MEASURING THE MEASURE: A MULTI-DIMENSIONAL SCALE MODEL TO MEASURE COMMUNITY DISASTER RESILIENCE IN THE U.S. GULF COAST REGION

A Dissertation

by

JOSEPH STEPHEN MAYUNGA

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2009

Major Subject: Urban and Regional Sciences

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ABSTRACT

Measuring the Measure: A Multi-dimensional Scale Model to Measure Community Disaster Resilience in the U.S. Gulf Coast Region. (May 2009)

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Over the past decades, coastal areas in the United States have experienced exponential increases in economic losses due to flooding, hurricanes, and tropical storms. This in part is due to increasing concentrations of human populations in high-risk coastal areas. Although significant progress has been made in developing mitigation measures to reduce losses in these areas, economic losses have continued to mount. The increase in losses has led to a significant change in hazard research by putting more emphasis on disaster resilience. While there has been a growing interest in the concept of disaster resilience, to date there is little or no empirical research that has focused on systematically measuring this concept. Therefore, the main objective of this dissertation was to develop a theoretically-driven index that can be used to measure disaster resilience in coastal communities.

This dissertation argues that a comprehensive measure of disaster resilience should address issues of relevance to all phases of disaster: mitigation, preparedness, response, and recovery. Furthermore, a fruitful approach to measure disaster resilience is to assess various forms of capital: social, economic, physical, and human. These capitals are important resources for communities to successfully perform disaster phases' activities. A conceptual model based on disaster phases' activities and community capitals was developed in which indicators for measuring disaster resilience were identified. The model was utilized by first identifying activities relevant to each disaster phase and then specifically identifying indicators from each form of capital that might be important for carrying out those activities. The selected indicators were aggregated and a composite index score was calculated using average method which is based on equal weighting.

The reliability and validity of the index were assessed using Cronbach's alpha, regression analysis, and GIS techniques. The results provided convincing empirical evidence that the index is a valid and reliable measure. The application of the measure indicated that disaster resilience is an important predictor of flood property damage and flood related deaths in the U.S. Gulf coast region. Also, the findings indicated that Florida counties are the most resilient whereas counties along the Texas-Mexico border region are the least resilient.

DEDICATION

I dedicate this dissertation to my late father Mzee Stephen Busiga Maziku and my late sister Helen Stephen Busiga.

ACKNOWLEDGEMENTS

In many ways, many people helped me to successfully accomplish this piece of work. First of all, I would like to thank my dissertation committee chair, Dr. Walter Gillis Peacock, for guiding me throughout the time of conducting this exploratory research. This research would not have been completed without his extraordinary support and encouragement. I would also like to thank my committee members, Dr. Michael K. Lindell, Dr. Carla S. Prater, and Dr. Anthony M. Filippi, for their assistance and valuable inputs to this work. Special thanks also go to Dr. Samuel D. Brody for his financial support through an assistantship when my Fulbright scholarship came to an end.

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CHAPTER I

INTRODUCTION

1.1. Background

Coastal areas in the United States and throughout the world are increasingly becoming more vulnerable to a wide range of natural hazards including hurricanes, tropical storms, tsunamis, floods, and other coastal hazards. The increase in vulnerability is partly due to the rapid population growth in high-risk coastal areas, unprecedented urban development, the prospects of global climate change, and sea-level rise (Adger, Hughes, Folke, Carpenter, & Rockstrom, 2005; Ahmed & White, 2006; Hanson & Robert, 2005). Studies have shown that the increase in human habitation and structural development along the coastlines contribute to the destruction of coastal resources such as wetlands that protect coastal areas from hazards e.g., hurricanes and tropical storms. In the United States, it is estimated that 150 million people (more than 50% of the national population) live in the coastal counties (Crossett, Culliton, Wiley, & Goodspeed, 2004). The population of the United States' coastal counties is projected to increase by more than 12 million people by the year 2025 (Crossett et al., 2004). This indicates that more people will potentially be at risk.

According to the Intergovernmental Panel on Climate Change (IPCC), the global sea-level has already risen about 10-25 cm over the past 100 years (IPCC, 2001). The IPCC now projects that sea-level will rise by 15-95 cm over the next century as a result of climate change (IPCC, 2001). Sea-level rise will increase flooding associated with storm surges even if the intensity or frequency of extreme weather events does not increase as many models currently suggest (US Climate Forum, 1997). A potential consequence of a higher mean sea-level is that

This dissertation follows the style of *Journal of the American Planning Association.*

coastal storms will likely be more destructive to people and infrastructure because storm surges will reach further inland and protective barrier islands may be destroyed (National Assessment Synthesis Team [NAST], 2001).

Tropical storms such as hurricane Katrina (2005) that devastated the entire Gulf coast of the United States are reminders that coastal communities are potentially becoming more and more vulnerable to natural hazards than in the past. Hurricane Katrina was recorded as one of the deadliest and costliest hurricanes in the history of the United States, killing more than 1,300 people (FEMA, 2006), leaving hundreds of thousands of people homeless and causing more than $250 billion (U.S.D.) in property damage (Birch & Wachter, 2006). The great body of hazard literature suggests that, in general, while hurricane related deaths have significantly decreased over the past two decades, property damage (even after taking into account the inflation factor) has been increasing (Blake, Rappaport, & Landsea, 2007; Gladwin, Lazo, Morrow, Peacock, & Willoughby, 2007). Figures 1.1 and 1.2 illustrate the trends of property damage and deaths due to hurricane hazards in the United States, respectively.

The graph in Figure 1.1 indicates that the trends in property damage have significantly increased in the recent years. The hazard literature points to socioeconomic factors such as human population growth, rapid urbanization, and increasing concentration of property in high-risk areas as contributing factors for increasing losses from hurricanes and tropical storms (Gladwin et al., 2007; Mileti, 1999; Smith, 2004). Conversely, the graph in Figure 1.2 suggests that the trends for hurricane related deaths has been consistent with the empirical observation that, because of improved forecasting and warning systems, deaths have been decreasing over the past decades. However, in 2004 and 2005 the trend started taking an upward turn; suggesting a potential for more loss of life in the future if protective measures are not taken.

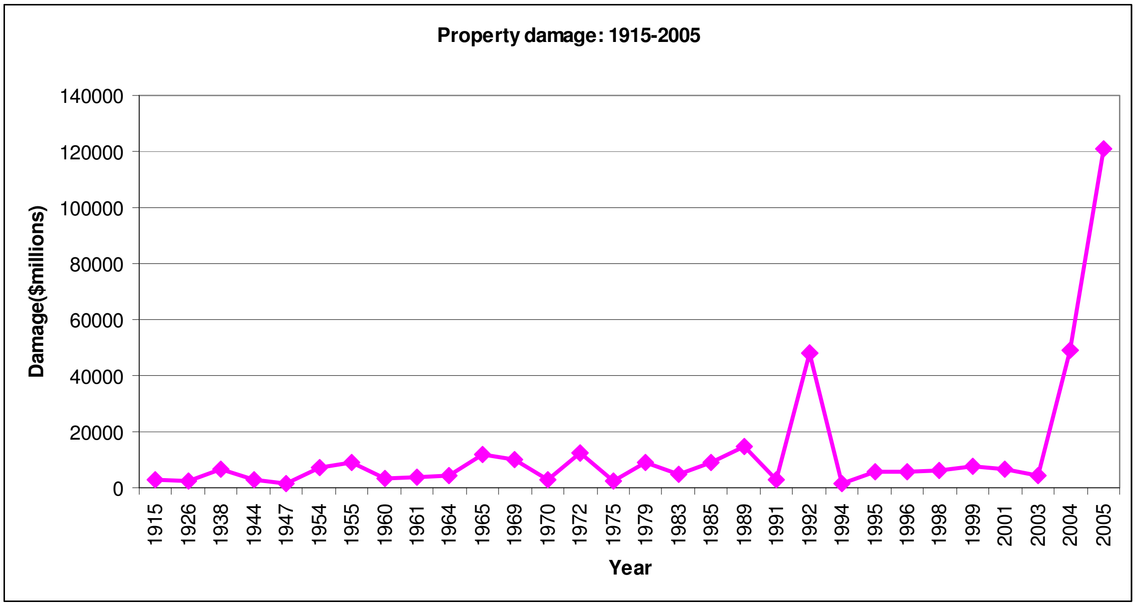


Figure 1.1. Estimated property damage from hurricanes for selected years in the United States; Damage is adjusted to 2006 U.S. dollars (Source: Blake et al., 2007)

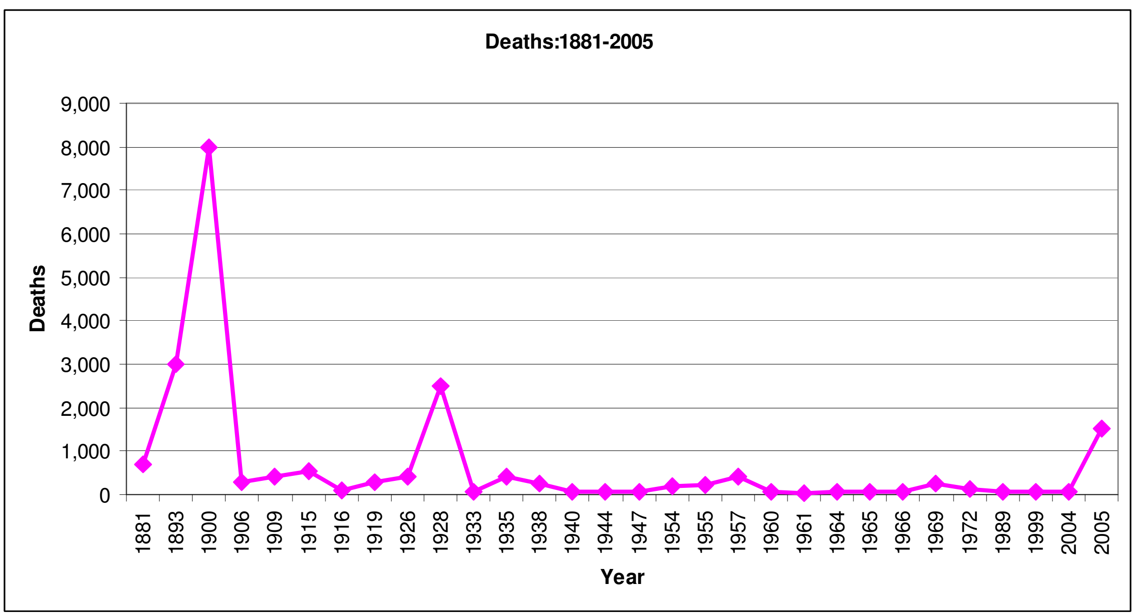


Figure 1.2. Estimated deaths from hurricanes for selected years in the United States (Source: Blake et al., 2007)

For many years, researchers have focused on understanding the geophysical and biophysical characteristics of natural hazards and significant progress has been made in developing models that can accurately predict locations and timing of hazard events such as hurricanes and tropical storms (Anderson, 2000). However, even if it appears that the knowledge of physical aspects of natural hazards has significantly improved over the past decades, property damage continues to mount and people continue to die (Anderson, 2000). Studies have shown that the impacts of natural hazards are not only a function of geophysical and biophysical processes but also of the relationship between humans and the natural system (Burton, Kates, & White, 1978). For many years, hazard researchers have agreed that natural disasters are not purely natural events. They are a result of the interaction of three systems: (1) the biophysical system, which includes the hazardous events, (2) the social system, which includes the demographic characteristics of the communities that experience the hazard events, and (3) the built environment system, which includes buildings, roads, bridges, and other components of built environments (Mileti, 1999).

The increase in hazard vulnerability and disaster losses has led to a significant shift in hazard research from the emphasis on vulnerability to an emphasis on understanding how to make communities more disaster-resilient. The concept of disaster resilience has emerged recently and is increasingly growing as a critical concept in hazard research. Generally, the concept of disaster resilience reflects the concerns that natural hazards are dynamic phenomena that involve not only people as victims but also as contributors. It is human actions such as global warming and poor planning that cause disasters. As a concept, disaster resilience is relatively new or rather still in its infant stage in disaster management and planning. In many cases, because it is still new, there is a limited theoretical understanding of the concept in terms of how it should be operationalized. Therefore, this research seeks to improve the current state of knowledge on the concept of disaster resilience with respect to disaster management and planning.

1.2. Problem statement

While there has been a growing application of the concept of disaster resilience in the hazard literature, a frequently asked question is: Can the concept of disaster resilience be measured, and if the answer is yes, then how should it be measured? There is currently little or no research that has developed an explicit set of procedures on identifying key indicators that can be used to measure and quantify the concept of disaster resilience. Moreover, there is little research that has suggested how communities could be compared in terms of their levels of disaster resilience, or how to determine whether a certain community is moving in the direction of becoming more resilient in the face of hazards. This research seeks to fill in this gap by using the United States Gulf coast region as a study area, to explore the utility of the concept of disaster resilience in view of improving our current understanding of the concept. The aim is to make the concept of disaster resilience operational so that it can support planning, management, decision making, and policy formulation.

1.3. Research objectives

The overall objective of this study is to empirically operationalize the concept of disaster resilience. In view of this overall objective, this study seeks to address the following five specific research objectives:

(1) To explore the theory, conceptual models, definitions, and applications of the concept of disaster resilience.

(2) To develop a conceptual framework that can be used to identify disaster resilience indicators in coastal communities.

(3) To develop a community disaster resilience index (CDRI) that can be used to compare and monitor resilience of coastal communities.

(4) To assess the reliability and validity of the proposed community disaster resilience index (CDRI).

(5) To identify and analyze the spatial patterns and clusters of disaster resilience in the study region.

1.4. Specific research questions

To achieve the research objectives outlined above, this research attempts to answer the following seven specific research questions.

Specific Question for Objective 1:

(1) What does the concept of disaster resilience mean and how can it be applied in disaster management in particular?

Specific Questions for Objective 2:

(2) What are the major components of community disaster resilience and how are they related?

(3) What are the key indicators of a disaster-resilient coastal community?

Specific Question for Objective 3:

(4) How can disaster resilience indicators be merged into an overall index as a measure of community disaster resilience?

Specific Questions for Objective 4:

(5) How valid and reliable is the proposed CDRI as a quantitative measure?

(6) To what extent does the CDRI capture the theoretical conception of disaster resilience and does it seem to work empirically?

Specific Question for Objective 5:

(7) Is there any spatial pattern or cluster of disaster resilience in the study region?

1.5. Significance of the research

This research is significant in two distinct ways: (1) it addresses the current need in the hazard literature of developing a methodology to operationalize the concept of disaster resilience. The concept of disaster resilience has shown great potential but also proven to be a difficult concept to operationalize. This research provides a model that will be used as a starting point in the process of operationalizing this concept, and (2) this research provides a useful measurement tool for emergency managers that will improve comparative assessments of disaster resilience at county level. Additionally, CDRI as a measure is an important planning tool that planners and emergency managers can utilize in a decision making process such as resource allocation.

1.6. Structure of the dissertation

This dissertation is organized into nine chapters including this introductory chapter (Chapter I). Figure 1.3 graphically illustrates the logical flow of the chapters. Generally, Chapter I sets the scene for this dissertation by providing the background of the research, the problem statement, the objectives, and the research questions. After the introduction chapter, the next two chapters focus on building the theoretical foundation of the study, which is based on the literature review. Chapter II reviews the literature on the definition of the concept of resilience from two perspectives; the fields of ecology and disasters and hazards. The purpose of Chapter III is (i) to develop a disaster resilience working definition for this dissertation and (i) to develop a conceptual framework in which disaster resilience indicators can be identified.

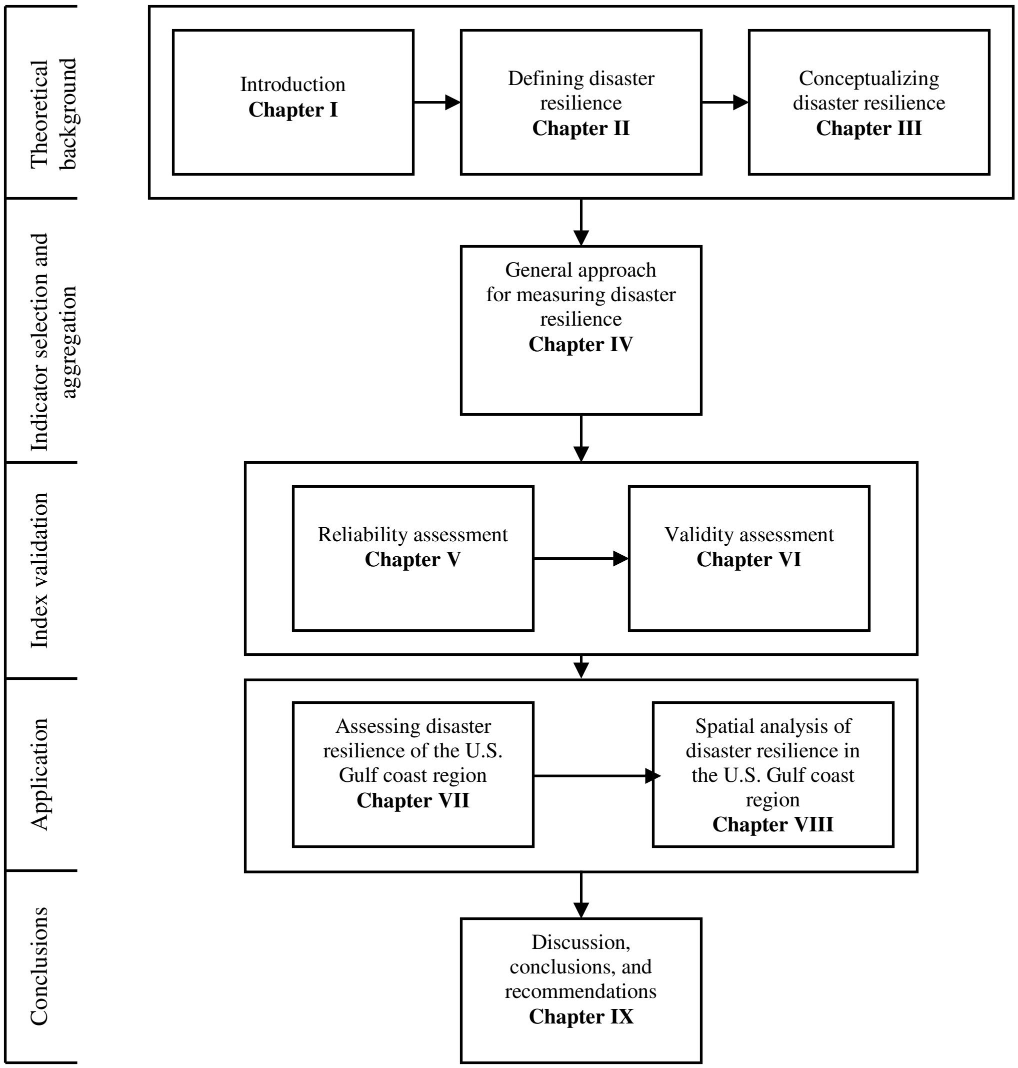


Figure 1.3. Logical flow of the dissertation chapters

Chapter IV describes in detail the general approach employed in this study to measure and quantify the concept of disaster resilience. First, the chapter introduces how the indicators were selected. Second, the chapter presents and discusses the final set of selected indicators used in this study. Third, the chapter discusses the mathematical aggregation methods used to combine the indicators and the approaches used to calculate the CDRI and sub-index scores.

Finally, the chapter introduces the study region, the unit of analysis, and the data sources for the selected set of indicators.

The purpose of Chapters V and VI is to assess the reliability and validity of the proposed CDRI as a measure of disaster resilience. After assessing the reliability and validity of the CDRI, the next two chapters (VII and VIII) further examine the validity and utility of the CDRI as a measure. Specifically Chapter VII discusses and presents the CDRI ranking scores by county and state, with the aim of identifying which states and counties are more disaster resilient. These rankings help to further evaluate the validity and utility of the CDRI. Another way of assessing the validity and utility of the CDRI is to visualize the scores spatially using GIS techniques and draw some conclusions. The results of the spatial analysis are summarized and presented in Chapter VIII. Finally, Chapter IX presents the general discussion of the results, conclusions, limitations of the study, and recommendations for future research.

CHAPTER II

DEFINING DISASTER RESILIENCE

2.1. Introduction

As a concept, resilience is applied in many disciplines including hazards, ecology, psychology, sociology, geography, psychiatry, and public health (Klein, Nicholls, & Thomalla, 2003; Manyena, 2006; Norris, Stevens, Pfefferbaum, Wyche, & Pfefferbaum, 2008). It has been defined in a variety of ways, and has many different connotations depending on the discipline. However, the primary focus of this dissertation is on the concept of “disaster resilience” as applied to the field of hazards and disasters. This chapter reviews the literature on disaster resilience to form a better understanding of its definition. Generally, the literature review provides a theoretical foundation for developing the conceptual framework for measuring the concept, which is discussed in Chapter III.

Arguably, resilience as a concept and/or theory is more widely used in the field of ecology than in any other field. Although it is still contested, many researchers argue that the concept of resilience originated in the field of ecology (Manyena, 2006). For that reason, this study reviews the definitions of resilience from two perspectives; the fields of ecology and environmental hazards.

In addition, as many researchers have already underscored, there is a clear relationship between the concept of disaster resilience and social vulnerability in the hazards literature. This chapter further discusses the relationship and argues that the concept of disaster resilience is more critical than the concept of social vulnerability. Finally, the chapter concludes by summarizing the factors that make the concept of disaster resilience more appealing to researchers and practitioners.

2.2. The concept of resilience in the field of ecology

The term resilience is often used in the same vein as the application of the notion of bouncing back, which reflects its Latin root *"resiliere";* meaning to jump back (Klein et al., 2003; Paton & Johnston, 2006). In the field of ecology, Holling (1973) is frequently cited as probably the first to introduce the concept of resilience after publishing his popular paper entitled "*Resilience and Stability of the Ecological Systems"*. According to Holling (1973), resilience determines the persistence of relationships within a system and is a measure of the ability of the system to absorb change in the face of extreme perturbation and continue to persist (Holling, 1973).

Since the publication of the work of Holling (1973) resilience has become the central concept in the field of ecology. Generally, resilience in the ecological literature is defined in two different ways (Gunderson, Holling, Pritchard, & Peterson, 2002; Holling & Gunderson, 2002). One definition focuses on efficiency, control, constancy, and predictability. This type of resilience in the ecological literature is termed as *engineering* resilience (Gunderson et al., 2002). The other definition of resilience focuses on persistence, adaptiveness, variability, and unpredictability and is termed as *ecological* resilience (Gunderson et al., 2002). The engineering definition focuses on stability and equilibrium; in this case resilience is measured by the ability to resist disturbance or perturbation and the speed of return to the equilibrium point (Pimm, 1984). The ecological definition emphasizes the condition of non-equilibrium whereby instabilities can flip a system into another stability domain (Berkes & Folke, 1998). Resilience in this case is measured by the magnitude of disturbances that can be absorbed before the system changes its structures by changing the variables and process that control behavior (Berkes & Folke, 1998; Gunderson et al., 2002).

The first definition implies an assumption of a global stability, i.e., an ecosystem has only one equilibrium or steady state. The second definition presupposes the existence of alternative regimes, i.e., ecological system can exhibit a shift regime from one regime to another. Although many ecologists generally seem to agree with both perspectives (engineering and ecological), over the past four decades many additional definitions have emerged (see Table 2.1). The multiple definitions surface in the field of ecology generally suggest that (1) resilience is a complex concept to define and (2) resilience is still an evolving concept.

Table 2.1. Selected definitions of the concept of resilience from the field of ecology

Author	Definition
Holling (1973)	Resilience of an ecosystem is the measure of the ability of an ecosystem to absorb changes and still persist.
Pimm (1984)	Resilience is the speed with which a system returns to its original state following a perturbation.
Holling et al.(1995)	Resilience is a buffer capacity or ability of a system to absorb perturbation, or the magnitude of the disturbance that can be absorbed before a system changes its structure by changing the variables and processes that control behavior.
Lebel (2001)	Resilience is the potential of a particular configuration of a system to maintain its structure/function in the face of disturbance, and the ability of the system to re-organize following disturbance-driven change and measured by size of stability domain
Walkers et al.(2002)	Resilience is a potential of a system to remain in a particular configuration and to maintain its feedbacks and functions, and involves the ability of the system to reorganize following the disturbance driven change.
Folke et al.(2002)	Resilience for social-ecological systems is related to three different characteristics: (a) the magnitude of shock that the system can absorb and remain in within a given state; (b) the degree to which the system is capable of self-organization, and (c) the degree to which the system can build capacity for learning and adaptation.
Walker & Salt (2006)	Resilience is the capacity of a system to absorb disturbances, to undergo changes, and still retain essentially the same function, structure, and feedbacks.
Resilience Alliance (2007)	Ecosystem resilience is the capacity of an ecosystem to tolerate disturbance without collapsing into a qualitatively different state that is controlled by different set of processes. Thus, a resilient ecosystem can withstand shocks and rebuild itself when necessary. Resilience in social systems has the added capacity of humans to anticipate and plan for the future.
Millennium Ecosystem Assessment (2007)	Resilience refers to the amount of disturbance or stress that a system can absorb and still remain capable of returning to its pre-disturbance state

2.3. The concept of resilience in the field of hazards and disasters

Over the past years, many scholars, organizations, and institutions in the field of hazards and disasters have emphasized the importance of the concept of disaster resilience in hazards and disaster research, policy, and risk reduction programs. The United Nations Commission on Sustainable Development (2001) emphasizes disaster risk reduction policies and strategies that enable communities to become more disaster-resilient. The increasing support of the concept of disaster resilience in the hazard field is also evident in the mitigation literature (see for example, Burby, 1998; Godschalk et al., 1999). The work of Mileti (1999) also suggests building a disaster resilient community as a new approach to dealing with natural disasters. Other studies that support building of disaster resilient communities include the work of Burby et al. (2000), which views disaster resilience as a primary goal of disaster management and planning. Furthermore, the 2004 world disaster report of the International Federation of Red Cross and Red Crescent Societies specifically focuses on building resilient communities.

More recently, the concept of disaster resilience has increased in popularity, especially after the adoption of the *Hyogo Framework for Action 2005-2015: Building the Resilience of Nations and Communities to Disasters*. The Hyogo Framework for Action (HFA) is the key instrument for implementing disaster risk reduction adopted by member States of the United Nations. Its overarching goal is to build resilience of nations and communities to disasters by achieving substantial reduction of losses by 2015 (UN/ISDR, 2005). Since the adoption of the HFA, the goal of hazard planning and disaster risk reduction among nations world wide has rapidly shifted; the focus now is more on building community disaster resilience rather than simply reducing vulnerability of communities (Manyena, 2006).

Perhaps the most important recent work that supports and has significantly contributed to the concept of disaster resilience is the new book titled "*Disaster Resilience: An Integrated*

Approach" by Paton and Johnson (2006). Overall, this publication has presented a basic foundation supporting the concept of disaster resilience and its application to the disaster management and planning. Twigg (2007) has taken the concept of disaster resilience to a new level by proposing the guidelines for identifying basic characteristics of a disaster resilient community; however, the work is still in progress.

Even though the concept of disaster resilience has received supports from many respected scholars and international organizations such as the United Nations, one fundamental question remains concerning the concept of disaster resilience: What is disaster resilience? This section reviews the definition of the concept of disaster resilience and how is applied in the field of hazards and disasters.

In the hazard and disaster research, Timmerman (1981) is probably the first to introduce the concept of resilience using climate change as an example in his paper entitled "*Vulnerability, Resilience, and the Collapse of Societies*" (Clark et al., 1998; Klein et al., 2003). Borrowing the concept of resilience from the field of ecology, Timmerman (1981) linked resilience to hazard vulnerability and defined resilience as the measure of a system's or sub-system's capacity to absorb and recover from hazardous event. Following the work of Timmerman (1981), many definitions of the concept of disaster resilience have emerged in the hazards and disasters field in the last three decades. As in the field of ecology, there is currently no single agreed-upon definition of disaster resilience in the field of hazards and disasters. Many authors have defined disaster resilience in different ways (see Table 2.2). This is perhaps not surprising because hazards and disaster research has been conducted by different researchers from different disciplines with different backgrounds.

Table 2.2. Selected definitions of the concept of disaster resilience from the field of disasters and hazards

Author	Definition
Timmerman (1981)	Resilience is the measure of a system's or part of the system's capacity to absorb and recover from occurrence of a hazardous event.
Wildavsky (1991)	Resilience is the capacity to cope with unanticipated dangers after they have become manifest, learning to bounce back.
Buckle (1998)	Resilience is the capacity that people or groups may possess to withstand or recover from the emergencies and which can stand as a counterbalance to vulnerability.
EMA (1998)	Resilience is a measure of how quickly a system recovers from failures.
Mileti(1999)	Local resiliency with regard to disasters means that a locale is able to withstand an extreme natural event without suffering devastating losses, damage, diminished productivity, or quality of life without a large amount of assistance from outside the community.
Comfort et al.(1999)	The capacity to adapt existing resources and skills to new systems and operating conditions.
Adger(2000)	Social resilience is the ability of groups or communities to cope with external stresses and disturbances as a result of social, political, and environmental change.
Paton et al.(2000)	Resilience describes an active process of self-righting, learned resourcefulness and growth — the ability to function psychologically at a level far greater than expected given the individual's capabilities and previous experiences.
Buckle et al.(2000)	Resilience is the quality of people, communities, agencies, and infrastructure that reduce vulnerability. Not just the absence of vulnerability rather the capacity to prevent or mitigate loss and then secondly, if damage does occur to maintain normal condition as far as possible, and thirdly to manage recovery from the impact.
Pelling (2003)	Resilience is the ability of an actor to cope with or adapt to hazard stress.
Godschalk (2003)	A resilient city is a sustainable network of physical systems and human communities.
Walter (2004)	Resilience is the capacity to survive, adapt and recover from a natural disaster. Resilience relies on understanding the nature of possible natural disasters and taking steps to reduce risk before an event as well as providing for quick recovery when a natural disaster occurs. These activities necessitate institutionalized planning and response networks to minimize diminished productivity, devastating losses and decreased quality of life in the event of a disaster.
UN/ISDR (2005)	Resilience is the capacity of a system, community or society potentially exposed to hazards to adapt, by resisting or changing in order to reach and maintain an acceptable level of functioning and structure. This is determined by the degree to which the social system is capable of organizing itself to increase this capacity for learning from past disasters for better future protection and to improve risk reduction measures.
Paton & Johnston (2006)	Resilience is a measure of how well people and societies can adapt to a changed reality and capitalize on the new possibilities offered.
Maguire & Hagan (2007)	Social resilience is the capacity of social entity e.g. group or community to bounce back or respond positively to adversity. Social resilience has three major properties, resistance, recovery, and creativity.

As the list in Table 2.2 indicates, the definitions of resilience in the field of hazards and disasters are diverse. However, all definitions have relatively similar but not identical properties. For example, from the list of definitions above, it is clear that the term *capacity/ability* is used by most of the authors as a property of resilience. This generally suggests that researchers agree that disaster resilience is the capacity/ability of people, a group of people, a community, or a society to continue functioning in the face of a disaster. In general, the following key points can be drawn from the definitions presented in Table 2.2.

First, some authors adopt the notion of ecological and engineering resilience from the ecological literature. These authors define resilience as the function of a system and its dynamics and self reorganizing capacity after a disturbance. In addition, these authors define the concept of resilience as a process rather than an end result or outcome.

Second, some definitions tend to take *a long term perspective,* which can be linked to the notion of bouncing back. For example, most authors define resilience as a long-term recovery process after a disaster. The implication is that a resilient system is one that bounces back and recovers itself from a disturbance or disaster. This also suggests that a criterion for understanding or assessing resilience might be the time it takes to recover or return to normalcy. A resilient community in this view would be the one that resumes its previous growth trajectory quickly.

Third, there is the notion of resistance. This implies that the system or units in the system will be able to absorb, deflect, lessen or otherwise modify impacts or the consequences of the potential impacts. For communities, this implies taking actions prior to an event to strengthen its social fabric or physical infrastructure such that potential impacts are reduced.

Fourth, some authors include *the notion of adaptive capacity* in their definitions. This implies the ability of a community to adapt to new environment following a disaster and the capacity to learn from past disasters. This suggests that the system will modify its structure or behavior in order to better address future problems; in the disaster sense, this suggests mitigation.

Fifth, some authors link the concept of resilience to *the concept of sustainability*. Extending the idea of ecologists who argue that resilience promotes sustainable ecosystems, some authors considered resilience as a property of sustainability.

Sixth, in some cases disaster resilience is also understood as the *opposite of vulnerability*. The argument here is that when vulnerability is high resilience will tend to be low and vice versa. Several studies have argued that there is a relationship between the concept of social vulnerability and community disaster resilience (Paton & Johnston, 2006). The next section discusses the relationship between social vulnerability and community disaster resilience and the potential limitations of the concept of social vulnerability.

2.4. Community disaster resilience versus social vulnerability

In many cases, both community disaster resilience and social vulnerability are central pillars in understanding the characteristics of natural hazards, their consequences, and how to deal with them (Paton & Johnston, 2006). The theoretical base of the concepts of community disaster resilience and social vulnerability has been derived from empirical studies in the past two decades (Manyena, 2006). Both concepts community disaster resilience and social vulnerability are based on the theory that communities, people or groups of people suffer different degrees of death, injury, loss, and disruption from the same type of hazard event. Also they may experience different degrees of difficulty, failure, or success during the process of recovery (Hewitt, 1983; Peacock, Morrow, & Gladwin, 1997; Wisner, Blaikie, Cannon, & Davis, 2004). While some communities can recover quickly following a disaster event, others take longer.

A great body of hazards literature suggests that the impacts of extreme natural events on a given community are not random but are determined by every day patterns of social interactions and organizations, especially access to resources (Lindell, Prater, & Perry, 2007; Morrow, 1999; Peacock et al., 1997). In light of this theoretical base, these two concepts are similar as ultimately both are geared toward saving lives and minimizing losses. However, significant conceptual and methodological differences between these two concepts exist. The following discussion highlights some of these differences.

2.4.1. Social vulnerability

The hazards literature suggests that the concept of hazard vulnerability has been in use since the late 1970s (Birkmann, 2006; Manyena, 2006). According to Cutter (1996) and National Research Council (2006) hazard vulnerability is generally characterized as being a function of hazard exposure (the risk of experiencing a hazard event), and physical vulnerability (the likelihood of elements of the built environment to sustain various degrees of damage from the hazard event). Currently, many definitions of hazard vulnerability exist in the literature. Mitchell (1989), for example, broadly defined hazard vulnerability as simply a potential for loss. Cutter (1996) has defined hazard vulnerability as the likelihood that an individual or group will be exposed to and adversely affected by a hazard.

In recent years, there has been increased recognition that to understand hazard vulnerability better requires also understanding the social vulnerability component. This implies that instead of considering disasters as purely physical occurrences, which require technological solutions such events can be understood better in terms of human actions (Bankoff, Frerks, & Hilhorst, 2003). Like the concepts of disaster resilience, the definitions of social vulnerability are many and diverse. Presently, there is no universally accepted definition of social vulnerability in the literature.

Wisner et al. (2004) defined social vulnerability as the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard, and that social vulnerability changes with time. Social vulnerability is deeply rooted and shaped by the social structures and political processes that determine access to resources such as income, education, housing, and political resources such as power and autonomy (Cutter, 1996; Morrow, 1999; Wisner et al., 2004). The hazards literature has identified several groups of people (vulnerable groups) that are more likely to need special attention in emergency situations (Cutter, 1996; Morrow, 1999; Peacock et al., 1997; Wisner et al., 2004). Such groups include: the elderly, the physically and/or mentally disabled, renters, poor households, households headed by women, ethnic or linguistic minorities, immigrants, and children. Other groups include the homeless, illegal aliens, tourists and transients. A large body of research demonstrated that these groups invariably suffer most during disasters (Cutter, Boruff, & Shirley, 2003; Morrow, 1999; Wisner et al., 2004).

For the past decades, the goal of social vulnerability has been to develop a better assessment method to identify those at risk. However, the current social vulnerability assessment methods are still problematic; much research is still needed to improve the current methods as well as our understanding on the concept of social vulnerability. Although the concept of social vulnerability has been instrumental and achieved a high degree of recognition in disaster management and planning, especially in improving community risk reduction programs and guiding policy formulation, the concept is still fuzzy (Birkmann, 2006). The concept of social vulnerability still faces a number of conceptual and methodological limitations that have yet to be resolved including:

(1) Social vulnerability assessment has focused only on individuals, and fails to recognize the complex social networks among members in a community in dealing with disasters.

Usually, people do not exist solely as individuals. Social behaviors often result in the formation of social groups and social networks (Paton & Johnston, 2006), which together can enhance their capacity in dealing with disasters.

(2) Social vulnerability assessment has been linear and static in that it has not taken into accounts the different dimensions and continuously changing nature of complex social and natural systems' interactions. It is important to consider both the social and physical elements in the assessment, because social vulnerability is intrinsically tied to both social and physical processes.

(3) Social vulnerability assessment usually tends to simply analyze vulnerability according to peoples' demographic characteristics, which are typically age, gender, race, and ethnicity. These demographic characteristics are not useful to emergency managers in developing strategies to reduce risk or enhance capacity or resilience. This is because they can not be changed and emergency manager can do little with them (Buckle, Marsh, & Smale, 2001). What is important to emergency managers and planners is not the kind of group a person belongs to, but the nature of their lifestyle, how they interact with each other, and most importantly the social networks they have (social capital).

(4) Most of the social vulnerability indicators currently developed in the literature are country specific and not universal, which may mean nothing to other countries. For example, percent of Hispanic population, as an indicator of social vulnerability in the United States, may mean nothing to a country such as Tanzania or Sweden.

These are some of the basic limitations facing the concept of social vulnerability, which have not yet been resolved. However, the fundamental question here is not whether researchers or emergency managers and planners can address these weaknesses, but rather the profound question is (particularly in hazard risk reduction) whether the concept can provide relevant information that emergency managers and planners can utilize in a decision making process.

2.4.2. Community disaster resilience

In contrast with social vulnerability, the concept of community disaster resilience tends to take a broader view of the risk spectrum, focusing on a range of issues such as hazards adjustments, learning and communications, coping, and adaptation rather than only focusing on social and/or economic disadvantages that limit the capacity to cope with disasters. The concept of resilience broadly encompasses the inter-relationship between hazards, humans, and natural systems, but also focuses attention to the attributes of the systems and their ability to 1) absorb, deflect or resist disaster impacts, and 2) when hit, bounce back in a relatively rapid fashion, as well as 3) learn from experience and modify its behavior and structure to adapt to future threats. Most importantly, it captures the social and cultural networks and political variables that are often underestimated in social vulnerability assessments. More specifically, community disaster resilience as a concept is growing and seems to be appealing to hazard researchers more than the concept of social vulnerability for the numerous reasons including:

(1) The concept of community disaster resilience reflects the desire to improve the capacity of both social and physical systems to respond to and recover from disaster (Tierney & Bruneau, 2007).

(2) The concept of community disaster resilience emphasizes the importance of pre-disaster and post-disaster measures that enhance the capacity of communities to reduce losses from a disaster (Maguire & Hagan, 2007; Tierney & Bruneau, 2007).

(3) The concept of community disaster resilience is seen as a desirable attribute of both social and physical systems in the face of disaster because it is a contributing factor to community sustainability (Klein et al., 2003).

(4) Disasters can not be completely predicted, which means that we cannot know exactly when, where, and how disasters will occur in the future; the concept of community disaster resilience is important because it provides a way of thinking about how to explore the options of dealing with uncertainties and unexpected changes (Berkes, 2007).

(5) While the notion of labeling an individual or group of individuals as "vulnerable" seems to discourage peoples' efforts in dealing with disasters; the concept of community disaster resilience appears to be more proactive and encourages collective efforts in a community to deal with disasters.

(6) Community disaster resilience is a broader concept which encompasses a large part of the risk spectrum (Twigg, 2007). It emphasizes the community's capacities and how to strengthen them, and it places less emphasis on the factors which make the community vulnerable.

2.5. Summary

In this chapter numerous studies have been reviewed in order to assess and understand the current state of the definition of resilience in both the fields of ecology and hazards. The definitions and various concepts reviewed in this chapter provide a better understanding of the concept of resilience, its key components, and how it should be conceptualized and applied in hazards and disaster research. An initial working definition of disaster resilience includes the ability of a system to absorb, resist or deflect disaster impact and when impacted to relatively quickly recover and learn or adapt to future risks.

Also, the literature review indicates that conceptual and methodological problems still exist with regard to social vulnerability assessment methods that need to be addressed. Furthermore, the literature review suggests that the concept of disaster resilience has more potential than the concept of social vulnerability in advancing the hazard and disaster research agenda. Communities and the way they function during disasters can be viewed as systems (Wenger & Parr, 1969) with complex interactions of people and the natural and build environments. The concept of disaster resilience seems to be central to understanding these interactions within and across communities and how communities respond and function during disasters.

Generally, the literature review provides the theoretical foundation for this research to develop a conceptual framework for measuring and quantifying the concept of disaster resilience, which is described in the next chapter.

CHAPTER III

CONCEPTUALIZING COMMUNITY DISASTER RESILIENCE

3.1. Introduction

The objective of this chapter is to develop a framework in which disaster resilience indicators can be identified. To achieve this objective a number of conceptual frameworks or models from the literature were critically reviewed in order to identify key elements that can be used to measure disaster resilience. Based on that review a disaster resilience working definition and a community disaster resilience framework (CDRF) are developed. In this dissertation, the CDRF is the critical component in identifying indicators for measuring the concept of disaster resilience.

3.2. Disaster resilience conceptual frameworks

Given the fact that the definition of the concept of disaster resilience is still fuzzy, and the fact that the dynamic interactions of people and the natural and built environments are complex, assessing community disaster resilience is a problematic process. It requires a clear understanding of the components of disaster resilience and how they relate to each other. There are currently a number of conceptual frameworks or models in the hazards and disasters literature that aim to measure or provide a general understanding of the concept of disaster resilience. It is important to review these frameworks, especially at this initial stage of developing the approach for measuring the concept of disaster resilience because they may provide some guidance. In addition, frameworks structurally provide a general overview of the main components of the concept and highlight the complex interactions of these components. Most importantly, these frameworks can provide a basic structure in which relevant indicators of disaster resilience can be identified and potentially measured.

For the purpose of this study, four frameworks were reviewed and are discussed in this chapter. Briefly, these frameworks are: (1) the sustainable and resilient community framework (Tobin, 1999), (2) the sustainable livelihood framework (Chambers & Conway, 1992; Glavovic, Scheyvens, & Overton, 2002), (3) the community disaster resilience framework (Maguire & Hagan, 2007), and (4) the disaster resilience of place (DROP) model (Cutter et al., 2008).

(1) Sustainable and resilient community framework

Tobin (1999) proposed a framework in which sustainable and resilient communities can be assessed. The framework comprises of three theoretical models that can be utilized to operationalize the concept of sustainability and community disaster resilience. These models are: (i) the mitigation model, (ii) the recovery model, and (iii) the structural cognitive model (see Figure 3.1).

Tobin (1999) argued that planning for sustainable and resilient communities requires a comprehensive planning approach that includes mitigation programs to reduce risk and exposure to hazards. It also requires post-disaster plans that promote short and long term recovery. In addition, it requires careful consideration of structural and cognitive factors that can effectively influence programs related to building sustainable and resilient communities. Tobin (1999) concluded that these three conceptual models are interrelated and together play a significant role in building sustainable and disaster resilient communities.

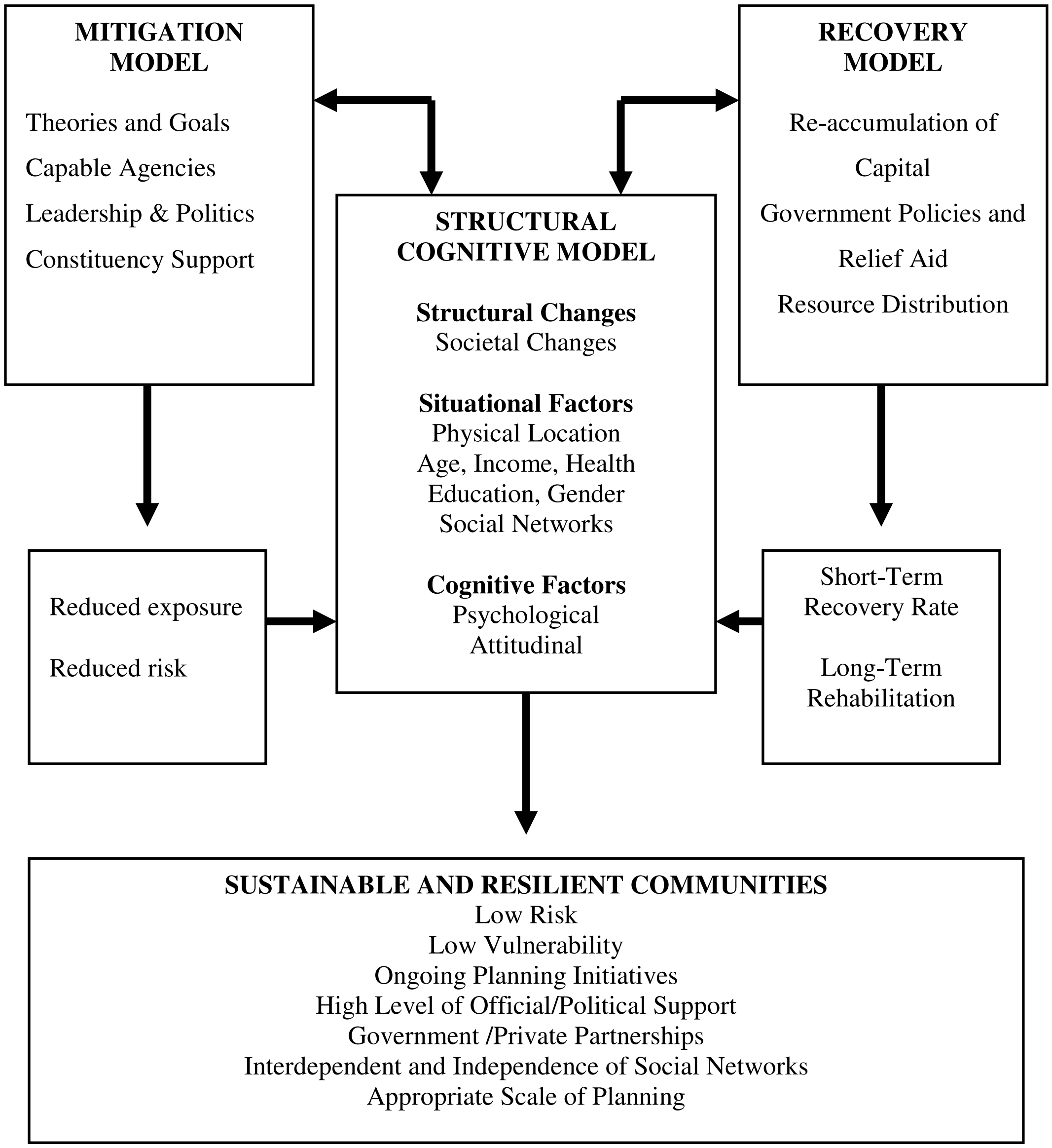


Figure 3.1. Sustainable and resilient community framework (Source: Tobin, 1999)

In general, Tobin's framework emphasizes mitigation, recovery, and cognitive factor as critical elements in building sustainable and resilient communities. However, Tobin's framework underestimates the role of other disaster management phases' activities such as disaster preparedness and disaster response. These are critical factors in planning for sustainable and resilient communities; in fact they are as important as hazard mitigation and disaster recovery. A great body of research has demonstrated that communities that are not well prepared can not effectively respond to disasters (Ronan & Johnson, 2005). Effective preparedness and response activities help to save lives and limit property damage (Mileti, 1999). So, a framework that only focuses on developing comprehensive mitigation and recovery programs is not adequate to achieve the goal of building sustainable and resilient communities.

Furthermore, Maguire and Hagan (2007) in their recent work on social resilience concluded that the greatest improvement in building sustainable and resilient communities can be achieved if all activities of disaster management phases (mitigation, preparedness, response, and recovery) are taken into account. The set of activities associated with each disaster phase has a role to play in building disaster resilience. By definition hazard mitigation refers to actions taken before a disaster to reduce vulnerability, primarily through measures that reduce causalities and exposure to damage and disruption or that provide passive protection during disaster impact (Lindell & Perry, 1992; Tierney, Lindell, & Perry, 2001). Disaster preparedness generally encompasses actions undertaken before disaster impact that enable social units to respond actively when disaster does strike (Lindell & Perry, 1992; Tierney et al., 2001). Disaster response consists of actions taken a short period prior to, during, and after disaster impact to reduce causalities, damage, and disruption and to respond to immediate needs of disaster victims (Lindell & Perry, 1992; Tierney et al., 2001). Finally, disaster recovery comprises actions taken to repair, rebuild, and reconstruct damaged properties and to restore disrupted community social routines and economic activities (Peacock et al., 1997; Tierney et al., 2001). Based on the discussion above it becomes clear that without considering all four disaster management phases' activities it is unlikely for a community to achieve the goal of becoming disaster-resilient.

(2) Sustainable livelihood framework

The sustainable livelihood framework was originally developed by Robert Chambers in the mid-1980s (Glavovic et al., 2002). The framework was further developed by Chambers and Conway (1992). Since that time, the use of the sustainable livelihood framework has been growing. Currently, a number of development agencies, donors, Non-governmental organizations (NGOs), Community based organizations (CBOs), and government bodies have adopted the livelihood concept (Glavovic et al., 2002). Most importantly, the livelihood concept has become a focus of research. The United Kingdom Department for International Development (DFID) has been an advocate of applying this framework in various countries, particularly developing countries where the level of poverty is high. The goal has been to promote disaster risk reduction programs and reduce poverty especially in rural communities.

Figure 3.2 depicts the sustainable livelihood framework, its main components, and how these components fit together. The arrows within the framework denote different types of relationships. Although they do not imply causality, they imply a certain level of influence (DFID, 1999). The vulnerability context denotes the external environment in which people live and through which their livelihoods can be affected by trends and shocks. In the context of sustainable livelihood framework, the concept of sustainability is linked to the ability of people to cope with and recover from shocks (DFID, 1999).

