SOCIAL VULNERABILITY AND PUBLIC HEALTH: DEVELOPING A METRIC FOR MEDICAL EMERGENCY MANAGEMENT IN FLORIDA

by

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DEDICATION

To my “brothers in arms”- Alex, Zach, Andy, Chris, Schuyler, David, and Kyle. You always have been, and forever will be my best friends-- in this life and the next.
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Individuals and communities with pre-existing medical conditions give rise to special needs populations that may require/necessitate additional resources in preparing for, responding to, and recovering from disasters. Emerging research in hazards and epidemiology has alluded to the inherent ties between indicators of social vulnerability and the quality of public health. With disparate access to finances, insurance, transportation, and medical services, areas of elevated social vulnerability tend to compound risk in terms of medical needs during a hazard event. While the concept of social vulnerability includes some indirect measures of special needs populations, these may be insufficient in adequately defining the true pre-existing medical need and health access that correlate with the responsibilities of Emergency Support Function 8 (public health and medical services). Consequently, this research develops the concept of medical vulnerability, an explicit construct that demonstrates those underrepresented vulnerable populations. The concept is operationalized in two subsequent analyses using the state of Florida as the research setting. First, drawing theoretical justification from the literature, an initial set of variables was culled to represent medical need (i.e. chronic or communicable disease, disability, drug dependence) and health care access (i.e. hospital beds, physicians, insurance). Using a principal component analysis, the initial collection of candidate variables was reduced to a smaller set of underlying components. These components are aggregated using a simple additive model to create a composite
indicator for medical vulnerability. The second analysis combines statistics and GIS to compare the overlap between medical vulnerability and its socioeconomic counterpart using Cutter et al.’s (2003) social vulnerability index. As this thesis contends, the inclusion of purely medical indicators in vulnerability analysis helps to describe a section of the marginalized population otherwise not acknowledged. The results of the analyses show that social vulnerability and medically vulnerability are both statistically and spatially disparate in Florida. Consequently, this thesis concludes that the Medical Vulnerability Index and the Social Vulnerability Index are indeed separate constructs measuring different aspects of vulnerable populations with little overlap.
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Chapter 1: Introduction

The disproportionate losses endured by certain communities in the wake of Hurricane Katrina provide stark evidence of the disparities between population groups. As a result, the concepts related to differential vulnerabilities have revived both public and academic interests in hazards and their impacts. While conservative estimates place Hurricane Katrina’s death toll above 1,700 (Petterson et al. 2006) and economic losses above $125 billion (U.S. Senate 2006), the intricate socio-political fabric of the Gulf Coast (from Louisiana through Alabama) and the differential impacts from this disaster reveal far greater disparities than simple loss statistics can indicate. More troubling than these impacts, however, are those projected for future scenarios. The implications of climate change on the frequency and severity of large-scale hazard events creates an increased scientific impetus toward hazard risk reduction. However, increases in physical risk alone cannot accurately foreshadow the potential for human losses associated with these events, nor can they account for a community’s resilience.

Social disparities in the wake of Hurricane Katrina were paramount in defining a community’s ability to respond. As the storm surged along the Gulf Coast, those with the ability to evacuate took advantage of their resources and lifelines and removed themselves from harm. Left behind were those populations lacking power, access, and resources: the poor black, elderly, and sick (Laska and Morrow 2007). More discouraging, the emergency management system designed to aid them quickly became
overwhelmed and experienced total collapse creating what some researchers referred to as a “social catastrophe” (Cutter and Emrich 2006:105).

The documented inabilities of the health care system in response to Hurricane Katrina are innumerable. Aside from direct mortality, the number of people affected by the destruction of healthcare infrastructure was unmanageable for many local disaster medical assistance teams (DMATs) (Ferdinand 2006; Petterson et al. 2006). Inadequate preparation left many medical DMATs without the supplies needed to handle even common medical conditions (i.e. asthma, hypertension, diabetes, pregnancy, dehydration), let alone mass care (Petterson et al. 2006).

The Federal Emergency Management Agency’s Emergency Support Function (ESF) 8 (i.e. public health and medical services) provides the mechanism for coordinated Federal assistance to supplement state, tribal, and local resources in response to a public health and medical disaster. This includes responding to medical needs associated members of the ‘at risk’ or ‘special needs’ population during a hazard event. Core functions of ESF 8 include assessment of public health/medical needs, health surveillance, provision of medical care personnel, medical supplies, and patient evacuation and care (FEMA 2008). This includes diverging scales of phenomena: community based needs (i.e. access) that can be mitigated; and individual health needs (i.e. chronic illness) that cannot. In the allocation of medical resources, these pre-event considerations help to dictate the need for particular medical supplies, and the amount and type of personnel required to respond.

Individuals and communities with pre-existing medical conditions give rise to special needs populations that may require/necessitate additional resources in preparing
for, responding to, and recovering from disasters. Emerging research in epidemiology has alluded to the inherent ties between indicators of social vulnerability and the quality of public health (Aday 2001). With disparate access to finances, insurance, transportation, and medical services, areas of elevated social vulnerability tend to compound risk in terms of medical needs during a hazard event. While the concept of social vulnerability includes some indirect measures of special needs populations, these may be insufficient in adequately defining the true pre-existing medical need and health access, or medical vulnerability that would correlate with ESF 8. Understanding the distribution of indicators of social and medical vulnerability across space will help to explain the underlying nature of the two constructs and will be essential for determining a hidden or causal relationship.

Florida provides a good example of an area in which these concepts are certainly relevant. The state’s unique peninsular geography leaves it exposed along both the Atlantic Ocean and the Gulf of Mexico, yielding what Bossak (2004) refers to as a “hurricane bull’s-eye” (541). This phenomenon was especially apparent during the 2004 hurricane season, in which four separate storms; Hurricanes Charley, Frances, Ivan and Jeanne; made direct landfall in Florida. Combining this physical exposure along nearly 1,200 miles of the hurricane coast with an ever-inflating coastal population leaves Florida at high risk for disaster. Furthermore, the fragile demographic situation becomes more unstable by the high incidence of socioeconomic sensitivity embodied by large minority and elderly populations (Cutter et al. 2007). The relative impacts suffered by these vulnerable populations will likely be greater than those weathered by their less-susceptible counterparts. What is unknown, however, is the spatial and statistical overlap
between these socially vulnerable groups and those with special medical needs. More specifically, is it unclear whether measures of social vulnerability alone can adequately foreshadow true medical need and healthcare access.

1.1 Research Questions

The purpose of this thesis is to create an empirical measure of medical vulnerability to disasters, and examine its relationship with social vulnerability. With an improved understanding of this relationship, medical emergency managers can tailor disaster preparedness plans to anticipate the needs of vulnerable communities. This thesis examines the following research questions:

1. Which variables provide the best characterization of medical vulnerability to disasters, including measures of both health access and pre-existing medical needs?
2. What is the statistical congruence or overlap between medical vulnerability and social vulnerability as measured by the Social Vulnerability Index?
3. Can social vulnerability explain the distribution of medical vulnerability or are they different in their spatial representations?

1.2 Organization of the Thesis

This thesis is organized into five chapters, a list of references, and three appendices. A review of the literature on vulnerability science theory, social vulnerability metrics, and public health and disasters is found in Chapter 2. Chapter 3 provides a comprehensive summary of the data and methodology used for analysis in the
thesis, and Chapter 4 includes the results from the analyses. A discussion linking the analyses to the research questions, as well as concluding suggestions for future research is found in Chapter 5. Finally, a list of references and three appendices including additional information regarding the results of the analyses can be found at the end of the thesis.
Chapter 2: Literature Review

2.1 Vulnerability

From a natural hazards perspective, Cutter (1996) broadly defines vulnerability as “the potential for loss” (p529). This essentially describes the pre-event characteristics that interact with the hazard event to produce disasters. These attributes are embodied in two main components: exposure and sensitivity (Adger 2006; Cutter 1996; Cutter et al. 2008). Exposure attempts to explain who and what are at risk, while sensitivity refers to the degree to which people and places can be harmed. Despite its general definition, the literature is divided when it comes to the explaining the causal structure of vulnerability. As such, many conceptual models are put forth. A brief overview of these theoretical frameworks is provided to outline the foundations of the vulnerability research perspective for this thesis.

Eakin and Luers (2006) suggest a distinction of models developed from a risk-hazard perspective and those hailing from political ecology/economy approaches. Risk-hazard approaches regard negative impacts as “…a function of both biophysical risk factors (for example, in the climate change literature, a change in temperature, precipitation or the frequency of extreme events) and the ‘potential for loss’ of a specific exposed population” (p369). Thus, the risk-hazard approach stands to answer the questions: (a) to what are we vulnerable, and (b) what are the expected impacts? As negative outcomes are realized (i.e. potential for loss) they serve as a rough equivalent to
vulnerability “…allowing the ex post identification of the existence of vulnerability in a specific system” (p396). In other words, damages are used as rough proxies for vulnerability, conflating causal processes with outcome conditions (Eakin and Luers 2006).

Examples of risk-hazard approaches to vulnerability include Kates’ (1971) framework in which the effects of hazard events are the result of the interaction between society and nature. However, as Schmidtlein (2008) points out, Kates’ model is limited by its restriction of human influences on the effects of hazards to include only those ways in which society structures itself in relation to the physical environment (i.e. occupancy patterns, alteration of the physical environment, hazard response processes). Mileti (1980) builds on Kates’ framework to include a consideration of certain societal traits, such as power and access. These qualities influence the probability that a social assembly will have increased capacity to mitigate hazard impacts.

Another major approach to hazard vulnerability is framed at the center of political ecology and political economy. This approach focuses more on the structural origins of vulnerability. As Eakin and Luers (2006) describe:

Political-economy perspectives on vulnerability emphasize the sociopolitical, cultural, and economic factors that together explain differential exposure to hazards, differential impacts, and, most importantly, differential capacities to recuperate from past impacts and/or to cope and adapt to future threats. (370)

In contrast to the risk-hazard approach, political ecology frameworks tend to focus on the interaction of social and economic processes focusing on the causation and stratification of vulnerability. Thus, the questions answered by this approach include: (a) why are particular populations vulnerable, and (b) how are they vulnerable (Eakin and Luers 2006)?
A major precept of the political ecology/economy approach, exhibited by O’Keefe et al. (1976) serves to strike the assumed relationship between vulnerability and natural events. A major contribution to this approach is the frequently-cited Pressure and Release (PAR) model by Blaikie et al. (1994). In this model, vulnerability is represented as a component of risk: Risk = Hazard + Vulnerability. As such, the model conceptualized vulnerability as a product of broad social structures, or root causes, which subsequently compounded as dynamic pressures and unsafe conditions. In turn, these conditions interacted with natural events to cause disasters. Shortcomings of the model include a failure to address the spatial proximity to the source of the threat, and the neglect of direct interactions between the social and natural systems. The model merely assumes the natural event is a given, discounting the dynamic nature of hazard events, and their particular interaction with vulnerable population to create disasters. The model instead puts emphasis on the complex structural factors influencing vulnerability. As a result the primary utility of this model is more descriptive analysis and less empirical measure (Cutter et al. 2008).

While the aforementioned frameworks mostly adhere to the theoretical boundaries of either the risk/hazard or the political ecology perspective, a third set of hybrid models exist that incorporates elements from both schools of thought. In 1996 Cutter introduced the hazards of place (HOP) model of vulnerability (Figure 2.1). Lending themes from both aforementioned approaches, its contribution is the integration of hazard potential with geographic context and pre-existing social fabric to reveal biophysical and social vulnerability. At the confluence of these individual vulnerabilities lies the hazardousness of place. Additionally, the model shows the potential feedback of place vulnerability on
risk and mitigation, representing the dynamic nature of vulnerability over time. By building in both the spatial and temporal components, the HOP model has utility for multiple events and regions (Cutter 1996; Schmidtlein 2008). The major critique of this framework is its “…fails to account for the root causes of the antecedent social vulnerability, larger contexts, and post-disaster impact and recovery” (Cutter et al. 2008: 601). However, the simplicity of the model allows for flexibility in empirical application.

![Figure 2.1: The Hazards of Place Model (from Cutter 1996)](image)

Lastly, a more recent hybrid framework attempting to bridge the gaps of its predecessors is Turner et al.’s (2003) Vulnerability Framework for Sustainability Science. This model represents local vulnerability as a function of the processes occurring in the larger (i.e. regional or global) context. However, regional and global influences can be altered by the impact responses, adjustments, and adaptations of places. More explicitly, vulnerability is modeled as the outcome of exposure, sensitivity, and resilience. While the model alludes that exposure and sensitivity are result from the
interactions of social and physical systems, it does not make an explicit distinction of how exposure and sensitivity are defined, and how they are different from each other. Additionally, the model lacks a temporal component, failing to indicate where/when vulnerability beings and ends. Because of these shortcomings, Turner et al.’s framework is overly complex, lacking parsimony and reducing its utility for empirical measures.

Despite the previously mentioned limitations, the most appropriate model for the foundation of this analysis is the hazards of place model of vulnerability (Cutter 1996). The HOP model recognizes vulnerability as a pre-event condition, independent of the hazard type, but also accounts for human adjustments post-event. Perhaps the most important aspect of this model is the focus on place. Variables used to characterize geographic place are dynamic across space and time. Different places often exhibit at least one unequivocal feature, be it physical or socioeconomic, which make them distinguishable from one another. The focuses on geographical and social spaces make the model operational at different scales.

2.2 Social Vulnerability

Vulnerability science techniques for hazards research are based on the understanding that social attributes interact with physical events to produce losses. As a result, disaster events are not fully represented without acknowledging the social context in which they occur (Mitchell et al. 1989; Schmidtlein 2008). The holistic influence of those social characteristics on the propensity for loss is collectively referred to as social vulnerability. The stratification of social space helps to explain why some communities experience hazard events differently, despite their equal exposure (Cutter 1996; Cutter et
al. 2000, 2003; Wu et al. 2002). Understanding the differential effects of hazards as a product of the social vulnerability of a place, independent of exposure, is a critical element in formulating comprehensive plans for emergency preparedness, response, and mitigation (Morrow, 1999).

An important precept in understanding the construct of social vulnerability is that it exists independent of hazard type and magnitude (Cutter 1996; Cutter et al 2003). This is in contrast to biophysical vulnerability, which is inherently a product of exposure. Social vulnerability describes those characteristics of the population that intervene between natural processes and the built environment to redistribute the risks and impacts of natural hazards, thus creating differential social burdens of hazards across space (Birkmann 2006; Cutter et al. 2003). These characteristics are different from place to place, consequently creating stratified social spaces (Maloney 1973). The hierarchy of social quality in a system that distinguishes between classes inevitably leads to discrimination of the socially, culturally and economically marginalized (Mustafa 1998). Morrow (2008) asserts, “The effects increase vulnerability, or potential for loss, at all levels of society—from individuals to communities to nations” (p4).

Though the concept of social vulnerability is certainly well developed, it is still the less understood component in the vulnerability of place. Cutter et al. (2003) explains, “Socially created vulnerabilities are largely ignored, mainly due to the difficulty in quantifying them, which also explains why social losses are normally absent in after-disaster cost/loss estimation reports. Instead, social vulnerability is most often described using the individual characteristics of people” (243).
2.2.1 Social Indicators

Examining these individual characteristics of social vulnerability, one finds a rich tradition in social indicators research, first evolving from the social sciences (Duncan 1969; Land and Spearman 1975; Maloney 1973), and the later finding its place in disasters research (Cutter 1996; Cutter et al. 2003; Heinz Center 2002; Morrow 1999; National Research Council 2006) in deriving the potential for loss. Characteristics most often discussed in the literature include socioeconomic status (see Clark et al. 1998; Fothergill and Peek 2004; Morrow 2008; Peacock et al. 2000;), race and ethnicity (see Fothergill et al 1999; Milet 1999; Morrow 1999; Saenz 2005; Tierney et al. 2001), gender (see Enarson et al. 2006; Enarson and Morrow 1998; Fothergill 1996; Peacock et al. 2000), age (see Fothergill and Peek 2004; Kar 2009; Ngo 2001), and special needs populations (see McGuire et al. 2007; Morrow 2008).

Socioeconomic status affects the ability to absorb disaster losses (Cutter et al. 2000; Morrow 2008; Peacock et al. 2000). Though the materials losses of wealthy communities post-disaster may disproportionately exceed those of their disadvantaged counterpart, the relative losses among the poor are suffered disproportionately (Morrow 1999, 2008). Poor communities lack the resources to invest in emergency preparedness, response, and recovery efforts (Clark et al. 1998; Yarnal 2007). Additionally the poor often live without insurance in substandard housing, compounding their disaster risk (Fothergill 1996). With decreased access to lifelines during disasters, such as transportation and communication infrastructure, poverty and class are often shown to limit both disaster evacuations and returns (Clark et al. 1998; Elliot and Pais 2006). This
may help to explain why the poor suffer from higher disaster mortality rates (Blaikie et al. 1994).

The literature discussing race and ethnicity often shows a key association with socioeconomic status, revealing a propensity of poverty (Fothergill et al. 1999; Fussel 2007; Mileti 1999; Tierney et al. 2001). Additionally, race and is often linked with differences in risk perception and disaster response. Minority groups are more likely to rely on social networks as information sources during a disaster, rather than legitimate warning systems (Morrow 1999; Tierney et al. 2001). Historical discrimination may have confined minorities to economically disadvantaged and highly exposed locales (Clark et al. 1998; Fothergill et al. 1999), while institutional isolation prevents their ability to obtain reliable insurance, and federal aid (Dash et al. 1997; Peacock and Girard 1997). Particularly for recent migrants and non-english speakers in the United States, there can be difficulty when interpreting warnings, and seeking information and assistance due to language barriers (Morrow 2008; Peacock et al. 2000).

Gender also plays a role in vulnerability. For many reasons, women often suffer the impacts of a disaster disproportionately, and struggle in disaster recovery (Enarson et al 2006; Enarson and Morrow 1998; Morrow 1999, 2008). Generally speaking, women are often more socioeconomically sensitive than men. For example, women are more likely than men are to hold low wage service industry jobs (Morrow 2008). Additionally single female householders are more much more likely to live in poverty (Bianchi and Spain 1996, Heinz Center 2002; Morrow 1999). The role of family caregiver often causes women to put the safety and needs of others before their own (Fothergill 1996; Peacock et al 2000).
At its extremes, age (i.e. the very young and very old) can affect an individual’s mobility during disasters (Heinz Center 2002; Kar 2009; Ngo 2001; Smith et al 2009). Children are entirely dependent on family or social caregivers during disasters (Morrow 1999). After a disaster, parents may lose time and money if childcare facilities are affected (Heinz Center 2002). In general terms, the elderly often lack the physical and financial capability necessary to respond to a disaster. They have higher propensity to experience health problems before and during the disaster, with slower recovery (Smith et al. 2009). Elderly shut-ins are often reluctant to evacuate during a disaster, due to both physical limitations and an unwillingness to forfeit their social independence (Gladwin and Peacock 1997). For both the young and old, stress created from disaster disruptions can lead to lasting psychological impacts (Kar 2009; Morrow 1999; Smith et al. 2009).

