data levels and predictors

Hierarchical models are appropriate for this research because the data occurs at two separate spatial scales – Census blocks and Census block groups. Table 3.1 describes each of the initial socioeconomic predictor inputs, how they fall into the INSeRT Framework, and their directionality. Indicator directionality reflects whether an indicator had a positive or negative influence on vulnerability based on existing literature (Morrow 1999: Cutter, Boruff, and Shirley 2003). All of these indicators have been previously identified as traditional indicators of vulnerability in existing natural hazards and vulnerability studies (H. John Heinz III Center for Science 2002; Cutter, Boruff, and Shirley 2003; Blaikie et al. 2004; Brooks, Neil Adger, and Mick Kelly 2005; Elliott and Pais 2006; Tierney 2006; Birkmann 2007; Cutter et al. 2008; Morrow 2008; Cutter, Burton, and Emrich 2010; Frazier, Thompson, et al. 2013; Frazier, Thompson, and Dezzani 2014; Norris et al. 2008). These indicators serve as the initial independent variables for all of the models used in the model building process. Not all of these occur in the finalized models, as some indicators do not have a significant influence on vulnerability in Sarasota County, FL, at different storm categories.

Table 3.1 Model indicators based on major INSeRT model framework components

Indicator	INSeRT Model Component	Directionality
Critical Facilities	Critical Infrastructure - Medical Facilities, Police & Fire Stations, Shelters, Emergency Response, Utilities & Communication, etc.	-
Medical Facilities	Critical Infrastructure - Infrastructure	-
Child Day Care Center	Dependent Populations - Children	+
Institutionalized population	Dependent Populations - Children / Shelters	+
Adult Residential Care	Dependent Populations - Elderly	+
Schools	Dependent Populations - Elderly/Disability	+
2016 Justified Parcel Value	Economic	+
Business	Economic	-
Employees	Economic	-
Employment or Unemployment	Economic	+/-
Female Employment	Economic	-
Median Income	Economic	-
On Social Security Income	Economic	+
Per Capita Income	Economic	-
Poverty Status	Economic	+
Sales Volume	Economic	-
Single sector employment dependence	Economic	+
Tourism	Economic - Day and Overnight Tourism	+
Wetlands	Environment - Ecological	-
High Intensity Development	Environment - Land Use	+
Low Intensity Development	Environment - Land Use	+
Medium Intensity Development	Environment - Land Use	+
Open Development	Environment - Land Use	-
Essential Facilities	Essential Infrastructure - Gas stations, Banks and Credit Unions, Retail Grocers, etc.	-
Evacuation Routes	Mitigation - Evacuation access/ potential	-
Agriculture	Natural Resources / Land Cover	-
Veterans	Social & Housing	+
Population over 65 years	Social & Housing - Age	+
Population under 5 years old	Social & Housing - Age	+
Single-Mother households	Social & Housing - Family type	+
Female Population	Social & Housing - Female Pop	+
Number of Households	Social & Housing - Housing	+
Renter-occupied housing units	Social & Housing - Housing	+
College Education	Social and Housing - Education	-
American Indian and Alaska Native	Social & Housing - Race/ Ethnicity	+
Asian	Social & Housing - Race/ Ethnicity	+
Black or African American	Social & Housing - Race/ Ethnicity	+
Hispanic or Latino population	Social & Housing - Race/ Ethnicity	+
Native Hawaiian /Other Pacific Islander	Social & Housing - Race/ Ethnicity	+
White	Social & Housing - Race/ Ethnicity	-
Religious Organizations	Social & Housing - Social Capital	-

In order to create the exposure datasets necessary for the model, methodologies developed by Scott (2011) and Thompson and Frazier (2014) were used to create the storm surge inundation extents for each of the five hurricane storm categories, using the Sea, Lake, and Overland Surges from Hurricanes (SLOSH) model. Several levels of government agencies utilize the SLOSH model to delineate storm surge and associated evacuation zones from hurricanes for emergency management and planning. SLOSH products are developed from a grid/basin that calculates potential maximum storm surge flood heights under different storm conditions, using hypothetical or historical storm track information, the radius of maximum winds and the pressure difference between the center of the storm and the peripheral pressure through several thousand model iterations (Glahn et al. 2009; Taylor and Glahn 2008). The resulting SLOSH products, called Maximum Envelopes of Water (MEOWs) and Maximum of MEOWs (MOMs), represent the maximum height of surge values for each grid for a given storm category (regardless of which hypothetical storm produced that value) and the composite of the maximum storm surge heights for a given storm category (based on all of the storm simulations), respectively (Glahn et al. 2009).

The model output are shapefile grids that do not actually delineate the storm surge extent, so they are manipulated in GIS to convert MOM outputs into more defined storm surge inundation layers using terrain analysis. This process, developed by Scott (2011) and Thompson and Frazier (2014), uses a LiDAR DEM, 12-digit HUC polygons representing watershed polygons, and the specified MOM shapefile (in this case the Fort Meyers basin) to create water surface terrain files that depict surge heights for each storm category. After creating the water surface terrain files, the outputs are subtracted from the DEM to determine the actual storm surge inundation height. These raster layers are converted to flood extent polygons that serve as the final storm surge flood extents for the five storm categories. These polygons represent the final deterministic output for storm surge extents for the contemporary storm.

In order to incorporate exposure as a variable in regression modeling, the physical hazard extents are overlayed with the main unit of analysis, the census block, to determine the areal percentage of each block within the storm surge hazard extent. Exposure serves as the dependent variable because it is based on the assumption that societal assets (which are described within census blocks) are exposed to a potential threat. In order for exposure to exist, societal assets must be present within potential hazard zone (Frazier, Thompson, and Dezzani 2014, 2013; Thompson and Frazier 2014). Physical exposure datasets were developed for each storm category, resulting in five separate exposure scenarios.

3.3.2 Development of Independent and Dependent Variables for Regression Modeling

Before conducting the initial regression modeling, the dependent and independent variables were defined based on the definition of vulnerability. Vulnerability is a function of exposure, sensitivity, and adaptive capacity, so initial version of the models attempted to utilized datasets that represented all three of these components as independent variables. Dependent variables represent the output variable that is being measured and monitored to determine how it is affected by the independent variables. For this study, using overall vulnerability as the dependent variable and physical and socioeconomic variables as the independent variables would be ideal, as this study examines how indicators of exposure, sensitivity, and adaptive capacity impact vulnerability. However, the issue that arises with this model form is that there is no empirical way to measure vulnerability accurately, especially since one of the components of vulnerability, exposure, is entirely dependent on the presence of sensitivity of adaptive capacity indicators. Sensitivity and adaptive capacity characteristics exist in people or societal assets and are independent of a physical hazard.

Exposure is unique in that it only exists where there is an intersection between human lives and property and a hazard event (Birkmann, Kienberger, and Alexander 2014; Eakin and Luers 2006; Frazier, Thompson, and Dezzani 2014). Therefore, if a natural hazard is present but it does not intersect with any societal assets or people, then there is no exposure. Exposure is the only component of vulnerability based on both the actual physical extent of the hazard and socio-economic factors that influence vulnerability as a whole. For this reason, the best option for a dependent variable in a regression model that measures overall vulnerability is percentage of exposure to storm surge within a census block, with sensitivity and adaptive capacity indicators serving as the independent variables.

This dependent variable is by no means perfect, but it is one of the better options available. Other variable options, such as using damages as the dependent variable or recovery potential, are limited in that damage estimating is often based on monetary measures of physical damages, not necessarily other forms of personal costs. It is also difficult to measure damages in terms of things other than cost, such as vulnerability or resilience, if those measures are based on characteristics that are difficult to quantify.

Other explored modeling options that also include using utility or loss functions to describe recovery potential given a specific set of criteria strictly related to basic goods and services necessary for immediate recovery to occur (Hershey and Schoemaker 1980). This type of function could examine recovery from an infrastructure perspective, using indicators such as the availability of electricity, drinking water, road network access, availability of gas stations, or grocery stores. Loss functions can describe how losses can be minimized if a certain set of these infrastructure factors are impacted in a specific manner (Ferreira, Mota de Sá, and Oliveira 2014; Gaudard and

Romerio 2015; Hershey and Schoemaker 1980). For example, if x amount of grocery stores are damaged by a storm, loss functions can determine how many gas stations and convenience stores can potentially be used to substitute access to those types of services (i.e. food or basic necessities, or gas too get to grocery stores further away) to increase recovery potential to its maximum capacity.

Utility theory and loss functions have also been used to predict human behavior in response to certain risks (i.e. investing money or living within a floodplain) (Ferreira, Mota de Sá, and Oliveira 2014; Gaudard and Romerio 2015; Hershey and Schoemaker 1980). Typically, these functions include some set of decisions and expected costs or benefits of those decisions to determine the probability that someone will undertake a specific behavior. However, these types of models are limited in that they do not account for a person's risk perception, which can influence how people actually perceive the costs or benefits and make decisions that do not necessarily fit the expected outcomes (Gaudard and Romerio 2015).

However, while loss functions can be used to describe ways to minimize loss in certain aspects of an impact system, they cannot describe the system impacts as a whole. This limitation exists because loss functions (and utility functions) are based on substitutions of goods or services to minimize loss. Some components of a system impacted by a natural disaster cannot necessarily be substituted for others (i.e. exposed populations are not services or goods that can be substituted for a certain level of functional critical infrastructure). These are both factors of a system that influence overall recovery potential, but they are not interchangeable factors within the system. Therefore, utility theory and loss functions in natural hazards studies cannot measure overall vulnerability/recovery potential based on non-substitutable factors in the system.

For these reasons, the best option for the dependent variable in a regression model that measures overall vulnerability is the percentage of exposure to storm surge within a census block, with sensitivity and adaptive capacity (socioeconomic) indicators serving as the independent variables.

3.3.3 Regression Model Development for Modeling Vulnerability

In order to develop a hierarchical model to measure vulnerability at multiple spatial scales (Subramanian, Duncan, and Jones 2001), several model development steps were employed to determine the most appropriate hierarchical model for measuring vulnerability. This process goes through the following steps: initial indicator development (for both dependent and independent variables), exploratory data analysis, classical regression (OLS), simultaneous autoregressive (SAR) modeling and finally hierarchical modeling. The following section details these steps and explains their importance in the model building process for measuring vulnerability from a multiscalar perspective. Initial vulnerability indicators were identified and developed from previous focus groups, interviews and traditional indicators in literature (H. John Heinz III Center for Science 2002; Cutter, Boruff, and Shirley 2003; Blaikie et al. 2004; Brooks, Neil Adger, and Mick Kelly 2005; Elliott and Pais 2006; Tierney 2006; Birkmann 2007; Cutter et al. 2008; Morrow 2008; Cutter, Burton, and Emrich 2010; Frazier, Thompson, et al. 2013; Frazier, Thompson, and Dezzani 2014; Norris et al. 2008). These indicators were initially analyzed using PCA to determine which factors are inter-correlated and have the greatest influence on vulnerability. These indicators serve as the socioeconomic and physical hazard independent variables for the OLS, SAR and hierarchical models (Frazier, Thompson, and Dezzani 2014). The final set of vulnerability indicators specific for Sarasota County (Table 3.1) serve as the initial inputs in the different regression models.

In order to develop the base regression model, traditional indicators were input into a classical OLS regression model. The classical OLS regression models utilized the initial socioeconomic indicators as the independent variables and percent exposure for each census block is the dependent variable, using the following equation:

$$Y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 \ldots \beta_k x_k + \varepsilon_i$$

where Y_i is the dependent variable, or percent exposure in a census block

$x_1 \ldots x_k$ = independent variables developed from socioeconomic and physical vulnerability indicators ε_i = error term.

The dependent variable is the percent of a census block exposed to each hurricane storm category, as it is dependent on the presence of human lives or societal assets. It would be ideal to utilize overall vulnerability as the dependent variable, but it is difficult to quantify vulnerability without a true dependent variable. It is possible to utilize a mix of socioeconomic indicators and physical exposure as independent variables, but that is not consistent with the notion that exposure is strictly based on where a physical hazard intersects with existing societal assets and populations. Therefore, percent exposure in a census block serves as the dependent variable in the regression equations. The previous section explains this in more detail.

The classical regression results demonstrated a low R^2 value, indicating some other process is not being explained by the model. The resulting variables were then run through exploratory spatial data analysis (ESDA) processes, specifically Moran's I, LISA, and GWR analyses, to determine any potential spatial effects that are not being accounted for in the classical regression model. These statistical methods signified that there were spatial patterns that exist in the data, meaning that the OLS models are not accounting for spatial issues. A Lagrange multiplier test statistic was then run using the OLS model residuals to measure the level of spatial autocorrelation in the residuals, which can help inform which SAR model would be the most appropriate for the data structure (Burt, Barber, and Rigby 2009; Anselin 1988; Anselin, Gallo, and Jayet 2008; Arbia and Petrarca 2011; Fotheringham, Brundson, and Charlton 2002; Fotheringham and Rogerson 2009).

Based on the ESDA and Lagrange multiplier test statistics, the spatial error was identified model as the most appropriate SAR model for modeling relationships within this dataset. The initial indicators used for the OLS models served as inputs for the SAR model to compare how space affected the relationships between the indicators and to determine if the SAR models corrected for a large amount of spatial processes occurring within the data. The AICc values and Moran's I of the SAR model error terms results suggested that these models, while an improvement on the OLS models, still had residuals that were spatially autocorrelated, indicating that the presence of a spatial process the model was unable to address (Anselin 1995; Anselin, Gallo, and Jayet 2008; Griffith 2003; Haining 2003). This could occur because the input variables differed between two scales (census blocks and census block groups).

3.3.4 Hierarchical Model Development

As a result, a varying-intercepts hierarchical model was developed that accounts for different spatial effects at multiple scales, specifically census block and census block groups. The model simultaneously measures the impacts of multiscalar indicators on vulnerability while retaining the integrity of the original datasets. This model was developed using a generalized linear hierarchical model (HGLM), which differs from traditional hierarchical models (HLM). Traditional HLMs assume that errors are *i.i.d*. and normally distributed, which are not typical in spatial data. Both the census block and census block group variables exhibit non-stationarity and spatial autocorrelation that violate the *i.i.d.* assumptions, meaning that a HGLM is more appropriate. HGLMs as they can be used model dataset sets that are not normally distributed or do not have an appropriate error distribution for the response variables (Bell, Ene, and Schoeneberger 2013; Ene et al. 2015; O'Connell and McCoach 2008; Subramanian, Duncan, and Jones 2001).

Because this research focuses on traditional datasets used to measure vulnerability, this model has two levels that represent the most commonly used data sources in current vulnerability modeling (Cutter, Boruff, and Shirley 2003; Frazier, Thompson, and Dezzani 2014; Wang and Yarnal 2012; Wood, Burton, and Cutter 2010). Level-1 predictors represent those found at the smallest spatial scale, the census blocks, while Level-2 predictors represent data found at the larger data scale, census bock groups. The mathematical equations for two-level HGMLs can be described by the following set of equations (Bell, Ene, and Schoeneberger 2013; Ene et al. 2015).

The census block, level-1 equation is denoted using the following:

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij} \qquad \textit{(Eq. 1)}$$

where:

Y_{ij} = vulnerability, as represented by percent exposure, for census block (i) in census block group (j);

β_{0j} = average vulnerability, as represented by percent exposure, in census block group (j);

β_{1j} = regression coefficient associated with X_{ij}, showing the relationship between census block variables and vulnerability, as represented by percent exposure;

X_{ij} = block-level predictor for block (i) in block group (j);

e_{ij} = block-level error term.

The census block group, level-2 equations are denoted using the following:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + \cdots \gamma_{0n}W_j + u_{0j} \quad \textit{(Eq. 2)}$$

$$\beta_{1j} = \gamma_{10}X_{ij} + \cdots \ \gamma_{n0}X_{ij} \qquad \textit{(Eq. 3)}$$

where:

γ_{00} = intercept; grand mean of vulnerability, as represented by percent exposure across blocks and block groups;

W_j = block group-level predictor;

γ_{01} = regression coefficient associated with block group level predictor W_j;

u_{0j} = level-2 error term representing unique effect associated with school j;

γ_{10} = average effect of block-level predictor.

These equations (Eq.1-3) can then be combined to form the following equation, where Y_{ij} is the vulnerability, as represented by percent exposure, for census block (i) in census tract (i):

$$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + \cdots \ \gamma_{n0}X_{ij} + \gamma_{01}W_j + \cdots \gamma_{0n}W_j + u_{0j} + e_{ij} \qquad \textit{(Eq. 4)}$$

This combined equation (Eq. 4) determines vulnerability using both census block and census block group level predictors (Bell, Ene, and Schoeneberger 2013; Ene et al. 2015). A varying-intercepts model structure was utilized for this research, as it is the least complex model that still successfully identifies variability in vulnerability levels across census block groups.

The HGLM model building process also includes several steps to develop the best-fitting model for the multiscalar datasets using this equation. Step 1 is to model just the random effect (Census block groups) for the intercept (with no predictors) to determine if there is variation between the level 2 units. If there is not variation between the Census block groups, then an HGLM that accounts for level-2 variation is unnecessary. Variation exists within variables in this dataset, so level-1 predictors were added to the initial model in step 2. Finally, in step 3, level-2 predictors were input into the model in conjunction with the level-1 predictors. Once the fit of the model with all predictors has been completed, the model is then further refined to make sure that the model predictors are not overestimated when both levels of predictors are present.

The multilevel modeling was conducted using the SAS® PROC GLIMMIX procedure, which had three main model statements: CLASS, MODEL and RANDOM. The CLASS statement describes the clustering/grouping variable, census block groups. The MODEL statement specifies the fixed effects to be included in the model (fixed effects for both level 1 and level 2 predictors), and the RANDOM statement specifies the random effects to be estimated (as this is only a varying-intercept model, only the intercept is used. Figure 3.1 is an example of the SAS® code used to model vulnerability to a Category 1 storm.

```
/***********PROC GLIMMIX Model Justified EXC1 and Group2 - Fixing
Overestimation******************************/

title "PROC GLIMMIX - Model 4 - Justified EXC1: Block and Block Group Predictors";

PROC GLIMMIX DATA=work.censusacs_combo METHOD=LAPLACE NOCLPRINT;
CLASS ACS_ID_CH;
MODEL JS1T_EXC1 = BDevLMH  HisLatBT FemBTP A5BTP A65BTP FHHBTP
CritBTP EssenBTP AgBTP EvacBTP ColgeBTP VetBTP2 SSTEMPBT FemEmpBT
Group2All / CL DIST=LOGNORMAL LINK=PROBIT SOLUTION ODDSRATIO (DIFF=FIRST LABEL);
RANDOM INTERCEPT / SUBJECT=ACS_ID_CH TYPE=VC SOLUTION CL;
COVTEST / WALD;
run;
```

Figure 3.1 – SAS® code for Category 1 multilevel model

The dependent variable, exposure, has a non-normal distribution, so it was transformed for both Category 1 and 2 using the SI Johnson transformation (JSTI_EXC1). This transformation method was characterized as the best fit for the data structure using JMP® software. Because the data is not normally distributed, the model was also estimated using a lognormal distribution (DIST=LOGNORMAL), which describes the built-in (conditional) probability distribution of the data and the probit link function (LINK=PROBIT) (SAS Institute 2005). The probit link function is described using the equation, $\Phi^{-1}(\mu)$, which denotes the quantile function of the standard normal distribution (Ene et al. 2015; SAS Institute 2005).

Improvement of model fit was determined using the corrected Akaike's Information Criterion (AICc) fit statistics. While the -2LL statistic can be used to compare whether differences between developed models are considered statistically significant using a likelihood ratio test similar to a chi^2 test, the AICc statistic actually determines the best-fitting model and is based on the -2LL value (Akaike 1987; Anselin, Gallo, and Jayet 2008).

3.3.5 Vulnerability Scoring Maps Development

Once the hierarchical models for each storm category were developed, researchers used the resulting coefficient estimates were input into the combined equation (Eq. 4) to calculate relative vulnerability scores (Y_{ij}) for each census block. Afterward, only blocks where exposure was greater than 0 were used to map the resulting Y_{ij} values, to follow the logic that in order to be vulnerable to a hazard, one must be exposed to said hazard. This demonstrates how vulnerability varies across census blocks when multiscalar variation is considered. In order to illustrate relative vulnerability within blocks, vulnerability values are symbolized using a standard deviation classification scheme comprised of 5 classes (Low, Low-Medium, Medium, Medium-High and High). These scores demonstrate how block vulnerability deviates from the mean vulnerability score (Cutter, Boruff, and Shirley 2003; Frazier, Thompson, and Dezzani 2014; Wood, Burton, and Cutter 2010), where positive values indicate higher vulnerability, and negative values indicate lower vulnerability. Because the statistical models were different based on the exposure level, this process was conducted separately for each storm category, resulting in 5 different hazard vulnerability maps.

3.4. Results

Initial vulnerability indicators were identified from previous literature and then used as inputs in the three types of regression models (OLS, SAR and hierarchical). The results of the classical OLS, SAR, and hierarchical regression models are listed side by side in a table for each category (Tables 3.3 thru 3.7). These tables indicate which vulnerability indicators are considered statistically significant for a given regression model (bolded in black), where the significance of those variables has changed in another regression model (highlighted in blue text) and indicators whose coefficients have changed from positive to negative, or vice versa (highlighted with red boxes). The results show that the overall explanatory power of the OLS models are limited, as the R^2 values are less than 10% for all storm categories models, but the AICc values for both the SAR and hierarchical models show significant model improvement.

3.4.1 Classical Regression (OLS) Results

The resulting significant indicators in the OLS models are known to influence vulnerability. Positive coefficients indicate the presence of variables whereas negative coefficients indicate variables that should be expected to decrease in the presence of positive variables. In regression, coefficients provide explanations that describe how the dependent variable (exposure) is expected to increase when an independent variable increases by 1. Therefore, coefficients describe how exposure is expected to increase or decrease when the independent vulnerability indicators increase by 1. The coefficient signage is also important because it indicates the relationship between the variable and the dependent variable or constant. In the OLS results for Category 1 (Table 3.3), the negative coefficient for the black population variable indicates that the greater the exposure, the lower the impact of the black population on vulnerability. However, an interesting pattern in the results is that several of the indicators that are typically believed to increase vulnerability have negative coefficients (i.e. black population, dependent populations like elderly or children, etc.), indicating that, combined with the low R^2, some process is not being accounted for with classical statistical measures.

3.4.2 Simultaneous Autoregressive Model (SAR) Results

In order to account for unknown processes that could be lowering the explanatory power of the OLS models, the same set of variables were input into SAR models. The resulting SAR models provided greater explanatory power, as seen in the larger AICc values for the SAR models in all 5 categories (Tables 3.3 thru 3.7). Several coefficients in the Category 1 OLS model changed from positive to negative in the SAR model (shown in red boxes in Table 3.3), indicating that exposure is actually expected to increase when variables like black populations increase. For some of these variables, this relationship is more consistent with known relationships of certain variables to vulnerability (i.e. presence of minority populations is thought to increase vulnerability), but other relationships, such as the elderly and presence of children, staying negative is not consistent with current literature.

3.4.3 Hierarchical Model Results

In order to determine if scale or the lack of consideration of variables occurring at different scales affects coefficient signage in both the OLS and SAR models, the hierarchical model results (Tables 3.3 to 3.4) were examined for similar patterns. Variables in the hierarchical regression analysis identifies several relationships that are not present in either the OLS or the SAR models.

An example of this can be seen in the category one comparison between classical aggression spatial error model and hierarchical model. As discussed in the previous section there are several changes in terms of significance and coefficients signage between the OLS and SAR model.

Table 3.2 – Demonstration of goodness of fit in Category 1 Hierarchical model with spatial predictor

Model Fit	**Model 1**	**Model 2**	**Model 3**	**Model 3 - no Coastal Y/N**	**Model 4**	**Model 4 - no Coastal Y/N**	**Model 5**
AICc (smaller is better)	-13584.3	-13289	-13584.3	-13577.4	-13602.4	-13605.3	-13615.1
	No predictors, just random effect (Block Group Effect) for intercept	Spatial predictor (Coastal vs. Inland) & random effect (Block Group Effect) for intercept	Random effects for intercept, spatial predictor (Coastal vs. Inland), & block-level 1 fixed effects predictors	Random effects for intercept & block-level 1 fixed effects predictors, with no spatial predictor (Coastal vs. Inland)	Random effects for intercept & block-(level 1) and block group (level 2) fixed effects predictors	Random effects for intercept & block-(level 1) and block group (level 2) fixed effects predictors, with spatial predictor	Finalized version of model with random effects for intercept & REDUCED block-(level 1) and block group (level 2) fixed effects predictors, with spatial predictor

Indicator coefficients in the hierarchical model are similar to SAR and OLS models in terms of coefficient values, but there are actually several changes in signage and statistical significant that occur between the model results. For one, the number of included and statistically significant variables is actually reduced in the hierarchical model, meaning that variables that were considered significant to the OLS and SAR models were not necessarily considered statistically significant when both scales of indicators were included in a singular model. This indicates that when multiscalar variables are not aggregated or downscaled, different relationships between the predictor variables and the response variable variables begin to emerge.

Table 3.3 - Category 1 Storm Surge – Regression Model Results Comparisons

	OLS		**SAR - Error**		**Hierarchical**	
Block Level Variables						
Variable	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
(Intercept)	**0.050**	**0.033**	**0.174**	**0.000**	**0.340**	**0.000**
Black	**-0.047**	**0.016**	0.008	0.502	-	
Other Minorities	0.007	0.807	-0.005	0.701	-	
Development	**0.057**	**0.016**	**-0.040**	**0.006**	**-0.024**	**0.000**
Hispanic/Latino	**-0.105**	**0.000**	-0.006	0.628	**-0.030**	**0.015**
Females	**-0.105**	**0.000**	**-0.074**	**0.000**	**-0.036**	**0.000**
Age Under 5	**-0.212**	**0.000**	-0.014	0.583	**-0.082**	**0.001**
Age Over 65	**0.071**	**0.000**	**-0.024**	**0.001**	0.006	0.213
Single Mother HH	-0.063	0.089	-0.002	0.888	-0.034	0.054
Tourism	**0.066**	**0.004**	-0.016	0.108	-	
Sales Volume	0.000	0.075	0.000	0.521	-	
Critical Fac.	**-0.033**	**0.016**	-0.007	0.325	**-0.017**	**0.019**
Essential Fac.	-0.009	0.416	-0.003	0.603	**-0.026**	**0.044**
Wetlands	**0.282**	**0.000**	**0.089**	**0.000**	-	
Agriculture	**-0.250**	**0.000**	-0.018	0.626	**-0.058**	**0.001**
Open Dev.	**-0.145**	**0.000**	**0.042**	**0.041**	-	
Evac Routes	**-12.630**	**0.002**	**-3.393**	**0.027**	**-6.954**	**0.000**
Parcels	**32.380**	**0.000**	2.091	0.235	-	
Block Group Level Variables						
(Intercept)	-0.126	0.429	**0.208**	**0.024**	-	
College Education	**0.431**	**0.002**	-0.066	0.376	**0.065**	**0.001**
Below Poverty	0.125	0.680	0.056	0.694	-	
Median Inc.	**-0.165**	**0.000**	-0.027	0.157	-	
Social Security Inc.	0.296	0.051	**0.148**	**0.043**	-	
Veterans	**-0.645**	**0.046**	-0.049	0.759	**-0.138**	**0.007**
Food Stamps	0.382	0.067	-0.161	0.119	-	
Seasonal/Temp Occupations	-1.053	0.086	-0.224	0.451	-0.213	0.090
Employed Pop.	0.437	0.116	0.232	0.071	-	
Employed - Female	**-1.163**	**0.004**	-0.358	0.055	**-0.096**	**0.031**
Variables in Hierarchical Model Only						
Coastal Y/N*	-		-		-0.007	0.269

*Spatial grouping variable to indicate Coastal versus Non-coastal blocks, as space is not explicitly included in HGLMs

Model Fit Statistics

For OLS and SAR only	R^2	AICc	AICc	Hierarchical AICc	
Block	0.089	1,191.4	-12,627.0	Model (2 levels)	-13615.1
Block Group	0.324	-81.1	-350.3		

For example, in Table 3.3, the response variable (Intercept) describes the dependent variable, exposure. The other variables describe the independent predictor variables that represent traditional socioeconomic indicators of vulnerability. The results in Table 3.3 illustrate changes in coefficient signage (indicated in red boxes) and statistical significance (indicated in blue text) between regression modeling types. These changes indicate that the inclusion of spatial and scalar influences in a regression model do influence the model explanatory power and variable associations. This pattern is evident when comparing the block and block group OLS regression models with the SAR error regression models. Several variables from OLS models experienced changing statistical significance or coefficient value changes in the SAR models. For example, The Black predictor variable in the OLS model has a coefficient of -0.047 is considered statistically significant in terms of its association with exposure (p-value = 0.016). This can be interpreted as the black predictor variable has a negative relationship with exposure in that when exposure increases the black variable will decrease. This relationship suggests that for every unit of increase in exposure, the impact of black populations on exposure should decrease. However, this relationship has flipped in the SAR model regression, where the coefficient for the Black predictor variable is now positive and the p-value is no longer statistically significant. This indicates that while the relationship between the Black predictor variable and exposure is now positive (which does match traditional natural hazard vulnerability literature), it is no longer significantly associated with changes in exposure.

This indicates that when regression models consider spatial processes, the influence of predictor variables on the response variable can become less significant and change coefficient signage. Coefficient signage changes, especially those that do not reflect known theory concerning that variable, can indicate shortcomings in the model, data or estimation procedure (Kennedy 2005). This can be the result of omitted variables that are correlated with an increase of that predictor variable, high variances in the data (due to multicollinearity within variable, small sample size or minimal variation in the predictor variables), or outliers (Kennedy 2005). Based on these issues, some independent variables can have unexpected negative coefficient values, especially if other independent variable values are high in comparison (Kennedy 2005). In the case of the Black predictor variable, this makes sense for this research, as the population for Sarasota County is predominantly White. Therefore, while being a minority is traditionally an indicator that contributes to increased vulnerability, the reduced variation of those variables may cause the nature and significance of their association to be masked variables in the global OLS regression.

When scale and spatial processes are simultaneously included in regression modeling, issues between traditional relationships between the predictor variables and vulnerability are further exemplified. In the hierarchical model column for Table 3.3, the Black predictor was removed, as it detracts from the overall model explanatory value (potentially due to overestimation from too many predictor variables) and was not statistically significant. The inclusion of spatial effects and scale in regression modeling can cause some variables to become unnecessary, especially those that are outliers and do not measure the largest amount of variation in the data. This has a large part to do with a lack of variation based on the overall population demographics.

This relationship is also visible in variables that were included in all three models (the OLS, SAR and HLGM). The Over65 variable experiences both statistical significance and coefficients signage changes throughout the three models types. In the OLS and SAR models, Over65 is statistically significant in both the OLS and SAR models, but the coefficient signage changes from positive in the OLS model to negative in the SAR model. Sarasota County has a large elderly population, so Over65 having a positive coefficient does correspond to traditional vulnerability literature and the county's population demographics. However, the Over65 coefficient signage goes form positive to negative in the SAR model, indicating that some type of spatial pattern that OLS regression does not account influence the overall influence of elderly populations on exposure. This would match the spatial distribution of the Over65 variable, as the Over65 LISA results indicated that there is more clustering of elderly population in specific areas along the coast.

However, the signage and statistical significance of the Over65 variable once again change from the SAR mode to the hierarchal model. The signage of Over65 in the hierarchical mode is once again positive, which could indicate that spatial processes alone cannot explain the relationship of Over65 on vulnerability. The inclusion of scalar block effects and spatial processes in the regression model demonstrate the true association relationship of the variable with exposure. Additionally, the Over65 variable is not statistically significant in the hierarchical model, indicating that while elderly populations are positively associated with exposure, the lack of variation in terms of spatial distribution or scalar effects could limit their overall effect on vulnerability.