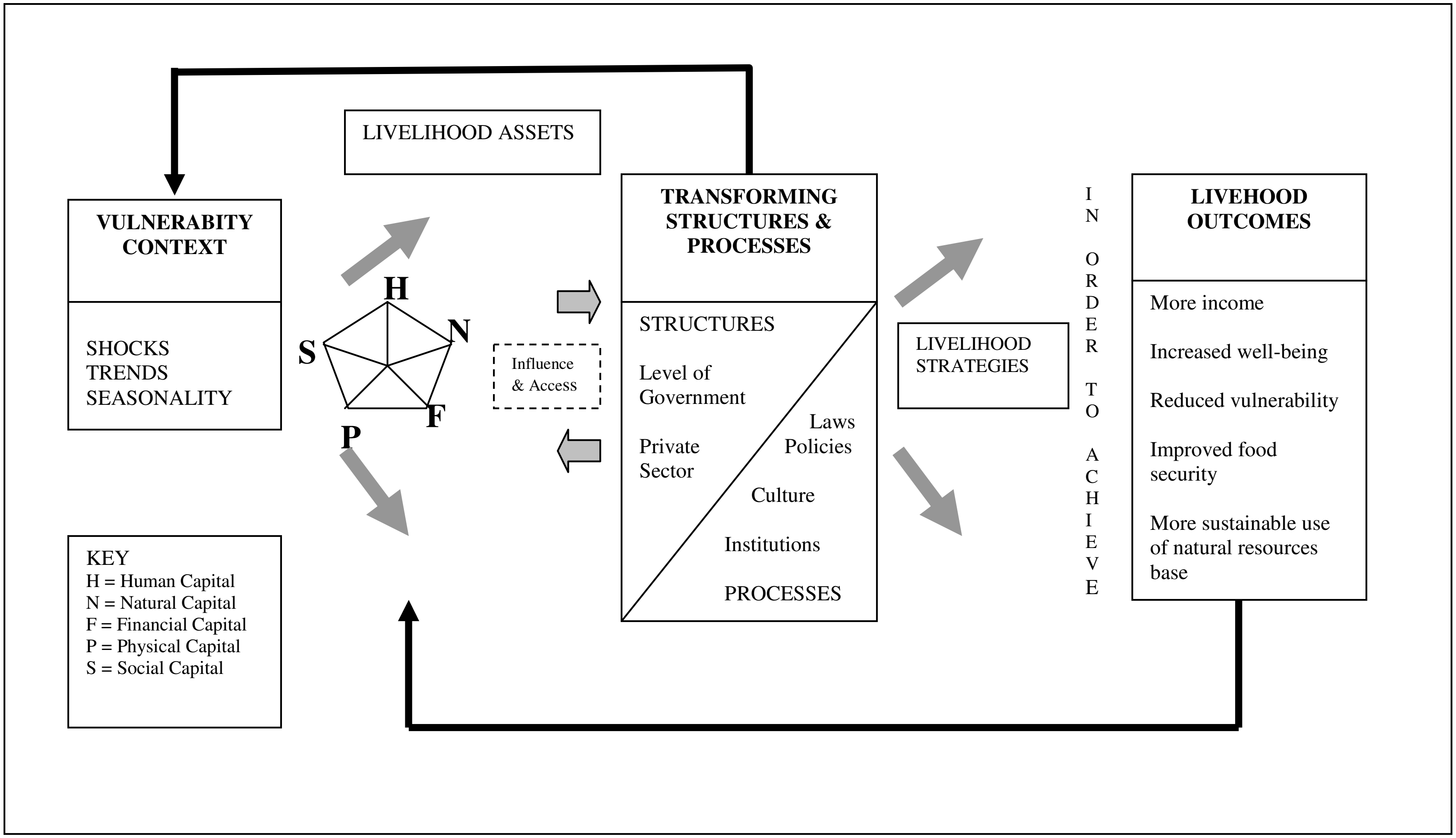


Figure 3.2. Sustainable livelihood framework (Source: DFID, 1999)

The asset pentagon is the core of the sustainable livelihood framework (see Figure 3.3). It consists of five types of capital: (1) human, (2) social, (3) natural, (4) physical, and (5) economic. The sustainable livelihood framework is based on the idea that these five types of capital are important assets in building disaster resilience.

Human capital includes skills, knowledge, good health, and ability to work that help people to achieve their livelihood objectives (DFID, 1999). In the context of disaster resilience human capital is important because, without human capital such as education communities can not be able to utilize other types of capital.

Social capital comprises the social resources that people can draw upon to support their livelihoods (DFID, 1999). It is developed through networks and connectedness, group associations and memberships, and relationships of trust. In the context of disaster resilience social capital is critical because many researchers have demonstrated that communities with higher levels of social capital are relatively wealthier (DFID, 1999; Rupasingha, Goetz, & Freshwater, 2006). In other words, there is a relationship between social capital and income. Therefore, in the context of disaster resilience, social capital can help people to increase their income, which will increase their disaster resilience.

Natural capital includes natural resource stocks from which resource flows and services useful for livelihoods are derived. Such resources include land, forests, water, and minerals. Studies have shown that there is a relationship between natural capital and disaster resilience. For example, alteration of wetlands is one of the significant contributing factors for increasing flood hazards in the United States (Highfield & Brody, 2006). Therefore, improving natural capital, for example by protecting coastal resources such as wetlands, will increase disaster resilience of communities.

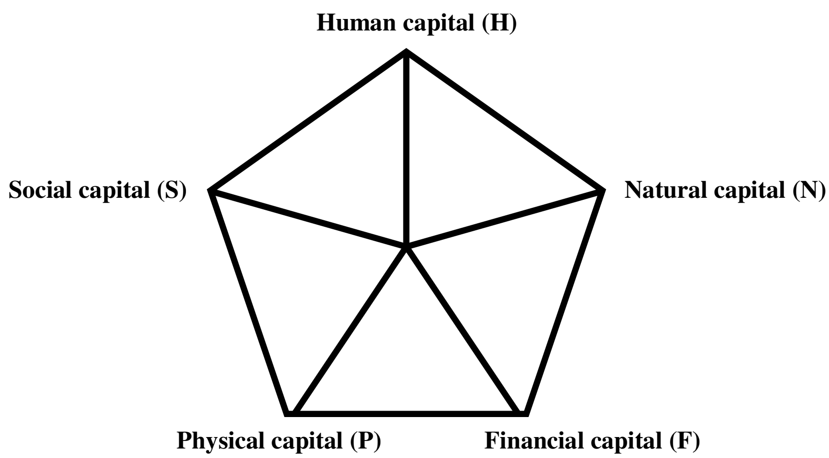


Figure 3.3. The asset pentagon of the sustainable livelihood framework

Physical capital consists of the basic infrastructure that can help people to support their livelihoods, which include housing (residential, commercial, and industrial), infrastructure (electric power, water, sewer, telecommunications, and transportation) and critical facilities such as hospitals, schools, nursing homes, and police and fire stations. Studies have shown that there is a clear relationship between disaster resilience and physical capital. For example, communities with poor transportation networks are more likely to face difficulties in evacuating people during disasters. Also, in the United States police officers and fire fighters play an important role in disaster response as first responders.

Finally, financial capital which includes financial resources that people use to support their livelihood. This can be in the form of savings or credit. The relationship between financial capital and disaster resilience is well documented. Studies have shown that households with higher socioeconomic status suffer less whereas low-income households are at greater risk because they lack access to financial resources. As a result low income households tend to live (but not always) in low quality housing located in high risk areas (Mileti, 1999).

From the discussion above, it becomes clear that capitals are important elements in building community disaster resilience. However, although the sustainable livelihood framework highlights the key components required in reducing vulnerability and poverty, the framework seems to be very general, which encompasses many variables. Thus, turning it into a practical measurement tool for policy and disaster risk reduction programs can be problematic.

(3) Community disaster resilience framework

Maguire and Hagan (2007) broadly defined social resilience as the capacity of social groups and communities to recover from, or respond positively to, disasters. These researchers argued that a resilient community should have the capacity to demonstrate three properties: (i) resistance, (ii) recovery, and (iii) creativity. Figure 3.4 presents Maguire and Hagan's concepts of the three properties of social resilience.

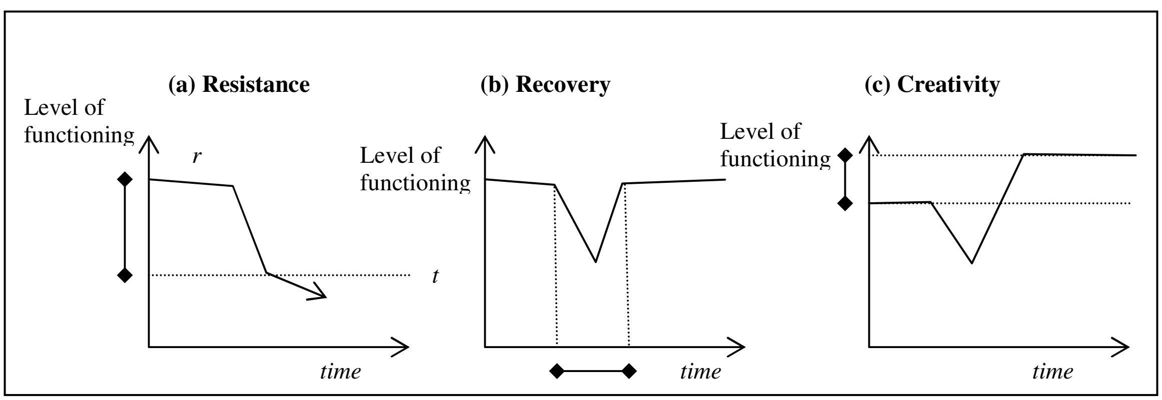


Figure 3.4. Properties of resilience (Source: Maguire & Hagan, 2007)

Figure 3.4(a) illustrates the resistance property, which is the community's effort to withstand disasters and their consequences. It is measured as a distance between a community's pre-disaster level of functioning (*r*) and the threshold (*t*) (represented by the doted line). A threshold is the limit which defines the point, which if crossed; a community will not be able to return to its pre-disaster state. Thus, for a highly resistant community, *r* and *t* are considerably far apart; meaning that it will require a significant disaster impact to push a community to this threshold. Conversely, for a less resistant community, the *r* and *t* are relatively close to each other, which means that even a comparatively small impact may push the community beyond the threshold. Figure 3.4(b) illustrates the recovery property, which is the ability of a community to bounce back to its pre-disaster level of functioning after a disaster. A more resilient community returns to its pre disaster level very quickly, while a less resilient community takes longer to recover. Figure 3.4(c) illustrates a creativity property, which is an optimal recovery. Maguire and Hagan (2007) argued that optimal recovery is not just the ability of a community to return to its pre-disaster level but also the ability to adapt to new circumstances and learn from the past disaster experience.

Maguire and Hagan (2007) further argued that in order for a community to achieve the goal of building disaster resilience, all four disaster management phases' activities should be considered (mitigation, preparedness, response, and recovery). That means all disaster phases' activities are important for building disaster resilience. For example, hazard mitigation and disaster preparedness activities help communities to build capacity to reduce impacts of future disasters. Disaster response and disaster recovery activities are important because they improve the capacity of communities to effectively respond to disaster and recover quickly from a disaster.

While the theoretical framework developed by Maguire and Hagan (2007) provides a better understanding of the concept of resilience, to a large extent it fails to clearly itemize the specific attributes of each property, especially the attributes of resistance and creativity. In other words, the framework fails to define the attributes of resistance and creativity so that emergency managers, for example, can utilize them in building disaster resilience.

(4)The disaster resilience of place (DROP) model

Recently, Cutter et al. (2008) have developed what they call a disaster resilience of place model (See Figure 3.5). In a nut shell, the DROP model has two main components. The first component consists of the antecedent conditions (the inherent vulnerability and inherent resilience) which are the product of the interactions of the social, natural and built environment systems. The hazard impacts are the results of the antecedent conditions, hazard events, and the ability to cope and respond. The second component consists of the actions to deal with the disaster impacts, which include hazard mitigation, disaster preparedness, disaster response, and disaster recovery. The DROP model is still under development and there is currently not much discussion of how the model will be operationalized. However, like the framework of Tobin (1999) and Maguire and Hagan (2007), the DROP model emphasizes the disaster management phases' activities as key factors for building disaster resilience.

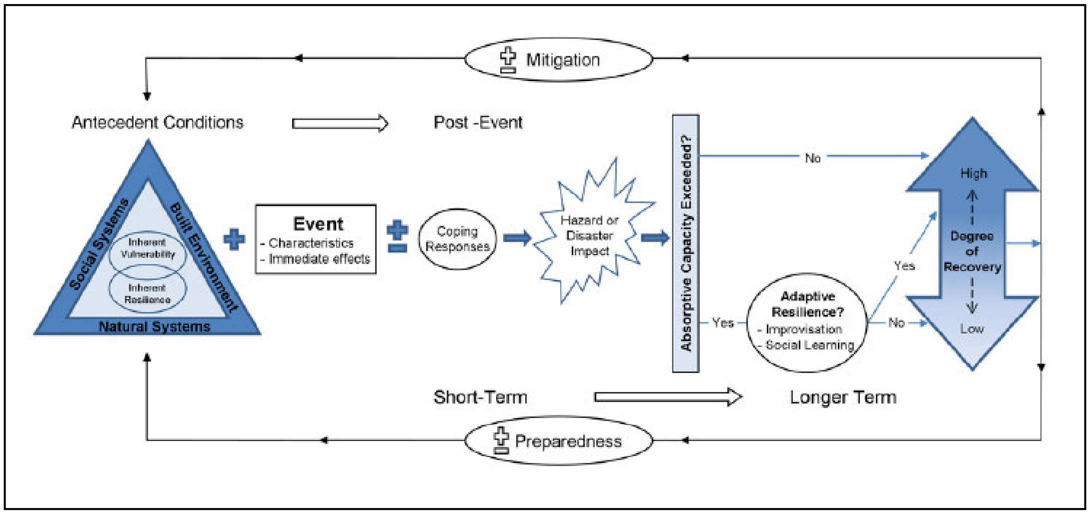


Figure 3.5. The disaster resilience of place model (DROP) (Source: Cutter et al., 2008)

To summarize the frameworks discussed above, generally have demonstrated that there are two important components that can be used to conceptualize community disaster resilience: (1) Disaster management phases' activities (mitigation, preparedness, response, and recovery) and (2) community capitals or assets (social, economic, human, physical, and natural). The frameworks developed by Tobin (1999), Maguire and Hagan (2007), and Cutter et al., (2008) seem to have common characteristics. They all emphasize the importance of disaster management phases' activities in building disaster resilience. On the other hand, the sustainable livelihood framework focuses on community capitals. Although these frameworks provide a general understanding of the concept of disaster resilience, they remain highly theoretical in nature and can not be easily operationalized for measuring disaster resilience.

Based on the review of the conceptual frameworks above and the definitions discussed in Chapter II a disaster resilience working definition for this dissertation is developed. Furthermore, a community disaster resilience framework in which indicators for measuring disaster resilience can be identified is developed. Both the working definition and the framework are discussed in the next sections.

3.3. Working definition of disaster resilience

For the purpose of this dissertation and given the focus on human communities, disaster resilience is defined as:

> *the capacity of communities and their built environments to mitigate, prepare for, respond to, and recover quickly from disasters, and adapt to new circumstances while learning from past disasters.*

This definition is linked specifically to the overall research objective of this dissertation. The definition is considered broad enough to encompass most of the potential meanings of disaster resilience as discussed earlier; yet is considered narrow enough to achieve the overall research objective of this dissertation.

First, this definition is built on the notion of disaster phases' activities (Mitigation, preparedness, response, and recovery), which plays a pivotal role on preventing and reducing impacts of natural disasters. Second, this definition puts social systems and their built environments at the center; meaning that it emphasizes their ability to deal with disasters and learn from them. Furthermore, this dissertation argues that the ability of a community to deal with disaster is based on the quality and quantity of community capitals (social, economic, physical, human, and natural). The learning component is a very critical aspect in this definition because studies have shown that disasters can be avoided if they are understood and the lessons from them are learned and applied.

It is quite clear that if we do not learn from past disasters we can not prevent or avoid the future ones. Third, the definition focuses specifically on the capacity of communities because, although in many cases the responsibility of dealing with disaster problems is at the national level, in the United States this responsibility is largely given to local communities (Wenger & Parr, 1969). Moreover, disasters are local phenomena, which make local communities the central points of both immediate disaster impacts and initial emergency response. Therefore, local communities are critical in saving lives.

3.4. Community disaster resilience framework (CDRF)

This dissertation combines the two notions of the frameworks discussed in the previous section and develops a composite framework, which includes both the disaster management phases' activities and the community capitals. However, because this dissertation focuses more on social systems rather than physical systems, natural capital is not included in the framework. This is because natural capital is considered more as part of the physical systems rather than social systems. Therefore, only four community capitals are used in this study (social, economic, physical, and human, see Figure 3.6). It is important to note that excluding natural capital does not mean that it is less important in building disaster resilience. As mentioned previously, natural capital such as wetlands play an important role in protecting costal communities.

As illustrated in Figure 3.6, the proposed CDRF has two main components; disaster management phases' activities (mitigation, preparedness, response, and recovery) and community capitals (social, economic, physical, and human).

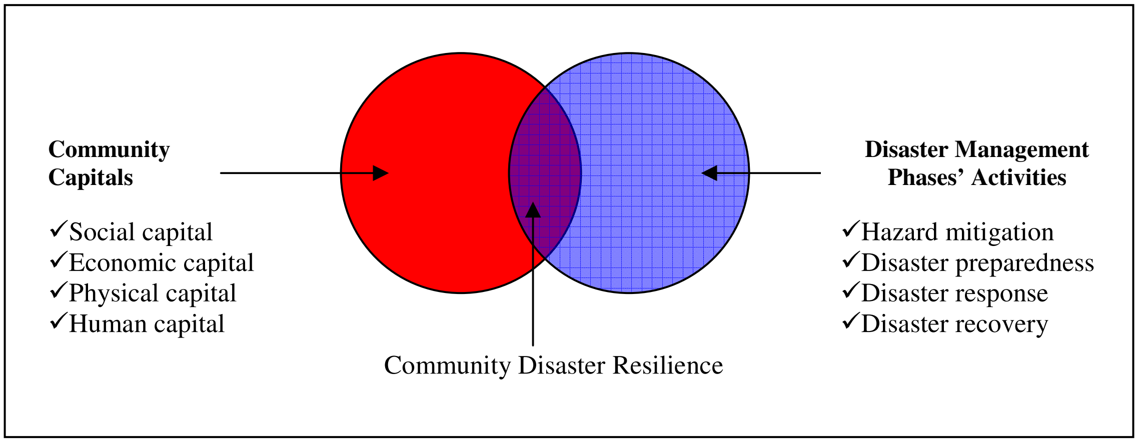


Figure 3.6. Community disaster resilience framework (CDRF)

The CDRF specifically emphasizes the importance of integrating the community capitals and the disaster management phases' activities to create a platform on which disaster resilience indicators can be developed. These indicators in turn will be used to measure the overall community disaster resilience. The CDRF views the four major forms of capital as important assets for successfully performing the activities of the four phases of disaster management. In other words, these four major forms of capital constitute the strength, capacity, and resources that enable a community to build resilience when undertaking the different types of activities of disaster management.

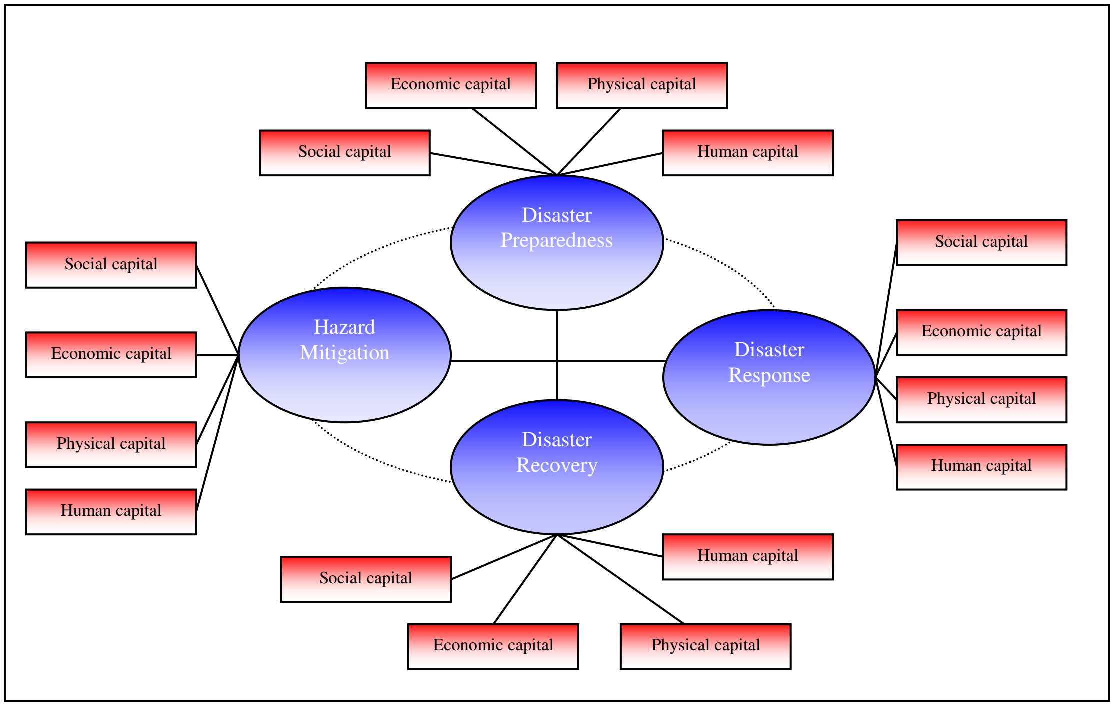


Figure 3.7. Schematic diagram of the CDRF showing the relationship between community capitals and disaster phases' activities

The disaster resilience of a community can therefore be understood and measured through assessing the major forms of capital a community has vis-à-vis the major activities that must be undertaken during the four phases of disaster. Figure 3.7 further illustrates the relationships of community capitals and disaster phases' activities. The framework shows that successful implementation of activities of each disaster phase depends on the four community capitals (social, economic, physical, and human).

The next sections discuss in detail the two components of the CDRF, i.e., the various activities undertaken in each phase and the properties of each community capital and how they contribute to building disaster resilience.

3.4.1. Disaster management phases' activities

This section describes the activities undertaken during the four disaster management phases: hazard mitigation, disaster preparedness, disaster response, and disaster recovery.

(a) Hazard mitigation

Hazard mitigation is defined as those advance actions taken to reduce or eliminate the long term risk to human life and property from natural hazards (Godschalk et al., 1999; Lindell & Perry, 1992). Hazard mitigation activities often focus on preventing disasters before they happen or reducing the likelihood of their occurrence. Such activities are termed either structural or nonstructural, depending on whether they affect buildings or land use (Godschalk et al., 1999; Mileti, 1999). These activities include: (i) strengthening buildings and infrastructure exposed to hazards by means of building codes, engineering design, and construction practices to increase the resilience and damage resistance of structures, as well as building protective structures such as dams, levees, and seawalls (these actions are termed structural mitigation measures), (ii) avoiding hazard prone areas by directing new development away from known hazards locations through comprehensive plans and zoning regulations (these actions are termed nonstructural mitigation measures), and (iii) maintaining protective features of the natural environment by protecting sand dunes, wetlands, vegetation cover, and other ecological elements that absorb and/or reduce hazard impacts, helping to protect exposed buildings and people (these actions are also termed non-structural mitigation measures).

(b) Disaster preparedness

Disaster preparedness activities are those that are undertaken to protect human lives and property in conjunction with threats that cannot be controlled by means of mitigation, or from which only partial protection can be achieved (Lindell & Perry, 1992). Such activities are based on the place where disaster impact will occur and the plans, procedures, and resources need to be prepared in advance to support a timely and effective response to the threat (Lindell & Perry, 1992). Lindell and Perry (1992) further pointed that there are two categories of activities of disaster preparedness: (i) activities that are related to warning the affected populations and emergency managers, such as the timing, and extent of the disaster magnitude, and (ii) activities that are designed to enhance the effectiveness of emergency operations. These activities include: developing plans for activation and coordination of emergency response organizations, devising standard operating procedures to guide organizations in the performance of their emergency functions, and training personnel in the use of those procedures. Disaster preparedness activities also include conducting drills and exercises, stockpiling resources such as protective equipment for emergency workers and medical suppliers for the injured, and assembling of community resources for use as needed in an emergency.

(c) Disaster response

Disaster response activities are those conducted during the time period that begins with detection of the event and ends with the stabilization of the situation following the impact (Lindell & Perry, 1992). Disaster response activities often focus on protecting the affected population, attempting to limit the damage from the initial impact, and minimizing damage from the secondary impacts (Mileti, 1999). According to Lindell, Prater and Perry (2007) such activities include: (i) securing the impacted area, (ii) warning the population, (iii) evacuating the threatened area, (iv) conducting search and rescue for the injured, (v) providing food and emergency medical care, and (vi) sheltering evacuees and other victims.

(d) Disaster recovery

Disaster recovery comprises actions taken to repair, rebuild, and reconstruct damaged properties and to restore disrupted community social routines and economic activities (Tierney et al., 2001). In addition Peacock et al. (1997) have defined community recovery as a process in which groups and organizations making up the community attempt to re-establish social networks to carry out the routines of daily life. Disaster recovery requires that people's lives within the community be restored to normal.

Often disaster recovery activities begin after the disaster impact has been stabilized and extends until a community has returned its normal activities (Lindell & Perry, 1992). The disaster literature categorizes disaster recovery into two phases based on time frame: (1) short term recovery (relief and rehabilitation) and (2) long term recovery (reconstruction). Relief and rehabilitation activities usually include: (i) restoration of access to impacted areas, (ii) re-establishment of economic activities (commercial and industrial), (iii) provision of housing, clothing, and food for the victims, (iv) restoration of critical facilities within the community such as water, power, and other community services, and (v) restoration of essential government or community services. Usually, reconstruction and rebuilding activities include: (i) rebuilding of major structures, e.g., buildings, roads, bridges, and dams, and (ii) revitalizing the economic system.

3.4.2. Community capitals

In recent years the major forms of capital (social, economic, physical, and human) have been recognized as important factors in building community capacities to deal with disasters (Callaghan & Colton, 2007; Dynes, 2002; Haque & Etkin, 2007; Walter, 2004). The hazard literature suggests that the sustainability and/or resilience of a community depends on its ability to access and utilize the major forms of capital (Beeton, 2006; Walter, 2004). The following discussion summarizes the four major forms of capital and how they can contribute to building community disaster resilience.

(a) Social capital

Currently many definitions of social capital exist in the literature (See for example, Bourdieu, 1986; Coleman, 1990; Putnam, 1995; Putnam, 2000). Putnam (1995) has defined social capital as the features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit. Although social capital has been defined in a variety of ways, there is a common emphasis on the aspect of social structure, trust, norms, and social networks that facilitate collective actions (Green & Haines, 2002). In the context of community disaster resilience, social capital reflects social cooperation or community connectedness, which provides an informal safety net during disasters and often helps people to access resources (Walter, 2004). For instance, community ties and networks are beneficial in building disaster resilience because they allow individuals to draw on the social resources in their communities and increase the likelihood that such communities will be able to adequately address their disaster concerns (Dynes, 2002; Walter, 2004). Similarly, social networks such as friends, relatives, and coworkers are important in building disaster resilience because they provide resources that can assist households during disaster response and recovery (Dynes, 2002; Lindell & Prater, 2003). Also social bonds have shown to influence adoption and implementation of hazard adjustment (Mileti, 1999). Furthermore, research has demonstrated that in circumstances where characteristics of social capital or connectedness are lacking in a community, members of that community tend to have less capacity in terms of networks for dealing with disasters (National Research Council, 2006; Walter, 2004).

(b) Economic capital

Fundamentally, economic capital denotes financial resources that people use to support their livelihoods (DFID, 1999; Smith, Simard, & Sharpe, 2001). It includes savings, income, investments or businesses, and credit. The importance of economic capital in building community disaster resilience is perhaps straightforward in the sense that economic resources increase the ability and capacity of individuals, groups, and communities to absorb disaster impacts and speed up the recovery process. People with access to financial resources recover more quickly from disasters (Mileti, 1999; Walter, 2004). Also access to credit and hazard insurance are associated with the level of household preparedness and ability to take protective measures (Lindell & Prater, 2003). The hazards literature suggests that a more stable and growing economy will generally enhance community disaster resilience, while an unhealthy or declining economy is an indication of increasing vulnerability (Buckle et al., 2001; Walter, 2004).

(c) Physical capital

Physical capital refers to the built environment, which comprises residential housing, commercial and industrial buildings, public buildings, and dams and levees. It also includes lifelines such as electricity, water, sewer, transportation, telecommunication facilities, as well as critical facilities such as hospitals, schools, fire and police stations, and nursing homes (DFID, 1999; Walter, 2004). The hazard literature suggests that physical capital is one of the most important resources in building a disaster-resilient community; because physical infrastructure such as roads, bridge, dams and levees as well as communication systems are essential elements for proper functioning of a community (Walter, 2004). Furthermore, critical facilities play an important role in ensuring that people have resources and support arrangements during disaster response and recovery. In general, lack of physical infrastructure or critical facilities may have a direct negative impact on a community’s capacity to prepare, respond, and recover from disasters.

(d) Human capital

Economists have defined human capital as the capabilities embodied in the working-age population that allow it to work productively with other forms of capital to sustain the economic production (Smith et al., 2001). Sometimes human capital is simply referred to as labor force or the ability to work. However, two main components of human capital are frequently mentioned in the literature; education and health of the working population group (DFID, 1999; Smith et al., 2001; Walter, 2004). Education which includes knowledge and skills that are accumulated through forms of educational attainment, training, and experience, is an essential component of human capital. Health of the working-age population is another important component of human capital. Health is considered as a critical component of human capital because an unhealthy population can not be able to harness other forms of capital (Smith et al., 2001). As a result a community can not fully engage in the process of building community disaster resilience.

For instance, knowledge and skills of local people on types of hazards, hazard history, and hazard risk in their community can be an important asset in building community disaster resilience. In general, the literature suggests that human capital in a form of knowledge, skills, health and physical ability determines an individual's level of disaster resilience more than other capitals (Walter, 2004).

3.5. Summary

This chapter has reviewed five conceptual frameworks with the aim of identifying important components of disaster resilience. Although these frameworks differ in disciplinary origin they offer a new way of thinking that helps to understand the concept of disaster resilience. Based on the literature review a disaster resilience working definition and a community disaster resilience framework (CDRF), which is a key aspect to identifying disaster resilience indicators, were developed. The CDRF has two components; disaster management phases' activities and community capitals. The literature suggests that the link between these two components is strong and clear and the importance of these components in building community disaster resilience is comprehensible. Using the CDRF as an analysis tool, the next chapter identifies disaster resilience indicators and develops a general approach to aggregate them to create the sub-indices and the overall CDRI.

CHAPTER IV

GENERAL APPROACH FOR MEASURING DISASTER RESILIENCE

4.1. Introduction

This chapter first discusses the use of indicators and indices as a general approach to measure disaster resilience. It highlights the importance and application of indicators and indices and the problems associated with creating and using them. Second, the chapter outlines a theoretical framework in which indicators for measuring disaster resilience were selected. Third, the chapter summarizes and describes the final selected set of indicators. Fourth, the chapter discusses the procedures employed in aggregating the indicators to calculate the sub-indices and the overall CDRI scores. Finally, the chapter introduces the study region, the data sources, and the unit of analysis.

As Chapter III indicates, disaster resilience is a multidimensional concept that encompasses many factors. Thus, developing a comprehensive approach to measure disaster resilience, which reflects its dimensions is undoubtedly challenging. There is currently no established methodological approach in the hazard literature to measure disaster resilience. Therefore, this research develops a measure of community disaster resilience following the basic logic of index construction. As discussed in Chapter III a comprehensive measure of disaster resilience should address issues of relevance to all four phases of disasters: mitigation, preparedness, response, and recovery. Furthermore, the literature on disaster resilience suggests that a fruitful approach for measuring disaster community resilience is to assess various forms of community capital domains. As noted in the previous chapter, this research considers four major forms of capital: social, economic, physical, and human. This chapter discusses how these four capital domains are employed to assess disaster resilience with respect to the four phases of disaster management and how these in turn will be combined to form a community disaster resilience index (CDRI).

4.2. Indicators and indices

The use of indicators and indices in social science research is not a new endeavor; it goes back as far as the early twentieth century (Birkmann, 2006; Cutter et al., 2003; King & MacGregor, 2000). In the field of economics for example, indicators had been in use since the 1940s (Birkmann, 2006). As a result economic indicators such as gross domestic product (GDP) and employment rates are widely used in many fields as measures of economic development (Birkmann, 2006).

For the past several decades, the use of indicators and indices has been significantly increasing in many fields including hazards and disasters. In the hazard and disaster research, there are currently a number of indices, which are increasingly being used in both research and policy formulation. Some of these indices include; the Earthquake Disaster Risk Index (EDRI) developed by Davidson (1997), the Social Vulnerability Index (SoVI) developed by Cutter et al. (2003), the Disaster Risk Index (DRI) developed by United Nations Development Program [UNDP] (2004), the Social Vulnerability Index to Climate Change for Africa developed by Vincent (2004), and the Prevalent Vulnerability Index (PVI) developed by the Inter-American Development Bank (2005). These indices play an important role as planning and management tools, for example, in facilitating resource allocation.

Indicators have been defined by different researchers in different ways for different purposes. There is no universally accepted definition of an indicator. For example, Chevalier et al. (1992) defined an indicator as a variable hypothetically linked to a phenomenon studied, which in itself cannot be directly measured. According to Wong (2001) an indicator is simply a proxy measure of some abstract, multidimensional concepts. Generally, an index is composed of several different indicators combined together using some mathematical formulae to give a single value called an index (Babbie, Halley, & Zaino, 2003; Simpson, 2006). Indices are powerful tools because of their ability to summarize more complicated technical data into a simpler way that both experts and non-experts can easily understand (Birkmann, 2006; Freudenberg, 2003). Indices can also be viewed as means of modeling a complex reality into a single construct (Vincent, 2004).

Even though the use of indices in the hazard and disaster research is growing, indices face a number of conceptual and methodological limitations. Literature suggests that indices should be used with great caution because they can be misleading (Freudenberg, 2003; Nardo et al., 2005). Some of the advantages and disadvantages of using indices are summarized in Table 4.1.

Table 4.1. Advantages and disadvantages of indices

Advantage	**Disadvantage**
(1) Indices can be used to summarize complex or multi-dimensional issues, in view of supporting decision-makers.	(1) Indices may send misleading, non-robust policy messages if they are poorly constructed or misinterpreted. Sensitivity analysis can be used to test composite indicators for robustness.
(2) Indices provide the big picture. They can be easier to interpret than trying to find a trend in many separate indicators. They facilitate the task of ranking communities on complex issues.	(2) The simple "big picture" results, which indices show may invite politicians to draw simplistic policy conclusions. Indices should be used in combination with the sub-indices to draw sophisticated policy conclusions.
(3) Indices can help attract public interest by providing a summary figure with which to compare the performance across communities and their progress over time.	(3) The construction of indices involves stages where judgment has to be made such as the selection of sub-indicators, choice of model, weighting indicators, and treatment of missing values. These judgments should be transparent and based on sound statistical principles.
(4) Indices could help to reduce the size of a list of indicators or to include more information within the existing size limit	(4) The selection of sub-indices and weights could be the target of political challenge.

Source: Nardo et al.(2005)

However, despite these limitations, the use of indicators and indices has continued to grow mainly because of two reasons; if they are properly constructed indices can be (1) effective communication and planning tools and (2) used effectively to compare performance and progress across space and time (Freudenberg, 2003).

4.3. Identification and selection of disaster resilience indicators

Construction of a composite index is a process that requires several steps to be systematically followed (Birkmann, 2006; Freudenberg, 2003; Nardo et al., 2005). These steps include: (1) Developing a theoretical framework for indicator selection; (2) Identifying and developing relevant indicators; (3) Standardizing indicators to allow comparisons; (4) Weighting indicators and groups of indicators; and (5) Testing the validity and reliability of the index.

This study follows similar basic steps in constructing the proposed community disaster resilience index (CDRI). While this chapter discusses steps one to four, step five will be introduced and discussed in Chapters V and VI.

4.3.1. Theoretical framework for indicator selection

The goal of indicator selection is to ensure that the selected indicators are relevant, measurable, practical, and most importantly reflect the concept being measured (Freudenberg, 2003; Nardo et al., 2005). Table 4.2 illustrates the theoretical framework or matrix that was used as a guide to achieve this goal. This framework is the key component to this dissertation; because it provides the basic logic followed in creating the CDRI. The framework represents a matrix of four by four cells. In total there are sixteen cells which represent sixteen disaster phase/capital domain sub indices that were used to develop the CDRI. These sub-indices will be discussed at length in the next section. The columns of the framework denote the community capitals while the rows represent the disaster phases' activities.

Based on this theoretical framework, disaster resilience indicators were selected by cross-classifying the four major forms of capital by the four disaster phases' activities. The first step was to identify the various activities of each disaster phase. Examples of the disaster phases' activities are provided in the first column. As can be recalled, these disaster phases' activities are discussed in Chapter III but also a detailed list of activities, stakeholders, and other actors that play a role in undertaking these activities is included in Appendix A. Then, based on the list of activities of each disaster phase, the second step was to identify indicators for each capital domain that are relevant to undertake each activity under each disaster phase. In the framework, these indicators are denoted by the word *indicator 1 to k*. These indicators will be discussed in detail in the next section.

Generally, the cross-classification method helped identify unique elements of community capital important in undertaking activities of each disaster phase. In addition, the cross-classification method helped to ensure content validity of the selected indicators. Specifically, one might simply combine together a host of capital indicators that appear to be relevant for measuring disaster resilience. However, this research takes a more theoretically driven approach by first identifying activities relevant to each disaster phase and then specifically identifying indicators from each form of capital that might be important for carrying out those activities. In addition the approach taken in this study begins to build the overall community disaster resilience index (CDRI) from the ground up, inductively, by first developing sub-indices for each disaster phase and capital domain. This process is driven by both theoretical and empirical decisions.

Table 4.2. Theoretical framework matrix for indicator selection

Disaster Phases' Activities	Capital Domains' Indicators			
	Social Capital	**Economic Capital**	**Physical Capital**	**Human Capital**
I: Hazard Mitigation *General definition:* Hazard mitigation is defined as those advance actions taken to reduce or eliminate the long term risk to human life and property from natural hazards *Example of activities:* • Building dams, levees, dikes, and floodwalls. • Landuse planning to prevent development in hazardous areas • Strengthening buildings through building codes and building standards. • Protecting natural environment e.g., wetlands	*Indicator 1* *to* *Indicator k*	*Indicator 1* *to* *Indicator k*	*Indicator 1* *to* *Indicator k*	*Indicator 1* *to* *Indicator k*
II: Disaster Preparedness *General definition:* Disaster preparedness is defined as those activities undertaken to protect human lives and property in conjunction with threats that cannot be controlled by means of mitigation *Example of activities:* • Developing response procedures • Design and installation of warning systems, • Developing plans for evacuation • Exercise to test emergency operations(Exercise & Drills) • Training of emergency personnel • Stockpiling of resources e.g., medical supplies	*Indicator 1* *to* *Indicator k*	*Indicator 1* *to* *Indicator k*	*Indicator 1* *to* *Indicator k*	*Indicator 1* *to* *Indicator k*
III Emergency Response *General definition:* Disaster response is defined as those activities that are conducted during the time period that begins with detection of the event and ends with the stabilization of the situation following the impact *Example of activities:* • Securing impacted area • Warning • Evacuation • Search & Rescue • Provision of medical care • Sheltering evacuees	*Indicator 1* *to* *Indicator k*	*Indicator 1* *to* *Indicator k*	*Indicator 1* *to* *Indicator k*	*Indicator 1* *to* *Indicator k*

Table 4.2 continued

Disaster Phases' Activities	**Capital Domains' Indicators**			
	Social Capital	**Economic Capital**	**Physical Capital**	**Human Capital**
IV: Disaster Recovery *General definition:* Disaster recovery comprises actions taken to repair, rebuild, and reconstruct damaged properties and to restore disrupted community social routines and economic activities	*Indicator 1*	*Indicator 1*	*Indicator 1*	*Indicator 1*
Example of activities: (i) Relief & rehabilitation • Re-establishment of economic activities • Provision of housing, clothing, and food • Restoration of critical facilities • Restoration of essential community services (ii) Reconstruction • Rebuilding of major structure e.g. public buildings, roads, bridges, and dams	*to*	*to*	*to*	*to*
• Revitalizing the economic system • Reconstruction of housing	*Indicator k*	*Indicator k*	*Indicator k*	*Indicator k*

Note: k is the number of indicators

4.3.2. Indicators of community capital domains

Prior discussion in Chapter III clearly defined each disaster phase and identified activities associated with each phase. These have been reproduced in Table 4.2 in the first column. What has yet to be completely discussed are the four capital domains, particularly with the types of indicators often associated with each domain. The following discussion summarizes how each capital domain is measured in this study in relation to disaster phases' activities. It is also important to stress that this discussion is of "raw" unstandardized data used to create the community disaster resilience index (CDRI). Later discussion will address how each measure is standardized.

(1) Indicators for measuring social capital

Social capital is probably the most studied form of capital among the four major forms of capital. Numerous studies have attempted to measure social capital and to quantify its effects. However, because of its multiple components, which require a broad measurement strategy, measuring social capital and its effects becomes extremely difficult. Yet, social capital is a theoretical construct that can not be directly measured. For that reason, empirical studies have used a wide range of variables as a measure or indicators of social capital.

While there is little consensus on the definition of social capital, at least there is an agreement among researchers that social capital is a group property rather than an individual property (Putnam, 2000). Therefore, social capital can best be measured by examining participation and involvement in social groups and civic engagement. For example, Putman (2000) has suggested measuring social capital by using composite indicators containing measures of involvement in community and organizational life, public engagement such as informal socializing (e.g. visiting friends), and reported level of inter-personal trust. However, while many researchers consider trust to be a good measure of social capital, trust itself is difficult to measure (Keeley, 2007), particularly using secondary data sources. In many cases, researchers have argued that there is no universal measure of social capita that is comprehensive enough to capture all elements of social capital.

Nonetheless, in relation to disaster phases' activities, social capital in this study was measured using the following six components suggested in the literature.

(i) *Participation in voluntary organizations (Volunteerism)*: This component was measured using registered non profit organizations.

(ii) *Involvement in social groups (Association densities):* The involvement in social groups was measured using recreational centers (bowling centers, and fitness centers), golf clubs, and sport organizations.

(iii) *Civic and political participation*: This social capital component was measured using three indicators: registered voters, civic and political organizations, and Census response rates for the decennial population and housing survey.

(iv) *Religious participation:* Religious participation was measured using religious organizations.

(v) *Community attachment*: The community attachment component was measured using owner-occupied housing units.

(vi) *Connection to working places*: This element was measured using two indicators: professional organizations and business organizations.

(2) Indicators for measuring economic capital

Economic capital means different things to different people, and many researchers have defined and measured economic capital differently (Keeley, 2007; Smith et al., 2001). For the purpose of this study, economic capital is broadly defined as financial resources that people use to support their livelihoods (DFID, 1999). It includes savings, income, investments, and credit. The literature suggests a variety of ways in which economic capital can be measured (Keeley, 2007). In this study, economic capital was measured using five components:

(i) *Income:* Income was measured using two indicators: per-capita income and median household income. Both per capita income and household median income were utilized mainly because the income distribution is skewed.

(ii) *Employment:* The employment component was measured using the percentage of people who are employed.

(iii) *Property value:* This component was measured using the median value of owner-occupied housing units.

(iv) *Business:* The business component was measured using business establishments.

(v) *Health insurance:* The health insurance component was measured using the percentage of people with health insurance.

(3) Indicators for measuring physical capital

Of the five major forms of capital, physical capital is probably the least studied form of capital in the literature that was reviewed. There is not much discussion in the literature on how it should be measured. However, in this study physical capital is loosely defined as the total built environment that helps people to support their livelihoods (DFID, 1999). It comprises of residential housing, commercial and industrial buildings, and public buildings, roads, bridges, dams, and levees. Also, it includes lifelines such as electricity, water, and telephone, and critical facilities such as hospitals, schools, fire and police stations, nursing homes, and emergency shelters. It is also important to note that most of the physical capital indicators utilized in this study were measured using establishments (rate). According to the U.S. Census an establishment is a single physical location at which business is conducted and/or service are provided. It is not necessarily identical with a company or enterprise, which may consist of one establishment or more (U.S. Census Bureau, 2000). Also note that the classifications and grouping of indicators are based on similarities of the indicators and/or the activities they can successfully perform.

In relation to disaster phases' activities, physical capital was measured using the following components:

(i) *Construction*: The construction component was measured using five indicators: building construction establishments, heavy and civil engineering construction establishments, highway, street, and bridge construction establishments, utility systems establishments and architecture and engineering establishments.

(ii) *Environment*: The environment component was measured using two indicators: environmental consulting establishments and environmental and conservation establishments.

(iii) *Land and building regulations*: This component was measured using three indicators: land subdivision establishments, legal services establishments, and building inspection establishments.

(iv) *Land use planning:* The land use planning component was measured using landscape architecture and planning establishments.

(v) *Property insurance:* This component was measured using property and causality insurance establishments

(vi) *Research*: The research component was measured using scientific research and development establishments.

(vii) *College*: The college component was measured using colleges, universities, and professional schools.

(viii) *Housing*: The housing component was measured using two indicators: occupied housing units and vacant housing units.

(ix) *Critical facilities:* This component was measured using eight indicators: hospitals, hospital beds, ambulances, fires stations, schools, licensed child care facilities, nursing homes, and hotels and motels.

(x) *Transportation:* The transportation component was measured using three indicators: occupied housing units with a vehicle available, special need transportation services, and school and employee buses.

(xi) *Communication:* The communication component was measured using five indicators: occupied housing units with telephone services, newspaper publishers, radio stations, television stations, and internet providers.

(xii) *Emergency shelter and relief services*: This component was measured using three indicators: temporary shelters, community housing, and community food services' facilities.

(4) Indicators for measuring human capital

Literature shows that there is little agreement among researchers on the definition of human capital or how it should be measured (Keeley, 2007). Many researchers have defined and measured human capital in different ways using different indicators. However, two most commonly used measures of human capital suggested in the literature are: (1) educational attainment of population, which is measured using the number of years of formal schooling of the working-age population, and (2) health, which is measured through self reported health status and life expectancy (Keeley, 2007). In relation to disaster phases human capital in this study was measured using three components: (i) educational attainment, (ii) health, and (iii) labor force (human resources).

(1) *Education attainment*: The education component was measured using percentage of population with more than high school education.

(2) *Health:* The health component was measured using two indicators: physicians and health care support workers.

(3) *Labor force (human resources)*: The labor force component in relation to disaster phase's activities was measured using the following sub-components:

(i) *Construction:* This sub-component was measured using four indicators: building construction workers, heavy and civil engineering construction workers, architecture and engineering workers, and highway, street, and bridge construction workers

(ii) *Environment:* The environment sub-component was measured using two indicators: environmental consulting workers and environmental and conservation workers.

(iii) *Land and building regulations:* This sub-component was measured using three indicators: land subdivision workers, population employed in legal services, and building inspectors.

(iv) *Land use planning*: The planning sub-component was measured using landscape architects and planners.

(v) *Property insurance:* This sub-component was measured using property and causality insurance workers.

(vi) *Mitigation:* The mitigation sub-component was measured using five indicators: FEMA community rating system (CRS) score, comprehensive plans, zoning regulations, FEMA approved mitigation plans, and building codes.

(vii) *Citizen protection:* The citizen protection sub-component was measured using the population employed as fire fighters, prevention, and law enforcement workers.

(viii) *Research:* The research sub-component was measured using the population employed in scientific research and development services.

(ix) *College:* The professional sub-component was measured using population employed in colleges, universities, and professional school.

(x) *Language:* The language sub-component was measured using the population that speaks English language very well.

(xi) *Transportation:* The transportation sub-component was measured using the population employed in special need transportation services.

(xii) *Community and social services:* This sub-component was measured using community and social workers.

4.3.3. Selected set of indicators for measuring disaster resilience

Initially**,** using the theoretical framework (Table 4.2), more than 120 indicators based on community capitals were identified that seemed theoretically relevant to the various disaster phases' activities. However, after further evaluation of each individual indicator using a reliability method (internal consistency) which will be discussed at greater length in Chapter V, only 75 indicators met the selection criteria. Table 4.3 presents the final set of selected indicators summarized by capital domains vis-à-vis disaster phases. In fact Table 4.3 is a new version of the framework matrix (Table 4.2). The rows represent the four community capitals' indicators and the columns represent the disaster phases' activities. In total, there are 75 indicators representing four types of capital: social capital, which consists of 9 indicators, economic capital (6), physical capital (35), and human capital (25).

The relevance of indicators to various disaster phases' activities is indicated by 1 and 0. A cell labeled 1 in Table 4.3 indicates that an indicator or set of indicators was used to develop a particular disaster phase sub-index. A cell labeled 0 indicates that an indicator or set of indicators was not used in creating that particular disaster phase sub-index. It is also important to note that during the indicator selection process, it became clear that social and economic capital indicators are critical to all disaster phases' activities. As shown in Table 4.3, each cell is labeled 1 in all social and economic capital indicators against all four disaster phases' activities. This indicates that these indicators are relevant to all disaster phases. As an example of the relevance of indicators, consider indicator # 31. Hospital (indicator # 31) is labeled 0 under hazard mitigation but the same indicator has been labeled 1 under disaster response, which indicates that hospital as an indicator is less relevant to hazard mitigation but is more relevant to disaster response.