Finally, people with special needs often have limited ability to respond to disasters. They require additional assistance in preparation for and recovery from disaster impacts (McGuire et al. 2007). Consequently, emergency managers should identify places exhibiting high concentrations of disabled people, and plan accordingly for timely evacuation (Morrow 2008).

It is important to note from the preceding discussion that while each proxy affects a person’s ability absorb disaster impacts, vulnerability cannot be adequately defined by a single measure. Instead, social vulnerability lies at the intersection of these factors, as variables interact to create socially vulnerable populations.
2.2.2 Social Vulnerability Metrics

Vulnerability analysis is a tool designed to help emergency managers find practical ways of identifying who is most vulnerable to hazards, where these populations reside, and what drives their vulnerability. As Cutter (1996) contends, the most vulnerable people may not live in the most vulnerable places. Thus, being able to locate populations of high social disparity proves its utility for emergency preparedness.

While the theoretical underpinnings of vulnerability science progressed over the past two decades, their application and implementation remain the most demanding endeavor (Cutter 1996; Gall 2007; Turner et al 2003). To comprehensively incorporate theoretical concepts into applied vulnerability assessments, the research from theoretical models and indicators must be translated into quantitative algorithms (Cutter 1996; Gall, 2007). Thus, we find the utility for social vulnerability indices as a metric for aggregating the existence of the indicators described in the previous section.

The methodological development of social vulnerability indices are focused around three major decisions: 1) the observational scale of the index; 2) the explicit proxies included in the index; and 3) the method of aggregation (Adger et al 2004; Barnett et al. 2008; Gall 2007). Variations in the development of the index inevitably produce different outcomes.

In perhaps the earliest application of quantitative social vulnerability analysis, Maloney (1973) chose eight variables (median income, percent poverty, percent families with mother and father present, percent unemployed, percent of houses lacking plumbing, percent without an automobile, rate of ambulance runs, and rate of tuberculosis) derived primarily from the Census to characterize social vulnerability for census tracts in
Indianapolis. Variables were standardized via z-score to make the range and distribution of the data negligible for comparison. The standardized variables were combined using factor analysis to create a single composite indicator of social vulnerability, explaining 76 percent of the variance at the tract level for the city of Indianapolis. As a result, no additional means of aggregation were used. Results were mapped by standard deviation per census tract. Though this analysis has relatively few inputs, the robustness of data reduction methods for the geographic comparison of vulnerability was largely ahead of its time.

Twenty-five years later, Clark et al. (1998) employed similar methods, this time using 34 Census derived variables to characterize vulnerability at the block group scale for the physically vulnerable city of Revere, MA. Again using a factor analytic approach, raw variables were reduced to 5 composite indicators explaining 55 percent of the variance. As a comparison of methods, two aggregation techniques used to arrive at the final social vulnerability score: weighted average (based on \textit{a priori} weights), and data envelopment analysis, which applied weighted averages “… obtained for each block group objectively through the use of an optimization model” (Clark et al. 1998: 71). Social vulnerability and physical vulnerability were mapped together using bivariate mapping techniques. While this analysis increased the depth of inputs from Maloney (1973) a failure to standardize the variables suggests that the results of the analysis have not accounted for the range and distribution of the data, convoluting the comparison of variables.

In 2000, Cutter et al. operationalized the Hazards of Place model to reveal the vulnerability of populations living inside hazard zones for Georgetown County, South
Carolina (Cutter et al. 2000). To quantify social vulnerability, nine indicators were chosen deductively. These were based on a priori knowledge and existing literature (Blaikie et al 1994; Hewitt 1997) and included: Total population, and total housing units (i.e. proxy of people/structures at risk); number of females, number of nonwhite residents, number of people under age 18, and number of people and over age 65; mean house value (i.e. proxy for wealth, resilience); and number of mobile homes (i.e. proxy level of structural vulnerability). Indicators were collected for block groups using 1990 US Census Statistics. Rather than using simple percentages to represent indicators, each social variable was standardized by determining a ratio of that variable in each census block to the total value of that variable for the entire county. This method creates a comparative proportion for each variable in each block. To produce an aggregate value for social vulnerability, standardized values were summed for each block. This score was then combined with the aggregate values for biophysical vulnerability (derived from frequency of hazard occurrence) using a GIS. The resultant totals—Place Vulnerability was achieved without the assignment of a priori weights. Lacking the reliable statistical evidence assign weights, all indicators were treated equally and assumed to have the same relative importance (Cutter et al. 2000).

Chakraborty et al. (2005) used those methods developed by Cutter et al. (2000) to develop the Social Vulnerability for Evacuation Assistance Index (SVEAI) for block groups in Hillsborough County Florida. SVEAI used 10 indicators, similar to those chosen by Cutter et al. (2000) changing slightly to include those populations that may have special evacuations needs (i.e. disabled) and those who have differential access to evacuation resources inside their home (i.e. no telephone or vehicle) (Chakraborty et al. 2005).
Rather than simply summing the standardized variables, values were averaged yielding aggregate vulnerability normalized between 0 and 1. In further contrast from Cutter et al.’s metric, Chakraborty et al. presented four alternative approaches for grouping the variables to calculate social vulnerability for evacuation and for examining the spatial distribution of each approach within the study area. These characteristics are listed below, along with the number of variables associated with each approach: Approach 1: Population and structure (three variables); Approach 2: Differential access to resources (three variables); Approach 3: Special evacuation needs (four variables); and Approach 4: All three characteristics (all 10 variables). Each approach addresses a specific dimension of evacuation assistance need that can be examined and visualized independently, a process that recognizes the different issues that local emergency managers face in developing evacuation plans. Using the methods of Cutter et al. 2000, SVEAI was combined with a geophysical risk without weights imposed. The resultant values indicate overall evacuation assistance need.

In 2003, Cutter et al. developed the Social Vulnerability Index (SoVI). Based on the social dimensions of the Hazards of Place model, SoVI is a place based algorithm for quantifying the relative socioeconomic and demographic dimensions of vulnerability. Using an inductive principal component analysis (PCA), 42 socioeconomic variables (derived from US Census and County Data Books) were reduced to 11 statistically independent factors that accounted for about 76 percent of the variance at the county level for the entire United States. These components were combined using a simple additive model to compute an aggregate summary score (i.e. the SoVI score) (Cutter et al. 2003). Again, no weights were assigned during aggregation, though a cardinality was
applied to each component to reflect its tendency to increase or decrease vulnerability. Additionally, since aggregate values were not averaged, county vulnerability was not marginalized, as each factor of vulnerability was used equally to arrive at an aggregate score (Adger et al. 2004). Those factors that contribute to the overall score often are different for each county, underscoring the interactive nature of social vulnerability; some components increase vulnerability while others reduce or moderate the SoVI score. SoVI attempts to uncover places having an uneven capacity for preparedness and response; places where resources might be used most effectively to reduce the pre-existing vulnerability (Cutter et al. 2003). Unlike previous indices, SoVI is not coupled with a biophysical counterpart. This is concurrent with the accepted theoretical understanding that social vulnerability is independent of hazard type. Zones of differential exposure to any or all hazards can be applied to SoVI to arrive at place vulnerability (Burton and Cutter 2008; Borden et al. 2007; Wood et al. 2009).

Cutter et al.’s contribution is particularly important for two reasons. First, the variables used to characterize social vulnerability were culled from widely available data sources, providing simple replication. Consequently, the SoVI method is the most widely cited technique in the social metric literature (Schmidtlein 2008). Though Cutter et al.’s SoVI (2003) was originally constructed for all counties in the US, the developed methods are both spatially and temporally scalable throughout the US and other developed countries (Borden et al. 2007; Boruff and Cutter 2007; Cutter and Finch 2008; Cutter and Emrich 2006; Schmidtlein 2008; Schmidtlein et al. 2008). Second, “…the results of the US SoVI were consistent with theoretical understandings and expert opinion of the distribution of social vulnerability in the US” (Schmidtlein 2008: 36). The SoVI method
is not without limitation, however. As Schmidtlein (2008) contends, SoVI’s heavy reliance on expert judgment throughout the PCA process may inhibit its application and understanding among non-experts. Some additional criticism stems from the use of inductive approaches, citing a lack of theoretical rigor compared to the deductive approach (Brooks et al. 2005). It seems, however, that this critique ignores the fact that use of PCA to construct components of social vulnerability occurs only after a theoretically-based selection of variables derived from the contextual literature.

From this often-cited work comes many variations in the development of social vulnerability metrics. Kleinosky et al. (2006) employ similar methods to those published by Cutter et al. (2003); the main deviation being the assignment of weights for aggregation based on a Pareto ranking of the factors. Cox et al. (2007) apply a weighting schema based on the percent variance explained by each factor. Other metrics suggest the use of weights based on *a priori* comprehension of differential hazards risks and the potential for damage (Lowry et al. 1995; Montz and Evans 2001).

A common critique of comparative statistical studies, particularly those focused on national level analyses, is that it fails to capture the spatial and social differentiation of vulnerability and local conditions that mediate the capacity to adapt (Cutter et al. 2003). Such macro scale analyses though easily sacrifice detail for common patterns and potentially fail to detect the heterogeneity of vulnerability at a subscale level (Adger et al. 2004; Barnett et al. 2008; Eyles and Furgal 2002). In contrast, sub-national level indices capture sufficient detail to be employed as intervention tools to ameliorate adverse vulnerability (Cutter et al. 2003). The drawback of micro level studies, however, is that a
high level of local detail limits the chance for generalizations and regional scalability (Eyles and Furgal 2002).

A final critique of vulnerability metrics as a whole is in regards to the lack of a consistent outcome measure by which the indices can be calibrated and validated (Schmidtlein 2008). The discovery of such an independent measure has so far been thwarted by the natural multidimensionality by which vulnerability is represented. As such, vulnerability metrics are not absolute predictors. Instead, they offer a static view of sensitive populations that have an increased potential for loss.

While vulnerability is place-sensitive, geographically scalable metrics have increased efficacy in coordinating emergency management at different scales. (Adger et al. 2004; Barnett et al. 2008; Cutter 1996; Cutter et al. 2000, 2003; Morrow 1999, 2008). Despite the utility of social vulnerability research, however, few attempts have been made to incorporate comparative vulnerability metrics into disaster planning (Cutter 1996). Techniques including the construction of composite indicators, or indices, provide methods for quantifying, mapping, and comparing the human constituent of vulnerability using widely available demographic data (i.e. race, class, socioeconomic status, gender, age), from the US Census (Morrow 1999). Including such methods into emergency management planning would provide a much needed static view of vulnerabilities which could then be utilized by planners, policy makers, and other stakeholders involved in the disaster management cycle.
2.3 Public Health and Disasters

This thesis draws from two main bodies of literature to outline public health: disasters literature, and general epidemiology literature. The disasters literature often draws empirical conclusions based on post-disaster surveillance. The implications and findings of disaster literature are usually fashioned for an emergency management audience focused on preparedness, response, and mitigation. Though the observations are sometimes context-specific, the findings can be applied and tested for many subsequent events. In contrast, the purely epidemiologic/medical literature introduces comprehensive theory in disease control, disabilities management, and quality of life studies. These studies, as with the social vulnerability literature, mostly view public health phenomena independent from an event context. Consequently, the literature is usually written for the public health community at large. It is important to note, however, that many of the heuristics used in health related disasters research are derived from this literature. Though the agreement between these two bodies of literature is unmistakable, their overlap is not absolute. Likewise, neither body completely represents medical vulnerability as it is defined in this research. Therefore, this thesis draws from both fields to derive a broad set of indicators for medical vulnerability used in the subsequent analysis.

2.3.1 General Epidemiology

Emerging research over the past two decades from epidemiology and public health has investigated the link between health and social vulnerability. In her comprehensive study *At Risk in America: Health Care Needs of Vulnerable Populations*
in the United States, Aday (2001) draws ties from the social science literature to identify the social characteristics of populations at highest health risk based on access to medical resources. Table 2.1 represents the social characteristics that correlate with health care access: social status, social capital, and human capital; showing unmistakable parity with those social indicators introduced by the social vulnerability literature in the previous section.

Similarly, numerous other researchers have made comparable ties. Freeman and Corey’s (1993) research scrutinized the relationship between insurance status and access to health services among those living in poverty. Here, the results indicated a causal relationship between poverty and limited access to health services. Again using health insurance coverage as a proxy for healthcare access, Shi (2001) examined the convergence of race and income with health insurance in the US. The results of the study implied a disproportionate lack of access in both the poor and minority populations throughout the country. In what Roos et al. (1995) refer to as the “social determinants of health” the researchers find an inherent lack of access to public health resources through a disproportionate deficiency of human capital. Cohen et al (2003) summarize similar findings in their analysis of community disadvantage and high disease-related mortality in Chicago.
Both Aday (1994, 2001) and Roos et al (1995), however, make a clear distinction between health risk and health need. While the social indicators of health risk help to identify sensitive populations, the indicators of health need identify individuals and communities with inherent medical vulnerability independent of outside stress. Using

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this definition, health need falls into three distinct categories: physical, mental, and social (Aday 1994, 2001). Examples of populations with physical health needs include the chronically ill and disabled, high risk mothers and infants, and those with immunodeficiency. Psychological health needs are exhibited by the mentally ill, and alcohol/drug addicts. Finally, populations exhibiting social health needs include abusive families, and the homeless (Aday 1994, 2001).

Applying these definitions Aday (1994) presents a simple framework for studying vulnerable populations (Figure 2.3). Noting the feedback between communities and individuals, the model derives wellbeing at the confluence of resources, vulnerability, and baseline health needs. As the model indicates, vulnerability and health needs are first a factor of the individual, but when these factors are aggregated, community phenomena are uncovered. At both scales, however, the model dictates a direct mutual relationship between health needs and vulnerability. Another contribution of Aday’s framework is the designated policy perspective for each component of wellbeing; resources are administrated by social and economic policy, vulnerability is mitigated through community oriented health policy, and health needs are accounted for by medical care and public health policy. This addition acknowledges appropriate points of intervention by responsible policymakers in the outcome of the framework. The simplicity and well-defined relationships between nodes of the model preserve its utility for empirical application.

Roos et al.’s (1995) conceptual framework, A Population Based Health Information System, takes a slightly different approach, focusing on the community background factors and individual health indicators that dictate the demands on the
healthcare system at a given time (Figure 2.4). Community derived socioeconomic factors interact with individual responses and wellbeing, yielding demand on the public health system. Additionally, the model depicts the subsequent feedback of the healthcare system on future wellbeing. While this model offers a much needed framework for predicting medical needs at a given time in a specific environment, the relationships between nodes are not well defined, and the inclusions of many variables make the overall system too complex. These shortcomings render the framework difficult to apply empirically.
Figure 2.2: Framework for studying vulnerable populations (Aday 1994: 488)
Figure 2.3: The population based health information system (Roos et al. 1995: DS17)
Similar complex frameworks have evolved from the medical surge literature. Hick et al. (2004) describe medical surge capacity as the ability to manage a sudden unexpected increase in patient volume that would otherwise severely challenge the health care system. While medical surge typically assumes that an event has occurred (such as an epidemic or natural hazard), vulnerable populations are generally anticipated using the theoretical heuristics described by Aday (1994, 2001) and Roos et al (1995). Hoare and Russel (2009) and the US Department of Health and Human Services (2007) propose similar frameworks in which medical burden is projected based on the incidence of the medically fragile in combination with communities’ social disparities.

To date, the quantification of community health remains a major challenge, due in part to the insufficiency and confidentiality of health incidence data (Aday 2001; Shaw-Taylor 1999). As a result, few quantitative health studies occur at the sub-national level focusing on community medical needs. Alternatively, comparative analyses often rely on social and environmental proxies, used in combination with concrete mortality statistics to derive health status.

The Social Health Index, constructed in 1987 by the Fordham institute provides a major example of using social indicators to measure community wellbeing (Shaw-Taylor 1999). The index is based on sixteen indicators including: infant mortality, child poverty, child abuse, teenage suicide, teenage drug abuse, high school dropouts, unemployment, wages, health insurance coverage, poverty among the elderly, out-of-pocket health costs among the elderly, homicides, alcohol-related traffic fatalities, food stamp coverage, affordable housing, and income inequality (Miringoff and Miringoff 1999). Overall wellbeing is captured as a composite of the input indicators. It is important to note,
however, that this index was constructed for use as an alternative to Gross Domestic Product to measure community performance and disadvantage, rather than a medically driven health index, and is generally regarded as a success (Miringoff and Miringoff 1999; Shaw-Taylor 1999).

As this research indicates, the definition, and subsequently, the indicators of health status can vary greatly based on a study’s intentions for end use. To illustrate this point, Bowling’s *Measuring Health* (1991) outlines 50 different measurement scales for assessing health quality of life. While these indices all strive to measure some facet of public health, the functional definition of what constitutes good health and poor health can be highly divergent. Some studies measure observed human functionality, while others gather subject responses in the form of a survey. Some studies focus on the physical dimensions of health while others derive wellbeing from mental and emotional status. In contrast to the Social Health Index, the scales described by Bowling typically procure data clinically at the individual case level.

While these measures combat the shortcomings afforded by the general lack of empirical health prevalence data, Shaw-Taylor (1999) criticizes the measurement of individuals’ health. The reason for such criticism is presented as a data collection versus data analysis predicament, citing Dean’s (1993) argument that, “Data collection often receives excessive resources while the analyses needed to extract meaningful information from the data are relatively neglected” (9). In this view, emphasis is shifted from primary data collection among individuals to analysis of more manageable community population indicators.
While the predicaments in measuring community health are certainly well documented, a few agencies have prevailed in compiling exhaustive community health indicators. Two major contributions include the US Dept. of Health and Human Services’ (HHS) Community Health Status Indicators (CHSI) (Heitgerd et al. 2008; Metzler et al. 2008) and the Centers for Disease Control’s (CDC) Behavioral Risk Factor Surveillance System (BRFSS).

The CHSI project was originally launched by HHS in 2000 with the goals of providing an overview of key health indicators for local communities and encouraging dialogue and action to improve community health (HHS 2010; Metzler et al. 2008). In 2006, the project was re-launched by a new partnership that included the CDC. Focusing mainly on mortality rates (per cause of death) and lifestyle choices, in addition to health perception, CHSI contains over 200 health measures for each of the 3,141 United States counties. As stated throughout the CHSI documentation, it is not only important to understand where certain causes of death (i.e. heart disease, cancer) prevail, but also to note that “…behavioral factors such as tobacco use, diet, physical activity, alcohol and drug use…substantially contribute to these deaths” (HHS 2010). The re-launch of CHSI is marked by a much needed update of the data and the construction of a web application for viewing reports, mapping select indicators, and downloading the most recent dataset (HHS 2010; Metzler et al. 2008).

The BRFSS is a state-based telephone health survey system that collects information on health risk behaviors, chronic disease prevalence, preventive health practices, and health care access primarily related to chronic disease and injury. First established by the CDC in 1984, the BRFSS is a continual process with data being
collected monthly. Today, more than 350,000 adults are interviewed each year, covering all 50 states. Data culled from the BRFSS are used by state and regional health officials to identify emerging health problems, establish and track health objectives, and develop and evaluate public health policies and programs (CDC 2010).