It is also important to remember that the impact of variables at one storm category may change as the level of exposure increases from larger storm events. The results discussed above are specific to Table 3.3, which is the hierarchical model for a Category 1 Storm. The exposure variable increases as the storm category increases, meaning that variables that are not as significant in lower storm categories may actually change in terms of their statistical association with exposure as exposure increases.

Table 3.4 - Category 2 Storm Surge – Regression Model Results Comparisons

	OLS		SAR - Error		Hierarchical	
Block Level Variables						
Variable	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
(Intercept)	0.176	**0.000**	0.466	**0.000**	-1.823	**0.000**
Black	-0.139	**0.000**	0.023	0.097	-0.018	0.633
Development	0.096	**0.009**	-0.077	**0.000**	-0.024	0.229
Hispanic/Latino	-0.289	**0.000**	-0.010	0.432	-0.054	0.192
Females	-0.117	**0.000**	-0.071	**0.000**	-0.072	**0.000**
Age Under 5	-0.259	**0.003**	-0.023	0.454	-0.261	**0.003**
Age Over 65	0.234	**0.000**	-0.019	**0.030**	0.029	0.065
Single Mother HH	-0.136	**0.016**	-0.036	0.069	-0.124	**0.056**
Tourism	0.113	**0.001**	-0.012	0.296	-	
Sales Volume	0.000	0.071	0.000	0.083	-	
Critical Fac.	-0.065	**0.002**	0.004	0.607	-0.01202	0.639
Essential Fac.	-0.021	0.208	-0.002	0.781	-0.062	0.129
Wetlands	0.397	**0.000**	0.046	**0.013**	0.067	**0.003**
Agriculture	-0.200	**0.019**	-0.032	0.457	-	
Open Dev.	-0.159	**0.002**	0.053	**0.029**	-	
Evac Routes	-9.086	0.136	-5.963	**0.001**	-42.3677	**0.000**
Block Group Level Variables						
(Intercept)	0.330	0.144	0.378	***0.009***	-	
College Education	-0.500	***0.023***	0.034	0.779	-0.102	0.482
Below Poverty	0.046	0.914	0.139	0.522	0.2318	0.480
Per Capita Income	-0.255	***0.000***	-0.043	0.077	-0.1014	**0.000**
Social Security Inc.	0.616	***0.003***	0.208	**0.056**	0.2071	0.131
Seasonal/Temp Occupations	-1.750	0.057	-0.109	0.819	-0.380	0.571
Employed Pop.	0.378	0.354	0.222	0.273	-0.1323	0.465
Employed - Female	-1.071	0.065	-0.330	0.257	-	
Variables in Hierarchical Model Only						
Coastal Y/N*	-		-		0.099	**0.005**

**Spatial grouping variable to indicate Coastal versus Non-coastal blocks, as space is not explicitly included in HGLMs*

	OLS R^2	OLS AICc	SAR AICc	Hierarchical AICc	
Block	0.09	10,762.0	-8,641.7	Model (2 levels)	-25,784.1
Block Group	0.31	118.71	-119.08		

This pattern is evident in the Over65 variable in both Table 3.3 and 3.4. The Over65 variable undergoes the same changes as in Table 3.3 in terms of going from positive to negative coefficients between the OLS and SAR model, but is statistically significant in both. However, in the hierarchical model the Over65 variable in Table 3.4 is only just under the alpha level of 0.05 (Over65 p-value is 0.058), whereas the p-value for the Over65 variable in Table 3.3 is higher (p-value = 0.213). The coefficient value for the variable also increases from 0.006 in Table 3.3 to 0.029

in Table 3.4. This increase the coefficient value and decrease in p-values demonstrate that as exposure increases due to large storm categories, the influence of similar variables also increases.

3.4.4 Combined SAR Model results

The Category 3, 4 and 5 storms, the hierarchical models were not used to estimate coefficients, as the hierarchical models for these storm categories would not converge and scalar interactions between variables could not be defined. This indicates that the variation within the variables was not great enough for the generalized hierarchical model to successfully measure vulnerability using this method. In response, a SAR model that contained both census block and downscaled census block group variables was employed. The combined SAR model for Categories 3-5 demonstrated a significant amount of improvement from the OLS model. The results of the variable coefficients are shown in Tables 3.5 to 3.7.

Table 3.5 - Category 3 Storm Surge – Regression Model Results Comparisons

	OLS		SAR - Error		Combined SAR Model	
Block Level Variables						
Variable	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
(Intercept)	0.559	**0.000**	0.761	**0.000**	0.763	**0.000**
Black	-0.238	**0.000**	0.013	0.295	-	
Minorities	-		-		0.015	0.110
Hispanic/Latino	-0.548	**0.000**	-0.005	0.691	-0.009	0.439
Females	-0.075	**0.002**	-0.057	**0.000**	-0.062	**0.000**
Age Under 5	-0.300	**0.002**	-0.055	**0.038**	-0.055	**0.038**
Age Over 65	0.270	**0.000**	0.007	0.356	0.002	0.850
Single Mother HH	-0.077	0.218	-0.011	0.534	0.029	0.058
Tourism	0.115	**0.004**	0.004	0.684	-	
Businesses	-0.057	**0.000**	-0.004	0.114	-0.010	0.551
Critical Fac.	-0.043	0.069	-0.004	0.580	-0.003	0.609
Essential Fac.	-0.004	0.828	0.009	0.096	0.008	0.102
Wetlands	0.203	**0.000**	0.005	0.714	-	
Agriculture	-0.161	0.065	-0.058	0.107	-0.064	0.067
Development	0.021	0.378	-0.073	**0.000**	-0.076	**0.000**
Evac Routes	-19.543	**0.004**	-5.133	**0.001**	-5.211	**0.001**
Parcels	-9.974	0.344	1.345	0.439	1.446	0.405
Block Group Level Variables						
(Intercept)	0.369	0.183	0.869	***0.000***	-	
College Education	-0.464	***0.079***	-0.053	0.629	-1.366	**0.010**
Below Poverty	-0.451	0.378	0.253	0.190	3.090	0.101
Social Security Inc.	0.639	***0.015***	0.041	0.695	-	
Per Capita Income	-0.186	***0.001***	-0.034	**0.116**	-0.015	**0.029**
Veterans	1.128	**0.046**	-0.027	0.904	5.619	**0.001**
Seasonal/Temp Occupations	-2.509	**0.021**	-0.297	0.479	-9.907	**0.019**
Labor Force	1.649	**0.030**	-0.452	0.129	-	
Employed Pop.	-1.780	**0.026**	0.380	0.219	0.414	0.478
Variables in Hierarchical Model Only						
Coastal Y/N*			-			

**Spatial grouping variable to indicate Coastal versus Non-coastal blocks NOT included in Combined SAR Model*

Model Fit Statistics	OLS		SAR	Combined SAR	
	R^2	AICc	AICc	OLS AICc	SAR AICc
Block	0.08	12,814.0	-11,544.0	12,233.0	-11,559.0
Block Group	0.284	202.0	-164.9		

Table 3.6 - Category 4 Storm Surge – Regression Model Results Comparisons

	OLS		SAR - Error		Combined SAR Model	
Block Level Variables						
Variable	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
(Intercept)	0.902	**0.000**	0.943	**0.000**	0.946	**0.000**
Minorities	-0.121	**0.000**	0.000	0.952	-	
Hispanic/Latino	-0.410	**0.000**	0.001	0.902	0.003	0.693
Females	0.055	**0.005**	-0.031	**0.000**	-0.023	**0.000**
Age Over 65	0.105	**0.000**	0.001	0.891	0.000	0.987
Single Mother HH	-0.114	**0.031**	0.012	0.337	0.013	0.294
Tourism	0.071	**0.038**	0.012	0.128	0.011	0.143
Schools	-0.157	0.067	-0.047	**0.020**	-0.049	**0.015**
Businesses	-0.104	**0.000**	-0.004	0.060	-0.004	0.102
Sales Volume	0.000	0.066	0.000	0.880	-	
Critical Fac.	0.042	**0.040**	0.000	0.968	0.000	0.998
Essential Fac.	0.016	0.326	-0.002	0.602	-0.002	0.573
Agriculture	-0.242	**0.001**	0.011	0.689	0.012	0.645
Development	-0.168	**0.000**	-0.067	**0.000**	-0.067	**0.000**
Open Development	0.355	**0.000**	-0.008	0.561	-0.008	0.546
Evac Routes	-20.260	**0.001**	-0.526	0.649	-0.395	0.732
Nursing Homes	0.317	0.073	0.039	0.374	-	
Institutionalized Populations	-0.290	**0.048**	-0.043	0.198	-0.027	0.339
Parcels	-26.310	**0.004**	-4.238	**0.001**	-4.117	**0.002**
Block Group Level Variables						
(Intercept)	0.478	**0.003**	0.718	**0.000**	-	
College Education	-0.296	0.260	0.049	0.685	-0.900	**0.007**
Below Poverty	-0.538	0.275	0.233	0.254	0.622	0.664
Social Security Inc.	0.527	**0.006**	0.123	0.162	-	
Per Capita Income	-0.106	0.063	-0.029	0.213	0.003	0.566
Veterans	1.006	0.071	0.115	0.630	3.687	**0.002**
Seasonal/Temp Occupations	-2.474	**0.019**	0.223	0.617	-14.443	**0.000**
Unemployed Pop.	1.323	0.080	-0.079	0.807	0.351	0.848
Variables in Hierarchical Model Only						
Coastal Y/N*	-					

**Spatial grouping variable to indicate Coastal versus Non-coastal blocks NOT included in Combined SAR Model*

Model Fit Statistics	OLS		SAR	Combined SAR Model	
	R^2	AICc	AICc	OLS AICc	SAR AICc
Block	0.096	9,419.7	-17,707.0	8,418.9	-17,741.0
Block Group	0.200	201.3	-130.0		

Table 3.7 - Category 5 Storm Surge – Regression Model Results Comparisons

	OLS		SAR - Error		Combined SAR Model	
Block Level Variables						
Variable	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
(Intercept)	0.902	**0.000**	0.923	**0.000**	0.950	**0.000**
Black	-0.126	**0.000**	0.001	0.897	-	
Asian	-0.130	0.066	-0.012	0.539	-	
Other Minorities	0.162	**0.010**	0.005	0.764	-	
Hispanic/Latino	-0.476	**0.000**	-0.010	0.328	-0.006	0.483
Females	0.054	**0.003**	-0.033	**0.000**	-0.027	**0.000**
Age Over 65	0.051	**0.002**	-0.001	0.798	-0.001	0.877
Single Mother HH	-0.068	0.155	0.007	0.599	0.009	0.483
Tourism	0.078	**0.011**	0.012	0.115	0.012	0.122
Businesses	-0.077	**0.000**	-0.006	**0.007**	-0.006	**0.006**
Sales Volume	0.000	0.068	0.000	0.569	-	
Critical Fac.	0.070	**0.000**	0.007	0.200	0.006	0.202
Essential Fac.	0.021	0.141	0.000	0.933	0.000	0.923
Wetlands	0.052	0.151	0.031	**0.012**	-	
Agriculture	-0.207	**0.004**	0.022	0.429	-0.002	0.926
Development	-0.089	**0.004**	-0.044	**0.000**	-0.068	**0.000**
Open Development	0.281	**0.000**	0.028	0.075	0.005	0.720
Evac Routes	-15.090	**0.004**	0.326	0.778	0.414	0.721
Parcels	-23.110	**0.005**	-2.950	**0.025**	-2.933	**0.026**
Block Group Level Variables						
(Intercept)	0.544	**0.000**	0.809	**0.000**	-	
Below Poverty	-0.833	0.081	0.038	0.844	-0.900	**0.007**
Social Security Inc.	0.338	0.055	0.099	0.194	-	
Per Capita Income	-0.050	0.217	-0.019	0.288	0.004	0.399
Veterans	0.681	0.179	0.104	0.616	0.030	0.962
Food Stamps	0.377	0.241	0.015	0.912	0.331	0.754
Seasonal/Temp Occupations	-2.146	***0.025***	0.246	0.533	-3.238	0.237
Unemployed Pop.	0.898	0.216	-0.003	0.993	1.667	0.379
Variables in Hierarchical Model Only						
Coastal Y/N*	-					

**Spatial grouping variable to indicate Coastal versus Non-coastal blocks NOT included in Combined SAR Model*

Model Fit Statistics	OLS		SAR	Combined SAR Model	
	R^2	AICc	AICc	OLS AICc	SAR AICc
Block	0.074	7,016.6	-17,951.0	6,282.6	-17,955.0
Block Group	0.140	162.2	-182.8		

Tables 3.5 thru 3.7 also demonstrate variable behavior similar to the hierarchical models in Tables 3.3 and 3.4, where several variables undergo changes in both coefficient signage and statistical significance across the three types of regression models. One the largest difference between the combined SAR models and the hierarchical models results, however, is that the

combined SAR models, overall, have more predictor variables that the final hierarchical models for Category 1 and 2 storms.

This could be the result of larger exposure areas in the higher category storms, which results in great data variation in the predictor variables or because of the data formatting changes in the disaggregated block group variables. The disaggregated block group variables in the combined SAR models were reformatted so that the block group percentages of those variables were proportionally distributed to each of the nested blocks (within the block group) based on overall population. For example, say that a block group has 100 people who are employed and the four blocks nested within that block group have 200 people in total, 150 people, 0 people and 250 people respectively. The block group employment data would be proportionally distributed among the blocks based on overall population. Therefore, the first block receives ~33% of those employed individuals (~33.33 people), the second block receives 25% of the 100 people (25 people), the third block receives no people (there is no population within the block), and the fourth block receives ~41.6% of the 100 people (~42 people).

The issue with this assumption is that the number of employed people many not be so uniformly distributed amongst the four blocks. Therefore, the combined SAR models may include more predictor variables in the final model than the hierarchical model because the distribution of the data is more evenly distributed amongst the census blocks. This could lead to skewed results in the combined SAR model in terms of what is considered statistically significant and what might be removed if a the multiscalar hierarchical model that considers block effects had properly converged.

3.4.5 Spatial Distribution of Vulnerability Scores

The results of the developed vulnerability scoring maps resulted in several patterns that demonstrate similar but slightly different spatial patterns of vulnerability, given different storm categories. Figures 3.1 and 3.2 are vulnerability scoring maps for Category 1 and 2 storms, which were both developed using the hierarchical models, while Figures 3.3 to 3.5 contain the scoring maps for Category 3, 4 and 5 storms, which were developed using the combined SAR models.

The results indicate that places along the coast where storm surge exposure was highest are typically the most vulnerable, but there are pockets of areas further inland that experience comparable relative vulnerability scores as those for places along the barrier islands that would traditionally be considered more vulnerable based on increased exposure alone. Additionally, some places along barrier islands with high exposure are not considered to have relatively high vulnerability, which likely is the result of the presence of several vulnerability indicators that reduce overall vulnerability. This pattern also changes between the five storm categories, where some census blocks in the barrier islands that were highly vulnerable in the lower storm categories become less vulnerable in higher categories. This occurs because these scores are relative vulnerability scores, meaning that they are calculated relative to other exposed census blocks in each storm scenario. When additional blocks are included in the exposed areas as the storm categories increase, the socioeconomic indicators within those blocks are also added to the vulnerability model, which can affect how on census blocks score relative to another. This same pattern can also occur in reverse, where blocks with low relative vulnerability in low storm categories show higher relative vulnerability in larger storm categories, which could be the results of higher exposure values in those blocks or the addition of census block neighbors that have fewer societal assets or populations than the original census block.

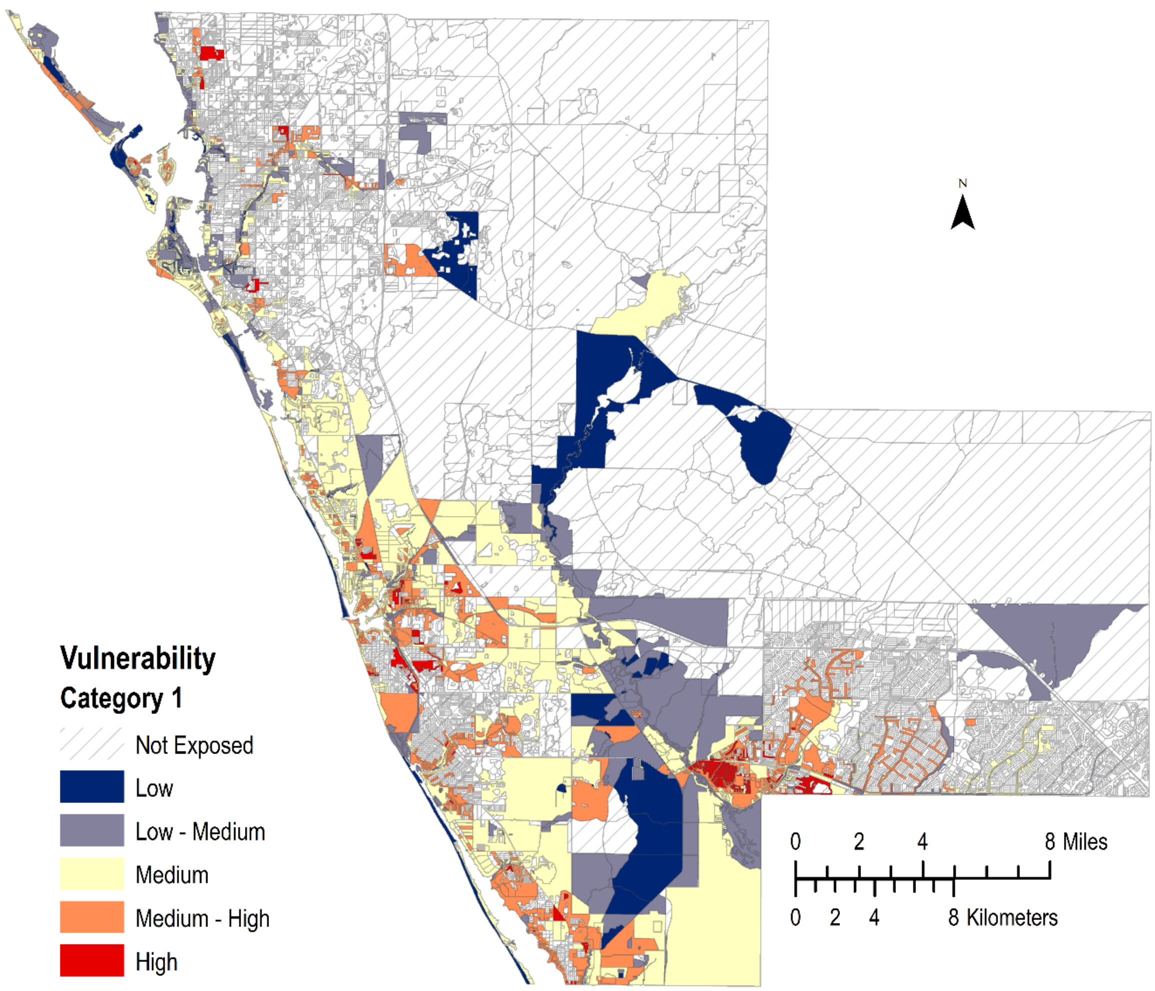

Figure 3.2 – Category 1 Vulnerability Scoring Maps based on Hierarchical Model Results

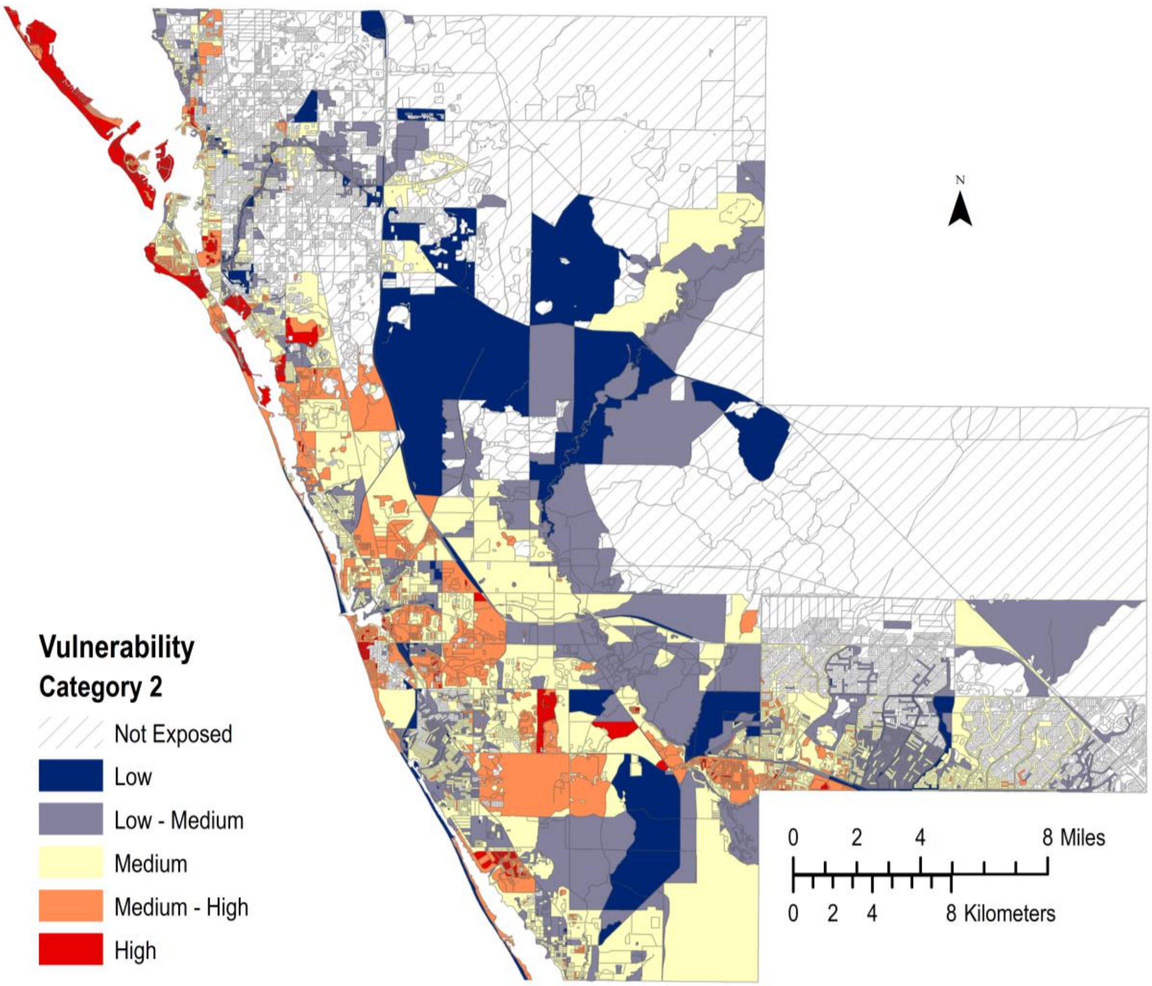

Figure 3.3 – Category 2 Vulnerability Scoring Maps based on Hierarchical Model Results

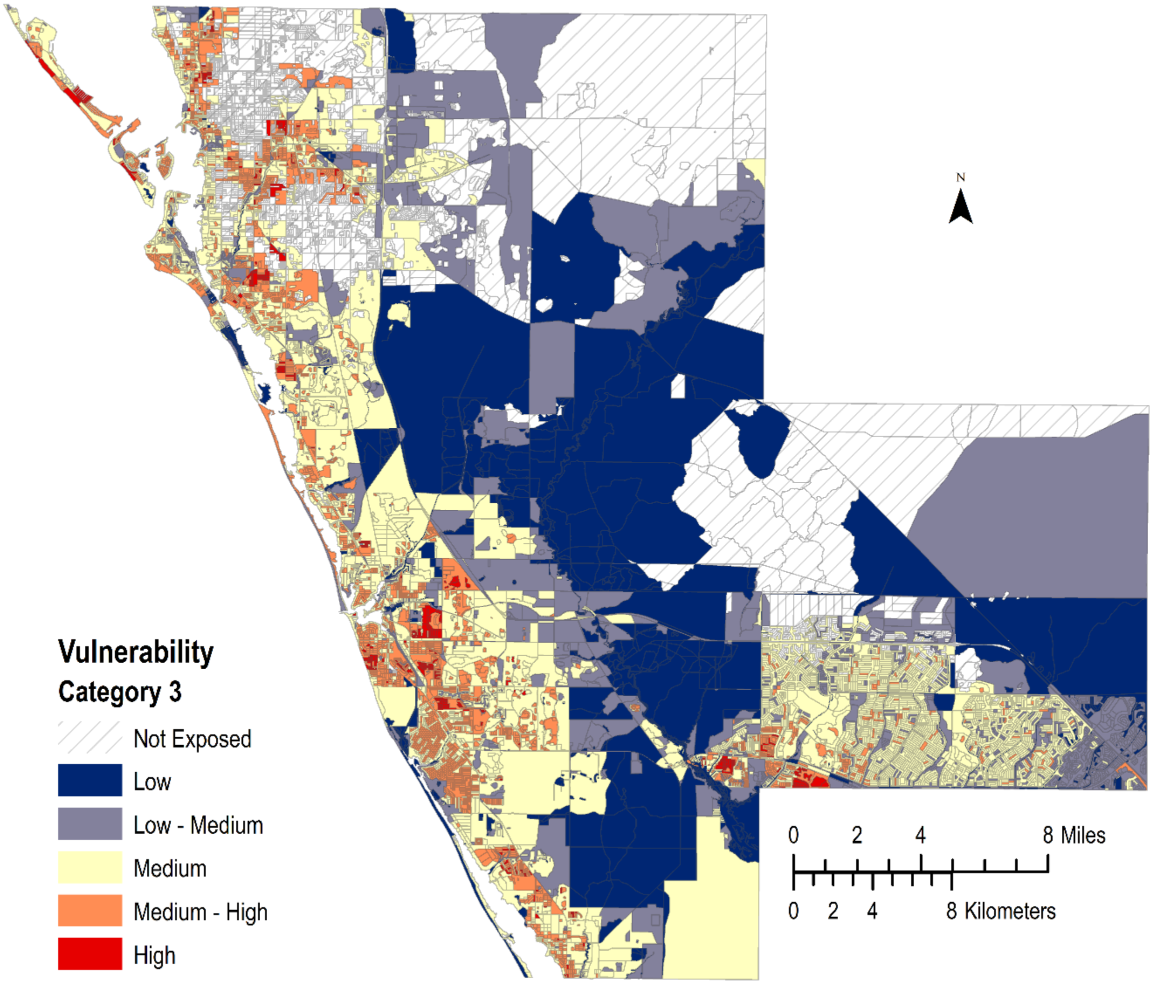

Figure 3.4 – Category 3 Vulnerability Scoring Maps based on Combined SAR Model Results

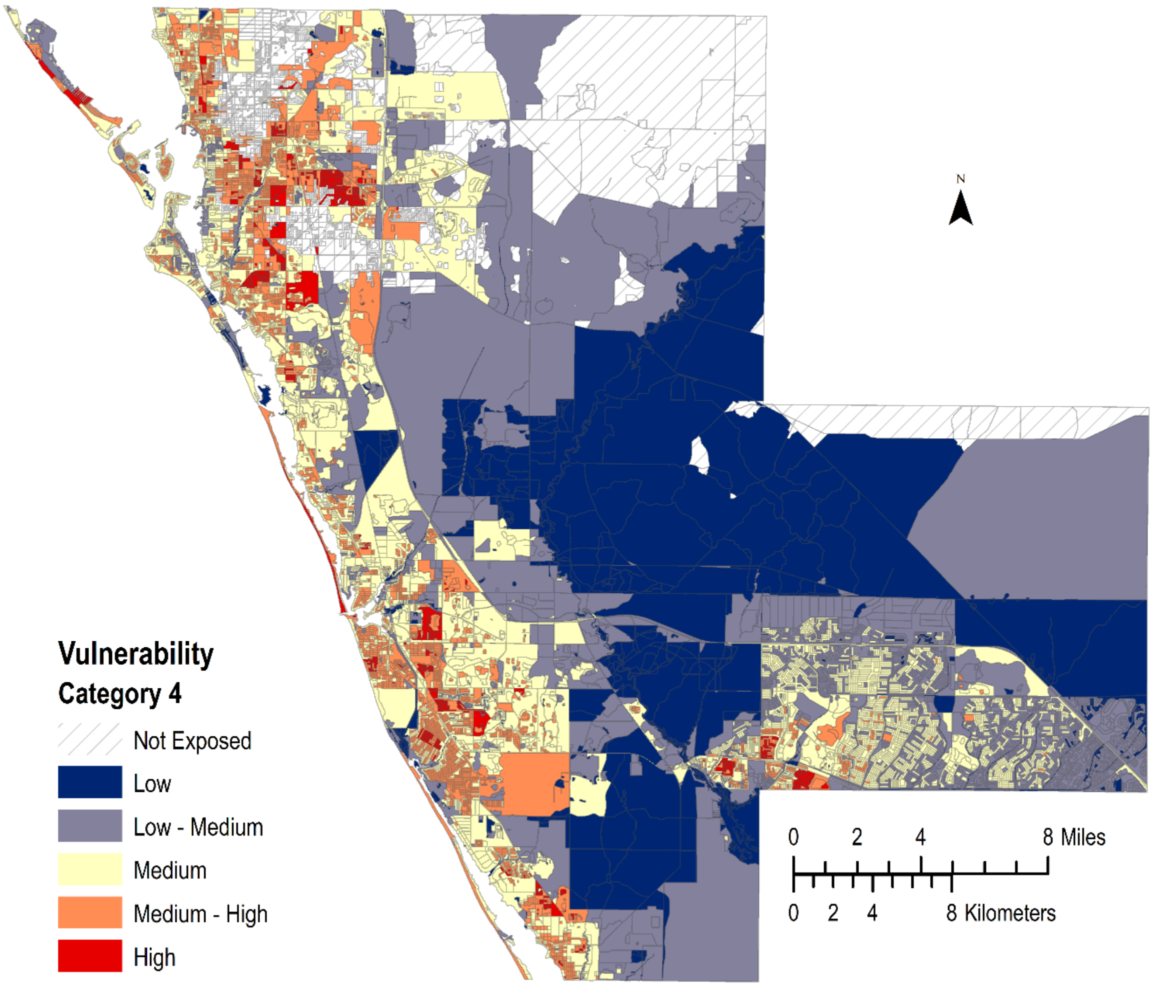

Figure 3.5 – Category 4 Vulnerability Scoring Maps based on Combined SAR Model Results

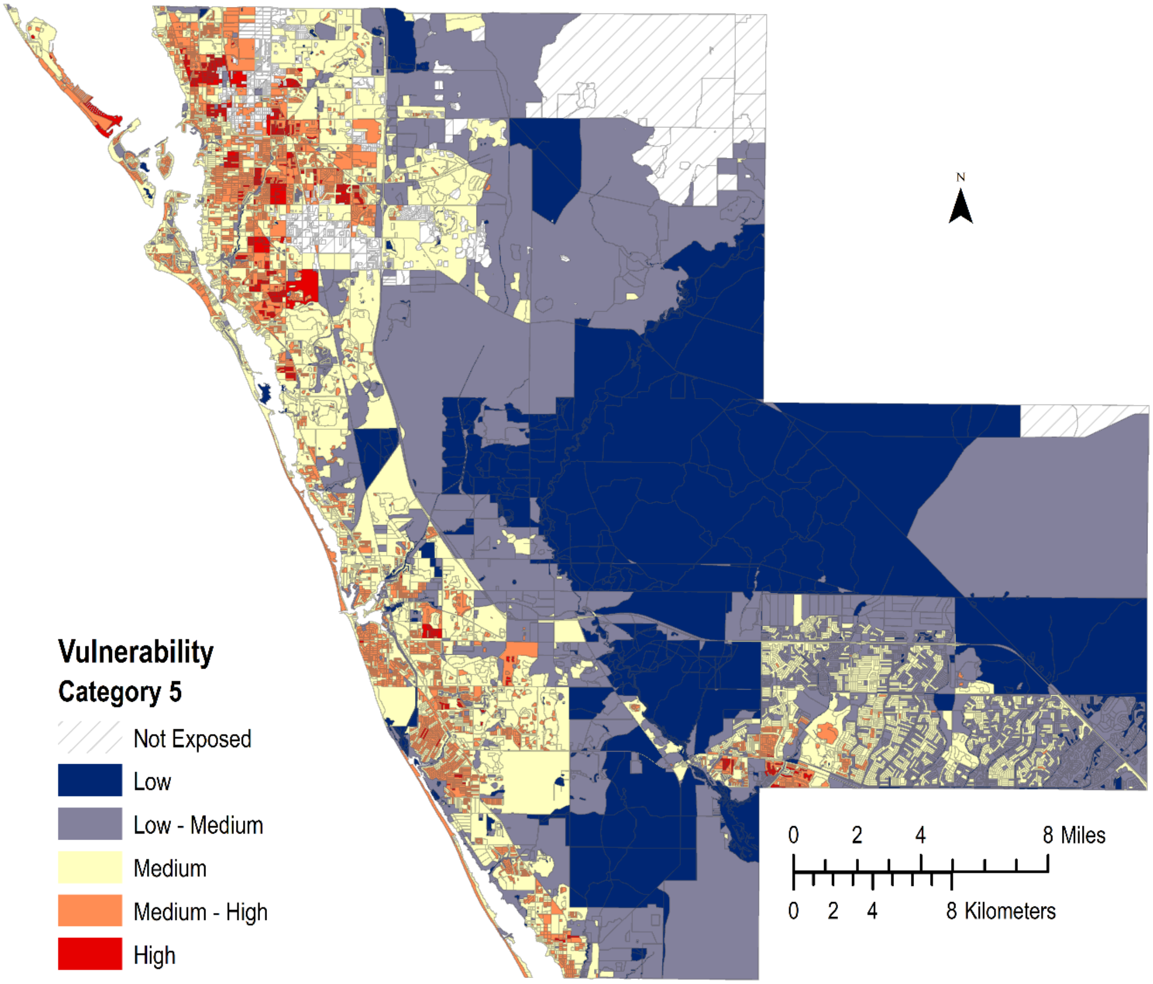

Figure 3.6 – Category 5 Vulnerability Scoring Maps based on Combined SAR Model Results

3.5 Discussion

In order to supplement existing natural hazards theory with greater theoretical and methodological foundations in vulnerability/resilience quantification methods, this paper presents a hierarchical framework that captures the social structuration of society to quantify overall system vulnerability (Morrow 1999). Structuration and political ecology serve as the theoretical foundations of both the indicators and model structure, as social structures systematically discriminate against marginalized populations, which increases vulnerability at several scales (Ugarte, Ibáñez, and Militino 2005; Morrow 2008). Additionally, the results of this research support model development from a more theoretical perspective in several ways.