Table 4.3. The final set of selected indicators used to construct the CDRI

Index item	Mitigation	Preparedness	Response	Recovery
I: Social capital indicators				
(1) Nonprofit organizations registered with the IRS	1	1	1	1
(2) Recreational centers(bowling, fitness, golf clubs) and sport organizations	1	1	1	1
(3) Registered voters	1	1	1	1
(4) Civic and political organizations	1	1	1	1
(5) Census response rates	1	1	1	1
(6) Religious organizations	1	1	1	1
(7) Owner-occupied housing units	1	1	1	1
(8) Professional organizations	1	1	1	1
(9) Business organizations	1	1	1	1
II: Economic capital indicators				
(10) Per capita income	1	1	1	1
(11) Median household income	1	1	1	1
(12) Employed civilian population	1	1	1	1
(13) Median value of owner-occupied housing units	1	1	1	1
(14) Business establishments	1	1	1	1
(15) Population with health insurance	1	1	1	1
III: Physical capital indicators				
(16) Building construction establishments	1	0	0	1
(17) Heavy and civil engineering construction establishments	1	0	0	1
(18) Highway, street, and bridge construction establishments	1	0	0	0
(19) Architecture and engineering establishments	1	1	0	1
(20) Land subdivision establishments	1	0	0	0
(21) Legal services establishments	1	0	0	0
(22) Property and causality insurance establishments	1	0	0	0
(23) Building inspection establishments	1	0	0	0
(24) Landscape architecture and planning establishments	1	0	0	0
(25) Environmental consulting establishments	1	0	0	0
(26) Environment and conservation establishments	1	0	0	0
(27) Scientific research and development establishments	0	1	0	0
(28) Colleges, Universities, and Professional schools	0	1	0	0
(29) Housing units	0	0	1	0
(30) Vacant housing units	0	0	1	0
(31) Hospitals	0	0	1	0
(32) Hospital beds	0	0	1	0
(33) Ambulances	0	0	1	0
(34) Fire stations	0	0	1	0
(35) Nursing homes	0	0	1	0
(36) Hotels and motels	0	0	1	0
(37) Occupied housing units with vehicle available	0	0	1	0
(38) Special need transportation services	0	0	1	0
(39) School and employee buses	0	0	1	0
(40) Owner-occupied housing units with telephone service	0	0	1	0
(41) Newspaper publishers	0	0	1	0
(42) Radio stations	0	0	1	0
(43) Television broadcasting	0	0	1	0
(44) Internet service providers	0	0	1	0
(45) Temporary shelters	0	0	1	0
(46) Community housing	0	0	1	0
(47) Community food service facilities	0	0	1	0
(48) Schools	0	0	1	0
(49) Licensed child care facilities	0	0	1	0
(50) Utility systems construction establishments	0	0	0	1

Table 4.3 continued

Index item	Mitigation	Preparedness	Response	Recovery
IV: Human capital indicators				
(51) Population with more than high school education	1	1	1	1
(52) Physicians	1	1	1	1
(53) Health care support workers	1	0	0	0
(54) Building construction workers	1	0	0	1
(55) Heavy and civil engineering construction workers	1	0	0	1
(56) Architecture and engineering workers	1	0	0	1
(57) Environmental consulting workers	1	0	0	0
(58) Environment and conservation workers	1	0	0	0
(59) Land subdivision workers	1	0	0	0
(60) Building inspectors	1	0	0	1
(61) Landscape architects and planners	1	1	1	0
(62) Property and causality insurance workers	1	0	0	0
(63) Highway, street, and bridge construction workers	1	0	0	1
(64) Population employed in legal services	1	0	0	0
(65) Percentage of population covered by comprehensive plan	1	0	0	0
(66) Percentage of population covered by zoning regulations	1	0	0	0
(67) Percentage of population covered by building codes	1	0	0	0
(68) Percentage of population covered by FEMA approved mitigation plan	1	0	0	0
(69) Community rating system(CRS) scores	1	0	0	0
(70) Fire fighters, prevention, and law enforcement workers	0	1	1	0
(71) Population employed in scientific research and development services	0	1	0	0
(72) Colleges, universities, and professional schools employees	0	1	0	0
(73) Population that speaks english language very well	0	1	1	1
(74) Population employed in special need transportation services	0	0	1	0
(75) Community and social workers	0	0	0	1

Note: (1) Most of the physical capital indicators were measured using establishments. According to the U.S. Census an establishment is a single physical location at which business is conducted and/or service are provided. It is not necessarily identical with a company or enterprise, which may consists of one establishment or more.
(2) Indicators were standardized by percentage or rate (per 1000)

The selected set of indicators is also more elaborated and included in Appendix B. The first column of each Table in Appendix B describes the activities that should be undertaken during a particular disaster phase. The second column shows the components that were used to measure a capital domain in relation to the disaster phase's activities, while the third column lists the specific indicators for each component. The indicators are further grouped into two major categories; generic indictors and specific indicators. Generic indicators refer to those indicators which are relevant to all disaster phases. For example, education as an indicator is important or relevant to all disaster phases. Specific indicators are those indicators which are only relevant to a specific type of disaster phase. For example, building code as an indicator is more relevant to measuring hazard mitigation than disaster response. As mentioned previously, unlike physical and human capital indicators, social and economic capital indicators are relevant to all disaster phases. Thus, all social and economic capital indicators fall under generic category.

4.4. Procedures for calculating the sub-index and CDRI scores

A four-step procedure was employed in calculating the CDRI and sub-index scores: (i) scale adjustment of indicators, (ii) standardization or normalization, (iii) creation of 16 sub-indices, and (iv) creation of the CDRI. These four steps are described below.

Step 1: Scale adjustment of indicators

The first step in calculating the sub-index scores and CDRI was to perform a scale adjustment of the selected indicators. From the mathematical point of view, it is important to do a scale adjustment before performing the mathematical combination of indicators so as to put the indicators in a common scale. Typically, indicators should be adjusted to a common dimensional scale e.g., number of deaths per live births (Freudenberg, 2003). Indicators in this study were adjusted by population size. The indicators were converted into either percentage or rate (per 1000), depending on the type of an indicator and the unit of measurement. The rate of per 1000 was chosen because given the ranges of values of the indicators this rate seemed a reasonable adjustment measure in order to avoid obtaining small fractions of numbers after adjusting the scale.

Step 2: Standardizing indicators

Data used to measure indicators come from different sources in a variety of statistical units, such as dollars, miles, degrees, hours, and number of people. To avoid adding up apples and oranges, it is imperative to standardize or normalize them before they are aggregated into a composite index. In addition, indicators are normalized in order to avoid having extreme values dominate and also to minimize the potential problems of data quality (Freudenberg, 2003;

Nardo et al., 2005). Most importantly, indicators are normalized or standardized in order to provide a way of comparing them that includes consideration of their distribution (Abdi, 2007).

Several methods have been suggested in the literature that can be used to standardize or normalize indicators such as Z-*score, Minimum-Maximum,* and *Distance from the mean* (Briguglio, 2003; Freudenberg, 2003; Nardo et al., 2005). Each of these methods has its own advantages and disadvantages. For the purpose of this study a z-score method was used to standardize the selected set of indicators. The z-score is given by equation 4.1 (Freudenberg, 2003).

$$\text{Z-Score} = \left(\frac{Actual\,Value - Mean\,Value}{Standard\ Deviation}\right) \tag{4.1}$$

The z-score method was chosen mainly because it is one of the most commonly used methods, which reflects its relevance and strength in standardizing indicators. In addition, the z-score method was preferred over other methods because it converts all indicators to a common scale (Abdi, 2007). So, the z-scores computed from different samples with different measurement units can be directly compared because these numbers do not express the original unit of measurements (Abdi, 2007; Freudenberg, 2003).

One of the major limitations of other methods such as *Minim-Maximum* method is that the scaling factor is based on range rather than standard deviation (Freudenberg, 2003). As a result extreme values such as outliers can have a large impact on the overall index, and hence misrepresent the results.

Step 3: Creation of 16 sub-indices

The first step in creating the CDRI was to combine indicators to create sub-indices. As mentioned earlier, the conceptual matrix (Table 4.2) denotes 16 cells. Each cell represents a disaster phase/capital domain sub-index. Conceptually 16 sub-indices can be created from the framework. However, because social and economic capitals both have the same set of indicators there are only 10 disaster phase/capital domain sub-indices. Thus, based on the conceptual matrix (Table 4.2) a total of 18 sub-indices can be created using three different "permutations" or approaches as referred to in this dissertation, to develop the final CDRI. These 18 sub-indices are listed in Table 4.4. Approach one consists of 4 capital domain sub-indices, approach two (10 disaster phase/capital domain sub-indices), and approach three (4 disaster phase sub-indices).

Table 4.4. The list of 18 sub-indices used to create CDRI

1	**Approach 1(Capital domain)**	
	Social capital	**CDRI-1**
	Economic capital	
	Physical capital	
	Human capital	
2	**Approach 2 (Disaster phase/capital domain)**	
	Social capital	**CDRI-2**
	Economic capital	
	Physical capital-hazard mitigation	
	Human capital-hazard mitigation	
	Physical capital-disaster preparedness	
	Human capital-disaster preparedness	
	Physical capital-disaster response	
	Human capital-disaster response	
	Physical capital-disaster recovery	
	Human capital-disaster recovery	
3	**Approach 3 (Disaster phases)**	
	Hazard mitigation	**CDRI-3**
	Disaster preparedness	
	Disaster response	
	Disaster recovery	

Although there are three different ways in which indicators can be combined to create the overall community disaster resilience index (CDRI), this research focuses on the first approach, which is based on capital domains. This is because there is a conceptual and/or methodological problem regarding approaches two and three. Conceptually, indicators of the second and third approach are counted more than once. Given the fact that these indicators can be relevant to more than one disaster phase, double counting becomes inevitable. Double counting of indicators should always be avoided because of the potential for bias. However, one may also argue that, if an indicator is relevant to all four disaster phases for example, this will imply that such an indicator is more important than say an indicator, which is relevant to only one disaster phase. It is also important to note that the problem of double counting arises only when these sub-indices are combined together to create the overall CDRI. However, there is no problem if individual sub-indices are used. While the primary focus of this dissertation is on CDRI-1, for comparison purposes all three approaches will be utilized.

Step 4: Creation of CDRI

Several mathematical aggregation methods have been suggested in the literature that can be utilized to calculate the final index score (Chakraborty, Tobin, & Montz, 2005; Vincent, 2004). In this study two mathematical aggregation methods were tested: The simple linear summation aggregation method (based on unequally weighted indicators) and the averaging method (based on equally weighted indicators). Using summation method the final score is obtained by simply adding up indicators whereas the score of averaging method is obtained by calculating the average of the indicators. The results of these two methods appeared to be similar but not identical. The averaging method seemed to yield better results than the simple linear summation method; therefore was used to calculate the sub-index and overall CDRI scores. Essentially, there are three reasons that make the average method more relevant to use than the simple linear summation method:

(i) Each sub-index has a different number of indicators, so if indicators are simply added together; the final score will tend to be highly influenced by the sub-indices with the highest numbers of indicators. That is, sub-indices with more indicators such as physical capital (35 indicators) will be weighted more heavily than the other sub-indices in the overall CDRI score.

(ii) The average method assumes equal weights among sub-indices. This assumption seems reasonable because, in essence, there is no theoretical reason to suggest that any of the capital domains (social, economic, physical, and human) or disaster phases' activities (mitigation, preparedness, response and recovery) is more important than the other.

(iii) Most importantly, the average method seemed to perform better with all the external criteria utilized in this study in assessing the validity of the CDRI.

(a) Calculating sub-index score

To obtain a score for each sub-index, indicators were aggregated by calculating an arithmetic mean score using equation 4.2. This is a general equation used to calculate the sub-indices' scores.

$$SI = \frac{\sum_{i=1}^{N} Z}{N} \tag{4.2}$$

Where:

SI = Sub-index score

Z = Standardized score of an indicator

N = Number of indicators of a sub-index

i = 1, 2, 3…..N

So, for example, the mean score of economic capital sub-index (EC)[1] is given by equation 4.3.

$$\text{EC} = \frac{per\_inco + med\_inco + employ + hsg\_value + buss + insurance}{6} \tag{4.3}$$

[1] *per_inco* = per capita income; *med_inco* = median household income; *employ* = employed civilian population; *hsg_value* = median value of owner occupied housing units; *buss* = business establishments; *insurance* = population with health insurance.

(b) Calculating the overall CDRI score

Utilizing the three approaches, the score for each CDRI was calculated as follows:

(i) Approach 1: Capital based approach

The capital based approach means that the CDRI was created based on four capital domain's sub-indices; and is referred as CDRI-1. While CDRI-2 and CDRI-3 are based on counting of indicators more than once, indicators used to calculate CDRI-1 were counted only once. Four capital sub-indices with a total of 75 indicators were used to calculate the CDRI-1 score using equation 4.4. The total number of indicators used to calculate the CDRI-1 score are summarized in Table 4.5.

$$CDRI\text{-}1 = (SC+EC+PC+HC)/4 \quad (4.4)$$

Where:

SC = Social capital sub-index

EC = Economic capital sub-index

PC = Physical capital sub-index

HC = Human capital sub-index

Table 4.5. Total number of indicators used to calculate CDRI-1 score

	Capital domain sub-index	**Number of indicators**
1	Social capital	9
2	Economic capital	6
3	Physical capital	35
4	Human capital	25
Total		**75**

(ii) Approach 2: Disaster phase/capital domain approach

The disaster phase/capital domain approach is the combination of capital domain's sub-indices and disaster phase's sub-indices as shown in Table 4.6. The CDRI calculated using the disaster phase/capital domain approach is referred as CDRI-2 and consists of ten sub-indices.

The CDRI-2 score was calculated by counting indicators of social capital and economic capital sub-indices only once even though they are relevant to all four phases of disaster whereas indicators for physical and human capital sub-indices were counted more than once depending on their relevance to disaster phases' activities (see Table 4.3). Given the fact that indicators were counted more than once; in total CDRI-2 consists of 95 indicators and was calculated using equation 4.5. Table 4.6 summarizes the total number of indicators and sub-indices used to calculate the CDRI-2 score.

$$\text{CDRI-2} = [(SC+EC) + \overbrace{(PC+HC)}^{\text{Mitigation}} + \overbrace{(PC+HC)}^{\text{Preparedness}} + \overbrace{(PC+HC)}^{\text{Response}} + \overbrace{(PC+HC)}^{\text{Recovery}}]/10 \qquad (4.5)$$

Where:

SC = Social capital sub-index

EC = Economic capital sub-index

PC = Physical capital sub-index

HC = Human capital sub-index

Table 4.6. Total number of indicators used to calculate CDRI-2 score

	Capital domain sub-index	**Number of indicators**
1	Social capital	9
2	Economic capital	6
3	Physical capital-Mitigation	11
4	Human capital-Mitigation	19
5	Physical capital-Preparedness	3
6	Human capital-Preparedness	7
7	Physical capital-Response	21
8	Human capital-Response	6
9	Physical capital-Recovery	4
10	Human capital-Recovery	9
Total		**95**

(iii) Approach 3: Disaster phase based approach

The disaster phase approach, which is based on disaster phase's sub-indices, is referred as CDRI-3. It was calculated using four disaster phase's sub-indices as shown in Table 4.7 with a total of 140 indicators. This implies that indicators were counted more than once; depending on the relevance of an individual indicator to the disaster phases' activities (see also Table 4.3). For example, social and economic capital indicators, which are relevant to all disaster phases' activities were counted four times or, in other words, were given a weight of four. The advantage of CDRI-3 is that it enables the assessment of disaster resilience based on individual disaster phases' activities, which could be very instrumental to emergency managers and planners in identifying areas where they can direct resources in building disaster-resilient communities. In addition, the CDRI-3 score can be used to compare levels of disaster resilience based on disaster phases across and within communities. The CDRI-3 score was calculated using equation 4.6. The total numbers of indicators and sub-indices used to calculate the CDRI-3 score are summarized in Table 4.7.

$$\text{CDRI-3} = [\,\overbrace{(SC + EC + PC + HC)}^{\text{Mitigation}} + \overbrace{(SC + EC + PC + HC)}^{\text{Preparedness}} + \overbrace{(SC + EC + PC + HC)}^{\text{Response}} + \overbrace{(SC + EC + PC + HC)}^{\text{Recovery}}\,]/4 \qquad (4.6)$$

Where:

SC = Social capital sub-index

EC = Economic capital sub-index

PC = Physical capital sub-index

HC = Human capital sub-index

Table 4.7. Total number of indicators used to calculate CDRI-3 score

		Mitigation	Preparedness	Response	Recovery
1	Social capital	9	9	9	9
2	Economic capital	6	6	6	6
3	Physical capital	11	3	21	4
4	Human capital	19	7	6	9
Total		**45**	**25**	**42**	**28**

4.5. Study region, unit of analysis, and data sources

(i) Study region

As mentioned previously in Chapter I, the study region for this research is the U.S. Gulf coast region. It was chosen because the region is one of the most vulnerable coastal regions in the nation to various weather related hazards such as hurricanes, tropical storms, and floods. The increasing hazard vulnerability in the U.S. Gulf coast region poses a challenge to planners and emergency managers on how to enhance local community coping capacities and foster disaster resilience within the region. This makes the U.S. Gulf coast region to be an excellent setting for studying disaster resilience at a regional scale.

This region extends from the Florida Keys westward to the Southern tip of Texas following the coast line of six states; Florida, Georgia, Alabama, Mississippi, Louisiana, and Texas (see Figure 4.1). More specifically, this study focuses on coastal counties of the U.S. Gulf coast region.

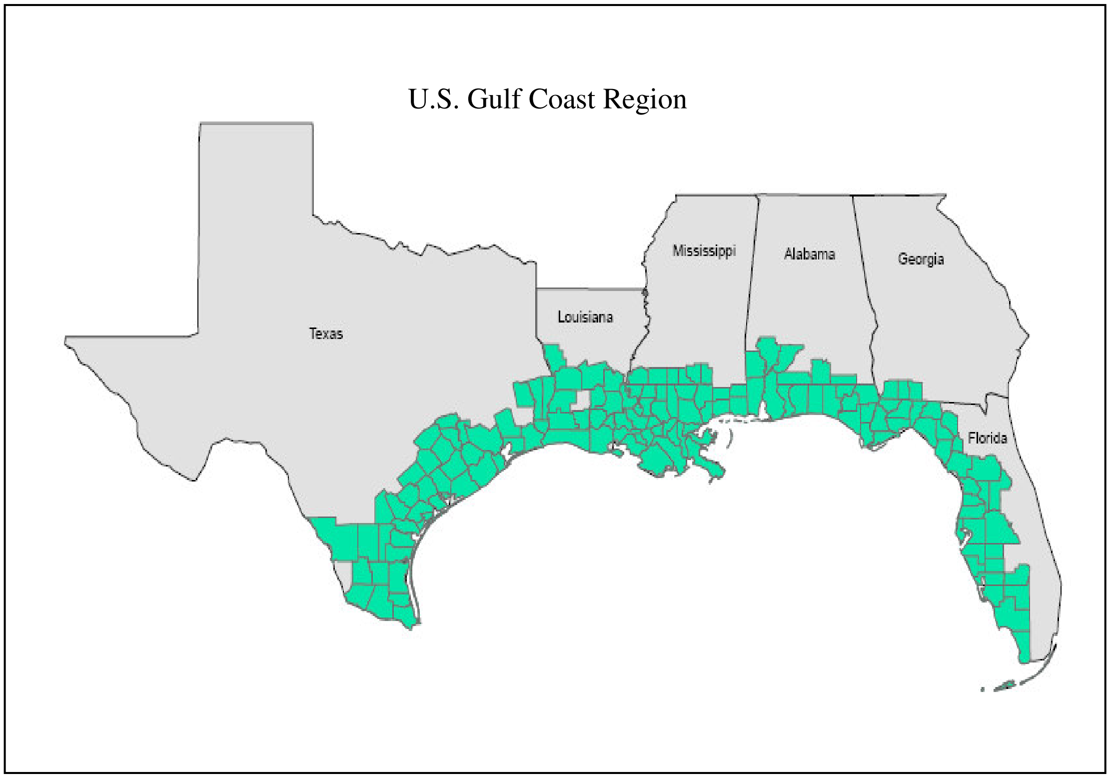


Figure 4.1. The U.S. Gulf coast region (the green area depicts the coastal counties and parishes)

According to the National Oceanic and Atmospheric Administration (NOAA) special projects' office, the U.S. Gulf coast region has a total of 144 coastal counties and parishes (Crossett et al., 2004). Florida has the largest number of coastal counties (42) followed by Texas (41), Louisiana (38), Mississippi (12), Alabama (8) and lastly Georgia (3). Table 4.8 summarizes the total number of coastal counties and parishes for each state in the U.S Gulf coast region.

Table 4.8. List of coastal counties and parishes of the U.S. Gulf coast region

I	**Florida**	31	Okaloosa	59	Lamar	89	St. Charles	119	Harris
1	Bay	32	Pasco	60	Marion	90	St. Helena	120	Hidalgo
2	Calhoun	33	Pinellas	61	Pearl River	91	St. James	121	Jackson
3	Charlotte	34	Polk	62	Pike	92	St. John the Baptist	122	Jasper
4	Citrus	35	Santa Rosa	63	Stone	93	St. Landry	123	Jefferson
5	Collier	36	Sarasota	64	Walthall	94	St. Martin	124	Jim Hogg
6	DeSoto	37	Sumter	65	Wilkinson	95	St. Mary	125	Jim Wells
7	Dixie	38	Suwannee	**V**	**Louisiana**	96	St. Tammany	126	Kenedy
8	Escambia	39	Taylor	66	Acadia	97	Tangipahoa	127	Kleberg
9	Franklin	40	Wakulla	67	Ascension	98	Terrebonne	128	Lavaca
10	Gadsden	41	Walton	68	Assumption	99	Vermilion	129	Liberty
11	Gilchrist	42	Washington	69	Avoyelles	100	Vernon	130	Live Oak
12	Glades	**II**	**Georgia**	70	Beauregard	101	Washington	131	Matagorda
13	Gulf	43	Decatur	71	Calcasieu	102	West Baton Rouge	132	Newton
14	Hardee	44	Grady	72	Cameron	103	West Feliciana	133	Nueces
15	Hendry	45	Thomas	73	East Baton Rouge	**VI**	**Texas**	134	Orange
16	Hernando	**III**	**Alabama**	74	East Feliciana	104	Aransas	135	Refugio
17	Hillsborough	46	Baldwin	75	Evangeline	105	Austin	136	San Patricio
18	Holmes	47	Clarke	76	Iberia	106	Bee	137	Starr
19	Jackson	48	Covington	77	Iberville	107	Brazoria	138	Tyler
20	Jefferson	49	Escambia	78	Jefferson	108	Brooks	139	Victoria
21	Lafayette	50	Geneva	79	Jefferson Davis	109	Calhoun	140	Waller
22	Lake	51	Mobile	80	Lafayette	110	Cameron	141	Washington
23	Lee	52	Monroe	81	Lafourche	111	Chambers	142	Webb
24	Leon	53	Washington	82	Livingston	112	Colorado	143	Wharton
25	Levy	**IV**	**Mississippi**	83	Orleans	113	DeWitt	144	Willacy
26	Liberty	54	Amite	84	Plaquemines	114	Duval		
27	Madison	55	George	85	Pointe Coupee	115	Fayette		
28	Manatee	56	Hancock	86	Rapides	116	Fort Bend		
29	Marion	57	Harrison	87	Sabine	117	Galveston		
30	Monroe	58	Jackson	88	St. Bernard	118	Goliad		

NOAA's special projects office defines a county as coastal if one of the following two criteria is met: (1) at a minimum, 15% of the county's total land area is located within a coastal watershed or, (2) a portion of, or an entire county accounts for at least 15% of a coastal cataloging unit. According to the U.S. Geologic Survey, hydrologic units are classified at four levels: regions, sub-regions, accounting units, and cataloging units. A cataloging unit is the smallest hydrologic unit in this hierarchy (Crossett et al., 2004).

(ii) Unit of analysis

As mentioned earlier, a county is the unit of analysis for this study. A county was chosen mainly because (with the exception of Texas) it is often where local decisions on community mitigation measures and risk reduction programs are directed. In additional, data at county scale are available and relatively easy to access.

However, the use of a county as the unit of analysis has some limitations. First, while some counties are limited in political powers, others are powerful central political units (Zahran, Brody, Kim, & Vedlitz, 2006). Second, counties vary considerably in geographical and population sizes. For example, Harris county (Texas) which includes Houston metropolitan area has a population of more than three million people whereas Kenedy county (Texas) has a total population of about four hundred people. Small counties such as Kenedy are more likely to be overshadowed by big counties such as Harris. Third, measuring disaster resilience at a county level is generally problematic because a county is not often considered as a real social unit. Few people think of a county as their community. This is because social interactions and networks take place in communities not counties. Nonetheless, taking into account all these factors, a county appeared to be a reasonable unit of analysis to explore the concept of disaster resilience both in terms of spatial and non-spatial dimensions.

(iii) Data sources

One of the critical elements of any research is the issue of data availability. Like any other research in social science, this research was somewhat shaped by the issue of data availability. Generally, the indicator selection was partly limited by the unavailability of data. Data for some potential indicators were not available or not easily accessible; for example, data on emergency response plans, disaster recovery plans, certified floodplain managers, certified planners, community emergency response teams, and volunteers. Most of these data can only be obtained by conducting a field survey.

In general, data for this study were obtained from a variety of secondary sources. However, most data were obtained from the U.S. Census Bureau; specifically from the County Business Patterns. Other main sources of data for this study included the U.S. Fire Administration, the U.S. Department of Health and Human Services, the U.S. Department of Education, the National Child Care Information Center, the International Code Council, the Association of Religious Data Archives, the National Center for Charitable Statistics, the FEMA National Flood Insurance Program, and the NOAA Coastal Risk Atlas. Also, data were obtained from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), the Center for Disease Control and Prevention (CDC), and various county and city websites. The data sources for each indicator used in this study are included in Appendix C.

4.6. Summary

In this chapter, a review of the use of indicators and indices was conducted, a final set of indicators was generated, three approaches for combining and aggregating the indicators to calculate the sub-indices and the overall CDRI scores were developed and finally a study region, a unit of analysis, and data sources were introduced. The following bullets summarize the key points from this chapter.

- The literature suggests that indices are a useful tool because of their ability to simplify complex data into a simpler way so that both experts and non-experts can understand them. However, poorly constructed indices can also provide misleading information; so indices should be interpreted with great caution.

- The theoretical framework or matrix developed for selecting indicators (see Table 4.2) is an easy and effective way to identify relevant disaster resilience indicators based on capital domains/disaster phases.
- A total of 75 disaster resilience indicators representing four capital domains was selected: Social capital (9), economic capital (6), physical capital (35), and human capital (25).
- Based on the conceptual matrix it became clear that social and economic capital indicators play an important role in undertaking all disaster phases' activities whereas physical and human capital indicators are relevant to specific disaster phases' activities.
- Three approaches were developed to aggregate the selected indicators and calculate the sub-indices and overall CDRI scores. Putting aside the conceptual limitations of CDRI-2 and CDRI-3, the approaches seem useful for comparison purposes.
- The overall CDRI scores were calculated using the average method, which is based on equal weighting of sub-indices and seemed to provide better results than the summation method.
- A county seems a reasonable unit of analysis to use for this type of research mainly because of easy data availability and is where hazard mitigation plans and risk reduction programs are directed

CHAPTER V

RELIABILITY ASSESSMENT

5.1. Introduction

Chapter IV presented and discussed the selected set of indicators, and the method used to calculate the sub-indices and the overall CDRI scores. This chapter will discuss the procedures used to assess the reliability of the sub-indices and CDRIs as measures of disaster community resilience.

Generally, reliability is concerned with consistency of a set of measurements or measuring instruments (Babbie, 2005; Carmines & Zeller, 1979). One way of assessing reliability of a composite index is to examine the internal consistency of individual indicators within the index on how they relate to the overall index score (Norusis, 2005). In this respect the greater the internal consistency (correlation), the more reliable the measure (Norusis, 2005). Cronbach's alpha coefficients were utilized in assessing the reliability of the CDRI and sub-indices.

The reliability assessment was employed to assess the internal consistency of the indicators as well as to facilitate the selection of indicators. Indicators were selected based on their performances in terms of the overall internal consistency (Cronbach's alpha level) and inter-item correlations. Additionally, the reliability assessment helped to examine whether the sub-indices had adequate precision. To ensure that the sub-indices had adequate precision, indicators that exhibited low "Corrected item-Total correlation" statistics were dropped from the scale. Corrected item-total correlation is the correlation of an item with the sum score of all other items in a scale (Norusis, 2005). This helped to maximize the Cronbach's alpha coefficients of the sub-indices.

5.2. Cronbach's alpha coefficients of the sub-indices

Cronbach's alpha is given by equation 5.1 (Norusis, 2005).

$$\alpha = \frac{\kappa}{\kappa - 1}\left(1 - \frac{\sum item \quad variances}{Scale \quad variance}\right) \tag{5.1}$$

Where κ = Number of items or indicators

The Cronbach's alpha coefficients can vary from zero to one; where one denotes perfect reliability and zero a very unreliable measure. While there is little agreement on the interpretation of alpha or what constitutes an acceptable level of alpha that is, even a low level of alpha may still be useful (Schmitt, 1996), a great body of literature suggests that for the early stages of research a Cronbach's alpha coefficient approaching .70 is acceptable (Norusis, 2005). Given the fact that research on disaster resilience in the hazards and disasters field is at its infant stage, it is therefore reasonable to use the alpha level of about .70 as a basic standard to ascertain the reliability of the overall index and sub-indices for this study.

As discussed in Chapter IV, the conceptual matrix (Table 4.2) was used as a guide for selecting indicators in this study, which conceptually represents 16 disaster phase/capital domain sub-indices. However, because social and economic capitals both have the same set of indicators; this reduces the number to only 10 sub-indices (See Table 5.1). Therefore, the reliability analysis focused on maximizing the Cronbach's alpha coefficients of the 10 sub-indices. Indicators which appeared not to perform well were dropped until the reasonable Cronbach's alpha coefficient of a sub-index was attained. The final total number of indicators for each sub-index is included in Table 5.1.

Table 5.1.Cronbach's alpha coefficients of the sub-indices used in indicator selection

Sub-index	Item	Alpha
Social capital	9	.659
Economic capital	6	.914
Physical capital-Mitigation	11	.771
Human capital-Mitigation	19	.693
Physical capital-Preparedness	3	.571
Human capital-Preparedness	7	.530
Physical capital-Response	21	.624
Human capital-Response	6	.466
Physical capital-Recovery	4	.651
Human capital-Recovery	9	.630

The results show that the highest Cronbach's alpha coefficient is exhibited by economic capital sub-index (alpha = .914), followed by the physical capital-mitigation (alpha = .771), human capital-mitigation (alpha = .693), social capital (alpha = .659), physical capital-recovery (alpha = .651), Human capital-recovery (alpha = .630), and physical capital- response (alpha = .624). Generally, these sub-indices demonstrated a relatively high level of internal consistency, which implies that these measures are reliable.

Also, as can be observed from Table 5.1, the lowest alpha is exhibited by three sub-indices: human capital-response (alpha = .466), human capital-preparedness (alpha =.530), and physical capital-preparedness (alpha = .571). Based on the threshold of a Cronbach's alpha coefficient of about .70, these alpha coefficients are relatively low. From a reliability analysis point of view, these results imply that these measures have comparatively low precision but are reasonable to use for this type of exploratory research. The next section discusses the inter-item correlations of each sub-index.

5.3. Inter-item correlations

This section examines the inter-item correlations among indicators for each sub-index. The results are presented in Tables 5.2 through 5.11. Tables 5.2 and 5.3 present the results of inter-item correlations for social capital and economic capital indicators, respectively. As expected, the economic capital indicators (Table 5.3), are all positively correlated and significant ($p \leq .01$). In contrast with the economic capital indicators, some of the social capital indicators (Table 5.2) are negatively correlated, or positively correlated but not statistically significant. For example, professional organization is negatively correlated with religious organization, but the correlation is not statistically significant. However, overall, more than 50% of the social capital indicators are positively correlated and statistically significant ($p \leq .05$, $p \leq .01$) as expected.

Table 5.2. Inter-item correlations among social capital indicators

Social capital indicators	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Religious organizations **(1)**								
Business organizations **(2)**	.209[b]							
Professional organizations **(3)**	-.039	.302[a]						
Non profit organizations **(4)**	.402[a]	.492[a]	.321[a]					
Home owners **(5)**	.123	.017	-.012	.061				
Registered voters **(6)**	.037	.071	.254[a]	.160	.614[a]			
Census response rate **(7)**	-.215[a]	-.101	.185[b]	.012	.157	.216[a]		
Recreational centers **(8)**	.062	.238[a]	.237[a]	.426[a]	.204[b]	.199[b]	.220[a]	
Civic & political organizations **(9)**	-.058	.239[a]	.354[a]	.451[a]	.021	-.013	.159	.351[a]

Note: a Correlation is significant at the 0.01 level (2-tailed); b Correlation is significant at the 0.05 level (2-tailed)

Table 5.3. Inter-item correlations among economic capital indicators

Economic capital indicators	**1**	**2**	**3**	**4**	**5**
Per-capita income **(1)**					
Median household income **(2)**	.807[a]				
Population employed **(3)**	.681[a]	.674[a]			
Median home value **(4)**	.836[a]	.738[a]	.626[a]		
Business establishments **(5)**	.691[a]	.430[a]	.542[a]	.695[a]	
Population with health insurance **(6)**	.646[a]	.574[a]	.621[a]	.550[a]	.485[a]

Note: a Correlation is significant at the 0.01 level (2-tailed)

The results of the inter-item correlations for the physical capital-mitigation sub-index and human capital-mitigation sub-index are presented in Tables 5.4 and 5.5, respectively. Overall, more than 60% of the indicators of physical capital-mitigation sub-index are statistically significant and positively correlated (see Table 5.4). In comparison with the physical-capital-mitigation sub-index, the human capital-mitigation sub-index (Table 5.5) has a fairly low number of positive and significant correlations (about 34%). Based on these results, physical capital-mitigation indicators performed better in terms of internal consistency than the indicators of human capital-mitigation sub-index.

Table 5.4. Inter-item correlations among physical capital-mitigation indicators

Physical capital-mitigation indicators	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Building construction establishments **(1)**										
Heavy & civil engineering construction establishments **(2)**	.274[a]									
Highway, street, and bridge construction establishments **(3)**	.005	.323[a]								
Architecture and engineering establishments **(4)**	.682[a]	.182[b]	-.045							
Land subdivision establishments **(5)**	.700[a]	.271[a]	-.068	.465[a]						
Legal services establishments **(6)**	.450[a]	.050	-.041	.690[a]	.347[a]					
Property and causality insurance companies **(7)**	.176[b]	.028	.020	.286[a]	.016	.394[a]				
Building inspections establishments **(8)**	.552[a]	.151	-.137	.540[a]	.323[a]	.240[a]	-.004			
Landscape architecture and planning establishments **(9)**	.526[a]	.075	-.202[b]	.473[a]	.498[a]	.362[a]	.182[b]	.367[a]		
Environmental consulting establishments **(10)**	.312[a]	.111	-.065	.446[a]	.275[a]	.409[a]	.209[b]	.221[a]	.325[a]	
Environment and conservation organizations **(11)**	.200[b]	-.021	.005	.124	.229[a]	.068	.025	.184[b]	.447[a]	.251[a]

Note: a Correlation is significant at the 0.01 level (2-tailed); b Correlation is significant at the 0.05 level (2-tailed)

Table 5.5. Inter-item correlations among human capital-mitigation indicators

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1																		
2	.372[a]																	
3	-.276[a]	-.137																
4	.331[a]	-.038	-.325[a]															
5	.074	.033	-.130	.225[a]														
6	.198[b]	.451[a]	-.383[a]	.360[a]	.191[b]													
7	.108	-.072	-.209[b]	.051	.039	.102												
8	.044	.010	-.002	.066	.306[a]	-.108	.096											
9	.283[a]	.090	-.106	.093	-.014	.031	.205[b]	.030										
10	.111	-.071	-.060	.222[a]	.021	-.001	.082	.068	.000									
11	.163	.074	.010	.042	-.050	-.100	.148	.371[a]	.183[b]	.180[b]								
12	.061	.098	.052	-.015	-.011	.036	-.014	-.065	-.074	-.091	-.030							
13	.073	-.092	-.077	.187[b]	.782[a]	.007	-.032	.435[a]	-.052	-.077	-.084	-.025						
14	.231[a]	.722[a]	-.157	-.051	.065	.335[a]	.147	-.029	.156	.003	.076	.096	-.130					
15	.484[a]	.315[a]	-.117	.077	.023	-.035	-.038	.207[b]	.271[a]	.119	.224[a]	.041	.116	.144				
16	.409[a]	.351[a]	-.091	.086	.080	.065	-.043	.178[b]	.225[a]	.125	.220[a]	.028	.098	.186[b]	.911[a]			
17	.307[a]	.353[a]	-.227[a]	.122	.115	.205[b]	.152	-.013	.080	.061	.063	.011	.067	.342[a]	.476[a]	.450[a]		
18	.370[a]	.149	-.330[a]	.136	.105	.294[a]	.067	-.077	.074	.051	-.086	.081	.028	.182[b]	.070	.078	.304[a]	
19	.539[a]	.579[a]	-.231[a]	.121	-.008	.372[a]	.021	.013	.199[b]	-.046	.176[b]	.057	-.064	.384[a]	.473[a]	.447[a]	.408[a]	.168[b]

Note: a Correlation is significant at the 0.01 level (2-tailed); b Correlation is significant at the 0.05 level (2-tailed)

Population with more than high school education **(1);** Physicians **(2);** Health care support workers **(3);** Building construction workers **(4);** Heavy and civil engineering construction workers **(5);** Architecture and engineering workers **(6);** Environmental consulting workers **(7);** Environment and conservation workers **(8);** Land subdivision workers **(9);** Building inspectors **(10);** Landscape architectures and planners **(11);** Property and causality insurance workers **(12)**; Highway, Street, and bridge construction workers **(13);** Population employed in legal services **(14);** Percentage of population covered by comprehensive plan **(15);** Percentage of population covered by zoning regulations **(16)**; Percentage of population covered by building codes **(17)**; Percentage of population covered by FEAM approved mitigation plans **(18)**; FEMA community rating system (CRS) scores **(19).**

Tables 5.6 and 5.7 show the results of the inter-item correlations of physical capital-preparedness and human capital-preparedness sub-indices, respectively. As shown in Table 5.6, the inter-item correlations of physical capital-preparedness are all positively correlated and significant as expected. In contrast with the physical capital-preparedness, the indicators of human capital-preparedness have a fairly low number of positive and statistically significant correlations (about 29%), which reflects its low level of Cronbach's alpha (.530). This result suggests that human capital-preparedness sub-index has a relatively low but reasonable internal consistency.

Table 5.6. Inter-item correlations among physical capital-preparedness indicators

Physical capital -preparedness	**1**	**2**
Scientific research and development services **(1)**		
College, universities, and professional schools **(2)**	.380[a]	
Landscape architecture and planning services **(3)**	.341[a]	.201[b]

Note: a Correlation is significant at the 0.01 level (2-tailed); b Correlation is significant at the 0.05 level (2-tailed)

Table 5.7. Inter-item correlations among human capital-preparedness indicators

	1	2	3	4	5	6
Population with more than high school education **(1)**						
Physicians **(2)**	.372[a]					
Fire fighting, prevention, and law enforcement workers **(3)**	.097	-.226[a]				
Landscape architectures and planners **(4)**	.163	.074	.075			
Scientific research and development services workers **(5)**	.202[b]	.314[a]	.034	.047		
Colleges, universities, and professional schools workers **(6)**	.105	.396[a]	-.009	.004	.184[b]	
Population that speaks English very well **(7)**	.732[a]	.119	.052	.010	.117	.056

Note: a Correlation is significant at the 0.01 level (2-tailed); b Correlation is significant at the 0.05 level (2-tailed)

Tables 5.8 through 5.11 summarize the results of inter-item correlations of the following sub-indices: physical capital-response, human capital-response, physical capital-recovery, and human capital-recovery. The results show that the following sub-indices generally demonstrated a fairly low number of significant and positively correlated indicators: physical capital-response sub-index, which has only 23% of significant positive correlations (Table 5.8), human capital-response sub-index, which has about 33% of positive and statistically significant correlations (Table 5.9), and human-capital recovery sub-index, which has about 39% of positive and significant correlations (Table 5.11). These results imply that these sub-indices have relatively low but reasonable internal consistency.

The physical capital-recovery sub-index (Table 5.10) has a comparatively high percentage of indicators that are statistically significant and positively correlated (more than 60%). This result indicates that physical capital-recovery sub-index has high internal consistency when compared with other sub-indices discussed above.

Table 5.8. Inter-item correlations among physical capital-response indicators

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1																				
2	.869[a]																			
3	-.066	-.087																		
4	.018	-.217[a]	.278[a]																	
5	.140	.224[a]	-.005	-.069																
6	.034	.043	.113	-.022	-.048															
7	-.001	-.031	.281[a]	.017	-.158	.142														
8	.374[a]	.359[a]	-.012	.015	.266[a]	-.072	-.064													
9	.511[a]	.183[b]	-.054	.041	-.027	.121	.085	-.023												
10	.272[a]	.299[a]	.189[b]	.053	.230[a]	-.085	-.102	.294[a]	.071											
11	.006	-.004	.141	.123	-.078	.189[b]	-.096	-.008	.008	-.040										
12	.511[a]	.171[b]	-.045	.045	-.024	.101	.090	-.010	.993[a]	.076	-.016									
13	.036	.119	.085	-.201[b]	.424[b]	.004	.190[b]	.194[b]	-.001	.045	.042	-.002								
14	.103	.011	.112	.323[a]	.021	.065	.056	.428[a]	-.060	-.039	-.029	-.056	.018							
15	.003	-.070	.049	.389[a]	-.021	-.133	-.125	.071	-.170[b]	-.014	-.028	-.158	-.246[a]	.227[a]						
16	.139	-.062	.121	.292[a]	-.113	-.072	.174[b]	.101	.185[b]	-.005	-.036	.192[b]	-.138	.095	.226[a]					
17	.135	.153	-.024	.006	.132	-.054	-.204[b]	.296[a]	-.046	.324[a]	-.070	-.031	.060	.107	.107	-.023				
18	.099	.073	.013	.123	.061	-.037	-.193[b]	.277[a]	-.092	.270[a]	-.030	-.071	-.019	.189[b]	.171[b]	.061	.887[a]			
19	.140	.171[b]	-.034	-.073	.030	.007	-.063	.257[a]	.033	.249[a]	-.057	.035	.015	.116	.033	-.082	.611[a]	.610[a]		
20	.185[b]	.446[a]	.050	-.236[a]	.083	.007	.192[b]	-.044	-.306[a]	.023	-.087	-.314[a]	.230[a]	-.100	-.174[b]	-.134	.133	.043	.120	
21	.118	.047	-.103	.073	-.056	-.055	.115	.180b	.126	.104	-.067	.144	.037	.114	.171[b]	.115	.107	.136	.204[b]	-.170[a]

Note: a Correlation is significant at the 0.01 level (2-tailed); b Correlation is significant at the 0.05 level (2-tailed)

Housing units **(1);** Vacant housing units **(2);** Hospitals **(3);** Hospital beds **(4;** Ambulances **(5);** Fire stations **(6);** Nursing homes (7); Hotels and Motels **(8);** Occupied housing units with vehicle available **(9);** Special need transportation services**(10);** School and employee buses **(11);** Occupied housing units with telephone service **(12);** Newspaper publishers **(13);** Radio stations **(14);** Television broadcasting **(15);** Internet service providers **(16);** Temporary shelters **(17);** Community housing **(18);** Community food services **(19);** Schools **(20)** Child care facilities **(21)**

Table 5.9. Inter-item correlations among human capital-response indicators

Human capital-response indicators	**1**	**2**	**3**	**4**	**5**
Population with more than high school education **(1)**					
Physicians **(2)**	.372[a]				
Fire fighting, prevention, and law enforcement workers **(3)**	.097	-.226[a]			
Population that speaks English very well **(4)**	.732[a]	.119	.052		
Special need transportation services workers **(5)**	.080	-.032	.002	.061	
Landscape architectures and planners **(6)**	.272[a]	.340[a]	.032	.035	.300[a]

Note: a Correlation is significant at the 0.01 level (2-tailed)

Table 5.10. Inter-item correlations among physical capital-recovery indicators

Physical capital-recovery indicators	**1**	**2**	**3**
Utility systems construction establishments **(1)**			
Architecture and engineering establishments **(2)**	-.018		
Building construction establishments **(3)**	-.035	.682[a]	
Heavy highway constructions establishments **(4)**	.821[a]	.182[b]	.274[a]

Note: a Correlation is significant at the 0.01 level (2-tailed); b Correlation is significant at the 0.05 level (2-tailed)

Table 5.11. Inter-item correlations among human capital-recovery indicators

Human capital-recovery indicators	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Population with more than high school education **(1)**								
Physicians **(2)**	.372[a]							
Population that speaks English very well **(3)**	.732[a]	.119						
Building construction workers **(4)**	.331[a]	-.038	.318[a]					
Architecture and engineering workers **(5)**	.198[b]	.451[a]	.221[a]	.360[a]				
Community and social workers **(6)**	.139	.231[a]	.090	-.101	.057			
Heavy highway construction workers **(7)**	.074	.033	.106	.225[a]	.191[b]	.049		
Building inspectors **(8)**	.111	-.071	.102	.222[a]	-.001	.125	.021	
Highway, street, and bridge construction workers **(9)**	.073	-.092	.100	.187[b]	.007	.081	.782[a]	-.077

Note: a Correlation is significant at the 0.01 level (2-tailed); b Correlation is significant at the 0.05 level (2-tailed)

Overall, the results on the inter-item correlations indicate that the majority of the indicators exhibited positive and significant correlations. The highest average inter-item correlation is exhibited by economic capital sub-index (.640), followed by physical capital-recovery (.318), physical capital-preparedness (.307), physical capital-mitigation (.235), social capital (.177), human capital-recovery (.159), human capital-preparedness (.139), human capital-response (.127), human capital-mitigation (.106), and lastly physical capital-response (.073). The average inter-item correlation ranges from high to low, suggesting that in general the indicators are positively correlated. This implies that most of these indicators are at least somewhat consistent with each other.

5.4. Cronbach's alpha coefficients of the CDRI

The Cronbach's alpha coefficients results for the three CDRIs developed and discussed in Chapter IV are summarized below.

(i) Cronbach's alpha coefficients for CDRI-1

Table 5.12 presents the Cronbach's alpha coefficients and the final total number of indicators used to construct the sub-indices and the overall CDRI-1. Table 5.13 shows the inter-item correlations among CDRI-1 sub-indices, which are positively correlated as expected. The results show that the highest Cronbach's alpha coefficient was exhibited by the economic capital sub-index (alpha = .914), followed by the physical capital sub-index (alpha = .786), the human capital sub-index (alpha = .731), and lastly the social capital sub-index (alpha = .659). The overall CDRI-1 which is the average of the four sub indices (social, economic, physical, and human) has a Cronbach's alpha coefficient of .844. Considering a threshold of alpha value of about .70, these Cronbach's alpha coefficients are sufficient and reasonable to suggest precision of both the sub-indices and the overall CDRI-1.

Table 5.12.Cronbach's alpha coefficients for CDRI-1

Index items	Item	Alpha
Social capital sub-index	9	.659
Economic capital sub-index	6	.914
Physical capital sub-index	35	.786
Human capital sub-index	25	.731
Overall CDRI-1	**4**	**.844**

Table 5.13. Inter-item correlations among CDRI-1 sub-indices

	Social capital sub-index	Economic capital sub-index	Physical capital sub-index
Social capital sub-index			
Economic capital sub-index	.563[a]		
Physical capital sub-index	.618[a]	.533[a]	
Human capital sub-index	.462[a]	.602[a]	.674[a]

Note: a Correlation is significant at the 0.01 level (2-tailed)

(ii) Cronbach's alpha coefficient for CDRI-2

The overall CDRI-2, which is the average of the ten sub-indices presented in Table 5.1, exhibited a relatively high Cronbach's alpha coefficient of .916. Evidently, this alpha level is indicative of adequate precision of the overall CDRI-2. The individual Cronbach's alpha of the 10 sub-indices can be seen in Tables 5.1.

(iii) Cronbach's alpha coefficients for CDRI-3

The Cronbach's alpha coefficients for CDRI-3 and the total number of indicators used to calculate each sub-index are summarized in Table 5.14. Table 5.15 shows the inter-item correlations among CDRI-3 sub-indices. The reliability analysis for CDRI-3 was intended to examine the precision of individual disaster phase's sub-indices. As expected, given the fact that indicators were counted more than once, the results show that the sub-indices exhibited a very high degree of Cronbach's alpha (see Table 5.14) and are highly correlated (see Table 5.15).

Table 5.14. Cronbach's alpha coefficients for CDRI-3

Index items	**Item**	**Alpha**
Hazard mitigation Sub-index	45	.862
Disaster preparedness Sub-index	25	.794
Disaster response Sub-index	42	.773
Disaster recovery Sub-index	28	.814
Overall CDRI-3	**4**	**.979**

Table 5.15. Inter-item correlations among CDRI-3 sub-indices

	Hazard mitigation	Disaster preparedness	Disaster response
Hazard mitigation			
Disaster preparedness	.922[a]		
Disaster response	.945[a]	.919[a]	
Disaster recovery	.955[a]	.861[a]	.914[a]

Note: a Correlation is significant at the 0.01 level (2-tailed)

Of the four disaster phase's sub-indices, the hazard mitigation sub-index exhibited the highest alpha coefficient (alpha =.862), followed by the disaster recovery (alpha = .814), disaster preparedness (alpha = .794), and disaster response (alpha = .773). The overall CDRI-3 which is the average of the four sub-indices has the Cronbach's alpha coefficient of .979. Considering the threshold of alpha value of .70, these alphas are higher enough to suggest that these measures are reliable.

5.5. Summary

This chapter has examined the reliability of the sub-indices and the CDRI as measures of disaster resilience using Cronbach's alpha coefficients. The end result of these analyses was the list of indicators selected to include in the CDRI (see Table 4.3). The following bullets summarize the key points of this chapter:

- Most of the sub-indices exhibited high Cronbach's alpha coefficients implying that they are fairly reliable measures.
- The results on the inter-item correlations show that the majority of the indicators are statistically significant and positively correlated ($p \leq .05, p \leq .01$), which implies a high degree of consistency of these measures.
- The results also show that few sub-indices did not perform as expected suggesting that they have relatively low levels of internal consistency.
- Some variations exist in terms of magnitude and strength of correlations and number of positive correlations that are statically significant at the .05 and .01 levels, but overall the correlation patterns are reasonable.
- Overall, the CDRI-1 which is the primary focus of this study exhibited a high level of Cronbach's alpha coefficients (.844), suggesting that it is a fairly reliable measure. Also as one would expect, the CDRI-2 and CDRI-3 both demonstrated high levels of Cronbach's alpha coefficients of .916 and .979, respectively.

CHAPTER VI

VALIDITY ASSESSMENT

6.1. Introduction

The purpose of this chapter is to assess the validity of the CDRI as a measure of disaster resilience. A measure is valid if it is measuring what it is intended to measure and it is invalid if it does not (Babbie et al., 2003; Carmines & Zeller, 1979). In the psychology literature, for a measure to be valid, it should be constructed according to psychometric principles related to different dimensions of validity. Some of the important examples of validity are content, construct, and predictive validity. These types of validity require different approaches in assessing the extent to which a measure is valid (Carmines & Zeller, 1979). However, it should be noted that while in some areas, such psychometrics assessment of validity are quite well defined, in others such as the sociological and indicator literatures, the approaches are not as formulaic. Regardless, in many circumstances the literature on indicators and indices has noted that validation of indices is a complex process (Cutter & Finch, 2008; Simpson, 2006; Vincent, 2004). The primary reason for this difficulty is because the empirical data needed to validate indices are not easily available, or may require expensive in-depth field surveys.