While many studies find agreement in the general characteristics of public health, few express an explicit list of indicators for analysis that capture the multidimensionality of health access and need. Though the frameworks for measuring public health often separate concrete indicators of medical need and health access from societal performance indicators, some community analyses simply tend to substitute them (Miringoff and Miringoff 2000; Shaw-Taylor 1999). Based on the intention of a study and its implied end use, social indicators alone may not adequately measure the intended health phenomenon. Though promising alternatives such as CHSI and BRFSS provide a wealth of data, it is not clear which variables are most applicable for this study. As the context of this thesis is emergency management, it is important to focus on a set of indicators that will dictate disparate access and specific community health needs during disasters. To uncover some contextual indicators that increase a community’s medical needs from emergency managers during hazard events, this research turns to the disasters literature.

2.3.2 Disasters Literature

In a recent editorial in the Journal of Emergency Management, Simmons (2009) discusses what he terms, “The deadly second wave that follows every disaster”(9):

Within a few days following every major natural disaster there comes a relatively silent, second medical tsunami that commonly overwhelms emergency rooms, clinics and temporary medical units. In simplest terms it is the exacerbation of chronic illnesses, the maintenance of care for the chronically ill, and a shortfall in
medications and equipment. This secondary disaster needs to be further addressed by all medical agencies far in advance. (9)

Throughout the disasters literature, public health is most often discussed in a post-impact context. Shoaf and Rottman (2000), for example, assert that the impacts of disasters on public health can be divided into four categories: (1) direct impacts of the health of the population; (2) direct impacts on the health care system; (3) indirect effects on the health of the population; and (4) indirect effects on the health care system.

Direct population impacts include those outcomes that negatively affect individuals. The most obvious direct population impacts following a disaster are casualties (Shoaf and Rottman 2000). Many studies have attempted to quantify hazard mortality as a means of assessing the links between hazard dynamics and the potential for loss. Though a few studies investigate all hazards (Borden and Cutter 2008; Thacker et al. 2008), most explore mortality on a single hazard basis (Ashley and Gilson 2009; Zahran et al. 2008). These studies not only examine where deaths occur, but also the general demographics of those affected. Similarly, many studies investigate non-lethal impacts of disasters on populations. These range from subsequent communicable diseases and illnesses in the short term, to lasting chronic illnesses and the long term effects on mental health (Shoaf and Rottman 2000).

Few and Matthies (2006) present a spectrum of direct health impacts that follow flood disasters, ranging from water-borne diarrheal diseases, skin and eye infection, and respiratory infection that result from contact with flood waters to the long term mental effects of displacement, loss, and stress that can lead to tangential health impacts. Similarly, Bourque et al.’s (2006) comprehensive survey of the physical and mental
impacts of hurricanes provides a complete analysis on short and long term health impacts resulting directly from hurricane disasters. Focusing on casualty, disease, and mental health surveillance, their study offers a temporal assessment of major US hurricane evacuations, starting with Hurricanes Elena and Gloria in 1985 through the 2005 hurricane season including Hurricane Katrina. A major finding of their study suggests that pre-existing psychological conditions contribute significantly to post-disaster mental health.

Studies such as these stand apart from general disasters surveillance in that their findings are collected temporally in the appraisal of emergency management and evacuation tactics. Few and Matthies’ report provides a collection of disaster case studies used to pinpoint potential medical intervention strategies based on the specific impact, and when it occurs. With emphasis on preparedness, their study criticizes the tendency for reactive emergency management, especially in areas prone to regular flooding. Likewise, Bourque et al.’s hurricane timeline examines the effect of efficient and timely evacuation on health related disaster impacts. Both studies correlate a reduction in hazard related deaths to improved education and evacuation timeliness. Bourque et al.’s focus on mental health and behavior in disaster victims suggests that the desire to return prematurely to precarious living spaces is causing a shift from direct casualty to indirect death and illness post-event.

In perhaps the most comprehensive resource in the direct impacts of disasters on public health, Noji’s The Public Health Consequences of Disasters (1996) outlines potential health impacts on populations as well as the healthcare system on a per hazard basis. Focusing not only on natural disasters, but also human generated catastrophes,
Noji incorporates event dynamics, outlining the need for medical emergency management at every stage of the disaster cycle (i.e. Interdisaster, Warning, Impact, Emergency, and Rehabilitation Phases) as specific health concerns arise at different phases. Additionally, Noji acknowledges the utility of aggregate disaster surveillance in emergency planning:

Sound epidemiologic knowledge of the morbidity and mortality caused by disasters is essential when determining what supplies, equipment, and personnel are needed to respond effectively in emergency situations. All disasters are unique because each affected region of the world has different social, economic, and baseline health conditions. (19)

This statement is concurrent with Cutter’s Hazards of Place Model (1996), described in the preceding section. Deriving hazard impacts from geographic context, Noji incorporates baseline health condition as a contribution to the severity of disaster impacts.

Other studies focus purely on the psychological impacts of disasters. Norris et al.’s (2002a, 2002b) exhaustive analysis culled 160 explicit samples of disaster victims from literature case studies covering disaster event worldwide from 1981 to 2001. Diverging from the tendency to draw conclusions from a single event, Norris et al. attempt to synthesize the results of twenty years of literature with the purpose of deriving (1) the extent that disasters affect mental health, and (2) the populations within communities at highest risk for adverse outcomes. Drawing connections between social indicators, baseline mental health, and mental illness prevalence following the disaster, the authors concluded that certain indicators, including age, ethnicity, gender, and baseline health provided amenable proxies for mental health issue post disaster (Norris et al. 2002a).
Kessler at al’s (2008) research examined trends in mental illness and suicidality in affected areas following Hurricane Katrina. Using a sample of 815 residents affected by Katrina, interviews were completed at five months and again at one year following the disaster to assess psychological wellbeing. Results of the survey indicated a significant temporal increase in serious mental illness, post traumatic stress disorder, and suicidality resulting from hurricane related stress between the initial baseline survey and the annual evaluation. The increase was especially apparent in areas outside the New Orleans Metro area. Another interesting contribution of this study was the statistical comparison of mental illness prevalence with social risk factors, yielding only a weak relationship. Such a finding, in contrast to the general conclusions of Norris et al. (2002a), indicates that high-risk demographics alone could not foreshadow mental health needs for this event (Kessler et al. 2008).

Direct impacts on the healthcare system describe those outcomes that immediately impede the dissemination of medical services to affected populations. These include both the damages to physical infrastructure and supplies and the shortages of medically trained personnel due to disaster impacts. These issues are often compounded as the need for medical care after a disaster usually exceeds the capability of even the most fully functional healthcare system. According to Clements (2009):

Public health emergencies are multidimensional, dynamic situations that overwhelm existing healthcare and public health infrastructure resulting in adverse community health effects. Large scale, unanticipated events can pose extraordinary challenges. (2)

In some cases, hospitals are so overwhelmed and understaffed that it necessitates the evacuation of pre-event patients, or the discontinuation of emergency service (Ferdinand 2006; Kleinpeter et al. 2006). Local physicians and medical technicians are
often victims of the disaster themselves, reducing their ability to provide care (Simmons 2009).

Indirect population impacts are those outcomes realized after the response phase of emergency management has ended. Most often, these impacts are described in the literature as loss of primary health care, and loss of normal living conditions (Ferdinand 2006; Shoaf and Rottman 2000). Indirect population impacts often occur following the overwhelming direct impacts on the healthcare system. In the disasters literature, indirect population health impacts are vast and well documented, especially following Hurricane Katrina. As disaster evacuees crowed into shelters, it quickly became apparent that a disproportionate amount of medical needs were resulting from pre-existing chronic conditions rather than injuries or illnesses caused by the event directly (Currier et al 2006; Gavagan et al. 2005; Miller and Arquilla 2008; Radhakrishnan and Jacelon 2009). Many patients were without medication and medical services for days or even weeks following the decimation of the healthcare system (Ferdinand 2006; Simmons 2009). Common chronic conditions exacerbated by the disaster included diabetes (Jhung et al. 2007; Miller and Arquilla 2008), renal failure (Kleinpeter et al. 2006; Miller and Arquilla 2008), cancer (Gavagan et al. 2005), heart disease and hypertension (Crook et al. 2010; Jhung et al. 2007), asthma (Krol 2007), and HIV/AIDS (Clark et al. 2006). Unprepared for the overwhelming demand for medication, medical treatment, and trained personnel, the first aid clinics and medical emergency support shelters were unable to provide care for many disaster evacuees. As a result, patient health was severely compromised, creating adverse, and in some cases, fatal outcomes (Miller and Arquilla 2008; Radhakrishnan and Jacelon 2009). Additionally, the indirect system impacts, described
by Shoaf and Rottman (2000), Cheu (1995), and Cole (1995) as damage to intermediate infrastructure (i.e. roads, water/sewer, communication) further delayed the recovery of healthcare system functionality.

In addition to chronic illnesses, several studies have focused on the special needs of disabled populations following the destruction of the healthcare system during a disaster. The literature forms a common objection to the blanket term “disabled” (Kailes 2005; Parr 1987). As Parr (1987) contends, disablement takes many forms, including physical disability or immobility, sensory disability including deafness or blindness, mental illness or developmental disability, and finally, the “multi-disabled” (148). As medical needs change from one disability another, it is important that disaster plans differentiate disabilities by the level and type of assistance required (Parr 1987). Deal et al. (2006) discuss a lack of skilled personnel following Hurricane Katrina to provide care and regulation to physically immobile and mentally retarded evacuees. Disabilities such as these present particular challenges due to the requirement of round the clock supervision to complete ordinary tasks such as eating and using the bathroom (Deal et al. 2006). Though people with certain disabilities, such as the sensory disabled, may maintain their independence for these simple responsibilities, they may require special assistance in evacuation and establishing a routine in a temporary shelter environment (Parr 1987). Unfortunately, disability is not well represented in the literature, appearing in only a few post-disaster discussions (Deal et al. 2006; Kailles 2005; Wisner 2002).

Edgington (2009) introduces another underrepresented vulnerable group: the homeless. Though not directly displaced by the disaster event, the loss of shelters, soup kitchens, and clinics deprives the homeless of what little resources they have. This loss,
together with a staggering estimate of mental illness prevalence (Edgington cites 1 in 3), substance abuse, and a wide array physical ailments, place an already medically disadvantaged group in the care of disaster evacuation services which may be hard to navigate and understand (Edgington 2009).

Another indirect result of disasters is the tangential effect of mental distress (a direct impact) on human behavior. Emerging research in disaster impacts and social vulnerability has focused on the prevalence of domestic violence following disasters (Enarson 1999; Jenkins and Phillips 2008; Wilson et al. 1998). The literature generally agrees that the post-disaster landscape creates a textbook environment for increased domestic violence. Specifically, the confluence of economic hardship, mental and emotional distress, and a major interruption in daily routine exacerbates the deterioration of family health (Enarson 1999; Jenkins and Phillips 2008). Examining several case studies including the Missouri Floods in 1993 and Hurricane Andrew in 1995, Jenkins and Phillips (2008) found steep increases in the volume of domestic violence victims using shelters and help lines. As with the other disaster victims exhibiting health needs, those suffering domestic violence also experience the hardships associated with a compromised healthcare system (Wilson et al. 1998). With limited communication, transportation and emergency services, victims of domestic violence have a much reduced support system following a disaster (Enarson 1999). Like disability, domestic violence is often glazed over in disaster surveillance literature (Wilson et al. 1998).

The documented inabilities of emergency medicine in the treatment of health related issues following a disaster underscore the need for updated medical emergency preparedness techniques. Many studies suggest a pre-hazard community health
surveillance system to monitor wellness and disability prevalence in the anticipation of specific medical needs in disaster-prone geographies (Bailey and DeShazo 2008; Ferdinand 2006; Mokdad et al. 2005; Noji 1996; Radhakrishnan and Jacelon 2009; Simmons 2009). Aside from health surveillance, such a tool could pinpoint areas of low health for pre-disaster intervention, including community education and individual preparation in addition to allocating monetary support from government and non-profit organizations. Specifically, some case studies discuss issues of patient unawareness regarding their medical needs, creating problems during evacuation and clinical prescription. By preparing individuals for a subsequent collapse in healthcare, simple issues, such as where to go during a disaster, and what information is needed to receive accurate emergency care would be alleviated.

Despite the multi-efficacy of a medical vulnerability measure discussed throughout the literature, a viable spatial quantitative metric has not yet emerged. Tangential research tools exist, such as those credited in Cromley and McLafferty’s GIS and Public Health (2002) which incorporates comprehensive geographic information science (GISci) and cartographic techniques for community wellness mapping and comparison, or Enders and Brandt’s (2007) incorporation of GISci technology with medical infrastructure for disabled populations in a spatial network analysis. However, these examples measure only single phenomenon rather than a holistic snapshot of community health.

Allen and Katz’ (2009) recent narrative suggests the use of demographic techniques for public health emergency preparedness (PHEP):

Though demographic techniques and data can assist in describing and evaluating the health characteristics of a given population, demography has not been used by
practitioners in the field of PHEP, despite the wealth of relevant information and expertise. In order to make effective preparedness plans, key methods in demography need to be systematically integrated into the discipline of PHEP. (2)

The methods described demonstrate distinct parity with metrics reviewed in section 2.2.2 (social vulnerability metrics), using widely available demographic data in statistical analyses to uncover the spatial trend of vulnerable populations. Applying these techniques to uncover populations that are “medically dependent” (8), Allen and Katz cite particular utility for demographic tools in medical emergency management planning and mitigation that “….target groups for additional preparedness efforts or different forms of communication” (8). To build a viable metric, however, requires a reflexive relationship between the disciplines of public health planning and demography. The scarcity of publicly available health data often prevents such ventures from being undertaken. Data sharing from public health entities needs to be systematic rather than “coincidental” (Allen and Katz 2009: 11). Likewise, results from demographic analysis can easily be skewed or misinterpreted without appropriate expertise. Moving forward, the authors conclude that the health of a population relies on sufficient and reliable information about said population. The collaboration of demographic techniques with public health information seeks to uncover the otherwise hidden patterns within a population.

2.4 Summary

Vulnerability is conceptualized in many ways throughout the literature, crossing disciplines, and evolving as new techniques and methods are applied. It is evident in the literature that social vulnerability and public health are theoretically linked. However,
many studies derive community wellness from both high-risk social groups (i.e. the socioeconomically disadvantaged) and baseline medical needs and healthcare access. Following recent disasters, the importance of these baseline needs was realized. Informal emergency medical shelters were not prepared to treat chronic preexisting conditions, and did not have enough skilled personnel to care for the physically and mentally disabled. As disasters continue to occur, the shortcomings of an unprepared emergency health system will be persistently amplified unless intervention occurs to mitigate disasters impacts. To improve public health emergency preparedness for future disasters continued research into baseline health metrics is necessary. Though many studies have cited the efficacy of a quantitative community health surveillance system, few suggestions have been offered as to a framework or method on which the metric should be based. Additionally, the relationship between indicators of social vulnerability and medical need are somewhat confounded in the literature. One method combines the inductive demographic techniques, such as those used in Cutter et al.’s (2003) Social Vulnerability Index, with public health information to create a place-based index of medical need and healthcare access. Using these methods, this thesis not only provides further insight into the indicators of community medical vulnerability, but also examines the relationship with social vulnerability, bringing the discipline closer to understanding emergency medical needs during disasters.
Chapter 3: Research Design and Methods

3.1 Study Area

3.1.1 Geographic Justification

Florida serves as an excellent study venue for this research for many reasons. First, and perhaps most important, Florida is exposed to many hazards due to its unique geography. Historically, Florida has endured 62 Major Presidential Disaster Declarations and 12 Emergency Declarations since 1953 (PERI 2010). In terms of event frequency, the most common hazards are wind, severe storm/thunderstorm, and hurricane/tropical storm. Of these events, the most costly hazard types, by far, are hurricanes and tropical storms, exceeding 81.4 billion dollars (standardized as 2008 dollars) (HVRI 2010). Concurrently, hurricanes and tropical storms also account for the greatest number of hazard related injuries in Florida with 2,928 since 1960. Fatalities, on the other hand, are primarily caused by lightning events with 441. Table 3.1 below summarizes Florida’s hazards profile from 1960 to 2008 using data from the Hazards and Vulnerability Research Institute’s (HVRI) Spatial Hazard Events and Losses Database for the United States (SHELDUS). Since 1960, the State’s aggregate losses exceed 92.5 billion dollars in property and crop damage in addition to 1,194 reported deaths and 7,470 injuries. Examining Florida’s most costly disasters, each was triggered by either a hurricane or tropical storm occurring within the last 18 years. Table 3.2 depicts the event data,
specific disaster, and total monetary damages (in 2008 dollars) for Florida’s ten costliest disasters (HVRI 2010).

Table 3.1: Florida Hazard Profile 1960-2008 (HVRI 2010).

<table>
<thead>
<tr>
<th>Hazard Type</th>
<th>Events*</th>
<th>Monetary Losses (2008 dollars)</th>
<th>Fatalities</th>
<th>Injuries</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coastal</td>
<td>317</td>
<td>$114,585,168</td>
<td>257</td>
<td>274</td>
</tr>
<tr>
<td>Drought</td>
<td>6</td>
<td>$120,964,992</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Flooding</td>
<td>630</td>
<td>$3,098,864,156</td>
<td>18</td>
<td>5</td>
</tr>
<tr>
<td>Fog</td>
<td>14</td>
<td>$2,201,260</td>
<td>6</td>
<td>47</td>
</tr>
<tr>
<td>Hail</td>
<td>319</td>
<td>$104,754,116</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>Heat</td>
<td>9</td>
<td>$0</td>
<td>9</td>
<td>2</td>
</tr>
<tr>
<td>Hurricane/Tropical Storm</td>
<td>952</td>
<td>$81,422,024,691</td>
<td>140</td>
<td>2,928</td>
</tr>
<tr>
<td>Lightning</td>
<td>791</td>
<td>$95,218,509</td>
<td>441</td>
<td>857</td>
</tr>
<tr>
<td>Severe Storm/Thunder Storm</td>
<td>1,340</td>
<td>$240,447,496</td>
<td>39</td>
<td>122</td>
</tr>
<tr>
<td>Tornado</td>
<td>853</td>
<td>$1,399,072,668</td>
<td>166</td>
<td>2,747</td>
</tr>
<tr>
<td>Wildfire</td>
<td>111</td>
<td>$784,642,166</td>
<td>0</td>
<td>255</td>
</tr>
<tr>
<td>Wind</td>
<td>1,406</td>
<td>$4,129,319,897</td>
<td>73</td>
<td>218</td>
</tr>
<tr>
<td>Winter Weather</td>
<td>471</td>
<td>$1,016,298,130</td>
<td>35</td>
<td>1</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>7,219</td>
<td><strong>$92,528,393,249</strong></td>
<td>1,194</td>
<td>7,470</td>
</tr>
</tbody>
</table>

* Events in SHELDUS do not represent discrete hazard events, but the number of events in a county. For example, if 1 tornado affected 6 counties, it is counted as 6 distinct county tornado events in the database.