The results indicate that the unit of analysis is a significant factor when considering different types of indicators of vulnerability and they scale at which they are measured (census block versus census block group). Hierarchical models estimate whether or not variables aggregated to a large spatial scale have a differential impact on the lower scale variables that occur within it (i.e. the census block groups influencing blocks within them). The results of the hierarchical models for Category 1 and 2 indicate that variables that occur at the block group level disproportionally affect blocks falling within that block group. This inter-scalar effect and variation is an interaction that classical regression and spatial, global regression modeling cannot identify, whereas hierarchical models can actually pinpoint what block groups have a statistically significant impact on the results of the model. An example of this is shown in Table 3.1, where the model fit improves from Model 1 to Model 2. The influence of each block group on the model fit is also mapped by their random effect coefficients, shown in Figure 3.7. These results indicate that block groups do have some random effect on the model output from a spatial perspective.

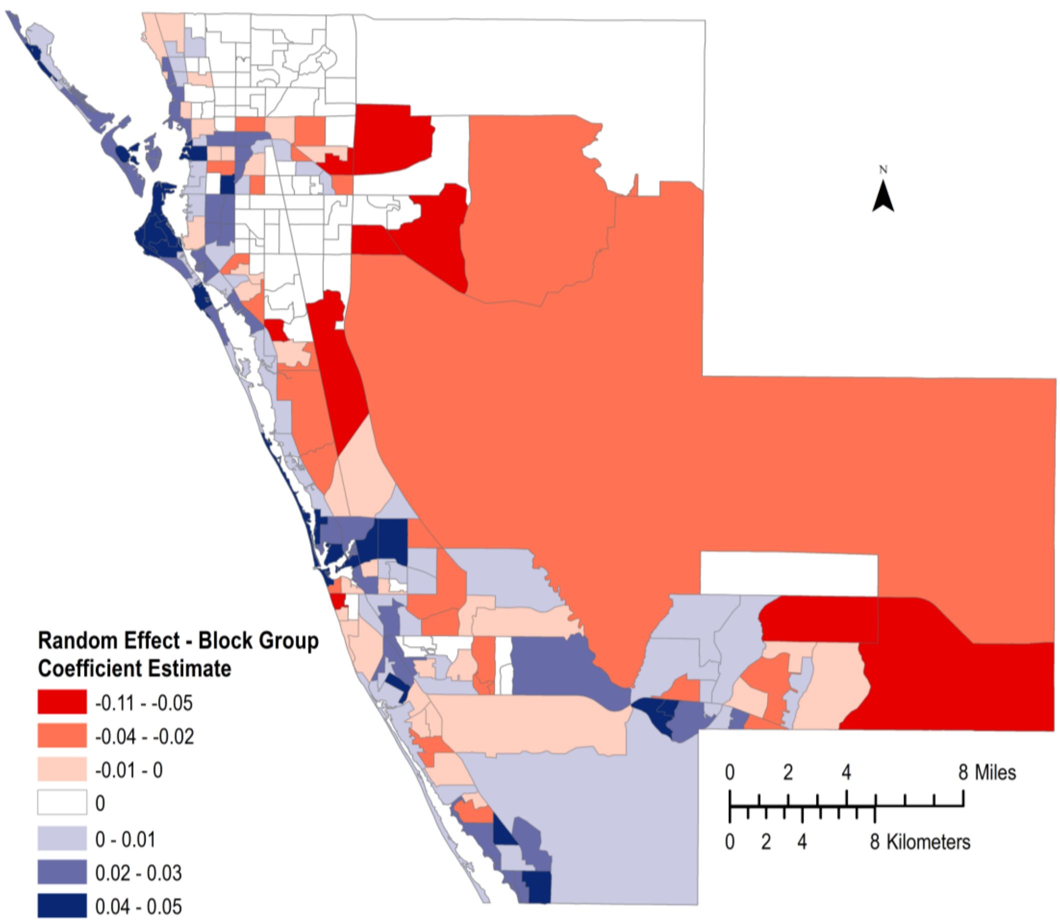

Figure 3.7 – Category 1 Mapped Coefficients for Random Effects, by Block Group

The results of the OLS, SAR and hierarchical models also suggest that the effect of certain variables is spatially and scalar dependent, providing evidence that examining vulnerability at a local and multiscalar perspective provides information about system vulnerability than classical or traditional statistical methods. These results suggest that including a hierarchical structure in vulnerability assessments can help to identify how society is structured and where certain vulnerability indicates are likely to emerge. Future research can be used to also examine the interaction between variables themselves, not just how they interact within a spatial blocking effect. The results of the hierarchical models also demonstrated that indicators at both scales sometimes change in terms of significance as the extent of inundation (exposure) increases. These differences are important to consider when conducting HMP in larger areas, as a one-size-fits-all plan may not be appropriate. If planners or decision makers only plan for a certain scenario, they may only focus on significant indicators for that specific level, thereby overlooking factors that may only be considered statistically significant at smaller inundation extents.

The results of the models also demonstrate that the form of the regression model used for analysis can also affect the manner in which certain indicators influence overall vulnerability. This pattern is demonstrated in the Tables 3.3 to 3.7, where indicators that have switched coefficient signage are highlighted in blue text. This change from positive or negative (or vice versa) signage for a given variable between the different model types demonstrates that when spatial variation or the influence of scale is not taken into account, there is the possibility that certain variables that do or do not have a positive influence on vulnerability are mistakenly thought to have greater importance. There is also a possibility that the coefficient signage changes are indicative of shortcomings in the models, which can be the result of high variances in the data, or outliers (Kennedy 2005). These issues are demonstrated in the Black predictors in Tables 3.3 and 3.4, as the population for Sarasota County is predominantly White. The Black predictor may have reduced variation that causes the nature and significance of its association with exposure to be masked, but it is at least identifiable in a global regression model like the OLS or SAR model. When multiscalar and spatial processes are both incorporated into a regression, the lack of variation in the Black predictor resulted in its removal from the hierarchical model column for Table 3.3, as it detracted from the overall model explanatory value. Based on these results, identifying predictor variables that are not outliers, and that exhibit sufficient variation (but not high variation) is critical for successfully conducting hierarchical vulnerability regression modeling.

Additionally, several statistically significant in the OLS models are not significant in the SAR model, but are in the hierarchical model. This indicates that certain variables are less significant to overall vulnerability when accounting for spatial effects at a global level (SAR model). However, when those variables are once again significant in the hierarchical model, this indicates that spatial effects alone do not influence those indicators and that scale can impact their influence on vulnerability in significant manners as well. The results of the hierarchical model also indicate that when multiscalar variables are used, fewer variables are needed in the model and too many variables can actually lead to model overestimation. This indicates that vulnerability measured at one scale or with spatial effects, may over/underestimate the importance of certain vulnerability indicators on vulnerability for a given area. This can lead to HMP strategies targeting indicators whose influence is potentially exaggerated while disregarding those that are influential on vulnerability. The hierarchical model with spatial effects uses a model structure that reflects the true structure of the human-environment system. This model provides a more accurate view of how both scale and spatial interactions impact vulnerability in a specific area and identifies those that are the most influential to that region.

The results of this study also demonstrate that physical and socioeconomic variables influence overall vulnerability in a heterogeneous spatial and scalar manner. Because certain indicators change based on the storm category, suggesting that vulnerability indicators are not only scale specific in terms of their interactions with one another, but also scale-specific in terms of differential magnitudes of exposure extents. While socioeconomic and physical data is typically collected at the same spatial scales, the magnitude of hurricane storm surge exposure increases as the hurricane strength increases, affecting more of the socioeconomic indicators. Storm categories are within each other's extent, so areas inundated during a smaller category storm would also be inundated from a larger category storm flooding. Therefore, regression model results may have some level of overlap or could hide some of the existing statistical significant indicators in the regression models for smaller storm inundation extents.

This can be problematic in larger exposure areas, as some indicators tend to cluster along the coast, which is highly exposed in all storm categories, not just lower storm categories. For example, the LISA analysis for elderly populations illustrates that there is clustering of elderly populations along the coast and barrier islands, which are heavily exposed to storm surge in all five storm categories. These variables are already considered influential on vulnerability when exposure is lowest, but because more variables are encompassed by storm surge extents in larger categories, these variables may be lost due to a lack of data variation in larger exposure areas. Therefore, when utilizing these results for planning purposes, variables that are identified as significant in lower categories should also be considered when planning for larger events, and their influence may not be as prevalent when more indicators are exposed. This is also important for planning because lower categories storms occur more frequently, meaning those vulnerability indicators are also more likely to be impacted by storm surge impacts more often that storm surge from larger category storms in the future. This type of composite and overall consideration would provide the most complete and holistic view of what actually influences vulnerability in specific areas within a county, and would aid decision makers in targeting hazard mitigation more effectively. This information also illustrates how certain indicators influence each other and lead to increased vulnerability in areas where exposure is not necessarily highest.

This methodology improves upon existing quantification methods of overall vulnerability by utilizing exposure as the dependent variable. Existing vulnerability indices predominately conduct an exposure or sensitivity analysis for vulnerability assessments. Some indices measure county level vulnerability using several sensitivity some adaptive capacity indicators (Cutter, Boruff, and Shirley 2003), but do not consider exposure (Cutter, Burton, and Emrich 2010; Frazier, Thompson, and Dezzani 2014). Exposure is the proximity of a hazard to a community; therefore, in order for vulnerability to present, societal assets must be at risk of intersecting with impacts from a natural hazard (Adger et al. 2004; Berkes 2007; Füssel 2007; Smit and Pilifosova 2003; Vincent 2007). Exposure is typically omitted from social vulnerability quantification methods, leading to results that identify potential socioeconomic indicators that could influence vulnerability, but are not necessarily in areas where physical vulnerability is present. Vulnerability is comprised of both physical and social vulnerability. Methods that neglect one aspect of total vulnerability do not provide vulnerability scores that are not truly holistic and can be misleading when they are utilized for HMP strategy development and implementation.

When compared to the results of other similar models, such as the SoVI or SERV models, the patterns of vulnerability are similar but also provide added information about the specific indicators. This methodology also identifies and utilizes multiscalar variables to identify indicators that influence vulnerability at several social levels. This research also addresses the presence of social theory in its practice and examine underlying social processes that cause certain social conditions to exist within society. The models provide information about how certain indicators predispose individuals to being more or less vulnerable or resilient to hazard events and how they interact with one another. If communities can develop mitigation that targets underlying social issues that predispose individuals to being more vulnerable, then the impact of those indicators on vulnerability will diminish as well.

3.6 Conclusions, Limitations and Future Considerations

The methodology presented in this research provides additional information about how indicators influence vulnerability and interact with one another within and across scales, something that current vulnerability indices and quantification methods do not consider. Hierarchical modeling makes it possible to utilize variables that exist at the county or city level (i.e. external/internal county or city funding sources) in conjunction with block level variables (Banerjee, Carlin, and Gelfand 2004; Subramanian, Duncan, and Jones 2001; Gelman and Hill 2007; Graña and Torrealdea 1986). For example, the impact of external and internal indicators and risk perception on vulnerability is not examined in traditional vulnerability and resilience research. The current indicators in the SERV model are based on local indicators of vulnerability from a sub-county perspective, but external indicators such as federal hazard mitigation funding, can also reduce overall vulnerability. Including these types of indicators provides information that is normally not collected at the block level, but can still influence sensitivity or adaptive capacity within a given community.

The information provided by the models goes beyond existing literature that often only describes how social conditions (i.e. poverty) influence or predispose individuals to being more or less vulnerable or resilient to hazard events. This research will address the presence of social theory in its practice and examine underlying social processes that cause certain social conditions to exist within society. This research also has the potential to help communities identify mitigation techniques that can better assist marginalized populations through the development and targeting of non-structural mitigation policies that historically are underutilized even though they more directly benefit many areas of communities where vulnerability is highest.

3.6.1 Policy Implications

This methodology goes beyond traditional hazard and vulnerability assessments by incorporating multiple levels of data scales in the statistical analysis. Traditional models utilize data a single resolution of data, meaning that some of the data is aggregated of downscaled, which introduces bias into the statistical model related to the MAUP or ecological fallacy problems. This methodology removes some of that bias by leaving the scale of the gathered datasets intact, which can improve results that are used to develop and implement hazard mitigation policies.

Additionally, this methodology addresses the influence of spatial autocorrelation and outliers on the regression results. The results of the OLS, SAR and hierarchical models illustrate how spatial effects can influence model results in terms of which variables are considered significant. Spatial effects can also lead to model results that highlight outlier variables, not necessarily indicators that have the largest influence on overall vulnerability. This can lead to over estimation or underestimation of indicators impacts on vulnerability during the planning process and resource distribution.

The presence of outliers in the modeling process can also lead to plans that focus more heavily on outliers that may not be significant indicators for the study area as a whole. This is a limitation of the SERV and SoVI model, which use PCA analysis to determine significant groupings of vulnerability indicators. PCA analysis has a tendency to identify outliers, whereas outliers in regression models can influence model results and reliability. Outliers in regression models can affect the estimation strength of the model, which make them less effective for planning purposes.

This type of modeling provides a way to better understand how vulnerability indicators behave at the scale at which they are gathered, while also providing information as to which indicators are actually significant to vulnerability in an area. Better modeling methodologies can lead to better planning for disaster events, as there is a deeper understanding of where vulnerability, not just exposure, is highest and which indicators are the most influential impactful. It is easier to implement structural mitigation strategies in high exposure areas than in higher vulnerability areas because exposure is a tangible concept for most decision makers. Creating holistic vulnerability maps provides a tangible way to provide decision makers with the ability to target mitigation to high vulnerability areas, not just high exposure areas.

3.6.2 Measuring Risk Perception and Agency

Hierarchical models provide a model structure that better represents the hierarchical and multiscalar aspect of society. This methodology advances current natural hazards literature by grounding the research in structuration and political economy and utilize those frameworks to drive the model structure development. Future work on this methodology will consider the inclusion of nontraditional variables in a holistic vulnerability model, such as risk perception, external funding sources or social agency, to determine how social conditions, social structure, social capital and risk perception influence vulnerability and resilience at the community level. Risk perception and agency are also interconnected in that while some people may have heightened risk perception, they may not have the agency to implement changes or mitigation that could help them decrease vulnerability. This would include qualitative work to determine potential indicators of risk perception or social agency and power. This information will in turn inform the parts of the hierarchical model that examine how risk perception affects an individual’s sensitivity and adaptive capacity why people develop those perceptions and how other social conditions impact community vulnerability.

Chapter 4 – Survey Analysis of Risk Perception and Structuration on Vulnerability

4.1 Introduction

The proliferation of development in hazardous areas has led to an increase in population, societal assets, and infrastructure vulnerable to natural hazards impacts. In order to reduce societal losses from natural hazards, communities often utilize hazard mitigation planning (HMP) to lower their vulnerability to hazard events (Adger et al. 2005; Rose 2007). However, vulnerability varies spatially as a result of development patterns that reflect constraints from the natural landscape as well as different cultures, beliefs, risk perceptions and attitudes that people attribute to different places (Chakraborty, Tobin, and Montz 2005; Knox and Marston 2013). The exposure of populations and societal assets to natural hazards also vary spatially variable, as different natural hazards develop in certain environmental conditions (Keller, DeVecchio, and Blodgett 2014). A combination of these social and physical factors shapes places differently, resulting in a uniqueness of place that leads to spatially variability in natural landscapes, population and distribution of social assets. Understanding how community vulnerability varies spatially is important for effective HMP and disaster response (Boin and McConnell 2007; Pederson et al. 2006).

Social processes can further complicate the distribution of vulnerability, as social factors can cause vulnerability to vary spatially in ways that extend beyond physical hazard exposure. Social vulnerability results from social inequalities that inhibit access to resources and information, which influences people's ability to cope with hazards and disasters impacts (Bogard 1988; Fothergill, Maestas, and Darlington 1999; Morrow 1999; Goldman and A. 2000; Eakin and Luers 2006). While many studies utilize traditional indicators of vulnerability (indicators of access to resources) to measure social vulnerability, access to information is often overlooked. This exemption is important for gathering a more complete measure of vulnerability because access to information is one of the main drivers of risk perception development. Risk perception describes how people identify and measure risk based on information they have about the risk and can come from a variety of sources and experiences (Kasperson et al. 1988; Slovic 1987).

Considering risk perception in natural hazard literature is important because perceptions directly and indirectly affect hazard mitigation and adaptation decision-making (Slovic and Weber 2002). People with different risk perceptions can make HMP implementation more difficult if they disagree on the best risk reduction strategies (Slovic and Weber 2002). This occurs because people make subjective judgments about a risk from gathered information to develop their perceived risk (Frewer 1999). However, perceived and "real risk" (risk that has been measured or assessed using substantiated methods, such as modeling) are not always the same (Sjöberg 1999) and people are typically bad risk estimators due to of a lack of knowledge about a risk, cultural and ethnic backgrounds, biases from media sources, vested interest and perceived benefits from partaking in risky behavior. People typically develop mitigation and adaptation strategies for contemporary and future hazards using existing risk perceptions of the consequences of those risks, not what might actually occur (for which they have no basis). Due to uncertainty in mitigation, there is no way to predict how future hazards will affect an area, leading to the implementation of mitigation based on past experience or risk expectations.

Additionally, risk perception can also influence risk tolerance, which often drives development patterns and mitigation strategy implementation. Risk perception of the hazard impacts how people respond to a hazard event, which could potentially influence their overall vulnerability. For example, a person's ethical or cultural background can influence how people perceive the hazard (i.e. as divine action), how they react to danger and how they deal with loss (Oliver-Smith 1996). Previous studies have also found that risk perception can influence evacuation behavior or mitigation strategy implementation (Barnett and Breakwell 2001; Frewer 1999; Matyas et al. 2011; Paton et al. 2008; Sjöberg 1999), which, in turn, can influence vulnerability. These studies are not always clear as to what specifically causes people to make those decisions (Peacock et al. 2005) and they do not necessarily show how individual risk perception affects vulnerability from systems level.

Another factor that influences risk perception in a way that can impact overall vulnerability (but is often omitted in both risk perception and natural hazards literature) is the impact of social structuration. Structuration theory defines social structure as roles and resources that people use when interacting within society (Giddens 1984; Cozzens and Gieryn 1990), which are affected by differing levels of power and agency. Different levels of power and agency affect an individual's ability to act in a way that actually results in changes to pre-existing conditions (Giddens 1984). Agency describes the capacity of an agent to act in society (Workman et al. 2008), whereas power, at some level, must be exercised in order for an individual to 'act' in a way that results in actual change (Giddens 1984; Turner 1986). Both social structure (which is a result of repetitive human behavior) and human agency influence social life (Giddens 1984; Turner 1986). Social vulnerability stems from inequality of power, which is necessary for agents to 'act' and affects access to resources (Lazrus et al. 2012). Therefore, power should be considered when discussing risk perceptions and likelihood of acting on those perceptions.

Past studies demonstrate that people are not motivated to mitigate against a threat based on their feeling of susceptibility alone (Martin, Martin, and Kent 2009; Miller, Adame, and Moore 2013; Powell et al. 2007). Oftentimes, there must be a combination of feeling susceptible and a heightened perceived severity of consequences for a person to undertake risk reduction behavior, which ties into vested interest theory and self-efficacy (Miller, Adame, and Moore 2013). These concepts demonstrate the connection between risk perceptions and structuration by linking the concepts having the power to act and the willingness to act. While risk perception and structuration influence hazard vulnerability and mitigation, they are difficult to measure with existing data sources. Qualitative measures (i.e. surveys and focus groups) traditionally used for determining potential indicators of vulnerability, are often represented in quantitative models with measured data proxies. Therefore, traditional vulnerability/resilience quantification methods often omit these types of indicators (Adger 2006; Cutter, Boruff, and Shirley 2003; Frazier, Thompson, and Dezzani 2013; Füssel 2007).

For these reasons, identifying risk perception indicators can provide information about existing public risk perception that is essential to the sociopolitical realm where politicians and decision makers develop and implement mitigation strategies (Leiserowitz 2005). Policy decisions are partly influenced by the desires of the public. Therefore, assessing how people interpret, organize and form that information into a perception or bias can provide insight about what drives those perceptions, and from what sources those develop (i.e. social structure or stake, etc.). Power is necessary to 'act' or behave in some manner, so identifying how risk perception and social structuration influence vulnerability both separately and interdependently provides insight about potential risk reduction behavior (Cozzens and Gieryn 1990; Giddens 1984; Lane 1999). Understating how risk perceptions develop can also illustrate how social structure information is processed and interpreted to create perceptions, which in turn, guides human behavior or responses to a risk (Lane 1999). This relates to Giddens (1984) concept of 'duality,' in that identifying how perceptions develop based on the social structure may explain how social structure also helps shape an individual's perception and resulting behavior (Cozzens and Gieryn 1990; Lane 1999).

This paper presents a conceptual framework and validation method for identifying and measuring the influence and interdependence of risk perception and social structuration indicators on vulnerability at the local scale. This research examines the relationship between risk perception, social structure and demographic indicators using surveys, contingency tables, and correspondence analysis. The validation methodology describes the relationship between risk perception and levels of agency to better understand how people react to or cope with hazard events at both the individual and community level. These statistical methods are more appropriate for categorical data analysis than traditional regression methods and can be used for hypothesis testing in terms of determining which indicators influence one another (Subramanian, Duncan, and Jones 2001). Additionally, they identify significant relationships between demographic indicators traditionally associated with vulnerability and risk perception and social structure indicators. Significant variables can then serve as indicator proxies for the likelihood of people implementing mitigation strategies in certain places and the impact of social structures on overall vulnerability. This research, therefore, connects risk perception to systems or collective vulnerability quantification method, providing a link to the impact of risk perception and structuration on vulnerability.

4.2 Review of Current Literature

This research utilizes theoretical backgrounds from both risk perception and natural hazards theory. This section contains general literature reviews for both fields and then synthesizes how they relate to measuring vulnerability.

4.2.1 Risk Perception Theory

People identify and measure risk based on information they have about the risk (Kasperson 1988; Slovic 1987). Past experience with a hazard, indirect information about risk events from government or media sources, trust or distrust in experts or government, cultural factors, self-efficacy (how people assess their own coping capacity) and lack of knowledge about the risk can all influence an individual's risk perception and risk communication (Miller, Adame, and Moore 2013; Siegrist, Keller, and Kiers 2005; Sjöberg 1999; Slovic 1987). Using this information, people make subjective judgments about a risk to develop their perceived risk, which does not always match "real risk" (Frewer 1999; Oren and Koepsell 2012).

Risk perception in response to natural hazards is traditionally associated with behaviors that fall under the theory of decision under uncertainty, in which people make decisions with the knowledge they have but do not assume that they know all of the alternatives (Kahneman 2003; Slovic 2016). While the theory of decision under uncertainty identifies basic reasons why people make certain risk decisions, it is technically a decision-making behavioral theory and does not identify specific factors that influence risk perception and risk tolerance, or their influence on mitigation implementation (Slovic 2016). In response, several risk perception theories have been developed to identify how different factors influence an individual's risk perception, to better understand how people form judgments about risks they face in everyday and how they act on those judgments (Wilkinson 2001).

Many early risk perception studies focused on the psychometric paradigm, which emphasizes that people develop risk perception through information about a risk as well as intuition or perceptions about the risk (Siegrist, Keller, and Kiers 2005; Park and Kim 2014; Slovic 1987). For example, a person may read that a nuclear power plant in the present day and time is significantly safer than when the Chernobyl incident occurred, but still fear the prospect of nuclear power because they perceive nuclear plants as having a high threat level (Slovic 1987). The psychometric paradigm examines why people perceive risks differently, and what specific factors cause that perception to differ based on familiarity with the hazard, severity of consequences and knowledge about the risk (Siegrist, Keller, and Kiers 2005).

Risk perception theories that attribute social influences to risk perception development are the theory of planned behavior, the Social Amplification of Risk (SARF) and cultural theory. The theory of planned behavior states that consequences of an event or action, social value of the consequences and perceived ability to act contribute to an individual's decision to take certain actions. People react to a hazard event based on what possible consequences the hazard may have on the individual. The social value of their reaction and their ability to react to are what drive their risk perception (Patuelli et al. 2012). For example, if individuals feel they are unable to evacuate from a hurricane event in time, or that the storm is not large enough to cause enough damage that would justify the expenses of evacuation, those that people are less likely to evacuate during a hurricane event. The SARF framework explores how social interactions and values influence how people perceive dangers or hazards. For example, if an individual's neighbors repeatedly claim that they survived one hurricane with manageable damage and, therefore, they can manage the next, the individual or other neighbors may take their underestimation as fact and view the next hazard as low risk (Kasperson et al. 2003; Kasperson and Kasperson 1996). For example, while nuclear energy plants now employ much safer conditions and safety precautions, Americans are much less inclined to allow the country to use nuclear power due to an increase perceived risk (Kasperson et al. 2003; Kasperson and Kasperson 1996). Media, public opinion and social values can also amplify risk, which may not accurately reflect "real risk".

Alternatively, cultural theory asserts that individuals develop risk perceptions based on cultural biases and social norms that influence how they acknowledge (or avoid) certain risks (Ng and Rayner 2010; Rayner 1992). Cultural theory focuses on active, not passive, perception and takes place from an institutional, not individual perspective. The institutional (or social) structure is the driving force behind risk perception, in that if dangers exist, social institutions will identify and stress risks that help reinforce social order (Douglas 2013; Ng and Rayner 2010; Rayner 1992). People's group membership, cultural values and prior experiences all affect how social groups view different risks (Douglas 2013; Ng and Rayner 2010; Rayner 1992).

Other theories, such as the vested interest theory, behavioral design theory and the theory of protective design, specifically look at the relationship between an individual’s attitude toward disaster preparedness and their behavior to prepare for a disaster event (Miller, Adame, and Moore 2013; Oren and Koepsell 2012). In vested interest theory, an individual will have certain attitudes towards hazard events, but their behavior may or may not reflect that attitude (Miller, Adame, and Moore 2013). For example, if a wealthy retiree with an insured winter home along the coast is warned of an incoming storm in that area in the summer, he/she likely will not mitigate possible damage as they will not be in the area at that time and will likely receive insurance payments to rebuild or repair (Crano 1995; Miller, Adame, and Moore 2013; Sivacek and Crano 1982). Vested interest theory asserts that five main components can be used to predict whether an individual’s attitude will result in behavior that reflects that attitude: a) a person’s stake in the outcomes of the disaster event, b) the relative importance or prominence of an attitude toward a disaster event c) the perceived certainty of potential consequences from a disaster event d) immediacy of the hazard event and consequences and e) self-efficacy (Miller, Adame, and Moore 2013). If one of these components is missing, the overall vestedness for the attitude, and therefore predictive behavior related to that attitude, will be reduced (Miller, Adame, and Moore 2013; Crano 1995).

Finally, the situational theory of publics (STP) addresses risk perception from a more complex social aspect than cultural theory or SARF. STP asserts that the public is not comprised of a singular type of public. Therefore, when people react to a disaster, the level of awareness about the disaster and the manner in which they respond will differ, which may result in the development of several publics (Grunig 1983; Hamilton 1992)). Grunig (1983) describes publics as groups of distributed people that communicate in a similar manner about similar issues (Hamilton 1992; Illia, Lurati, and Casalaz 2013). The situational theory of publics examines how individuals become aware of or identify possible risks and the extent to which they react to or mitigate those risks. This theory identifies and classifies individuals’ level of awareness concerning a hazard or risk and determines the extent to which they react to that hazard or risk. Grunig (1983) originally developed this theory to determine why certain individuals take an active or passive role in risky situations. People are described as passive or active based on three independent variables and two dependent variables: problem recognition (independent), constraint recognition (independent), level of involvement (independent), information seeking (dependent) and information processing (dependent) (Hamilton 1992; Illia, Lurati, and Casalaz 2013; Major 1999). Several studies have also demonstrated that certain demographic variables such as age, gender or education can also influence how people fall into certain publics (Hamilton 1992; Illia, Lurati, and Casalaz 2013). This information could be used to determine if certain groups are more of less active during hazard situations, and how that could affect their overall response to risk situations.

4.2.2 Traditional Factors Affecting Natural Hazards Risk Perception

Risk perceptions directly and indirectly affect how people react and cope with risks, which affects vulnerability. These behaviors, in turn, impact how people develop and implement hazard mitigation and adaptation strategies addressing those risks (Martin, Martin, and Kent 2009). When faced with a threat, people evaluate how the threat concerns them and whether they feel that they can do anything about the threat (i.e. power to act) (Miller, Adame, and Moore 2013). For this reason, risk perception is important to consider when planning for natural hazards and disasters because it influences the implementation of hazard mitigation strategies and behaviors that influence overall vulnerability (in either a positive or a negative fashion).