The validity of the CDRI as a disaster resilience measure was assessed by examining the measures of its content and construct validity. Content validity is essentially concerned with whether or not a measure captures the various dimensions or the domain of a construct and, in the sociological literature is sometimes referred to as sampling validity. In general, construct validity is the degree to which a measure relates to other variables as expected within a system of theoretical relationships (Babbie, 2005; Carmines & Zeller, 1979). It is often based on the extent to which empirical results are consistent with logically or theoretically anticipated relationships among variables (Babbie, 2005). In other words, the question is do we see the relationship pattern (positive or negative correlations) among the measures of concepts anticipated by the literature. In addition, construct validation is extended by not simply examining the interrelationship patterns among variables, but also by examining the ability of the CDRI scores to predict potential expected outcomes. This assessment is sometimes referred to as predictive validity in that CDRI measures are employed to predict disaster outcomes (deaths, losses, etc.) in order to determine its ability to account for these outcomes after controlling for other related measures. Predictive validity is extended further by addressing the incremental validity of the CDRI measure. Incremental validity is essentially concerned with whether a newly proposed measure adds incrementally to our ability to predict or account for a phenomenon of interest. The next sections discusses how each of these four types of validity was assessed

6.2. Content validity

Content validity is often concerned with the actual content of a measure (Carmines & Zeller, 1979; Trochim, 2006), which means that based on the procedure (operationalization of the concept), would the measure appear to capture the theoretical concept. Babbie (2005) has defined content validity as the degree to which a measure covers the range of meanings included within a concept. This dimension of content validity is sometimes referred to as sampling validity, in that the concern is if the measure captures the conceptual or theoretical "sampling space" or the domain associated with the concept. In other words, if a concept includes three dimensions of conceptual space, *a, b,* and *c,* then a measure should also capture *a, b*, and *c,* otherwise it fails with respect to sampling validity. In the psychometric literature content validity is generally assessed by utilizing a panel of expert raters to assess the various components proposed to be utilized to measure a concept to determine if the set of component does indeed capture the domain associated with the theoretical concept. Oftentimes this entails assessing inter-rater agreement on the extent to which the components capture the concept. Unfortunately, given limited resources a panel could not be employed, instead two raters, working within the formalized operationalization procedure itself should provide a degree of content validity.

Ideally, as Babbie (2005) notes, content validity should be a guiding principle in the initial development of a measure to ensure that all domains of the concept to be measured are included in the measure. Indeed sampling validity has been employed and has guided the development of the CDRI measure since the beginning. Sampling validity was at play in Chapter III when it was noted that some measures of disaster resilience tended to focus on recovery and reconstruction, because of the centrality of "bouncing back" element in the concept. And, yet, resistance or reducing impact is equally important. Hence, the decision was made to ensure that the measure assesses community resources (types of capitals) important for undertaking activities associated with all four phases of disaster: mitigation, preparedness, response, and recovery. In other words, the CDRI measure seeks to cover the full range of dimensions associated with disaster resilience. In addition, as seen in Chapter IV, one of the reasons for using the cross-classification method was to facilitate and ensure that indicators associated with all phases of disaster and four community capitals were selected for inclusion in the measure. Together the four dimensions of disaster phases and the four community capitals provided a CDRI conceptual framework defining the conceptual space or conceptual domain for which indicators were selected. Utilizing this framework, two raters worked to select subsets of indicators associated with the 16 disaster phase/capital sub-indices.

6.3. Construct validation

Construct validity is the degree to which a measure relates to other variables as expected within a system of theoretical relationships (Babbie, 2005; Carmines & Zeller, 1979). It is often based on the extent to which empirical results are consistent with logically or theoretically anticipated relationships among variables (Babbie, 2005). In other words, the question is do we see the relationship pattern (positive or negative correlations) among the measures of concepts anticipated by the literature. In particular, construct validation was extended by not simply examining the interrelationship patterns among variables, but also by examining the ability of the CDRI scores to predict expected outcomes. This assessment is sometimes referred to as predictive validity in that CDRI as a measure is employed to predict disaster outcomes (e.g., death and losses) in order to determine its ability to account for these outcomes after controlling for other related measures. In addition the validity assessment was taken a step further by examining the CDRI's incremental validity as a measure of community disaster resilience.

By definition, incremental validity refers to the capacity of one measure to improve prediction over one or more alternative measures (Meyer, 2000). This means that if a new measure is able to improve the prediction of a theoretically relevant criterion over the existing measure, one can conclude that the new measure contributes meaningful information that could not have been obtained from the existing measure.

Construct validity in this study was assessed by examining a relationship between the CDRI scores and the following theoretically relevant measures: *(1) Flood related deaths*: These are deaths due to flood related hazards that occurred between 2000 and 2005 as reported by the Centers for Diseases Control and Prevention; *(2) Total property damage due to flooding*: This is the flood property damage that occurred between 2000 and 2005.The data on total flood property damage were obtained from the SHELDUS database, at Hazard Research Lab, at the University of South Carolina; (3) *Insured flood property damage:* This is the total of payments made to flood property damage claims between 2000 and 2005. The data on insured flood property damage were obtained from FEMA. (4) *Uninsured flood property damage:* This is the difference between the total flood damage and insured property damage; (5) *Social vulnerability*: This is an index based on 2000 census data, developed by the Hazard Vulnerability Research Institute, at the University of South Carolina; and (6) *Physical risk*, which includes (a) flood risk, (b) wind risk, (c) surge risk, and (d) total risk, which is the sum of flood, wind, and surge risk. Data on physical risk were obtained from the Coastal Risk Atlas. The theoretical expectations of the relationship between the external criteria and the CDRI scores were as follows:

(i) A disaster resilient community is more likely to experience a low number of flooding related deaths. In other words, there should be a negative relationship between CDRI measures and flooding related deaths. This is expected because disaster resilient communities should be more likely to have effective hazard mitigation, disaster preparedness, and disaster response plans, which should result in lower flooding related deaths.

(ii) Disaster resilient communities should suffer from lower levels of total property damage due to flooding than less disaster resilient communities. In other words, there should be a negative relationship between CDRI scores and total property losses. This is so because disaster resilient communities are more likely to take protective measures to reduce flood damage.

(iii) A disaster resilient community is more likely to experience a high level of insured flood property damage. At first blush this might seem counter intuitive, given the previous expectation above, however with respect to this expectation; the issue is insured versus uninsured losses. This expectation is based on the assumption that in a disaster resilient community, most people are more likely to participate in flood insurance programs because the community will promote participation to ensure recovery process and community residence will have greater capital to invest in insurance.

(iv) A disaster resilient community is more likely to experience a low level of uninsured flood property damage. This expectation is simply the opposite of the above, for now we are addressing uninsured losses. This is expected because less resilient communities will not be addressing flood hazard effectively and because less resilient communities are likely to have residents without the capital to invest in insurance.

(v) A disaster resilient community is more likely to have a low level of social vulnerability. Several studies have characterized the concept of social vulnerability and disaster resilience as being opposite (Buckle et al., 2001; Manyena, 2006; Pelling, 2003). Hence it is expected that there will be a negative relationship between social vulnerability and resilience. This is expected because disaster resilience activities such as hazard mitigation programs are more likely to reduce social vulnerability.

(vi) Coastal communities, which are located in high risk areas, are more likely to have high levels of disaster resilience. In some sense, this might be thought of as a hope, rather than an expectation. However, this expectation is perhaps valid because coastal communities with high levels of risk are more likely to have high perception of risk, which is often considered as a determinant factor for a community to take disaster protective measures and hazard adjustments. Also, these communities are more likely to have experience of coastal hazards and frequent occurrence of disasters in high risk areas is more likely to result in a community developing better disaster preparedness programs. In addition, previous studies have shown that experience is an important predictor of higher level of disaster preparedness and more effective disaster response; largely because it leads to greater awareness of consequences of dissenters (Lindell & Perry, 2000; Mileti, 1999). The expectation then is that high levels of hazard risk should be positively associated with community resilience.

Two methods were employed in assessing the construct validity of the overall CDRIs: (1) correlational analysis, and (2) regression analysis

6.3.1. Construct validity: Correlational analysis

The validity of the CDRI was assessed by conducting a Pearson's product-moment correlation (correlation of zero-order) analysis to examine the degree to which the CDRI is correlated with the external criteria described in the previous section. The primary focus of this analysis is on the correlations between the CDRI-1 measure and the external criteria; however the other CDRI scores are also included for comparison purpose. Table 6.1 presents the results of correlations between the CDRIs and external criteria.

Table 6.1. Bivariate correlations between external criteria and CDRIs

Validity measure	**CDRI-1**	**CDRI-2**	**CDRI-3**
(1) Deaths due to flooding	-.420[b]	-.332[c]	-.387[b]
(2) Total flood property damage	-.239[a]	-.222[a]	-.224[a]
(3) Insured flood property damage	.385[a]	.415[a]	.411[a]
(4) Uninsured flood property damage	-.223[a]	-.214[a]	-.214[a]
(5) Social vulnerability index	-.308[a]	-.332[a]	-.319[a]
(6) Wind risk	.291[a]	.324[a]	.310[a]
(7) Flood risk	.270[a]	.272[a]	.270[a]
(8) Surge risk	.141[b]	.125[c]	.146[b]
(9) Total risk (wind, flood, and surge)	.266[a]	.267[a]	.273[a]

Note: a = prob (r) $\leq$ .01; b = prob (r) $\leq$ .05; c = prob (r) $\leq$ .10; N = 144; (one-tailed tests)

Consistent with theoretical expectations, the results in Table 6.1 indicate that all the external criteria examined have statistically significant correlations with the overall CDRI-1 measure. The directions of the relationships for all the CDRIs performed as expected, although there are some variations with regard to the strength of the relationships. On the whole, the significant statistical relationship suggests that the CDRIs are indeed valid measures. Table 6.2 presents the complete correlation matrix between the CDRIs and all the external criteria employed in assessing the construct validity.

Table 6.2. A complete correlation matrix between external criteria and CDRIs

	1	2	3	4	5	6	7	8	9	10	11
1											
2	.672[a]										
3	.509[a]	.548[a]									
4	.797[a]	.896[a]	.832[a]								
5	-.121	-.113	.019	-.077							
6	.291[a]	.270[a]	.141[c]	.266[a]	-.308[a]						
7	.324[a]	.272[a]	.125	.267[a]	-.332[a]	.951[a]					
8	.310[a]	.270[a]	.146[c]	.273[a]	-.319[a]	.993[a]	.968[a]				
9	.321	.280	.217	.294	.082	-.420[c]	-.332	-.387[c]			
10	-.141	-.098	.099	-.039	-.060	-.239[a]	-2.22[a]	-.224[a]	.423[b]		
11	.638[a]	.542[a]	.362[a]	.581[a]	-.057	.385[a]	.415[a]	.411[a]	.364[c]	-.038	
12	-.182[b]	-.101	.066	-.065	-.072	-.223[a]	-.214[b]	-.214[a]	-.352	.919[a]	-.201[b]

Note: a p < .01; b p < .05; c p <.10; N = 144; (2 tailed tests)

Wind risk (**1**); Flood risk (**2**); Surge risk (**3**); Total risk (**4**); Social vulnerability index (**5**); CDRI-1(**6**); CDRI-2 (**7**);CDRI-3 (**8**); Flood related-deaths (**9**); Total flood property damage(**10**); Insured flood property damage (**11**); Uninsured property damage (**12**)

The following provides a more detailed discussion of the relationships between the external criteria and the CDRI-1 as the primary measure. Examining the results more closely, the relationships suggest that:

(i) There is a statistically significant negative relationship ($r = -.420$, $p \leq .05$) between the number of deaths due to flooding and the overall community disaster resilience index in the U.S Gulf coast region. Based on how disaster resilience is measured in this study, this relationship suggest that counties with a relatively high level of disaster resilience in the U.S. Gulf coast region are more likely to experience a low level of deaths due to flooding.

(ii) The total flood property damage is negatively correlated with the overall community disaster resilience index and the correlation is statistically significant ($r = -.239$, $p \leq .01$). This result is consistent with the expectation that counties with a comparatively high level of disaster resilience in the U.S. Gulf coast region are more likely to experience a relatively low level of total property damage due to flooding.

(iii) As anticipated, the insured and uninsured flood property damage is significantly correlated with the overall community disaster resilience index. The insured flood property damage is positively correlated with community disaster resilience index ($r = .385$, $p \leq .01$), supporting the theoretical expectation that counties with a comparatively high level of disaster resilience in the U.S. Gulf coast region are more likely to experience a high level of insured flood property losses. Conversely, uninsured flood property damage is negatively correlated with the community disaster resilience index ($r = -.223$, $p \leq .01$), supporting the hypothesis that counties with a high level of disaster resilience are less likely to suffer a high level of uninsured flood property losses.

(iv) As expected, the social vulnerability index is negatively correlated with the community disaster resilience index ($r = -.308$, $p \leq .01$). This result is consistent with the proposition that there is a negative relationship between social vulnerability and community disaster resilience. This result implies that counties with a high level of resilience are more likely to have a low level of social vulnerability.

(v) Finally, regarding physical risk; as anticipated, the results indicate that the total risk is positively correlated with community disaster resilience and the correlation is statistically significant ($r = .266$, $p \leq .01$). This result supports the hypothesis that counties with a high level of risk are more likely to have a high level of disaster resilience.

6.3.2. Predictive validity: Regression analysis

Regression analysis techniques were also utilized to extend construct validation of the CDRI measure in this study by assessing its predictive validity. While the bivariate correlations suggest that the measure is valid, it is also important to assess whether the CDRI measure performs as expected after controlling other factors. Specifically regression analysis was employed to determine if the CDRI measure still has a significant impact on flood property damage and flood related deaths after controlling for total physical risk and social vulnerability. More specifically, the aim was to explicitly examine if community disaster resilience has:

(i) a negative impact on deaths due to flooding

(ii) a positive impact on total property damage due to flood related hazards

(iii) a positive impact on insured flood property damage, and

(iv) a negative impact on uninsured flood property damage

To achieve this goal two regression methods were utilized (1) the ordinary least square (OLS) regression model, and (2) the zero-truncated poisson (ZTP) regression model.

(a) Ordinary least square (OLS) regression model

An OLS regression model was used to predict the flood-related property damage in the U.S. Gulf coast region from 2000 to 2005. Before estimating the effect of the CDRI on property damage, this section briefly reviews the trend of property damage in the U.S. Gulf coast region from 2000 to 2005 to get a better understanding of property losses in the region. Generally, among the natural hazards, floods are the most common and frequently cause the greatest threat to property and human life in the United States. The economic impacts from flood-related property damage are significantly increasing and estimated in billions of dollars annually (Brody, Zahran, Maghelal, Grover, & Highfield, 2007).

Figure 6.7 shows the estimated total flood property damage, insured flood property damage, and uninsured flood property damage from 2000 to 2005 in the U.S. Gulf coast region (damage is adjusted to 2005 U.S. dollar value). The total flood property damage data were obtained from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), Version 6.2 (Hazards & Vulnerability Research Institute, 2008). The insured flood property damage data were obtained from FEMA-National Flood Insurance Program (NFIP) and the uninsured flood property damage is the difference between the total flood property damage and the insured flood property damage.

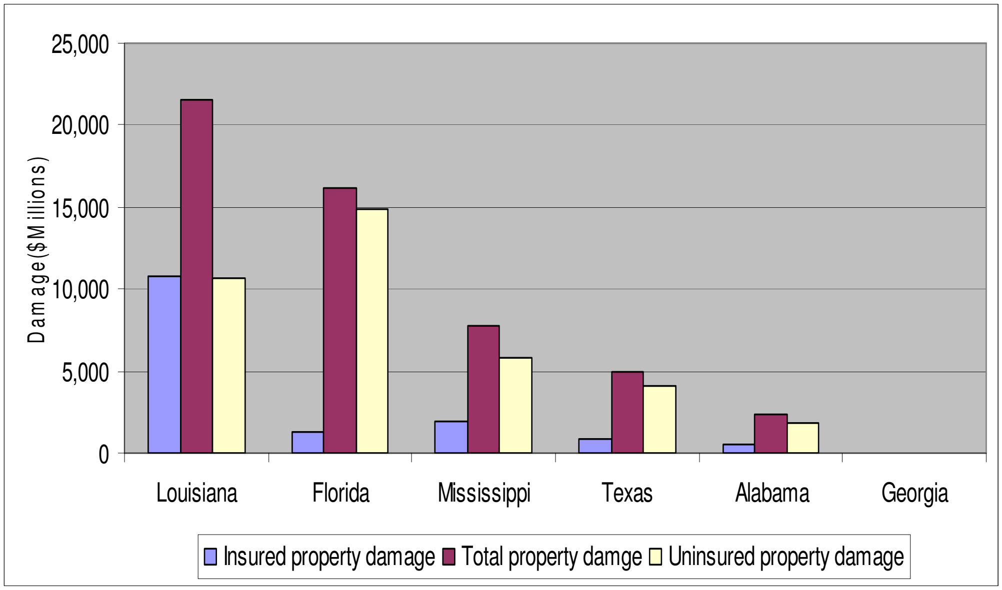


Figure 6.1. Estimated total flood property damage, insured flood property damage, and uninsured flood property damage in the U.S. Gulf coast region from 2000 to 2005 (damage adjusted to 2005 U.S. dollar's value)

As shown in Figure 6.1, the estimated losses from the SHELDUS data indicate that from 2000 to 2005 Louisiana suffered the highest total flood-related damage in the region when compared with the other states. Within that time period Louisiana experienced a total flood property damage of more than $20 billion, followed by Florida ($16 billion), Mississippi ($7 billion), Texas ($4 billion), Alabama ($2 billion) and, last Georgia ($6 million). The high total property damage exhibited by Louisiana is due to hurricane Katrina in 2005, which is one of costliest hurricanes in the United States history. The data from FEMA indicate that from 2000 to 2005 Louisiana had the highest insured flood property damage of more than $10 billion, followed by Mississippi ($1.9 billion), Florida ($1.3 billion), Texas ($900 million), Alabama ($500 million), and Georgia ($21,000).

The results on uninsured flood property damage, which is the difference between the total flood property damage and insured flood property damage, shows that Florida has the highest losses. From 2000 to 2005, Florida experienced uninsured property damage of about \$15 billion, followed by Louisiana (\$10 billion), Mississippi (\$6 billion), Texas (\$4 billion), Alabama (\$2 billion) and, last Georgia (\$6 million). However it is also important to stress that the results on uninsured property damage should be interpreted with extra caution because the data come from completely two different sources (FEMA and SHELDUS).

Three OLS regression models were employed. The first model examined the impact of the CDRI on the total flood property damage, the second model examined the impact of the CDRI on the insured flood property damage, and the third model assessed the impact of the CDRI on uninsured flood property damage. As mentioned earlier, the Social Vulnerability Index and total physical risk were both used as control variables in the models. The OLS models were performed by fitting the following parameters:

(1) $ln(\gamma_{01}) = \beta_0 + \beta_1 CDRI + \beta_2 Total\_risk + \beta_3 Social\_vulnerability + \varepsilon$

(2) $ln(\gamma_{02}) = \beta_0 + \beta_1 CDRI + \beta_2 Total\_risk + \beta_3 Social\_vulnerability + \varepsilon$

(3) $ln(\gamma_{03}) = \beta_0 + \beta_1 CDRI + \beta_2 Total\_risk + \beta_3 Social\_vulnerability + \varepsilon$

Where:

$ln(\gamma_{01})$ = Natural log of total flood property damage

$ln(\gamma_{01})$ = Natural log of insured flood property damage

$ln(\gamma_{01})$ = Natural log of uninsured flood Property damage

β_0 = Y-intercept

β = Regression coefficients

ε = Error component

Property damage was measured in dollars. Like any other variable often measured in monetary terms, its distribution was somewhat skewed. In order to achieve a normal distribution, all three dependent variables (total flood property damage, insured flood property damage, and uninsured flood property damage) were log-transformed. Furthermore, threats due to heteroskedasticity were diagnosed using residual plots, Breusch-Pagan and Koenker-Bassett tests (Allison, 1999). Zero-order correlations and the variance inflation factor (VIF) tests were used to detect multicollinearity problems (Allison, 1999). All the tests performed to diagnose heteroskedasticity and multicollinearity suggested no violation of the OLS regression model assumptions. The results of the OLS regression models are summarized in Tables 6.3 through 6.11 which provide the regression results with respect to the unstandardized coefficients (b), standardized coefficients (Beta), standard errors, t-values, and one-tailed significant levels. F-statistics, R^2, and adjusted R^2 are also presented.

Tables 6.3 to 6.5 summarize the results of model 1, which examines the effect of CDRI on the total property damage. The results show that for all the three models, about 13% of the variance in the total property damage is explained by each model. As expected, in all the models, for every increase in CDRI, there is a significant decrease in total property damage, even after controlling for social vulnerability and total physical risk. However, the effect of CDRI-3 is not statistically significant. Furthermore, the results indicate that the increase in total risk also leads to increase in total property damage, which is consistent with the expectation. Finally, the results show that social vulnerability is significant but not in the anticipated direction.

Table 6.3. Effect of CDRI-1 on the total flood property damage

Variable	Unstandardized Coefficient	Standardized Coefficient	Standard error	t-value	Significance
CDRI-1	-.507	-.162	.276	-1.836	.035
Social vulnerability index	-.120	-.314	.032	-3.701	.000
Total risk	.110	.250	.037	2.925	.002
Constant	6.007		.221	27.183	.000

Note: N =144; F-statistic = 7.428; Significance = .000; R^2 = .150; adjusted R^2 = .130

Table 6.4. Effect of CDRI-2 on the total flood property damage

Variable	Unstandardized Coefficient	Standardized Coefficient	Standard error	t-value	Significance
CDRI-2	-.528	-.168	.281	-1.878	.032
Social vulnerability index	-.123	-.323	.033	-3.759	.000
Total risk	.111	.253	.038	2.948	.002
Constant	6.007		.221	27.208	.000

Note: N =144; F-statistic = 7.486; Significance = .000; R^2 = .151; adjusted R^2 = .131

Table 6.5. Effect of CDRI-3 on the total flood property damage

Variable	Unstandardized Coefficient	Standardized Coefficient	Standard error	t-value	Significance
CDRI-3	-.400	-.141	.252	-1.585	.058
Social vulnerability index	-.118	-.311	.033	-3.640	.000
Total risk	.108	.246	.038	2.857	.003
Constant	6.013		.222	27.104	.000

Note: N =144; F-statistic = 7.100; Significance = .000; R^2 = .145; adjusted R^2 = .124

The results of model 2, which examines the effect of the CDRIs on insured flood property damage, are presented in Tables 6.6 to 6.8. These results indicate that each model explained about 40% of the variance in insured flood property damage. Overall, the results suggest that the CDRIs have a significant positive impact on the insured flood property damage. Consistent with expectations, the increase in CDRI leads to an increase in insured flood property damage. These results suggest that counties with a high level of disaster resilience are more likely to have a high number of flood insurance claims, because highly resilient communities will promote participation in flood insurance programs and most high-income counties are likely to be able to afford participating in flood insurance programs.

The results also reveal that risk is significantly positive related with insured flood property damage, implying that people in counties located in relatively high risk areas are more likely to purchase flood insurance. This result is consistent with FEMA's findings that about 75% of the flood insurance claims come from high-risk areas, and only 25% come from outside high-risk areas (FEMA, 2008).

Table 6.6. Effect of CDRI-1 on insured flood property damage

Variable	Unstandardized Coefficient	Standardized Coefficient	Standard error	t-value	Significance
CDRI-1	.874	.274	.238	3.667	.000
Social vulnerability index	.020	.052	.028	.723	.236
Total risk	.233	.512	.033	7.166	.000
Constant	4.969		.196	25.319	.000

Note: N =144; F-statistic = 28.296; Significance = .000; R^2 = .403; adjusted R^2 = .388

Table 6.7. Effect of CDRI-2 on insured flood property damage

Variable	Unstandardized Coefficient	Standardized Coefficient	Standard error	t-value	Significance
CDRI-2	.972	.303	.239	4.065	.000
Social vulnerability index	.026	.067	.028	.935	.176
Total risk	.230	.505	.032	7.153	.000
Constant	4.972		.194	25.633	.000

Note: N =144; F-statistic = 29.849; Significance = .000; R^2 = .415; adjusted R^2 = .402

Table 6.8. Effect of CDRI-3 insured flood property damage

Variable	Unstandardized Coefficient	Standardized Coefficient	Standard error	t-value	Significance
CDRI-3	.870	.301	.216	4.034	.000
Social vulnerability index	.025	.065	.028	.899	.185
Total risk	.229	.504	.032	7.113	.000
Constant	4.975		.194	25.613	.000

Note: N =144; F-statistic = 29.723; Significance = .000; R^2 = .414; adjusted R^2 = .400

However, the results show that one of the control variables (social vulnerability) did not work as expected, because the coefficient is not in the anticipated direction and not statistically significant.

The results of the effect of disaster resilience on uninsured flood property damage are presented in Tables 6.9 through 6.11. Generally, each model accounted for about 13% of the variance in uninsured flood property damage. As anticipated, the results show that an increase in disaster resilience leads to a decrease in uninsured flood property damage. These results suggest that counties with high level of disaster resilience are more likely to have low level of uninsured property damage. Neither control variable performed as expected. These results are somewhat surprising because one would expect counties with a high level of social vulnerability to have high uninsured flood property damage, while counties located in relatively high risk areas should have low uninsured property damage.

Table 6.9. Effect of CDRI-1 on uninsured flood property damage

Variable	Unstandardized Coefficient	Standardized Coefficient	Standard error	t-value	Significance
CDRI-1	-.614	-.207	.275	-2.236	.014
Social vulnerability index	-.117	-.333	.032	-3.684	.000
Total risk	.069	.178	.035	1.937	.028
Constant	6.368		.212	30.019	.000

Note: N =144; F-statistic = 6.531; Significance = .000; R^2 = .156; adjusted R^2 = .132

Table 6.10. Effect of CDRI-2 on uninsured flood property damage

Variable	Unstandardized Coefficient	Standardized Coefficient	Standard error	t-value	Significance
CDRI-2	-.616	-.202	.285	-2.161	.017
Social vulnerability index	-.120	-.341	.032	-3.740	.000
Total risk	.068	.176	.035	1.914	.029
Constant	6.371		.212	29.996	.000

Note: N =144; F-statistic = 6.406; Significance = .000; R^2 = .153; adjusted R^2 = .130

Table 6.11. Effect of CDRI-3 on uninsured flood property damage

Variable	Unstandardized Coefficient	Standardized Coefficient	Standard error	t-value	Significance
CDRI-3	-.483	-.182	.249	-1.941	.028
Social vulnerability index	-.116	-.331	.032	-3.636	.000
Total risk	.067	.174	.036	1.881	.032
Constant	6.373		.214	29.841	.000

Note: N =144; F-statistic = 6.067; Significance = .001; R^2 = .147; adjusted R^2 = .122

(b) Zero-truncated poisson (ZTP) regression model

A zero-truncated poisson (ZTP) regression model was employed to examine the impact of CDRI on flood related deaths because this is a count variable, with a large number of zero counts, which can not be modeled using OLS regression model (Long & Freese, 2006). The zero-truncated poisson regression model was employed using Stata SE 10.0 software. The ZTP is designed for data in which observations with an outcome of zero have been excluded from the sample. Since the counts are truncated at zero, ZTP computes the probability of positive outcomes, or outcomes which are greater than zero (Long & Freese, 2006). Literature suggests that when using ZTP models, the presence of overdispersion may result in biased estimates. The assumption of the ZTP model is that the mean and the variance functions are equal. When the variance exceeds the mean, the model is overdispersed (Long & Freese, 2006). Thus, overdispersion was checked by first fitting a zero-truncated negative binomial (ZTNB) model (Long & Freese, 2006), which revealed that there was no problem of overdispersion.

Before presenting the results of the ZTP regression model analysis, the descriptive statistics of the number of deaths due to flooding in the U.S. Gulf coast region from 2000 to 2005 are summarized in order to provide a better understanding of the trend of flood related deaths in the region. Figure 6.2 summarizes the number of flood related deaths occurred between 2000 and 2005 in the U.S. Gulf coast region.

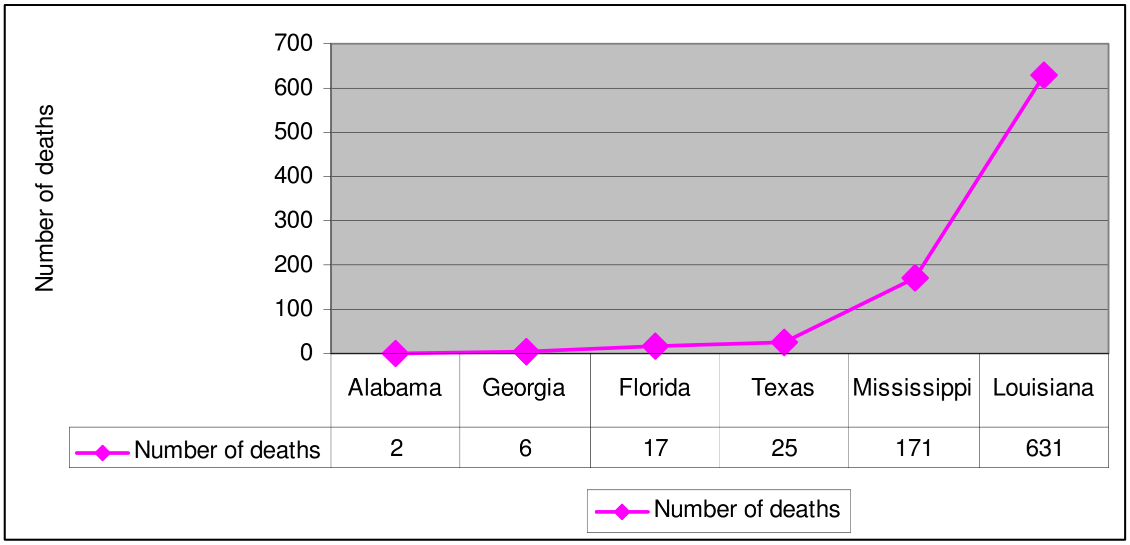


Figure 6.2. Number of deaths due to flooding in the U.S. Gulf coast region from 2000-2005

The data on flood related deaths were obtained from the Center for Disease Control and Prevention. Overall, the deaths indicate that a total of 852 people died due to flooding in the U.S. Gulf coast region between 2000 and 2005. As reported in Figure 6.2, Louisiana suffered the highest number of flood related deaths during this period; approximately 631 people died there, followed by Mississippi (171), Texas (25), Florida (6) and, last Alabama (2). At a count level, the results show that the majority of the deaths during this period of time occurred in Orleans parish, Louisiana, which recorded 475 deaths, followed by St. Bernard parish, Louisiana (121), Harrison county, Mississippi (104), Hancock county, Mississippi (55), Harris county Texas (21), Jefferson parish, Louisianan (19), and Jackson county, Mississippi (12).

The results of the ZTP regression models are summarized in Tables 6.12 through 6.14. Overall, the results indicate that CDRI-1 and CDRI-3 performed as expected while CDRI-2 did not meet the theoretical expectations. Both models employing CDR-1 and CDRI-3 are statistically significant. The results indicate that model one (CDRI-1) presented in Table 6.12, is statistically significant (Chi-squared = 1492.74, df = 3, p ≤ .001). Similarly, model 3 (CDRI-3) which is presented in Table 6.14, is statistically significant (Chi-Squared = 1460.34, df = 3, p ≤ .001).

As expected, the results of both models employing CDRI-1 and CDRI-3 show that the increase in community disaster resilience leads to a decrease in a number of deaths due to flooding, controlling for social vulnerability and total physical risk. In other words, counties with a high level of disaster resilience are more likely to experience a low number of deaths due to flooding in the U.S. Gulf coast region. Moreover, the results support the hypothesis that a high level of social vulnerability significantly contributes to an increase in the number of deaths due to flooding. Finally, and consistent with theoretical expectations, the results indicate that counties located in high risk areas are more likely to experience a high number of deaths due to flooding.

Table 6.12. Effect of the CDRI-1 on deaths due to flooding

Variable	Coefficient	Standard error	z	P>|z|	95% Conf. Interval	95% Conf. Interval
CDRI-1	-1.916	.213	-8.97	0.000	-2.334	-1.497
Social vulnerability	.374	.015	24.50	0.000	.344	.404
Total risk	.162	.015	11.00	0.000	.133	.190
Constant	1.174	.162	7.23	0.000	.855	1.492

Note: N =22; Chi^2 = 1492.74, df = 3, Significance = .001; Pseudo R^2 = 0.5563

Table 6.13. Effect of the CDRI-2 on deaths due to flooding

Variable	Coefficient	Standard error	z	P>|z|	95% Conf. Interval	95% Conf. Interval
CDRI-1	.008	.142	0.05	0.957	-.271	.287
Social vulnerability	.376	.015	25.39	0.000	.347	.405
Total risk	.247	.014	18.38	0.000	.221	.274
Constant	.136	.151	0.91	0.364	-.159	.433

Note: N =22; Chi^2 = 1402.73, df = 3, Significance = .001; Pseudo R^2 = 0.5228

Table 6.14. Effect of the CDRI-3 on deaths due to flooding

Variable	Coefficient	Standard error	z	P>|z|	95% Conf. Interval	95% Conf. Interval
CDRI-3	-1.316	.183	-7.20	0.000	-1.674	-.958
Social vulnerability	.375	.015	24.87	0.000	.346	.405
Total risk	.190	.014	13.34	0.000	.162	.218
Constant	.884	.163	5.42	0.000	.564	1.204

Note: N =22; Chi^2 = 1460.34, df = 3, Significance = .001; Pseudo R^2 = 0.5443

Table 6.13 presents the results of model 2 (CDRI-2). As mentioned previously, the results of this model generally suggest that the CDRI-2 did not theoretically perform as expected. The relationship between CDRI-2 and the number of deaths turned out to be statistically insignificant. The control variables, however, worked as expected. Both social vulnerability and total physical risk are significantly positive correlated with the number of deaths due to flooding, supporting the proposition that counties with a high level of social vulnerability and physical risk are more likely to experience a high number of deaths due to flooding.

In conclusion, the results of the ZTP regression models discussed above generally exhibited a satisfactory explanatory power, which empirically supports the hypothesis that community disaster resilience will decrease the number of flood related deaths in a community. Consistent with the results of the zero-order correlations and the OLS regression models, the results of the ZTP regression models also strongly confirm that the CDRIs are indeed valid measures.

6.3.3. Incremental validity

Yet another approach in assessing validity of a measure is an assessment of the measure's "incremental validity" or its ability to incrementally add to a model predicting a criterion measure over alternative measures available to assess the same or closely related constructs (Hunsley and Meyer, 2003). In other words, does the measure add to the prediction of criterion above what can be predicted or accounted for by other alternative measures? Studies have suggested that a newly developed measure should demonstrate an ability to add to the prediction of outcomes beyond that which was possible with the best available measures (Dawes, 1999; Haynes & Lench, 2003; Hunsley & Meyer, 2003).

The previous section has, in some sense assessed this, in that it has assessed the ability of CDRI to predict criterion measures such as flood property losses and flood related deaths while controlling for Social Vulnerability Index (SoVI). It was shown that the CDRI measure has performed as expected and has done well relative to SoVI a closely related measure. Indeed, SoVI sometimes did not perform well at all, yielding insignificant results or results that were completely counter to the theoretical expectations. Here the validity assessment is taken a step further by assessing the incremental validity of CDRI[2] not only with respect to SoVI, but also with respect to a county's median income. Specifically, an argument might well be offered that in many respects CDRI could perhaps be more parsimoniously measured by simply employing median income. It is somewhat conspicuous that, when viewing the maps in Chapter VIII, that poorer and more rural areas appear to score lower on the overall CDRI score. From the perspectives of this study, CDRI, while related to median income is of course much more in that it assesses a broad range of capital resources, not simply economic resources such as income, necessary for addressing hazard mitigation, disaster preparation, response, and recovery.

[2] The incremental validity analysis is only preformed with the CDRI-1, a primary measure for this study

Nevertheless, the aforementioned argument might be advanced. For that matter, a similar argument might be suggested that SoVI could also be more parsimoniously measured by income, with median income simply being the opposite of social vulnerability. Hence, this application of incremental validity assesses if CDRI contributes to predicting flood property losses (total, insured, and uninsured) and flood related deaths, after total risk, median income, and SoVI are entered in the model. Then CDRI is entered to determine if it contributes to the ability of the model to account for the variance in the respective variables. The initial step in this analysis begins with an examination of the zero order correlations between the independent and dependent variables presented in Table 6.15.

The intercorrelations among the independent variables suggest that there are indeed moderate, negative, and significant correlations between SoVI and median income (-.298) and CDRI-1 (-.308). In addition there is a relatively strong positive relationship between CDRI-1 and median income (.630), though it is far from perfect as might be anticipated if median income was a more simple measure of CDRI-1. Interestingly, there are moderate correlations between total risk and CDRI-1 and median income, but an insignificant negative relationship between SoVI and total risk. Even more interesting are the correlations between the dependent variables and SoVI, median income, and CDRI-1. There are no significant correlations between SoVI and total, insured, and uninsured flooding losses nor is there a relationship with flooding deaths. Median income only has a significant positive relationship with insured losses. However, CDRI-1, as seen before, has a significant positive relationship with insured losses and the anticipated negative significant relationships with total and uninsured losses as well as with flood related deaths. Clearly, CDRI-1 appears to perform better than either SoVI or median income at least with respect to zero order correlations. The question remains if it will perform equally well when other factors are controlled for in a regression format.

Table 6.15. Correlation matrix among variables used to assess incremental validity

Variable	1	2	3	4	5	6	7
Total risk **(1)**							
Social vulnerability index-SoVI **(2)**	-.077						
Median Income **(3)**	.381[a]	-.298[a]					
CDRI-1 **(4)**	.266[a]	-.308[a]	.630[a]				
Flood related deaths **(5)**	.294	.082	-.298	-.420[c]			
Total flood damage **(6)**	-.039	-.060	-.076	-.239[a]	.423[b]		
Insured flood damage **(7)**	.581[a]	-.057	.441[a]	.385[a]	.364[c]	-.038	
Uninsured flood damage **(8)**	-.065	-.072	-.070	-.223[a]	-.352	.919[a]	-.201[b]

Note: N = 144; a p < .01; b p < .05; c p <.10 (two-tailed tests)

Table 6.16 presents the OLS results for three models predicting total flood property damage. As with the predictive validity analysis above, CDRI-1 should have a negative effect while SoVI should have a positive effective and median income should also have a negative effect. The first model regresses total flood losses on the control variable, total risk, and median income. The second model then adds SoVI, while the third model includes CDRI-1. Since a single variable is added in models 2 and 3, the t-test for the coefficients is the appropriate test to determine if the new variable adds incrementally to the model. The first model, which includes only total risk and median income accounts for 5.4% of the variance, but it should be noted that only the total risk measure is significant, median income is not significant. The second model, in which SoVI is added, has a significantly higher R^2 of 12.8% and SoVI is significant but not in the anticipated direction. The third model has an even higher R^2 of 15.6% and the CDRI-1 measure is both significant and in the anticipated positive direction. The significant t-test for the CDRI-1 suggest that it does indeed contribute to the model and is indeed contributing, even with the inclusion of median income, which remains non-significant, and SoVI, which is not performing as expected.

Table 6.16. OLS regression model: SoVI, median income, and CDRI-1 predicting total flood property damage

Model	Variable	Unstandardized Coefficients	Standardize Coefficients	t-value	P-value	R^2	Adj.R^2
1	Total risk	.090	.205	2.187	.016[b]		
	Median income	.075	.056	0.593	..278	.054[b]	.039
2	Total risk	.094	.215	2.376	.010[a]		
	Median income	-.026	-.019	-0.206	.419		
	SoVI	-.107	-.281	-3.265	.000[a]	.128[a]	.107
3	Total risk	.099	.226	2.524	.007[a]		
	Median income	.135	.101	0.922	.179		
	SoVI	.-.115	-.303	-3.537	.000[a]		
	CDRI-1	-.670	-.213	-2.043	.022[b]	.156[a]	.129

Note: N = 144; a $p < .01$; b $p <.05$; c $p < .10$ (one-tailed tests)

The results for the models predicting insured flood property damage presented in Table 6.17, are equally supportive of CDRI's incremental validity. The first model accounts for 40% of the variance in insured flood property damage, with both total risk and median income having significant positive effects. The second model suggests that SoVI does not significantly contribute; its t-test is not significant. The third model however does account for significantly more of the variance in insured losses, with R^2 of 42.2%, and CDRI is statistically significant and positive as expected. Also in the third model, median income and total risk remain significant and positive, but SoVI remains non-significant and not performing as expected.

Table 6.17. OLS regression model: SoVI, median income, and CDRI-1 predicting insured flood property damage

Model	Variable	Unstandardized Coefficients	Standardize Coefficients	t-value	P-value	R^2	Adj.R^2
1	Total risk	.220	.484	6.547	.000[a]		
	Median income	.367	.266	3.605	.000[a]	.400[a]	.390
2	Total risk	.219	.480	6.475	.000[a]		
	Median income	.396	.287	3.676	.000[a]		
	SoVI	.023	.060	.829	.205	.403[a]	.389
3	Total risk	.214	.471	6.413	.000[a]		
	Median income	.258	.188	2.052	.021[b]		
	SoVI	.031	.081	1.115	.134		
	CDRI-1	.568	.178	2.036	..022[b]	.422[a]	.403

Note: N = 144; a $p < .01$; b $p <.05$; c $p < .10$ (one-tailed tests)

The results for the models predicting uninsured flood damage are presented in Table 6.18. The first model accounts for 2.8% of the variance in uninsured flood property damage, with both total risk and median income not performing as expected. The second model in which SoVI is added has a significantly higher R^2 of 11.6% and SoVI is significant but not in the anticipated direction. It would be expected that SoVI should have a positive effect. The third model does account for significantly more of the variance in uninsured losses, with R^2 of 17.3%, and CDRI is statistically significant and negative as expected. Also in the third model, median income, total risk, and SoVI remain significant, but again, SoVI is not performing as expected. Clearly these results add increasing confidence in CDRI.

Table 6.18. OLS regression model: SoVI, median income, and CDRI-1 predicting uninsured flood property damage

Model	Variable	Unstandardized Coefficients	Standardize Coefficients	t-value	P-value	R^2	Adj.R^2
1	Total risk	.049	.126	1.206	.112		
	Median income	.081	.070	.665	.254	.028[c]	.010
2	Total risk	.053	.137	1.366	.088[c]		
	Median income	-.017	-.015	-.141	.444		
	SOVI	-.108	-.308	-3.255	.001[a]	.116[a]	.091
3	Total risk	.049	.127	1.306	.097[c]		
	Median income	.218	.186	1.485	.070[c]		
	SOVI	-.107	-.305	-3.313	.000[a]		
	CDRI-1	-.914	-.309	-2.691	.004[a]	.173[a]	.143

Note: N = 144; a $p < .01$; b $p < .05$; c $p < .10$ (one-tailed tests)

The results for the models predicting flood related deaths presented in Table 6.19, are also supportive of CDRI's incremental validity. The first model which includes total risk and median income performs as expected, with total risk having a positive effect while median income having a negative effect on flood related deaths. The second model which includes SoVI is significant and SoVI performed as expected. The third model indicates that CDRI-1 is statistically significant and negative as expected suggesting that it does indeed contribute to the model. Also in the third model, total risk, median income, and SoVI are significant and perform as expected.

Table 6.19. ZTP regression model: SoVI, median income, and CDRI-1 predicting deaths due to flooding

Model	Variable	Coefficient	Standard error	z	P>|z|	Pseudo R^2
1	Total risk	.223	.013	17.30	.000	
	Median income	-1.657	.053	-31.14	.000	0.6485
2	Total risk	.196	.014	13.57	.000	
	Median income	-1.406	.078	-18.02	.000	
	SoVI	.862	.020	4.30	.000	0.6553
3	Total risk	.163	.015	11.01	.000	
	Median income	-1.229	.077	-16.04	.000	
	SoVI	.125	.012	5.90	.000	
	CDRI-1	-1.496	.224	-6.67	.000	0.6722

Note: N = 22; prob>Ch^2 = 0.000; Model 1: Chi^2 = 1739.97, df = 2; Model 2: Chi^2 = 1758.20; df = 3; Model 3: Chi^2 = 1803.54; df = 4; Pseudo R^2 = 0.6722.

In conclusion, clearly CDRI as a measure has made a unique contribution to the prediction of flood losses and flood related deaths that could not have been obtained from SoVI and/or median income. The significant incremental validity of CDRI over SoVI and median income in predicting flood losses and flood related deaths suggest that adding CDRI as new measure in the hazard literature will be beneficial to planners and emergency managers.

6.4. Summary

This chapter has examined the validity of the CDRI using two methods; the zero-order correlation and the regression analyses. The key findings of this chapter can be summarized as follows.

First, there is a negative correlation between the CDRI and the number of flood related deaths in the U.S. Gulf coast region. This result implies that communities that engage in activities related to building disaster resilience are more likely to significantly reduce the number of deaths due to flooding. These include activities of the four phases of disaster: mitigation, preparedness, response, and disaster and the resources or community capitals, which help to undertake the activities to build disaster resilience: social, economic, physical, and human. This result is consistent with the findings by Zahran et al. (2008) who found that counties in Texas that frequently suffered from flooding but had strong hazard mitigation plans in place experienced fewer flood related deaths and injuries.

Second, there is a negative correlation between the CDRI and the total flood property damage in the U.S. Gulf coast region. This finding implies that communities with a high level of resilience or those which engage in activities that foster disaster resilience are more likely to significantly reduce flood related property damage. For example, communities which engage in hazard mitigation activities such as re-directing developments out of floodplains are more likely to reduce the flood related property damage.

Third, the results suggest that there is a positive correlation between the CDRI and the insured flood property damage in the U.S. Gulf coast region. This finding implies that counties with a high level of disaster resilience are more likely to insure their property against flood damage because they have access to financial resources.

Fourth, the results also indicate that there is a negative relationship between the CDRI and the uninsured flood property damage. These results suggest that most people residing in communities with a comparatively high level of disaster resilience are more likely to afford to buy flood insurance because they have access to financial resources.

Fifth, there is a negative correlation between the CDRI and social vulnerability. This result suggests that communities that have high disaster resilience have low social vulnerability.

Sixth, as expected, the results show that there is a negative correlation between social vulnerability and the number of deaths due to flooding in the U.S. Gulf coast region. This result implies that communities with a high number of socially vulnerable populations are more likely to experience more flood related deaths. This is not surprising because in recent years, hazard researchers have reached the consensus that demographic differences play an important role in determining the risk people face. It has been found that households with higher socioeconomic status suffer less when compared with low income households (Cutter et al., 2003; Morrow, 1999; Peacock et al., 1997). Perhaps the most recent evidence was from the hurricanes Katrina and Rita (2005) which revealed that poor communities often suffer disproportionately in terms of human deaths and injuries.

Seventh, there is a positive correlation between the CDRI and the total physical risk. This result implies that communities located in high risk areas are more likely to engage in disaster resilience related activities such as hazard mitigation and disaster preparedness. Although there is no perfect correlation between perceive risk and scientifically estimated risk, studies have found that perceived risk is a significant predictor of hazard adjustment adoption (Lindell & Perry, 2000). High perceived risk is more likely to lead to a community to take hazard protective measures such as hazard mitigation or preparedness (Peacock, 2003; Peacock, Brody, & Highfield, 2005).

Eighth, CDRI has shown some evidence of incremental validity. It has demonstrated unique contributions to the prediction of flood losses and flood related deaths that could not have been obtained from SoVI and/or median income.

Finally, on the whole, the CDRI-1 measure, which is the primary focus in this study performed as expected. The results on correlational and regression analyses clearly suggest construct and incremental validation of the measure implying that the measure is theoretically and empirically valid.

CHAPTER VII

ASSESSING DISASTER RESILIENCE OF THE U.S. GULF COAST REGION

7.1. Introduction

The main objective of this chapter is to employ the final disaster resilience index scores with the aim of identifying which states and counties are comparatively more disaster resilient in the Gulf coast region. This exercise provides not only information about the relative disaster resilience of states and counties in the region, but also additional confidence in the validity and utility of the CDRI scores as well as the subcomponent measures associated with disaster phases and community capitals. Throughout this exercise emphasis is placed on the CDRI-1 score, although again the other CDRI scores are displayed for comparison purposes. In this analysis the disaster phases and community capitals sub-indices are employed to gain additional insight in their utility and to gain additional understanding on how these components are operating within the CDRI.

In order to maximize the ability of this essentially descriptive analysis, in terms of providing additional feedback regarding the utility and validity of the CDRI measurement approach developed in this dissertation, it is important to outline, at least in general terms the expectations of this analysis. In other words, what are the general expectations with respect to disaster resilience across states and counties along the Gulf coast? In an ideal analysis, it would be advantageous to have a set of hypotheses to test regarding which state and/or county should score highest on the CDRI index when compared to others. Unfortunately the literature and previous research on disaster resilience is not sufficiently developed to allow for formal hypothesis testing. Nevertheless, the literature does suggest some general expectations.

7.2. Disaster resilience expectations along the U.S. Gulf coast

The literature on local land use planning suggests that communities with high quality and effective comprehensive plans are more likely to have a high level of disaster resilience and a low level of vulnerability (Burby, 1998; Burby et al., 2000). A great body of literature has demonstrated that local land use planning is an important element in dealing with disasters (Berke & Beatley, 1992; Brody, 2003; Brody & Highfield, 2005). These researchers found that local land use planning is a key to improving hazard mitigation which is an important element in building disaster-resilient communities. Generally speaking, hazard and disaster planning are measures undertaken prior to disasters to help avoid and reduce loss of human life and property damage (Burby, 1998). Land use planning for example, can help to identify high risk areas so that developments can be re-directed away from these areas (Burby, 1998).

Overall the literature suggest that states or counties which mandate comprehensive plans, adopt building codes and zoning regulations, or participate in the FEMA's Community Rating System are more resilient, particularly with respect to mitigation activities, than other communities. Indeed the importance of these planning elements necessitated their inclusion as a small part of the set of indicators included in the CDRI. Specifically of the 75 indicators incorporated in the CDRI scores, five indicators address: (1) land use planning and zoning regulations, (2) FEMA approved mitigation plans, (3) comprehensive plans, (4) building codes, and (5) FEMA's Community Rating System participation. The following brief discussion draws on the planning research literature with respect to these five planning elements to address which state or states appear to make better use of them and therefore suggest which states and subsequently counties should score better on the CDRI indices.

(i) *Land use planning and zoning regulations*: There are significant differences in planning powers and authority between Florida and the rest of the states in the U.S. Gulf coast region. Most of the U.S. Gulf coast counties have zoning regulations to regulate development but Florida is the only state in the region to mandate local plans. Also, in Florida both counties and cities have what is known as the "Home Rule" and the authority to plan (Jacob & Showalter, 2007). Home rule is the power and authority a local government is granted to plan by the state. It enables the local government to exercise all governmental powers except those limited by the state. Generally, the ability to develop, implement, and enforce local plans depends predominantly on home rule power (Jacob & Showalter, 2007). In contrast, municipalities in Texas, for example, have planning and enforcement power but counties have no planning power (Jacob & Showalter, 2007). This implies that Texas provides little or no intervention in guiding local planning or specifying elements to include in local plans. These findings suggest that Florida and its counties should be at the upper end of the CDRI index while Texas should be at the lower end, with other states falling in between.