Table 3.2: Florida’s ten costliest disasters standardized in 2008 dollars (HVRI 2010)

<table>
<thead>
<tr>
<th>Disaster</th>
<th>Date</th>
<th>Monetary Losses</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Hurricane Andrew</td>
<td>8/24/1992</td>
<td>$39.4 billion</td>
</tr>
<tr>
<td>2 Hurricane Wilma</td>
<td>10/24/2005</td>
<td>$11.3 billion</td>
</tr>
<tr>
<td>3 Hurricane Charley and Tropical Storm Bonnie</td>
<td>8/13/2004</td>
<td>$9.4 billion</td>
</tr>
<tr>
<td>4 Hurricane Frances</td>
<td>9/4/2004</td>
<td>$6.5 billion</td>
</tr>
<tr>
<td>5 Hurricane Ivan</td>
<td>9/13/2004</td>
<td>$4.6 billion</td>
</tr>
<tr>
<td>6 Hurricane Opal</td>
<td>10/3/1995</td>
<td>$4.4 billion</td>
</tr>
<tr>
<td>7 Hurricane Jeanne</td>
<td>9/25/2004</td>
<td>$2.0 billion</td>
</tr>
<tr>
<td>8 Hurricane Dennis</td>
<td>7/9/2005</td>
<td>$1.7 billion</td>
</tr>
<tr>
<td>9 Hurricane Irene</td>
<td>10/14/1999</td>
<td>$1.5 billion</td>
</tr>
<tr>
<td>10 Tropical Storm Helene and other Severe Storms and Flooding</td>
<td>10/3/2000</td>
<td>$1.2 billion</td>
</tr>
</tbody>
</table>
In addition to Florida’s hazardous physical setting, the state has an increasingly large population with a disproportionately high percentage of people living along the coast. In 2008, the US Census Bureau approximated Florida’s coastal population at 17.9 million, representing nearly 98 percent of the state’s total population (US Census Bureau 2009a). The draws of coastal real estate for retirees and increasing economic opportunities have resulted in steady migration to the Florida coast from other regions of the United States. Remarkably, the total population in Florida is estimated to have grown by 9.2 million between the years of 1980 and 2010. This change represents a 98 percent increase in total population for the 30-year period; more than any other state (US Census Bureau 2009b, 2010). The confluence of hazard frequency and dense population creates a dangerous scenario in which many people have increased risk and vulnerability to hazard impacts. This exposed population provides an interesting location to examine the relationship between social vulnerability and public health.

3.1.2 Background

Florida is the fourth most populous state in the nation with an estimated 19.2 million people, located at the southeast tip of the Country, bordering Georgia and Alabama (US Census Bureau 2010). The State is a peninsula with its eastern shore facing the Atlantic Ocean and the western shore bordering the Gulf of Mexico.

Florida covers 54,252 square miles of land with approximately 1,197 miles of shoreline (American Safety Council for Florida Residents and Visitors 2008). The state is comprised of 67 counties with its capital in Tallahassee. Figure 3.1 provides a county map of the state. Economically, Florida’s State GDP is driven primarily by finance,
insurance and real estate, accounting for about 24 percent of the total state GDP in 2008 (BEA 2008). A major demographic attribute of Florida is its age distribution. The last decennial census revealed that Florida was home to the largest proportion of people aged 65 and older, comprising 17.6 percent of the total state population, making Florida the ‘oldest’ state in the nation (Hetzel and Smith, 2001).

Figure 3.1: Florida counties
3.2 Data and Methods

Several datasets were required to address the thesis research questions. To appropriately examine the relationship between social vulnerability and medical vulnerability, two separate metrics had to be constructed. All data were collected for the most recent calendar year in which the variables were available. Due to medical data confidentiality and availability constraints, county level aggregation was used for indicator collection and analysis.

3.2.1 Social Vulnerability Indicators

The first component of the analysis requires an examination of social vulnerability. To create a robust measurement of social vulnerability that captures the multi-dimensionality of the construct, this thesis drew upon the quantitative methodology developed for Cutter et al.’s (2003) Social Vulnerability Index (SoVI). This index was chosen based on its scalability, allowing for the comparison of social vulnerability at several levels of sub-state geography in the United States. Since this research takes place at the county level\(^1\), SoVI provides an appropriate methodology for this application.

Though SoVI 2000 data are publicly available for the entire US at the county level from the Hazards and Vulnerability Research Institute (HVRI), this source was not used for this analysis for several reasons. First, the HVRI dataset is based on analysis completed for the entire country, with Florida available as a subset. As a result, the SoVI scores are relative to the entire US. Since this is a place-based case study interested in

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\(^1\) County level analysis was chosen largely as a result of limited medical data availability at finer geographic resolutions (discussed in more detail in following sections). To provide spatial parity for the subsequent comparative analysis, SoVI and MedVI were constructed for Florida Counties.
the explicit spatiality of the drivers of vulnerability in Florida counties, the methodology was replicated to reflect the unique vulnerability of the study area. Second, the original conceptualization of the SoVI used 42 variables to represent social vulnerability. Following the approaches taken by Borden et al. (2007), Cutter and Finch (2008), and Schmidtlein (2008), variables pertaining to the built environment aspects of vulnerability were removed from this analysis. As a result, the index constructed for Florida focuses expressly on the societal contributions to vulnerability. This reduced the initial set of input variables from 42 to 32, leaving only the variables that describe the human aspects of community vulnerability. Finally, as this thesis intends to examine the statistical overlap in measures of social vulnerability and medical vulnerability, it was necessary to exclude any variables from SoVI that could be used as a clear indicator of medical need or health access. In this way, the statistical comparisons will not reflect any blatant similarities that could be instituted by using an identical variable in each measure. This exclusion reduced the previous set of 32 variables to a final set of 29. Table 3.3 reflects the final target variable list.

Table 3.3: SoVI target variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MEDAGE</td>
<td>Median Age</td>
</tr>
<tr>
<td>QBLACK</td>
<td>Percent African American</td>
</tr>
<tr>
<td>QINDIAN</td>
<td>Percent Native American</td>
</tr>
<tr>
<td>QASIAN</td>
<td>Percent Asian and Hawaiian Islanders</td>
</tr>
<tr>
<td>QSPANISH</td>
<td>Percent Hispanic</td>
</tr>
<tr>
<td>QKIDS</td>
<td>Percent of population under 5 yrs of age</td>
</tr>
<tr>
<td>QPOP65O</td>
<td>Percent of population 65 and over</td>
</tr>
<tr>
<td>PPUNIT</td>
<td>Average number of people per household</td>
</tr>
<tr>
<td>QRENTER</td>
<td>Percent renter occupied housing units</td>
</tr>
<tr>
<td>QFEMALE</td>
<td>Percent female population</td>
</tr>
</tbody>
</table>
Raw data were culled from the 2000 US Decennial Census using the US Census Bureau’s Census Data Engine software. Data were drawn from Census Summary File 1 (i.e. complete data from census short form) where available, however, any economic or employment data required the use of Summary File 3 (i.e. estimate from census long form). The raw data were imported into the Statistical Package for Social Sciences (SPSS) version 17 for processing and analysis. Each variable was normalized using population, or in the case of housing density, area was used for each enumeration unit. The normalization reflects the variables as rates (i.e. percentage, per capita, or density) rather than raw counts.

Following the suggestion of Booysen (2002) each of the variables was evaluated based on its theoretical effect on the overall construct being modeled (social vulnerability) for the assignment of cardinality pre-adjustment. As a result, the sign of
each input variable is representative of its tendency to increase or decrease community vulnerability. Five variables warranted a negative (-) sign adjustment; percent rich, mean house value, mean rent, per capita income, and percent employment; as these variables are theoretically understood to decrease vulnerability. This pre-adjustment is sometimes known to aid in the subsequent synthesis of principal components by preventing conflicting signs on component loadings (Booysen 2002). In the subsequent sections, variables that have inverted cardinality pre-adjustment are indicated with the prefix $i$.

Descriptive statistics including minimum, maximum, mean, and standard deviation were performed for each variable as a means of examining the distribution of the data, and inspecting for errors. These descriptives are listed in Appendix A. As a final preprocessing step, the variables were converted to z-scores. The z-score provides a standardized value so that the data are distributed on a relative scale with a mean of 0 and a standard deviation of 1. Since the nature of the variables is delineated in a number of statistical units with diverging ranges or distributions, variables are standardized to avoid problems inherent when mixing measurement units, and to prevent having extreme values skew a statistical analysis (Nardo et al 2008).

To determine which variables contribute most to social vulnerability in Florida, a principal component analysis (PCA) was used. PCA is a factor analytic approach that reduces an initial collection of variables into a smaller set of multidimensional components, yielding the indicators of social vulnerability that contribute the most explained variance overall (Shlens 2009). Each of the components represents a linear combination of the intercorrelated variables (Nardo et al. 2008). Since the components extracted by PCA are orthogonal in nature, multicollinearity is not exhibited as each
component represents an exclusive segment of the total variance. A Varimax rotation was applied to the variables prior to the synthesis of the components. In PCA, rotation is often applied to simplify the interpretation of the principal components. Specifically, Varimax is an orthogonal rotation that, when applied, results in relatively few variables exhibiting large loadings and many variables having small, negligible loadings. Additionally, following the rotation, each variable tends to be significantly associated with only one principal component (Abdi 2003). Formally, Varimax maximizes the sums of the squared variances, allowing the majority of the total variance to be captured by the first few components (Abdi 2003; Kaiser 1958).

As a default, the total number of components constructed by PCA is equal to the number of input variables. However, not all of these components explain a significant portion of the variance. As a result, this research applied the Kaiser Criterion for the formal extraction of factors. According to Kaiser’s (1960) rule, an appropriate threshold for component extraction includes those components having an eigenvalue greater than 1.00. Such a limit dictates which components significantly contribute most to the overall variance (Jolliffe 2002; Kaiser 1960). Upon the completion of the PCA, all components not meeting the Kaiser Criterion were eliminated from further analysis. The final order of the extracted components indicates the amount of variance explained by each, with the first component contributing the most explained variance, and the last component contributing the least explained variance, comparatively.

Next, the individual component loadings were examined for the purposes of naming the components and assigning cardinality. Component loadings represent an individual variable’s correlation with the principal component. The greater the loading
(positive or negative), the more strongly related the variable is to the overall component. Focusing on the strongest statistical relationships (i.e. component loadings greater than 0.500 and less than -0.500) trends were identified and subsequently used to define each component. After the nature of each component was determined, cardinality was applied to reflect the tendency of the component to increase or decrease social vulnerability. For example, if the component embodied wealth, and the component loadings were positive on the dominant variables positive, a negative cardinality is applied to indicate wealth’s tendency to decrease overall community vulnerability. Standardized component scores were produced in SPSS for each component in each county. The component scores were then mapped using ArcGIS to verify the assumptions made in the assignment of cardinality. Following this verification, as a final step, the individual component scores were summed to produce the composite SoVI score. Data were exported to ArcMap for mapping and descriptive visual analysis. High positive values indicate counties with elevated social vulnerability, while high negative values indicate low social vulnerability. It is important to mention that these aggregate scores represent a relative measure should not be interpreted on an absolute scale. The aggregate SoVI scores can ordinal information, however. For example, you can deduce from the SoVI score that Place A, which has a SoVI score of 10 is more vulnerable that Place B, which has a SoVI score of 1. You cannot deduce, however, that Place A is 10 times more vulnerable than Place B. To graphically represent the relative nature of the metric, SoVI scores for Florida counties were mapped using 5 divergent classes based on standard deviations from -1.50 standard deviations to +1.50 standard deviations from the mean. This classification scheme is also useful in depicting SoVI’s outliers at the tails of the distribution. Areas
with relatively disproportionate SoVI scores are of particular importance in vulnerability analysis, as they indicate the areas where disaster intervention may be needed most.

### 3.2.2 Medical Vulnerability Data

The comparison of social vulnerability to community medical needs and healthcare access required the construction of a separate metric. An exhaustive review of the epidemiology and disasters literature did not produce the metric needed to quantify the necessary phenomena. Consequently, inductive methods were borrowed from Cutter et al.’s (2003) SoVI and applied using an array of public health data. A target list of medical need and public health access indicators was compiled using theoretical guidelines found in the literature in conjunction with expert opinion culled from research contacts made with the Florida Department of Health (FLDOH). Using the heuristics developed primarily by Aday (1994, 2001) three general categories of medical vulnerability were derived for data collection: physical medical needs, psychological medical needs, and healthcare access.

Persons with physical medical needs describe members of the population that require support from the medical community to sustain life and well-being in treating bodily illnesses and disabilities. This includes people with chronic diseases such as cancer, hypertension, asthma, or diabetes in addition to those with communicable diseases such as HIV/AIDS or tuberculosis. Illnesses such as these can require medication, hospitalization, and in some cases, special medical equipment such as supplementary oxygen or dialysis machines as part of the condition’s treatment and therapy. Beside illness, physical disabilities often limit a person’s ability to carry out typical daily
activities. This may include limitations to mobility, or sensory limitations that require auxiliary medical equipment, or specialized medical supervision. While specific physical medical needs may vary in type and severity, the indicators chosen for this thesis signify an individual’s inherent reliance on medical care. In the collection of indicators, lifestyle proxy variables such as obesity and smoking prevalence were included, as they are well documented contributors to chronic physical illness (HHS 2010; Ulbricht 2009).

Similarly, people with psychological medical needs specify populations living with psychosomatic disorders or mental limitations that often require medical consideration, including medication, supervision, therapy, and in acute cases, institutionalization. Psychological conditions include not only depression and mental illness, but also drug and alcohol addiction, and mental retardation.

Finally, healthcare access describes an individual or community’s ability to receive medical services. Indicators of healthcare access are not limited to the measurement of medical facilities and personnel within reachable means, but also include a measurement in the capacity to afford health care. As such, proxies for healthcare access include in health insurance status, and homelessness in addition to the number of accessible hospital beds, emergency services, and clinics.

Limited by data availability and confidentiality constraints, variables were collected using several discrete resources. A majority of the data were culled directly from the Florida Department of Health’s Community Health Assessment Resource Tool Set (CHARTS) and County Vulnerable Populations Profiles. Other data sources included The US Dept. of Health and Human Services’ (HHS) Community Health Status Indicators, the Florida Agency for Healthcare Administration, and the US Census.
Florida CHARTS is a statewide online public health data warehouse, combining data collected primarily by bureaus across FLDOH, in addition to data collected using the Centers for Disease Control’s (CDC) Behavioral Risk Factors Surveillance Survey (BRFSS). The Florida BRFSS is a statewide telephone survey conducted by FLDOH through funding from CDC. The survey is designed to collect data on individual risk behaviors and preventive health practices related to the leading causes of morbidity and mortality for adults in the United States. Information from the survey is used for health planning, program evaluation, and monitoring health objectives within FLDOH (FLDOH 2010a). Data downloaded from CHARTS represented a broad spectrum or persons with physical and psychological health needs, populations at high risk of physical health problems, and healthcare access indicators. A summary of the data collected from CHARTS, including the variable name, description, indicator type, and year available is given in table 3.4 below. In the case of BRFSS, variables are described using the language presented in the survey.

Table 3.4: FLDOH CHARTS data summary

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Indicator type</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q_TB</td>
<td>Percent with tuberculosis</td>
<td>Physical Need</td>
<td>2008</td>
</tr>
<tr>
<td>QHIV/AIDS</td>
<td>Percent with HIV or AIDS</td>
<td>Physical Need</td>
<td>2006</td>
</tr>
<tr>
<td>QCANCER</td>
<td>Percent with cancer of any kind</td>
<td>Physical Need</td>
<td>2006</td>
</tr>
<tr>
<td>VIOLENCE_PC</td>
<td>Domestic violence cases reported per capita</td>
<td>Physical and/or Psychological Need</td>
<td>2007</td>
</tr>
<tr>
<td>LBW_PC</td>
<td>Low birth weight babies born per capita</td>
<td>High Risk of Physical Need</td>
<td>2007</td>
</tr>
<tr>
<td>EMS_PC</td>
<td>Emergency Medical Service personnel per capita</td>
<td>Increased Healthcare Resource Access</td>
<td>2002</td>
</tr>
<tr>
<td>PHYSICN_PC</td>
<td>Physicians per capita</td>
<td>Increased Healthcare Resource Access</td>
<td>2008</td>
</tr>
<tr>
<td>QLOW_HEALTH</td>
<td>BRFSS: Percent reporting ‘poor’ or ‘fair’ perception of personal health out of</td>
<td>Physical and/or Psychological Need</td>
<td>2007</td>
</tr>
</tbody>
</table>

55
<table>
<thead>
<tr>
<th>QALCOHOL</th>
<th>BRFSS: Percent reporting engagement in regular heavy or binge drinking (2+ drinks per day for men, 1+ drinks per day for women)</th>
<th>Physical and/or Psychological Need</th>
<th>2007</th>
</tr>
</thead>
<tbody>
<tr>
<td>QDIABETIC</td>
<td>BRFSS: Percent ‘told by a doctor’ they have diabetes</td>
<td>Physical Need</td>
<td>2007</td>
</tr>
<tr>
<td>QASTHMA</td>
<td>BRFSS: Percent ‘told by a doctor’ they have asthma</td>
<td>Physical Need</td>
<td>2007</td>
</tr>
<tr>
<td>QHEART</td>
<td>BRFSS: Percent who have ever had a heart attack, angina, or coronary heart disease</td>
<td>Physical Need</td>
<td>2007</td>
</tr>
<tr>
<td>QHYPERTENS</td>
<td>BRFSS: Percent ‘told by a doctor’ they have hypertension</td>
<td>Physical Need</td>
<td>2007</td>
</tr>
<tr>
<td>QSEVERE_ARTH</td>
<td>BRFSS: Percent reporting limitations is ‘usual activities’ because of arthritis or chronic joint symptoms</td>
<td>Physical Need</td>
<td>2007</td>
</tr>
<tr>
<td>QSMOKER</td>
<td>BRFSS: Percent current smokers</td>
<td>High Risk of Physical Need</td>
<td>2007</td>
</tr>
<tr>
<td>QOBESITY</td>
<td>BRFSS: Percent considered obese based on reported height/weight</td>
<td>High Risk of Physical Need</td>
<td>2007</td>
</tr>
</tbody>
</table>

BRFSS data downloaded from CHARTS were reported as a percentage of total population, using a 95 percent confidence interval for estimation. All other variables collected from CHARTS (i.e. non-BRFSS) were reported as raw counts and normalized manually in SPSS using supplementary county population estimates. Variables indicating the percentage of the population having TB, HIV/AIDS, or cancer were derived by dividing single year disease incidence by the total population for each county, and multiplying by 100.