Several risk perception studies identify and examine factors of risk perception (Frewer 1999; Lazo, Kinnell, and Fisher 2000; Miller, Adame, and Moore 2013), but do not necessarily examine multiple factors simultaneously in a single study. Factors such as vested interest, outrage, social trust, knowledge, real or perceived risk, possible benefits or losses, relevance to individual and potential for control can all influence how people develop their own risk perception, but are not measured in the same research (Frewer 1999; Lazo, Kinnell, and Fisher 2000; Miller, Adame, and Moore 2013). In other studies, researchers examined the relationship between risk perception and the demand for risk reduction and mitigation (Oren and Koepsell 2012; Powell et al. 2007; Sjöberg 1999; Tansel 1995). Some results suggest that risk perception influences a person's 'perceived risk', which drives their individual risk tolerance and directs disaster preparedness (Tansel 1995). People with low risk perception often experience higher risk tolerance, and are less likely to support mitigation to help minimize damage, whereas people with high risk perception experience lowered risk tolerance and become more likely to demand mitigation policies or programs that help minimize hazards losses (Sjöberg 1999).

Oren and Koepsell (2012) and Miller, Adame, and Moore (2013) utilize risk perception frameworks, such as vested interest theory and the theory of protective design, that emphasizes an individual's attitude toward a risk is not necessarily reflected in their behavior to actually prepare for a disaster event. An individual's attitude about the probability of a risk occurring is not enough of an impetus for someone to engage in risk reduction strategies (Frewer 1999; Oren and Koepsell 2012; Miller, Adame, and Moore 2013). Factors other than the possibility of a risk also drive people to act, such as previous knowledge and experience or the hazard, the expected severity of consequences (not just the perceived certainty of disaster consequences) and self-efficacy (Sloggett and Joshi 1994; Scoones 1998). Therefore, people may have a high risk perception to a hazard, but still choose to not implement mitigation (Scoones 1998; Park and Kim 2014).

There is uncertainty in all forms of mitigation, so there is no way to fully predict how future hazards will impact an area. This leads to people implementing risk reduction techniques based on past experience where hazard impacts were significant, or where they expect future events to have severe impacts, not necessarily where vulnerability (Sloggett and Joshi 1994; Oren and Koepsell 2012; Scoones 1998) or risk is highest. The presence of one of these factors alone is often not enough to cause someone to undergo risk reduction activities (Sloggett and Joshi 1994). A balance of knowledge, experience, responsibility, and belief that something can be done to mitigate the disaster impacts and a cost-benefit analysis of possible trade-offs in terms of conducting mitigation is necessary for reducing vulnerability before a hazard event rather than just responding directly impacts.

Additionally, many risk perception studies focus heavily on the importance of experience on hazard mitigation and implementation (Barnett and Breakwell 2001; Lindell and Perry 2012; Peacock et al. 2005; Raaijmakers, Krywkow, and Veen 2008; Wachinger et al. 2013). Risk perception studies can provide insight about how people's risk perceptions have been influenced by past events and how that influence can affect the mitigation implementation (McGee, McFarlane, and Varghese 2009; Ainuddin et al. 2013; Barnett and Breakwell 2001; Martin, Martin, and Kent 2009; Wachinger et al. 2013; Wachinger et al. 2010). However, several studies have contradictory results, where some communities adopted more mitigation and pre-disaster measures, whereas other experienced a drop in mitigation adoptions, in those communities who have experience with an impactful disaster. However, McGee, McFarlane, and Varghese (2009) is critical of how risk perception models are conducted, as they often utilized experience as a key risk perception factor.

Recent studies, such as McGee, McFarlane, and Varghese (2009), Winter and Fried (2000) and have demonstrated that the influence of experience varies both by hazard types and spatially, demonstrating that the relationship between risk perceptions and actual implementation of risk reduction behavior remains unclear (Lindell and Perry 2012; Martin, Martin, and Kent 2009; McGee, McFarlane, and Varghese 2009; Peacock et al. 2005; Tierney, Lindell, and Perry 2001). In response, McGee, McFarlane, and Varghese (2009) provides a framework for addressing why residents within a hazard-affected community have different experiences and also demonstrated that risk perceptions can also vary within the community, such as some people choosing not to evacuate while other residents choose to leave. Lindell and Perry (2012) developed the Protective Action Decision Model (PADM) model to help explain how certain risk perception factors lead to specific protective actions or risk reduction behaviors, both from a pre-and post-disaster perspective. In contrast, Wachinger et al. (2013) conducted a meta-analysis papers of risk perception factor identification, and the results suggest that personal experience and trust levels with decision makers or experts have a great influence on personal risk perception development. This suggests that while experience is important in terms of how risk perceptions are developed, those perceptions are not necessarily reflected in risk reduction behaviors. For these reasons, using several different types of risk perception indicators in a single model may be beneficial for obtaining a more complete view of how individual's risk perception to certain hazards develop and how those perceptions are reflected in risk reduction.

Another limitation of current risk perception studies is their use of regression analysis with categorical data. Using categorical data in regression models is not statistically consistent because categorical and frequency data cannot be represented with continuous, normally distributed data (Agresti and Kateri 2011; Tutz 2011). Classical regression assumes that data is normally distributed and continuous, whereas categorical data is often measured through counts and has a multinomial distribution that nullifies *i.i.d.* assumptions (Agresti and Kateri 2011; Bishop, Fienberg, and Holland 1975; Burt, Barber, and Rigby 2009). Additionally, Likert question scaling automatically assumes that attitudes are at least partially formed by some latent or natural variable that cannot be fully characterized in a single scale (Clason and Dormody 1994; Sullivan and Artino 2013). Parametric statistical tests assume that data is continuous and often aggregates data by populations or location, which can mask potential latent variables that influence discrete attitudes. Aggregating or averaging responses for a given question does not address individual differentiation between responses, and provides inaccurate results about attitudes (Subramanian, Duncan, and Jones 2001; Newell et al. 2005). Therefore, utilizing statistical methods suited for categorical data analysis would improve the inferential abilities of qualitative studies on risk perception.

4.2.3 Risk Perception and Agency Incorporation in Natural Hazards and Vulnerability Literature

Some natural hazard theories briefly discuss risk perception and structuration as being impactful on disaster response and impacts, but they are not directly included in the model indicators. For example, the Pressure and Release model (PAR) examines both the social processes that lead to vulnerability and increased exposure to unsafe conditions, the model does not take the role of human agency on access to resources into account (Pelling 1998). Other studies in the natural hazards literature, such as the Pressure and Release (PAR) Model, the Turner et al. (2003) framework, the Spatially-Explicit Resilience/Vulnerability (SERV) model, the Social Vulnerability Index (SoVI), and the Baseline Resilience Indicators for Communities (BRIC) model, have developed conceptual frameworks and/or quantification methods to examine the influence of sociodemographic indicators on vulnerability and/or resilience (Abuodha and Woodroffe 2010; Blaikie et al. 2004; Cutter 2003; Cutter et al. 2008; Frazier, Thompson, and Dezzani 2014; Turner et al. 2003). These models utilize political economy and political ecology as the basis for indicator development and the quantification of social vulnerability; however, these models do not explicitly incorporate the effects of risk perception of social structuration and agency into their frameworks (Zhou et al. 2010). For example, the SoVI model utilizes sociodemographic variables such as age, race, economics and infrastructure to identify statistically significant socioeconomic, demographic and built environment variables that are empirically considered to have an influence on vulnerability (Cutter, Boruff, and Shirley 2003). However, the indicators do not include information on risk perception of social structuration, meaning the model cannot be used to underlying causes of social vulnerability indicators within the social structure (Cutter et al. 2009). Similarly, the BRIC model measures baseline resilience using indicators based on five sub-dimensions: social, economic, institutional, infrastructure, and community capital (Cutter et al. 2008; Cutter, Burton, and Emrich 2010). While the BRIC model measures resilience using traditionally vetted resilience indicators (Cutter et al. 2008; Cutter, Burton, and Emrich 2010), it also excludes explicit indicators of risk perception or structuration. Some of mitigation indicators in the institutional component and social capital indicators in the community capital component could be potential data proxies for agency or structuration, but none of these specifically measure the potential influence structuration has on risk perception, or how risk perception influences mitigation behavior.

Power and agency are terms that are associated with the theory of structuration, developed by Giddens (1984), which defines social structure as roles and resources that actors use when interacting within society (Cozzens and Gieryn 1990). A person’s agency is described as their capacity to act or engage in specific forms of behavior (Giddens 1984; Turner 1986). In order to ‘act’ in a way that results in some desired change, an individual must exercise power (Giddens 1984; Turner 1986). Structuration theory defines social structure as roles and resources that actors use when interacting within society (Giddens 1984; Cozzens and Gieryn 1990), and each role and resource provides different levels of power and agency. Unequal levels of power and agency can affect an individual's ability to act in a way that results in change, or specific forms of behavior (Giddens 1984).

Agency is related to the impact of risk perception on vulnerability because the way that people identify and measure risk is based on information they have about the risk (Slovic 1987; Kasperson et al. 1988). People typically develop mitigation and adaptation strategies for contemporary and future hazards using existing risk perceptions of the consequences of those risks, not what might actually occur. This type of behavior is associated with the theory of decision under uncertainty, where people make the best decision possible with the knowledge they have and within socioeconomic constraints (Kahneman 2003; Simon 1972). Social structuration and agency are important to consider when identifying factors associated with risk perception development, as they can influence the socioeconomic constraints on access to resources (i.e. knowledge). Mitigation strategies for future hazards are often developed through perceptions of the consequences of future risks, not what might actually occur. People make decisions with the knowledge they have but do not assume that they know all of the alternative options (Bang 2008; Barnett and Breakwell 2001; Fischhoff et al. 2009; Frewer 1999), which emphasizes how much risk perception and risk tolerance drives mitigation practices.

Risk perception and agency are interconnected in that while some people may have heightened risk perception, they may not have the agency or feel empowered to implement changes or mitigation that could help them decrease vulnerability. Different levels of power and agency affect what resources people can access, thereby affecting an individual's ability to act or cope with a hazard event (Giddens 1984). For example, a person who has the financial ability to implement hurricane hazard mitigation on their home may not have the power to obtain building permits that allow those renovations to occur in accordance with zoning polices. This person has access to the economic resources necessary to physically make changes to their home, but lacks the agency to obtain authoritative resources to implement those mitigation strategies. The spatial levels of societal organization, especially as they relate to administrative or institutional levels, may constrain a person or agency's ability to implement disaster reduction techniques. The people that are most impacted by hazards are typically those with the least agency and often have or feel they have less power to enact or influence hazard mitigation planning or policy. Therefore, a model that includes both levels of risk perception, power, and agency within the community as separate components in the presented model could provide a measure of community resilience and vulnerability from a more holistic social-structure perspective.

For these reasons, understanding risk perception of the public can provide insight into why certain mitigation strategies are/are not considered and how those actions/inactions may influence overall vulnerability. This information can also provide information about how social structures and access to resources influence risk perceptions, thereby influencing risk-reducing behaviors. Based on these challenges, this research examines the relationships between sociodemographic, risk perception and structuration factors to determine how community reception and mitigation can be driven by existing individual perceptions and social structures. This information can be used to inform community policies that are meant to improve mitigation and that will be effective mitigation strategies in terms of any type of risk reduction.

4.3 Methods

In order to gather risk perception and structuration data for individuals in Sarasota County Florida, the researchers developed a survey, whose purpose was to capture information about risk perception, structure and agency factors. The survey questions are developed using past studies in risk perception, structuration and natural hazards literature that have only examined specific aspects of risk perception or structuration as references (Alsop, Bertelsen, and Holland 2006; Ibrahim and Alkire 2007; Lazo, Kinnell, and Fisher 2000; Martin, Martin, and Kent 2009; Miller, Adame, and Moore 2013; Siegrist, Keller, and Kiers 2005; Sjöberg 1999). These studies often only examine specific components of risk perception and structuration; this survey combines questions that target all of these factors to create a comprehensive survey that can provide information on all of these components. The results of the surveys were then used in statistical analysis to determine significant relationships between risk perception, structuration and demographic characteristics that may influence vulnerability and risk reduction behaviors.

4.3.1 Study Area

Sarasota County, Florida is located on the west coast of the Florida peninsula with low average elevation. The physical characteristics of the county cause a large portion of the county to be susceptible to coastal hazard inundation impacts, such as inland precipitation flooding and storm surge inundation, with ~45% of the county falling within the 100-year floodplain (Sarasota County 2015; Sarasota County Department of Planning 2016; Frazier, Thompson, and Dezzani 2013). The county has also experienced significant population growth within the last decade, experiencing approximately 16% population increase from 2000 to 2010 (Bureau 2010) and is highly developed along the coast due to the Urban Service Area (USA) delineation. The USA describes the general area along the coast that Sarasota County has prioritized in terms of urban services (i.e. central water and sewer utilities, stormwater management systems, neighborhood parks, and street facilities, etc.) (Sarasota County 2015; Sarasota County Department of Planning 2016; Frazier, Thompson, et al. 2013). Future development will likely continue to increase along the coast due to the location of Interstate Highway 75 and the urban service boundary, leading increased societal exposure and vulnerability to coastal inundation hazards.

4.3.2 Survey Development

Risk perception, structure and agency data were gathered through a mix of phone and online surveys distributed to residents within Sarasota County through the survey distribution service Qualtrics. Based on the demographics of Sarasota County's demographics, the sampling in the survey was given the following sampling limitations: 1) residents must reside in Sarasota County, 2) 5% to 15% of the sample must include minority populations, 3) 40% to 60% responses must be from females, and 4) 20% to 40% of the responses must be from elderly populations (age 65 or older). Based on the population of Sarasota County at the time of the survey, a sample size of 317 surveys was required in order to get a survey sample with a 95% confidence level and 5.5% margin of error.

The survey consisted of three main question sections: demographic questions, questions identifying risk perception attributes and questions identifying social structure and agency attributes. The majority of the risk perception and structuration questions were measured on a Likert scale (discrete nominal or ordinal data), while the remaining questions were nominal categorical questions. The survey questions are ordered by category in Appendix A. The inclusion of demographic questions is consistent with most survey structures, as they are used to find relationships between risk perception and structuration factors. Demographic factors play a large role in measuring socioeconomic vulnerability and resilience, so researchers structured the demographic questions so that they could later tie the results to traditional components of vulnerability, such as age race, dependent populations or economic factors. Several studies have shown that demographic variables can influence levels of preparedness and the motivation to mitigate for hazard events. For example, people who care for children or the elderly typically undertake a higher level of preparedness due to the perceived added stresses that dependent populations can place on coping capacities (Miller, Adame, and Moore 2013). In addition, factors such as income or education may indicate access to information or resources that would allow them to prepare for hazards events (Illia, Lurati, and Casalaz 2013; Kim and Grunig 2011; Major 1999).

The second section of the survey was comprised of questions that examine different components of risk perception to hurricane impacts. These questions were developed based on previous literature that examines vested interest theory, STP and protective decision theory (Miller, Adame, and Moore 2013; Oren and Koepsell 2012), with questions addressing the influence of location, risk knowledge, hazard risk, perceived susceptibility, and self-efficacy on overall risk perception. *Location* addresses the question of why people chose to live in places potentially exposed to natural hazards, which can provide insight into existing incentives to reside in areas that are vulnerable to coastal hazards. These questions address the relative proximity of where people live the coast and specific characteristics that influenced their decision to live there (i.e. sense community, employment, recreation, etc.) (Martin, Martin, and Kent 2009; Matyas et al. 2011; Miller, Adame, and Moore 2013). *Risk knowledge* addresses the level of perceived risk knowledge people in hazardous areas have about local risks. This information is often used to reflect how much people perceive that they know about a specific hazard. While those perceived risk may not necessarily accurately describe actual risk, several studies suggest that people are more likely to think and act based on what they perceive they know rather that what is considered "correct" knowledge (Powell et al. 2007). Additionally, knowledge has been found to be correlated to engaging in risk-reducing behaviors (Lindell and Whitney 2000; Martin, Martin, and Kent 2009). Therefore, these questions can provide insight about what information people are likely to use when developing their ideas and actions towards risk. This information can be used in conjunction with the location questions to determine whether people live in risky areas willingly, or if they are unknowingly placing themselves in risky areas.

The next two sections of questions address risk perception indicators that can help potentially identify when people are more likely to engage in mitigation or risk reduction behavior. The questions concerning *susceptibility* address perceptions about how vulnerable to harm or at risk people feel they or their property are to a particular threat (Miller, Adame, and Moore 2013). Susceptibility is important to consider because it influences a person's willingness to engage in risk reduction behavior (Miller, Adame, and Moore 2013). Susceptibility alone is not enough for someone to mitigate against a threat, which is why this section also contains questions about perceived severity of consequences. The combination of both of these factors influence whether a person will undertake mitigation efforts to reduce impacts of a hazard (Powell et al. 2007). The next section addresses the issues of *self-efficacy*, which refers to how capable a person believes they of affecting change (in this case, in terms of reducing risk). If someone feels that engaging in mitigation techniques is not worth the required cost and effort, or they are incapable of doing so effectively, then are more likely to not engage in that behaviors, even if their risk perception is high (Martin, Martin, and Kent 2009; Miller, Adame, and Moore 2013). All of these components impact risk perception, which in turn can influence how people prepare for, mitigate against or react to a hazard event (Frewer 1999; Lazo, Kinnell, and Fisher 2000; Martin, Martin, and Kent 2009; Matyas et al. 2011; Miller, Adame, and Moore 2013). Previous studies, however, have not combined these risk perception components in a singular survey that specifically addresses the impact of risk perception on overall vulnerability, nor have they been specifically tied to existing demographic vulnerability indicators in this manner.

The social structuration questions were developed based several sources that use survey analysis to determine indicators of empowerment and agency (Alsop, Bertelsen, and Holland 2006; Ibrahim and Alkire 2007). These studies specifically address questions about social structuration in terms of empowerment and agency, where agency is an actor's ability to make effective choices and decisions and empowerment is the ability to make translate those choices into actions. These questions, listed under the *Community Interest* subset, address social structuration factors in terms hazard mitigation and preparedness, such as how much agency and empowerment a person feels in terms of making changes in their household or in community decision making (Alsop, Bertelsen, and Holland 2006; Ibrahim and Alkire 2007). While the risk perception questions utilize Likert scale questions to measure attitudes towards hazards and engaging in risk reduction behavior, the structuration questions address how capable a person's feels to put those attitudes into practice at different social structures (i.e. household versus community) (Alsop, Bertelsen, and Holland 2006; Ibrahim and Alkire 2007). These questions help identify interconnections between power and agency and risk perception and vulnerability.

4.3.3 Statistical Analyses

Once the surveys were completed, the data was processed to calculate basic demographics of the respondents (such as percent minority respondents) to determine how representative the sample is of the overall county population. The data was then processed for use in contingency table analyses. Some studies in the past have utilized parametric regression analysis to analyze survey data with attitude-based questions; however, this practice may result in inferential errors in the model, especially if the model is parametric. Likert scale data, originally developed by Likert 1932 as a way to assess respondent's attitudes (Newell et al. 2005). Questions developed on the Likert scale are considered ordinal categorical responses, which can be difficult to analyze using traditional regression modeling due the implied ranking and discrete nature of the data (Clason and Dormody 1994).

Due to limitations in regression analysis for categorical, ordinal data, using contingency tables and related statistics can provide more accurate statistical methods of modeling indicator influences on vulnerability. Contingency table analysis (or cross-tabulation) is a statistical method often used in survey research to demonstrate relationships between two (or more) categorical variables in a frequency distribution matrix where variable A is represented in rows, and variable B is represented in columns (Agresti and Kateri 2011; Fienberg 2007; Kaplan 2004). While multiple variables can be compared in a single table, the simplest and most common form of contingency tables only examines the relationship between two variables, and is often called a two-dimensional contingency table, or *two-way* table. Contingency tables provide frequency distributions that can be used to determine if some level of dependence exists between two (or more) variables (Agresti and Kateri 2011). This is done by conducting hypothesis testing on relationships between row and column variables (also known as effects). Significance in hypothesis testing for contingency tables is conducted using the Chi-Square test for contingency table independence, which determines whether the row and column variables are independent of one another. Row-column independence is based on the following hypotheses:

$$H_o: P(\text{row } i, \text{ column } j) = P(\text{row } i)\, P(\text{column } j)$$

$$H_1: P(\text{row } i, \text{ column } j) \neq P(\text{row } i)\, P(\text{column } j)$$

The null hypothesis (H_o) assumes that the row-column variables are independent and cannot be predicted from one another. If the null hypothesis is *not* rejected, this indicates that no effects were discovered and the observed differences in the cells could be explained by random chance. If the null hypothesis *is* rejected, then the alternative hypothesis (H_1) assumes that there is some level of dependence between the row-column variables, and they can be used in some fashion to predict the presence of the other (Agresti and Kateri 2011). In order to calculate the Chi-square, frequencies in the table must first be converted to expected cell frequencies using the following equation (Burt, Barber, and Rigby 2009):

$$E_{ij} = \frac{R_i C_j}{n}$$

where:

R_i = count for row I;

C_j = count for column I;

n = Total number of observations.

The expected cell value is then used to calculate the Chi Square statistic (X^2), using the following equation (Burt, Barber, and Rigby 2009):

$$X^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\frac{(O_{ij} - E_{ij})^2}{E_{ij}}$$

where:

O_{ij} = observed frequency for any cell;

E_{ij} = expected frequency for any cell.

The test decision rule is to reject H_o if the Chi Square statistic exceeds the 1-α quantile of a chi-square random variable with (r-1)(c-1) degrees of freedom. If X^2 exceeds the computed or tabulated Chi-square distribution value at a specific probability level (in this study $\alpha = 0.05$) then the null hypothesis must be rejected (Agresti and Kateri 2011; Fienberg 2007; Tutz 2011).

For this study, *two-way* contingency tables were conducted for all possible combinations between 3 main variable groupings: 1) demographic and risk perception variables, 2) demographic and structuration variables, and 3) risk perception and structuration variables using JMP. The Contingency table function in JMP automatically calculates cell counts, row and column percents, expected values, deviates (observed – expects) and a Chi^2 test statistics for each combination of variables. Contingency tables with significant Chi Square statistics were recorded, separated into their respective category of variable grouping, and then ranked, first on their p-value and then by their associated Chi-Square Test value. The ranking of the Chi-Square test value was done because the greater the Chi-Square Test value, the stronger the relationship between the two variables. The significant tables were then examined to identify specific relationships between variables that could affect vulnerability. Researchers identified these significant relationships by comparing the percentages of different combinations of responses between two variables and analyzing expected versus observed counts. Comparing percentages between response combinations provides information about how responses to specific demographic, risk perception or structuration variables can be unevenly distributed across different categories of the second, compared variable. Additionally, analyzing expected versus observed counts can also provide information about potential reasons that this relationship occurs. The power of these results is discussed further in the Results and Discussion sections, with specific examples.

Due to the size of this dataset, the number of *two-way* tables utilized for Correspondence Analysis (CA) was reduced to make the results and discussion more manageable. The reduced dataset was determined by extracting the top 20% of the ranked *two-way* tables in each of the 3 variable grouping sets and using those variable combinations as the inputs for the CA section of the methodology. CA is an exploratory statistical technique that is used to graphically represent data structures within contingency tables (Schelling 1969; Greenacre and Blasius 2006). Visual graphics such as CA are often utilized to facilitate the communication of numerical data in a different format. CA maps illustrate the relationship between row and column percents in a contingency table with three main measurements: profiles, masses and chi-squared distances (Greenacre and Blasius 2006). Profiles describe row or column percentages (cell frequencies divided by individual row or columns totals), which are most commonly used to draw comparisons between variable groups. Profiles are created for both rows and columns, and *average* profiles for both are calculated separately (i.e. there are average profiles for rows and an average profiles for columns). Row and column profiles serve as row points and column points that function as mathematical vectors that can be plotted in a four-dimensional space. Masses deal with the overall weight of cases or respondents in relationship to the grand total of the sample size (see Table 1.1) (Greenacre and Blasius 2006). Finally, chi-squared distances are calculated in order to illustrate distances between points. Chi-squared distances are a weighted variant on Euclidian distances that utilize the row profiles and the average profiles to calculate distances. These are called chi-square distances because they are formulated with similar structures, but utilize row/column profiles and average columns in place of observed versus expected values (equation below) (Greenacre and Blasius 2006).

$$d = \sqrt{\sum \frac{(r_{in} - r_{jn})^2}{r_\mu}}$$

where:

i = row of profile point 1;

j =column of profile point 1;

n=number of columns in row;

μ = average row profile.

Once the masses and chi-squared distances have been calculated, CA uses these values to calculate inertia between points (Greenacre and Blasius 2006; Nenadic and Greenacre 2007). Profiles and masses are used in CA analysis to determine where points will be plotted in a space, with average profiles serving as the center points (origin) of a cloud of points (Bartholomew et al.

2008; Greenacre and Blasius 2006). In mechanics, each object has a center of gravity and particles surrounding that object (or centroid) has a certain mass and distance from the centroid. Inertia is a function of mass and distance from the centroid that describes the tendency of an object to stay at rest or in motion. In CA analysis, this concept can be described in terms of CA masses (*r*) and chi-squared distances (*d*), and describes where points fall in relationship to the centroid (average profiles) of the data (equation below) (Bartholomew et al. 2008; Greenacre and Blasius 2006; Nenadic and Greenacre 2007).

$$inertia = md$$

where *m* is equal to the row mass and *d* is equal to the chi^2 distance. These coordinates are based strictly on either row or columns calculations, and therefore must be scaled in order to be depicted in a singular bi-plot. CA for this research was conducted using JMP, which automatically re-scale the data in a manner that illustrates the relationship between both row and column variables in a singular plot.

CA analysis is an exploratory technique that graphically communicates the relationship between two or more variables. Because the distances between points for both variables are not defined (as the coordinates have been rescaled), there are no significance tests for variable interactions for CA as with contingency tables (Clausen 1998; Greenacre and Blasius 2006; Nenadic and Greenacre 2007). While CA is more suited toward exploration data analysis, it can be used to guide more rigorous modeling of two-way relationships such as log linear models. Loglinear models are commonly used to model the associations and interactions of categorical variables that are not statistically measured in CA (Clausen 1998; Greenacre and Blasius 2006). They provide more than a single summary statistic (typical in a contingency table), as they test for significant interactions between all possible associations between variables. CA is typically more suited for data with variables with a large number of categories, while loglinear analysis works best with fewer categories. This research does not use loglinear modeling to test the significance of interrelationships between two variables, but it is important to note that the results of the CA can be used to guide loglinear modeling for significant variables pairings in the future (Clausen 1998).

4.4 Results

4.4.1 Surveys

Researchers received a survey sample of 315, which is slightly lower that the intended target of 317 surveys. Due to participant limitations and cost, the sample also does not fully represent the applied sampling limitations for elderly populations. Minority and female responses fell within the expected range of responses, with 8.25% and 54.2% respectively, but people aged 65 or over are underrepresented with only 5.71% responses, instead of within the optimal 20% to 40% range.

4.4.2 Contingency Tables

Conducting contingency tables for all possible pairs of either demographic and risk perception variables, demographic and structuration variables, and risk perception and structuration variables resulted in a total 1,214 contingency tables. Of these tables, a large percentage (~75%) are statistically significant, and the risk and structuration pairs had the highest within group percentage of statistically significant pairs (~83%). Table 4.1 provides a full summary of the total number of tables and the percentage of which were considered statistically significant or not, by variable pair group.

Table 4.1 – Number of significant variable pairs by survey response types

	Significant Pairs			**Non-Significant Pairs**			
Variable Pair Types	**Count**	**% Group Pairs**	**% of all Pairs**	**Count**	**% Group Pairs**	**% of all Pairs**	**Total**
Demographic x Risk	196	70.25%	16.14%	83	29.75%	6.84%	279
Demographic x Structuration	118	54.63%	9.72%	98	45.37%	8.07%	216
Risk x Structuration	596	82.89%	49.09%	123	17.11%	10.13%	719
Total/%	910	-	74.96%	304	-	25.04%	**1214**

Table 4.1 demonstrates the percentage of statistically significant tables that resulted from the possible pairs of demographic and risk perception variables and demographic and structuration variables. This table provides information about the degree of interdependence that exists between variables and demonstrates that there is significant interdependence between all three variable categories. However, the degree of interdependence is variable across different demographic variables, as demonstrated in Table 4.2 below, suggesting that specific demographic characteristics are more interconnected with how risk perception or perceived power and agency is developed. Identifying potential interdependence between demographic variables and risk perception and structure links those factors directly to demographic variables that are often used as proxies for vulnerability and resilience assessments. Researchers did not create a similar table for the risk

perception and structuration pairs because those indicators are not considered in current vulnerability/resilience assessments. This paper demonstrates how these indicators cannot only be linked to existing demographic variables but also to one another.

Table 4.2 – Percent of significant response pairings by demographic characteristics

Demographic Variable	Demo Risk Pairs *(31)*		Demo Structure Pairs *(24)*	
	% Significant	Range of Chi^2 Values	% Significant	Range of Chi^2 Values
Age	**77.4%**	6.27 - 52.73	50.0%	6.0 - 36.4
Child 5	**96.8%**	37.19 - 194.31	**91.7%**	10.9 - 181.9
Education	32.3%	9.58 - 94.72	**79.2%**	12.2 - 104.6
Employment	**77.4%**	7.35 - 33.94	12.5%	7.5 - 26.3
Median Income	**93.5%**	11.64 - 110.03	**66.7%**	15.1 - 123.8
Over 65	**80.6%**	30.25 - 163.58	**83.3%**	12.4 - 139.1
Race	45.2%	9.85 - 18.26	12.5%	7.3 - 16.9
Sex	45.2%	18.00 - 138.10	37.5%	6.1 - 69.7
Tenure	**83.9%**	19.45 - 80.52	**58.3%**	11.5 - 77.7

Table 4.2 demonstrates the demographic variables children under five (Child 5) and persons over 65 (Over 65) resulted in the highest number of significant pairings between demographic indicators risk perception (96.8% and 80.6% respectively) structuration indicators (91.7% and 83.3%). This indicates that people's risk perception and social structuration are not independent of demographic variables involving dependent populations. Median Income also has a high percentage of significant pairings in the risk perception pairs (93.5%), but fewer significant pairings with social structuration indicators (66.7%), whereas Education has more significant pairing with Structuration indicators than Risk Perception (79.2% and 32.3% respectively). This indicates that different risk perception and social structuration indicators influence demographic variables at differing levels and in different ways.

Contingency tables provide information about how variables interact, in terms of what demographic groups is more likely to choose certain responses to risk perception or structuration questions. While Table 4.1 illustrates where the majority of significant pairings occur, it does not explain specific influences on responses. For this reason, examining the percentage of responses for certain variable response pairing is critical for understanding how demographics might be influenced by risk perception or structuration (and vice versa).

Due to the large amount of tables considered to be statistically significant, this paper focuses on select pairs within each of the three variable groupings to demonstrate how these methods can identify or connect demographic variables with risk perception and structuration indicators. Pairs chosen for discussion are part of variable pairs with the highest percentage of statistically significant tables and the largest Chi^2-values within their respective variable groups are listed in Table 4.3.