(ii) *Comprehensive plans and hazard mitigation plans:* Florida requires its coastal counties to have comprehensive plans and local mitigation plans (Brody, Godschalk, & Burby, 2003). Most importantly, Florida is the only U.S. Gulf coast state to include hazard mitigation within a state plan. Texas and others in the U.S. Gulf coast region do not require inclusion of hazard mitigation component in a state plan (Jacob & Showalter, 2007), although there are may be independent mitigation plans. Texas and other states in the region take what Jacob and Showalter (2007) called a "fairly laissez faire" approach towards planning. In other words, local municipalities and counties (except in Florida) are free to develop comprehensive plans, with or without mitigation plans, but the state does not mandate these plans. These finding suggest that Florida should be near the top of the CDRI scores.

(iii) *Building codes:* In general, there are two building codes that states often adopt: the International Building Code (IBC) for commercial and multifamily structures, and the International Residential Code (IRC) for single and two-family structures (Jacob & Showalter, 2007). The current version of these building codes is 2006, and they include wind and flood elements. Only Florida and very recently Louisiana mandate state building codes both IBC and IRC. Alabama and Mississippi have state codes that apply to state buildings only, although building codes were developed for coastal areas in Mississippi following Hurricane Katrina and some coastal counties did adopt these measures. Texas has no officially mandated state building code for either residential or commercial constructions but it recommends adoption of the 2000 IBC and IRC codes (Jacob & Showalter, 2007). More specifically, Texas, through its department of insurance, does develop its own version of IBC and IRC, but local communities, not counties are free to adopt or not to adopt the codes.

(iv) *Community Rating System (CRS):* Local communities in the United States can obtain substantial reductions in flood insurance premiums by participating in the Community Rating System of the National Flood Insurance Program (NFIP). The NFIP's Community Rating System encourages communities to keep new development out of flood plains. The main goal of the NFIP program is to reduce flood losses. The CRS has been designed to provide incentives in terms of flood insurance premium discounts, (up to a maximum of 45%) for communities to go beyond the minimum flood management requirements (Brody et al., 2007). The rating scores are divided into 10 classes, which correspond to flood insurance premium discount rate from 5% to 45%. Class 1 requires the most credit points and receives the highest premium discount (45%) whereas Class 9 receives the lowest premium discount (5%) (Brody et al., 2007). Class 10 does not obtain a minimum number of credit points and therefore receives no discount. The CRS classes are based on 18 activities, which are grouped into the following four main categories: (1) public information, (2) mapping and regulation, (3) flood damage reduction, and (4) flood preparedness (Brody et al., 2007). Communities that implement most of these measures receive high CRS scores. The results of this research show that Florida counties exhibited higher CRS scores, suggesting that most of the counties have implemented the NFIP's required flood management measures.

Clearly the above discussions suggest that of the entire Gulf coast states, Florida and its counties should rank near the top in terms of disaster resilience. It should also be recalled however, that the above elements are much more focused on hazard mitigation issues and do not necessarily capture other dimensions of disaster preparedness, response, and recovery. Furthermore, these elements capture only a small part of the full complement of community capital elements. Nevertheless the discussion does suggest that Florida, with its much more comprehensive approach to addressing natural hazards and disasters, should rank higher than other states in the Gulf coast. Furthermore, while information on other states is more limited, the discussion also suggests that Texas, with its relatively more laissez-faire approach and inability of counties to be involved in planning process might well be expected to fall at the lower end of the CDRIs.

The following discussion begins by examining the states in terms of their CDRI score rankings, followed by an examination of state rakings on the disaster phases and community capitals sub-indices. The final section presents a brief discussion of county rankings.

7.3. CDRI scores by state

This section discusses the results of the CDRI mean scores in the study region. As it can be recalled, in the development of the CDRI and sub-indices, standardized scores or z-scores were employed. Therefore, the scores are centered, or have a mean of zero and positive scores indicate rankings above the mean and negative scores indicate rankings below the mean. In addition, it should be recalled that the unit of analysis in development of the CDRIs was the county or parish; therefore the state averages were calculated based on the coastal counties/parishes falling in each states. Again, the numbers of counties/parishes for each state are: Florida, 42; Texas, 41; Louisiana, 38; Mississippi, 12; Alabama, 8; and Georgia, 3. As with previous discussion the focus is on the CDRI-I scores, with the other two CDRIs displayed for comparison purposes.

The assessment of the state results begins by examining the box plots of the CDRI scores across all states. Box plots are efficient tools to visualize and compare distributions of data in several samples (Dumbgen & Riedwyl, 2007). They can easily depict the locality, spread, and skewness of data. The box plots use the median, the approximate quartiles, and the lowest and highest data points to convey the level, spread, and symmetry of a distribution of data values (Dumbgen & Riedwyl, 2007). They can also be easily used to identify outlier data values. The box bounds the first and the third quartiles, commonly known as the inter-quartile range (IQR) which represents the middle 50% of the data distribution (Coolidge, 2006). The length of the box is used to compare the spread of the distribution of the data. If the box is small, it means that the middle data are tightly packed around the median. If the box is large, it means that the middle data spread out far from the median. The median value is represented by a horizontal line within a box. The vertical line is used to identify outliers; the mild outliers are marked by a circle (o) and the extreme outliers are marked by a star (*).

Figures 7.1 through 7.3 present the box plots for the individual CDRIs for each state. Not surprisingly, the plots for the individual CDRI scores are very similar.

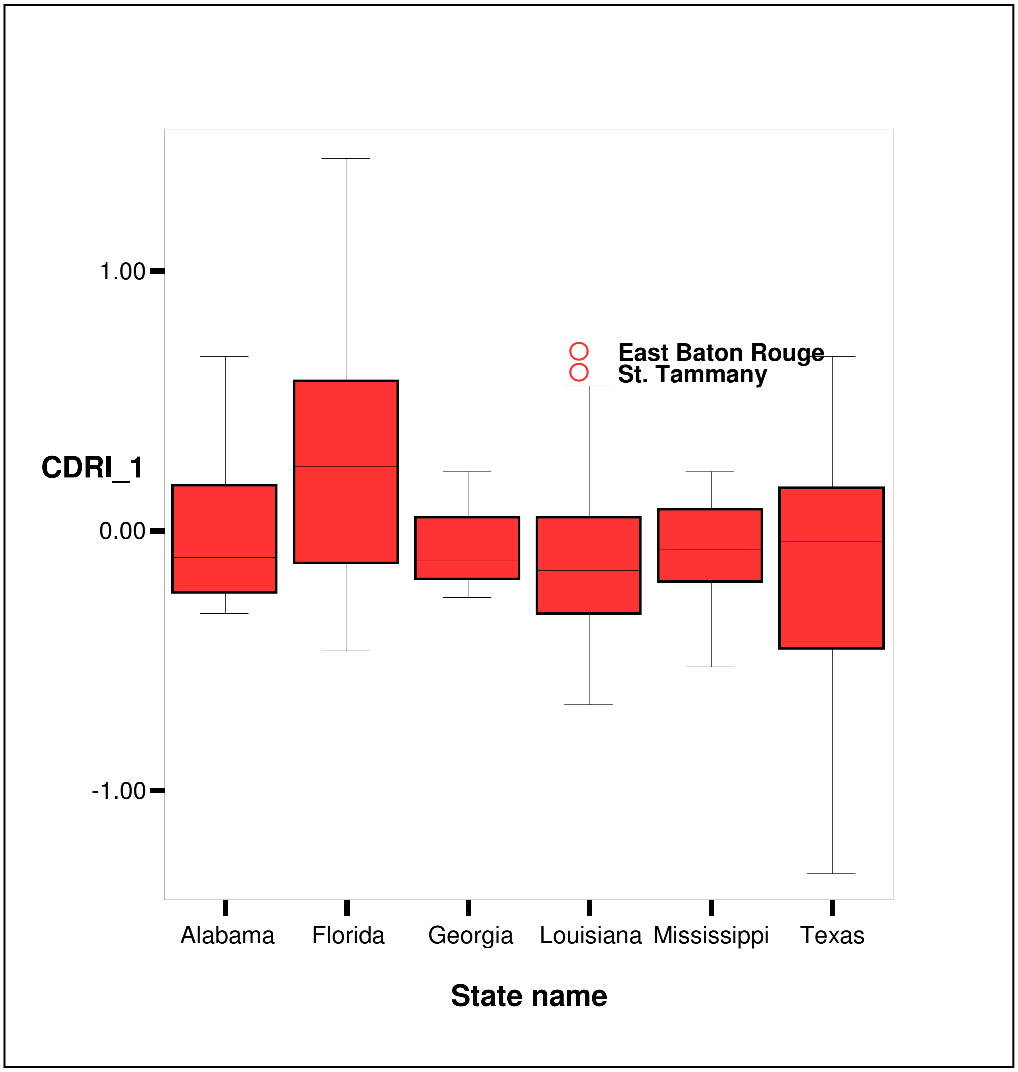


Figure 7.1. Box plots for CDRI-1

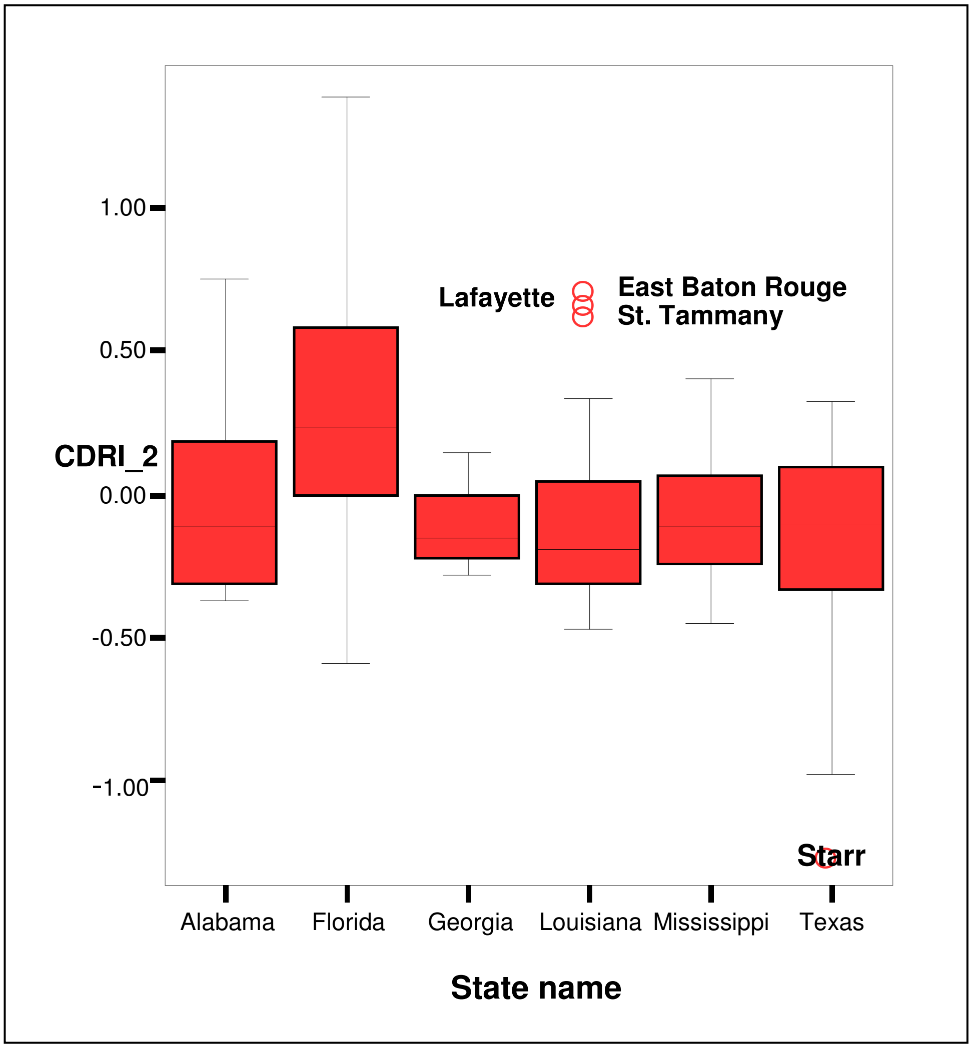


Figure 7.2. Box plots for CDRI-2

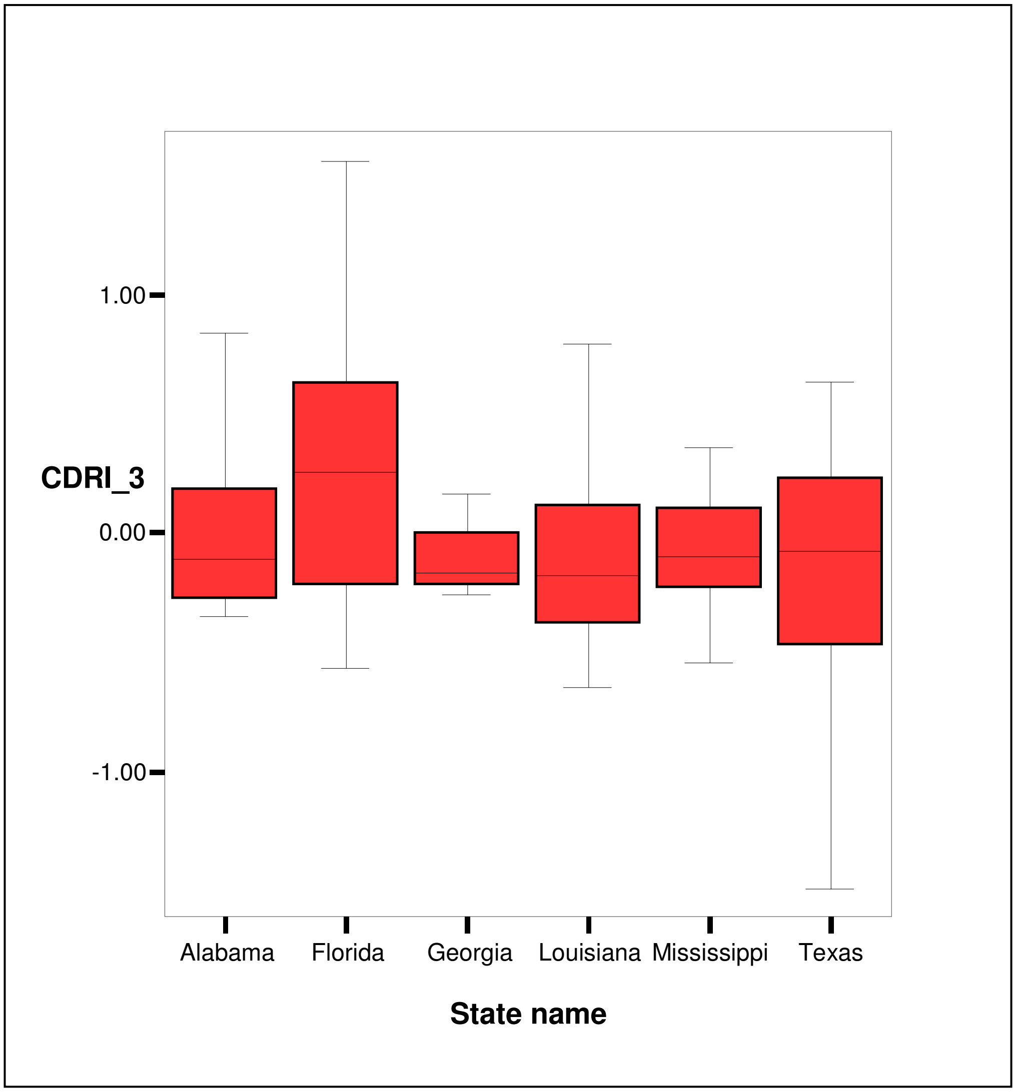


Figure 7.3. Box plots for CDRI-3

Focusing on Figure 7.1, which displays the results for the preferred CDRI-1 score, the results suggest that there is a good deal of dispersion among the counties in Florida and Texas, however, as noted above, these two states also included the greatest number of coastal counties. Nevertheless, it is interesting to note that the Florida dispersion has a slight positive skew, while Texas's dispersion has a slight negative skew. Furthermore, the results show that Florida has the highest median score in all the CDRIs; supporting the previously discussed findings that Florida is the most disaster resilient state in the study region. The results also suggest that Louisiana demonstrated the lowest median scores in almost all the CDRIs. Additionally, the box plots in Figures 7.1(CDRI-1) and 7.2 (CDRI-2) indicate that East Baton Rouge, Lafayette, and St. Tammany parishes (Louisiana) are a good bit higher than other parishes in Louisiana, designating them as outliers on these graphs. Also, in Figure 7.2 Starr county in Texas appears as an outlier on the lower end, indicating that this county scores a good deal lower on the CDRI-2 index than others in the state. Table 7.1 presents the mean CDRI scores for each Gulf coast state and Figure 7.4 displays these average for each state graphically. As can be seen by comparing across CDRI scores in Table 7.1 or Figure 7.4, there is a good deal of similarity in the CDRIs for each state. While there is some variation, for the most part the CDRIs scores for each state tend to cluster.

Table 7.1. CDRI mean scores by state

State	CDRI-1		CDRI-2		CDRI-3	
	Mean Score	Rank	Mean Score	Rank	Mean Score	Rank
Florida	.2539	1	.3035	1	.2759	1
Alabama	.0067	2	-.0125	2	.0137	2
Georgia	-.0479	3	-.1004	5	-.0856	4
Mississippi	-.0860	4	-.0785	3	-.0780	3
Louisiana	-.0981	5	-.0994	4	-.0968	5
Texas	-.1418	6	-.1861	6	-.1665	6

Most important however, there appears to be variations among the states and the patterns are consistent with the general expectations discussed above. Specifically, the mean scores among states indicate that, on average, Florida performed better by scoring the highest scores in all the three CDRIs, followed by Alabama, which scored above average with regard to CDRI-1 and CDRI-3, and near average in terms of CDRI-2. The results also indicate that Texas scored the lowest scores in all the three CDRIs, suggesting that on average Texas counties are the least disaster resilient in the U.S. Gulf coast region. Furthermore the results suggest that on average parishes in Louisiana are comparable to the averages for counties in Mississippi and Georgia.

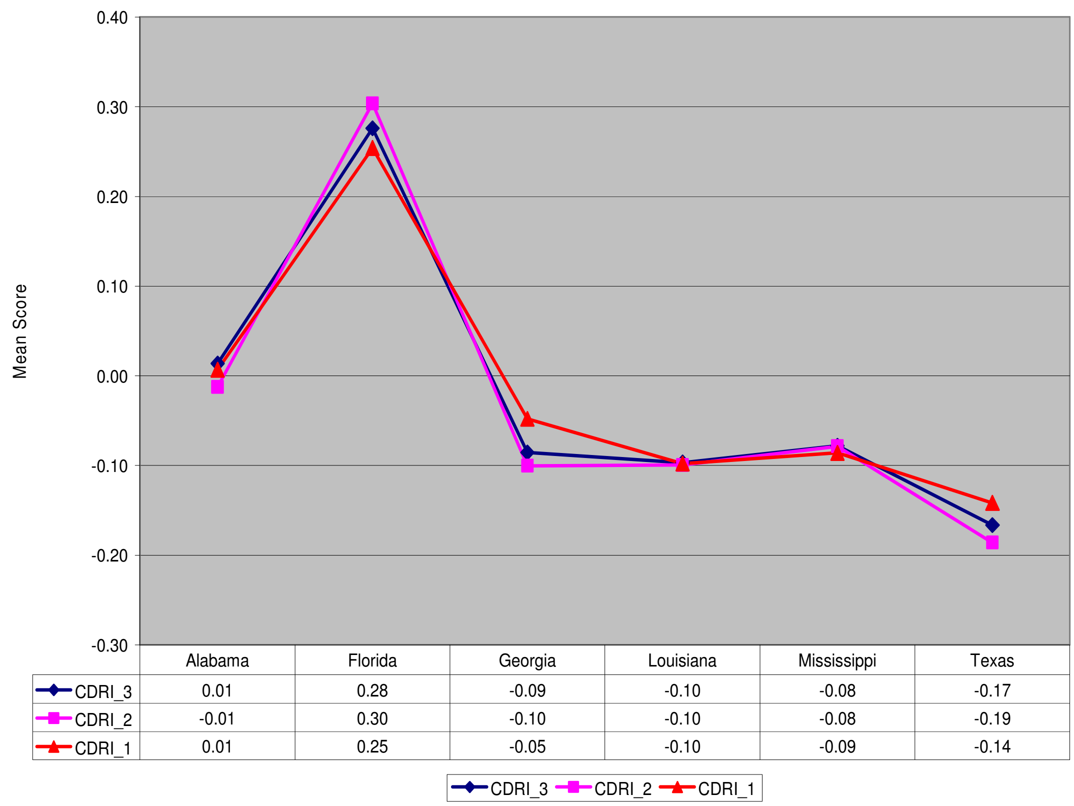


Figure 7.4. Distribution of mean score for CDRIs

An analysis of variance (one-way ANOVA) was performed, and if necessary, post-hoc testing was undertaken to determine if the apparent differences in the mean CDRI scores seen in Table 7.1 reflect statistically significant variations among Gulf coast states. The results of those tests are displayed in Table 7.2. The results suggest that there are indeed statistically significant differences among the states with respect to all three CDRI measures. Specifically, a significant F-test simply indicates that at least one mean is different from one other mean, while a multiple comparison test reveals the trend of significant differences between the means (Coolidge, 2006; Turner & Thayer, 2001; Weiss, 2006). There is a variety of multiple comparison methods suggested in the literature. Some of the more commonly used methods include Fisher's least significant difference (LSD), Tukey's honestly significant difference (HSD), Scheffe's test, Bonferroni correction, and Duncan's new multiple range test (Coolidge, 2006; Turner & Thayer, 2001; Weiss, 2006). Some of these methods are considered to be more conservative in terms of controlling the Type I error (rejecting the null hypothesis when it is actually true) and others are considered more liberal (Coolidge, 2006). In this study, a multiple comparison test using Fisher's least significant difference (LSD) was used to determine the pattern of the means difference.

The results for ANOVA tests of CDRI score differences among the Gulf coastal states are presented in Table 7.2. All F-tests are statistically significant, suggesting that there are statistically differences among the states with respect to the mean CDRI scores.

Table 7.2. ANOVA F-test for the CDRIs

CDRI	Source	Sum of Squares	df	Mean Square	F	Sig.
CDRI-1	Between Groups	3.994	5	.799	4.912	.000
	Within Groups	22.445	138	.163		
	Total	26.439	143			
CDRI-2	Between Groups	5.770	5	1.154	7.856	.000
	Within Groups	20.271	138	.147		
	Total	26.041	143			
CDRI-3	Between Groups	4.787	5	.957	4.821	.000
	Within Groups	27.402	138	.199		
	Total	32.189	143			

In light of these results it makes sense to assess for significant differences among the states. Tables 7.3 through 7.5 display the results for Fisher's Least Significant Difference (LSD) tests among the state means. In every real sense, the results for differences among states with respect to the primary measure, CDRI-1, are not surprising, on the whole they confirm that Florida's counties have on average higher community disaster resilience scores than those of Texas, Louisiana, and Mississippi. More specifically, the results confirm that the Florida mean is higher than the mean county scores for these three states. However, the difference of Florida from Alabama and Georgia is not significant ($p < .05$). Very similar patterns emerge when comparing county mean scores for the CDR-2 and CDRI-3. The only variation is that mean for Florida's CDRI-2 score is significantly higher than the means for all other states. There are no statistically significant differences among the county means for other states. In general these results are consistent with the expectations that Florida counties would have higher community disaster resilience than the other states. While the mean for Texas counties is lower than all other states, the differences are not statistically significant.

Table 7.3. Fisher's LSD post-hoc test for CDRI-1

(I) State	**(J) State**	**Mean Difference (I-J)**	**Std. Error**	**Sig.**	**95% Confidence Interval**	
					Lower Bound	**Upper Bound**
1. Florida	2. Texas	.396[b]	.089	.000	.220	.571
	3. Louisiana	.352[b]	.090	.000	.173	.531
	4. Mississippi	.340[b]	.132	.011	.079	.601
	5. Alabama	.247	.156	.114	-.060	.555
	6. Georgia	.302	.241	.213	-.175	.778
2. Texas	3. Louisiana	-.044	.091	.630	-.223	.136
	4. Mississippi	-.056	.132	.674	-.318	.206
	5. Alabama	-.149	.156	.342	-.457	.160
	6. Georgia	-.094	.241	.698	-.571	.383
3. Louisiana	4. Mississippi	-.012	.134	.928	-.276	.252
	5. Alabama	-.105	.157	.506	-.415	.206
	6. Georgia	-.050	.242	.836	-.528	.428
4. Mississippi	5. Alabama	-.093	.184	.615	-.457	.271
	6. Georgia	-.038	.260	.884	-.553	.477
5. Alabama	6. Georgia	.055	.273	.842	-.485	.595

Note: b $p < 0.05$

Table 7.4. Fisher's LSD post-hoc test for CDRI-2

(I) State	(J) State	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1. Florida	2. Texas	.490[b]	.084	.000	.323	.656
	3. Louisiana	.403[b]	.086	.000	.233	.573
	4. Mississippi	.382[b]	.126	.003	.134	.630
	5. Alabama	.316[b]	.148	.034	.024	.608
	6. Georgia	.404[c]	.229	.080	-.049	.857
2. Texas	3. Louisiana	-.087	.086	.317	-.257	.084
	4. Mississippi	-.108	.126	.394	-.356	.141
	5. Alabama	-.174	.148	.243	-.467	.119
	6. Georgia	-.086	.229	.709	-.539	.368
3. Louisiana	4. Mississippi	-.021	.127	.870	-.272	.230
	5. Alabama	-.087	.149	.561	-.382	.208
	6. Georgia	.001	.230	.996	-.453	.456
4. Mississippi	5. Alabama	-.066	.175	.706	-.412	.280
	6. Georgia	.022	.247	.930	-.467	.511
5. Alabama	6. Georgia	.088	.260	.735	-.425	.601

Note: b $p < 0.05$; c $p < 0.10$

Table 7.5. Fisher's LSD post-hoc test for CDRI-3

(I) State	(J) State	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1. Florida	2. Texas	.442[b]	.098	.000	.249	.636
	3. Louisiana	.373[b]	.100	.000	.176	.570
	4. Mississippi	.354[b]	.146	.017	.066	.642
	5. Alabama	.262	.172	.129	-.078	.602
	6. Georgia	.362	.266	.177	-.165	.888
2. Texas	3. Louisiana	-.070	.100	.489	-.268	.129
	4. Mississippi	-.089	.146	.546	-.378	.201
	5. Alabama	-.180	.172	.297	-.521	.160
	6. Georgia	-.081	.267	.762	-.608	.446
3. Louisiana	4. Mississippi	-.019	.148	.899	-.311	.273
	5. Alabama	-.111	.173	.525	-.453	.232
	6. Georgia	-.011	.267	.966	-.540	.517
4. Mississippi	5. Alabama	-.092	.203	.653	-.494	.310
	6. Georgia	.008	.288	.979	-.561	.576
5. Alabama	6. Georgia	.099	.302	.743	-.497	.696

Note: b $p < 0.05$

Before leaving the overall CDRI measures, it might be illustrative to examine in more detail the scores among the coastal counties included in the sample. Tables 7.6 through 7.8 present the top 10 and bottom 10 counties for each of the CDRI measures. The complete listing of the 144 counties for each CDRI score is included in Appendix D. Interestingly, when examining the top 10 CDRI-1 scores in Table 7.6; seven out of ten counties are located in Florida. Monroe county (the Florida Keys) was the county that had the highest CDRI score. This clearly is good, because this is probably the most vulnerable Gulf coast county for hurricanes and hurricane impacts in the United States. On the lower end of the ranking, we find that eight of the ten counties with the lowest CDRI-1scores, are located in Texas. Most of these Texas counties are located along the southern tip of Texas along the Mexico-Texas border. The interesting exception to the top/bottom split between Florida and Texas is that one county in Texas, Fayette, is in the top ten list.

Table 7.6. CDRI-1 ranking scores by top and bottom 10 lists

TOP 10 LIST				**BOTTOM 10 LIST**			
Rank	**County**	**State**	**Score**	**Rank**	**County**	**State**	**Score**
1	Monroe	Florida	1.44	**135**	West Feliciana	Louisiana	-0.61
2	Leon	Florida	1.12	**136**	Kenedy	Texas	-0.61
3	Collier	Florida	1.03	**137**	Vernon	Louisiana	-0.67
4	Sarasota	Florida	1.02	**138**	Webb	Texas	-0.68
5	Franklin	Florida	0.90	**139**	Cameron	Texas	-0.72
6	Lee	Florida	0.72	**140**	Bee	Texas	-0.73
7	East Baton Rouge	Louisiana	0.69	**141**	Hidalgo	Texas	-0.81
8	Baldwin	Alabama	0.68	**142**	Duval	Texas	-0.92
9	Fayette	Texas	0.68	**143**	Willacy	Texas	-0.98
10	Okaloosa	Florida	0.67	**144**	Starr	Texas	-1.32

Table 7.7. CDRI-2 ranking scores by top and bottom 10 lists

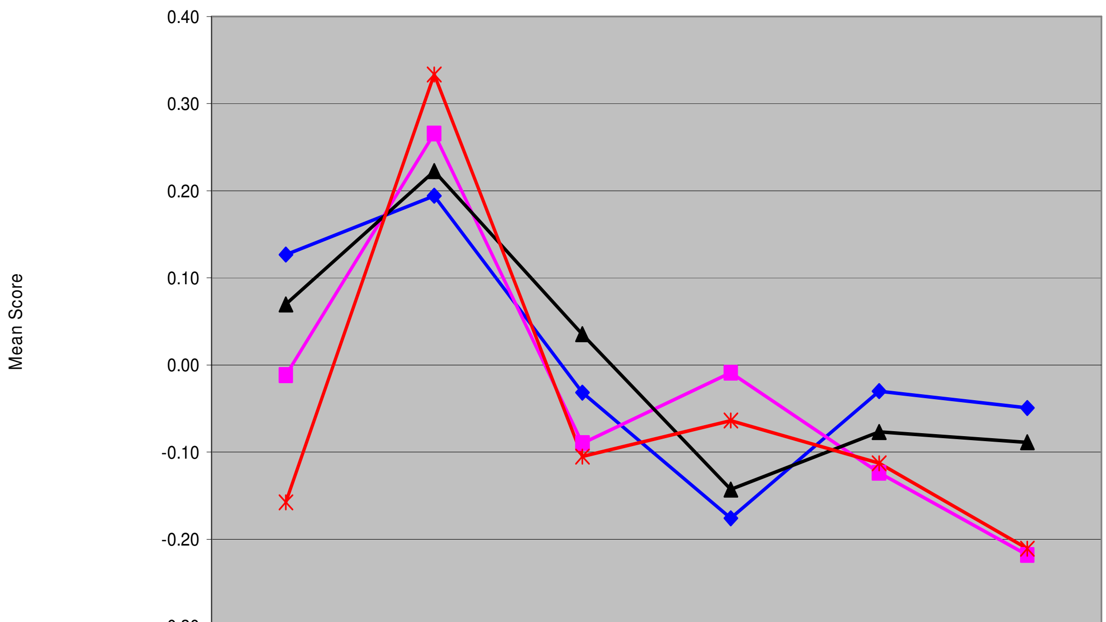
TOP 10 LIST				BOTTOM 10 LIST			
Rank	**County**	**State**	**Score**	**Rank**	**County**	**State**	**Score**
1	Monroe	Florida	1.39	**135**	Vernon	Louisiana	-0.48
2	Franklin	Florida	1.24	**136**	Jim Wells	Texas	-0.50
3	Sarasota	Florida	1.13	**137**	Hardee	Florida	-0.59
4	Collier	Florida	1.08	**138**	Cameron	Texas	-0.71
5	Walton	Florida	0.94	**139**	Webb	Texas	-0.76
6	Okaloosa	Florida	0.85	**140**	Hidalgo	Texas	-0.77
7	Leon	Florida	0.82	**141**	Kenedy	Texas	-0.80
8	Baldwin	Alabama	0.75	**142**	Duval	Texas	-0.87
9	Lee	Florida	0.71	**143**	Willacy	Texas	-0.98
10	East Baton Rouge	Louisiana	0.71	**144**	Starr	Texas	-1.27

Table 7.8. CDRI-3 ranking scores by top and bottom 10 lists

TOP 10 LIST				BOTTOM 10 LIST			
Rank	**County**	**State**	**Score**	**Rank**	**County**	**State**	**Score**
1	Monroe	Florida	1.56	**135**	Evangeline	Louisiana	-0.58
2	Collier	Florida	1.25	**136**	Vernon	Louisiana	-0.65
3	Sarasota	Florida	1.21	**137**	Bee	Texas	-0.69
4	Leon	Florida	1.11	**138**	Kenedy	Texas	-0.70
5	Franklin	Florida	0.88	**139**	Cameron	Texas	-0.82
6	Baldwin	Alabama	0.84	**140**	Webb	Texas	-0.82
7	Lee	Florida	0.83	**141**	Hidalgo	Texas	-0.91
8	Okaloosa	Florida	0.81	**142**	Duval	Texas	-1.03
9	Walton	Florida	0.79	**143**	Willacy	Texas	-1.11
10	East Baton Rouge	Louisiana	0.79	**144**	Starr	Texas	-1.49

There is a good deal of similarity between top and bottom listings among the three CDRI scores. The top listings among all the CDRI scores are dominated by Florida counties, which include Monroe, Leon, Collier, Sarasota, Franklin, Lee, and Okaloosa. The list also includes Baldwin county (Alabama) and East Baton Rouge parish (Louisiana). The highest scores exhibited by these counties suggest that these are most disaster resilient counties in the U.S. Gulf coast region. At the bottom 10 of the list, three Texas counties (Starr, Willacy, and Duval) are consistently ranked on the same positions for all the three CDRIs. Starr county is at the bottommost, followed by Willacy county, and Duval county, consecutively. These results suggest that these three counties are the least disaster resilient counties not only in Texas but also in the U.S. Gulf coast region as a whole.

The following sections undertake a brief examination of two of the main sets of sub-indices associated with the CDRI measure. The first examines the capital domain sub-indices and the second focuses on the disaster phases. These sections should provide additional insight in terms of how the components of the CDRI are operating and provide some insight into potential utility of these sub-indices for examining important dimensions of community disaster resilience.



	Alabama	Florida	Georgia	Louisiana	Mississippi	Texas
Social_capital	0.13	0.19	-0.03	-0.18	-0.03	-0.05
Economic_capital	-0.01	0.27	-0.09	-0.01	-0.12	-0.22
Physical_capital	0.07	0.22	0.04	-0.14	-0.08	-0.09
Human_capital	-0.16	0.33	-0.11	-0.06	-0.11	-0.21

Social_capital Economic_capital Physical_capital Human_capital

Figure 7.5. Distribution of mean score for capital domain's sub-indices

7.4. Mean scores of capital domain's sub-indices

Table 7.5 presents the county mean scores for each of the four capital domains – social, economic, physical, and human – for each of the six Gulf coast states (see also Figure 7.5 for graphical display of the these means). As might have been expected, given the results for the CDRI scores, the county averages for Florida are the highest across all capital dimensions. Texas has the lowest county mean for economic and human capital, while Louisiana has the lowest county mean for social capital and physical capital. However, while Texas has the second lowest county means on social and physical capital indices, Louisiana has the second highest for economic and human capital. Thus, while the Texas county means are consistently near the bottom of these rankings, the parish means for Louisiana are not consistent. These results again suggest that, on average, Texas counties are less disaster resilient across the four capital domains, while Florida counties are again, at least in terms of their means, quite resilient across all capital domains.

Table 7.9. Mean scores of capital domain's sub-indices by state

State	Social Capital		Economic Capital		Physical Capital		Human Capital	
	Mean score	Rank	Mean score	Rank	Mean score	Rank	Mean score	Rank
Florida	.1942	1	.2655	1	.2224	1	.3335	1
Alabama	.1267	2	-.0119	3	.0696	3	-.1578	5
Mississippi	-.0301	3	-.1241	5	-.0770	4	-.1129	4
Georgia	-.0319	4	-.0899	4	.0353	2	-.1052	3
Texas	-.0494	5	-.2183	6	-.0889	5	-.2108	6
Louisiana	-.1760	6	-.0092	2	-.1430	6	-.0640	2

Table 7.10. ANOVA F-test for capital domain's sub-indices

Sub-index	Source	Sum of Squares	df	Mean Square	F	Sig.
Social capital	Between Groups	3.004	5	.601	2.347	.044
	Within Groups	35.327	138	.256		
	Total	38.331	143			
Economic capital	Between Groups	5.128	5	1.026	1.491	.197
	Within Groups	94.930	138	.688		
	Total	100.058	143			
Physical capital	Between Groups	3.293	5	.659	6.497	.000
	Within Groups	13.990	138	.101		
	Total	17.283	143			
Human capital	Between Groups	7.033	5	1.407	16.000	.000
	Within Groups	12.131	138	.088		
	Total	19.164	143			

Table 7.10 presents the results from the ANOVA testing for significant differences among the states with respect to the four capital domain means. The results suggest that there are significant differences among the six Gulf coast states with respect to social, physical, and human capitals, but no differences with respect to economic capital. Tables 7.11, 7.12, and 7.13 present the results for Fisher's LSD test for social, physical, and human capitals respectively.

Table 7.11. Fisher's LSD post-hoc test for social capital sub-index

(I) State	(J) State	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1.Florida	2. Texas	.244[b]	.111	.030	.024	.463
	3. Louisiana	.370[b]	.113	.001	.146	.594
	4. Mississippi	.224	.166	.178	-.103	.552
	5. Alabama	.068	.195	.730	-.318	.454
	6. Georgia	.226	.302	.456	-.372	.824
2. Texas	3. Louisiana	.127	.114	.268	-.099	.352
	4. Mississippi	-.019	.166	.908	-.348	.309
	5. Alabama	-.176	.196	.369	-.563	.211
	6. Georgia	-.018	.303	.954	-.616	.581
3. Louisiana	4. Mississippi	-.146	.168	.385	-.477	.185
	5. Alabama	-.303	.197	.126	-.692	.087
	6. Georgia	-.144	.303	.636	-.744	.456
4. Mississippi	5. Alabama	-.157	.231	.498	-.614	.300
	6. Georgia	.002	.327	.996	-.644	.648
5. Alabama	6. Georgia	.159	.343	.644	-.519	.836

Note: b P< 0.05

Table 7.12. Fisher's LSD post-hoc test for physical capital sub-index

(I) Sates	(J) States	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1.Florida	2. Texas	.311[b]	.070	.000	.173	.450
	3. Louisiana	.366[b]	.071	.000	.225	.506
	4. Mississippi	.299[b]	.104	.005	.093	.506
	5. Alabama	.153	.123	.215	-.090	.396
	6. Georgia	.187	.190	.327	-.189	.563
2. Texas	3. Louisiana	.054	.072	.452	-.088	.196
	4. Mississippi	-.012	.105	.909	-.219	.195
	5. Alabama	-.159	.123	.200	-.402	.085
	6. Georgia	-.124	.190	.515	-.501	.252
3. Louisiana	4. Mississippi	-.066	.105	.532	-.275	.142
	5. Alabama	-.213	.124	.088	-.458	.032
	6. Georgia	-.178	.191	.352	-.556	.199
4. Mississippi	5. Alabama	-.147	.145	.315	-.434	.141
	6. Georgia	-.112	.206	.586	-.519	.294
5. Alabama	6. Georgia	.034	.216	.874	-.392	.461

Note: b p < 0.05

Table 7.13. Fisher's LSD post-hoc test for human capital sub-index

(I) States	(J) States	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1. Florida	2. Texas	.544[b]	.065	.000	.416	.673
	3. Louisiana	.398[b]	.066	.000	.266	.529
	4. Mississippi	.446[b]	.097	.000	.255	.638
	5. Alabama	.491[b]	.114	.000	.265	.717
	6. Georgia	.439[b]	.177	.015	.088	.789
2. Texas	3. Louisiana	-.147[b]	.067	.030	-.279	-.015
	4. Mississippi	-.098	.097	.317	-.290	.095
	5. Alabama	-.053	.115	.645	-.280	.174
	6. Georgia	-.106	.177	.553	-.456	.245
3. Louisiana	4. Mississippi	.049	.098	.619	-.145	.243
	5. Alabama	.094	.115	.418	-.134	.322
	6. Georgia	.041	.178	.817	-.310	.393
4. Mississippi	5. Alabama	.045	.135	.741	-.223	.312
	6. Georgia	-.008	.191	.968	-.386	.371
5. Alabama	6. Georgia	-.053	.201	.794	-.450	.344

Note: b $p < 0.05$

The results for the three capital indices display patterns similar to those found among the CDRI measures. With respect to social capital, the Florida county mean is significantly higher than those of Texas and Louisiana. Similarly, with respect to physical capital, the mean for counties in Florida is again higher than those of the Texas and Louisiana, as well as Mississippi. And, finally, when considering human capital, the Florida mean is significantly higher than those of each of other five Gulf coast states. Yet again, there are no significant differences among the means of the other states. Overall, these findings again suggest that Florida's counties on average have consistently higher scores with respect to social, physical, and human capital than counties in Texas and parishes in Louisiana. In addition, Florida counties also have higher average scores than counties in Alabama and Georgia with respect to human capital.

Tables 7.14 through 7.17 present the top and bottom 10 scoring counties for each of the capital sub-indices: Economic, physical, human, and social capital (for a complete listing of counties, see Appendix E). When examining the results for economic capital (Table 7.14), physical capital (Table 7.15) and human capital (Table 7.15), a similar pattern emerges. In each of these listings Florida counties dominated the top 10, taking 7 to 8 out of the top 10 slots in each. Furthermore, Texas counties dominated the bottom 10 holding 6 to 8 of the bottom 10 slots. There is, however an interesting exception to this pattern when examining the top and bottom ten counties with respect to social capital (Table 7.17).

Table 7.14. Economic capital sub-index scores by top and bottom 10 lists

TOP 10 LIST				**BOTTOM 10 LIST**			
Rank	**County**	**State**	**Score**	**Rank**	**County**	**State**	**Score**
1	Monroe	Florida	2.90	**135**	St. Helena	Louisiana	-0.97
2	Collier	Florida	2.59	**136**	Cameron	Texas	-1.10
3	Fort Bend	Texas	2.01	**137**	Evangeline	Louisiana	-1.12
4	Sarasota	Florida	1.99	**138**	Hidalgo	Texas	-1.29
5	St. Tammany	Louisiana	1.68	**139**	Wilkinson	Mississippi	-1.49
6	Lee	Florida	1.50	**140**	Bee	Texas	-1.51
7	Baldwin	Alabama	1.40	**141**	Duval	Texas	-1.51
8	Hillsborough	Florida	1.36	**142**	Brooks	Texas	-1.61
9	Leon	Florida	1.30	**143**	Willacy	Texas	-1.85
10	Pinellas	Florida	1.24	**144**	Starr	Texas	-2.31

Table 7.15. Physical capital sub-index scores by top and bottom 10 lists

TOP 10 LIST				BOTTOM 10 LIST			
Rank	**County**	**State**	**Score**	**Rank**	**County**	**State**	**Score**
1	Franklin	Florida	1.72	**135**	Webb	Texas	-0.42
2	Monroe	Florida	1.43	**136**	St. John the Baptist	Louisiana	-0.43
3	Walton	Florida	0.96	**137**	Bee	Texas	-0.44
4	Leon	Florida	0.75	**138**	Hardee	Florida	-0.48
5	Bay	Florida	0.69	**139**	Kenedy	Texas	-0.49
6	Sarasota	Florida	0.68	**140**	Duval	Texas	-0.49
7	Lafayette	Louisiana	0.66	**141**	West Feliciana	Louisiana	-0.50
8	Collier	Florida	0.64	**142**	Willacy	Texas	-0.51
9	Okaloosa	Florida	0.57	**143**	St. Bernard	Louisiana	-0.54
10	Baldwin	Alabama	0.51	**144**	Starr	Texas	-0.63

Table 7.16. Human capital sub-index scores by top and bottom 10 lists

TOP 10 LIST				BOTTOM 10 LIST			
Rank	**County**	**State**	**Score**	**Rank**	**County**	**State**	**Score**
1	Franklin	Florida	1.34	**135**	Monroe	Alabama	-0.44
2	Liberty	Florida	1.09	**136**	Webb	Texas	-0.51
3	Orleans	Louisiana	0.81	**137**	Cameron	Texas	-0.52
4	Bay	Florida	0.73	**138**	Walthall	Mississippi	-0.57
5	Sarasota	Florida	0.73	**139**	Jim Hogg	Texas	-0.62
6	Gulf	Florida	0.71	**140**	Hidalgo	Texas	-0.64
7	Monroe	Florida	0.65	**141**	Duval	Texas	-0.64
8	East Baton Rouge	Louisiana	0.64	**142**	Willacy	Texas	-0.75
9	Okaloosa	Florida	0.61	**143**	Kenedy	Texas	-0.92
10	Walton	Florida	0.59	**144**	Starr	Texas	-0.92

Table 7.17. Social capital sub-index scores by top and bottom 10 lists

TOP 10 LIST				BOTTOM 10 LIST			
Rank	**County**	**State**	**Score**	**Rank**	**County**	**State**	**Score**
1	Goliad	Texas	1.97	**135**	Glades	Florida	-0.63
2	Leon	Florida	1.91	**136**	Willacy	Texas	-0.80
3	Fayette	Texas	1.65	**137**	Liberty	Florida	-0.88
4	Lavaca	Texas	1.19	**138**	Cameron	Texas	-0.90
5	Austin	Texas	0.97	**139**	Hidalgo	Texas	-1.02
6	Washington	Texas	0.91	**140**	Webb	Texas	-1.03
7	East Baton Rouge	Louisiana	0.84	**141**	West Feliciana	Louisiana	-1.04
8	Citrus	Florida	0.82	**142**	Duval	Texas	-1.06
9	Colorado	Texas	0.81	**143**	Vernon	Louisiana	-1.07
10	Monroe	Florida	0.76	**144**	Starr	Texas	-1.40

Table 7.17 displays the county listings for the social capital sub-index. While the by now familiar pattern holds for the bottom 10, in that six of these ten are counties in Texas, a very different pattern holds for the top 10. Specifically rather than the top 10 being dominated by counties from Florida, for the social capital listings, we find only three counties from Florida. Instead, Texas has 6 of the top 10 positions. As can be recalled social capital was measured using six components participation in voluntary organizations (volunteerism), involvement in social groups (group associations), civic and political participation, religious participations, community attachments and connection in working places. When compared to other Gulf coast states, Texas seems to perform comparatively better in almost all of these components.

In conclusion, while there are certainly some variations, at least in terms of the top and bottom ten counties, on the whole the results suggest that on average, counties in Florida scored more highly on four community capital indices. It must be recalled that when considering these indices, while they do capture important dimensions of community capital, the goal in the selection of capital indicators was dictated by those capital elements most closely associated with disaster phases. Hence, they may not be relevant to researchers simply wanting valid indicators of capital dimension.

7.5. Mean scores of disaster phase's sub-indices

The final section examines the disaster phase's sub-indices which assess resilience with respect to hazard mitigation, and disaster preparedness, response, and recovery. Table 7.18 displays the county averages for each state with respect to each disaster phases. The averages are also displayed graphically in Figure 7.6 which displays the relative clustering of each of the four indices with respect to each state as well as the relative magnitude of these scores between the states. Consistent with the findings thus far, the results in Table 7.18 indicate that the means for counties in Florida are consistently higher across all disaster phases, as is more easily seen in Figure 7.6; these averages are much higher than those of the other states. In addition, the means for counties in Alabama consistently are ranked second across all disaster phases. On the other hand, the average for counties in Texas is again the lowest or nearly the lowest. Specifically, the average for Texas counties is in sixth or last place for hazard mitigation and disaster preparedness and response. Furthermore, Texas counties have the second to the lowest average in disaster recovery.

Table 7.18. Mean scores of disaster phase's sub-indices by state

State	Hazard Mitigation		Disaster Preparedness		Disaster Response		Disaster Recovery	
	Mean score	Rank	Mean score	Rank	Mean score	Rank	Mean score	Rank
Florida	.2806	1	.3031	1	.2688	1	.2511	1
Alabama	.0055	2	-.0202	2	.0384	2	.0312	2
Louisiana	-.0919	3	-.0836	5	-.1074	5	-.1045	4
Mississippi	-.0964	4	-.0603	4	-.0603	4	-.0951	3
Georgia	-.1469	5	-.0410	3	-.0030	3	-.1514	6
Texas	-.1644	6	-.2085	6	-.1655	6	-.1276	5

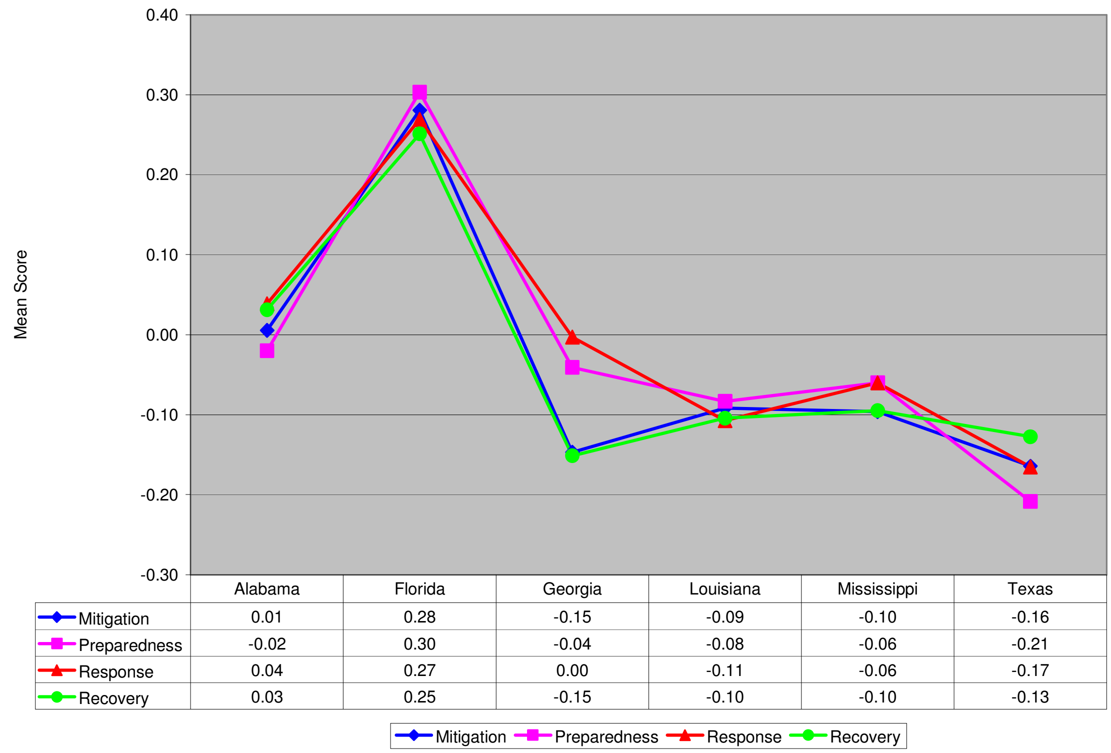


Figure 7.6. Distribution of mean score for disaster phase's sub-indices

Table 7.19. ANOVA F-test for disaster phase's sub-indices

Sub-index	Source	Sum of Squares	df	Mean Square	F	Sig.
Mitigation	Between Groups	4.911	5	.982	4.674	.001
	Within Groups	29.003	138	.210		
	Total	33.914	143			
Preparedness	Between Groups	5.959	5	1.192	5.102	.000
	Within Groups	32.236	138	.234		
	Total	38.195	143			
Response	Between Groups	4.652	5	.930	5.650	.000
	Within Groups	22.722	138	.165		
	Total	27.374	143			
Recovery	Between Groups	3.916	5	.783	3.145	.010
	Within Groups	34.362	138	.249		
	Total	38.278	143			

The results for ANOVAs testing for significant difference in mean disaster phases among the six Gulf coast states are presented in Table 7.19. The findings again suggest that there are statistically significant differences among the states with respect to all four disaster phases: mitigation, preparedness, response, and recovery. Therefore, it makes sense to perform the multiple comparison tests. Tables 7.20 through 77.23 present the results for Fisher's LSD test for hazard mitigation, disaster preparedness, disaster response, and disaster recovery, respectively.