County Vulnerable Population Profiles were compiled in 2009 by FLDOH’s Bureau of Response and Preparedness as a tool kit for community planners who seek to better understand the needs of vulnerable populations before, during and after a disaster. Available on the web, the indicators are designed to enhance awareness of at risk populations to improve community assessment and communication (FLDOH 2010b). Each profile includes a number of baseline indicators for medical needs and healthcare.
access. A Summary of the data collected from FLDOH’s County Vulnerable Population Profiles is given in table 3.5 below

Table 3.5: FLDOH County Population Profiles data summary

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Indicator type</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>QMEDICAID‡</td>
<td>Percent on Medicaid</td>
<td>Decreased Resource Access Physical and/or Psychological Need</td>
<td>2009</td>
</tr>
<tr>
<td>QCMS**</td>
<td>Percent Children's Medical Service Clients</td>
<td>Physical and/or Psychological Need</td>
<td>2009</td>
</tr>
<tr>
<td>HMLESS_PC</td>
<td>Homeless per capita</td>
<td>Resource Access, Physical and/or Psychological Need</td>
<td>2009</td>
</tr>
<tr>
<td>QDEV_DIS</td>
<td>Percent developmentally disabled</td>
<td>Physical and/or Psychological Need</td>
<td>2009</td>
</tr>
<tr>
<td>QDIST_CHLD</td>
<td>Percent seriously emotionally disturbed children</td>
<td>Physical and/or Psychological Need</td>
<td>2009</td>
</tr>
<tr>
<td>QMENTAL_ILL</td>
<td>Percent seriously mentally ill adults</td>
<td>Physical and/or Psychological Need</td>
<td>2009</td>
</tr>
<tr>
<td>QBRN_SPN</td>
<td>Percent with brain or spine injury</td>
<td>Physical Need</td>
<td>2009</td>
</tr>
<tr>
<td>QOXYGEN</td>
<td>Percent O2 dependent</td>
<td>Physical Need</td>
<td>2009</td>
</tr>
<tr>
<td>QDEMENTIA</td>
<td>Percent with dementia</td>
<td>Physical and/or Psychological Need</td>
<td>2009</td>
</tr>
<tr>
<td>QDIALYSIS</td>
<td>Percent Dialysis Patients</td>
<td>Physical Need</td>
<td>2009</td>
</tr>
</tbody>
</table>

* Medicaid is a jointly funded, Federal-State health insurance program for low-income and special needs populations. It provides coverage for the disabled and other people who are eligible to receive federally assisted income maintenance payments (SSA 2010).

** Children’s Medical Services (CMS) is Florida’s integrated system of care for children from birth to 21 years of age whose serious or chronic physical or developmental conditions require extensive medical care. CMS also provides medical and supportive services to women in the case of high-risk pregnancy (OPPAGA 2010).

Unfortunately, data culled from the County Vulnerable Population profiles were not available in a digital format. Consequently, the raw data were entered by hand into SPSS. Following a QA/QC, the data were normalized using the accompanying population estimates given in each county profile. With the exception of homeless, the normalized variables were converted to percentages by multiplying by 100. For certain variables, data were not provided in some counties. In this instance, the average calculated value for all other counties was substituted (Nardo et al. 2008).
The Community Health Status Indicators (CHSI), compiled for the entire US at the county level by the Dept. of Health and Human Services (HHS), provide a comprehensive overview of health proxies with a focus on local health behavior and prevalent causes of mortality. The goal of CHSI is to encourage local action and dialogue for the improvement of community health (Metzler et al. 2008). Raw data from the most recent compilation of indicators (2006) was publicly available in digital format through the CHSI website (HHS 2010). Only two indicators were gathered, both primarily as proxies for psychological health needs. A brief summary of the variables is shown in table 3.6. To normalize these data, annual population estimates from FLDOH’s CHARTS were used, as population information was not provided by CHSI.

Table 3.6: CHSI data summary

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Indicator type</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>QMJR_DEPRES</td>
<td>Percent having a major depressive episode in the past year</td>
<td>Psychological Need</td>
<td>2005</td>
</tr>
<tr>
<td>QDRUGS</td>
<td>Percent illegal drug users</td>
<td>Psychological Need</td>
<td>2002</td>
</tr>
</tbody>
</table>

The Florida Agency for Health Care Administration (AHCA) is responsible for the licensure and regulation of health facilities across the state. Additionally, AHCA maintains an online database containing up-to-date vocational and administrative information for every type of healthcare facility in Florida. Consequently, AHCA’s database provided reliable spatial indicators for critical health facilities: hospitals, clinics, and special needs homes (i.e. nursing home, hospice and group homes). A summary of the indicators provided by AHCA is shown in table 3.7 below.

Tabular address information was downloaded for each facility type and imported into Microsoft Excel. In the case of clinics and special needs homes, the total number of
each type of facility was tallied for each county. To normalize this data, facility counts were divided by population estimates from FLDOH’s CHARTS yielding a per capita measure.

Table 3.7: AHCA data summary

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Indicator type</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>SpecNdsHm_PC</td>
<td>Nursing home, hospice, and assisted living facilities per capita</td>
<td>Physical and/or Psychological Need</td>
<td>2009</td>
</tr>
<tr>
<td>BEDACC_PC</td>
<td>Average number of hospital beds (inside a 50 miles buffer) per capita</td>
<td>Increased Healthcare Resource Access</td>
<td>2009</td>
</tr>
<tr>
<td>CLINICS_PC</td>
<td>Clinics (including rural clinics) per capita</td>
<td>Increased Healthcare Resource Access</td>
<td>2009</td>
</tr>
</tbody>
</table>

Hospital data were preprocessed using different methods, primarily to take advantage of bed count information not available for the other facilities. To create a more realistic indicator of hospital access than a simple ‘hospital per capita’ measure can provide, addresses were first converted to geographic point locations by geocoding. For addresses that could not be accurately matched, latitude and longitude were gathered manually using Google Earth. Next, the tabular x, y coordinates were imported into ArcMap and converted to a point level shapefile. A Euclidean buffer was then applied to each hospital to represent maximum service area. Following a fruitless review of the literature, the appropriate size of the buffer was determined using an inductive spatial analysis measuring the maximum possible Euclidean distance that can be achieved between (A) any point in the state of Florida and (B) the nearest hospital in the state. Using the Distance tool in ArcMap’s Spatial Analyst, this maximum distance was estimated as ~ 50 miles. Next, the buffers were converted from vector to raster format using a 30 meter grid cell size, and assigned a value respective to the number of licensed
hospital beds. A major pitfall in vector-to-raster conversion for multi-feature shapefiles is that overlapping features are not separately preserved (i.e. there can only be one value per grid cell in a single grid) (ESRI 2009). To ameliorate this issue, each buffer feature from the initial shapefile was converted individually, producing one grid for each of the hospital buffers. Batch processing was performed using Python scripting in ArcMap. Buffers values were then spatially summed using ArcMap’s Raster Calculator. The resulting grid represents the maximum number of hospital beds accessible within a maximum distance of 50 miles for each 30 x 30 location in the state (Figure 3.2).

Figure 3.2: Hospital bed density (intermediate processing in ArcMap)
Zonal statistics were used to produce an average hospital bed per county value. Values were normalized using CHARTS county population estimates for 2009 to yield a final indicator of average hospital bed access per capita. Technical details, including a GIS process flow diagram, and sample Python script are available in Appendix B.

The product of this ancillary analysis is shown in Figure 3.3. Using 3 classes based on standard deviations, counties with increased hospital bed access per capita are shown in green, while counties with less access are tan.

Figure 3.3: Hospital beds per capita for Florida counties
Despite the high density of hospitals (and subsequently, hospital beds) throughout the urban areas across the state, such as those counties along the southeast peninsula (see Figure 3.2), the dense population along the heavily developed coast effectively reduces individual access to hospital beds. Instead, increased hospital bed access is evident throughout the less populous counties of rural Florida, most notably Liberty, Union, Bradford, Hardee, and Baker Counties.

The final source of data for this thesis was the US Census Bureau. While public health data available through the Decennial Census is limited, certain variables such as nursing home residents, specific disability prevalence. Data from the decennial census were downloaded using the US Census Data Engine Summary File 3 and were normalized using the corresponding census population values. Additionally, the US Census Bureau’s model-based Small Area Health Insurance Estimates (SAHIE) program produces estimates of health insurance coverage for populations under age 65 in all states and counties. The first release of a county level nationwide dataset was 2005, and is available for download online via the SAHIE website. Estimates for the number of uninsured, as well the analogous population estimates were downloaded in tabular format and normalized in SPSS. Table 3.8 below summarizes that data culled from the US census.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Indicator type</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>QUNINSURED</td>
<td>Percent under age 65 without health insurance</td>
<td>Decreased Healthcare Resource Access</td>
<td>2005</td>
</tr>
<tr>
<td>QSENSORY_DIS</td>
<td>Percent with a sensory disability</td>
<td>Physical Need</td>
<td>2000</td>
</tr>
<tr>
<td>QPHYSICAL_DIS</td>
<td>Percent with a physical disability</td>
<td>Physical Need</td>
<td>2000</td>
</tr>
<tr>
<td>QMENTAL_DIS</td>
<td>Percent with a mental disability</td>
<td>Psychological Need</td>
<td>2000</td>
</tr>
<tr>
<td>NRRESPC</td>
<td>Nursing home residents per capita</td>
<td>Physical and/or Psychological Need</td>
<td>2000</td>
</tr>
</tbody>
</table>
Subsequently, data collection produced a compilation of 36 target variables. Descriptive statistics for the MedVI variables are available in Appendix A. To reduce the dimensionality of the dataset, and explore the underlying relationships among the variables, a PCA was performed. Preprocessing steps and analysis thresholds were transplanted from the construction of SoVI. Again using Booysen’s (2002) methods for cardinality pre-adjustment, variables were evaluated based on their theoretical tendency to increase or decrease medical vulnerability. Three variables warranted a negative (-) sign adjustment; physicians per capita, emergency medical service personnel per capita, and average hospital bed access per capita; as these variables are theoretically understood to indicate increased access to medical resources, thus decreasing vulnerability. As with the adjusted social vulnerability indicators, inverted medical variables are denoted by the $i$ prefix. Next, descriptive statistics were produced for each variable (Appendix A) and inspected to ensure the distribution of the data, and data quality. For complete recollection of the PCA process, refer to section 3.2.1. Methods and thresholds were replicated entirely, with the only divergence being the implicit measurement of community medical vulnerability in place of social vulnerability. Following an analysis of the PCA results, the components were summed based on the assigned cardinality to produce an aggregate medical vulnerability index (or, MedVI) score. Data were exported to ArcMap for mapping and descriptive visual analysis.

Though the construction of MedVI was required for parity in the subsequent comparative analysis with SoVI, it was also paramount in addressing the first research question: Which variables provide the best characterization of medical vulnerability to disasters, including measures of both health access and pre-existing medical needs?
While the original list of target variables was justified using literature and expert a priori knowledge from FLDOH, the PCA determines which variables contribute most to medical vulnerability in Florida using explained variance.

### 3.2.3 Data Caveats

The construction of quantitative indices requires transparency in data sources, data quality, and methodology. Though the data representing the social and medical indicators were chosen using theoretical and empirical cues from literature, and collected from reputable sources some caveats warrant a short discussion. Mentioned throughout the literature is an inherent difficulty in the collection of health data, especially concerning indicators of disease prevalence and incidence due in part to the confidential nature of this information. Separate from the general scarcity of these variables is the issue of how the available data are actually collected and represented. For many variables, counts were culled using a survey instrument, which collects data for only a sample of the population. Using statistical sampling methods in combination with known population counts these raw sample data are used to estimate a normalized rate of prevalence countywide. While many of the variables assume a 95 percent confidence interval, the sample size and margin of error are often not given for each variable and county.

Additionally, the availability of data for a given year was not universal. In some cases, indicators were only available for a single year. The years of availability range from 2000 (Decennial Census Data) to 2009 (FLDOH Vulnerable Population Profiles). While a 9 year span in data is not desired, it was unavoidable for this research. Each
variable was normalized using corresponding population values for the specific year of data collection, as not to presume that the raw counts were temporally representative.

3.3 Research Design

Once the indices had been constructed and aggregated appropriately, the data were mapped and analyzed. This descriptive analysis of the data provides a starting point for understanding the distribution of the data across the state of Florida. Additionally, a post-processing verification test of MedVI and SoVI was performed with the intention of outcome-measure evaluation. Next, several spatial and statistical analyses were implemented, including correlation and partial correlation analyses, reliability analysis, simple and multiple linear regression, bivariate mapping, and spatial analysis of regression residuals. These tests were chosen with the intention of thoroughly addressing each of the research questions. Figure 3.3 provides a data model of the steps taken in the methodology. The following sections briefly describe each component of the analysis process.
3.3.1 Outcome Measure Testing

Outcome measures are ex post disaster phenomena used to gauge the utility of a metric in forecasting future outcomes. As discussed in the previous chapter, vulnerability metrics are often criticized as a result of the inability to define a consistent outcome measure by which the indices can be calibrated and validated. This is an attribute of the natural multidimensionality by which vulnerability is represented. Though SoVI and MedVI are also comprised of several dimensions of social and medical vulnerability
respectively, a handful of contextual outcome measures were tested with the hopeful intention of discovering a useful calibration instrument for the indices. Data compiled by FEMA region 4’s Individual Assistance Branch provided information regarding all individual disaster assistance applications at the county level following the 2004 hurricane season in Florida. FEMA defines disaster assistance as money or direct assistance to individuals in areas where property has been damaged or destroyed and whose losses are not covered by insurance. Extending beyond property damage, the assistance is meant to help with critical expenses that cannot be covered in other ways (FEMA 2010). Data were provided for each major hurricane disaster in the 2004 season: Charley, Frances, Ivan and Jeanne. The data included total applicants with emergency needs, applicants requesting medical or dental expense assistance, and applicants requesting funeral expense assistance following each disaster. To test the efficacy of the data as an outcome measure for SoVI and MedVI, total applicants were first aggregated to the county level for the entire 2004 hurricane season. The data were then normalized using population estimates from FLDOH to represent a per capita measure. To examine the statistical association between the individual assistance data, and SoVI and MedVI, the individual variables for the 2004 hurricanes were correlated with SoVI, MedVI and their respective components using Spearman’s rho to test for an underlying monotonic relationship. The correlation coefficients were examined to determine the strength and direction of the relationship.
3.3.2 Correlation, Reliability, and Regression Analyses

To answer the second thesis research question, “What is the statistical congruence or overlap between medical vulnerability and social vulnerability as measured by the Social Vulnerability Index?” the relationship between the indices needed to be statistically compared. This was carried out through a series of comparisons using correlation, reliability, and regression analyses.

First, the individual components and aggregate scores for both SoVI and MedVI were tested for normality using descriptive statistics in SPSS. Next, Spearman’s Rank Correlation was run to determine the relationship between SoVI and MedVI and their components. Spearman’s Rank is a nonparametric correlation statistic, meaning that it makes no distributional assumptions. The correlation coefficient $\rho (r_s)$ was then examined to determine the statistical strength and direction of the monotonic relationship between the variables. The magnitude of $\rho$ effectively demonstrates possible correlations between the variables. Correlations were assumed to be significant using a threshold of Sig < 0.050. The values of the correlation coefficients also give insight into the ability of SoVI and its components to act as an indicator of medical vulnerability by evaluating the relationships between the indices and their subsequent components. The strength and direction of these relationships and their significance were thoroughly examined.

Following the initial correlation analysis, an analysis of nonparametric partial correlation was performed. Partial correlation is similar to Spearman’s Rank, except that it allows for the addition of a control variable. Control variables are usually identified as those suspected to influence the relationship between the variables of interest. By
statistically controlling the influence of the variable, the relationship between the variables of interest, and the impact of the controlled variable are learned. In this analysis, partial correlation was used to hold constant those underlying SoVI and MedVI components exhibiting strong relationships to determine their impact on the rho coefficient between the MedVI and SoVI scores.

The reliability of a metric indicates how free it is from random error (Pallant 2007). Internal consistency is a frequently used measure in testing reliability within or between quantitative metrics. It describes the degree to which the items that derive the metric are all naturally measuring the same underlying attribute (Pallant 2007; Nardo et al. 2008). A commonly used measure of internal consistency is Cronbach’s coefficient alpha. Scaled between 0 and 1, Cronbach’s alpha is considered to demonstrate significant internal consistency when values exceed $\alpha > 0.700$. Cronbach’s alpha was calculated for MedVI and SoVI using SPSS.

Following the correlation and reliability tests, the next step was to determine the linear relationship between the MedVI and SoVI. The goal of this portion of the analysis is to verify whether medical vulnerability could be predicted based from social vulnerability and its factors. A regression analysis was utilized because it allowed for multiple variables within the dataset to be tested and quantified the predictive relationship assuming significant results (Rogerson 2006). Once the assumptions were met, a linear regression was run in SPSS with the standardized (i.e. z-score) MedVI score as the dependent variable and the standardized SoVI score as independent variable. Next, standard multiple regression was run substituting the standardized SoVI components in place of the SoVI score. Each independent variable was evaluated based on predictive
power “over and above” that offered by the other components (Pallant 2007: 147). This technique demonstrates the amount of unique variance in the MedVI score is explained by each of the independent variables. Regression results were considered significant at $\text{Sig} < 0.050$.

### 3.3.3 Bivariate and Residual Mapping Analysis

To answer the final research question, “Can social vulnerability explain the distribution of medical vulnerability or are they different in their spatial representations?” the distribution of SoVI and MedVI needed to be compared spatially. This was accomplished through two simple methods of comparison: bivariate mapping and the spatial representation of regression residuals.

Statistical bivariate maps offer an amenable alternative to side-by-side map comparison. Using statistical classification ranges, such as standard deviations, variables are transformed from a standardized rate to a categorical value based on the distribution of the data (Trumbo 1981). This also allows the data to be summarized in a format that improves viewability. Using two variables, SoVI score and MedVI score, each variable was summarized using three classes based on standard deviation from the respective distribution: Class 1= values $< -0.500$ standard deviations; Class 2= values between $-0.500$ and $0.500$ standard deviations; Class 3= values $> 0.500$ standard deviations. The resulting map depicts 9 categories representing each possible class combination (i.e. 1,1; 1,2; 1,3; 2,1; 2,2; 2,3; 3,1; 3,2; 3,3) for each county in Florida. For example, the combination 1,3 represents each county where the standard deviation category is 1 based on the SoVI score, but is characterized by category 3 according to the MedVI score.
Using this logic, the three classes indicating counties that did not shift between mapped categories from SoVI to MedVI classification are 1,1; 2,2; and 3,3. Generally, this mapping technique depicts the areas where parity between SoVI score and MedVI score are prevalent. It does not, however, indicate specific areas where SoVI can accurately predict MedVI.