Tables 4.3 – Highlighted Response Pairs

Demographics versus Risk Perception					
Variable 1	**Variable 2**	**Chi^2 Value**	**p-value**		
Median Income (**MedInc**)	Do you feel that you have the financial capability to recover quickly after a hurricane event? (**SE_FinCap**)	110	> 0.000		
# of children under 5 (Child5)	How likely are you to: Take the time to prepare for hurricane impacts? (**Prepare**) OR Evacuate during a hurricane? (**Evac**)	Prepare		Evacuate	
		40.683	0.000	111.183	0.000
Dependent Populations		Children Under 5		Age Over 65	
# of children under 5 (**Child5**) or persons over 65 (**Over65**) in household	How vulnerable do you feel in terms of hurricane impacts affecting you and your family (i.e. death or injury)? (**Su_Affect**)	148.5	0.000	122.8	0.000
Demographics versus Structure					
Dependent Populations		Children Under 5		Age Over 65	
# of children under 5 (**Child5**) or persons over 65 (**Over65**) in household	How involved do you feel in the hurricane preparedness decision-making within your community? (**C_Invol**)	178.9	0.000	126.2	0.000
# of children under 5 (**Child5**) or persons over 65 (**Over65**) in household	How much influence do you feel you have in community level decision-making processes? (**C_Influence**)	167.6	0.000	114.232	0.000
Risk Perception versus Structure					
Do you feel that you have the financial capability to recover quickly after a hurricane event? (**SE_FinCap**)	Do you feel that people like yourself can generally change things in your community if they want to? (**C_Change**)	150.7	0.000		
In general, compared to 5 years ago, has your access to information about hurricanes and hurricane impacts improved, decreased, or stayed about the same? (**Knowledge**)	How involved do you feel in the hurricane preparedness decision-making within your community? (**C_Invol**)	106.6	0.000		

The results of these tables describe variable pairs where the null hypothesis is rejected, meaning that there is some level of dependence between the row-column variables. This interdependence suggests that they can be used to predict the presence of the other. A more in-depth discussion inferences made from the results is contained in the discussion section. Tables B.1 thru B.9 in Appendix B depict the results of these highlighted contingency tables. Figures B.1 thru B.18 also include the associated mosaic plot and correspondence analysis results for each of these pairings. The results in Appendix B reveal several relationships between demographic and risk perception indicators. The contingency table in Table B.1 demonstrate that there is interdependence between median income (MedInc) and perceived financial capability to recover quickly. A higher percentage of respondents in lower income brackets (Poverty, Lower Middle Class and Middle Class) responded that they were *very financially capable* to recover quickly after a hurricane event (100%, 61.29% and 57.66%), whereas respondents in the higher income brackets (Upper middle and Upper Class) feel they were only *capable* of financially recovering quickly (41.38%, 54.17%, and 45% respectively).

Interdependence between variables is also illustrated when comparing perceived hurricane vulnerability and dependent populations. In the Su_Affect and Child5 and Over65 variables pairings (Tables B.2 and B.3), there is a relationship between the presences of or elderly persons in a household and respondents feeling that they or their family have an *increased* or *potentially increased* vulnerability to hurricane impacts in the form of death or injury. 82.2% and 88% of households with 1 child or elderly person and 94.1% and 72.7% of households with 2-3 children or elderly persons responded *potentially vulnerable or very vulnerable*. Comparatively, 34.6% and 37% of households with no presence of children of elderly persons responded *potentially vulnerable or very vulnerable*. This relationship is visually demonstrated in the associated Mosaic plots (Figure B.3), which are graphical representations of contingency table results. Mosaic plots are comprised of rectangles whose heights are proportional to the proportions of variable 1 (i.e. Child5) in each level of variable 2 (Su_Affect).

The results of the contingency tables can also be used to determine which factors could be used to better explain causes of vulnerability based on risk perception, demographics or social structuration using the differences between the observed and expected variables. In general, the larger the difference between the observed and expected values, the greater the Chi^2 value. This information allows people make inferences from the data tables. For example, in the Su_Affect and Child5 table (Tables B.2), columns where the deviation of observed and expected values is TRUE indicates that the observed number of observations is larger than the expected. The distribution in responses and cell chi^2 values demonstrate that households with no children have a greater incidence of feeling *potentially not vulnerable* and *not vulnerable* than expected, while households with 1-3 (child)ren had a lesser occurrence. This sort of evidence can be used to infer causes for this variable feeling of susceptibility within populations based on the presence of children.

4.4.3 Correspondence Analysis (CA)

In addition to the contingency tables analysis, CA for each of featured variable pairs was conducted in conjunction with the contingency tables. The CA results graphically communicate how the categories of one variable fall relative to each along an axis, as well as how the categories of another variable spread relative to the first. For example, Figure B.14 illustrates the CA results for comparison between persons 65 and over (Over65) and “How much influence do you feel you have in community level decision-making processes?” (C_Influence). The first dimension (horizontal axis) shows a somewhat distinct division between responses concerning the Over65 variable, where *No people 65+* is the farthest left, and the remaining groups lining up in order as they move right along the graph. The intervals between *No people 65+*, *1 person 65+*, and *2-3 people 65+* are small, but there is a clear division (the vertical center line) between responses with no presences of people aged 65 or over and at least 1 person aged over 65. The C_Influence responses then fall along the vertical axis relative to the Over65 responses. Based on the gradient of responses for C_Influence, Those households with *1 person 65+*, and *2-3 people 65+* are associated with those who feel they have *more influence* or *a great deal of influence*, while households with *No people 65+* are associated with responses relating to a lesser amount of or no influence on community level decision making.

CA results are interpreted in terms of the associations between responses of both variables, where one variable typically follows the vertical axis and the other falls along the horizontal axis. Figure B.4 illustrates this pattern in the CA graph that plots responses concerning the presence of children under 5 (Child5) and “How vulnerable do you feel in terms of hurricane impacts affecting you and your family (i.e. death or injury)?” (Su_Affect). In Figure B.4, there is a vertical gradient of responses correlated to households with the presence of children under 5, with households with *no children* being associated with the responses *not at all vulnerable*, *potentially vulnerable* and *neither*, while households with 1-3 (child)ren are associated with feeling *potentially vulnerable*. There is an obvious vertical interval between households with no children and those with children, with the exception of homes with 4 or more children, which is heavily skewed to the top right. This occurs when the responses for that particular category are much lower than the other variable categories (only 2 out of 315 respondents have 4 or more children under the age of 5).

The results of the CA provide graphical representations of response associations that are not easily determined from contingency tables or more complex mosaic plots. Additionally, researchers can use this type of association information to generate inferences as to latent variables that cause these intervals to develop. The discussion section examines the other CA results and relationships in more detail to provide potential inferences about latent variables within specific variable pairings.

4.5 Discussion

Identifying potential interdependence between demographic variables and risk perception and structuration links those factors directly to demographic variables often used as data proxies in vulnerability and resilience assessments. The contingency table and CA results in Appendix B reveal several relationships between demographic and risk perception indicators that provide information about components of vulnerability that existing vulnerability/resilience assessments often overlook or omit. The following section discusses how the results of the surveys, contingency tables and CA can be used to determine variable interdependence and inferences that can be made from those relationships. This type of methodology is important to consider in vulnerability and resilience assessments because it ties natural variables such as demographics to structuration and risk perception attitudes. Researchers can use this to infer how individuals develop risk perceptions and act on those perceptions in the form of individual mitigation.

An example of the relationship between risk perception and demographics is demonstrated when examining in the contingency table (Tables B.9 and B.10) mosaic plots and CA (Figures B.19-B.22) results for the comparison of presence of children under 5 and how likely a person was to take the time to prepare for hurricane impacts or to evacuate. 60.27% and 97.62% of populations with 1-3 (child)ren, respectively, responded *likely* to *very likely* to preparing for hurricanes, but only 27.40% and 4.76% of those same populations responded *likely* to *very likely* to evacuation. This pattern indicates that while both are risk-reducing actions, one is more likely to be undertaken by populations with children than the other. This could be due in part to the obstacles that evacuating with young children can entail, as children under the age of 5 are not typically mature enough to fully understand the purpose of evacuation and often require more guidance or assistance during hazard events (Cutter, Boruff, and Shirley 2003; Frazier, Thompson, and Dezzani 2014; Morrow 1999; Wood, Burton, and Cutter 2010).

The CA analysis mirrors these results in a more straightforward manner, where there is a clear gradient of respondents taking the time to prepare for hurricane impacts and evacuating. Those with children are *likely to very likely* to prepare for hurricane impacts, but in the evacuation CA, this gradient changes, where those with children are more closely associated with being *somewhat likely* to evacuate. Decision makers can use this information to develop larger scale policies that take these types of latent variables into account while addressing mitigation gaps that individuals cannot manage alone. This, in turn, can inform community policies that aim to improve mitigation in ways that provide effective risk-reduction strategies for populations limited by social or demographic factors.

The relationship between risk perception and demographic variables and structuration variables also helps illustrate how structuration and access to resources influence risk perceptions. For example, CA pairings results examining children or elderly populations and structuration variables concerning involvement and overall influence on community decision-making depict interesting relationships when these dependent populations are present. In the CA analysis for dependent populations (presence of children under 5 or elderly persons over 65) and community involvement, there are relatively more families with 1-3 child(ren) or elderly persons that responded feeling more involved or very involved in the hurricane preparedness decision-making within their than families with no children or elderly persons (Figures B.8 and B.10).

This pattern is also evident when respondents were asked how much influence they feel they have in community level decision-making processes, where there are relatively more families with 1-3 child(ren) or elderly persons who feel they have *more* to *a great deal of influence* on community decision-making than those with none (Figures B.12 and B.14). These patterns provide an interesting perceptive on perceived vulnerability versus perceived agency. While those living with dependent populations are more likely to respond that they or their family have an *increased* or *potentially increased* vulnerability to hurricane impacts (Tables B.2 and B.3), they also exhibit more perceived power and agency in terms of mitigating those risks at a community level. This pattern suggests that, while the presence of dependent populations may increase an individual's vulnerability or sensitivity to a hazard event (Adger et al. 2004; Frazier, Thompson, and Dezzani 2014, 2013), it also affords those respondents with greater (perceived) agency than households without. This could indicate that while these dependent populations are present, the actual level of vulnerability experienced by these households is less than the level of vulnerability typically associated with traditional indicator proxy measures due to an increased level of agency and empowerment in the hurricane preparedness decision-making process. Incorporating this information into vulnerability/resilience assessments could help address discrepancies or overestimations of vulnerability that can occur in traditional vulnerability/ resilience assessments that only take raw numbers of these types of populations into account.

Understanding how people develop risk perceptions may also illustrate how social structure information is processed and interpreted to create risk perceptions and how those perceptions guide human behavior (Lane 1999). The variable pairings between risk perception and structuration depict several relationships that demonstrate how these two concepts are interdependent. For example, there is a relationship between how people perceive their access to information about hurricanes and hurricane impacts as being either *improved*, *decreased*, or *stayed about the same* in comparison and how involved people feel in the hurricane preparedness community decision-making process. Table B.8 suggests that people who are involved in the community and are more likely to have the attitude that their access to information has increased. 86% of people who feel *involved* in the community felt that there was an *increase* in access to information compared to the 50% of those who are *not at all involved*, the 32% of those who are *not involved*, the 15% of those who are *somewhat involved*, and in the 6% of those who are *very involved*. While the majority of respondents stated that they felt their access to information and hurricanes impacts did increase, the CA results show that relatively speaking, more respondents who feel *involved* or *very involved* in community planning generally have a perceived increase to information. This is evident in Figure B.16, which shows *increased* access to knowledge very closely situated next to *involved* or *very involved* responses. Therefore, while access to information is highly regarded as *not decreasing*, those who are actively involved in the community are more likely to feel that their access has *increased*. This could be associated with different forms of risk communication, where those involved in the community have greater access to agency-based risk education and outreach, not just information about risk.

Risk communication in general refers to the social process of exchanging information (purposefully or non-purposefully) about risk between two social entities (individuals, publics, etc.) (Höppner, Buchecker, and Bründl 2010). In risk communication, education and public outreach and information are different forms of communication that are often required in conjunction with one another to be effective. For example, simply providing the public with information on a risk does not necessarily increase their knowledge of the risk. Public outreach refers to the process of getting information about a risk to the public (Heath, Bradshaw, and Lee 2002). However, if the information provided to the public is not developed in a way they can successfully process into knowledge, then that public information (and outreach) has failed to educate (impart knowledge) the public about that risk (Heath, Bradshaw, and Lee 2002). This is important for risk communicators to take into account because it impacts people's knowledge and perceptions about risks, which influences risk tolerance (amount of risk people are willing to accept) (Tansel 1995). When people experience low risk perception, they often experience increased risk tolerance and are less likely to support mitigation to help minimize damage (Frewer 1999; Höppner, Buchecker, and Bründl 2010; Tansel 1995). This information connects risk perception to hazard vulnerability, which, when aggregated from individual data, can potentially serve as a proxy for the likelihood of people implementing mitigation strategies in certain places.

Another example of interdependence existing between social structure indicators and the risk perception variables emerges in the comparison between a person's perceived financial capability to recover quickly after a hurricane event and their perceived ability to change things in their community if they choose to. The contingency table (Table B.9) and CA results (Figure B.17) illustrate that those who feel *very capable* of recovering financially quickly after a disaster event also *agree to strongly agree* that they are able to enforce some level of change in their community if they choose. However, as the responses move away from those options, they become less closely related. This suggests a strong relative relationship between higher levels of perceived power and agency in a community (people feel they can invoke change effectively) and a perceived ability to effectively financially recover quickly after a disaster event. Those without that confidence in their own power vary in their confidence in their ability to recover quickly. This information can be used to address social issues that might limit or reduce a person's feeling of empowerment in terms of making changes in their community, which can potentially led to inaction in terms of risk reduction and potentially decrease overall disaster recovery.

4.5.1 Methodological Advancements and Synthesizing Interdependence between 3 or More Variables

One of the main advantages of using 2-way tables for categorical data analysis of risk perception and structuration indicators and their impact on vulnerability is that they use hypothesis testing and can reduce inferential errors from model results. Contingency tables use hypothesis testing to identify interdependence between demographic variables and risk perception and structure. This is important in HMP, as hypothesis testing determines whether there is sufficient evidence from a sample dataset to make inferences about specific parameters (variable parings) that can be applied to the entire population (Burt, Barber, and Rigby 2009). Therefore, hypothesis testing for interdependence between demographic, risk perception and structure variables pairs provides evidence that researchers can link those attributes directly to demographic variables for the entire population in a vulnerability or resilience assessment.

Reducing inferential errors in statistical analysis is also important as many latent variables are inferred from statistical models using observed (directly measured) variables (Greenacre and Blasius 2006; Nenadic and Greenacre 2007). This research provides a methodology for tying risk perception and social structuration attitudes, and potentially latent variables, to traditional indicators in vulnerability assessments. This methodology also reduces the potential of inferential errors in non-traditional indicator data proxies, as contingency table analysis and CA are appropriate statistical methods for discrete, ordinal frequency data. This allows hazards researchers to more accurately infer how certain groups or populations feel about certain risks and risk reduction behaviors and the likelihood that they would effectively act in ways that reflect those attitudes, using non-traditional dataset that are typically omitted from traditional assessments (Frazier, Thompson, and Dezzani 2014; Dezzani and Frazier 2015). Decision makers can use this information to determine the likelihood of people engaging in risk reduction behaviors or evacuation and probable levels of community involvement in HMP. This information also provides context concerning potential gaps in knowledge or agency in certain groups that limit their ability to engage in these types behaviors, as traditional regression analysis would not be able to identify possible latent variables that play a role in how people respond to hazards.

This information can also be associated with demographic indicators how all three aspects of vulnerability (demographic, risk perception and structuration) are interdependent. For example, Table B.9 and its associated mosaic plot and CA graph (Figure B.17 and B.18) demonstrates a correlation between those who feel that they are very capable of making changes in their community and feeling very capable of recovering quickly, financially. The contingency tables and CA results for these variables demonstrate that, while most people feel they are *somewhat capable to very capable* of recovering quickly, those in lower income brackets (poverty to middle class) feel *very capable* of financial recovery whereas those in the upper brackets (upper middle and upper class) feel like they are only *somewhat capable or capable*. This suggests that, while people in higher income classes might have a greater access to resources in terms of money or property, they do not feel as capable of financially recovering quickly after a disaster event as those in lower income brackets. Typically, if someone is in a higher income, traditional literature states that they have a better coping capacity or lower sensitivity because they are considered financially stable (Adger et al. 2005; Birkmann 2007; Cutter, Boruff, and Shirley 2003; Cutter, Burton, and Emrich 2010; Cutter et al. 2009; Frazier, Thompson, and Dezzani 2014; Hufschmidt 2011; Morrow 1999). This pattern does not necessarily correspond to current natural hazards literature that suggests that lower income can make recovering from a hazard event more difficult (Morrow 1999; Wood et al. 2007), suggesting that this attitude is based on a latent variable that is not explicitly explained in this table alone.

Alternatively, risk perception and demographics pairings between recovery and median income in Table B.1 and Figures B.1 and B.2 reveal that those who feel that they can recover quickly financially often fall within lower income brackets. The results illustrate that those who feel *very capable* of recovering financially quickly after a disaster event also *agree to strongly agree* that they are able to enforce some level of change in their community if they choose (structuration variable). However, as distance increases from that response cluster in the CA plot, the other responses become less closely related. Those who do not *agree to strongly agree*, however have variable confidence in their ability to recover quickly. This shows a strong relative relationship between peoples' feeling they can invoke change in their community versus how well they feel that they can financially recover after a disaster event.

The combination of information from these two tables and their common variable (capability to recover quickly) can illustrate interdependence between demographic, risk perception and structuration variables. For example, it can be inferred from the results for these two variable pairs that lower income groups are also likely to experience higher perceived levels of empowerment at the community scale. While this relationship cannot be statistically tested by examining the two tables and their common factor alone, this information can be used to guide multiway contingency table analyses that statistically measure interdependence between the three variables (median income, recovery capability and ability to enact change). Multiway contingency tables examine how multiple categorical variables are correlated, and can potentially identify latent variables that are missed in 2-way tables. Further analysis using multiway tables could examine whether structuration indicators could be a potential latent variable in the demographic and risk perception relationship, or if all three variables are interdependent in ways that 2-way tables cannot address.

4.6 Conclusions

Understanding the influence of risk perception and structuration on vulnerability can provide a more holistic view of how vulnerability develops and differs throughout a study area. This information is important to consider because it provides a methodology for identifying significant relationships between traditional vulnerability indicators and non-traditional indicators like risk perception and social structure that are more difficult to quantify. This research provides a measureable link between social structures, risk perception and demographics to that can be used enhance existing vulnerability/resilience assessments to provide a holistic measure of vulnerability. Variables with significant interdependence can serve as indicator proxies in more traditional quantification methods, such as the INSeRT, SERV or SoVI models, to provide a more complete measure of overall vulnerability.

This validation methodology also provides information about how risk perception and structuration impact the way people react to or cope with hazard events at an individual level. Decision makers can use this information to identify non-traditional, spatially explicit vulnerability indicators and examine social or individual processes that cause unequal access to information or risk reduction/mitigation resources. These methods enhance existing natural hazards literature that typically focus how social conditions (i.e. poverty) influence or predispose individuals to being more or less vulnerable or resilient to hazard events, rather than how those same processes perpetuate vulnerability. Therefore, the results of this research can help communities identify mitigation techniques that address marginalized populations that are unable to act as effectively in terms of risk reduction behavior, or guide development of non-structural mitigation policies that benefit areas where vulnerability is highest, but power and agency are low.

One of the main advantages of using 2-way tables for categorical data analysis of risk perception and structuration indicators and their impact on vulnerability is that they can reduce inferential errors from model results. Reducing inferential errors in statistical analysis is important as many latent variables are inferred from statistical models using observed (directly measured) variables. This research provides a methodology for tying risk perception and social structuration attitudes to natural variables that often serve as traditional indicators in vulnerability assessments. This methodology also reduces the potential of inferential errors, as contingency table analysis and CA are appropriate statistical methods for discrete, ordinal frequency data. This allows hazards researchers to more accurately infer how certain groups or populations feel about certain risks and risk reduction behaviors and the likelihood that they would effectively act in ways that reflect those attitudes. This could be very helpful in terms of hazard mitigation planning and determining the likelihood that people would engage in risk reduction behaviors or evacuation, and how involved they would be in the hazard mitigation and planning process at the individual, community or county level. This information provides context concerning potential gaps in knowledge or agency in certain groups that limit their ability to engage in these types behaviors. Traditional regression analysis would not be able to identify possible latent variables that play a role in how people respond to hazards. Decision makers can use this information to target educational outreach or mitigation strategies where these issues are most prevalent.

4.6.1 Policy Implications

There are several aspects of this methodology that could be used to enhance current vulnerability modeling for policy development. This work enhances current vulnerability assessments by incorporating non-traditional vulnerability indicators that concern people's cognitive processes that influence the likelihood of them undertaking risk reduction behaviors. For example, some people may demonstrate increased knowledge about a hazard being present, but they do not necessarily engage in risk reduction behaviors such as mitigation or evacuation due to other factors such as past experience, lowered vested interest, limited institutional trust, or a general lack of resources (Wachinger et al. 2013; Wachinger et al. 2010; Wildavsky and Dake 1990; Wilkinson 2001). This type of methodology can provide insight into potential reasons why people do not engage in risk reduction behaviors and help decision makers develop strategies that better fit public perceptions. If risk perception, in terms of how residents view evacuation and hazard risk, is not taken into account during the planning process, then people's behaviors toward those risks may not match mitigation or evacuation policies that are already in place (Dibben and Chester 1999; Tobin and Whiteford 2002).

This work also provides a measurable way to determine how much agency people feel they have within their community and associated HMP. Community HMP that incorporates local input is often more effective because it matches local needs (Frazier, Walker, et al. 2013; Frazier, Wood, and Yarnal 2010). If residents are less likely to or feel that they are unable to participate community HMP, resulting policies may not reflect local priorities and could potentially be less effective, long term. This work also provides a link between structuration and risk perception indicators and associated demographic characteristics that are already included in traditional vulnerability assessments. This allows researchers to link structuration and risk perception indicators with existing metrics used for vulnerability assessments, providing a method for incorporating non-traditional indicators that are difficult to quantify into existing assessments.

4.6.1 Future Work

Future research will focus on incorporating risk perception and agency indicators within the community as separate components in a hierarchical model through a mix of qualitative and quantitative methods. Future work will result in a model that can provide a measure of community recovery potential from a more holistic social-structure perspective, based on existing vulnerability and resilience levels. Future work will manipulate this data for inclusion into the INSeRT model that uses hierarchical modeling to show how vulnerability resilience indicators connect you very across scale and have different influences on overall resilience in vulnerability.

Contingency table analyses are limited, as they only look at relationships between two variable groups, not all three. Future work will utilize multiway contingency tables and correspondence analysis to examine multiple variables simultaneously. This type of analysis further determines if potentially latent variables exists within one of the other two variable themes. Additional modeling will also be conducted on significant variable pairs in the form of loglinear modeling. Loglinear modeling provides information about interactions between response variable categories, which can identify which variable response categories have more significant cross-effects. This can help me identify specific variable category interactions that have a greater influence on variable response associations, which can be used to ascertain whether certain demographic response categories, not just those variables as a whole, have a statistically significant influence on specific risk perception or structuration responses.

The resulting information concerning the relationship between demographic variables and risk perception and structuration variables will also be manipulated into derived values or a format appropriate for regression analysis. Reformatting the data will allow risk perception and structuration information to be integrated into a hierarchal regression model that examines the multiscalar behavior of vulnerability, as they can be directly tied to existing vulnerability indicators, such as age income or gender.

Chapter 5 - Summary

5.1 Summary

The overall goal of this research was to develop new conceptual frameworks and quantitative models that advances the natural hazards literature and examines not only indicators of vulnerability but also analyzes how social conditions, social structure, and risk perception influence vulnerability and resilience at the community level. This information provides more robust and representative models of vulnerability that can better assist stakeholders in targeting hazard mitigation to highly vulnerable areas. This research addresses these goals by creating a vulnerability/resilience quantification method that is structured on political ecology and structuration theory through the use of multiscalar traditional, external and non-tradition vulnerability indicators.

This dissertation research achieves this goal by answering the following three research questions:

1. What existing theories can be injected into current natural hazards and vulnerability literature to enhance the explanatory value of these types of assessments?

To answer this question, Chapter Two examines gaps in natural hazards literature in terms of theoretical focus in both conceptual framework development and vulnerability/resilience assessment methodologies. Once I identified gaps in the natural hazards literature, I examined alternative theories outside of the geography discipline that can help explain existing patterns of vulnerability and resilience in ways current literature cannot. Based on the survey of theories, I determined that theory from several other disciplines could be integrated into natural hazards research, including political ecology, structuration, and risk perception theory. Political ecology foundations applied to statistical modeling methods can address issues surrounding the inclusion of multiscalar vulnerability/resilience indicators. Structuration theory foundations can guide statistical model development to model how differential levels of power and agency affect vulnerability in terms of how they create social structures that limit access to resources.

Risk perception theory can be used to identify and measure how people use information about risk to make decisions concerning mitigation and risk reduction. In order to incorporate these theories into natural hazards research, I developed the INSeRT conceptual framework, which is structured to reflect the multiscalar and hierarchical nature of a human-environment system. The INSeRT framework uses hierarchical modeling to measure vulnerability, which better represents processes occurring within the current social structure. The INSeRT framework can help explain why people live in risky areas and helps develop ways to mitigate against policies or social processes that perpetuate these types of development patterns. The INSeRT framework also serves as the theoretical foundation for and guides the development of the quantitative regression modeling methodology developed and presented in Chapter Three.

2. Is it possible to create a vulnerability quantification methodology that more accurately measures overall community vulnerability in a more theoretically robust manner using multiscalar, spatially explicit vulnerability indicators for Sarasota County?

Chapter Three addresses this question by developing a vulnerability quantification model that incorporates place, spatial, and multiscalar indicators into a multilevel vulnerability regression model. The hierarchical model examines the impact of spatially-explicitly and multi-scalar socioeconomic and physical factors on vulnerability using structuration theory and political ecology as its major theoretical foundations. In order to determine the impact of spatial effects on vulnerability regression studies, a series of OLS, SAR and hierarchical regression models were conducted to determine which model best explains the data structure. This methodology also utilizes social theory in the indicator development process to identify individual factors that comprise the social system that may perpetuate certain social processes that lead to uneven distribution of social vulnerability at different spatial scales. The OLS models had the lowest explanatory power compared to the SAR and hierarchical models. Therefore, a model that takes space and differences in scale into account are more robust. There were also several changes between the OLS and SAR models in terms of coefficient signage, indicating that demonstrate that the form of the regression model used for analysis can also affect the manner in which certain indicators influence overall vulnerability. Changes in signage and statistical significance in variables suggest that vulnerability measured at one scale or with spatial effects may over/underestimate the importance of certain vulnerability indicators on vulnerability for a given area, leading to HMP strategies that targeting indicators whose influence is potentially exaggerated.

In order to determine if scale or the lack of consideration of variables occurring at different scales affects coefficient signage in both the OLS and SAR models, the hierarchical model results. The hierarchical modeling results suggest that the effect of certain variables is spatially and scalar dependent, providing evidence that examining vulnerability from a multiscalar perspective provides more accurate information about system vulnerability. Therefore, including a hierarchical structure in vulnerability assessments can help to identify how society is structured and where certain vulnerability indicates are likely to emerge. The hierarchical modeling results were only obtained for Categories 1 and 2, as the hierarchical models for the larger storm categories would not converge, indicating a lack of variation within the variables required for hierarchical modeling. The Category 3, 4 and 5 regression models were then re-run using a combined SAR model that used census block and downscaled census block group variables. The combined SAR model for Categories 3-5 demonstrated a significant amount of improvement from the OLS model and scale-specific SAR models.

Vulnerability distribution maps were developed for each storm category using the coefficients from the best-fitting regression model. The results indicate that places along the coast where storm surge exposure was highest are typically the most vulnerable, but there are pockets of areas further inland that experience comparable relative vulnerability scores. The models provide information about how certain indicators predispose individuals to being more or less vulnerable or resilient to hazard events and how they interact with one another. If communities can develop mitigation that targets underlying social issues that predispose individuals to being more vulnerable, then the impact of those indicators on vulnerability will diminish as well. This research can help communities identify mitigation techniques that can better assist marginalized populations through the development and targeting of non-structural mitigation policies that historically are underutilized even though they more directly benefit many areas of communities where vulnerability is highest.

3. Can the influence of risk perception and structuration on vulnerability be identified and quantitatively measured?

Chapter Four addresses this question through the development, implementation and analysis of surveys that captured information about risk perception, structure and agency factors. The survey consisted of three main question sections (demographics, risk perception attributes and social structure and agency attributes) and were measured on a largely LIKERT scale. Once completed, I processed the survey data for use in contingency table and correspondence analyses, which provide frequency distributions that can determine if dependence exists between two response variables. The contingency table results demonstrate that there is interdependence between several demographic, risk perception and social structuration responses, but the degree of interdependence varies between demographic responses. The results suggest that specific demographic characteristics are more interconnected with how risk perception or perceived power and agency is developed than others. The use of contingency tables also allows researchers to use hypothesis testing to identify interdependence between demographic variables and risk perception and structure.

This is important in HMP, as hypothesis testing determines whether there is sufficient evidence from a sample dataset to make inferences about specific parameters (alternative hypothesis) that can be applied to the entire population. Therefore, hypothesis testing for interdependence between demographic, risk perception and structure variables allows researchers to link those attributes directly to demographic variables used as proxies for vulnerability and resilience assessment indicators. Correspondence analysis provides an additional visual representation of these relationships and can help researchers make inferences about potential latent variables that cause these specific graphical relationships to develop. The results of this research may potentially to help communities identify mitigation techniques that better address marginalized populations that are unable to act as effectively in terms of risk reduction behavior by developing non-structural mitigation policies can directly benefit areas of communities where vulnerability is highest but power and agency are lowered.

5.2 Significance of Research

My dissertation research advances vulnerability and resilience science by incorporating theory into what has predominately been an applied science field. This research advances the natural hazards literature by examining social vulnerability from a political economy, social theory and resilience theory perspective and incorporating those concepts in the INSeRT conceptual framework. Several outside theories are complementary for inclusion into human/environment research, but they are typically limited in application, overlooked or not explicitly stated in current studies. The INSeRT framework also incorporates multiscalar, spatially explicit, and social and environmental indicators to provide a systems-based vulnerability assessment framework that demonstrates how both the built/human and natural environment are impacted by natural hazards.

In addition, my dissertation presents a hierarchical vulnerability model that incorporates spatially explicit, multiscalar, traditional, and nontraditional vulnerability indicators into a singular framework that reflects the social structure. This type of framework that is grounded in social theory provides information about how social conditions, agency and risk perception influence vulnerability and resilience at the community level. Additionally, the hierarchical modeling method serves as an improvement on existing vulnerability/resilience assessment methods. The hierarchical modeling methodology presented in Chapter 3 provides additional information about how multiscalar indicators influence vulnerability and interact with one another within and across scales, something that current vulnerability indices and quantification methods do not consider. The results of the models also demonstrate that physical and socioeconomic variables influence overall vulnerability in a heterogeneous spatial and scalar manner. The significance of certain indicators change based on the storm category, suggesting that vulnerability indicators are not only scale specific in terms of their interactions with one another, but also scale specific in terms of differential magnitudes of exposure extents.

This research also determined if and how risk perception affects an individual’s choice to engage in risk reduction behavior and perceived social agency through surveys that ask participants questions about their knowledge about the hazard, vested interest, information about the risk and structuration related questions. These responses provided information about how people develop those perceptions and how certain social conditions impact those perceptions. Through surveys and more appropriate statistical methods for categorical data, such as contingency tables and correspondence analysis, this validation methodology examines the relationship between risk perception and levels of agency to better understand how people react to or cope with hazard events at both the individual and community level. This research provides a more tangible link between social structure and risk perception to systems or collective vulnerability quantification methods. Policy and decision makers can use this information to identify indicators of vulnerability and examine social or individual processes that cause unequal distributions of vulnerability (i.e. unequal access to information or risk reduction/mitigation resources).

These methods allow my research to go beyond existing literature that often only describes how social conditions influence or predispose individuals to being more or less vulnerable or resilient to hazard events at a superficial level. This research has the potential to help communities identify mitigation techniques that can better assist marginalized populations through the development and targeting of non-structural mitigation policies that historically are underutilized even though they more directly benefit many areas of communities where vulnerability is highest. This information is critical for guiding mitigation and adaption planning in toward higher vulnerability areas and underlying social processes in order to decrease overall vulnerability and increase resilience.

5.2.1 Policy Implications

The methodologies and frameworks presented in Chapters 2 and 3 go beyond traditional hazard and vulnerability assessments by incorporating multiple levels of data scales in the statistical analysis. Traditional models utilize data a single resolution of data, meaning that some of the data is aggregated of downscaled, which introduces bias into the statistical model related to the MAUP or ecological fallacy problems. This methodology removes some of that bias by leaving the scale of the gathered datasets intact, which can improve results that are used to develop and implement hazard mitigation policies.