Table 7.20. Fisher's LSD post-hoc test for hazard mitigation sub-index

(I) State	**(J) State**	**Mean Difference (I-J)**	**Std. Error**	**Sig.**	**95% Confidence Interval**	
					Lower Bound	**Upper Bound**
1.Florida	2. Texas	.445[b]	.101	.000	.246	.644
	3. Louisiana	.373[b]	.103	.000	.170	.575
	4. Mississippi	.377[b]	.150	.013	.080	.674
	5. Alabama	.275	.177	.122	-.075	.625
	6. Georgia	.428	.274	.121	-.114	.969
2. Texas	3. Louisiana	-.073	.103	.484	-.277	.132
	4. Mississippi	-.068	.151	.652	-.366	.230
	5. Alabama	-.170	.177	.340	-.520	.181
	6. Georgia	-.017	.274	.949	-.560	.525
3. Louisiana	4. Mississippi	.005	.152	.976	-.296	.305
	5. Alabama	-.097	.178	.586	-.450	.255
	6. Georgia	.055	.275	.842	-.489	.599
4. Mississippi	5. Alabama	-.102	.209	.627	-.516	.312
	6. Georgia	.051	.296	.865	-.535	.636
5. Alabama	6. Georgia	.152	.310	.624	-.461	.766

Note: b $p < 0.05$

Table 7.21. Fisher's LSD post-hoc test for disaster preparedness sub-index

(I) State	(J) State	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1.Florida	2. Texas	.512[b]	.106	.000	.302	.722
	3. Louisiana	.387[b]	.108	.000	.1727	.601
	4. Mississippi	.363[b]	.158	.023	.051	.676
	5. Alabama	.323[c]	.186	.085	-.045	.692
	6. Georgia	.344	.289	.236	-.227	.915
2. Texas	3. Louisiana	-.125	.109	.253	-.340	.090
	4. Mississippi	-.148	.159	.352	-.462	.165
	5. Alabama	-.188	.187	.315	-.558	.181
	6. Georgia	-.168	.289	.563	-.739	.404
3. Louisiana	4. Mississippi	-.023	.160	.885	-.340	.293
	5. Alabama	-.063	.188	.737	-.435	.308
	6. Georgia	-.043	.290	.883	-.616	.531
4. Mississippi	5. Alabama	-.040	.221	.856	-.476	.396
	6. Georgia	-.019	.312	.951	-.636	.598
5. Alabama	6. Georgia	.021	.327	.949	-.626	.668

Note: b $p < 0.05$; c $p < 0.10$

Table 7.22. Fisher's LSD post-hoc test for disaster response sub-index

(I) Sate	(J) Sate	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1.Florida	2. Texas	.434[b]	.089	.000	.258	.611
	3. Louisiana	.376[b]	.091	.000	.197	.556
	4. Mississippi	.329[b]	.133	.014	.067	.592
	5. Alabama	.230	.157	.143	-.079	.540
	6. Georgia	.272	.243	.264	-.208	.751
2. Texas	3. Louisiana	-.058	.091	.526	-.239	.123
	4. Mississippi	-.105	.133	.431	-.369	.158
	5. Alabama	-.204	.157	.196	-.514	.106
	6. Georgia	-.163	.243	.504	-.642	.317
3. Louisiana	4. Mississippi	-.047	.134	.727	-.313	.219
	5. Alabama	-.146	.158	.357	-.458	.166
	6. Georgia	-.104	.243	.669	-.586	.377
4. Mississippi	5. Alabama	-.099	.185	.595	-.465	.268
	6. Georgia	-.057	.262	.827	-.575	.461
5. Alabama	6. Georgia	.041	.275	.880	-.502	.585

Note: b $p < 0.05$

Table 7.23. Fisher's LSD post-hoc test for disaster recovery sub-index

(I) State	(J) State	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1.Florida	2. Texas	.379[b]	.110	.001	.162	.595
	3. Louisiana	.356[b]	.112	.002	.135	.577
	4. Mississippi	.346[b]	.163	.036	.023	.669
	5. Alabama	.220	.193	.255	-.161	.601
	6. Georgia	.403	.298	.179	-.187	.992
2. Texas	3. Louisiana	-.023	.112	.837	-.245	.199
	4. Mississippi	-.033	.164	.843	-.356	.291
	5. Alabama	-.159	.193	.412	-.540	.223
	6. Georgia	.024	.299	.937	-.566	.614
3. Louisiana	4. Mississippi	-.009	.165	.955	-.336	.317
	5. Alabama	-.136	.194	.486	-.520	.248
	6. Georgia	.047	.299	.876	-.545	.639
4. Mississippi	5. Alabama	-.126	.228	.580	-.577	.324
	6. Georgia	.056	.322	.861	-.580	.693
5. Alabama	6. Georgia	.183	.338	.590	-.485	.851

Note: b $p < 0.05$

The results of Fisher's test for the disaster phases show similar pattern to those found among the community capitals as well as the CDRI measures. As expected, with respect to hazard mitigation the mean for Florida is significantly higher than that of Texas, Louisiana, and Mississippi. With respect to disaster preparedness, again the Florida mean is significantly higher than those of Texas, Louisiana, Mississippi, and Alabama. Finally, with respect to disaster preparedness and response, the mean for counties in Florida is again higher than those of Texas, Louisiana, and Mississippi. The results also show no significant differences among the means of other Gulf coast states. Overall, these findings further suggest that Florida counties on average have scored higher with respect to all phases of disaster.

Tables 7.24 through 7.27 present the top and bottom 10 scoring counties for each disaster phases' sub-indices: mitigation, preparedness, response, and recovery. The complete listing of the 144 counties for each disaster phase is included in Appendix F. The results show similar pattern for all disaster phases with very minimal variations. In each of the rankings, Florida counties dominate the top 10, taking 6 to 8 of the top ten slots in each. In additional, Texas counties continue to dominate the bottom 10, taking 7 to 9 of the bottom slots.

In conclusion, although there are some slightly variations, overall the results again suggest that counties in Florida scored comparatively higher in all phases of disaster; suggesting that, on average, Florida counties are the most disaster resilient in terms of disaster phases. Furthermore, the results also suggest that, on overage, the majority of counties in Texas are at the lowest end of disaster resilience scale.

Table 7.24. Hazard mitigation sub-index scores by top and bottom 10 lists

TOP 10 LIST				**BOTTOM 10 LIST**			
Rank	**County**	**State**	**Score**	**Rank**	**County**	**State**	**Score**
1	Monroe	Florida	1.38	**135**	West Feliciana	Louisiana	-0.67
2	Collier	Florida	1.28	**136**	Newton	Texas	-0.67
3	Leon	Florida	1.25	**137**	Cameron	Texas	-0.72
4	Sarasota	Florida	1.24	**138**	Vernon	Louisiana	-0.77
5	Franklin	Florida	0.89	**139**	Hidalgo	Texas	-0.79
6	Walton	Florida	0.87	**140**	Kenedy	Texas	-0.79
7	Lee	Florida	0.87	**141**	Bee	Texas	-0.83
8	East Baton Rouge	Louisiana	0.86	**142**	Duval	Texas	-1.04
9	Baldwin	Alabama	0.86	**143**	Willacy	Texas	-1.07
10	Hillsborough	Florida	0.79	**144**	Starr	Texas	-1.30

Table 7.25. Disaster preparedness sub-index scores by top and bottom 10 lists

TOP 10 LIST				BOTTOM 10 LIST			
Rank	**County**	**State**	**Score**	**Rank**	**County**	**State**	**Score**
1	Monroe	Florida	2.01	**135**	Jim Wells	Texas	-0.59
2	Collier	Florida	1.39	**136**	Hardee	Florida	-0.60
3	Sarasota	Florida	1.38	**137**	Bee	Texas	-0.66
4	Okaloosa	Florida	1.12	**138**	Jim Hogg	Texas	-0.73
5	Leon	Florida	1.10	**139**	Cameron	Texas	-0.80
6	Hancock	Mississippi	1.09	**140**	Webb	Texas	-0.86
7	Franklin	Florida	0.90	**141**	Hidalgo	Texas	-0.95
8	Baldwin	Alabama	0.90	**142**	Duval	Texas	-1.01
9	East Baton Rouge	Louisiana	0.88	**143**	Willacy	Texas	-1.07
10	St. Tammany	Louisiana	0.84	**144**	Starr	Texas	-1.50

Table 7.26. Disaster response sub-index scores by top and bottom 10 lists

TOP 10 LIST				BOTTOM 10 LIST			
Rank	**County**	**State**	**Score**	**Rank**	**County**	**State**	**Score**
1	Monroe	Florida	1.58	**135**	Evangeline	Louisiana	-0.51
2	Franklin	Florida	1.24	**136**	Hardee	Florida	-0.56
3	Sarasota	Florida	1.07	**137**	Bee	Texas	-0.60
4	Collier	Florida	1.03	**138**	Vernon	Louisiana	-0.62
5	Leon	Florida	1.02	**139**	Cameron	Texas	-0.85
6	Lee	Florida	0.75	**140**	Webb	Texas	-0.88
7	Baldwin	Alabama	0.68	**141**	Duval	Texas	-0.96
8	Fayette	Texas	0.64	**142**	Hidalgo	Texas	-0.97
9	St. Tammany	Louisiana	0.59	**143**	Willacy	Texas	-1.03
10	Pinellas	Florida	0.59	**144**	Starr	Texas	-1.55

Table 7.27. Disaster recovery sub-index scores by top and bottom 10 lists

TOP 10 LIST				BOTTOM 10 LIST			
Rank	**County**	**State**	**Score**	**Rank**	**County**	**State**	**Score**
1	Collier	Florida	1.29	**135**	West Feliciana	Louisiana	-0.77
2	Monroe	Florida	1.27	**136**	Vernon	Louisiana	-0.81
3	Walton	Florida	1.18	**137**	Webb	Texas	-0.88
4	Sarasota	Florida	1.13	**138**	Cameron	Texas	-0.90
5	Leon	Florida	1.08	**139**	Kenedy	Texas	-0.94
6	Lee	Florida	0.96	**140**	Hidalgo	Texas	-0.95
7	Baldwin	Alabama	0.91	**141**	Brooks	Texas	-0.97
8	East Baton Rouge	Louisiana	0.87	**142**	Duval	Texas	-1.11
9	St. Tammany	Louisiana	0.79	**143**	Willacy	Texas	-1.27
10	Okaloosa	Florida	0.78	**144**	Starr	Texas	-1.60

7.6. Summary

This chapter has assessed the level of disaster resilience in the study region by comparing county average scores across the six Gulf coast states, as well as more detailed examination of the top and bottom ten counties for the entire Gulf coast region. The key findings of this assessment are summarized as follows:

- Florida has the most disaster resilient coastal counties in the U.S. Gulf coast region. Florida counties scored the highest scores in all the CDRIs and sub-indices, which is consistent with Florida planning powers.
- On average, Alabama consistently has the second most disaster resilient coastal counties in the U.S. Gulf coast region. Alabama counties scored relatively high scores in both the CDRIs and sub-indices.
- Texas has the least disaster resilient coastal counties in the U.S. Gulf coast region. Most Texas counties scored the lowest scores in almost all the CDRIs and the sub-indices.

- Louisiana has the second least disaster resilient coastal counties in the U.S. Gulf coast region. Most Louisiana counties scored relatively low scores in almost all the CDRI measures and the sub-indices.
- On average Mississippi coastal counties tended to be more disaster resilient than counties in Georgia, Texas, and Louisiana.
- While the CDRI measures seek to capture the overall disaster resilience of a community by assessing community capitals across four phases of disaster–mitigation, preparedness, response, and recovery – it is interesting to note that overall the findings are consistent with the general expectations of the planning literature which more generally focus on disaster and hazard mitigation planning, not actually dimensions of capital. The differences in the levels of disaster resilience demonstrated by states/counties in the U.S. Gulf coast region in part can be explained by their local planning powers. The way states plan and mandate local plans significantly influences the level of disaster resilience and the degree to which the goal of building disaster resilience can be achieved.

CHAPTER VIII

SPATIAL ANALYSIS OF DISASTER RESILIENCE IN THE U.S. GULF COAST REGION

8.1. Introduction

The objective of this chapter is to explore and analyze the spatial dimensions of disaster resilience in the study region. To achieve this objective, a Geographical Information System (GIS) was used to identify the presence of spatial patterns and clusters (hot spots) of disaster resilience. The first step was to simply examine the spatial patterns of the CDRI scores and their components by simply mapping the respective scores for coastal counties throughout the region. This assessment provides a visual representation of the analysis of the state means undertaken in Chapter VII. However, this analysis takes the results a step further in that county scores for the CDRI and the component scores are mapped. Our general expectation is again that Florida's counties will rank high and hence will show a clear pattern of high ranking on the map. However, since all coastal county data scores are mapped, we will be able to detect the patterns of resilience across all coastal counties.

In addition to generally noting the spatial distribution and patterns of CDRI measures an important element is to note clusters of counties that have similar CDRI measures in a further attempt to further assess the validity and potential utility of these indices. It might be expected that a county that scores high on the CDRI index would more likely be surrounded or near other counties that score similarly. In addition, those counties that score low might also be expected to be clustered with other low scoring counties. There are a number of reasons to anticipate these patterns of clustering. First, as discussed previously in Chapter VII, the planning environments can be considerably different across states. While Florida has a rigorous planning environment, mandating comprehensive and mitigation planning, Texas has an extreme laissez-faire approach and is further thwarted by the inability of counties to engage in meaningful planning activities because they lack “Home Rule”. It can therefore be expected that mapping should yield low-low resilience clusters in Texas, but high-high clusters in Florida. The variability of the state planning environment in the remaining states makes it difficult to predict clustering. Yet another reason to anticipate clustering is due to the focus of the CDRI approach on community capitals. At least three of the community capital dimensions – economic, physical, and human – are necessarily related to the overall levels of development and development patterns themselves tend to cluster. As municipal areas develop, that development all too often begins to spread into adjacent counties either directly through the proximate placement of business activities or because of suburb and exurban development. These development patterns suggest that clustering might appear in and around development concentrations as well.

In light of these expectations, one might well expect to see clustering. But the question that can arise from a simple visual interpretation of a map is when a visual cluster is significant. In other words, when is a cluster sufficiently different from other potential clusters to warrant attention? There are several spatial data analysis techniques that can be used to detect spatial patterns or clusters of the georeferenced data such as Moran’s I, Getis-Ord G*, and Geary’s C (Anselin, 1995; Mitchell, 2005). This dissertation employs the most commonly used method – the local Moran’s I, also known as LISA to locate spatial clusters of disaster resilience (hot spot) in the study region.

Moran’s I statistic is used as a local indicator of spatial association to identify spatial clusters. In this study, the local Moran’s I statistic was calculated using GeoDa 0.9.5-i software. To calculate LISA or local Moran’s I statistic requires a weight matrix, which, defines a local neighborhood around each geographical unit (Anselin, Syabri, & Kho, 2006). In this study, a county is used as the geographical unit. The value of each unit is compared with the weighted average of the value of its neighbors (Anselin et al., 2006). A weight matrix based on rook contiguity was created using GeoDa 0.9.5-i software (Mitchell, 2005). Generally, the rook contiguity method assumes that neighbors are those which share a common boundary. The weight matrix is defined by the following equation (Mitchell, 2005).

$$W_{ij} = \frac{C_{ij}}{\sum_{j=1}^{N} C_{ij}} \qquad (8.1)$$

Where:

C_{ij} = 1 when i is linked to j; and Cij = 0 when otherwise

N = Number of units

Given the weight matrix (Equation 8.1), the local Moran's I statistic is defined by the following equation (Mitchell, 2005).

$$I_i = z_i \sum_j W_{ij} z_j \qquad (8.2)$$

Where:

Z_i and Z_j = Standardized scores of attribute value for unit i and j.

j is among the identified neighbors of i according to the weights matrix w_{ij}.

Generally, a LISA cluster map indicates the location with significant local Moran's I statistic. The interpretation of the local Moran's I statistic is that a large positive value indicates that a county has a high disaster resilience score and is surrounded by similar counties with high resilience scores (high-high), also known as hot spot. A low positive value indicates that a county has a low disaster resilience score and is surrounded by similar counties with low resilience scores (low-low), also known as cold spot. A negative value for local Moran's I statistic indicates that a county is surrounded by counties with dissimilar scores. A large negative value indicates that a county has a high resilience score but is surrounded by counties with low resilience scores (high-low); such a county is considered an outlier. A low negative value indicates that a county has a low resilience score but is surrounded by counties with high resilience scores (low-high); such a county is also considered an outlier. The focus, again, in this analysis is in the low-low and high-high clusters.

The following analysis proceeds in two parts for each set of CDRI measures: overall measures, community capital measures, and disaster phase measures. The first step focuses on identifying general spatial patterns of disaster resilience scores, which provides the overall spatial distribution of the level of disaster resilience in the study region. During this process clusters are noted. Then, the apparent clustering is assessed using the LISA clustering analysis which identifies the spatial hot spots of disaster resilience.

8.2. Spatial distribution patterns of CDRI scores

The maps for the CDRIs are displayed in Figures 9.1 through 9.3. The maps display the CDRI scores classified into four classes based on quartiles to provide a fairly simple comparison of high or low community disaster resilience scores among counties. The dark brown color in the maps reflects high disaster resilience whereas the light yellow color reflects low disaster resilience.

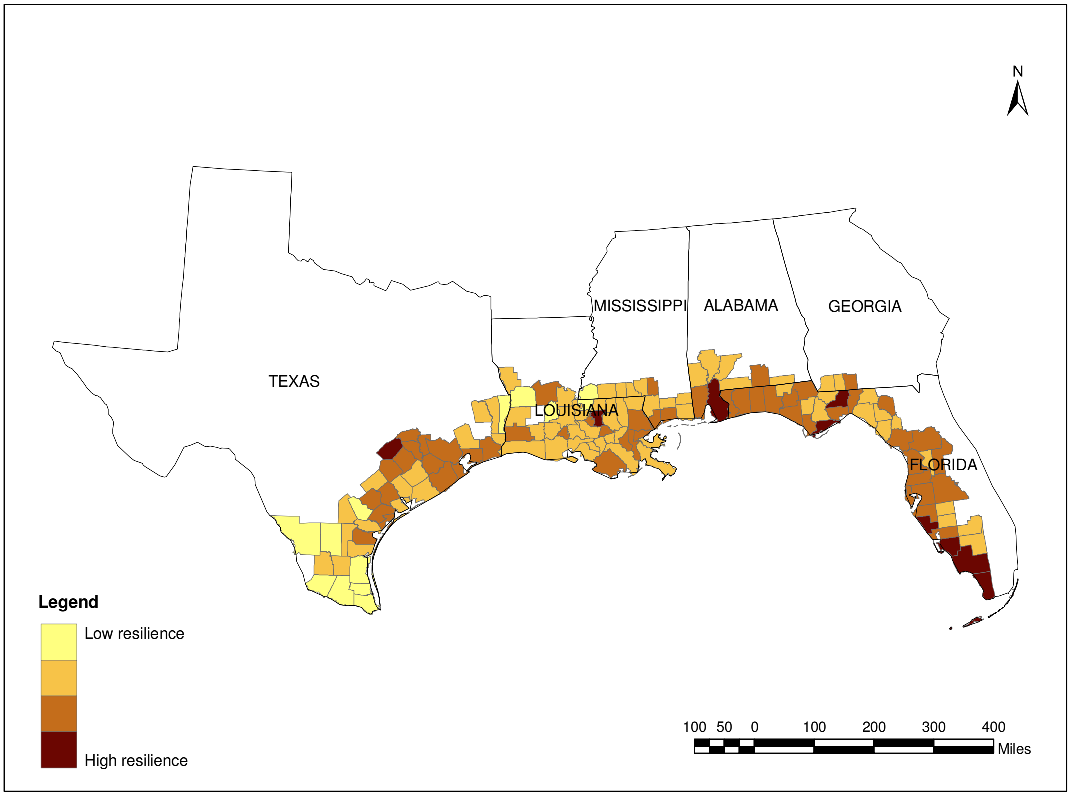


Figure 8.1. Spatial distribution patterns of CDRI-1 scores

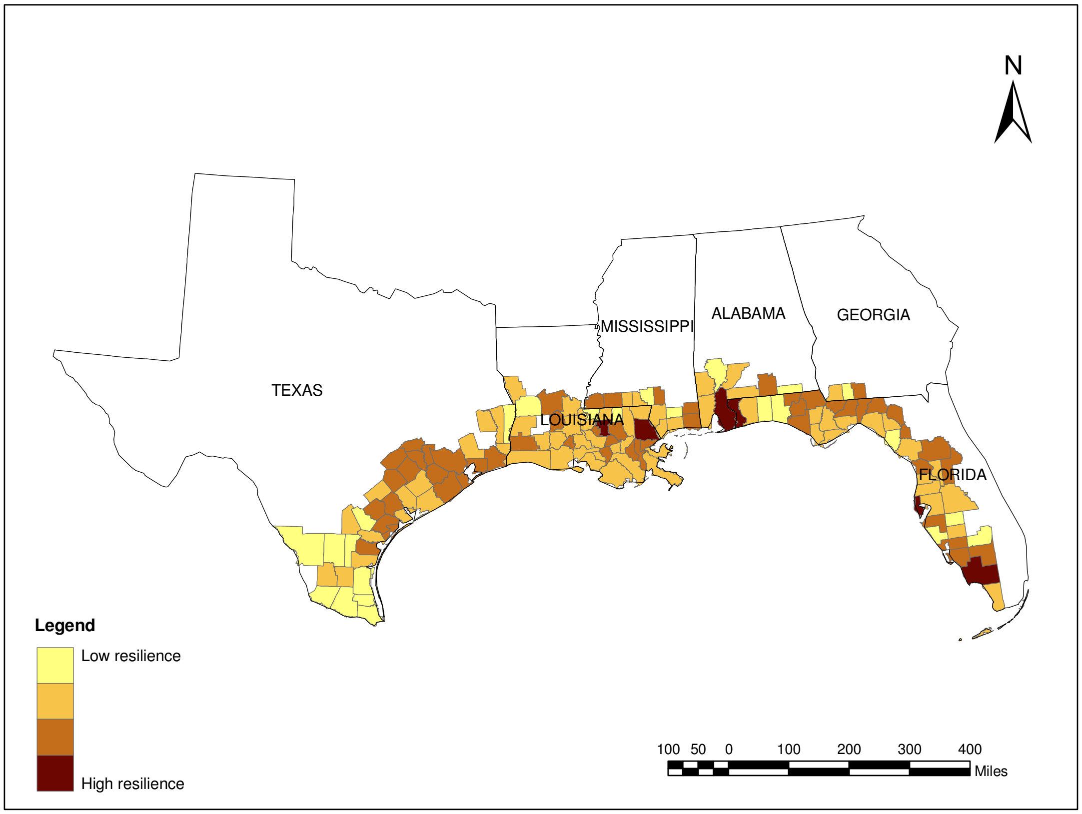


Figure 8.2. Spatial distribution patterns of CDRI-2 scores

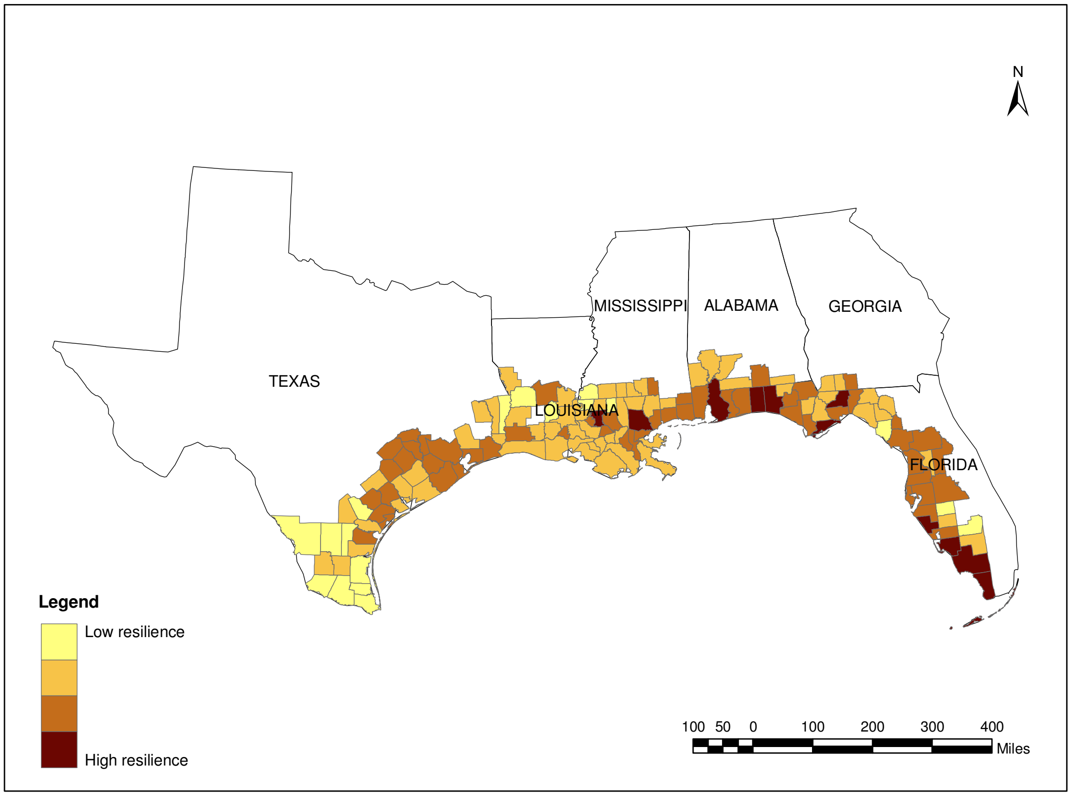


Figure 8.3. Spatial distribution patterns of CDRI-3 scores

Generally, Figures 8.1 to 8.3 revealed some similar interesting spatial patterns with respect to the levels of disaster resilience in the study region. First, as expected, all the three maps indicate that the majority of counties having the highest levels of disaster resilience in the U.S. Gulf coast region, which scored the highest (i.e., score > .67), are located in Florida. Focusing on CDRI-1 scores, these counties include: Monroe, Collier, Sarasota, Franklin, Leon, Lee, Escambia, Okaloosa, and Walton. The non-Florida counties in the highest quartile are: Fayette county (Texas), Baldwin county (Alabama), and East Baton Rouge parish (Louisiana) all exhibited high levels of disaster resilience by obtaining highest scores (i.e., score > .67). There are some minor variations with respect to the other CDRI measures, but this general pattern holds.

Second, the CDRI-1 map indicates that most counties in the southern part of Texas, along the U.S.-Mexico border region exhibited a fairly low level of disaster resilience with scores less than -.48, suggesting a cluster of low scoring counties. These counties include; Starr, Hidalgo, Cameron, Willacy, Kenedy, Brooks, Jim Hogg, Jim Wells, Duval, and Webb. This result is consistent with previous research findings, which found that counties along the U.S.-Mexico border region are comparatively poor with a high level of social vulnerability (Cutter & Finch, 2008). Moreover, the 2000 U.S. Census data indicated that the majority of counties in the U.S.-Mexico border region are relatively poor (U.S. Census Bureau, 2000). According to the 2000 U.S. Census data, counties along the Texas-Mexico border region had the largest population of poor people living below the poverty line. Furthermore, studies suggest that counties along the Texas-Mexico border region are characterized by settlements called *Colonias*[3]. Colonias are mostly semirural, unzoned, and unregulated communities, with low income, high unemployment rate, and poor housing conditions (Cisneros, 2001; Loustaunau & Sanchez-Bane, 1999). Most Colonias lack basic infrastructure services such as access to safe drinking water, sewage systems, garbage disposal services, health services, and electricity (Loustaunau & Sanchez-Bane, 1999). Most Colonia residents are extremely poor with incomes far below the poverty line (Cisneros, 2001). Although Colonias can be found in Texas, New Mexico, Arizona, and California, the literature indicates that Texas has both the largest number of colonia settlements and the largest population living in Colonias (Cisneros, 2001; Community Affair Department, 1995; Loustaunau & Sanchez-Bane, 1999). It is estimated that more than 400,000 Texans live in Colonias (Cisneros, 2001; Community Affair Department, 1995).

[3] *Colonia* is a Spanish word for neighborhood or community (Cisneros, 2001).

Generally, the Colonia population is predominately Hispanic, which constitutes more than 60% of the total Colonia population (Cisneros, 2001; Community Affair Department, 1995).

Third, counties in and around the Greater-Houston region also known as Houston-Sugar Land-Baytown Metropolitan Statistical Area has a high level of disaster resilience, which ranges from moderate to high. These counties include: Harris, Galveston, Chambers, Fort Bend, Brazoria, Waller, and Austin.

Fourth, all the three maps indicate two clusters of counties in Texas, which demonstrated a moderately high level of disaster resilience, with scores ranging from .40 to .67. The first cluster includes the following counties: Fayette, Washington, Colorado, and Lavaca while the second cluster includes Goliad, Victoria, Refugio, Aransas, and Nueces.

Fifth, there also appears to be a slight tendency to see slightly higher scores around areas with more concentrated development such as the Houston-Galveston area, Beaumont, New Orleans, Mobile, Pensacola, and Ft. Myers areas. These areas are not the highest but the scores around these areas appear to be relatively higher.

Maps displayed in Figures 8.4 through 8.6 show the LISA cluster maps for CDRIs. These maps show significant clusters based on the concentration of different types of counties. Specifically the red clusters indicate high-high clusters and darker blue clusters indicate significant low-low clusters. In addition, disjointed clusters low-high (light blue) and high-low (pink) are also displayed. The primary focus in the following discussion concerns of the high-high and low-low clusters and their consistency with the general expectations of the spatial maps above.

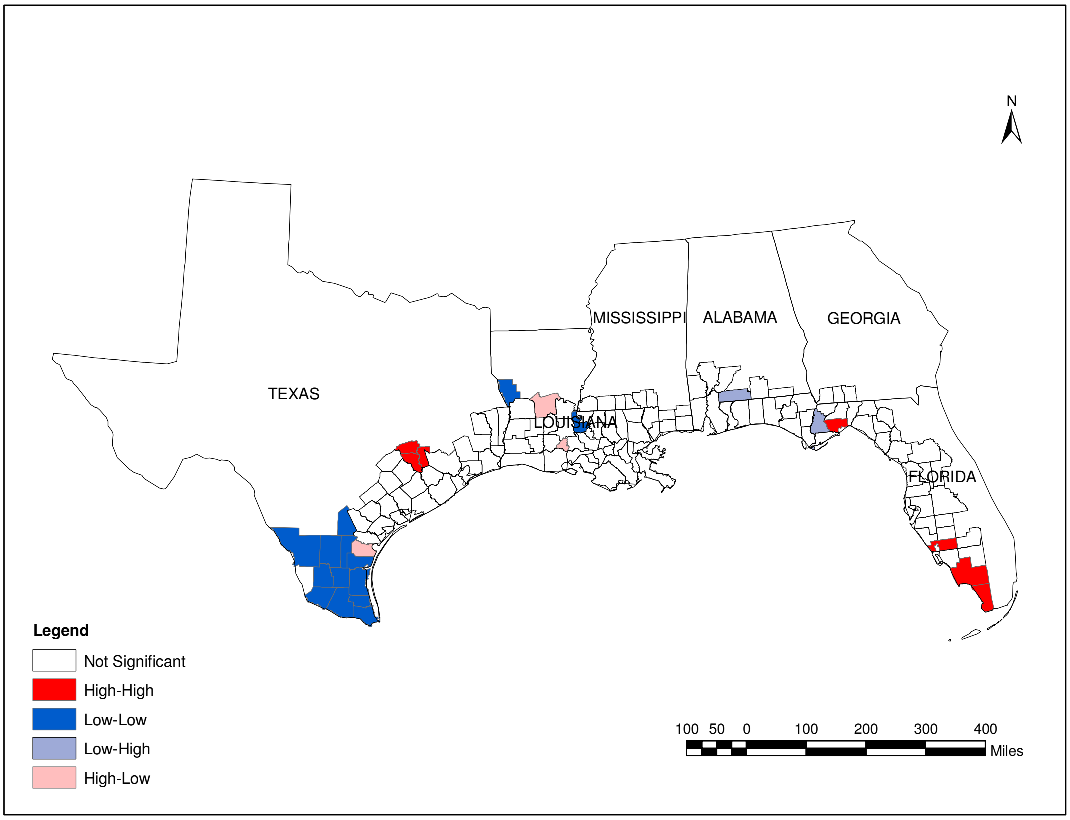


Figure 8.4. LISA cluster map for CDRI-1

Overall, all the three CDRI cluster maps show a similar spatial pattern. Figure 8.4 presents the LISA cluster map for the primary measure, the CDRI-1 (Moran's I = .432, $p < .05$). The map clearly shows three statistically significant clusters: (1) counties in Texas along the U.S.-Mexico border region indicate a large cluster of counties with a low level of disaster resilience (cold spot), (2) there is a statistically significant cluster of counties with a high level of disaster resilience (hot spot) in Texas; these counties include Fayette, Washington, and Waller, and (3) there is a significant cluster of counties with a high level of disaster resilience (hot spot) located in the Florida peninsula, which includes the following counties: Monroe, Collier, and

Charlotte. While few counties seem to be outliers, Figure 8.4 indicates that most counties in the region appeared to be not statistically significant.

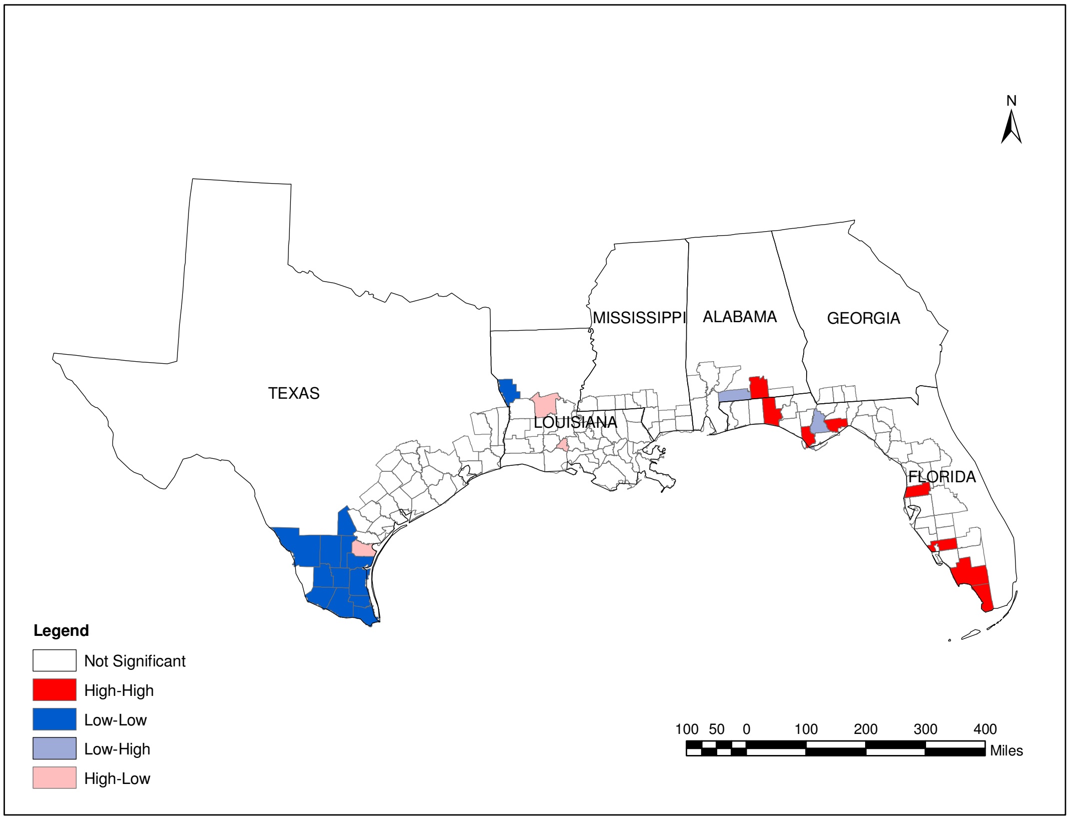


Figure 8.5. LISA cluster map for CDRI-2

Figure 8.5 displays the LISA cluster map for CDRI-2 (Moran's I = .411, $p < .05$). The map shows some similar spatial patterns as exhibited by CDRI-1. It also points to the counties along the U.S.-Mexico border region in Texas as the largest significant cluster of counties that exhibit a low level of resilience (cold spot). Generally, the map in Figure 8.5 does not indicate a well-defined cluster of counties that has a high level of disaster resilience (hot spot). However, there is a small cluster of counties, which has a high level of disaster resilience (hot spot) in the

Florida peninsula area, which includes Collier, Monroe, and Charlotte. Furthermore, few counties, turned out to be outliers; these counties include Liberty (Florida), Escambia (Alabama), Rapides (Louisiana), Lafayette (Louisiana), and Nueces (Texas), but the majority of counties in the region are not statistically significant.

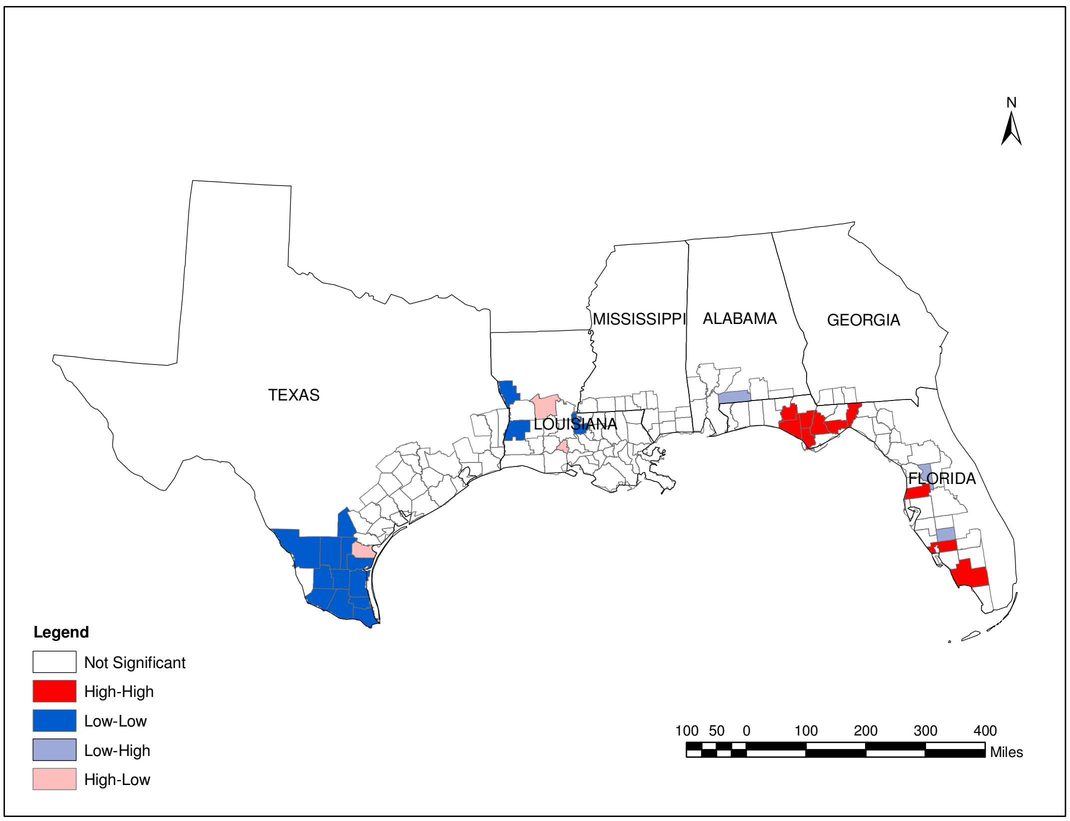


Figure 8.6. LISA cluster map for CDRI-3

The LISA cluster map for the CDRI-3 is presented in Figure 8.6 (Moran's I = .422, $p < .05$). The map clearly shows the presence of two noticeable clusters. First and as expected, the map indicates a presence of a significant cluster of counties in the southern part of Texas, along the U.S.-Mexico border region, which has a low level of disaster resilience (cold spot). Second, the map indicates a presence of a cluster of counties with a high level of disaster resilience (hot spot) in the Florida Panhandle area, which includes the following counties: Bay, Calhoun, Washington, Gulf, Wakulla, Liberty, and Jefferson. Figure 8.6 further indicates the presence of a few counties, which appeared to be outliers in the region and most of the counties are statistically not significant.

8.3. Spatial distribution patterns of capital domain's sub-indices

This section examines the spatial distribution of scores for capital domain's sub-indices: Social, economic, physical, and human. The maps are displayed in Figures 8.7 through 8.10.

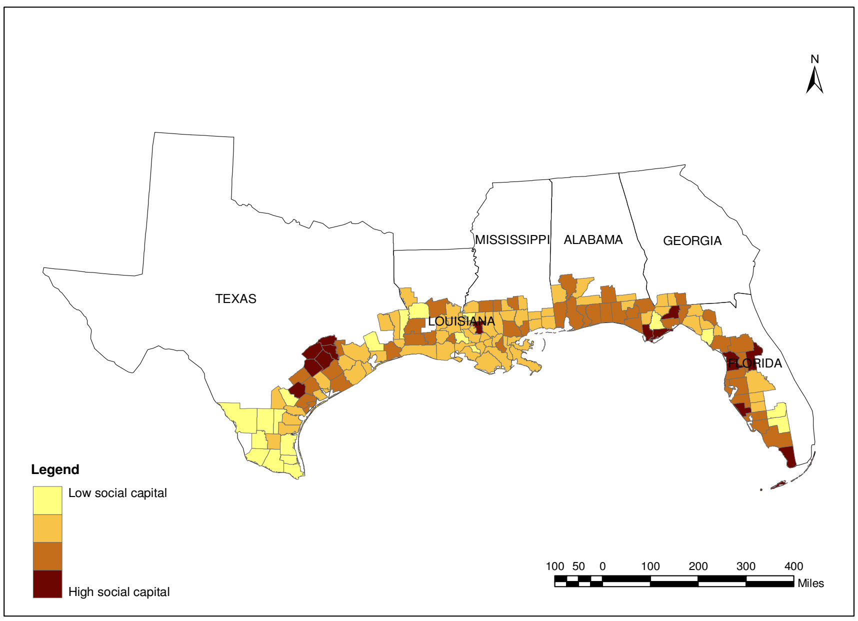


Figure 8.7. Spatial distribution patterns of social capital scores

The spatial distribution pattern for social capital (Figure 8.7) indicates that there is a high concentration of counties, which demonstrated a comparatively high level of social capital in Texas, with the score greater than .56. These counties include: Lavaca, Colorado, Austin, Fayette, Goliad, and Washington. As expected, most Texas counties, along the U.S.-Mexico border region have low levels of social capital with the majority of these counties falling in the lowest quartile. Not surprising the map of social capital indicates a high concentration of counties with moderate to high level of social capital in Florida; with scores ranging between .56 and 1.97. These counties include: Monroe, Sarasota, Hernando, Citrus, Lake, Gulf, Franklin, and Leon.

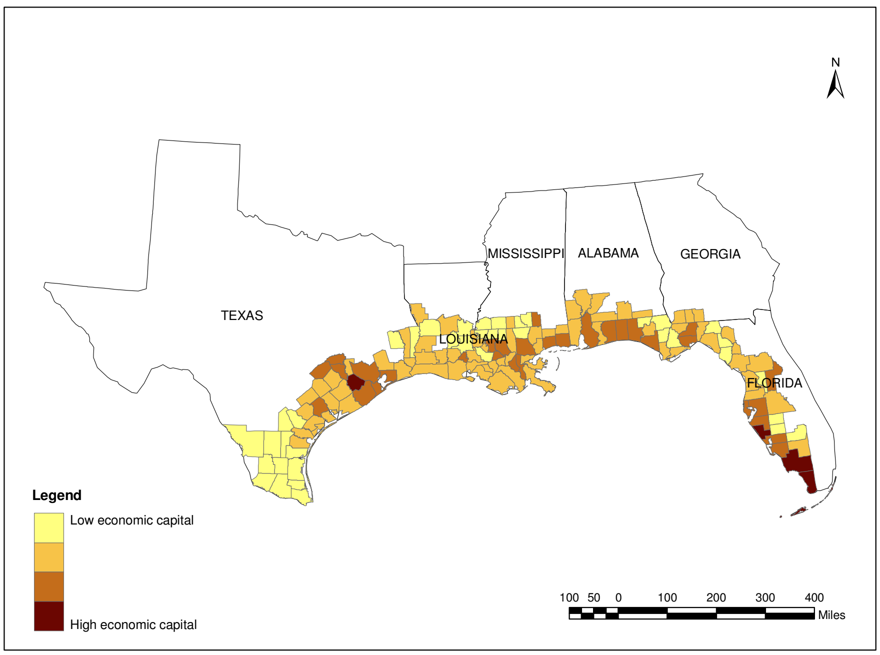


Figure 8.8. Spatial distribution patterns of economic capital scores

As expected and consistent with the previous research findings (Cisneros, 2001; Cutter & Finch, 2008; Loustaunau & Sanchez-Bane, 1999), the economic capital map (Figure 8.8) indicates that there is a high concentration of counties with low levels of economic capital in Texas, along the U.S.-Mexico border region, with scores less than -2.3. Similarly, the map also indicates a large number of counties with a low level of economic capital in Louisiana and

Mississippi, which is also not surprising; because these states are among the poorest in the nation (U.S. Census Bureau, 2000). In addition, the map indicates that Fort Bend county (Texas), Monroe county (Florida), Collier county (Florida), and Sarasota county (Florida) all demonstrated a high level of economic capital in the region with scores greater than 1.69.

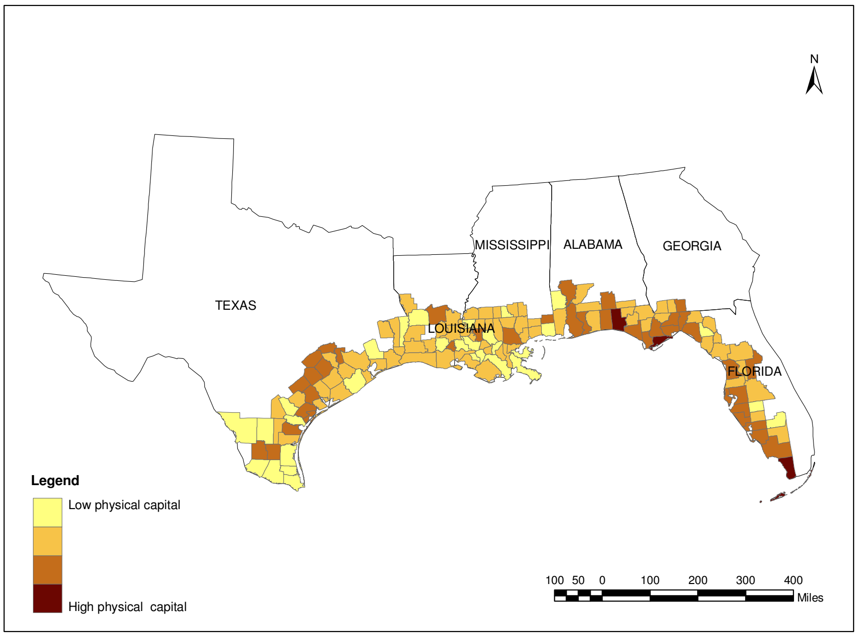


Figure 8.9. Spatial distribution patterns of physical capital scores

The physical capital map (Figure 8.9) indicates that Louisiana, Mississippi, and the southern part of Texas have more counties that obtained the lowest scores (less than -.63). These results are consistent with the positive relationship that exists between physical capital and economic capital, which implies that the higher the economic capital the better the physical capital. These counties also demonstrated low levels of economic capital. As might be expected, counties in Florida (Walton, Franklin, and Monroe) have the highest levels of physical capital with scores ranging from .76 to 1.72. This result is not surprising because these counties also demonstrated a moderately high economic capital.