To provide a more detailed representation of SoVI’s explanatory power, regression residuals were produced in SPSS. Using the results of the regression analysis discussed in the previous section, the regression residual, or statistical error, is computed by subtracting the predicted MedVI score (from the regression equation produced by SoVI) from the actual observed MedVI score. These values indicate the range between the predicted and actual values of MedVI. Negative values indicate underestimation, while positive values demonstrate overestimation. Residual values close to zero suggest higher prevalence of predictability. Standardized residuals were imported into ArcMap for mapping. The values were classified using three divergent classes based on a 95% confidence interval drawn along the both sides of the regression line. Counties in the middle classification indicate residuals within the 95% confidence interval, as thus provide adequate prediction for MedVI. All counties exhibiting observations above the confidence interval indicate over-predictions, while counties below the confidence interval show under-prediction. This method effectively depicts the counties in Florida where SoVI’s explanatory power was more or less dependable.
3.4 Summary

Following the construction of the two vulnerability indices, SoVI and MedVI, a battery of analyses were applied to determine the statistical and spatial relationships between the two. To measure the statistical overlap of the indices, four main tests were used. Spearman’s correlation and partial correlation tests examined the monotonic statistical relationship between each of the variables, giving insight on the strength and direction of the relationship. Cronbach’s alpha produced a reliability test measuring internal consistency between social and medical vulnerability. Finally, the regression analysis demonstrates the predictive capability of SoVI and its components in producing a MedVI score. To determine the spatial relationship between SoVI and MedVI, two techniques were utilized. Bivariate mapping offered a simple approach for providing a visual comparison in the distributions of SoVI and MedVI scores in a single map, while regression residual mapping gave insight on the where SoVI’s predictive efficacy was highest and lowest. Additionally, MedVI and SoVI were compared to FEMA’s individual disaster assistance data for outcome measure testing.
Chapter 4: Results and Analysis

4.1 Descriptive Results

4.1.1 Florida SoVI

Examining the results of the PCA, the 29 computed target variables were reduced to 7 composite principle components and were extracted based on Kaiser’s Rule (i.e. eigenvalues greater than 1). Cumulatively, the components explain 84.94 percent of the variance in the dataset. In exploring the associated component loadings, each component was summarized with a component description and cardinality. Table 4.1 below represents this portion of the analysis, demonstrating the ranking of the components, cardinality, description, and the percent variance explained by each component, as well as the dominant variables used in naming and assigning the cardinality. Adjusting each component based on its tendency to increase or decrease social vulnerability, a simple additive equation was produced to calculate an aggregate SoVI score for each county:

SoVI Score = Component 1 – Component 2 + Component 3 + Component 4 + Component 5 + Component 6 – Component 7. A map of the aggregate SoVI score is presented in figure 4.3.
Aside from examining the aggregate SoVI score, it is imperative to evaluate the individual components that contributed to social vulnerability overall. By doing this, the foremost drivers of counties’ social vulnerability can be discovered. Uncovering the spatial distribution of these preceding components may also improve the understanding of social vulnerability’s interaction with medical vulnerability in the subsequent analyses. The scores for each individual component, with cardinality applied, are mapped in Figures 4.1 and 4.2.
The first component demonstrates significant indicators characteristic of the rural poor and working class. With high positive component loadings among the percent living in mobile homes, percent on rural farms, and percent without a high school diploma, as well as several indicators implying a lack of wealth, component 1 was named using these characteristics, and given a positive (+) cardinality based on the tendency to increase social vulnerability. The map of the first component shows a higher prevalence of the indicators throughout the counties in the Florida panhandle extending somewhat through the interior or south Florida. As expected, lower component scores are evident along the heavily urbanized and wealthy Florida coastline. The overall variance explained by component 1 is 24.14 percent.

The second component is characterized by the combination of strong component loadings on percent social security recipients, percent over age 65, and median age. These indicators characterize Florida’s elderly population, and the component was named as such. Since the component loadings were negative, a negative (-) cardinality was applied to invert the sign of the loadings and reflect the tendency of the component to increase social vulnerability. High component scores were prevalent throughout central and southern Florida, especially in counties along the Gulf coast and portions of the Atlantic coast north of Palm Beach County. Component 2 accounts for 19.07 percent of the overall variance explained in SoVI.

The third component demonstrates a collection of indicators, including percent unemployment, percent living in poverty, as well as the inverted variable representations of per capita income and mean house value. Collectively, this composite was named “unemployment and socioeconomic status” to characterize the component as a general
indicator for the lack of economic capital. As, such, the cardinality of the component was positive (+). The regionalization of component 3 is somewhat more ambiguous than in the previous two components, with moderately high component scores extending from the panhandle through central Florida. Component 3’s prevalence was highest among a few counties along the state’s northern border, and in the southeast corner of the state in Miami-Dade County. Scores for component 3 were lowest mainly in the northeast corner of the state and the eastern portion of Florida’s southern tip. The overall variance explained by component 3 is 14.08 percent.

The fourth component was given the name “Hispanic agricultural workers” based on the significant component loadings among indicators of percent Hispanic ethnicity, percent employed in the primary industries of farming, fishing, mining, or forestry, and percent recent international migrants. This component illustrates Florida’s highly vulnerable Hispanic agricultural labor force, prevalent throughout southern tip of the Florida peninsula, through the interior counties of southern Florida. Again, cardinality remained positive (+) to indicate increased social vulnerability. Component 4 represents 11.07 percent of the variance explained in SoVI.
Figure 4.1: SoVI components 1 through 4
Component 5 is characterized primarily by the variable indicating percent employed in the service industry, undoubtedly linked to Florida’s reputation as a versatile vacation state. The component was named accordingly and positive (+) cardinality was applied to demarcate the tendency of the component to increase social vulnerability. As with component 3, definitive regions indicating prevalence of the component 5 score were somewhat vague. Clusters of high prevalence of service employment are seen isolated in the central panhandle and throughout northern Florida. Other small patches of high component 5 scores are evident through southern Florida and in the southwest corner of the peninsula. Lower scores for component 5 were ubiquitous throughout central and some of south Florida. The overall variance explained by component 5 is 6.32 percent.

Component 6 was again comprised principally by a workforce indicator, this time focusing on the percentage of the population employed in the transportation, communications, and public utilities industry. Again the component was named using the characteristic variable, “transportation and infrastructure industry employees”, and a positive (+) cardinality was applied. When mapped, clusters representing high scores for component 5 are evident primarily in northeast corner of the state. In general, southern coastal counties along the gulf and most of the panhandle exhibited lower component 6 scores. Overall, component 6 accounts for 5.26 percent of the variance explained in SoVI.
Figure 4.2: SoVI components 5 through 7
Component 7, the last component extracted in SoVI, demonstrates only one indicator with a significant component loading: percent Native American. Since the sign on the loading was negative, a negative (-) cardinality was applied, thus inverting the sign to reflect an increase in social vulnerability. In examining the map, high values for component 7 are heavily regionalized in the counties of the western panhandle, with the exception of Glades, DeSoto, and Monroe Counties to the south. Lower scores for component 7 are seen along the northern border of the state at the east end of the panhandle. The overall variance explained by component 7 is 5.00 percent.

The overall Florida SoVI score has some discrete visible clustering of lower social vulnerability in the northeast corner of the state as well as the eastern portion of the panhandle region (Figure 4.3). With the exception of Miami-Dade, coastal counties lining the southern coastline exhibit moderately low to moderate vulnerability from the eastern portion of central Florida circling westward toward the Gulf. This trend is interrupted by a patch of higher social vulnerability throughout the counties in the northwest section of central Florida (i.e. Hernando, Citrus and Sumter Counties). A larger group of counties with higher social vulnerability is depicted in the interior of southern Florida. Moderately high vulnerability is also present toward the center of the panhandle region and peppered throughout northern Florida. The ten counties with the highest and lowest social vulnerability along with their respective SoVI score are listed in Table 4.2.
Figure 4.3: Overall social vulnerability for Florida counties

Table 4.2: Florida counties exhibiting highest and lowest social vulnerability

<table>
<thead>
<tr>
<th>Highest Social Vulnerability</th>
<th>Score</th>
<th>Lowest Social Vulnerability</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Glades</td>
<td>7.91</td>
<td>Leon</td>
<td>-6.48</td>
</tr>
<tr>
<td>Union</td>
<td>5.07</td>
<td>Alachua</td>
<td>-5.24</td>
</tr>
<tr>
<td>DeSoto</td>
<td>4.45</td>
<td>Seminole</td>
<td>-5.14</td>
</tr>
<tr>
<td>Sumter</td>
<td>4.24</td>
<td>Saint Johns</td>
<td>-4.13</td>
</tr>
<tr>
<td>Hendry</td>
<td>3.79</td>
<td>Jefferson</td>
<td>-3.38</td>
</tr>
<tr>
<td>Citrus</td>
<td>3.64</td>
<td>Duval</td>
<td>-3.10</td>
</tr>
<tr>
<td>Calhoun</td>
<td>3.58</td>
<td>Orange</td>
<td>-2.79</td>
</tr>
<tr>
<td>Dixie</td>
<td>3.09</td>
<td>Gadsden</td>
<td>-2.78</td>
</tr>
<tr>
<td>Hardee</td>
<td>2.90</td>
<td>Hillsborough</td>
<td>-2.78</td>
</tr>
<tr>
<td>Liberty</td>
<td>2.77</td>
<td>Wakulla</td>
<td>-2.76</td>
</tr>
</tbody>
</table>
4.1.2 Florida MedVI

Following the PCA, the original set of 36 medical variables was statistically reduced to 10 principal components using the Kaiser criterion. All together, the components explain 74.87 percent of the variance in the dataset. Replicating the post-processing techniques used in the construction of the SoVI score, each of the medical components were reviewed for the purposes of naming and assigning cardinality. Table 4.3 this summarizes this portion of the analysis, demonstrating the ranked components, cardinality, description, and the percent variance explained by each component, as well as the dominant variables used in naming and assigning the cardinality. After each component was adjusted based on its tendency to increase or decrease medical vulnerability, a simple additive equation was produced to calculate an aggregate MedVI score for each county: \( \text{MedVI Score} = \text{Component 1} + \text{Component 2} + \text{Component 3} + \text{Component 4} + \text{Component 5} + \text{Component 6} - \text{Component 7} - \text{Component 8} + \text{Component 9} + \text{Component 10} \). As with SoVI, the components contributing the overall medical vulnerability were examined spatially to determine the patterns of the foremost drivers of MedVI across Florida. The scores for each individual component, with cardinality applied, are mapped in Figures 4.4, 4.5, and 4.6. A map of the aggregate MedVI score is presented in Figure 4.7.
Table 4.3: Summary of medical vulnerability PCA

<table>
<thead>
<tr>
<th>Component</th>
<th>Cardinality</th>
<th>Description</th>
<th>Dominant Variables</th>
<th>Component Loading</th>
<th>% Variance Explained</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>+</td>
<td>Disability and Low Health Perception</td>
<td>QPhysical_dis, QSensory_dis, QSevere_arth, QMental_dis, QLow_health, Qhypertension</td>
<td>0.877, 0.859, 0.842, 0.835, 0.752, 0.661</td>
<td>19.528</td>
</tr>
<tr>
<td>2</td>
<td>+</td>
<td>Chronic Illness and Medical Dependence</td>
<td>QDementia, QOxygen, QCancer, QMjr_depres</td>
<td>0.909, 0.902, 0.768, 0.721</td>
<td>14.307</td>
</tr>
<tr>
<td>3</td>
<td>+</td>
<td>Healthcare Access</td>
<td>QUninsured, Homeless_PC, Q_TB</td>
<td>0.787, 0.747, 0.741</td>
<td>6.947</td>
</tr>
<tr>
<td>4</td>
<td>+</td>
<td>Dialysis Dependents</td>
<td>QDialysis, iBedAccess_PC*</td>
<td>0.893, -0.543</td>
<td>6.687</td>
</tr>
<tr>
<td>5</td>
<td>+</td>
<td>Domestic Violence Propensity</td>
<td>Violence_PC</td>
<td>0.851</td>
<td>5.689</td>
</tr>
<tr>
<td>6</td>
<td>+</td>
<td>Special Needs Institutions</td>
<td>SpecNdsHm_PC, iClinics_PC*</td>
<td>0.764, -0.626</td>
<td>5.323</td>
</tr>
<tr>
<td>7</td>
<td>-</td>
<td>Alcohol Abuse</td>
<td>QAAlcohol</td>
<td>-0.692</td>
<td>4.916</td>
</tr>
<tr>
<td>8</td>
<td>-</td>
<td>Drug Abuse</td>
<td>QDrugs</td>
<td>-0.770</td>
<td>4.398</td>
</tr>
<tr>
<td>9</td>
<td>+</td>
<td>Mental Health</td>
<td>QMental_ill, QDist_Child</td>
<td>0.773, 0.573</td>
<td>3.747</td>
</tr>
<tr>
<td>10</td>
<td>+</td>
<td>Developmental Disability</td>
<td>QDev_dis</td>
<td>0.837</td>
<td>3.329</td>
</tr>
</tbody>
</table>

Total Variance Explained 74.871

* prefix Indicates directional preadjustment. Variable can be read as "a lack of..." or "diminished..."

Component 1 is characterized by high component loadings on the indicators of percent with a disability (i.e. physical, sensory and mental), percent with severe arthritis, percent reporting ‘poor’ or ‘fair’ personal health, and percent with hypertension. To adequately represent the dominant variables, the component was given the name “disability, and low health perception” and assigned a positive (+) cardinality to indicate the tendency of the variables to increase medical vulnerability. The map of the first
component suggests a higher prevalence of the indicators in the central panhandle region and throughout central Florida, especially near the Gulf. Lower component scores are evident throughout coastal South Florida, especially in the southeast tip of the peninsula. The overall variance explained by component 1 is 19.53 percent.

The second component demonstrates significant indicators with high component loadings among the percent with dementia, percent oxygen dependents, percent with cancer, and percent reporting a recent major depressive episode. To summarize the variables, the component was named “chronic illness and medical dependence”, indicating the frequent and inherent medical needs of these populations. Again, a positive cardinality (+) was applied. Counties with higher scores for component 2 line the coasts of southern Florida with the exception of Miami-Dade County in the southeast. Low and moderate scores appear in clusters across the northern border, and through the interior counties of south Florida. Component 2 accounts for 14.31 percent of the overall variance explained in MedVI.

The third component reveals a small collection of indicators including percent without health insurance, homeless per capita, and percent with tuberculosis. In general, these indicators point to an overall lack of healthcare access. The component was named accordingly, and assigned positive cardinality (+) to reflect the inclination of the variables to increase medical vulnerability. In the map, higher values of component 3 are noticeably regionalized in the southern tip of the peninsula, extending north through the interior counties of South Florida. Moderately low values of component 3 appear in patches across the panhandle region through to the Atlantic coast of central Florida. Component 3 accounts for 6.95 percent of the variance explained in MedVI.
Figure 4.4: MedVI components 1 through 4
The fourth component of MedVI is characterized mainly by percent dialysis clients, and to a lesser extent, average hospital bed access per capita. While these indicators may seem to suggest opposing effects on medical vulnerability, the combination advocates the idea that dialysis clients may intentionally locate near hospitals and treatment facilities. As a result, the component was named “dialysis dependence” and assigned a positive (+) cardinality to designate the tendency to increase medical vulnerability. The distribution of component 4 suggests limited outliers on both sides of the mean, with most counties showing moderate scores (i.e. -0.50 to 0.50 std deviations). Some patches of moderately low component 5 scores are evident in the western panhandle and at the southernmost portion of the state. The portion of overall variance explained by component 4 is 6.69 percent.

Component 5 is significantly marked by only one variable: domestic violence cases per capita. As a result, the component was simply named “domestic violence propensity” and a positive (+) cardinality was assigned. Low component 5 scores are visibly clustered in the southern section of the central panhandle, while higher scores for are prevalent primarily in central Florida extending through the interior counties in the southern part of the state. Component 5 accounts for 5.69 percent of the overall variance explained in MedVI.

The sixth component is characterized by significant component loadings on special needs homes (i.e. nursing homes, group homes, and hospices) per capita and clinics per capita. Since these variables are indicators of healthcare institutions and infrastructure for the sick and disabled, the component was given the name “special needs institutions”. Alluding to higher concentrations of medical needs, component 6 was
assigned a positive (+) cardinality. When mapped, higher scores for component 6 are located mainly in the counties of the eastern panhandle and in the southeast corner of the peninsula. Lower scores are prevalent in parts of the western panhandle, scattered throughout South Florida into the southwest corner of the peninsula. Component 6 accounts for 5.32 percent of the variance explained in MedVI.

Component 7 was named “alcohol abuse” based on a high component loading for the percent who engage in regular heavy or binge drinking. Since the sign on the component loading was negative, a negative (-) cardinality was applied to flip the sign, reflecting a tendency to increase medical vulnerability. Lower scores for component 7 characterize most of the Florida panhandle, with the major exception of Liberty County, and most of western South Florida except Monroe and Lee Counties. Counties exhibiting high component 7 scores are limited to a small patch around Dixie County in Central Florida near the southern edge of the eastern panhandle. Component 7 represents 4.92 percent of the overall variance explained in MedVI.

Component 8 only exhibited one variable with a significant component loading: percent illegal drug use. The component was named accordingly, and, as with the previous component, a negative cardinality was applied to invert the sign on the variable’s component loading to indicate an increase in vulnerability. When mapped, component 8 was somewhat less distinctly regionalized than some of the other components. A band of higher scores lines the northern end of central Florida, especially in Gilchrist, Bradford and Flagler Counties, with others peppered throughout the counties of the panhandle, extending through South Florida. Low component 8 scores have a slightly inconsistent spatial distribution as well, with the exception of a noticeable cluster
in the southeastern peninsula. The portion of overall variance explained by component 4 is 4.40 percent.

MedVI’s ninth component, “mental health”, was characterized by two indicators, percent seriously mentally ill adults, and percent seriously emotionally disturbed children. A positive (+) cardinality was applied. As with some of the previous components, the distribution of component 9 scores are more highly centered around the mean. Much of the map depicts counties with moderate of the mental health indicators, with higher scores scattered along the Atlantic Coast. Only 9 counties depict low scores for component 9, most notably St. Lucie County in the southeast, and Leon County along the central northern border. The portion of overall variance explained by component 4 is 3.75 percent.

The final component in MedVI, Component 10, is characterized only by the variable: percent with developmental disability. Applying this as a component name, and a positive (+) cardinality, the map for component 10 again does not show definite regionality. There are some clusters demonstrating higher component 10 scores in the central panhandle, as well as in the eastern South Florida around Manatee County. Lower scores for component 10 are more prevalent in clusters through central Florida, and at the southern tip of the peninsula. The total variance explained by this final MedVI component is 3.33 percent.
Figure 4.5: MedVI components 5 through 8
When mapped, the overall Florida MedVI depicts some distinct visual clusters of lower medical vulnerability throughout the western panhandle region and the northeast corner of the state (Figure 4.7). With the exceptions of Sumter, Osceola, and Monroe Counties, much of central and south Florida demonstrate moderate to high medical vulnerability, with especially high MedVI scores in Lake, Putnam and Manatee Counties. Liberty County also illustrates high medical vulnerability, amidst a cluster of counties with much lower MedVI scores in the central panhandle. The ten counties with the
highest and lowest medical vulnerability along with their respective MedVI score are listed in Table 4.4 below.