Additionally, this methodology addresses the influence of spatial autocorrelation and outliers on the regression results. The results of the OLS, SAR and hierarchical models illustrate how spatial effects can influence model results in terms of which variables are considered significant. Spatial effects can also lead to model results that highlight outlier variables, not necessarily indicators that have the largest influence on overall vulnerability. This can lead to over estimation or underestimation of indicators impacts on vulnerability during the planning process and resource distribution.

The presence of outliers in the modeling process can also lead to plans that focus more heavily on outliers that may not be significant indicators for the study area as a whole. This is a limitation of the SERV and SoVI model, which use PCA analysis to determine significant groupings of vulnerability indicators. PCA analysis has a tendency to identify outliers, whereas outliers in regression models can influence model results and reliability. Outliers in regression models can affect the estimation strength of the model, which make them less effective for planning purposes. This type of modeling provides a way to better understand how vulnerability indicators behave at the scale at which they are gathered, while also providing information as to which indicators are actually significant to vulnerability in an area.

From Chapter 3, there are several aspects of this methodology that could be used to enhance current vulnerability modeling for policy development. This work enhances current vulnerability assessments by incorporating non-traditional vulnerability indicators that concern people's cognitive processes that influence the likelihood of them undertaking risk reduction behaviors. For example, some people may demonstrate increased knowledge about a hazard being present, but they do not necessarily engage in risk reduction behaviors such as mitigation or evacuation due to other factors such as past experience, lowered vested interest, limited institutional trust, or a general lack of resources (Wachinger et al. 2013; Wachinger et al. 2010; Wildavsky and Dake 1990; Wilkinson 2001). If risk perception in terms of how residents view evacuation and risk to hazards is not taken into account during the planning process, then people's behaviors toward those risks may not match mitigation or evacuation policies that are already in place (Dibben and Chester 1999; Tobin and Whiteford 2002).

This work also provides a measurable way to determine how much agency people feel they have within their community and associated HMP. Community HMP that incorporates local input is often more effective because it matches local needs (Frazier, Walker, et al. 2013; Frazier, Wood, and Yarnal 2010). If residents are more likely to or feel that they are able to participate community HMP, the resulting policies should reflect local priorities. This work also provides a link between structuration and risk perception indicators and associated demographic characteristics that are already included in traditional vulnerability assessments. This allows researchers to link structuration and risk perception indicators with existing metrics used for vulnerability assessments, providing a method for incorporating non-traditional indicators that are difficult to quantify into existing assessments.

Better modeling methodologies can lead to better planning for disaster events, as there is a deeper understanding of where vulnerability, not just exposure, is highest and which indicators are the most influential impactful. It is easier to implement structural mitigation strategies in high exposure areas than in higher vulnerability areas because exposure is a tangible concept for most decision makers. Creating holistic vulnerability maps provides a tangible way to provide decision makers with the ability to target mitigation to high vulnerability areas, not just high exposure areas.

5.3 Limitations of Study and Future Research

Despite the benefits that this research provides, in terms of enhancing and advancing natural hazards literature and methodologies, several limitations exist. These limitations and opportunities for advancement in future research as discussed in Chapters 2, 3 and 4, are summarized here. While the multilevel modeling aspect of makes the inclusion of multiscalar indicators of vulnerability possible, there is one major limitation that needs to be addressed. Traditional hierarchical models do not address spatial processes that violate classical statistical assumptions, so the multilevel modeling of the INSeRT model would need to be modified to account for spatial processes. This limitations is actually addressed in Chapter Two, as the hierarchical model includes a spatial grouping variable that describes whether a census clock is considered coastal versus non-coastal.

Hierarchical models provide a model structure that better represents the hierarchical and multiscalar aspect if society. This methodology advances current natural hazards literature by grounding the research in structuration and political economy and utilize those frameworks to drive the model structure development. However, a major limitation of both the INSeRT model and the hierarchical vulnerability model is that there is not yet a method for including nontraditional variables like risk perception and agency in a holistic vulnerability model.

It is difficult to include risk perception and agency as individual indicator components in a quantitative model because these two components are typically gathered using qualitative measures (i.e. surveys and focus groups), as seen in Chapter Four. The proposed framework describes socioeconomic vulnerability and resilience from a systems perspective, and risk perception and levels of agency can influence how people react to or cope with hazard events at both the individual and community level. Therefore, future research will focus on developing methods for including the results of the surveys in Chapter Four as risk perception and agency indicators as separate components in the INSeRT model through a mix of qualitative and quantitative methods.

Additionally, future research will address the limitations the survey analyses methods. Two-way contingency table analyses are limited in that they only look at relationships between two variable groups, not all three. Future work will utilize multiway contingency tables and correspondence analysis to examine multiple variables simultaneously. This type of analysis further determines if potentially latent variables exists within one of the other two variable themes. Additional modeling will also be conducted on significant variable pairs in the form of loglinear modeling. Loglinear modeling provides information about interactions between response variable categories, which can identify which variable response categories have more cross-effects that are significant. This can help me identify specific variable category interactions that have a greater influence on variable response associations, which can be used to ascertain whether certain demographic response categories, not just those variables as a whole, have a statistically significant influence on specific risk perception or structuration responses.

The resulting information concerning the relationship between demographic variables and risk perception and structuration variables will also be manipulated into derived values or a format appropriate for regression analysis. Reformatting the data will allow risk perception and structuration information to be integrated into a hierarchal regression model that examines the multiscalar behavior of vulnerability, as they can be directly tied to existing vulnerability indicators, such as age income or gender. This future work will result in a model that can provide a measure of community recovery potential from a holistic social-structure perspective, based on existing vulnerability and resilience levels.

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Appendix A – Survey Questionnaire

University of Idaho

Title of Project: Development of a Spatially Explicit Resilience-Vulnerability Model through Integration of Social, Physical Modeling, and Stakeholder Perspectives

Investigators: Dr. Raymond J. Dezzani and Courtney Thompson, PhD Candidate

INFORMED CONSENT FORM

This survey is part of a University of Idaho dissertation research project that is being conducted in Sarasota County, Florida to understand how we as humans interact and cope with hurricane impacts. Sampled households in Sarasota County, Florida are receiving this short survey. This research may provide new insights to increasing local capacities to address and reduce vulnerability to coastal hazards. It may also provide insight to policy makers to design systems and mitigation strategies to better mitigate potential disasters and increase community resilience. Participants will be asked to answers questions concerning their perception of hurricane risks in Sarasota County, FL. We greatly appreciate your willingness to participate. If there is more than one person in your household, please have the adult resident whose birthday was most recent complete this survey. You do not have to participate in this research. You will have the opportunity to give feedback as you see fit, and you can stop the survey at any time should you experience discomfort or no longer wish to answer any more questions. All information collected will be held confidentially upon compliance with protection of human assurances within University policies. No identifying information will be used in association with analyzing or presenting results of the study. Only University of Idaho Geography research personnel will have access to the survey results. Please contact Courtney Thompson at 201 McClure Hall University of Idaho Moscow, ID 83844 (208) 949-39436, thom7660@vandals.uidaho.edu if you have questions, complaints or concerns about the research. If you have questions about your rights as a research participant, contact University of Idaho's Office of Research Assurances at (208) 885-6162. You must be 18 years of age or older to consent to participate in this research study. If you consent to participate in this research study and to the terms above, please indicate this consent below.

- Yes, I agree to participate in this survey
- No, I do not agree to participate in this survey

Please select the county in which you currently reside:

- Sarasota County
- Manatee County
- Charlotte County
- Desoto County
- Hardee County
- Hillsborough County
- Other

Residency and Demographics
The following are questions about your demographic background and residency.

1. How long have you lived in Sarasota County, Florida?
   - Less than 1 year
   - 1 to 3 years
   - 4 - 10 years
   - 11 - 20 years
   - More than 20 years

2. Where in Sarasota County, Florida, do you live? (please the zip code, if possible).

3. What is your age?
   - Under 18 years
   - 18 - 24 years
   - 25 - 34 years
   - 35 - 44 years
   - 45 - 54 years
   - 55 - 64 years
   - 65 years of age or older

4. How many people in your household are under the age of 5?
   - 0
   - 1
   - 2
   - 3
   - 4+
   - Prefer not to answer

5. How many people in your household are 65 years of age or older?
   - 0
   - 1
   - 2
   - 3
   - 4+
   - Prefer not to answer

6. Which of the following describes your race? You can select as many as apply.
   - White
   - Black or African-American
   - Asian or Asian-American
   - Native American
   - Hispanic/Latino/Spanish
   - Other

7. What is your gender?
   - Male
   - Female
   - Prefer not to answer

8. What is your combined annual household income?
   - Below $20,000
   - $20,000 - $29,999
   - $30,000 - $39,999
   - $40,000 - $49,999
   - $50,000 - $59,999
   - $60,000 - $69,999
   - $70,000 - $79,999
   - $80,000 - $89,999
   - $90,000 or more
   - Prefer not to answer

9. What is your current employment status?
   - Full Time Employed
   - Part-Time Employed
   - Unemployed
   - Retired
   - Prefer not to answer

10. What is the highest level of education you have completed?
    - Some High School
    - High School Graduate
    - Some College
    - Trade/ Technical/ Vocational School
    - College Graduate
    - Some Post-Graduate College
    - Post-graduate Degree
    - Prefer not to answer

Location

The following are questions about where you live and why you choose to live there.

1. How close to the coast do you live?
   - More than 55 miles
   - 46 to 55 miles
   - 36 to 45 miles
   - 26 to 35 miles
   - 16 to 25 miles
   - 6 to 15 miles
   - Within 5 miles

2. Please indicate the importance of each of the following relative to the reason you live in this area.

	Not at all important	Very unimportant	Somewhat unimportant	Neither important nor unimportant	Somewhat important	Very important	Extremely important
Employment	❍	❍	❍	❍	❍	❍	❍
Sense of Community	❍	❍	❍	❍	❍	❍	❍
Family	❍	❍	❍	❍	❍	❍	❍
Friends	❍	❍	❍	❍	❍	❍	❍
Weather/Climate	❍	❍	❍	❍	❍	❍	❍
Recreation opportunities (i.e. fishing, water sports, etc.)	❍	❍	❍	❍	❍	❍	❍
Coastal views	❍	❍	❍	❍	❍	❍	❍
Beach access	❍	❍	❍	❍	❍	❍	❍

Knowledge
The following are questions about your general knowledge of or about hurricane impacts.

1. How well informed are you about the potential impacts of a hurricane hitting Sarasota County?
   - ○ 1 = Not Well Informed
   - ○ 2
   - ○ 3
   - ○ 4 = Neither informed nor uninformed
   - ○ 5
   - ○ 6
   - ○ 7 = Very well informed

2. Have you, personally, been affected by hurricane impacts in the past?
    - Yes
    - No

3. When you moved to Sarasota County, did you have prior knowledge about hurricanes that you learned from friends, historical sources or others' experiences?
    - Yes
    - No

4. How relevant do you feel information about hurricanes and their potential impacts is to you personally?
    - Not at all relevant
    - Very irrelevant
    - Somewhat irrelevant
    - Neither relevant nor irrelevant
    - Somewhat relevant
    - Very relevant
    - Extremely relevant

5. How motivated are you to learn more about different mitigation practices that can help you reduce hurricane impacts?
    - Not at all motivated
    - Very unmotivated
    - Somewhat unmotivated
    - Neither motivated nor unmotivated
    - Somewhat motivated
    - Very motivated
    - Extremely motivated

6. To your knowledge, is there an official plan or documentation for your area that discusses ways to mitigate or plan for hurricane impacts, should one occur?
    - Yes
    - No
    - Don't know

7. In general, compared to 5 years ago, has your access to information about hurricanes and hurricane impacts improved, decreased, or stayed about the same?
    - 1 = Decreased
    - 2
    - 3
    - 4 = Stayed the same
    - 5
    - 6
    - 7 = Increased

Hurricane Risk

The following questions relate to how likely you feel hurricanes will occur in your community. Risk is the likelihood that a hurricane will occur.

1. How likely is your community to be affected by hurricanes in the next 10 years?
    - Very unlikely
    - Unlikely
    - Somewhat unlikely
    - Neither likely nor unlikely
    - Somewhat likely
    - Likely
    - Very likely

2. In the past five years, do you feel the risk from hurricanes in Sarasota County has:
    - 1 = Decreased
    - 2
    - 3
    - 4 = Stayed the same
    - 5
    - 6
    - 7 = Increased

3. For you personally, are hurricane risks relatively easy to avoid?
    - 1 = Very Difficult to Avoid
    - 2
    - 3
    - 4
    - 5
    - 6
    - 7 = Very Easy to Avoid

Susceptibility

The following are questions about how vulnerable or susceptible you feel your personal property or family are to hurricane impacts. Vulnerability is the potential for loss (this could include loss of life, injury or property).

1. How susceptible do you feel Sarasota County is to damages from hurricane impacts?
    - 1 = Not at all susceptible
    - 2
    - 3
    - 4
    - 5
    - 6
    - 7 = Very susceptible

2. How vulnerable do you feel in terms of hurricane impacts affecting:

	Not at all vulnerable						Very Vulnerable
You and your family (i.e. death or injury)	❍	❍	❍	❍	❍	❍	❍
Your property and/or possessions	❍	❍	❍	❍	❍	❍	❍

3. How likely is it that you would be unable to work or conduct business after a hurricane event?
   - Very unlikely
   - Unlikely
   - Somewhat unlikely
   - Neither likely nor unlikely
   - Somewhat likely
   - Likely
   - Very likely

4. How likely is it that you would lose income because you cannot work due to impacts from a hurricane event?
   - Very unlikely
   - Unlikely
   - Somewhat unlikely
   - Neither likely nor unlikely
   - Somewhat likely
   - Likely
   - Very likely

Self-efficacy
The following are questions about your ability to prepare for or react to hurricane impacts.

1. Do you feel that you have the financial capability to recover quickly after a hurricane event?
   - 1 = Not Capable
   - 2
   - 3
   - 4 = Somewhat Capable
   - 5
   - 6
   - 7 = Very Capable

2. Would implementing preventative measures (e.g., adding storm shutters to your home) be effective at preventing hurricane damage to your personal property?
    - Very ineffective
    - Ineffective
    - Somewhat ineffective
    - Neither effective nor ineffective
    - Somewhat effective
    - Effective
    - Very effective

3. How confident are you that you can protect your property from impacts associated with hurricanes?
    - 1 = Not at all confident
    - 2
    - 3
    - 4 = Somewhat confident
    - 5
    - 6
    - 7 = Very confident

4. Please indicate how much you agree with the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I have ample time to prepare for hurricane impacts	❍	❍	❍	❍	❍	❍	❍
It is easy for me to prepare for a hurricane.	❍	❍	❍	❍	❍	❍	❍

5. How likely are you to do each of the following:

	Very unlikely	Unlikely	Somewhat unlikely	Neither likely nor unlikely	Somewhat likely	Likely	Very likely
Take time to prepare for hurricane impacts?	❍	❍	❍	❍	❍	❍	❍
Evacuate during a hurricane?	❍	❍	❍	❍	❍	❍	❍

Community Involvement

The following are questions about who you feel is responsible for preparing for hurricane events, impacts and recovery and how involved you feel in that process within your community.

1. How much do you feel that preparing for hurricane impacts is your personal responsibility?
    - ○ 1 = Not at all my responsibility
    - ○ 2
    - ○ 3
    - ○ 4 = Somewhat my responsibility
    - ○ 5
    - ○ 6
    - ○ 7 = Very much my responsibility

2. To what degree do you feel the following organizations are responsible for preparing for hurricane impacts in Sarasota County?

	Not responsible			Somewhat responsible			Very responsible
Sarasota County Emergency Management	❍	❍	❍	❍	❍	❍	❍
City Governments Emergency Management (i.e. – City of Sarasota, City of North Port, etc.)	❍	❍	❍	❍	❍	❍	❍
Florida State Emergency Management	❍	❍	❍	❍	❍	❍	❍
Federal Emergency Management Agency	❍	❍	❍	❍	❍	❍	❍
Neighbors	❍	❍	❍	❍	❍	❍	❍
General Public (All public, not specifically your neighbors)	❍	❍	❍	❍	❍	❍	❍

3. What publicly provided services are generally available to people in your area during or after a hurricane event? Pick all that apply.
   - ☐ Shelters
   - ☐ Evacuation Routes
   - ☐ Medical
   - ☐ Hospital
   - ☐ Transportation
   - ☐ Water Supply
   - ☐ Sanitation
   - ☐ Waste Disposal
   - ☐ Electricity
   - ☐ Other ____________________
   - ☐ None of the Above

4. Are the following programs or aid programs available to vulnerable people during a hurricane event?

	Not at all available			Somewhat available			Easily available
Government Programs or Federal Aid Programs	❍	❍	❍	❍	❍	❍	❍
Non-government programs or aid programs (i.e. Red Cross, NGOs, etc.)	❍	❍	❍	❍	❍	❍	❍

5. How involved do you feel in the hurricane preparedness decision-making within your community?
   - ○ 1 = Not involved
   - ○ 2
   - ○ 3
   - ○ 4 = Somewhat involved
   - ○ 5
   - ○ 6
   - ○ 7 = Very involved

6. How much influence do you feel you have in community level decision-making processes?
   - ○ 1 = No influence at all
   - ○ 2
   - ○ 3
   - ○ 4 = Some influence
   - ○ 5
   - ○ 6
   - ○ 7 = A great deal of influence

7. Do you feel that people like yourself can generally change things in your community if they want to?
    - Strongly agree
    - Agree
    - Somewhat agree
    - Neither agree nor disagree
    - Somewhat disagree
    - Disagree
    - Strongly disagree

8. Are you aware of community or city meetings that held to inform the community about hurricane hazard mitigation and related impacts?
    - Yes
    - No

Appendix B – Contingency Tables, Mosaic Plots and Correspondence Analysis (CA) Results for Highlighted Variable Pairs

Table B.1 – Contingency table for comparison between Median Income (MedInc) and "Do you feel that you have the financial capability to recover quickly after a hurricane event?" (SE_FinCap)

Do you feel that you have the financial capability to recover quickly after a hurricane event?

Median Household Income	**Not at all Capable**	**Mostly Not Capable**	**Somewhat Capable**	**Capable**	**Very Capable**	**Total**
Poverty - >$30,000	0 0 0 0 0.1 TRUE 0.1016	0 0 0 0 0.4 TRUE 0.4063	0 0 0 0 0.8 TRUE 0.7873	0 0 0 0 1.3 TRUE 1.2571	4 1.3 3.5 100.0 1.4 FALSE 4.5003	4 1.27% Responded: Somewhat Capable - 0% Capable - 0% **Very Capable - 100%**
Lower Middle Class - $30,000 - $49,999	2 0.6 25.0 6.5 0.8 FALSE 1.8679	3 1.0 9.4 9.7 3.1 TRUE 0.0071	7 2.2 11.3 22.6 6.1 FALSE 0.1323	0 0 0 0 9.7 TRUE 9.7429	19 6.0 16.7 61.3 11.2 FALSE 5.3965	31 9.84% Responded: Somewhat Capable - 22.58% Capable - 0% **Very Capable - 61.29%**
Middle Class - $50,000 - $79,999	4 1.3 50.0 3.6 2.8 FALSE 0.4947	14 4.4 43.8 12.6 11.3 FALSE 0.6579	16 5.1 25.8 14.4 21.8 TRUE 1.5651	13 4.1 13.1 11.7 34.9 TRUE 13.7301	64 20.3 56.1 57.7 40.2 FALSE 14.1344	111 35.24% Responded: Somewhat Capable - 14.41% Capable - 11.71% **Very Capable - 57.66%**
Upper Middle Class - $80,000 - $89,999	1 0.3 12.5 3.5 0.7 FALSE 0.0943	6 1.9 18.8 20.7 2.9 FALSE 3.1659	8 2.5 12.9 27.6 5.7 FALSE 0.9204	12 3.8 12.1 41.4 9.1 FALSE 0.9137	2 0.6 1.8 6.9 10.5 TRUE 6.8764	29 9.21% Responded: Somewhat Capable - 27.59% Capable - 41.38% **Very Capable - 6.9%**
Upper Class - > $90,000	0 0.0 0.0 0.0 3.0 TRUE 3.0476	6 1.9 18.8 5.0 12.2 TRUE 3.1436	25 7.9 40.3 20.8 23.6 FALSE 0.0807	65 20.6 65.7 54.2 37.7 FALSE 19.7408	24 7.6 21.1 20.0 43.4 TRUE 8.6917	120 38.10% Responded: Somewhat Capable - 20.83% Capable - 54.17% **Very Capable - 20%**
Prefer not to answer	1 0.3 12.5 5.0 0.5 FALSE 0.4767	3 1.0 9.4 15.0 2.0 FALSE 0.4614	6 1.9 9.7 30.0 3.9 FALSE 1.0817	9 2.9 9.1 45.0 6.3 FALSE 1.1721	1 0.3 0.9 5.0 7.2 TRUE 5.3763	20 6.35% Responded: Somewhat Capable - 30% Capable - 45% **Very Capable - 5%**
Total	8 2.54%	32 10.16%	62 19.68%	99 31.43%	114 36.19%	315

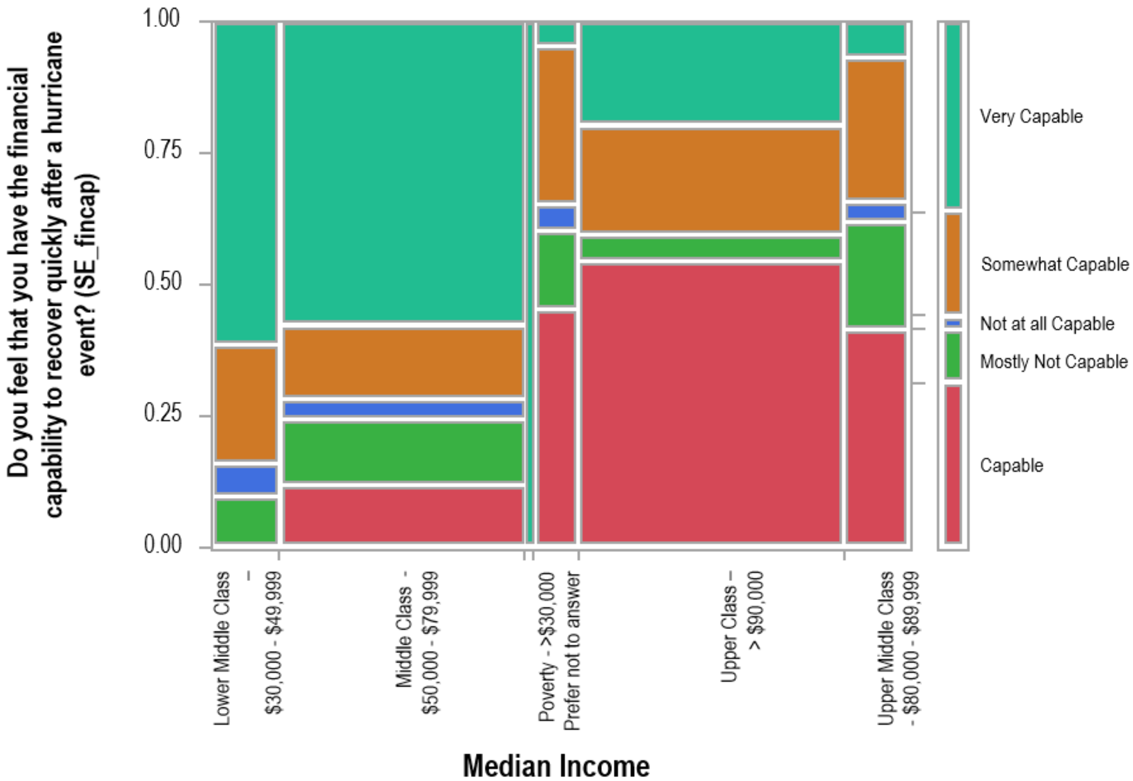

Figure B.1 – Mosaic plot for comparison between Median Income (MedInc) and “Do you feel that you have the financial capability to recover quickly after a hurricane event?” (SE_FinCap)

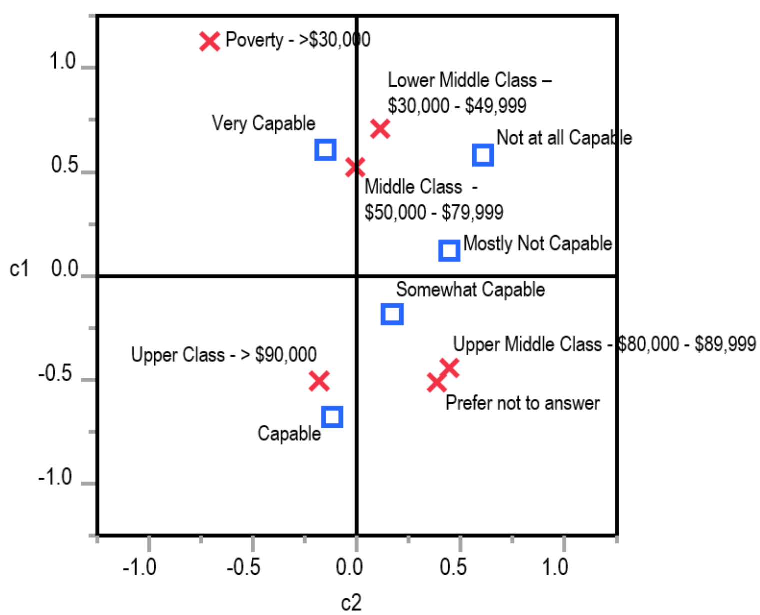

Figure B.2 – CA results for comparison between Median Income (MedInc) and “Do you feel that you have the financial capability to recover quickly after a hurricane event?” (SE_FinCap)

Table B.2 – Contingency table for comparison between presence of children under 5 (Child5) and "How vulnerable do you feel in terms of hurricane impacts affecting you and your family (i.e. death or injury)?" (Su_Affect)

	How vulnerable do you feel in terms of hurricane impacts affecting you and your family (i.e. death or injury)? (Su_Affect)					
Presence of Children	**Very Vulnerable**	**Potentially Vulnerable**	**Neither**	**Potentially Not Vulnerable**	**Not at all Vulnerable**	**Total**
>4 Children	0 0 0 0 0.28571 TRUE 0.2857	0 0 0 0 0.93968 TRUE 0.9397	1 0.32 2.86 50 0.22222 FALSE 2.7222	0 0 0 0 0.24127 TRUE 0.2413	1 0.32 2.04 50 0.31111 FALSE 1.5254	2 0.63% **0%** Responded Very Vulnerable or Potentially Vulnerable
2 - 3 Children	3 0.95 6.67 3.57 12 TRUE 6.75	76 24.13 51.35 90.48 39.4667 FALSE 33.818	1 0.32 2.86 1.19 9.33333 TRUE 7.4405	2 0.63 5.26 2.38 10.1333 TRUE 6.5281	2 0.63 4.08 2.38 13.0667 TRUE 9.3728	84 26.67% **94.05%** Responded Very Vulnerable or Potentially Vulnerable
1 Child	12 3.81 26.67 16.44 10.4286 FALSE 0.2368	48 15.24 32.43 65.75 34.2984 FALSE 5.4735	5 1.59 14.29 6.85 8.11111 TRUE 1.1933	3 0.95 7.89 4.11 8.80635 TRUE 3.8283	5 1.59 10.2 6.85 11.3556 TRUE 3.5571	73 23.17% **82.19%** Responded Very Vulnerable or Potentially Vulnerable
No Children	30 9.52 66.67 19.23 22.2857 FALSE 2.6703	24 7.62 16.22 15.38 73.2952 TRUE 33.1539	28 8.89 80 17.95 17.3333 FALSE 6.5641	33 10.48 86.84 21.15 18.819 FALSE 10.686	41 13.02 83.67 26.28 24.2667 FALSE 11.5386	156 49.52% **34.61%** Responded Very Vulnerable or Potentially Vulnerable
Total	45 14.29%	148 46.98%	35 11.11%	38 12.06%	49 15.56%	315

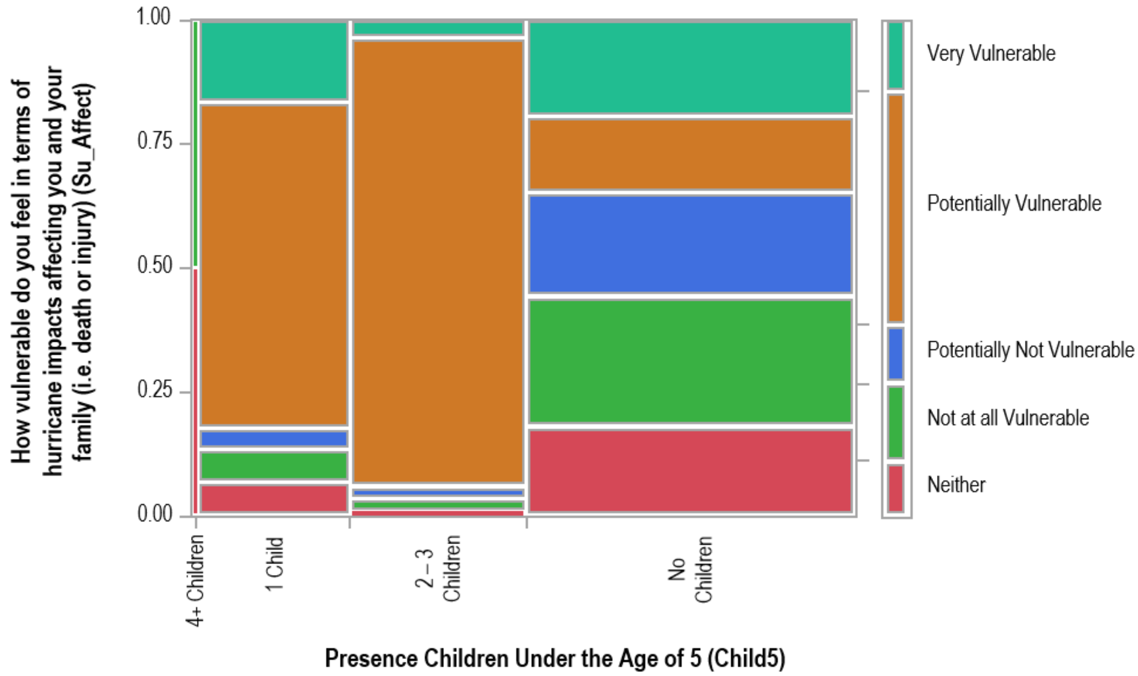

Figure B.3 – Mosaic plot for comparison between presence of children under 5 (Child5) and "How vulnerable do you feel in terms of hurricane impacts affecting you and your family (i.e. death or injury)?" (Su_Affect)

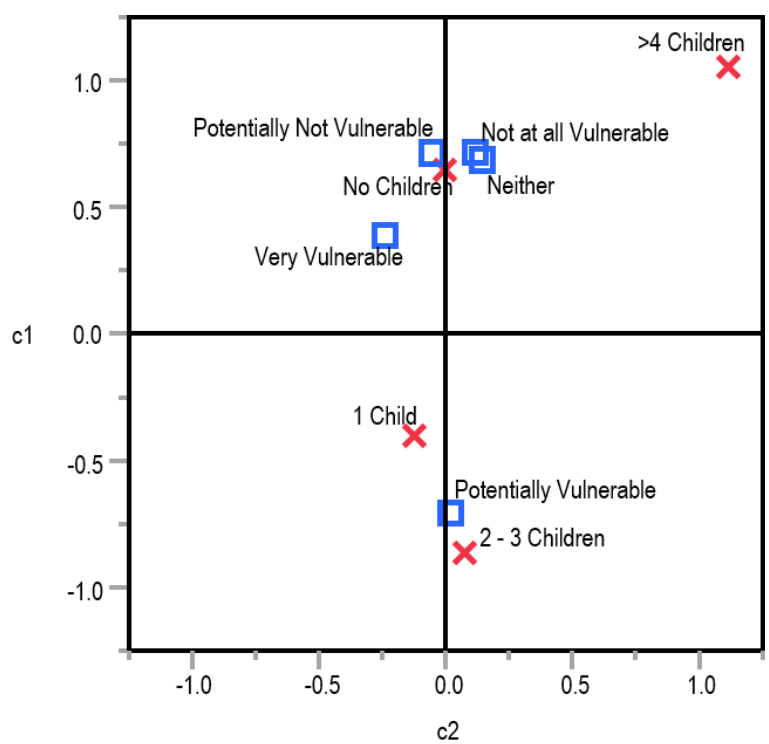

Figure B.4 – CA results for comparison between presence of children under 5 (Child5) and "How vulnerable do you feel in terms of hurricane impacts affecting you and your family (i.e. death or injury)?" (Su_Affect)