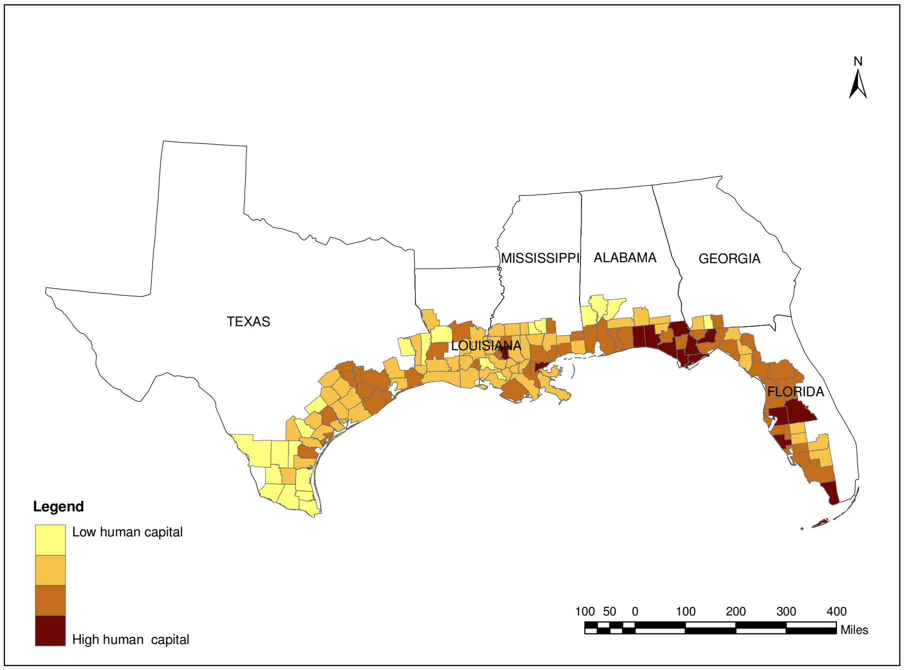


Figure 8.10. Spatial distribution patterns of human capital scores

Figure 8.10 shows that most Florida counties have higher levels of human capital than counties in the other states. These counties include: Monroe, Sarasota, Hillsborough, Polk, Gulf, Franklin, Liberty, Bay, Jackson, Okaloosa, and Walton. The map also indicates that there is a high concentration of counties that exhibit moderately high levels of human capital in the Greater-Houston region of Texas, which include Harris, Galveston, Fort Bend, Austin, Brazoria, and Waller. Other counties in Texas which exhibit a moderately high level of human capital include Victoria, Nueces, Aransas, Washington, and Jefferson. The human capital spatial patterns shown by the majority of counties in the region are not surprising because human capital is highly correlated with economic capital. Therefore, counties with high levels of human capital are more likely to exhibit high levels of economic capital. Most importantly, the Greater-Houston region of Texas is one of the biggest economic centers in the United States with the highest rate of employment (U.S. Census Bureau, 2000). Furthermore, the map also shows that most counties in Louisiana, Mississippi, Alabama, and Georgia exhibit a moderately low level of human capital, which is consistent with the low level of economic capital demonstrated by most of these states.

The maps in Figures 8.11 through 8.14 display the LISA cluster maps for community capital sub-indices. The LISA maps are used to confirm whether the spatial clusters discussed above are statistically significant. Again the primary focus is in the high-high and the low-low clusters of community capital sub-indices.

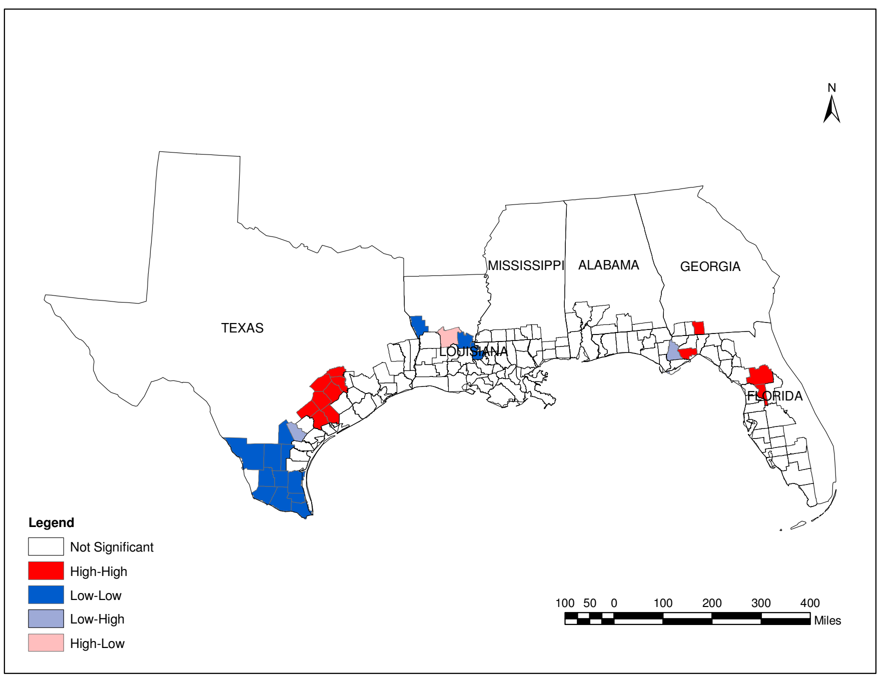


Figure 8.11. LISA Cluster map for social capital sub-index

The LISA cluster map for social capital sub-index (Moran's I = .366, $p < .05$) indicates that there are two noticeable social capital clusters in Texas (see Figure 8.11). As expected, given the spatial distribution map discussed earlier, there is a cluster of counties with a low level of social capital (cold spot) in Texas along the U.S.-Mexico border region. In addition, the map also uncovers the presence of a spatial hot spot of social capital in Texas, which includes the following counties: Jackson, Victory, Dewitt, Colorado, Austin, Fayette, Lavaca, and Washington. Overall, the majority of the counties in the region with respect to social capital cluster analysis are not statistically significant.

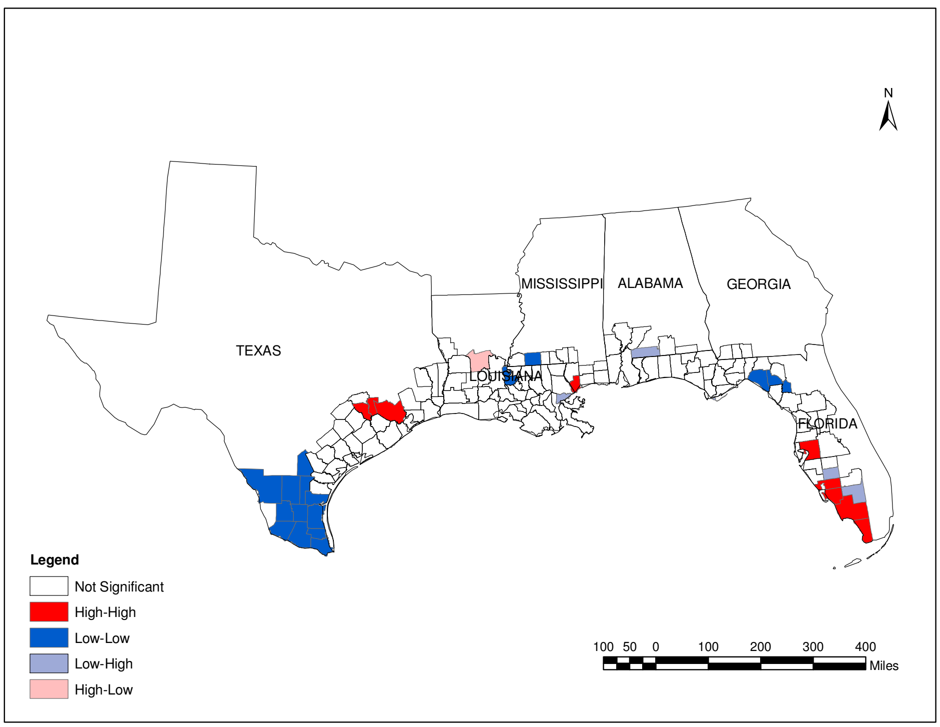


Figure 8.12. LISA Cluster map for economic capital sub-index

The LISA cluster map for economic capital sub-index (Moran's I = .479, $p < .05$) shows three significant clusters (see Figure 8.12). First, and as expected, the Texas-Mexico border region is a large economic capital cold spot in the U.S. Gulf coast region. Second, the map indicates that the Greater-Houston region of Texas is an economic capital hot spot, which has a high level of economic capital, which is consistent with our expectation that in and around this area there is a high concentration of business activities. Third, the map indicates a presence of a significant spatial hot spot of economic capital in the Florida peninsula, which consists of Monroe, Collier, Lee, Charlotte, and Hillsborough counties. The map also revealed the presence of a few outlier counties in Louisiana, Mississippi, Alabama, and Florida.

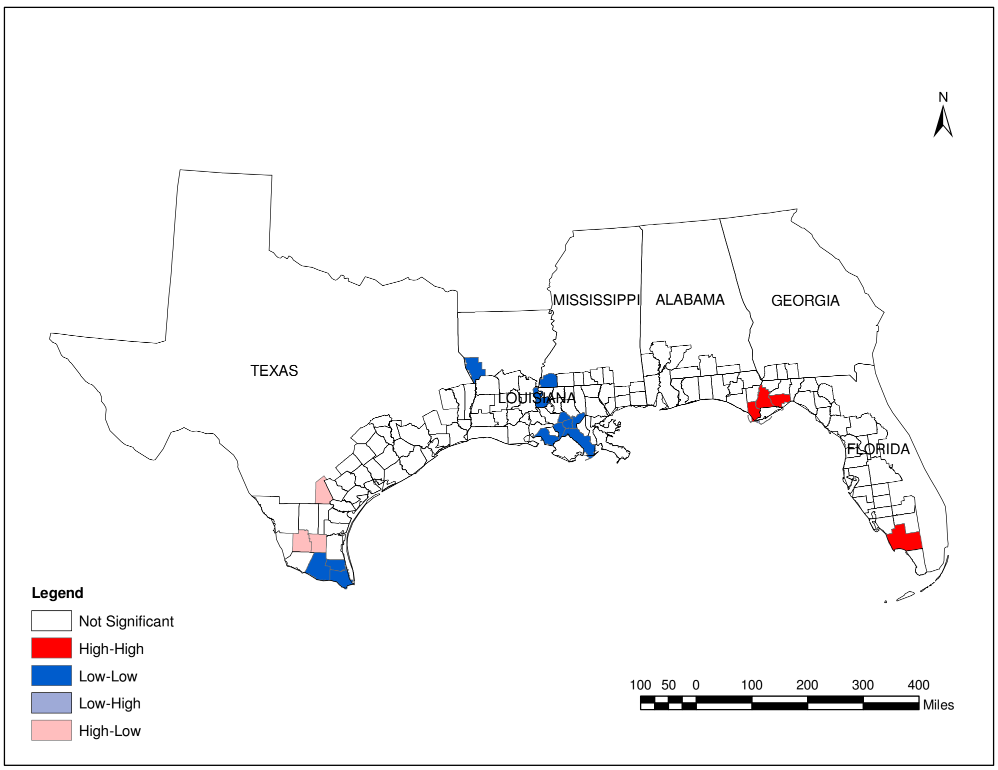


Figure 8.13. LISA Cluster map for physical capital sub-index

The LISA cluster map for the physical capital sub-index (Moran's I = .244, $p < .05$) shows a presence of relatively small clusters (see Figure 8.13). Generally the majority of the counties are not statistically significant. This results is not surprising because such a small value of Moran's I statistic (.244) is not a strong indication of a presence of clusters. The map indicates a small cluster (cold spot) of physical capital in Texas, which consists of Hidalgo, Cameron, and Willacy counties. In addition, the map indicates a presence of cold spot in Louisiana, which includes Lafourche, St. Mary, Assumption, St. James, St. John, and Ascension counties. Finally, there is a significant hot spot of physical capital in the Florida area, which includes Gulf, Liberty, and Wakulla counties.

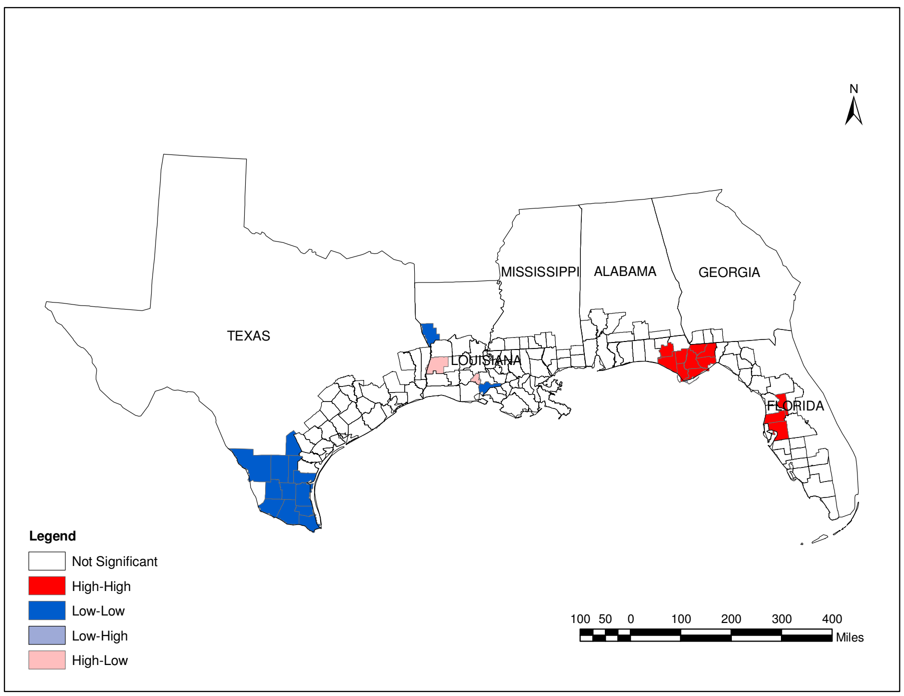


Figure 8.14. LISA cluster map for human capital sub-index

The LISA cluster map for the human capital sub-index (Figure 8.14) indicates that there are three significant clusters in the region (Moran's I = .458, $p < .05$). First and not surprising, the counties along the Texas-Mexico border region formed a human capital cold spot. Second, the map shows that there is a relatively large hot spot of human capital located in Florida, which includes Franklin, Gulf, Bay, Washington, Liberty, Calhoun, Gadsden, and Wakulla counties. Third, the map also indicates a presence of a relatively small hot spot cluster located in the Tampa Bay area, which includes two counties, Hillsborough and Pasco. These two hot spot areas are not surprising because they both consist of the largest cities in Florida: Tallahassee, Panama, and St. Petersburg. These cities/metropolitan areas form the largest economic centers that provide employment opportunities in these areas, which is one of the important indicators of human capital.

8.4. Spatial distribution patterns of disaster phase's sub-indices

This section summarizes the results of the spatial distribution scores for disaster phase's sub-indices (mitigation, preparedness, response, and recovery). The maps are displayed in Figures 8.15 through 8.18.

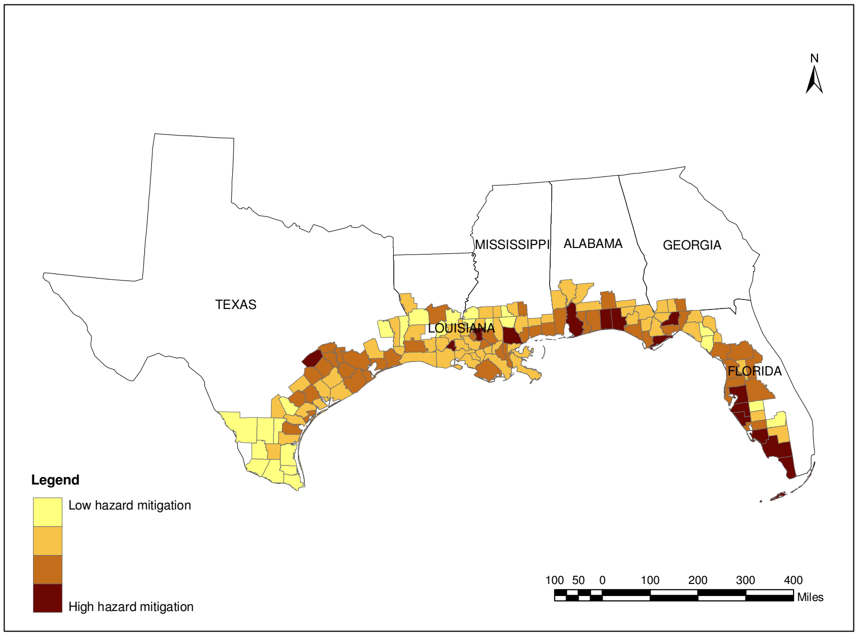


Figure 8.15. Spatial distribution patterns of hazard mitigation sub-index scores

As expected, the map of hazard mitigation sub-index (Figure 8.15) indicates that counties in Texas along the U.S.-Mexico border region exhibited a very low level of hazard mitigation with scores less than -.44. Also a substantial number of counties in Louisiana, Alabama, Mississippi and Georgia demonstrated a low level of hazard mitigation. As discussed previously in Chapter VII, this result is not surprising because Texas, Louisiana, Mississippi, Alabama, and Georgia do not mandate comprehensive plans, or require counties and municipalities to incorporate hazard mitigation plans in comprehensive plans. Florida which mandates comprehensive plans and requires inclusion of hazard mitigation plans demonstrated a high level of disaster resilience with respect to hazard mitigation. Specifically the following counties are in the highest quartile: Okaloosa, Walton, Franklin, Monroe, Collier, Lee, Leon, Sarasota, Manatee, and Hillsborough.

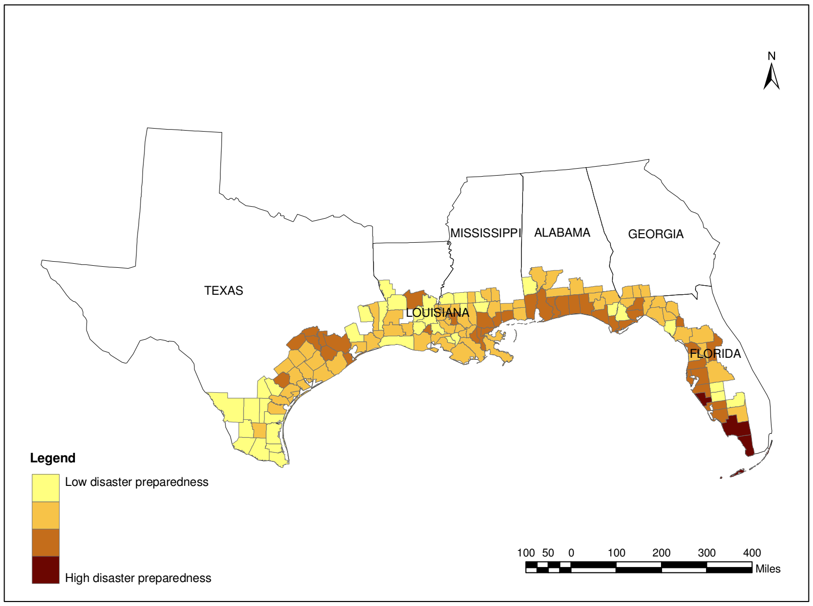


Figure 8.16. Spatial distribution patterns of disaster preparedness sub-index scores

The map of disaster preparedness (Figure 8.16) shows that there are three counties in Florida (Monroe, Collier, and Sarasota) that demonstrated high levels of disaster preparedness in the region, with scores ranging between 1.13 and 2.01. Additionally, counties in the Florida panhandle area and the Florida peninsula have moderately high levels of disaster preparedness with scores ranging between 0.23 and 1.12. Also the Greater-Houston region of Texas has a noticeable cluster of counties, which exhibit a moderately high level of disaster preparedness, with scores ranging from 0.23 to 1.12. These results suggest that counties in the Florida peninsula, the Florida Panhandle, and the Texas Greater–Houston area are comparatively more disaster resilient with respect to disaster preparedness in the U.S. Gulf coast region. Finally, as anticipated, counties along the Texas-Mexico border region demonstrated very low levels of disaster preparedness with the scores below -.22, which suggests that these counties are the least disaster resilient in the U.S. Gulf coast region with respect to disaster preparedness.

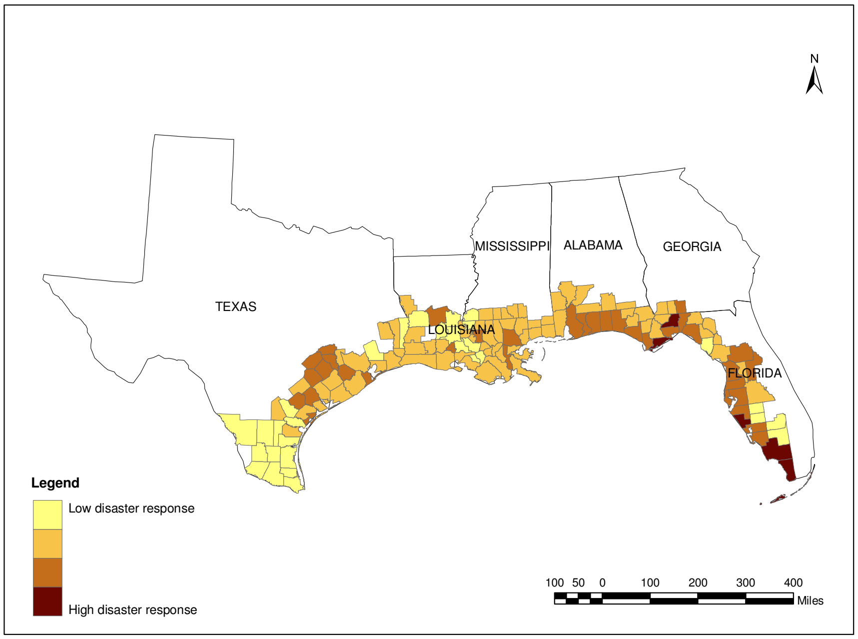


Figure 8.17. Spatial distribution patterns of disaster response sub-index scores

Generally, the disaster response map (Figure 8.17) indicates three noticeable clusters of counties with a low level of disaster response in the region, which scored less than -.31. First and as expected, the counties in Texas along the U.S.-Mexico border region indicate a very low level of disaster response. Second, there is a cluster of parishes in the central part of Louisiana, which demonstrated very low levels of disaster response with score less than -.31. These parishes include Vernon, Avoyelles, West Feliciana, St. Martin, Assumption, Iberville, Evangeline, and St. Landry. Third, the following Florida counties also demonstrated very low levels of disaster response falling in the lowest quartile: Hendry, Glades, DeSoto, Hardee, and Dixie.

Furthermore, the disaster response map shows that Florida is the only state that has counties with the highest level of disaster response in the U.S. Gulf coast region, with scores greater than .76. These counties include, Monroe, Collier, Franklin, Sarasota, and Leon. Similarly, the Florida peninsula, the Florida Panhandle area, and some counties in the Greater-Houston region (Austin, Fort Bend, and Galveston), all demonstrated a moderately high level of disaster response with scores ranging between .19 and .75.

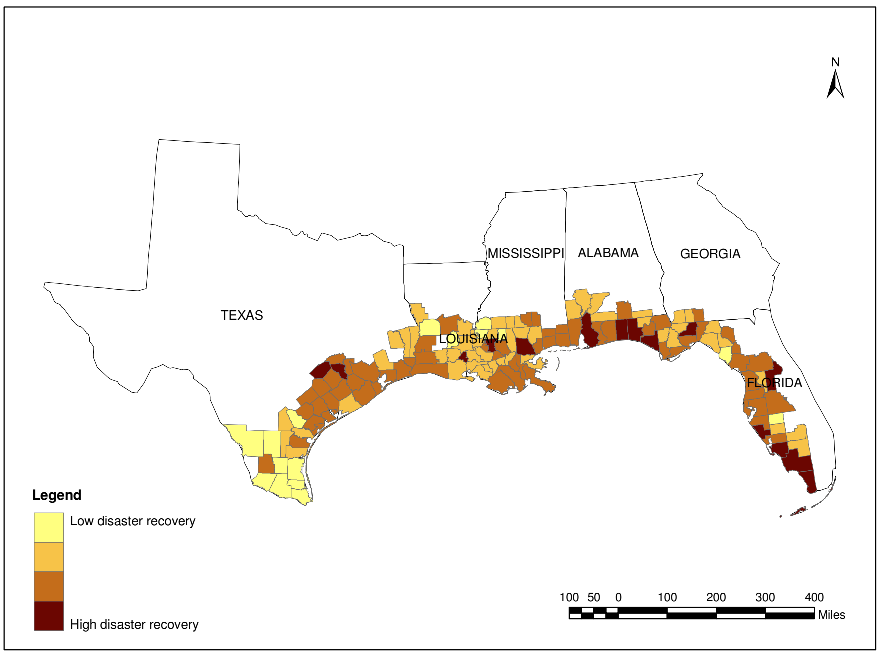


Figure 8.18. Spatial distribution patterns of disaster recovery sub-index scores

The spatial distribution map of disaster recovery (Figure 8.18) generally demonstrated few counties that fall into the lowest quartile. However, as expected, most counties that have low levels of disaster recovery are located in Texas along the U.S.-Mexico border region (Starr, Hidalgo, Cameron, Willacy, Kenedy, Brooks, Duval, and Webb counties) and Louisiana (Vernon, Evangeline, West Feliciana, and St. Helena parishes).

Furthermore, the map shows a significant number of counties that have high levels of disaster recovery in the region with scores greater than .64. In Florida, counties that fall into the highest quartile are located in the Florida Panhandle area and the Florida peninsula. These counties include Okaloosa, Washington, Bay, Leon, Monroe, Collier, Lee, Sarasota, and Lake. In Louisiana, the following parishes have high levels of disaster recovery: Fayette, East Baton Rouge, and St. Tammany. Other counties that show high levels of disaster recovery include Austin (Texas) Fayette (Texas), and Baldwin (Alabama).

The LISA maps for disaster phases' sub-indices (mitigation, preparedness, response, and recovery) are displayed in Figures 8.19 through 8.22. Again the LISA maps are used to confirm whether the spatial clusters with respect to disaster phases discussed above are statically significant. More specifically, the discussion focuses on high-high and low-low clusters.

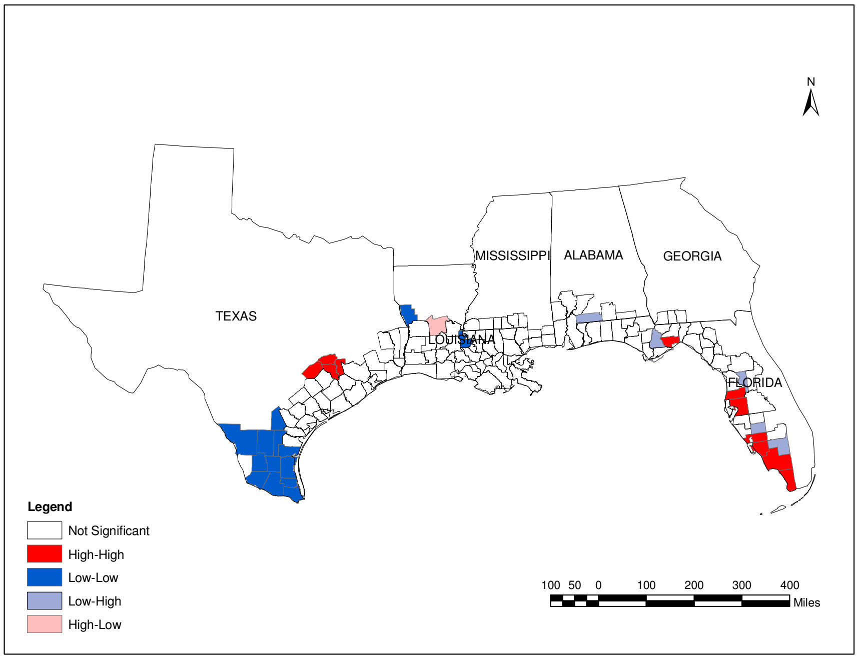


Figure 8.19. LISA cluster map for Hazard mitigation sub-index

The cluster map for hazard mitigation sub-index (Moran's I = .413, $p < .05$) shows three significant clusters in the region (see Figure 8.19). Consistent with the previously discussed results, there is a cluster of counties with a low level of hazard mitigation (cold spot) in Texas along the U.S.-Mexico border region. There is also a significant hot spot of hazard mitigation in Texas that exhibit a high level of hazard mitigation, which includes: Fayette, Washington, Austin, and Waller. As expected, there is a presence of a significant hot spot of hazard mitigation in the Florida peninsula area, which consists of Monroe, Collier, Lee, and Charlotte.

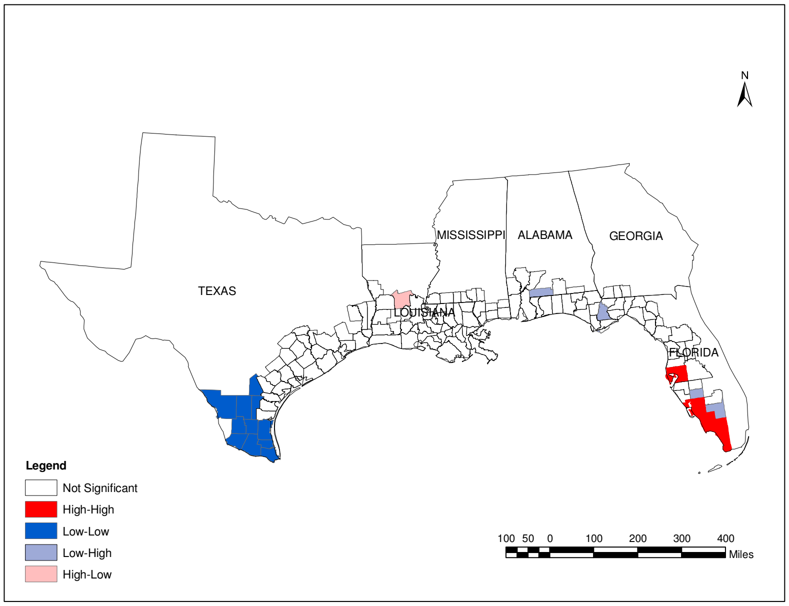


Figure 8.20. LISA cluster map for Disaster preparedness sub-index

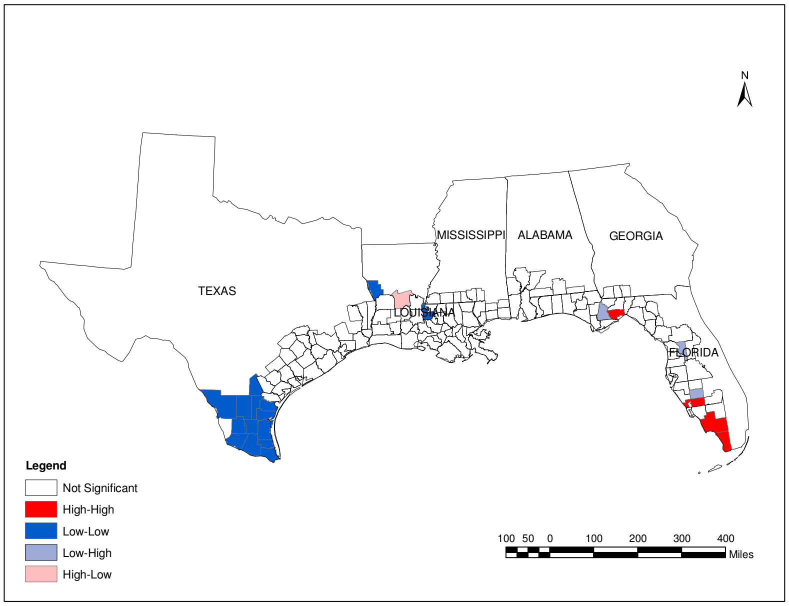


Figure 8.21. LISA cluster map for disaster response sub-index

The LISA cluster maps for disaster preparedness sub-index (Moran's I = .345, $p < .05$) and disaster response sub-index (Moran's I = .411, $p < .05$) shown in Figures 8.21 and 8.20 both revealed similar but not identical spatial clusters. They are similar because each map indicates two significant spatial clusters in the region. They both show a significant cold spot along the Texas-Mexico border region and a presence of hot spot in the Florida peninsula area. Overall, the majority of counties in both maps turned out to be statistically not significant.

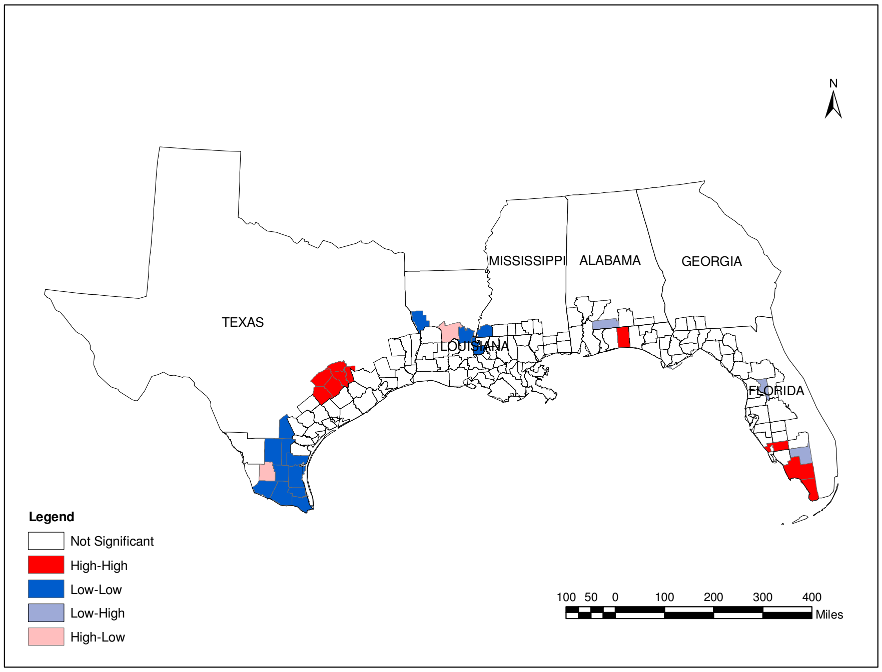


Figure 8.22. Cluster map for disaster recovery sub-index.

The LISA cluster map for disaster recovery (Moran's I = .438, $p < .05$) revealed four significant clusters of disaster recovery in the region (see Figure 8.22). However, only two of them are relatively large in size. The map shows a presence of hot spots in Texas, which includes Waller, Austin, Colorado, Lavaca, Fayette, and Washington counties. There is also a hot spot in the Florida peninsula area, which includes the following counties, Monroe, Collier, and Charlotte. Generally, these areas exhibited a high level of disaster recovery when compared with other areas in the region. Finally, as expected the there is a presence of significant cold spots in the Texas-Mexico border region and in the northern part of Louisiana. These areas demonstrated fairly low levels of disaster recovery when compared with the other areas in the region.

8.5. Summary

The aim of the spatial analyses was to further assess the validity and utility of the CDRI and the sub-indices as measures of disaster resilience by examining the spatial distribution of the scores and testing for significance of spatial clusters. As expected, the results showed a great deal of consistency between the spatial patterns of disaster resilience in the study region and the theoretical expectations discussed in the introduction section of this chapter as well as in Chapter VII. Consistent with the theoretical expectations, most clusters were found in and around areas with high concentration of business activities, and the LISA analyses results further confirmed that the clusters are statistically significant. These significant clusters support the hypothesis that counties with high levels of disaster resilience are more likely to be surrounded by similar counties with a high level of disaster resilience. Conversely, counties with low levels of resilience are more likely to be surrounded by counties with low levels of disaster resilience.

CHAPTER IX

DISCUSSION, CONCLUSIONS, AND RECOMMEDATIONS

9.1. Introduction

The overall goal of this research has been to improve the current state of knowledge on the concept of disaster resilience by developing a theoretically sound and empirically valid measure of disaster resilience. To adequately accomplish this task, several steps were undertaken in a process to develop this measure. This chapter discusses the steps by reviewing the five specific research objectives outlined in Chapter I and summarizes the major findings of the study. Based on the findings, this chapter draws conclusions, formulates some recommendations and subsequently highlights the limitations of the research. The chapter concludes by summarizing the theoretical contributions of the research and the practical implications.

9.2. Discussion

As outlined in Chapter I, this research aimed to achieve five specific research objectives. This section reviews each objective in relation to the steps followed in developing the index for measuring disaster resilience and summarizes the major findings.

9.2.1. Defining disaster resilience

The first objective was to explore the theory, definitions, and applications of the concept of disaster resilience. The rationale for this objective was to provide the theoretical foundation for developing the index to measure and quantify the concept of disaster resilience. With regard to this objective, the findings suggest that although the application of the concept of disaster resilience is growing in the hazard research community, the definition of the concept of disaster resilience is still rather fuzzy. Many definitions of disaster resilience exist in the literature as illustrated by the multiple definitions listed in Table 2.2. These multiple definitions are perhaps not surprising because, even in the field of ecology where the concept of resilience originated before was introduced in hazards research, it appears that there is no consensus on how the concept should be defined (see Table 2.1). As of yet there is no universally agreed-upon definition although there is a good deal of commonality among these definitions in the hazards and disasters literature.

Although some researchers have argued that there is no problem of having multiple definitions so long as they do not contradict each other (Manyena, 2006), it would be advantageous for the hazard and disaster research community to have a clearer common definition, if we want to advance our understanding on this concept and better ensure an integrated research agenda. A common definition of disaster resilience would inevitably help to reach consensus on how to measure and operationalize the concept.

Given the fact that there is currently no universally agreed-upon definition of disaster resilience in the hazard literature, this dissertation developed a working definition, which formed the basis for establishing the key components of disaster resilience and finally the approach to measure the concept. In shaping this working definition the target was a definition that would be applicable for addressing community disaster resilience. The initial working definition adopts common elements from the disaster resilience literature, which includes the ability of a community, defined as a space based network of social systems and their built environment, to organize and structure themselves to (1) absorb, deflect or resist disaster impacts, (2) bounce back in a relatively rapid fashion when impacted, and (3) learn from the experience and modify behavior and structure to adapt to future threats.

9.2.2. Conceptualizing community disaster resilience

Having discussed the general definition of disaster resilience, attention was then turned to an examination of various conceptual frameworks or theoretical models of relevance for community disaster resilience upon which to base the development of the conceptual framework, or Community Disaster Resilience Framework (CDRF) that can be used to identify disaster resilience indicators for coastal communities. Four frameworks were discussed that included (1) the sustainable and resilient community framework (Tobin, 1999), (2) the sustainable livelihood framework (Chambers & Conway, 1992; Glavovic et al., 2002), (3) the community resilience framework (Maguire & Hagan, 2007), and (4) the disaster resilience of place (DROP) model (Cutter et al., 2008). Emerging from the comparison of these frameworks was the principle that it was critical to consider all phases of disaster: mitigation, preparedness, response, and recovery. Consideration of these phases was important because they encompass critical elements with respect to a system's ability to absorb, deflect or resist disaster impacts and when impacted, bounce back in a relatively rapid fashion as well as the ability to learn from the experience and modify its behavior and structure to adapt to future threats. An important result of this analysis was the understanding that a capital approach to disaster resilience provides a logic and basis for considering and selecting community resources that are critical for addressing dimensions of resilience based on disaster phases. Hence the final working definition of community disaster resilience was:

> *"the capacity of communities and their built environment to mitigate, prepare for, respond to, and recover quickly from disasters, and adapt to new circumstances while learning from past disasters"*

This definition is built on the notion of disaster phases, captures the important dimensions of preventing and reducing impacts of natural disasters as well as recovering from and learning/adapting to disaster impacts. Second, it implicitly emphasizes the "capacities" of a community to address issues, which were addressed by considering a community's capital as resources that make it possible for communities to successfully undertake the various disaster phases' activities. Third, this definition puts a community's network of social systems, as well as the people that populate the system and the built and modified environment created by those systems at the center.

The community disaster resilience framework (CDRF) that was developed in this study is based on the contention that disaster resilience is the function of both the disaster phases' activities (hazard mitigation, disaster preparedness, disaster response, and disaster recovery) and the community capitals (social, economic, physical, and human). It is also based on the logic that each community capital has a role to play in the various disaster phases' activities.

Conceptually, a critical step in developing the community disaster resilience index (CDRI) was the identification and selection of relevant indicators to include in the index. Based on the CDRF a framework matrix (see Table 4.2) was created by cross-classifying the four major forms of capitals (social, economic, physical, and human) by the four disaster phases (hazard mitigation, disaster preparedness, disaster response, and disaster recovery). In addition, critical activities associated with each disaster phase were identified along with critical actors/stakeholders (community organizations and actors) and resources that are generally involved in addressing the disaster phases' activities were also identified (see Appendix A). The phase-capital matrix has 16 cells which represent 16 phase/capital sub-indices. These sub-indices represented the initial starting point for index development in that the activities, actors/stakeholders, and resources associated with each phase/capital sub-index were first identified and then capital indicators were selected to capture the community capital associated with each cell. This method appeared to be both theoretically sound and practically useful in that specific capital resources were specifically assessed and selected for each phase-capital cell. It enabled the selection of not only theoretically relevant indicators but also ensured the content and face validity of the selected indicators. Based on this procedure over 120 capital based indicators were winnowed down to 75 indicators[4] that appeared to best fit the activities/indicators/resources necessary for each phase-capital combination and yet across cells captured the multi-dimension nature of community resilience.

During the item selection process, it became clear that social and economic capital resources were the same regardless of disaster phase, and yet there were often very unique physical and human capital resources for each phase. In total 95 indicators of capital resources were employed, while some of these were employed in several phases. The number of indicators for each phase-capital sub-index is indicated in Table 9.1 below. Over 75 unique indicators were employed across each capital domain, which includes 9 social capital indicators, 6 economic capital indicators, 35 physical capital indicators, and 25 human capital indicators.

Table 9.1. Number of indicators

Sub-index	**item**
Social capital	9
Economic capital	6
Physical capital-Mitigation	11
Human capital-Mitigation	19
Physical capital-Preparedness	3
Human capital-Preparedness	7
Physical capital-Response	21
Human capital-Response	6
Physical capital-Recovery	4
Human capital-Recovery	9
Index item	**Item**
Social capital	9
Economic capital	6
Physical capital	35
Human capital	25

[4] Each indicator was first converted into a relative measure, such as percentage or rate(per 1000)

9.2.3. Development of the CDRI

The third specific objective of this study was, of course, to develop a community disaster resilience index (CDRI) that can be used to compare and monitor disaster resilience of coastal communities.

CDRI indicators were aggregated to create three different indices namely CDRI-1, CDRI-2, and CDRI-3. The CDRI-1 is based on the capital domains and was developed by averaging four sub-indices (social, economic, physical, and human). Specifically, each indicator was first converted into a z-score, average scores were then calculated for each capital domain, creating capital indices, and these in turn were averaged to create a CDRI-1score. Indicators within each capital domain were averaged, because there were varying numbers of indicators in each domain which would have resulted in unequal weighting of domains had they simply been added. Finally, this approach insured that each indicator was counted only once in the CDRI-1 measure.

The CDRI-3 is based on the disaster phases and was developed by averaging four sub-indices (hazard mitigation, disaster preparedness, disaster response, and disaster recovery). With this measure, each indicator was potentially counted multiple times. The CDRI-2 is the combination of both the capital domains and disaster phases. It was developed by first calculating an index for each of the ten sub-indices listed in Table 9.1(Social capital, Economic capital, Physical capital-hazard mitigation, Human capital-hazard mitigation, Physical capital-disaster preparedness, Human capital-disaster preparedness, Physical capital-disaster response, Human capital-disaster response, Physical capital-disaster recovery, and Human capital-disaster recovery) and then computing an average across these ten sub-indices.

The findings of this research suggest that these three approaches generated similar but not identical results. Each approach provides unique information which may not be obtained from other approaches. Approach one (CDRI-1) assesses the level of disaster resilience based on the community capitals whereas approach three (CDRI-3), assesses disaster resilience based on disaster phases. Approach two (CDRI-2) is basically a combination of approach one and three. It is unique in that it provides a high level of detailed information, which can be very useful to emergency managers in assessing disaster resilience. For example, approach two can help to determine if a community has sufficient physical capital resources to successfully undertake disaster response activities. Nevertheless, the CDRI-1 measure is preferred because each capital indicator is only included once in the overall measure. However, in generating the overall CDRI scores, the sub-indices for capital domains and disaster phases could prove useful for a variety of research and practical applications.

9.2.4. Reliability and validity of the CDRI

The fourth specific objective of this study was to assess the reliability and validity of the proposed community disaster resilience index (CDRI). The rationale for this objective was to examine whether the developed CDRI is a theoretically and empirically valid and reliable measure. Generally, a disaster resilience index is a complex multidimensional scale that encompasses many variables. Therefore, identifying appropriate variables for statistical validation becomes more problematic.

(i) Reliability assessment

Cronbach's alpha statistical method was used to assess the reliability of the CDRI as a measure of disaster resilience. The reliability analysis helped to ensure a high level of internal consistency or precision of a measure. Alpha was used at a variety of points, but was most critical when assessing the potential consistency of each of the 10 sub-indices associated with the initial phase-capital sub-index development. Specifically, it was at this point that specific indicators were selected to capture the unique set of phase-capital resources, and the set of potential indicators was relatively small. The final set of indicators ranged from 3 to 21 for each of the 10 sub-indices (see Table 5.1). The findings of this research on reliability assessment suggest that the sub-indices and the CDRIs exhibited a relatively high level of consistency as indicated by the Cronbach's alpha coefficients ranging from .466 to .976. Not surprising, sub-indices containing large numbers of indicators tended to yield higher alphas (see Table 5.1).

(ii) Validity assessment

This research examined four types of validity; content, construct, predictive, and incremental validity. The content validity played an important role in the indicator selection process, which was performed using a cross-classification method. Generally, indicator selection is a subjective process (Esty et al., 2006; Simpson, 2006), which involves subjective judgments. The cross-classification method provided a framework in which only relevant indicators were selected and therefore significantly reduced the potential for subjectivity. In addition, completing the indicator selection across the phase and capital, insured that the various dimensions of disaster resilience, consistent with the working definition, were included and hence high sampling validity.

The construct validity is the degree to which a measure is empirically related to theoretically relevant variables in a real world setting. This study attempted to establish the construct validity of the disaster resilience index by examining how well it correlates with the relevant variables in a real world setting. Based on the literature, four external criteria were utilized to validate the index; flood property damage (insured, uninsured, and total), flood-related deaths, social vulnerability, and physical risk. The findings of this research suggest that the correlations between the disaster resilience index and the validity measures are consistent with theoretical expectations. In addition, predictive validity was assessed by regressing flood related deaths and flood damage measures on the CDRI score, after controlling for risk and social vulnerability. First, the findings of this research suggest that disaster resilience is related to and an important predictor of flood property damage and flood-related deaths in the U.S. Gulf coast region. Second, there is a positive correlation between disaster resilience and physical risk.

Furthermore, an important consideration associated with any new measure is its incremental validity over alternative measures available to assess the same construct. In other words, does the measure add to the prediction of criterion above what can be predicted by other alternative measures? In its most basic definition, incremental validity refers to the capacity of one measure to improve prediction over one or more alternative measures. In this study incremental validity of CDRI was measured by assessing its ability to predict flood property losses and flood related deaths in relation to Social Vulnerability Index and median income as alternative measures. It was hypothesized that the CDRI measure would provide incremental validity to Social Vulnerability Index and median income in predicting flood property losses and flood related deaths. The evidence accumulated in this study suggests that CDRI measure has incremental validity and can make contributions to predicting flood losses and flood related deaths in ways that Social Vulnerability Index or median income cannot.

These are important findings this research has contributed to the hazards literature toward improving our current understanding of the concept of disaster resilience. However, although these measures seem to work both theoretically and empirically further reliability and validity tests are needed to improve these measures.

9.2.5. Disaster resilience spatial hot spots

The fifth specific objective of this study was to identify and analyze spatial patterns and clusters (hot spots) of disaster resilience within coastal counties in the U.S. Gulf coast region. The rationale for this objective was to further evaluate the validity and utility of the CDRI by examining the spatial distribution patterns of the index scores among counties in the U.S. Gulf coast region. The spatial distribution analysis helped to assess if there was a presence of patterns or clusters of counties that were consistent with the theoretical expectations in the study region. For example, it was expected that counties with a high concentration of poor population are more likely to form a cluster of low disaster resilience (cold spot) and vice versa. It was also expected that counties/states which adopted comprehensive plans, building codes, FEMA approved hazard mitigation plans, or participate in FEMA Community Rating Systems are more likely to be disaster resilient or form a cluster of disaster resilient counties (hot spot). Furthermore, it was also expected that counties in and around areas where there is high concentration of business activities are more likely to form clusters of high disaster resilience.

To achieve this objective a three-step procedure was employed to analyze the data. First, the scores were analyzed and ranked so as to compare and identify which county/state performed better in terms of the overall disaster resilience index and the sub-indices. Second, the scores were further analyzed using analysis of variance (one-way ANOVA). The ANOVA analysis method was used to compare the scores among states and determine if their means were statistically significant different. The comparison provided more insights on which state performed comparatively better. Third, the Local Indicators of Spatial Association (LISA) analysis method was used to detect the presence and the location of disaster resilience clusters (hot spots) in the study region. The key findings of these analyses are summarizes below.

With regard to the mean score, the findings of this research suggest that Florida had the highest scores and was ranked the first in all the three approaches (see Table 7.2). This finding corresponds with the theoretical expectation that Florida is the strongest state in terms of local planning in the U.S. Gulf coast region (Brody et al., 2003; Jacob & Showalter, 2007). In contrast, Texas had the lowest scores and was ranked the last (6^{th} place) in almost every approach. This finding is also consistent with the theoretical expectation that counties along the Texas-Mexico border region are characterized by colonia settlements, which are very poor communities (Cisneros, 2001; Loustaunau & Sanchez-Bane, 1999) with high social vulnerability (Cutter & Finch, 2008). The ANOVA analysis results indicated that the means among states were statistically significant different ($p < .01$, $P < .05$), and overall, the results on Fisher's post hoc tests indicated that the mean for Florida was significantly higher than the means for all other states in the U.S. Gulf coast region.

With regard to the LISA analysis, the key findings of this research suggest that (1) there is a cluster of low levels of disaster resilience in the southern part of Texas along the U.S.-Mexico border region, which includes the following counties: Starr, Hidalgo, Cameron, Willacy, Kenedy, Brooks, Jim Hogg, Jim Wells, Duval, Live Oak, Kleberg, and Webb. This finding suggests that these are the least disaster resilient counties in the U.S. coast region; (2) there is a presence of disaster resilience hot spots in the Florida peninsula (Monroe, Collier, and Charlotte) and the Florida Panhandle area (Bay, Calhoun, Washington, Gulf, Wakulla, Liberty, and Jefferson). This finding implies that these are the most disaster resilient counties in the U.S. Gulf coast region.

9.3. Conclusions

The conclusions of the main findings of this research are summarized as follows:

First, based on the evidence accumulated from the data analyzed in this study, it can be concluded that the overall goal of this research, which was to develop and validate a theoretically-driven index for measuring and quantifying community disaster resilience, was achieved. The findings of this study provided convincing empirical evidence that the community disaster resilience index (CDRI) has potential to enhance our understanding of the concept of disaster resilience.

Second, it can also be concluded that the methodology developed in this study for measuring disaster resilience, which emphasizes on integration of disaster phases' activities and community capitals appeared to be theoretically sound and practically useful.

Third, disaster research needs a reliable, valid, and well tested measure to use in assessing and quantifying community disaster resilience. The disaster resilience index developed in this study is based on those premises. This measure was tested using a combination of statistical and GIS techniques to evaluate its reliability and validity. Based on the findings of this study it is reasonable to conclude that this measure is theoretically and empirically reliable and valid. However, further validation is needed before the measure is put on operational.

Overall, the findings of this research are potentially promising and provided valuable information particularly to planners and emergency managers. However, while the results of this research seemed to be plausible, they should be considered as preliminary until additional research has been conducted to further validate the measure.