Figure 4.7: Overall medical vulnerability for Florida counties
Table 4.4: Counties exhibiting highest and lower medical vulnerability

<table>
<thead>
<tr>
<th>Highest Medical Vulnerability</th>
<th>Score</th>
<th>Lowest Medical Vulnerability</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liberty</td>
<td>6.71</td>
<td>Leon</td>
<td>-10.95</td>
</tr>
<tr>
<td>Lake</td>
<td>5.48</td>
<td>Okaloosa</td>
<td>-5.87</td>
</tr>
<tr>
<td>Manatee</td>
<td>5.41</td>
<td>Sumter</td>
<td>-5.39</td>
</tr>
<tr>
<td>Putnam</td>
<td>4.74</td>
<td>Franklin</td>
<td>-5.00</td>
</tr>
<tr>
<td>Indian River</td>
<td>4.50</td>
<td>Gulf</td>
<td>-4.39</td>
</tr>
<tr>
<td>Okeechobee</td>
<td>4.45</td>
<td>Calhoun</td>
<td>-4.14</td>
</tr>
<tr>
<td>Hardee</td>
<td>4.30</td>
<td>Wakulla</td>
<td>-3.99</td>
</tr>
<tr>
<td>Gilchrist</td>
<td>4.28</td>
<td>Monroe</td>
<td>-3.60</td>
</tr>
<tr>
<td>Bradford</td>
<td>4.26</td>
<td>Santa Rosa</td>
<td>-3.10</td>
</tr>
<tr>
<td>Highlands</td>
<td>3.94</td>
<td>Clay</td>
<td>-2.86</td>
</tr>
</tbody>
</table>

4.2 Outcome Measure Testing

Outcome measures are post disaster phenomena used to determine the utility of a metric in forecasting future disaster outcomes. Robust outcome measures provide the means for metric calibration and validation. To test the efficacy of FEMA Region 4’s individual assistance data as an outcome measure for SoVI and MedVI, a Spearman’s Rank correlation was used to test the strength of the relationship following the 2004 hurricane season including Hurricanes Charley, Frances, Ivan, and Jeanne. The resulting correlation coefficients ($r_s$) between the individual assistance variables, MedVI, SoVI, and their components are recorded in Table 4.5.

At best, the individual assistance data exhibited only moderate correlation with MedVI and SoVI. The highest correlating variable with the overall MedVI score was funeral assistance applicants per capita with $r_s = .437$ followed by all emergency needs applicants per capita ($r_s = .422$) and medical/dental assistance applicants per capita ($r_s = .387$). Each of these correlations is significant at the 0.01 level (2-tailed). None of the MedVI components produced a stronger correlation coefficient. Despite the general
weakness of MedVI’s associations, they still proved to be both stronger and more statistically significant than those of SoVI. SoVI score is significantly correlated with only one variable: medical and dental applicants per capita ($r_s = .282$). Interestingly, two of SoVI’s components; component 2 (elderly), and component 4 (Hispanic agriculture workers); exhibited stronger associations with the assistance variables than the overall SoVI score. The strongest of these relationships was between the elderly and all emergency needs applicants per capita ($r_s = .334$) significant at the 0.01 level (2-tailed), followed by the slightly weaker associations between elderly and funeral assistance applicants per capita ($r_s = .300$) and Hispanic agriculture workers and all emergency needs applicants per capita ($r_s = .298$), both significant at the 0.05 level.

Overall, these outcome measures did not perform well with MedVI or SoVI. As discussed throughout this thesis, however, such results are common in testing disaster outcome measures with multidimensional vulnerability constructs. Several underlying issues may have played a role in this case. First, since the PCA produced inductive results based on statewide phenomena, and because the hurricane impacts were not equally distributed in each event, the results may be somewhat skewed. Some counties may have been affected by each of the four hurricanes, while others may have only been exposed to only one or two. Though outcome measure testing typically assumes equal exposure, the dynamic nature of hazards and disasters rarely distributes impacts universally.
Another issue is the assumption that medical and social vulnerability can be adequately summarized by a single, usually unidimensional, disaster outcome. Both MedVI and SoVI and each of their compositional components represent a statistically derived composite of variables that contribute to overall vulnerability. The difficulty in discovering a disaster outcome with dimensional equivalence hampers the significance of
statistical comparison. Despite only having a moderate correlation with the individual assistance data, the robustness of the two indices is not refuted. The results simply suggest that SoVI and MedVI are not reliable proxies for post disaster assistance. Similarly, this particular assistance data do not provide an appropriate measure for index calibration or validation.

4.3 Correlation, Reliability and Regression Analyses

4.3.1 Correlations and Reliability

To determine the strength and direction of the monotonic relationships between MedVI and SoVI and their compositional components, Spearman’s Rank correlation was used. The results are found in Table 4.6. The association between the aggregate SoVI and MedVI scores, though significant at the 0.01 level (2-tailed), proved to be rather weak at $r_s = .320$. The positive sign of the correlation coefficient does indicate, however, that as SoVI increases, MedVI increases and vice versa. Upon further examination, though, several strong, significant relationships exist among the individual components. For example, the correlation between SoVI component 1, “rural working class poor”, and MedVI component 1, “disability and low health perception” is $r_s = .744$, suggesting a potential predictive capability between those components. Similarly, the correlation between component 2 from each index (i.e. “elderly” in SoVI and “chronic illness and medical dependence” in MedVI) also indicates a strong positive association at $r_s = .877$. To a slightly lesser extent, a third moderately strong association is evident between SoVI component 4, “Hispanic agriculture workers”, and MedVI component 3 “healthcare access” with $r_s = .624$. 

95
Table 4.6: Spearman's Rank correlations for MedVI, SoVI, and their components

<table>
<thead>
<tr>
<th>SoVI Score</th>
<th>SoVI Comp. 1 (Rural Poor)</th>
<th>SoVI Comp. 2 (Elderly)</th>
<th>SoVI Comp. 3 (Unemploy)</th>
<th>SoVI Comp. 4 (Hisp. Ag)</th>
<th>SoVI Comp. 5 (Service)</th>
<th>SoVI Comp. 6 (Trans. and infras.)</th>
<th>SoVI Comp. 7 (Native Amer.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MedVI Score</td>
<td>.320**</td>
<td>.184</td>
<td>.382**</td>
<td>.172</td>
<td>.235</td>
<td>-.128</td>
<td>.076</td>
</tr>
<tr>
<td>MedVI Comp. 1 (Disability)</td>
<td>.545**</td>
<td>.744**</td>
<td>.222</td>
<td>.394**</td>
<td>-.248*</td>
<td>.036</td>
<td>.069</td>
</tr>
<tr>
<td>MedVI Comp. 2 (Chronic Illness)</td>
<td>.209</td>
<td>-.042</td>
<td>.877**</td>
<td>-.223</td>
<td>.078</td>
<td>.027</td>
<td>-.060</td>
</tr>
<tr>
<td>MedVI Comp. 3 (Healthcare Access)</td>
<td>.203</td>
<td>.051</td>
<td>.201</td>
<td>.062</td>
<td>.624**</td>
<td>.081</td>
<td>-.174</td>
</tr>
<tr>
<td>MedVI Comp. 4 (Dialysis)</td>
<td>.113</td>
<td>.056</td>
<td>-.148</td>
<td>.366**</td>
<td>-.052</td>
<td>.065</td>
<td>.073</td>
</tr>
<tr>
<td>MedVI Comp. 5 (Domestic Violence)</td>
<td>-.184</td>
<td>-.359**</td>
<td>.084</td>
<td>.317**</td>
<td>-.009</td>
<td>-.244*</td>
<td>.106</td>
</tr>
<tr>
<td>MedVI Comp. 6 (Spec. Needs Institutions)</td>
<td>.021</td>
<td>.015</td>
<td>.124</td>
<td>.230</td>
<td>.089</td>
<td>.073</td>
<td>-.152</td>
</tr>
<tr>
<td>MedVI Comp. 7 (Alcohol)</td>
<td>.015</td>
<td>-.107</td>
<td>.107</td>
<td>-.184</td>
<td>.343**</td>
<td>.091</td>
<td>.024</td>
</tr>
<tr>
<td>MedVI Comp. 8 (Drugs)</td>
<td>.001</td>
<td>.192</td>
<td>-.068</td>
<td>-.290*</td>
<td>.062</td>
<td>-.360**</td>
<td>.238</td>
</tr>
<tr>
<td>MedVI Comp. 9 (Mental Health)</td>
<td>.035</td>
<td>-.001</td>
<td>-.100</td>
<td>-.229</td>
<td>.068</td>
<td>-.257*</td>
<td>.322**</td>
</tr>
<tr>
<td>MedVI Comp. 10 (Develop. Disability)</td>
<td>-.126</td>
<td>-.057</td>
<td>.069</td>
<td>.188</td>
<td>-.091</td>
<td>.020</td>
<td>-.138</td>
</tr>
</tbody>
</table>

* correlation significant at the 0.05 level (2-tailed)  
** correlation significant at the 0.01 level (2-tailed)

As one may expect, these significant relationships may also be realized in the examination of the mapped components. Though the associations signify some parity between sections of the socially and medically vulnerable, their correlation does not adequately speak for the overall predictability from one aggregate index to the other. To assume such would discount the phenomena and variance explained by the remaining dimensions in each index. To gain further insight on the influence of these components on the overall correlation between SoVI and MedVI scores, partial Spearman’s Rank
correlations were calculated using SAS. By holding individual, or sets of the components constant, their association within the indices is removed from the correlation. A summary of the partial correlations, noting the variables held constant, and the partial correlation coefficient is found in Table 4.7.

Table 4.7: Partial correlation summary

<table>
<thead>
<tr>
<th>Variables Held Constant</th>
<th>Partial Correlation (SoVI and MedVI score)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SoVI Component 1</td>
<td>.271*</td>
</tr>
<tr>
<td>MedVI Component 1</td>
<td>.193</td>
</tr>
<tr>
<td>SoVI Component 1 and MedVI Component 1</td>
<td>.198</td>
</tr>
<tr>
<td>SoVI Component 2</td>
<td>.206</td>
</tr>
<tr>
<td>MedVI Component 2</td>
<td>.273*</td>
</tr>
<tr>
<td>SoVI Component 2 and MedVI Component 2</td>
<td>.204</td>
</tr>
<tr>
<td>SoVI Component 4</td>
<td>.268*</td>
</tr>
<tr>
<td>MedVI Component 3</td>
<td>.272*</td>
</tr>
<tr>
<td>SoVI Component 4 and MedVI Component 3</td>
<td>.273*</td>
</tr>
<tr>
<td>SoVI Components 1, 2, 4</td>
<td>.059</td>
</tr>
<tr>
<td>MedVI Component 1, 2, 3</td>
<td>.048</td>
</tr>
<tr>
<td>SoVI Components 1, 2, 4; and MedVI Components 1, 2, 3</td>
<td>-.028</td>
</tr>
</tbody>
</table>

* correlation significant at the 0.05 level (2-tailed)

As expected, both the strength of the correlation coefficient, and the significance of the association between the SoVI and MedVI score is reduced in each partial correlation, most notably after holding constant the individual variables of MedVI component 1 (rₛ = .193, Sig = 0.120), and SoVI component 2 (rₛ = .204, Sig = 0.100). The collective influence of the correlated variables is remarkably demonstrated in holding the entire group constant (i.e. SoVI components 1, 2, 4 and MedVI components 1, 2, 3).
yielding a weak negative relationship that is not statistically significant (r_s = -.028, Sig = 0.832).

Finally, as a test of reliability, Cronbach’s coefficient alpha was used to measure the internal consistency between MedVI and SoVI. Results were considered significant at α > 0.700. First, the aggregate index scores were compared yielding the result α = .502. Next, an all-inclusive comparison was run using all 17 components from MedVI and SoVI, resulting in α = .268. These results agree with those found following the correlation analysis. While some associations exist between certain components of MedVI and SoVI the overall aggregate scores and complete combination of components are not internally consistent. From these results, it is deduced that SoVI does not reliably demonstrate MedVI, or vice versa. In other words, social vulnerability is not the same as medical vulnerability, and one cannot be used to predict the other.

4.3.2 Regression Analyses

While the correlation analyses were utilized to measure the strength of the monotonic relationship between SoVI and MedVI, the regression analysis refers to a more complete process where the predictive relationship between the indices is assessed. First, using standardized MedVI score as the dependent variable and standardized SoVI score as the independent variable, a simple linear regression was carried out. Results are reported in Table 4.8.
As expected following the correlation and reliability analyses, SoVI score performs poorly as a predictor of MedVI score. Several important inferences can be made from the regression output, however. First, as indicated by the F-test, the results are statistically significant. Second, the Beta coefficient suggests that for every one unit increase in MedVI score, SoVI increases by 0.342. Conversely, the adjusted $R^2$ value for the global regression is only .103, indicating low explanatory power and leaving nearly 90 percent of the variance in the MedVI score to be explained by factors other than SoVI score.

As a subsequent test to further explore the unidentified variation within the dataset, a multiple linear regression was used, substituting the 7 SoVI component scores for the aggregate SoVI score. Since multicollinearity does not exist among the orthogonal components, each was used as an independent variable in the multiple regression. Results for the multiple linear regression appear in Table 4.9.

![Table 4.9: Multiple linear regression results, MedVI as dependent variable](image)
Despite a small improvement in the $R^2$ (i.e. from 0.103 to 0.194), the results of the model are consistent with the preceding analyses, demonstrating weak predictive capability between the SoVI components and MedVI score. Nearly 81 percent of the variance in MedVI still remains unexplained. Of the seven SoVI components, only two are statistically significant: component 2, an indicator of elderly populations, with $\beta = .349$, Sig. = .002; and component 4, an indicator of Hispanic agriculture workers, with $\beta = .243$, Sig. = .032. Though these associations are noteworthy, the inability to produce a stronger $R^2$ suggests that MedVI captures a significantly different aspect of population characteristics than SoVI. Technical details for both regression analyses including residual histograms and partial regression plots are provided in Appendix C.

4.4 Spatial Analysis

To spatially represent the explanatory power of SoVI in determining the distribution of medical vulnerability, two spatial techniques were used. The first was simple bivariate mapping, whereby the two phenomena are mapped simultaneously using statistical classification. Referring to Chapter 3, three classes derived from standard deviation were used to categorize SoVI and MedVI scores (i.e. Class 1= values < -0.500 standard deviations; Class 2= values between -0.500 and 0.500 standard deviations; Class 3= values > 0.500 standard deviations). Class 1 represents low index scores, class 2 indicates medium or middle index scores, and class 3 designates high scores. Using this classification scheme, the resulting map shown in figure 4.8 depicts the combination of classified SoVI and MedVI scores.
As indicated by the class combination (i.e. SoVI classification, MedVI classification) the counties are color coded based on dominant type of vulnerability and the intensity (i.e. low, medium, high). Red hues mark the counties predominantly affected by social vulnerability, while blue hues denote areas where medical vulnerability is more prevalent. Darker colors indicate a higher classified index score. Additionally, areas where the classified SoVI and MedVI scores are congruent are represented by three possible combinations: low-low (white), medium-medium (grey), and high-high (dark maroon). As such, the bivariate map not only allows the two phenomena to be mapped simultaneously, but also to examine the shift in classification from SoVI score to MedVI score.

Examining the map, less than half of the counties in Florida (41.7%) exhibited the same mapped category for SoVI and MedVI scores, with 32.8% exhibiting higher MedVI classification and 25.4% indicating higher SoVI classification. Only 3 counties: Manatee, Brevard, and Madison change from the lowest category in SoVI to the highest in MedVI (4.5%). Conversely, 4 counties, Sumter, Hamilton, Calhoun, and Gulf shifted in the opposite direction, from highest SoVI to lowest MedVI (6.0%). The distribution of mapped combinations shows some general regionality for higher SoVI classification (i.e. red) along the western panhandle, with some small clusters in central Florida and at the Southern tip on the peninsula. Areas with higher classified MedVI score (i.e. blue) are prevalent along the northern border of the state at the eastern panhandle, in a large cluster through central Florida, and through the Gulf coast counties in South Florida. A distinct cluster of high SoVI and high MedVI scores is evident among five of South Florida’s interior counties: Hardee, Highland, DeSoto, Okeechobee, and Glades. This cluster
represents a strong confluence of socially and medically vulnerable populations for the aforementioned counties. This assumes that vulnerability in this area is not driven by a single factor, but a combination of medical and social indicators including mental health, healthcare access, chronic illness, socioeconomic status, Hispanic agriculture workers, the elderly, and concentrated Native American populations. Conversely, counties exhibiting low SoVI and MedVI scores are located in a cluster in the northeast corner of the state, including Nassau, Duval, St. Johns, Clay and Alachua Counties.

Figure 4.8: SoVI-MedVI bivariate map
While this method generally indicates places where SoVI and MedVI diverge, it does not adequately represent the spatiality of SoVI’s explanatory power for MedVI. To visualize this phenomena, the standardized residuals from the simple linear regression analysis were mapped. Based on the 95 percent confidence interval of the regression line, residuals where classified as either 1) below the 95 percent confidence interval (under-prediction), 2) within the 95 percent confidence interval (adequate prediction), or 3) above the 95 percent confidence interval (over-prediction). Figure 4.9 represents the scatter plot of standardized MedVI and SoVI score, depicting the regression line and the 95 percent confidence interval used to classify the residuals. The results show that 19 counties (28.4%) exhibited under-prediction, 22 counties (32.8%) displayed over-prediction, and 26 counties (38.8%) showed adequate prediction.

![Figure 4.9: Scatter plot (independent: SoVI score, dependent: MedVI score) with regression line and 95% confidence interval](image-url)
The spatial distribution of the residuals is shown in Figure 4.10 below. Areas colored in red depict over-prediction (i.e. large positive residuals), while blue shows under-prediction (i.e. large negative residuals). Finally, counties colored grey indicate the smallest residual values (i.e. areas where predicted values of MedVI score were nearest the truth, inside the 95% confidence interval).

In general, over-prediction of the MedVI score was prevalent between Central and South Florida with distinct clusters throughout, as well as a few extremes in northern Florida and the panhandle (i.e. Liberty, Jefferson, and Madison Counties). Areas of under-prediction were clustered in the western and central panhandle, as well as a few counties encroaching into South Florida (i.e. Sumter, Osceola, St. Lucie, and Monroe Counties). Areas depicting adequate prediction, though visibly clustered, were somewhat less regionalized, with patches of counties along the south side of Lake Okeechobee, in western South Florida, in northeast portion of the state, and in the central panhandle.
Despite the presence of clusters, the spatial distribution of the residuals did not appear to be driven by an obvious demographic boundary, such as the urban-rural divide. In an attempt to explain the spatial disparity of SoVI’s explanatory power, a subsequent Mann-Whitney U Test was performed to test for differences in median between the over- and under-predicted counties for a small set of demographic variables including: percent rich, percent in poverty; per capita income; percent over age 65; median age; percent black; percent Hispanic; percent recent migrants; percent over age 25 without a diploma;
and percent living in urban areas. Test variables were chosen based on *a priori* knowledge of prevalent demographic phenomena contributing to the social vulnerability for the study area, combined with empirical suggestions culled from the SoVI PCA. The Mann-Whitney U test is the nonparametric alternative to the t-test for independent groups. It operates by converting the values of the continuous variables to ranks, and evaluates for significant difference (Pallant 2007). Since some of variables are not normally distributed, this method is more amenable for this application than the standard t-test. Results were considered significant at \( p < 0.050 \) (i.e. significant difference in medians). Table 4.10 below summarizes the findings of the Mann-Whitney U test.