Table B.3 – Contingency table for comparison between persons 65 and over (Over65) and "How vulnerable do you feel in terms of hurricane impacts affecting you and your family (i.e. death or injury)?" (Su_Affect)

How vulnerable do you feel in terms of hurricane impacts affecting you and your family (i.e. death or injury)? (Su_Affect)

Presence of Elderly	Very Vulnerable	Potentially Vulnerable	Neither	Potentially Not Vulnerable	Not at all Vulnerable	Total
>4 people 65+	1 0.32 2.22 **33.33** 0.42857 FALSE 0.7619	0 0 0 **0** 1.40952 TRUE 1.4095	1 0.32 2.86 **33.33** 0.33333 FALSE 1.3333	0 0 0 **0** 0.3619 TRUE 0.3619	1 0.32 2.04 **33.33** 0.46667 FALSE 0.6095	3 0.95% **33.33%** Responded Very Vulnerable or Potentially Vulnerable
2 -3 people 65+	14 4.44 31.11 **42.42** 4.71429 FALSE 18.29	10 3.17 6.76 **30.3** 15.5048 TRUE 1.9544	2 0.63 5.71 **6.06** 3.66667 TRUE 0.7576	1 0.32 2.63 **3.03** 3.98095 TRUE 2.2321	6 1.9 12.24 **18.18** 5.13333 FALSE 0.1463	33 10.48% **72.72%** Responded Very Vulnerable or Potentially Vulnerable
1 person 65+	12 3.81 26.67 **9.6** 17.8571 TRUE 1.9211	99 31.43 66.89 **79.2** 58.7302 FALSE 27.6121	6 1.9 17.14 **4.8** 13.8889 TRUE 4.4809	6 1.9 15.79 **4.8** 15.0794 TRUE 5.4667	2 0.63 4.08 **1.6** 19.4444 TRUE 15.6502	125 39.68% **88.8%** Responded Very Vulnerable or Potentially Vulnerable
No people 65+	18 5.71 40 **11.69** 22 TRUE 0.7273	39 12.38 26.35 **25.32** 72.3556 TRUE 15.3767	26 8.25 74.29 **16.88** 17.1111 FALSE 4.6176	31 9.84 81.58 **20.13** 18.5778 FALSE 8.3062	40 12.7 81.63 **25.97** 23.9556 FALSE 10.7459	154 48.89% **37.01%** Responded Very Vulnerable or Potentially Vulnerable
Total	45 14.29%	148 46.98%	35 11.11%	38 12.06%	49 15.56%	315

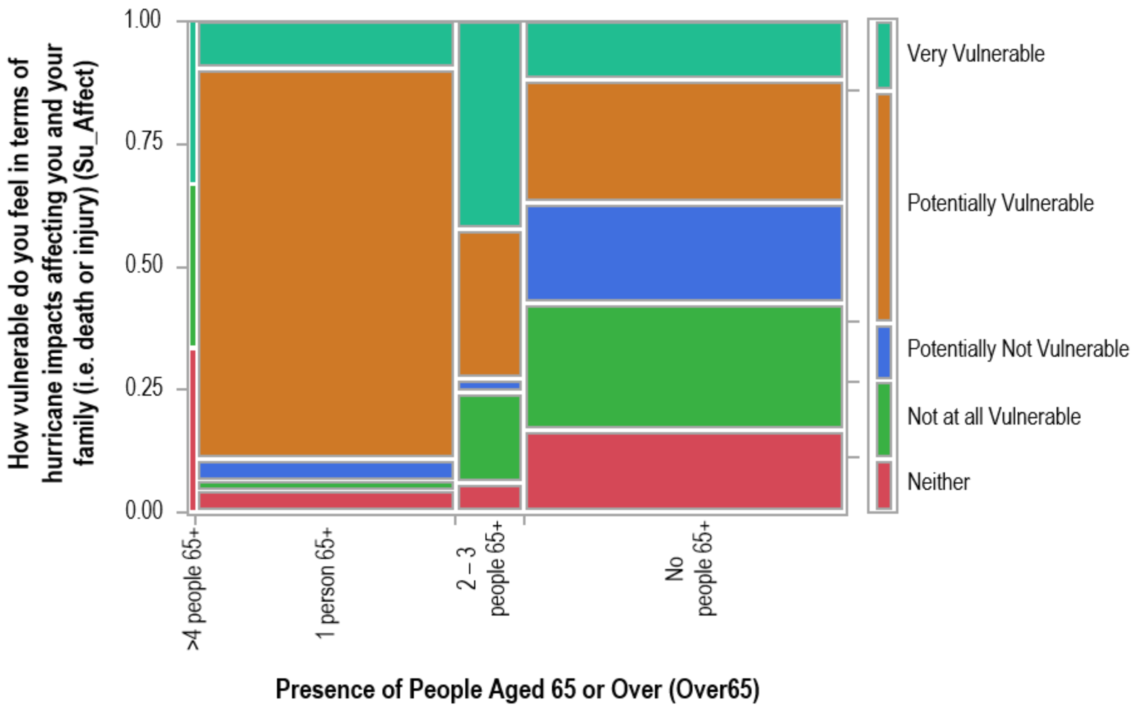

Figure B.5 – Mosaic plot for comparison between persons 65 and over (Over65) and "How vulnerable do you feel in terms of hurricane impacts affecting you and your family (i.e. death or injury)?" (Su_Affect)

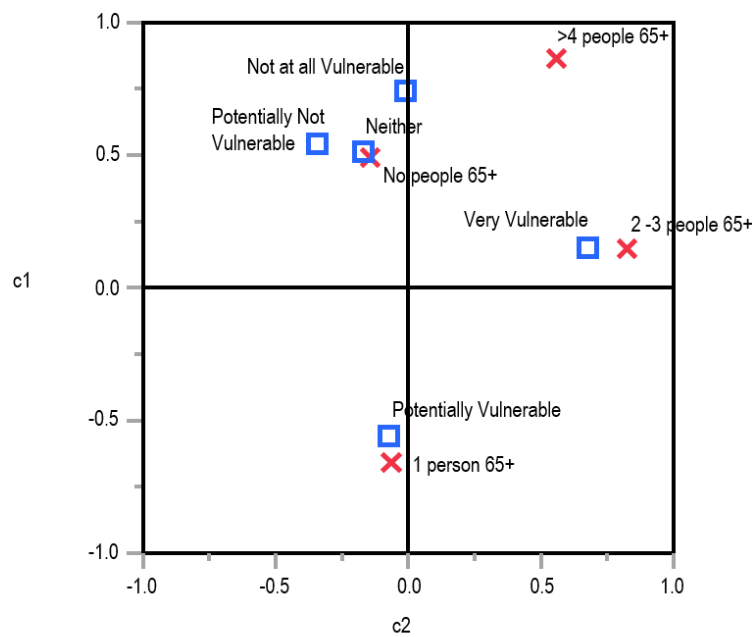

Figure B.6 – CA results for comparison between persons 65 and over (Over65) and "How vulnerable do you feel in terms of hurricane impacts affecting you and your family (i.e. death or injury)?" (Su_Affect)

Table B.4 – Contingency table for comparison between presence of children under 5 (Child5) and "How involved do you feel in the hurricane preparedness decision-making within your community?" (C_Invol)

How involved do you feel in the hurricane preparedness decision-making within your community? (C_Invol)

Presence of Children	Involved	Not at all Involved	Not Involved	Somewhat Involved	Very Involved	Total
>4 Children	0	1	0	0	1	2
	0	0.32	0	0	0.32	0.63%
	0	1.2	0	0	9.09	
	0	50	0	0	50	**50%**
	0.90159	0.52698	0.34286	0.15873	0.06984	Responded Involved or Very Involved
	FALSE	TRUE	FALSE	FALSE	TRUE	
	0.9016	0.4246	0.3429	0.1587	12.388	
2 - 3 Children	75	1	6	1	1	84
	23.81	0.32	1.9	0.32	0.32	26.67%
	52.82	1.2	11.11	4	9.09	
	89.29	1.19	7.14	1.19	1.19	**90.48%**
	37.8667	22.1333	14.4	6.66667	2.93333	Responded Involved or Very Involved
	TRUE	FALSE	FALSE	FALSE	FALSE	
	36.4142	20.1785	4.9	4.8167	1.2742	
1 Child	49	7	8	4	5	73
	15.56	2.22	2.54	1.27	1.59	23.17%
	34.51	8.43	14.81	16	45.45	
	67.12	9.59	10.96	5.48	6.85	**73.97%**
	32.9079	19.2349	12.5143	5.79365	2.54921	Responded Involved or Very Involved
	TRUE	FALSE	FALSE	FALSE	TRUE	
	7.8691	7.7824	1.6284	0.5553	2.3562	
No Children	18	74	40	20	4	156
	5.71	23.49	12.7	6.35	1.27	49.52%
	12.68	89.16	74.07	80	36.36	
	11.54	47.44	25.64	12.82	2.56	**14.1%**
	70.3238	41.1048	26.7429	12.381	5.44762	Responded Involved or Very Involved
	FALSE	TRUE	TRUE	TRUE	FALSE	
	38.9311	26.3253	6.5719	4.6886	0.3847	
Total	142	83	54	25	11	315
	45.08%	26.35%	17.14%	7.94%	3.49%	

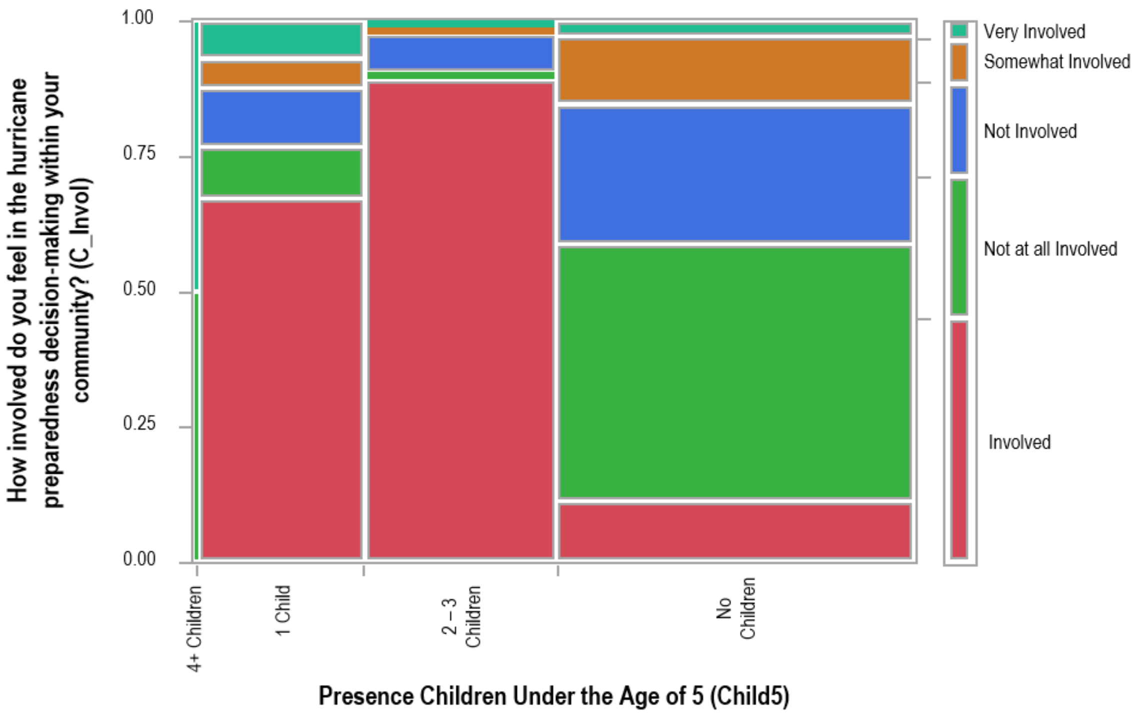

Figure B.7 – Mosaic plot for comparison between presence of children under 5 (Child5) and “How involved do you feel in the hurricane preparedness decision-making within your community?” (C_Invol)

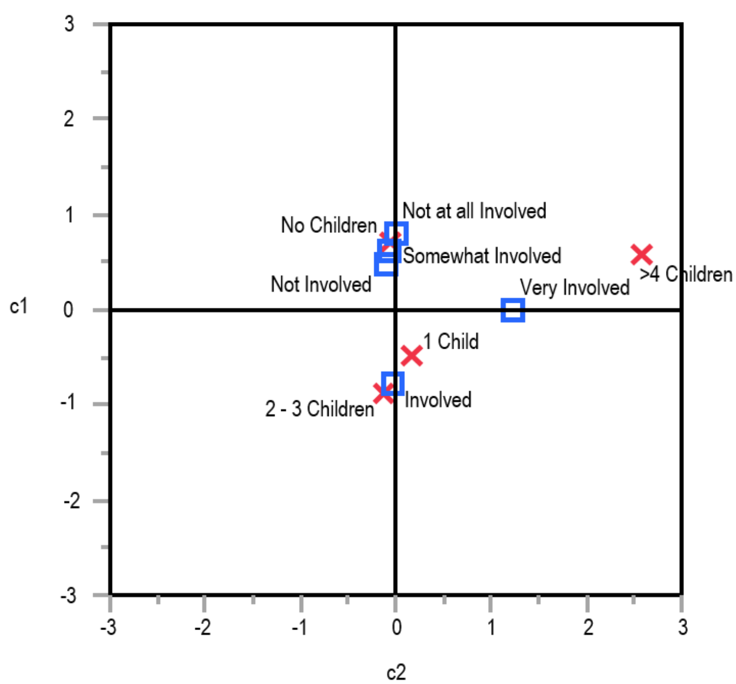

Figure B.8 – CA results for comparison between presence of children under 5 (Child5) and “How involved do you feel in the hurricane preparedness decision-making within your community?” (C_Invol)

Table B.5 – Contingency table for comparison between persons 65 and over (Over65) and "How involved do you feel in the hurricane preparedness decision-making within your community?" (C_Invol)

How involved do you feel in the hurricane preparedness decision-making within your community? (C_Invol)

Presence of Elderly	Involved	Not at all Involved	Not Involved	Somewhat Involved	Very Involved	Total
>4 people 65+	1	0	1	0	1	3
	0.32	0	0.32	0	0.32	0.95%
	2.04	0	2.86	0	2.22	
	33.33	**0**	**33.33**	**0**	**33.33**	**66.66%**
	0.46667	0.3619	0.33333	1.40952	0.42857	Responded Involved or Very Involved
	TRUE	FALSE	TRUE	FALSE	TRUE	
	0.6095	0.3619	1.3333	1.4095	0.7619	
2 -3 people 65+	6	1	2	10	14	33
	1.9	0.32	0.63	3.17	4.44	10.48%
	12.24	2.63	5.71	6.76	31.11	
	18.18	**3.03**	**6.06**	**30.3**	**42.42**	**60.6%**
	5.13333	3.98095	3.66667	15.5048	4.71429	Responded Involved or Very Involved
	TRUE	FALSE	FALSE	FALSE	TRUE	
	0.1463	2.2321	0.7576	1.9544	18.29	
1 person 65+	2	6	6	99	12	125
	0.63	1.9	1.9	31.43	3.81	39.68%
	4.08	15.79	17.14	66.89	26.67	
	1.6	**4.8**	**4.8**	**79.2**	**9.6**	**11.2%**
	19.4444	15.0794	13.8889	58.7302	17.8571	Responded Involved or Very Involved
	FALSE	FALSE	FALSE	TRUE	FALSE	
	15.6502	5.4667	4.4809	27.6121	1.9211	
No people 65+	40	31	26	39	18	154
	12.7	9.84	8.25	12.38	5.71	48.89%
	81.63	81.58	74.29	26.35	40	
	25.97	**20.13**	**16.88**	**25.32**	**11.69**	**37.66%**
	23.9556	18.5778	17.1111	72.3556	22	Responded Involved or Very Involved
	TRUE	TRUE	TRUE	FALSE	FALSE	
	10.7459	8.3062	4.6176	15.3767	0.7273	
Total	49	38	35	148	45	315
	15.56%	12.06%	11.11%	46.98%	14.29%	

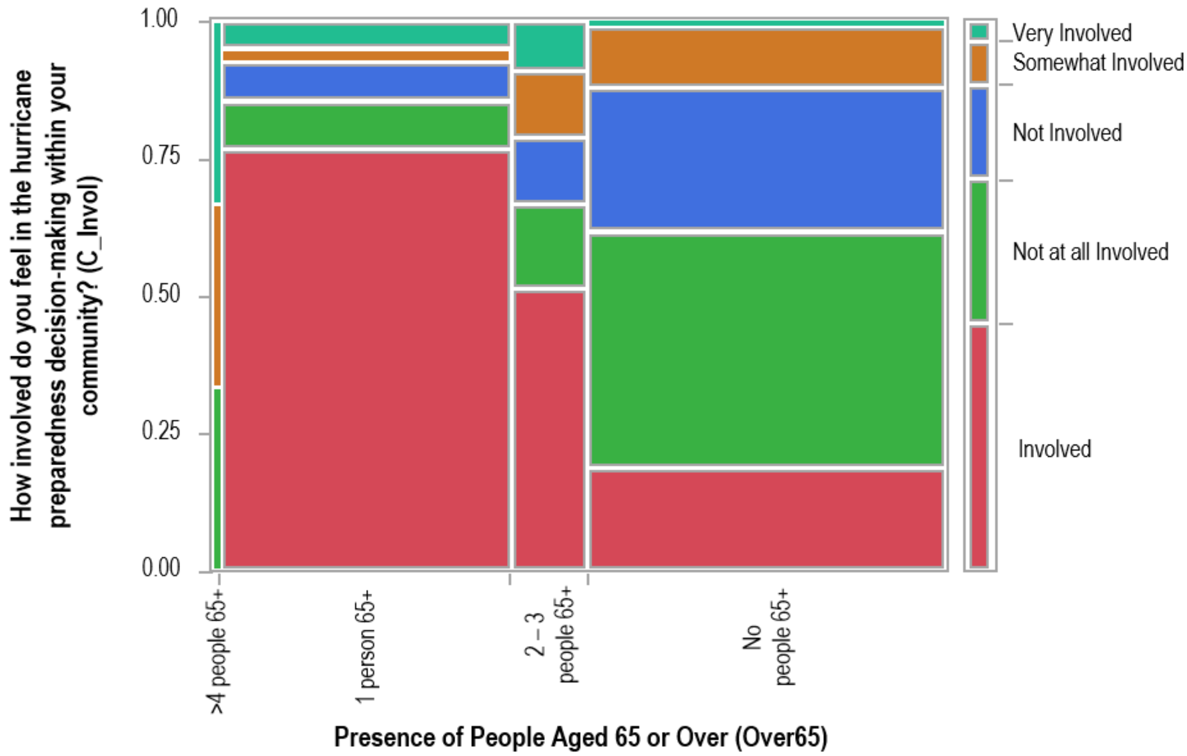

Figure B.9 – Mosaic plot for comparison between persons 65 and over (Over65) and "How involved do you feel in the hurricane preparedness decision-making within your community?" (C_Invol)

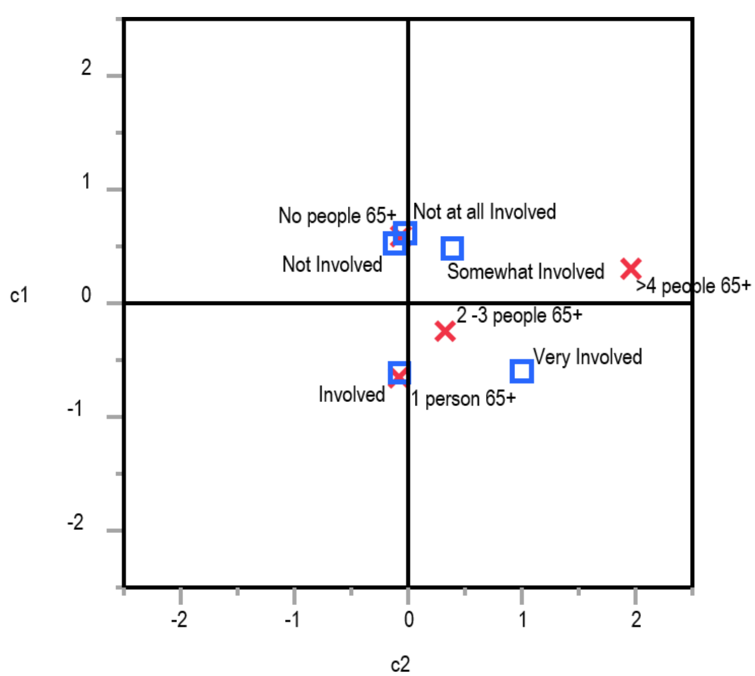

Figure B.10 – CA results for comparison between persons 65 and over (Over65) and "How involved do you feel in the hurricane preparedness decision-making within your community?" (C_Invol)

Table B.6 – Contingency table for comparison between presence of children under 5 (Child5) "How much influence do you feel you have in community level decision-making processes?" (C_Influence)

Presence of Children	How much influence do you feel you have in community level decision-making processes? (C_Influence) A Great Deal of Influence	More Influence	Mostly No Influence	No Influence at all	Some Influence	Total
>4 Children	0	0	1	1	0	2
	0	0	0.32	0.32	0	0.63%
	0	0	1.27	2	0	
	0	0	50	50	0	**0%** Responded More Influence or A Great Deal of Influence
	0.0254	0.92063	0.50159	0.31746	0.23492	
	FALSE	FALSE	TRUE	TRUE	FALSE	
	0.0254	0.9206	0.4953	1.4675	0.2349	
2 - 3 Children	2	70	7	1	4	84
	0.63	22.22	2.22	0.32	1.27	26.67%
	50	48.28	8.86	2	10.81	
	2.38	83.33	8.33	1.19	4.76	**85.71%** Responded More Influence or A Great Deal of Influence
	1.06667	38.6667	21.0667	13.3333	9.86667	
	TRUE	TRUE	FALSE	FALSE	FALSE	
	0.8167	25.3908	9.3926	11.4083	3.4883	
1 Child	2	57	8	4	2	73
	0.63	18.1	2.54	1.27	0.63	23.17%
	50	39.31	10.13	8	5.41	
	2.74	78.08	10.96	5.48	2.74	**80.82%** Responded More Influence or A Great Deal of Influence
	0.92698	33.6032	18.3079	11.5873	8.5746	
	TRUE	TRUE	FALSE	FALSE	FALSE	
	1.2421	16.2905	5.8037	4.9681	5.0411	
No Children	0	18	63	44	31	156
	0	5.71	20	13.97	9.84	49.52%
	0	12.41	79.75	88	83.78	
	0	11.54	40.38	28.21	19.87	**11.54%** Responded More Influence or A Great Deal of Influence
	1.98095	71.8095	39.1238	24.7619	18.3238	
	FALSE	FALSE	TRUE	TRUE	TRUE	
	1.981	40.3215	14.571	14.9465	8.7692	
Total	49	38	35	148	45	315
	15.56%	12.06%	11.11%	46.98%	14.29%	

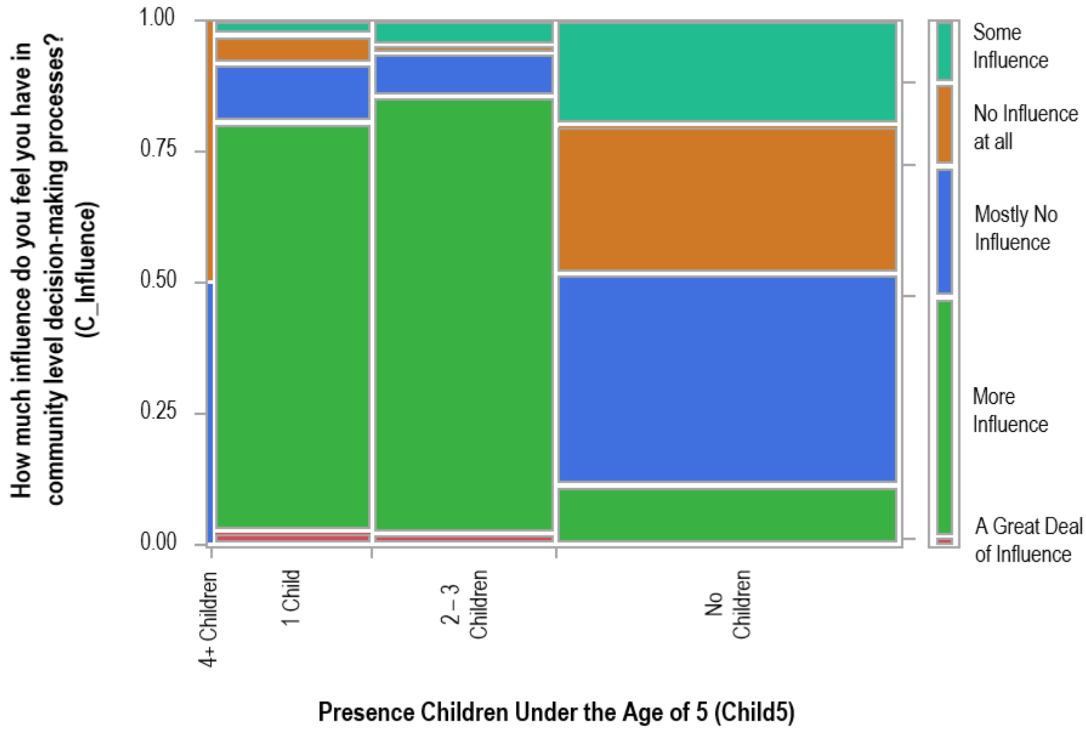

Figure B.11 – Mosaic plot for comparison between presence of children under 5 (Child5) and "How much influence do you feel you have in community level decision-making processes?" (C_Influence)

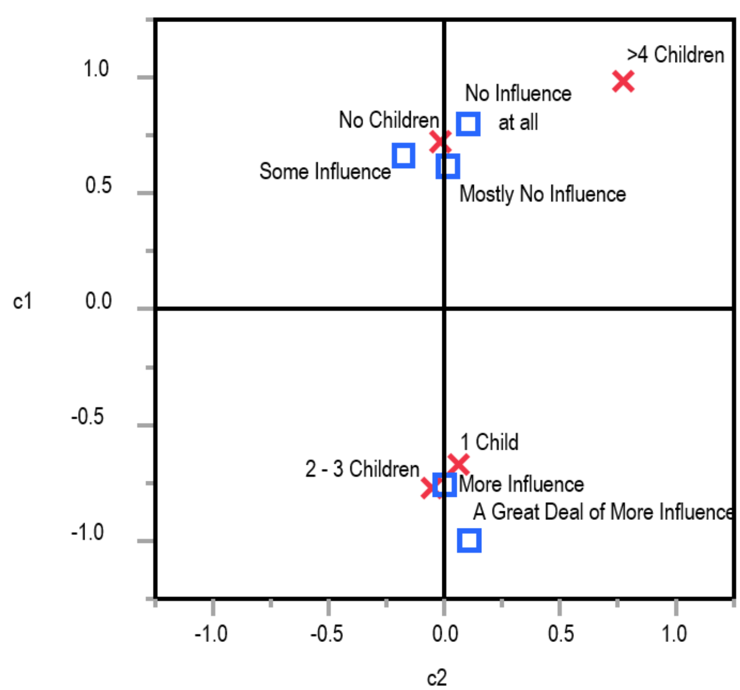

Figure B.12 – CA results for comparison between presence of children under 5 (Child5) and "How much influence do you feel you have in community level decision-making processes?" (C_Influence)

Table B.7 – Contingency table for comparison between persons 65 and over (Over65) and "How much influence do you feel you have in community level decision-making processes?" (C_Influence)

How much influence do you feel you have in community level decision-making processes? (C_Influence)

Presence of Elderly	A Great Deal of More Influence	More Influence	Mostly No Influence	No Influence at all	Some Influence	Total
>4 people 65+	0	0	3	0	0	3
	0	0	0.95	0	0	0.95%
	0	0	3.8	0	0	
	0	**0**	**100**	**0**	**0**	**0%**
	0.0381	1.38095	0.75238	0.47619	0.35238	Responded More Influence or A Great Deal of Influence
	FALSE	FALSE	TRUE	FALSE	FALSE	
	0.0381	1.381	6.7144	0.4762	0.3524	
2 -3 people 65+	1	19	8	3	2	33
	0.32	6.03	2.54	0.95	0.63	21.43%
	25	13.1	10.13	6	5.41	
	3.03	**57.58**	**24.24**	**9.09**	**6.06**	**60.61%**
	0.41905	15.1905	8.27619	5.2381	3.87619	Responded More Influence or A Great Deal of Influence
	TRUE	TRUE	FALSE	FALSE	FALSE	
	0.8054	0.9554	0.0092	0.9563	0.9081	
1 person 65+	3	96	12	5	9	125
	0.95	30.48	3.81	1.59	2.86	39.68%
	75	66.21	15.19	10	24.32	
	2.4	**76.8**	**9.6**	**4**	**7.2**	**79.2%**
	1.5873	57.5397	31.3492	19.8413	14.6825	Responded More Influence or A Great Deal of Influence
	TRUE	TRUE	FALSE	FALSE	FALSE	
	1.2573	25.7074	11.9426	11.1013	2.1993	
No people 65+	0	30	56	42	26	154
	0	9.52	17.78	13.33	8.25	48.89%
	0	20.69	70.89	84	70.27	
	0	**19.48**	**36.36**	**27.27**	**16.88**	**19.48%**
	1.95556	70.8889	38.6222	24.4444	18.0889	Responded More Influence or A Great Deal of Influence
	FALSE	FALSE	TRUE	TRUE	TRUE	
	1.9556	23.5848	7.819	12.6081	3.4599	
Total	49	38	35	148	45	315
	15.56%	12.06%	11.11%	46.98%	14.29%	