Only three variables were found to have significantly different medians for the two groups, indicating potential demographic drivers for the spatial disparity of SoVI’s capability in predicting MedVI: percent over age 65 (\( Z = -3.007, p = 0.003 \)), median age (\( Z = -2.105, p = 0.035 \)), and percent Hispanic population (\( Z = -2.196, p = 0.028 \)). Interestingly, these variables were also identified as major correlates to MedVI components in the correlation and regression analyses. For each of the three variables, the mean rank of the over-predicted group is significantly higher, driving SoVI’s over-prediction of the MedVI score.
Table 4.10: Results of Mann-Whitney U test

<table>
<thead>
<tr>
<th></th>
<th>Prediction</th>
<th>N</th>
<th>Mean Rank</th>
<th>Sum of Ranks</th>
<th>Mann-Whitney U</th>
<th>Wilcoxon W</th>
<th>Z</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>% rich</td>
<td>Under</td>
<td>19</td>
<td>20.74</td>
<td>394.00</td>
<td>204</td>
<td>394</td>
<td>-0.131</td>
<td>0.896</td>
</tr>
<tr>
<td></td>
<td>Over</td>
<td>22</td>
<td>21.23</td>
<td>467.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% in povty</td>
<td>Under</td>
<td>19</td>
<td>20.53</td>
<td>390.00</td>
<td>200</td>
<td>390</td>
<td>-0.235</td>
<td>0.814</td>
</tr>
<tr>
<td></td>
<td>Over</td>
<td>22</td>
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<td>471.00</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>percap. income</td>
<td>Under</td>
<td>19</td>
<td>20.00</td>
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<td>190</td>
<td>380</td>
<td>-0.497</td>
<td>0.619</td>
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<tr>
<td></td>
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<td>22</td>
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<td>481.00</td>
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<td></td>
</tr>
<tr>
<td>% pop. over 65</td>
<td>Under</td>
<td>19</td>
<td>14.95</td>
<td>284.00</td>
<td>94</td>
<td>284</td>
<td>-3.007</td>
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</tr>
<tr>
<td></td>
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<tr>
<td>median age</td>
<td>Under</td>
<td>19</td>
<td>16.76</td>
<td>318.50</td>
<td>128.5</td>
<td>318.5</td>
<td>-2.105</td>
<td>0.035</td>
</tr>
<tr>
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<td>542.50</td>
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<tr>
<td>% black</td>
<td>Under</td>
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<td>415.00</td>
<td>193</td>
<td>446</td>
<td>-0.418</td>
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<tr>
<td></td>
<td>Over</td>
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<td>446.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Hispanic</td>
<td>Under</td>
<td>19</td>
<td>16.58</td>
<td>315.00</td>
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<td>345</td>
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</tr>
<tr>
<td></td>
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<td>546.00</td>
<td></td>
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<td></td>
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<tr>
<td>% recent migrants</td>
<td>Under</td>
<td>19</td>
<td>20.37</td>
<td>387.00</td>
<td>197</td>
<td>387</td>
<td>-0.314</td>
<td>0.754</td>
</tr>
<tr>
<td></td>
<td>Over</td>
<td>22</td>
<td>21.55</td>
<td>474.00</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>% over 25, no diploma</td>
<td>Under</td>
<td>19</td>
<td>19.95</td>
<td>379.00</td>
<td>189</td>
<td>379</td>
<td>-0.523</td>
<td>0.601</td>
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<tr>
<td></td>
<td>Over</td>
<td>22</td>
<td>21.91</td>
<td>482.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% living in urban area</td>
<td>Under</td>
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<td>19.89</td>
<td>378.00</td>
<td>188</td>
<td>378</td>
<td>-0.550</td>
<td>0.582</td>
</tr>
<tr>
<td></td>
<td>Over</td>
<td>22</td>
<td>21.95</td>
<td>483.00</td>
<td></td>
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<td></td>
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4.5 Summary

The principal component analyses for social and medical vulnerability effectively produced two statistically optimized sets of composite components, one for each phenomenon. Following descriptive analysis, the components were aggregated, producing two independent indices: SoVI and MedVI. FEMA Region 4’s individual emergency assistance application data were tested as a possible outcome measure for SoVI and MedVI yielding marginal and inconclusive results for both. The spatial and
statistical analyses of the social and medical vulnerabilities captured by the two indices produced several significant findings. The correlation analysis illustrated some interesting relationships between the indices and their components, most notably a weak monotonic relationship between the two overall index scores. Despite the weak overall relationship, some strong associations between the individual components were found. The influence of these associations was tested using partial correlation. Two linear regressions were used to gauge the explanatory power of the SoVI score and the SoVI components upon the overall aggregate MedVI score. Although the results were statistically significant, the low adjusted R² indicates that much of the variance in MedVI was not captured by either model. To capture the spatiality of the two indices and examined the overlap in spatial distributions, bivariate and residual mapping techniques were employed. Results showed only marginal spatial parity, confirming the concept that SoVI and MedVI capture separate sections of the vulnerable population.
Chapter 5: Conclusions and Directions for Future Research

Anticipating communities’ medical needs during disasters has long been a daunting venture. Following Hurricane Katrina, a wealth of literature surfaced citing the need for community health surveillance for improving medical emergency preparedness. Though quantitative demographic techniques have frequently been applied in measuring community social disparity, few studies apply these methods for geographic comparisons of public health data. Some emerging research suggests that social disparity is inherently linked with health risk factors; however, few studies have tested the social proxies of health in the context of disaster medicine. The overview of previous literature presented in this thesis examines themes in hazards geography, general epidemiology, and disaster medicine in an effort to construct a metric indicative of baseline community medical needs, and healthcare access. Subsequently, the assumption that social vulnerability is a useful proxy for community health was tested statistically and spatially.

The research questions posed in this thesis were designed to provide insight into the relationship between metrics of social and medical vulnerability in a context useful for medical emergency managers. Such insight is meant to inspire incremental advancement in medical disaster preparedness, as well as instigate further research in vulnerability science. In this chapter, conclusions to the research questions are offered, followed by a discussion of research caveats, and suggestions for future research.
5.1 Addressing the Research Questions

The questions asked in this thesis were formulated to address two lingering themes in the epidemiology and disasters literature: the quantification of baseline community health, and the relationships between community social vulnerability and public health. The first research question sought to alleviate the former of the aforementioned issues by constructing an inductive place-based metric for quantifying community medical needs and healthcare access. The latter theme is addressed by the second and third research questions, using Cutter et al.’s (2003) SoVI as the social counterpart to the medical vulnerability index for comparative analyses. The following sections summarize the methods employed in addressing each research question, and briefly reiterate the results.

5.1.1 Research Question 1: Indicators of Medical Vulnerability

To determine the best characterization of medical vulnerability, this thesis first turned to the literature. While the general epidemiology literature offered some comprehensive theoretical heuristics for choosing pertinent indicators, a wealth of empirical post-disaster case studies provided contextual suggestions for emergency medical needs. Additional suggestions were then culled using professional opinion from personnel at the Florida Dept. of Health. Using these sources, a deductive set of target variables was entered into a PCA. The efficacy of the PCA in this analysis was twofold. First, the results of PCA are place sensitive, and thus the composite components inductively produced are specific to the geographic area. Second, the PCA reduced the
dimensionality of the raw variables based on the explanatory power (i.e. explained variance) for the entire dataset. As a result, only the most statistically significant variables remained following the analysis.

Using these methods, the initial set of 36 raw variables representing medical needs and healthcare access was reduced to 10 composite principal components, explaining 74.87 percent of the overall variance in the dataset. Using the significant component loadings among the dominant variables in each component for descriptive purposes, the most statistically important components of medical vulnerability were found to be:

1. Disability and Low Health Perception
2. Chronic Illness and Medical Dependence
3. Healthcare Access
4. Dialysis Dependents
5. Domestic Violence Propensity
6. Special Needs Institutions
7. Alcohol Abuse
8. Drug Abuse
9. Mental Health
10. Developmental Disability

The component scores were summed to produce a single aggregate score for overall community medical vulnerability (i.e. MedVI score). FEMA’s individual disaster assistance data for Florida’s 2004 hurricane season was statistically compared to the MedVI (and subsequently, SoVI) for outcome measure testing. This was done in an attempt to discover a robust measure by which MedVI and/or SoVI could by calibrated and verified. Spearman’s Rank correlation proved only moderate association between the indices, their components, and the assistance data. Despite the marginal correlation with the individual assistance data, the vigor of the two indices is not discounted. The results
simply suggest that SoVI and MedVI are not reliable proxies for post disaster assistance. Similarly, these particular assistance data do not provide an appropriate measure for index calibration or validation.

5.1.2 Research Question 2: Statistical Overlap Social and Medical Vulnerability

Throughout the literature, the ties between social status, personal economic capital, gender, race, and age, and public health are commonly cited. Post-disaster, however, empirical determinants of medical needs are retroactively discussed more in terms of common baseline health conditions. Chronic illnesses, disabilities, and pre-existing mental health issues are prominently cited as conditions for which emergency medical support units are often unprepared. To determine the strength of the relationships between medical and social vulnerability, this thesis adopted Cutter et al.’s (2003) SoVI. Empirically derived, SoVI is perhaps the most often cited and widely used metric for social vulnerability throughout the hazards research, and provided amenable parity for comparison with MedVI.

A battery of tests were applied to determine the statistical overlap between SoVI and MedVI and their compositional components including correlation, partial correlation, reliability testing, and regression. The results of the correlation analysis revealed a weak but statistically significant monotonic relationship between MedVI and SoVI. More notably, the correlations revealed strong positive associations between three pairs of SoVI and MedVI components: 1) The rural working class poor, and disability and low health perception; 2) Elderly, and chronic illness and medical dependence; and 3) Hispanic agriculture workers and healthcare access. As the results of the partial
correlations indicate, these associations account for the much of the influence between
the overall correlation of SoVI and MedVI scores. Two reliability tests of internal
consistency were performed based on Cronbach’s alpha. The first test used only two
variables, SoVI and MedVI score, to determine if there was a latent construct between
these two indices. A second test included all of the components from SoVI and MedVI,
17 in total. Both tests showed marginal internal consistency between the metrics. Such
findings were echoed in the regression analyses. Using SoVI score as the independent
variable in simple linear regression with MedVI score left nearly 90 percent of the
variance in MedVI unexplained. Though this value improved slightly to 81 percent after
substituting the SoVI components in multiple regression, the predictive power of social
vulnerability was too low to warrant itself as a robust and reliable indicator of medical
vulnerability. Despite the model’s poor performance, two statistically significant linear
relationships between the components of SoVI and the MedVI score did exist. Elderly
populations exhibited the strongest association ($\beta = 0.349$), while Hispanic agriculture
workers also had notable influence ($\beta = 0.243$). Both of these indicators appeared in the
preceding correlation as well. Comprehensively, the statistical analysis suggests that
MedVI and SoVI are indeed different constructs, with little overlap.

5.1.3 Research Question 3: Spatial Distributions of Medical Vulnerability

The final research question sought to determine if the spatial patterns of SoVI and
MedVI exhibited any similarity in their distribution. Bivariate mapping of the SoVI and
MedVI score revealed that only 41.7 percent of counties remained in the same mapped
category for the two indices. Similarly, in mapping the standardized regression residuals
from the simple linear regression, only 38.8 percent of Florida’s counties exhibited adequate predictions of the MedVI score. The results of a Mann-Whitney U tests suggest that the spatial disparity in SoVI’s explanatory power is potentially driven by age (i.e. the elderly) and Hispanic ethnicity. Generally, the spatiality of SoVI and MedVI differ enough to significantly limit the efficacy of one index’s spatial pattern to adequately portray the other; a final confirmation that SoVI and MedVI are independent constructs, measuring different vulnerable subpopulations.

5.2 Limitations and Future Research

This research does not come without its limitations. As discussed briefly in this thesis, the availability of public health data played a major role, not only in sources used, but also in the geographic scale of the analysis. Due to data confidentiality, most of the variables required for analysis were not available at finer levels of geography than the county. Ideally, place based vulnerability analyses should be performed at the census tract or block group level to provide the geographic specificity needed for intervention and emergency preparedness at the community level. For this reason, future research should attempt to downscale this analysis. It is important as well to note that the geographic sensitivity of PCA limits the results of this analysis to Florida alone. As a result, the conclusions drawn in this thesis should not be applied universally. Although Florida provides an interesting and certainly viable case study, including more states in the analysis would provide a more complete understanding of social vulnerability’s abilities as an indicator of medical needs and healthcare access. Temporal data
availability was another issue. In some cases, indicators were only available for a single year, creating a temporal lag in the variables of up to nine years. Future research may seek to alleviate this problem, including only data sources updated within a small span of years. Inevitably, however, such exclusion may seriously reduce the dataset. The outcome measures tested in this research provided only marginal association with SoVI and MedVI. Though this does not refute the study’s findings, future research should continue to unearth potential measures for index calibration and validation. Another lingering issue in this research is data quality. For many of the estimated variables, the margin of error or sample size was simply not given. Future endeavors may include uncertainty and sensitivity analyses to confirm the robustness of the MedVI metric. Finally, it is important to note that the particular variant of SoVI used for analysis in this research differs slightly from Cutter et al.’s (2003) original SoVI construction, and some subsequent SoVI applications (see Borden et al. 2007; Cutter and Finch 2008; Schmidtlein 2008). Though the deviations from the original published method were minimal, this thesis tested only one variant of SoVI. Future research may take into account the various nuances of each variant in testing the spatial and statistical overlap between social and medical vulnerabilities. Such an analysis might also provide insight on the sensitivity of the results to small changes in index construction.

Despite the undesirability of these limitations, they do not prevent this research from achieving its goal of assessing the relationships between medical and social vulnerabilities in Florida. This thesis is exploratory in nature, and as such, does not strive to reach a single and absolute conclusion, but rather to stimulate academic discussion and continued research into disaster vulnerability. The completion of this thesis is marked by
three major contributions upon which future research can build. First, borrowing methods from vulnerability science and hazards research, an index of medical vulnerability was constructed. MedVI provides a mechanism for studying baseline public health, which can be used in the anticipation of needs and the allocation of resources by medical emergency managers during disasters. Second, in statistically comparing medical and social vulnerabilities, the results of this research suggest that a considerable portion of the medically vulnerable population is not captured by social vulnerability alone. Finally, two socially vulnerable subpopulations were discovered to influence medical vulnerability in Florida: the elderly, and Hispanic agriculture workers. Future works might seek to qualitatively explain these relationships in building a better understanding of the relationships between socially and medically vulnerable populations.

The contributions of this thesis demonstrate the impetus for improving public health emergency preparedness and medical emergency management. The construction of MedVI provides emergency managers with a compulsory tool for pre-hazard baseline health surveillance, including the medical needs of individuals, and the healthcare access of communities. The place-based nature of the Medical Vulnerability Index allows for the relative comparison of vulnerability across Florida counties. As such, MedVI can help emergency managers pinpoint communities with disproportionate medical vulnerability, and provide decision support for community intervention strategies including the allocation of public health resources, and community education programs in disaster-prone areas. Additionally, through a battery of spatial and statistical analyses, this research strongly suggests that the overlap between the indicators of social
vulnerability and medical vulnerability is only marginal. As a result, social vulnerability measures such as the Social Vulnerability Index cannot provide an adequate surrogate for baseline community health surveillance, and should not be substituted in medical emergency management plans. While this thesis found that some associations did exist between certain components of social and medical vulnerability in Florida, the qualitative nature of these relationships is not realized without supplementary observation at the local scale. Combining the experience and expertise of the emergency management community with this empirical analysis creates an opportunity to adapt emergency preparedness plans to ameliorate public health access and acknowledge medical needs before the next disaster occurs.
References


Department of Health and Human Services (2007). Medical Surge Capacity and Capability: A Management System for Integrating Medical and Health Resources During Large-Scale Emergencies, CNA Corp.


## Appendix A: Descriptive Statistics

### Table A1: Descriptive statistics for SoVI Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Variance</th>
<th>Kurtosis</th>
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Table A2: Descriptive statistics for MedVI variables

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<th>Variance</th>
<th>Kurtosis</th>
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Appendix B: Hospital Bed Access Modeling

Figure B1: Data processing flow diagram for hospital bed access per capita measure

The following code provides a sample of the Python scripting used in the hospital bed access analysis:

```python
import arcgisscripting
import os
gp = arcgisscripting.create(9.3)
gp.workspace = "C:\\...\\
out_workspace = "C:\\...\\

# Get a list of feature classes in the workspace.
try:
    # Create search cursor
    fc = "C:/.../
    rows = gp.SearchCursor(fc)
    row = rows.Next()
i = 0
while row:
    # Create the geometry object
```
output2 = out_workspace + os.sep + 'raster' + str(i)
InField = "Int_Beds"
InCellSize = "30"
rowID = row.OBJECTID
beds = str(row.Int_Beds)
gp.AddMessage(str(i))

# Make a layer from the feature class
gp.MakeFeatureLayer(fc, "lyr", "OBJECTID = " + str(rowID) + ")")
gp.AddMessage('Layer Created Successfully')
result = gp.GetCount_management("lyr")
count = int(result.GetOutput(0))
gp.AddMessage(str(count))
gp.AddMessage(output2)

# Process: FeatureToRaster_conversion
gp.FeatureToRaster_conversion("lyr", "Int_Beds", output2, "30")
reclassstr = beds + ' ' + beds + ';NODATA 0'
gp.AddMessage(str(reclassstr))
csfiedfc = out_workspace + os.sep + 'csfied' + str(i)
gp.AddMessage(str(csfiedfc))
gp.Reclassify_sa(output2, "VALUE", reclassstr, csfiedfc, "DATA")
gp.AddMessage('Reclassification Successful')
gp.delete_management("lyr")
gp.AddMessage("Next Object")
i = i + 1
row = rows.Next()

except:
# If an error occurred when running the tool, print out the error message.
    print gp.GetMessages()
Appendix C: Regression Diagnostics

Figure C1: Histogram of standardized regression residuals for simple linear regression (Independent variable: SoVI score)
Figure C2: Scatter plot of predicted values and residuals for simple linear regression (Independent variable: SoVI score)

Figure C3: Histogram of standardized regression residuals for multiple linear regression (Independent variables: SoVI components)
Figure C4: Scatter plot of predicted values and residuals for multiple linear regression (Independent variables: SoVI components)

Figure C5: Partial regression plot of MedVI Score and SoVI Comp. 1
Figure C6: Partial regression plot of MedVI Score and SoVI Comp. 2

Figure C7: Partial regression plot of MedVI Score and SoVI Comp. 3
Figure C8: Partial regression plot of MedVI Score and SoVI Comp. 4

Figure C9: Partial regression plot of MedVI Score and SoVI Comp. 5
Figure C10: Partial regression plot of MedVI Score and SoVI Comp. 6

Figure C11: Partial regression plot of MedVI Score and SoVI Comp. 7