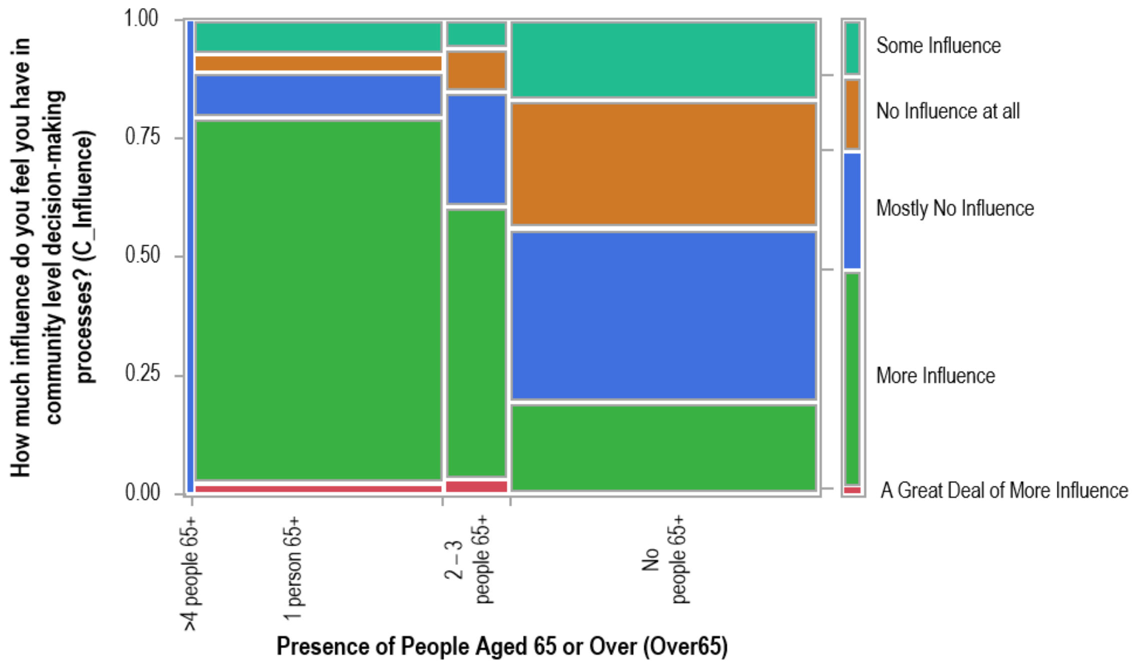

Figure B.13 – Mosaic plot for comparison between persons 65 and over (Over65) and "How much influence do you feel you have in community level decision-making processes?" (C_Influence)

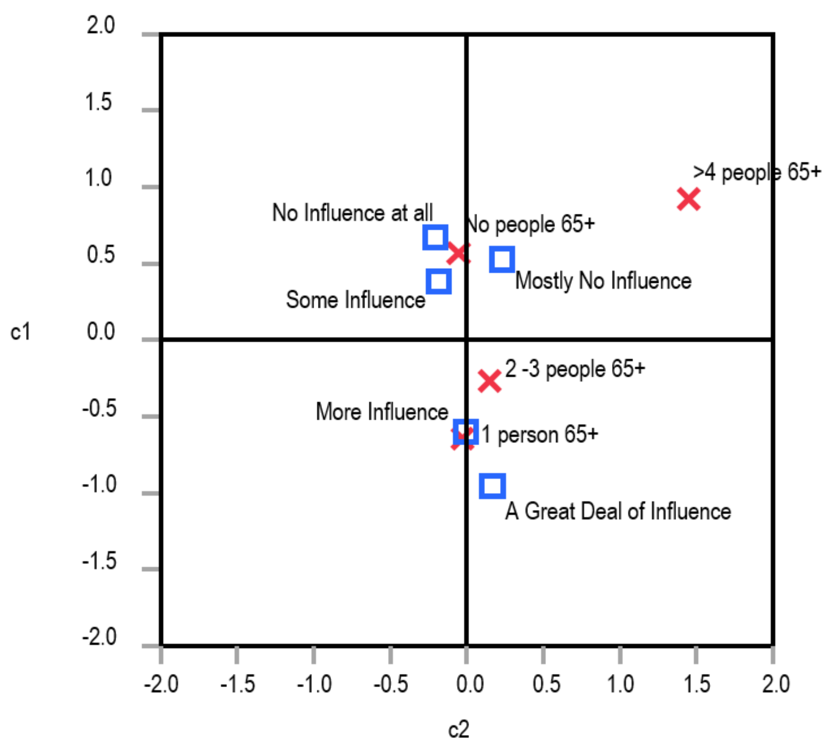

Figure B.14 – CA results for comparison between persons 65 and over (Over65) and "How much influence do you feel you have in community level decision-making processes?" (C_Influence)

Table B.8 – Contingency table for comparison between "In general, compared to 5 years ago, has your access to information about hurricanes and hurricane impacts improved, decreased, or stayed about the same?" (Knowledge) and "How involved do you feel in the hurricane preparedness decision-making within your community?" (C_Invol)

	In general, compared to 5 years ago, has your access to information about hurricanes and hurricane impacts improved, decreased, or stayed about the same? (Knowledge)					
How involved do you feel in the hurricane preparedness decision-making within your community? (C_Invol)	**Increased**	**Potentially Increased**	**Stayed the Same**	**Potentially Decreased**	**Decreased**	**Total**
Very Involved	10 3.17 5.21 90.91 6.70476 FALSE 1.6195	1 0.32 2 9.09 1.74603 TRUE 0.3188	0 0 0 0 2.33968 TRUE 2.3397	0 0 0 0 0.1746 TRUE 0.1746	0 0 0 0 0.03492 TRUE 0.0349	11 3.49% **100%** Responded Increased or Potentially Increased
Involved	126 40 65.63 88.73 86.5524 FALSE 17.9789	10 3.17 20 7.04 22.5397 TRUE 6.9763	4 1.27 5.97 2.82 30.2032 TRUE 22.7329	2 0.63 40 1.41 2.25397 TRUE 0.0286	0 0 0 0 0.45079 TRUE 0.4508	142 45.07% **95.77%** Responded Increased or Potentially Increased
Somewhat Involved	11 3.49 5.73 44 15.2381 TRUE 1.1787	4 1.27 8 16 3.96825 FALSE 0.0003	10 3.17 14.93 40 5.31746 FALSE 4.1234	0 0 0 0 0.39683 TRUE 0.3968	0 0 0 0 0.07937 TRUE 0.0794	25 7.93% **60%** Responded Increased or Potentially Increased
Not Involved	19 6.03 9.9 35.19 32.9143 TRUE 5.8822	14 4.44 28 25.93 8.57143 FALSE 3.4381	20 6.35 29.85 37.04 11.4857 FALSE 6.3116	1 0.32 20 1.85 0.85714 FALSE 0.0238	0 0 0 0 0.17143 TRUE 0.1714	54 17.14% **61.12%** Responded Increased or Potentially Increased
Not at all Involved	26 8.25 13.54 31.33 50.5905 TRUE 11.9527	21 6.67 42 25.3 13.1746 FALSE 4.6481	33 10.48 49.25 39.76 17.654 FALSE 13.3398	2 0.63 40 2.41 1.31746 FALSE 0.3536	1 0.32 100 1.2 0.26349 FALSE 2.0587	83 26.35% **56.63%** Responded Increased or Potentially Increased
Total	192 60.95%	50 15.87%	67 21.27%	5 1.59%	1 0.32%	315

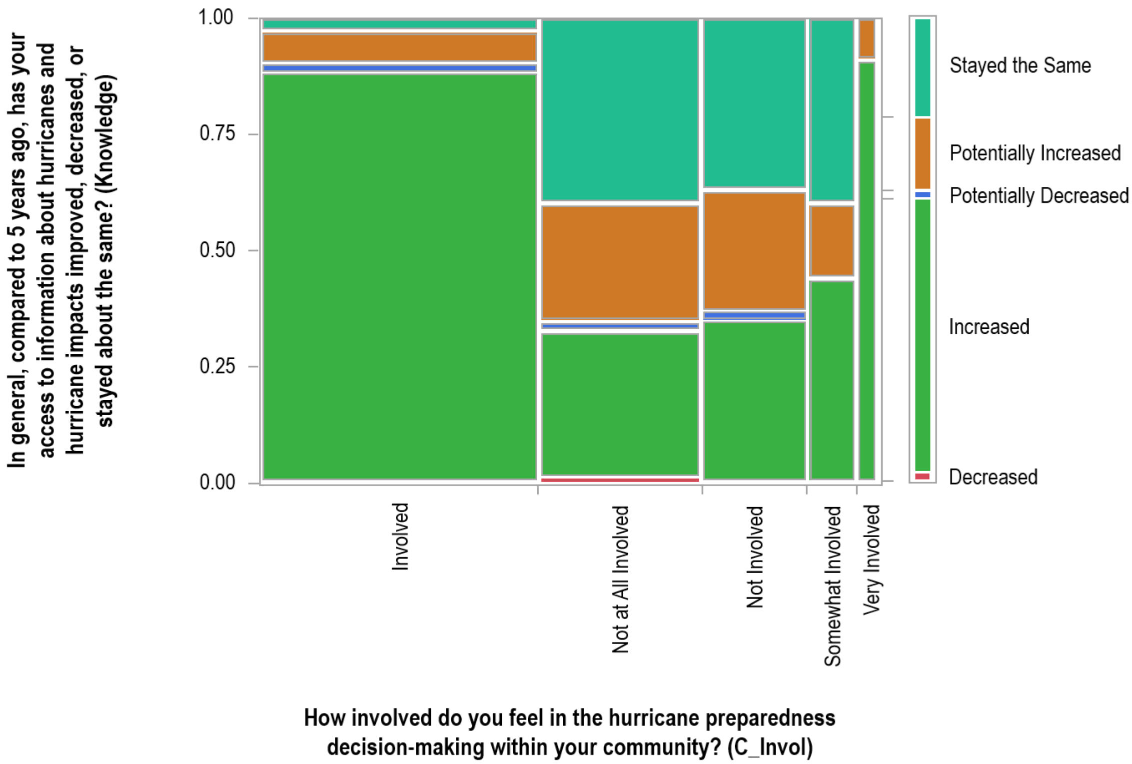

Figure B.15 – Mosaic plot for comparison between "In general, compared to 5 years ago, has your access to information about hurricanes and hurricane impacts improved, decreased, or stayed about the same?" (Knowledge) and "How involved do you feel in the hurricane preparedness decision-making within your community?" (C_Invol)

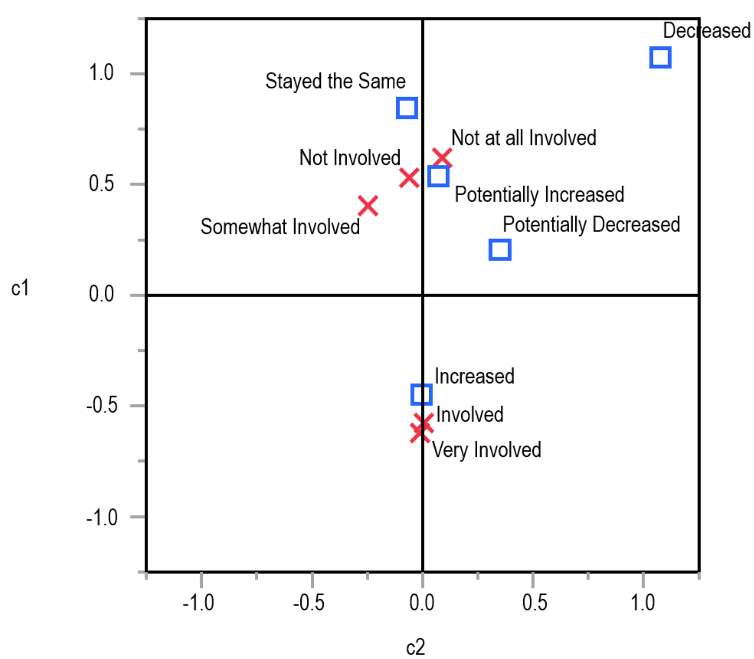

Figure B.16 – CA results for comparison between "In general, compared to 5 years ago, has your access to information about hurricanes and hurricane impacts improved, decreased, or stayed about the same?" (Knowledge) and "How involved do you feel in the hurricane preparedness decision-making within your community?" (C_Invol)

Table B.9 – Contingency table for comparison between "Do you feel that you have the financial capability to recover quickly after a hurricane event?" (SE_FinCap) and "Do you feel that people like yourself can generally change things in your community if they want to?" (C_Change)

	Do you feel that you have the financial capability to recover quickly after a hurricane event?					
Do you feel that people like yourself can generally change things in your community if they want to?	**Very Capable**	**Capable**	**Somewhat Capable**	**Mostly Not Capable**	**Not at all Capable**	**Total**
Agree to Strongly Agree	101 32.06 88.6 66.45 55.0095 FALSE 38.4501	26 8.25 26.26 17.11 47.7714 TRUE 9.9221	17 5.4 27.42 11.18 29.9175 TRUE 5.5774	8 2.54 25 5.26 15.4413 TRUE 3.586	0 0 0 0 3.86032 TRUE 3.8603	152 48.25% **83.56%** Responded Very Capable or Capable
Somewhat Agree	6 1.9 5.26 7.06 30.7619 TRUE 19.9322	48 15.24 48.48 56.47 26.7143 FALSE 16.9603	20 6.35 32.26 23.53 16.7302 FALSE 0.6391	8 2.54 25 9.41 8.63492 TRUE 0.0467	3 0.95 37.5 3.53 2.15873 FALSE 0.3278	85 26.98% **63.53%** Responded Very Capable or Capable
Neither	1 0.32 0.88 3.7 9.77143 TRUE 7.8738	9 2.86 9.09 33.33 8.48571 FALSE 0.0312	13 4.13 20.97 48.15 5.31429 FALSE 11.1154	3 0.95 9.38 11.11 2.74286 FALSE 0.0241	1 0.32 12.5 3.7 0.68571 FALSE 0.144	27 8.57% **37.03%** Responded Very Capable or Capable
Somewhat Disagree	2 0.63 1.75 7.41 9.77143 TRUE 6.1808	9 2.86 9.09 33.33 8.48571 FALSE 0.0312	9 2.86 14.52 33.33 5.31429 FALSE 2.5562	5 1.59 15.63 18.52 2.74286 FALSE 1.8574	2 0.63 25 7.41 0.68571 FALSE 2.519	27 8.57% **40.74%** Responded Very Capable or Capable
Disagree to Strongly Disagree	4 1.27 3.51 16.67 8.68571 TRUE 2.5278	7 2.22 7.07 29.17 7.54286 TRUE 0.0391	3 0.95 4.84 12.5 4.72381 TRUE 0.6291	8 2.54 25 33.33 2.4381 FALSE 12.6881	2 0.63 25 8.33 0.60952 FALSE 3.172	24 7.62% **45.84%** Responded Very Capable or Capable
Total	114 36.19%	99 31.43%	62 19.68%	32 10.16%	8 2.54%	315

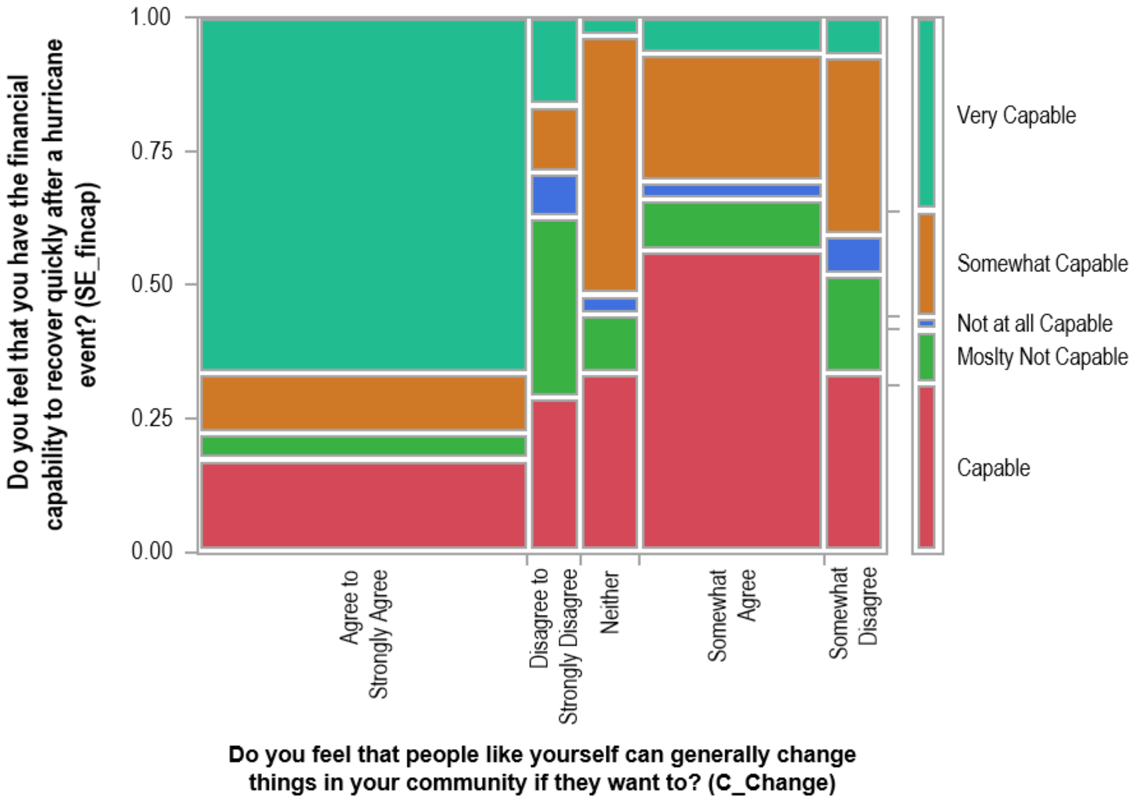

Figure B.17 – Mosaic plot for comparison between "Do you feel that you have the financial capability to recover quickly after a hurricane event?" (SE_FinCap) and "Do you feel that people like yourself can generally change things in your community if they want to?" (C_Change)

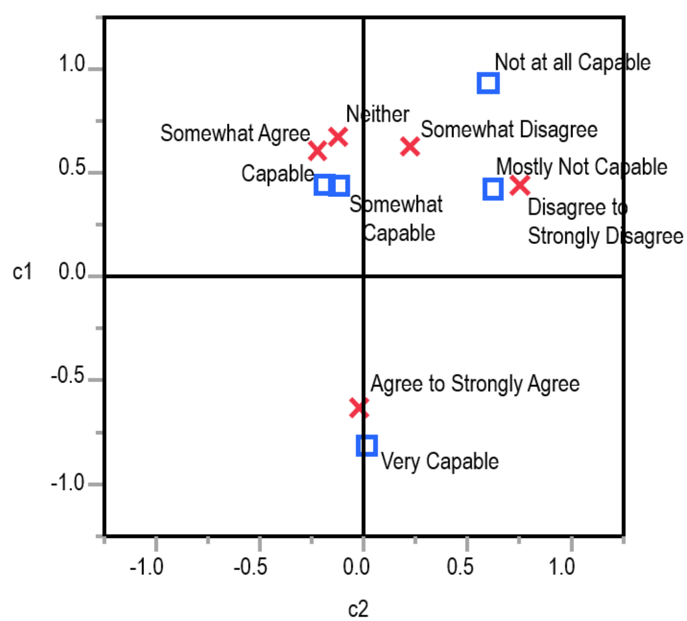

Figure B.18 – CA results for comparison between "Do you feel that you have the financial capability to recover quickly after a hurricane event?" (SE_FinCap) and "Do you feel that people like yourself can generally change things in your community if they want to?" (C_Change)

Table B.10 – Contingency table for comparison between presence of children under 5 (Child5) and "How likely are you to: a) take time to for hurricane impacts? (Prepare) or b) evacuate during a hurricane?" (Evacuation)

Take the time to prepare for hurricane impacts? (Prepare)

Presence of Children	Likely/ Very Likely	Somewhat Likely	Neither Likely or Unlikely	Somewhat Unlikely	Unlikely to Very Unlikely	Total
>4 Children	1	1	0	0	0	2
	0.32	0.32	0	0	0	0.64%
	0.42	1.56	0	0	0	
	50	50	0	0	0	**100%**
	1.49841	0.40635	0.03175	0.05714	0.00635	Responded Likely/
	TRUE	FALSE	TRUE	TRUE	TRUE	Very Likely or
	0.1658	0.8673	0.0317	0.0571	0.0063	Somewhat Likely
2 - 3 Children	82	2	0	0	0	84
	26.03	0.63	0	0	0	26.66%
	34.75	3.13	0	0	0	
	97.62	2.38	0	0	0	**100%**
	62.9333	17.0667	1.33333	2.4	0.26667	Responded Likely/
	FALSE	TRUE	TRUE	TRUE	TRUE	Very Likely or
	5.7766	13.301	1.3333	2.4	0.2667	Somewhat Likely
1 Child	44	25	0	4	0	73
	13.97	7.94	0	1.27	0	23.18%
	18.64	39.06	0	44.44	0	
	60.27	34.25	0	5.48	0	**94.52%**
	54.6921	14.8317	1.15873	2.08571	0.23175	Responded Likely/
	TRUE	FALSE	TRUE	FALSE	TRUE	Very Likely or
	2.0903	6.9711	1.1587	1.7569	0.2317	Somewhat Likely
No Children	109	36	5	5	1	156
	34.6	11.43	1.59	1.59	0.32	49.53%
	46.19	56.25	100	55.56	100	
	69.87	23.08	3.21	3.21	0.64	**92.95%**
	116.876	31.6952	2.47619	4.45714	0.49524	Responded Likely/
	TRUE	FALSE	FALSE	FALSE	FALSE	Very Likely or
	0.5308	0.5847	2.5723	0.0661	0.5145	Somewhat Likely
Total	236	64	5	9	1	315
	74.92%	**20.32%**	1.59%	2.86%	0.32%	

Evacuate during a hurricane? (Evacuation)

Presence of Children	Likely/ Very Likely	Somewhat Likely	Neither Likely or Unlikely	Somewhat Unlikely	Unlikely to Very Unlikely	Total
>4 Children	0	0	0	1	1	2
	0	0	0	0.32	0.32	0.64%
	0	0	0	3.45	4.76	
	0	0	0	50	50	**0%**
	0.55238	1.06032	0.06984	0.18413	0.13333	Responded Likely/
	TRUE	TRUE	TRUE	FALSE	FALSE	Very Likely or
	0.5524	1.0603	0.0698	3.6152	5.6333	Somewhat Likely
2 - 3 Children	4	77	0	2	1	84
	1.27	24.44	0	0.63	0.32	26.66%
	4.6	46.11	0	6.9	4.76	
	4.76	91.67	0	2.38	1.19	**96.43%**
	23.2	44.5333	2.93333	7.73333	5.6	Responded Likely/
	TRUE	FALSE	TRUE	TRUE	TRUE	Very Likely or
	15.8897	23.6696	2.9333	4.2506	3.7786	Somewhat Likely
1 Child	20	47	1	1	4	73
	6.35	14.92	0.32	0.32	1.27	23.18%
	22.99	28.14	9.09	3.45	19.05	
	27.4	64.38	1.37	1.37	5.48	**91.78%**
	20.1619	38.7016	2.54921	6.72063	4.86667	Responded Likely/
	TRUE	FALSE	TRUE	TRUE	TRUE	Very Likely or
	0.0013	1.7793	0.9415	4.8694	0.1543	Somewhat Likely
No Children	63	43	10	25	15	156
	20	13.65	3.17	7.94	4.76	49.52%
	72.41	25.75	90.91	86.21	71.43	
	40.38	27.56	6.41	16.03	9.62	**67.94%**
	43.0857	82.7048	5.44762	14.3619	10.4	Responded Likely/
	FALSE	TRUE	FALSE	FALSE	FALSE	Very Likely or
	9.2044	19.0614	3.8043	7.8798	2.0346	Somewhat Likely
Total	87	167	11	29	21	315
	27.62%	**53.02%**	3.49%	9.21%	6.67%	

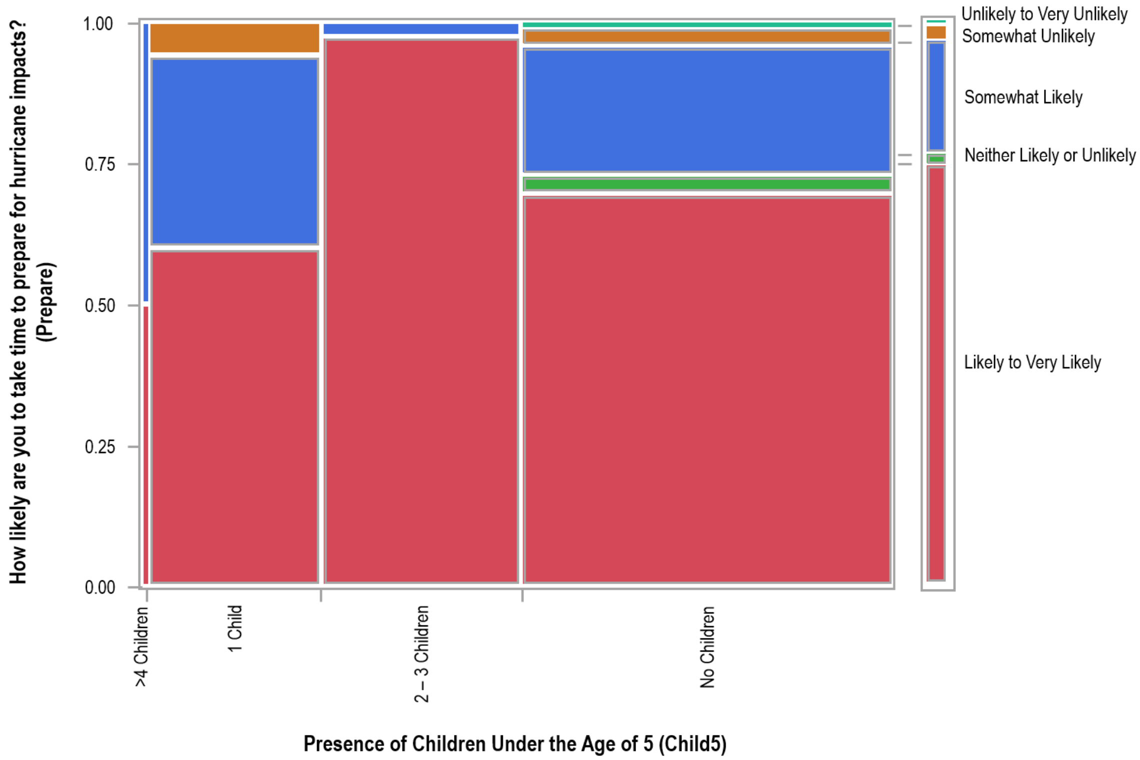

Figure B.19 – Mosaic plot for comparison between presence of children under 5 (Child5) and "How likely are you to take time to for hurricane impacts?" (Prepare)

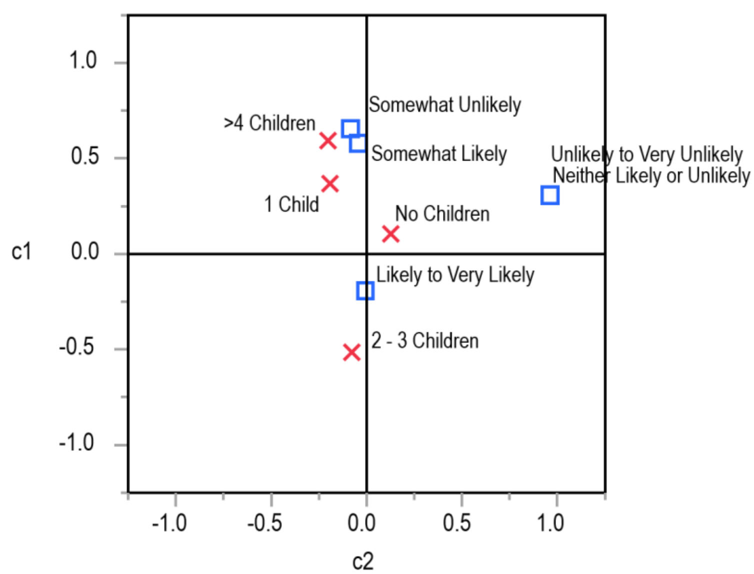

Figure B.20 – CA results for comparison between presence of children under 5 (Child5) and "How likely are you to take time to for hurricane impacts?" (Prepare)

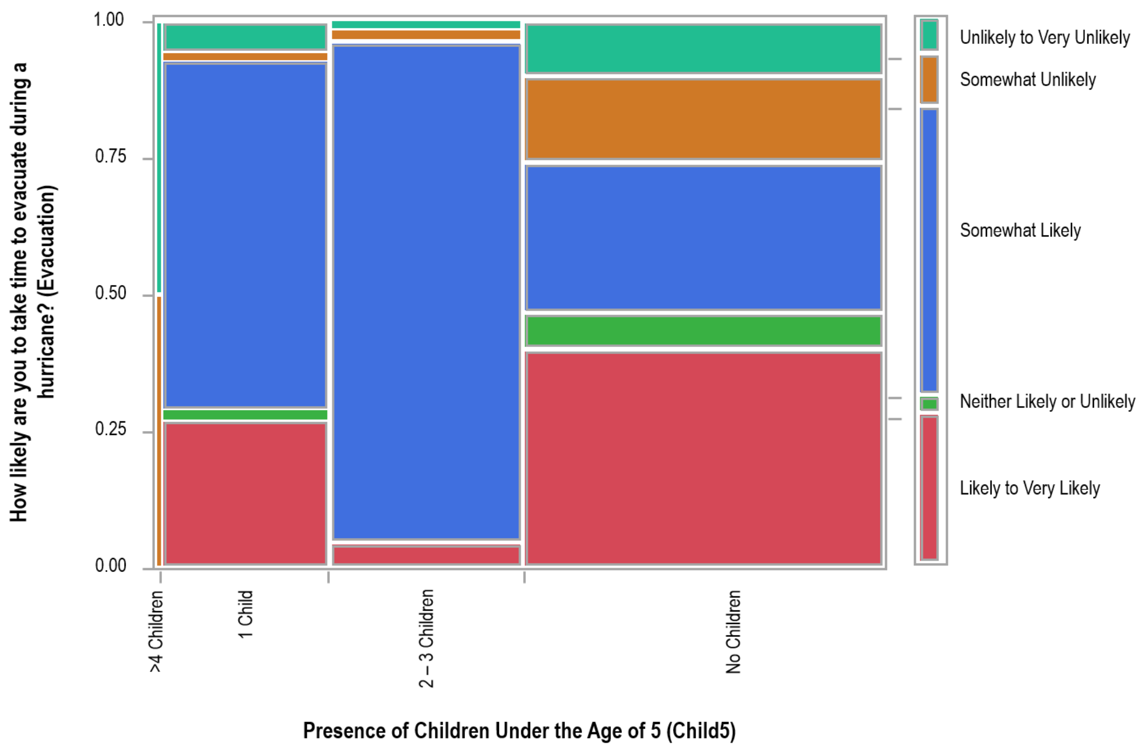

Figure B.21 – Mosaic plot for comparison between presence of children under 5 (Child5) and "How likely are you to evacuate during a hurricane?" (Evacuation)

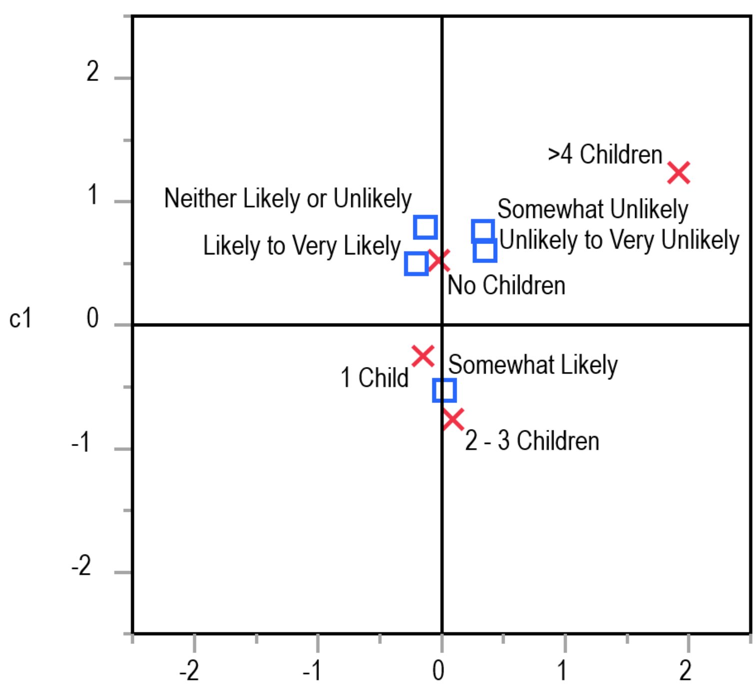

Figure B.22 – CA results for comparison between presence of children under 5 (Child5) and "How likely are you to evacuate during a hurricane?" (Evacuation)