9.4. Limitations and recommendations for future research

There is no research that is without limitations and this study is no exception. Several limitations were encountered in conducting this research. The following bullets highlight some of these limitations and also provide some recommendations for future research direction.

- This research attempted to measure a very complex multidimensional concept of disaster resilience at a relatively large spatial scale (regional level), using a county as a unit of analysis. In the United States, communities are a central focus of the hazard mitigation, disaster preparedness, disaster response, and disaster recovery. Thus, assessing disaster resilience at a county level may not be useful or may not meet some other needs especially for planners. A smaller scale unit would probably provide a more contextual picture on how communities in the U.S. Gulf coast are performing with regard to disaster resilience. Thus, future research should focus on replicating the proposed methodology at a smaller scale such as a city or block group.
- Like other social science studies, this research was limited by availability of data. While this research was primarily based on secondary data (mainly from the U.S. Census), more refined field survey data on emergency response plans, disaster recovery plans, floodplain managers, community emergency response team, volunteers and data on social capital, e.g., social networks and trust, may improve the results of future research. Thus, future research should focus on integrating both secondary and field survey data.
- The CDRI is a multidimensional scale, which includes many factors. Validation of such a measure is problematic. Therefore, future research should focus on developing more external criteria. For example, one important validity measure could be the time taken by a community to recover after a disaster. The expectation is that a disaster resilient community will take a shorter period to recover while a less disaster resilient community

will take a longer period to recovery. However, data for this type of analysis can not be obtained from secondary sources; it requires longitudinal or panel data (data observed over time as well as space).

- There is a limited understanding in the literature of indicators that can be used to measure community capitals (social, economic, physical, and human). For example, there is an overlap between economic capital indicators and human capital indicators. Some researchers for example argue that education is an indicator of human capital, while others consider education as an indicator of economic capital, which is perhaps not very surprising because education is positively related with income. Equally, some researchers treat unemployment as an indicator of economic capital, while others consider it as a human capital indicator. Conceptually, it becomes more problematic to identify which indicator fits better to which capital type.
- The CDRI measure developed in this dissertation is based on only four community capitals (social, economic, physical, and human). To make the dissertation manageable, natural capital was not included in this study. However, a great body of literature has demonstrated that natural capital such as wetlands provide important buffers against hurricane damage. Therefore, future research should focus on how all five capitals (social, economic, physical, human, and natural) might be incorporated into a measure. On the other hand, the amount of natural capital and changes in natural capital might also be viewed as important indicators related to the context in which resilience should be assessed.
- The CDRI measure developed in this research is a snapshot in time with limited ability to predict the future status of community disaster resilience. Thus, future research should focus on capturing both the spatial and temporal dimensions of disaster resilience. This

will inevitably help to determine whether a certain community is moving in the direction of becoming more disaster resilient in the face of hazards or not.

9.5. Theoretical contributions and practical implications

Despite the limitations outlined in the preceding section, this research has significant theoretical contributions to the disaster resilience literature in the hazards and disaster research. First, it has generally contributed to the current state of the knowledge on the concept of disaster resilience. Second, in the recent years much research has been focusing on the concept of disaster resilience, but little or no research has attempted to empirically measure the concept of disaster resilience. This research has contributed to this knowledge gap by developing a theoretically-driven index that can be used to measure disaster resilience. Third, most research in the hazards and disasters literature, which embarked on developing composite indices fail to empirically validate the measures especially in terms of incremental validity. This research has attempted theoretically and empirically to validate the CDRI measure and plausible results were obtained. This is an important contribution to this knowledge gap in terms of disaster resilience index validation. Fourth, the disaster resilience hot spot maps generated in this study provide a new way of thinking on how disaster resilience concept can be used to enhance disaster planning and management.

Although this research has demonstrated significant theoretical contributions to the resilience literature, it should be considered only as an entry point towards bridging the gap between theory and practice.

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APPENDIX A

DISASTER PHASE'S ACTIVITIES, STAKEHOLDERS/ACTORS, GOVERNMENT AGENCIES, AND COMMUNITY RESOURCES

Table A-1: Hazard mitigation activities, stakeholders/actors, Government agencies, and community resources

Hazard Mitigation Activities	Actors/Stakeholders	Community Resources
(1) Building dams, levees, dikes, floodwalls/seawalls, and stream channelization	‣ Department of Transportation ‣ US Army Corps of Engineers ‣ Construction companies ‣ Community	‣ Transportation employees ‣ Engineers ‣ Construction employees ‣ Local population
(2) Landuse planning to prevent development in hazardous areas	‣ Planners ‣ Developers ‣ Construction companies ‣ Local population	‣ Planners ‣ Construction employees ‣ Economic incentive e.g. Tax benefit and insurance discount
(3) Protecting structures through strong building codes and building standards, e.g. installing window shutters for buildings located in Hurricane prone areas	‣ Planners ‣ Developers ‣ Department of insurance ‣ Home owners ‣ Business owners	‣ Legal officers ‣ Building inspection officers ‣ Planners ‣ Home owners ‣ Business owners
(4) Acquiring and relocating damaged structures; Purchasing undeveloped floodplains and making them open spaces; Acquisition of development rights; and Zoning regulations	‣ Federal, State, and Local governments ‣ Planners ‣ Developers ‣ Home owners ‣ Business owners	‣ Community financial resources ‣ Local population
(5) Preserving the natural environment to serve as a buffer against hazard impacts	‣ Environmental NGOs ‣ US Army Corps of Engineers ‣ Forest department ‣ Parks and Wildlife department ‣ Developers ‣ Local population	‣ Environmental experts ‣ Non-Governmental Organizations(NGOs)
(6) Educating the public about hazards and ways to reduce risk	‣ Emergency managers ‣ Local population ‣ Home owners ‣ Business owners ‣ Developers	‣ Trained personnel ‣ Emergency Managers ‣ Planners ‣ NGOs

Table A-2: Disaster preparedness activities, stakeholders/actors, Government agencies, and community resources

Disaster preparedness Activities	Actors/Stakeholders	Community resources
(1) Development of response procedures	‣ Emergency managers	‣ Emergency managers
(2) Design and installation of warning systems, detection and monitoring systems	‣ Emergency managers ‣ National weather service ‣ National Hurricane Center ‣ NOAA	‣ Emergency managers
(3) Developing plans for evacuation	‣ Emergency managers	‣ Emergency managers

	‣ Department of Transportation ‣ Local population	‣ Transportation employees
(4) Exercise to test emergency operations(Exercise & Drills)	‣ Emergency managers ‣ First responders ‣ Public officials ‣ Volunteers ‣ NGOs ‣ Local population	‣ Emergency managers ‣ First responders ‣ Public officials ‣ Volunteers ‣ NGOs
(5) Training of emergency personnel	‣ Emergency managers ‣ First responders	‣ Emergency managers ‣ First responders
(6) Stockpiling of resources e.g. medical supplies	‣ Emergency Medical Services(EMS) personnel ‣ Emergency managers ‣ First responders	‣ EMS personnel ‣ Hospitals ‣ First responders

Table-A-3: Disaster response activities, stakeholders/actors, Government agencies, and community resources

Emergency Response Activities	**Actors/Stakeholders**	**Community resources**
(1) Securing the impacted area	‣ Police department ‣ Fire department	‣ Police officers ‣ Fire fighters ‣ EMS personnel ‣ Fire Fighters vehicles
(2) Warning	‣ Police department ‣ Media ‣ Peers	‣ Police officers ‣ Fire fighters ‣ Television ‣ Radio ‣ Newspapers ‣ Internet ‣ Telephone ‣ Family and friends
(3) Evacuating the threatened area	‣ Local population	‣ Personal vehicles ‣ Social networks(Family and Friends)
(4) Conducting search and rescue for the injured	‣ Police department ‣ Fire department ‣ NGOs ‣ Community Emergency Response Team (CERT) ‣ Volunteers	‣ Police officers ‣ Fire fighters personnel ‣ CERT ‣ Volunteers
(5) Providing emergency medical care	‣ EMS ‣ NGOs, e.g. Red Cross	‣ EMS personnel ‣ Hospitals ‣ Ambulances ‣ Firefighters vehicles
(6) Sheltering evacuees and other victims	‣ NGOs, e.g. Red Cross ‣ Faith Based Organizations(FBOs)	‣ NGOs ‣ FBOs

	e.g. Salvation Army ‣ Nonprofit organizations(NPOs)	‣ NPOs ‣ Hotels/Motels ‣ Churches & Schools ‣ Family and Friends

Table A-4: Disaster recovery activities, stakeholders/actors, Government agencies, and community resources

(1) Relief and rehabilitation activities	**Actors/Stakeholders**	**Community resources**
▪ Restoration of access to impacted area	‣ Police department ‣ Fire department ‣ Department of public works	‣ Police officers ‣ Fire fighters personnel ‣ Volunteers
▪ Re-establishment of economic activities (commercial and industrial)	‣ Business organizations	‣ Businesses organizations
▪ Provision of housing, clothing, and food for the victims	‣ NGOs, e.g. Red Cross ‣ FBOs, e.g. Salvation Army ‣ NPOs ‣ Family and Friends	‣ NGOs ‣ FBOs ‣ NPOs ‣ Family and Friends
▪ Restoration of critical facilities within the community	‣ Utility company ‣ Department of public works	‣ Utility employees ‣ Volunteers
▪ Restoration of essential government or community services	‣ Federal, State, and Local governments ‣ Local population	‣ Local population
(2) Reconstruction activities		
▪ Rebuilding of major structure e.g. public buildings, roads, bridges, and dams	‣ Federal, State, and Local governments ‣ Department of public works	‣ Local population
▪ Revitalizing the economic system	‣ Local government ‣ Economic groups or Business	‣ Businesses organizations
▪ Reconstruction of residential housing	‣ Federal, State, and Local governments ‣ Insurance companies ‣ Construction companies ‣ Family and Friends	‣ Household income ‣ Property insurance ‣ Family and Friends

APPENDIX B

SELECTED INDICATORS FOR MEASURING RESILIENCE

Table B-1(a): Social capital indicators for measuring hazard mitigation resilience sub-index

Mitigation Activity	Generic Indicators	
	Component	**Indicator**
‣ Building dams, levees, dikes, and floodwalls ‣ Landuse planning to prevent development in hazardous areas ‣ Building codes and building standards, ‣ Acquiring and relocating damaged structures ‣ Purchasing undeveloped floodplains and making them open spaces ‣ Acquisition of development rights ‣ Zoning regulations ‣ Preserving the natural environment to serve as a buffer against hazard impacts ‣ Educating the public about hazards and ways to reduce risk	(1) Volunteerism	Registered nonprofit organizations
	(2) Sociability	Recreational centers (bowling, fitness, golf clubs) and sport organizations
	(3) Civic and political participation	Registered voters
		Civic and political organizations
		Census response rate
	(4) Religious participation	Religious organizations
	(5) Community attachment	Owner-occupied housing units
	(6) Connections in work place	Professional organizations
		Business organizations

Table B-1(b): Economic capital indicators for measuring hazard mitigation resilience sub-index

Mitigation Activity	Generic Indicators	
	Component	**Indicator**
‣ Building dams, levees, dikes, and floodwalls ‣ Landuse planning to prevent development in hazardous areas ‣ Building codes and building standards ‣ Acquiring and relocating damaged structures ‣ Purchasing undeveloped floodplains and making them open spaces ‣ Acquisition of development rights ‣ Zoning regulations ‣ Preserving the natural environment to serve as a buffer against hazard impacts ‣ Educating the public about hazards and ways to reduce risk	(1) Income	Per capita income
		Median household income
	(2) Employment	Population in labour force, employed
	(3) Home value	Median value of owner-occupied housing units
	(4) Business	Business establishments
	(5) Health insurance	Population with health insurance

Table B-1 (c): Physical capital indicators for measuring hazard mitigation resilience sub-index

Mitigation Activity	Specific Indicators: Component	Specific Indicators: Indicator
‣ Building dams, levees, dikes, and floodwalls ‣ Landuse planning to prevent development in hazardous areas ‣ Building codes and building standards ‣ Acquiring and relocating damaged structures ‣ Purchasing undeveloped floodplains and making them open spaces ‣ Acquisition of development rights ‣ Zoning regulations ‣ Preserving the natural environment to serve as a buffer against hazard impacts ‣ Educating the public about hazards and ways to reduce risk	(1) Construction services	Building construction establishments
		Heavy and civil engineering constructions
		Highway, street, and bridge construction establishments
		Architecture and engineering establishments
	(2) Environment	Environmental consulting establishments
		Environment and conservation organizations
	(3) Land and building regulations	Land subdivision establishments
		Legal services establishments
		Building inspection establishments
	(4) Planning	Landscape architecture and planning establishments
	(5) Property insurance	Property and causality insurance companies

Table B-1(d): Human capital indicators for measuring hazard mitigation resilience sub-index

Mitigation Activity	Component	Indicator
	Generic Indicators	
‣ Building dams, levees, dikes, and floodwalls ‣ Landuse planning to prevent development in hazardous areas ‣ Building codes and building standards, ‣ Acquiring and relocating damaged structures ‣ Purchasing undeveloped floodplains and making them open spaces ‣ Acquisition of development rights ‣ Zoning regulations ‣ Preserving the natural environment to serve as a buffer against hazard impacts ‣ Educating the public about hazards and ways to reduce risk	(1) Education	Population with more than high school education
	(2) Health	Physicians
		Population employed in health care support occupations
	Specific Indicators	
	Component	**Indicator**
	(3) Construction services	Population employed in building construction establishments
		Population employed in heavy and civil engineering constructions
		Population employed in Highway, Street, and Bridge construction establishments
		Population employed in architecture and engineering establishments
	(4) Environment	Population employed in environmental consulting services
		Population employed in environment and conservation organizations
	(5) Land and building regulations	Population employed in land subdivision services
		Population employed in legal services
		Population employed in building inspection services
	(6) Planning	Population employed in landscape architecture and planning services
	(7) Property insurance	Population employed in property and causality insurance services
	(8) Mitigation plan	Population covered by comprehensive plans
		Population covered by zoning regulations
		Population covered by building codes
		Population covered by FEMA approved mitigation plans
		FEMA community rating system(CRS) scores

Table B-2 (a): Social capital indicators for measuring Disaster preparedness resilience sub-index

Preparedness Activity	Generic Indicators	
	Component	**Indicator**
‣ Development of response procedures ‣ Design and installation of warning systems, detection and monitoring systems e.g. radar detection and tracking severe storms ‣ Developing plans for evacuation ‣ Exercise to test emergency operations (Exercise & Drills) ‣ Training of emergency personnel ‣ Stockpiling of resources e.g. medical supplies	(1) Volunteerism	Registered nonprofit organizations
	(2) Sociability	Recreational centers (bowling, fitness, golf clubs) and sport organizations
	(3) Civic and political participation	Registered voters
		Civic and political organizations
		Census response rate
	(4) Religious participation	Religious organizations
	(5) Community attachment	Owner-occupied housing units
	(6) Connections in work place	Professional organizations
		Business organizations

Table B-2 (b): Economic capital indicators for measuring disaster preparedness resilience sub-index

Preparedness Activity	Generic Indicators	
	Component	**Indicator**
‣ Development of response procedures ‣ Design and installation of warning systems, detection and monitoring systems e.g. radar detection and tracking severe storms ‣ Developing plans for evacuation ‣ Exercise to test emergency operations (Exercise & Drills) ‣ Training of emergency personnel ‣ Stockpiling of resources e.g. medical supplies	(1) Income	Per capita income
		Median household income
	(2) Employment	Population in labour force, employed
	(3) Home value	Median value of owner-occupied housing units
	(4) Business	Business establishments
	(5) Health insurance	Population with health insurance

Table B-2(c): Physical capital indicators for measuring disaster preparedness resilience sub-index

Preparedness Activity	Specific indicators	
	Component	**Indicator**
‣ Development of response procedures ‣ Design and installation of warning systems, detection and monitoring systems e.g. radar detection and tracking severe storms ‣ Developing plans for evacuation ‣ Exercise to test emergency operations (Exercise & Drills) ‣ Training of emergency personnel ‣ Stockpiling of resources e.g. medical supplies	(1) Research	Scientific research and development services
	(2) Colleges	Colleges, universities, and professional schools
	(3) Planning	Landscape architecture and planning services

Table B-2 (d): Human capital indicators for measuring disaster preparedness resilience sub-index

Preparedness Activity	Generic Indicators	
	Component	**Indicator**
‣ Development of response procedures ‣ Design and installation of warning systems, detection and monitoring systems e.g. radar detection and tracking severe storms ‣ Developing plans for evacuation ‣ Exercise to test emergency operations (Exercise & Drills) ‣ Training of emergency personnel ‣ Stockpiling of resources e.g. medical supplies	(1) Education	Population with more than high school education
	(2) Health	Physicians
	Specific Indicators	
	Component	**Indicator**
	(3) Protective services	Population employed as fire fighting, prevention, or law enforcement workers
	(4) Planning	Population employed in landscape architecture and planning services
	(5) Research	Population employed in scientific research and development services
	(6) Colleges	Population employed in colleges, universities, and professional schools
	(7) communication	Population who speak english language very well

Table B-3(a): Social capital indicators for measuring disaster response resilience sub-index

Response Activity	Generic Indicators	
	Component	**Indicator**
‣ Securing the impacted area ‣ Warning ‣ Evacuation ‣ Search & Rescue ‣ Provision of medical care ‣ Sheltering the evacuees	(1) Volunteerism	Registered nonprofit organizations
	(2) Sociability	Recreational centers (bowling, fitness, golf clubs) and sport organizations
	(3) Civic and Political participation	Registered voters
		Civic and political organizations
		Census response rate
	(4 Religious participation	Religious organizations
	(5) Community attachment	Owner-occupied housing units
	(6) Connections in work place	Professional organizations
		Business organizations

Table B-3(b): Economic capital indicators for measuring disaster response resilience sub-index

Response Activity	Generic Indicators	
	Component	**Indicator**
‣ Securing the impacted area ‣ Warning ‣ Evacuation ‣ Search & Rescue ‣ Provision of medical care ‣ Sheltering the evacuees	(1) Income	Per capita income
		Median household income
	(2) Employment	Population in labour force, employed
	(3) Home value	Median value of owner-occupied housing units
	(4) Business	Business establishments
	(5) Health insurance	Population with health insurance

Table B-3(c): Physical capital indicators for measuring disaster response resilience sub-index

Response Activity	Generic Indicators	
	Component	**Indicator**
‣ Securing the impacted area ‣ Warning ‣ Evacuation ‣ Search & Rescue ‣ Provision of medical care ‣ Sheltering the evacuees	(1) Housing services	Housing units
		Vacant housing units
	(2) Critical facilities	Hospitals
		Hospital beds
		Ambulances
		Fire stations
		Schools
		Licensed child care facilities
		Nursing homes
		Hotels and motels
	(3) Transportation services	Occupied housing units with vehicle available
		Special need transportation services
		School and employee buses
	(4) Communication services	Housing units with telephone service available
		Newspaper publishers
		Radio stations
		Television broadcasting
		Internet service providers
	(5) Emergency shelters & relief services	Temporary shelters
		Community housing
		Community food service facilities

Table B-3(d): Human capital indicators for measuring disaster response resilience sub-index

Response Activity	Generic Indicators	
	Component	**Indicator**
‣ Securing the impacted area ‣ Warning ‣ Evacuation ‣ Search & Rescue ‣ Provision of medical care ‣ Sheltering the evacuees	(1) Education	Population with more than high school education
	(2) Health	Physicians
	Specific Indictors	
	Component	**Indicator**
	(3) Protective services	Population employed as fire fighting, prevention, or law enforcement workers
	(4) Communication	Population who speak english language very well
	(5)Transportation	Population employed in special need transportation services
	(6) Planning	Population employed in landscape architecture and planning services

Table B-4(a): Social capital indicators for measuring disaster recovery resilience sub-index

Recovery Activity	Generic Indicators	
	Component	**Indicator**
(i) Relief & rehabilitation ▪ Restoration of access to impacted area ▪ Re-establishment of economic activities ▪ Provision of housing, clothing, and food ▪ Restoration of critical facilities ▪ Restoration of essential community services (ii) Reconstruction ▪ Rebuilding of major structure e.g. public buildings, roads, bridges, and dams ▪ Revitalizing the economic system ▪ Reconstruction of housing	(1) Volunteerism	Registered nonprofit organizations
	(2) Sociability	Recreational centers (bowling, fitness, golf clubs) and sport organizations
	(3) Civic and Political participation	Registered voters
		Civic and political organizations
		Census response rate
	(4) Religious participation	Religious organizations
	(5) Community attachment	Owner-occupied housing units
	(6) Connections in work place	Professional organizations
		Business organizations

Table B-4(b): Economic capital indicators for measuring disaster recovery resilience sub-index

Recovery activity	Generic Indicators	
	Component	**Indicator**
(i) Relief & rehabilitation ▪ Restoration of access to impacted area ▪ Re-establishment of economic activities ▪ Provision of housing, clothing, and food ▪ Restoration of critical facilities ▪ Restoration of essential community services (ii) Reconstruction ▪ Rebuilding of major structure e.g. public buildings, roads, bridges, and dams ▪ Revitalizing the economic system ▪ Reconstruction of housing	(1) Income	Per capita income
		Median household income
	(2) Employment	Population in labour force, employed
	(3) Home value	Median value of owner-occupied housing units
	(4) Business	Business establishments
	(5) Health insurance	Population with health insurance

Table B-4(c): Physical capital indicators for measuring disaster recovery resilience sub-index

Recovery Activity	Specific Indicators	
	Component	**Indicator**
(i) Relief & rehabilitation ▪ Restoration of access to impacted area ▪ Re-establishment of economic activities ▪ Provision of housing, clothing, and food ▪ Restoration of critical facilities ▪ Restoration of essential community services (ii) Reconstruction ▪ Rebuilding of major structure e.g. public buildings, roads, bridges, and dams ▪ Revitalizing the economic system ▪ Reconstruction of housing	Construction services	Building construction establishments
		Utility systems construction establishments
		Architecture and engineering establishments
		Heavy highway construction establishments

Table B-4(d): Human capital indicators for measuring disaster recovery sub-index

Recovery Activity	Generic Indicators	
	Component	**Indicator**
(i) Relief & rehabilitation ▪ Restoration of access to impacted area ▪ Re-establishment of economic activities ▪ Provision of housing, clothing, and food ▪ Restoration of critical facilities ▪ Restoration of essential community services (ii) Reconstruction ▪ Rebuilding of major structure e.g. public buildings, roads, bridges, and dams ▪ Revitalizing the economic system ▪ Reconstruction of housing	(1) Education	Population with more than high school education
	(2) Health	Physicians
	Specific Indicators	
	Component	**Indicator**
	(3) Communication language	Population who speak english language very well
	(4) Construction services	Population employed in building construction industry
		Population employed in heavy highway construction establishments
		Population employed in highway, street, and bridge construction establishments
		Population employed in building inspection services
		Population employed in architecture and engineering establishments
	(5) Community and social services	Population employed in community and social services

APPENDIX C

DATA TYPE AND DATA SOURCES

Table C-1: Social capital indicators and data sources

Indicator	Description	Source of data
(1) Registered nonprofit organizations	Number of non-profit organization registered with IRS per 1000 persons.	County Business Patterns, 2005
(2) Recreational centers (bowling, fitness, golf clubs) and sport organizations	Number of recreational centers (bowling, fitness, golf clubs) and sport organizations per 1000 persons	County Business Patterns, 2005
(3) Registered voters	Number of registered voters who voted for 2004 presidential election per 1000 persons	U.S. Census Bureau, 2000, U.S. Counties
(4) Civic and political organizations	Number of civic and political organizations per 1000 persons	County Business Patterns, 2005
(5) Census response rate	Census response rate	U.S. Census Bureau, 2000
(6) Religious organizations	Number of religious organizations per 1000 persons	County Business Patterns, 2005
(7) Owner-occupied housing units	Number of owner-occupied housing units per 1000 persons	U.S. Census Bureau, 2000
(8) Professional organizations	Number of professional organizations per 1000 persons	County Business Patterns, 2005
(9) Business organizations	Number of business organizations per 1000 persons	County Business Patterns, 2005

Table C-2: Economic capital indicators and data sources

Indicator	Description	Source of data
(1) Per capita income	Per capita income	U.S. Census Bureau, 2000, U.S. Counties
(2) Median household income	Median household income	U.S. Census Bureau, 2000, U.S. Counties
(3) Population in labour force, employed	Civilian population, 16 years and over in labour force, employed per 1000 person	U.S. Census Bureau, 2000, U.S. Counties
(4) Median value of owner-occupied housing units	Median value of owner-occupied housing units	U.S. Census Bureau, 2000, U.S. Counties
(5) Business establishments	Number of business establishments per 1000 persons	U.S. Census Bureau, 2000
(6)Population with health insurance	Percentage of population with health insurance	U.S. Census Bureau, 2000, U.S. Counties

Table C-3: Physical capital indicators and data sources

Indicator	Description	Source of data
(1) Building construction establishments	Number of building construction establishments per 1000 persons	County Business Patterns, 2005
(2) Heavy and civil engineering construction establishments	Number of heavy and civil engineering construction establishments per 1000 persons	County Business Patterns, 2005
(3) Highway, street, and bridge construction establishments	Number of highway, street, and bridge construction establishments per 1000 persons	County Business Patterns, 2005
(4) Architecture and engineering establishments	Number of architecture and engineering establishments per 1000 persons	County Business Patterns, 2005
(5) Land subdivision establishments	Number of land subdivision establishments per 1000 persons	County Business Patterns, 2005
(6) Legal services establishments	Number of legal services establishments per 1000 persons	County Business Patterns, 2005
(7) Property and causality insurance companies	Number of property and causality insurance companies per 1000 persons	County Business Patterns, 2005
(8) Building inspection establishments	Number of building inspection establishments per 1000 persons	County Business Patterns, 2005
(9) Landscape Architecture and planning establishments	Number of landscape architecture and planning establishments per 1000 persons	County Business Patterns, 2005
(10) Environmental consulting establishments	Number of environmental consulting establishments per 1000 persons	County Business Patterns, 2005
(11) Environment and conservation organizations	Number of environment and conservation organizations per 1000 persons	County Business Patterns, 2005
(12) Scientific research and development services	Number of scientific research and development services per 1000 persons	County Business Patterns, 2005

(13) Colleges, universities, and professional schools	Number of colleges, universities, and professional schools per 1000 persons	County Business Patterns, 2005
(14) Housing units	Number of housing units per 1000 persons	U.S. Census Bureau, 2000
(15) Vacant housing units	(15) Number of vacant housing units per 1000 persons	U.S. Census Bureau, 2000
(16) Hospitals	Number of hospitals per 1000 persons	County Business Patterns, 2005
(17) Hospital beds	Number of hospital beds per 1000 persons	County Business Patterns, 2005
(18) Ambulances	Number of ambulances per 1000 persons	County Business Patterns, 2005
(19) Fire stations	Number of fire stations per 1000 people	FEMA, U.S. Fire Administration
(20) Nursing homes	Number of nursing homes per 1000 persons	U.S. Department of Health and Human Services
(21) Hotels and motels	Number of hotels and motels per 1000 persons	County Business Patterns, 2005
(22) Occupied housing units with vehicle available	Number of occupied housing units with vehicle available per 1000 persons	U.S. Census Bureau, 2000
(23) Special need transportation services	Number of special need transportation services per 1000 persons	County Business Patterns, 2005
(24) School and employee buses	Number of school and employee buses per 1000 persons	County Business Patterns, 2005
(25) Owner-occupied housing units with telephone service	Number of owner-occupied housing units with telephone service per 1000 persons	U.S. Census Bureau, 2000
(26) Newspaper publishers	Number of newspaper publishers per 1000 people	County Business Patterns, 2005
(27) Radio stations	Number of radio stations per 1000 persons	County Business Patterns, 2005
(28) Television broadcasting	Number of television broadcasting per 1000 persons	County Business Patterns , 2005
(29) Internet service providers	Number of internet service providers per 1000 persons	County Business Patterns , 2005
(30) Temporary shelters	Number of temporary shelters per 1000 persons	County Business Patterns , 2005
(31) Community housing	Number of community housing per 1000 persons	County Business Patterns , 2005
(32) Community food service facilities	Number of community food service facilities per 1000 persons	County Business Patterns , 2005
(33) Schools	Number of schools per 1000 persons	U.S. Department of Education
(34) Licensed child care facilities	Number of licensed child care facilities per 1000 persons	National Child Care Information Center (NCCIC)
(35) Utility systems construction establishments	Number of utility systems construction establishments per 1000 persons	County Business Patterns, 2005

Table C-4: Human capital indicators and data sources

Indicator	Description	Source of data
(1) Population with more than high school education	Population with more than high school education (per 1000 persons)	U.S. Census Bureau, 2000
(2) Physicians	Number of physicians per 1000 persons	U.S. Census Bureau, 2000, U.S. Counties
(3) Population employed in health care support	Population employed in health care support (per 1000 persons)	U.S. Census Bureau, 2000
(4) Population employed in building construction establishments	Population employed in building construction establishments (per 1000 persons)	U.S. Census Bureau, 2000
(5) Population employed in heavy and civil engineering constructions	Population employed in heavy and civil engineering constructions (per 1000 persons)	County Business Patterns , 2005
(6) Population employed in Architecture and engineering establishments	Population employed in architecture and engineering establishments (per 1000 persons)	County Business Patterns , 2005
(7) Population employed in environmental consulting services	Population employed in environmental consulting services (per 1000 persons)	County Business Patterns , 2005
(8) Population employed in environment and conservation organizations	Population employed in environment and conservation organizations(per 1000 persons)	County Business Patterns , 2005

(9) Population employed in land subdivision services	Population employed in land subdivision services (per 1000 persons)	County Business Patterns , 2005
(10) Population employed in building inspection services	Population employed in building inspection services (per 1000 persons)	County Business Patterns , 2005
(11) Population employed in landscape Architecture and planning establishments	Population employed in landscape architecture and planning services (per 1000 persons)	County Business Patterns , 2005
(12) Population employed in property and causality insurance companies	Population employed in property and causality insurance companies (per 1000 persons)	County Business Patterns , 2005
(13) Population employed in highway, street, and bridge construction	Population employed in highway, street, and bridge construction (per 1000 persons)	County Business Patterns , 2005
(14) Population employed in legal services	Population employed in legal services (per 1000 persons)	County Business Patterns , 2005
(15) Population covered by comprehensive plan	Percent of population covered by comprehensive plan	County/city website
(16) Population covered by zoning regulations	Percent of population covered by zoning regulations per 1000 persons	County/city website
(17) Population covered by building codes	Percent of population covered by building codes	International Code Council (ICC)
(18) Population covered by FEMA approved mitigation plan	Percent of population covered by FEMA approved mitigation plan	FEMA
(19) Community rating system(CRS) score	Community rating system(CRS) score	FEMA
(20) Population employed as fire fighting , prevention, or law enforcement workers	Population employed as fire fighting , prevention, or law enforcement workers (per 1000 persons)	U.S. Census Bureau, 2000
(21) Population employed in scientific research and development services	Population employed in scientific research and development services (per 1000 persons)	County Business Patterns ,2005
(22) Population employed in Colleges, Universities, and Professional schools	Population employed in Colleges, Universities, and Professional schools (per 1000 persons)	County Business Patterns ,2005
(23) Population who speak english language very well	Population who speak english language very well (per 1000 persons)	U.S. Census Bureau, 2000
(24) Population employed in special need transportation services	Population employed in special need transportation services (per 1000 persons)	County Business Patterns , 2005
(25) Population employed in community and social services	Population employed in community and social services (per 1000 persons)	County Business Patterns , 2005

Table C-5: External criteria and data sources

Indicator	Description	Source of data
(1) Deaths	Number of deaths due to flooding and cataclysmic storm (2000-2005)	CDC
(2) Total property damage	Total property damage due to weather related disasters adjusted to 2005 U.S. dollar value	SHELDUS version 6.2
(3) Insured flood property damage	Total payments made to flood property damage claim (2000-2005)	FEMA
(4) Uninsured flood property damage	Total property damage minus total payment made to flood property damage (2000-2005)	FEMA
(5) Wind risk	Total wind risk scores based on wind categories	The Coastal Risk Atlas (CRA)
(6) Flood risk	Total flood risk scores based on the likelihood of the area to flood	The Coastal Risk Atlas (CRA)
(7) Surge risk	Total surge risk scores based on the hurricane categories	The Coastal Risk Atlas (CRA)
(8)Total risk	Total Wind risk scores plus total flood risk scores plus total surge risk scores	The Coastal Risk Atlas (CRA)
(9) Social vulnerability Index	Social Vulnerability Index score	Hazard and Vulnerability Research Institute (HVRI)

APPENDIX D

CDRI MEAN SCORE BY COUNTY

Table D-1: CDRI_1 Ranking Score by County

Rank	County	State	CDRI_1 Score	Rank	County	State	CDRI_1 Score
1	Monroe	Florida	1.44	73	George	Mississippi	-0.05
2	Leon	Florida	1.12	74	Pike	Mississippi	-0.06
3	Collier	Florida	1.03	75	Clarke	Alabama	-0.07
4	Sarasota	Florida	1.02	76	Orange	Texas	-0.07
5	Franklin	Florida	0.90	77	Gilchrist	Florida	-0.08
6	Lee	Florida	0.72	78	Matagorda	Texas	-0.08
7	East Baton Rouge	Louisiana	0.69	79	Pearl River	Mississippi	-0.09
8	Baldwin	Alabama	0.68	80	Liberty	Florida	-0.10
9	Fayette	Texas	0.68	81	Marion	Mississippi	-0.11
10	Okaloosa	Florida	0.67	82	Decatur	Georgia	-0.12
11	Walton	Florida	0.66	83	Sumter	Florida	-0.13
12	Bay	Florida	0.61	84	Geneva	Alabama	-0.14
13	Hillsborough	Florida	0.61	85	Plaquemines	Louisiana	-0.14
14	St. Tammany	Louisiana	0.61	86	St. Bernard	Louisiana	-0.14
15	Pinellas	Florida	0.58	87	Tangipahoa	Louisiana	-0.14
16	Manatee	Florida	0.56	88	Stone	Mississippi	-0.14
17	Lafayette	Louisiana	0.56	89	Jasper	Texas	-0.14
18	Austin	Texas	0.51	90	Jefferson Davis	Louisiana	-0.15
19	Lake	Florida	0.50	91	Vermilion	Louisiana	-0.15
20	Fort Bend	Texas	0.49	92	Gadsden	Florida	-0.16
21	Washington	Texas	0.49	93	St. James	Louisiana	-0.16
22	Charlotte	Florida	0.46	94	Cameron	Louisiana	-0.17
23	Lavaca	Texas	0.44	95	Iberia	Louisiana	-0.17
24	Goliad	Texas	0.41	96	St. Mary	Louisiana	-0.17
25	Citrus	Florida	0.40	97	St. John the Baptist	Louisiana	-0.18
26	Santa Rosa	Florida	0.39	98	Escambia	Alabama	-0.19
27	Gulf	Florida	0.35	99	Sabine	Louisiana	-0.19
28	Hernando	Florida	0.34	100	Pointe Coupee	Louisiana	-0.2
29	Colorado	Texas	0.31	101	East Feliciana	Louisiana	-0.21
30	Victoria	Texas	0.31	102	Holmes	Florida	-0.22
31	Wakulla	Florida	0.30	103	Madison	Florida	-0.23
32	Jefferson	Louisiana	0.30	104	Live Oak	Texas	-0.23
33	Jefferson	Florida	0.28	105	Calhoun	Florida	-0.25
34	St. Charles	Louisiana	0.27	106	Grady	Georgia	-0.25
35	Pasco	Florida	0.26	107	Amite	Mississippi	-0.25
36	Galveston	Texas	0.26	108	Assumption	Louisiana	-0.26
37	Escambia	Florida	0.25	109	Monroe	Alabama	-0.27
38	Polk	Florida	0.24	110	Kleberg	Texas	-0.27
39	Rapides	Louisiana	0.24	111	DeSoto	Florida	-0.28
40	Hancock	Mississippi	0.23	112	Acadia	Louisiana	-0.31
41	Thomas	Georgia	0.22	113	San Patricio	Texas	-0.31
42	Mobile	Alabama	0.20	114	Washington	Alabama	-0.32
43	Marion	Florida	0.20	115	Hendry	Florida	-0.32
44	Lamar	Mississippi	0.18	116	Lafayette	Florida	-0.33
45	Harris	Texas	0.18	117	Liberty	Texas	-0.33
46	Ascension	Louisiana	0.17	118	Washington	Louisiana	-0.36
47	Waller	Texas	0.17	119	St. Helena	Louisiana	-0.37
48	Covington	Alabama	0.16	120	Iberville	Louisiana	-0.38
49	Calcasieu	Louisiana	0.14	121	St. Landry	Louisiana	-0.38
50	Harrison	Mississippi	0.14	122	St. Martin	Louisiana	-0.38
51	Aransas	Texas	0.14	123	Tyler	Texas	-0.38
52	Chambers	Texas	0.11	124	Walthall	Mississippi	-0.39
53	Brazoria	Texas	0.09	125	Avoyelles	Louisiana	-0.41
54	Levy	Florida	0.08	126	Glades	Florida	-0.43
55	Refugio	Texas	0.07	127	Hardee	Florida	-0.44
56	Orleans	Louisiana	0.06	128	Jim Wells	Texas	-0.44
57	West Baton Rouge	Louisiana	0.06	129	Brooks	Texas	-0.45
58	Jefferson	Texas	0.06	130	Dixie	Florida	-0.46
59	Jackson	Florida	0.05	131	Jim Hogg	Texas	-0.46

60	Suwannee	Florida	0.05	132	Evangeline	Louisiana	-0.51
61	Nueces	Texas	0.05	133	Wilkinson	Mississippi	-0.53
62	Washington	Florida	0.04	134	Newton	Texas	-0.56
63	Terrebonne	Louisiana	0.04	135	West Feliciana	Louisiana	-0.61
64	Jackson	Mississippi	0.03	136	Kenedy	Texas	-0.61
65	Taylor	Florida	0.01	137	Vernon	Louisiana	-0.67
66	Livingston	Louisiana	0.01	138	Webb	Texas	-0.68
67	Wharton	Texas	0.00	139	Cameron	Texas	-0.72
68	Beauregard	Louisiana	-0.01	140	Bee	Texas	-0.73
69	Jackson	Texas	-0.01	141	Hidalgo	Texas	-0.81
70	Calhoun	Texas	-0.03	142	Duval	Texas	-0.92
71	DeWitt	Texas	-0.04	143	Willacy	Texas	-0.98
72	Lafourche	Louisiana	-0.05	144	Starr	Texas	-1.32

Table D-2: CDRI_2 Ranking Score by County

Rank	County	State	CDRI_2 Score	Rank	County	State	CDRI_2 Score
1	Monroe	Florida	1.39	73	Jefferson Davis	Louisiana	-0.07
2	Franklin	Florida	1.24	74	Madison	Florida	-0.07
3	Sarasota	Florida	1.13	75	Chambers	Texas	-0.08
4	Collier	Florida	1.08	76	Plaquemines	Louisiana	-0.08
5	Walton	Florida	0.94	77	Wharton	Texas	-0.10
6	Okaloosa	Florida	0.85	78	Jasper	Texas	-0.10
7	Leon	Florida	0.82	79	Stone	Mississippi	-0.11
8	Baldwin	Alabama	0.75	80	Pike	Mississippi	-0.12
9	Lee	Florida	0.71	81	Calhoun	Florida	-0.12
10	East Baton Rouge	Louisiana	0.71	82	Beauregard	Louisiana	-0.13
11	Lafayette	Louisiana	0.67	83	DeWitt	Texas	-0.13
12	Bay	Florida	0.66	84	Matagorda	Texas	-0.13
13	St. Tammany	Louisiana	0.63	85	Marion	Mississippi	-0.13
14	Hillsborough	Florida	0.60	86	Cameron	Louisiana	-0.13
15	Gulf	Florida	0.59	87	Orange	Texas	-0.15
16	Manatee	Florida	0.57	88	Pearl River	Mississippi	-0.15
17	Lake	Florida	0.56	89	Lafourche	Louisiana	-0.16
18	Pinellas	Florida	0.53	90	Decatur	Georgia	-0.16
19	Charlotte	Florida	0.42	91	East Feliciana	Louisiana	-0.16
20	Wakulla	Florida	0.41	92	Clarke	Alabama	-0.17
21	Hancock	Mississippi	0.41	93	Tangipahoa	Louisiana	-0.17
22	Santa Rosa	Florida	0.39	94	Live Oak	Texas	-0.17
23	Citrus	Florida	0.38	95	Gadsden	Florida	-0.18
24	Rapides	Louisiana	0.33	96	Holmes	Florida	-0.19
25	Orleans	Louisiana	0.33	97	Iberia	Louisiana	-0.21
26	Fort Bend	Texas	0.32	98	St. Mary	Louisiana	-0.21
27	Escambia	Florida	0.30	99	Pointe Coupee	Louisiana	-0.21
28	Austin	Texas	0.29	100	Jim Hogg	Texas	-0.21
29	Jefferson	Louisiana	0.29	101	Brooks	Texas	-0.22
30	Gilchrist	Florida	0.29	102	Escambia	Alabama	-0.25
31	Waller	Texas	0.28	103	DeSoto	Florida	-0.25
32	Galveston	Texas	0.27	104	Hendry	Florida	-0.26
33	Pasco	Florida	0.25	105	Vermilion	Louisiana	-0.27
34	Fayette	Texas	0.24	106	St. John the Baptist	Louisiana	-0.28
35	Washington	Texas	0.23	107	Lafayette	Florida	-0.28
36	George	Mississippi	0.23	108	St. Bernard	Louisiana	-0.29
37	Harris	Texas	0.22	109	St. James	Louisiana	-0.29
38	Mobile	Alabama	0.21	110	Sabine	Louisiana	-0.29
39	Marion	Florida	0.21	111	Grady	Georgia	-0.29
40	Polk	Florida	0.20	112	San Patricio	Texas	-0.29
41	Hernando	Florida	0.19	113	St. Landry	Louisiana	-0.30
42	Aransas	Texas	0.19	114	Tyler	Texas	-0.30
43	Jackson	Florida	0.19	115	Washington	Louisiana	-0.31
44	Lavaca	Texas	0.16	116	West Feliciana	Louisiana	-0.31
45	Covington	Alabama	0.16	117	Assumption	Louisiana	-0.32

46	Jefferson	Florida	0.14		118	Liberty	Texas	-0.32
47	Thomas	Georgia	0.14		119	Avoyelles	Louisiana	-0.32
48	Harrison	Mississippi	0.14		120	Amite	Mississippi	-0.33
49	Liberty	Florida	0.14		121	Iberville	Louisiana	-0.33
50	Taylor	Florida	0.13		122	Kleberg	Texas	-0.34
51	Washington	Florida	0.12		123	Dixie	Florida	-0.36
52	Colorado	Texas	0.11		124	Wilkinson	Mississippi	-0.36
53	Victoria	Texas	0.10		125	Monroe	Alabama	-0.38
54	Ascension	Louisiana	0.10		126	Washington	Alabama	-0.38
55	St. Charles	Louisiana	0.09		127	St. Helena	Louisiana	-0.38
56	West Baton Rouge	Louisiana	0.09		128	Glades	Florida	-0.38
57	Nueces	Texas	0.08		129	Acadia	Louisiana	-0.39
58	Brazoria	Texas	0.05		130	St. Martin	Louisiana	-0.40
59	Jefferson	Texas	0.05		131	Newton	Texas	-0.43
60	Calcasieu	Louisiana	0.04		132	Walthall	Mississippi	-0.46
61	Refugio	Texas	0.02		133	Bee	Texas	-0.46
62	Levy	Florida	0.01		134	Evangeline	Louisiana	-0.47
63	Suwannee	Florida	0.00		135	Vernon	Louisiana	-0.48
64	Lamar	Mississippi	-0.01		136	Jim Wells	Texas	-0.50
65	Sumter	Florida	-0.01		137	Hardee	Florida	-0.59
66	Goliad	Texas	-0.03		138	Cameron	Texas	-0.71
67	Jackson	Texas	-0.04		139	Webb	Texas	-0.76
68	Terrebonne	Louisiana	-0.05		140	Hidalgo	Texas	-0.77
69	Jackson	Mississippi	-0.05		141	Kenedy	Texas	-0.80
70	Livingston	Louisiana	-0.05		142	Duval	Texas	-0.87
71	Geneva	Alabama	-0.05		143	Willacy	Texas	-0.98
72	Calhoun	Texas	-0.07		144	Starr	Texas	-1.27

Table D-3: CDRI_3 Ranking Score by County

Rank	County	State	CDRI_3 Score		Rank	County	State	CDRI_3 Score
1	Monroe	Florida	1.56		73	Beauregard	Louisiana	-0.06
2	Collier	Florida	1.25		74	Plaquemines	Louisiana	-0.08
3	Sarasota	Florida	1.21		75	DeWitt	Texas	-0.08
4	Leon	Florida	1.11		76	Pike	Mississippi	-0.09
5	Franklin	Florida	0.88		77	Sumter	Florida	-0.10
6	Baldwin	Alabama	0.84		78	Geneva	Alabama	-0.10
7	Lee	Florida	0.83		79	Jefferson Davis	Louisiana	-0.10
8	Okaloosa	Florida	0.81		80	Matagorda	Texas	-0.10
9	Walton	Florida	0.79		81	Marion	Mississippi	-0.10
10	East Baton Rouge	Louisiana	0.79		82	Orange	Texas	-0.10
11	St. Tammany	Louisiana	0.75		83	Jasper	Texas	-0.11
12	Lafayette	Louisiana	0.67		84	Stone	Mississippi	-0.11
13	Hillsborough	Florida	0.66		85	Clarke	Alabama	-0.12
14	Manatee	Florida	0.63		86	Pearl River	Mississippi	-0.13
15	Lake	Florida	0.63		87	Cameron	Louisiana	-0.16
16	Fayette	Texas	0.63		88	Tangipahoa	Louisiana	-0.16
17	Pinellas	Florida	0.61		89	Decatur	Georgia	-0.17
18	Bay	Florida	0.60		90	Iberia	Louisiana	-0.17
19	Fort Bend	Texas	0.57		91	St. Bernard	Louisiana	-0.18
20	Austin	Texas	0.52		92	St. John the Baptist	Louisiana	-0.19
21	Charlotte	Florida	0.50		93	Pointe Coupee	Louisiana	-0.20
22	Santa Rosa	Florida	0.49		94	Madison	Florida	-0.21
23	Washington	Texas	0.44		95	Vermilion	Louisiana	-0.21
24	Gulf	Florida	0.43		96	Gadsden	Florida	-0.22
25	Citrus	Florida	0.41		97	St. Mary	Louisiana	-0.22
26	Wakulla	Florida	0.38		98	Escambia	Alabama	-0.22
27	Jefferson	Louisiana	0.38		99	St. James	Louisiana	-0.23
28	Goliad	Texas	0.36		100	East Feliciana	Louisiana	-0.24
29	Hancock	Mississippi	0.35		101	Live Oak	Texas	-0.25
30	Lavaca	Texas	0.35		102	Liberty	Florida	-0.26
31	Galveston	Texas	0.33		103	Grady	Georgia	-0.26

32	Hernando	Florida	0.31		104	Holmes	Florida	-0.27
33	Escambia	Florida	0.29		105	Sabine	Louisiana	-0.27
34	St. Charles	Louisiana	0.29		106	Calhoun	Florida	-0.28
35	Pasco	Florida	0.28		107	Assumption	Louisiana	-0.29
36	Rapides	Louisiana	0.27		108	San Patricio	Texas	-0.31
37	Colorado	Texas	0.27		109	Amite	Mississippi	-0.31
38	Waller	Texas	0.26		110	DeSoto	Florida	-0.32
39	Harris	Texas	0.24		111	Monroe	Alabama	-0.32
40	Marion	Florida	0.24		112	Hendry	Florida	-0.33
41	Mobile	Alabama	0.23		113	Liberty	Texas	-0.34
42	Victoria	Texas	0.23		114	Washington	Alabama	-0.35
43	Ascension	Louisiana	0.23		115	Lafayette	Florida	-0.37
44	Polk	Florida	0.21		116	Iberville	Louisiana	-0.37
45	Aransas	Texas	0.19		117	Kleberg	Texas	-0.38
46	Thomas	Georgia	0.17		118	Acadia	Louisiana	-0.38
47	Covington	Alabama	0.16		119	Tyler	Texas	-0.39
48	Jefferson	Florida	0.16		120	Washington	Louisiana	-0.40
49	Harrison	Mississippi	0.16		121	St. Martin	Louisiana	-0.40
50	Brazoria	Texas	0.15		122	St. Landry	Louisiana	-0.41
51	Lamar	Mississippi	0.14		123	Walthall	Mississippi	-0.42
52	Calcasieu	Louisiana	0.13		124	Jim Hogg	Texas	-0.43
53	Orleans	Louisiana	0.12		125	Avoyelles	Louisiana	-0.44
54	West Baton Rouge	Louisiana	0.11		126	Brooks	Texas	-0.46
55	Chambers	Texas	0.09		127	St. Helena	Louisiana	-0.49
56	Gilchrist	Florida	0.08		128	Glades	Florida	-0.49
57	Washington	Florida	0.07		129	Dixie	Florida	-0.50
58	George	Mississippi	0.06		130	Jim Wells	Texas	-0.53
59	Jackson	Florida	0.05		131	West Feliciana	Louisiana	-0.54
60	Nueces	Texas	0.05		132	Wilkinson	Mississippi	-0.54
61	Jefferson	Texas	0.05		133	Newton	Texas	-0.54
62	Refugio	Texas	0.05		134	Hardee	Florida	-0.57
63	Levy	Florida	0.05		135	Evangeline	Louisiana	-0.58
64	Jackson	Mississippi	0.05		136	Vernon	Louisiana	-0.65
65	Livingston	Louisiana	0.04		137	Bee	Texas	-0.69
66	Wharton	Texas	0.03		138	Kenedy	Texas	-0.70
67	Taylor	Florida	0.01		139	Cameron	Texas	-0.82
68	Terrebonne	Louisiana	0.01		140	Webb	Texas	-0.82
69	Suwannee	Florida	-0.01		141	Hidalgo	Texas	-0.91
70	Jackson	Texas	-0.01		142	Duval	Texas	-1.03
71	Calhoun	Texas	-0.05		143	Willacy	Texas	-1.11
72	Lafourche	Louisiana	-0.05		144	Starr	Texas	-1.49

APPENDIX E

CAPITAL DOMAIN'S SUB-INDEX MEAN SCORE BY COUNTY

Table E-1: Social Capital Sub-index Ranking Score by County

Rank	County	State	Social capital Score	Rank	County	State	Social capital Score
1	Goliad	Texas	1.97	73	St. James	Louisiana	-0.06
2	Leon	Florida	1.91	74	Chambers	Texas	-0.07
3	Fayette	Texas	1.65	75	Iberia	Louisiana	-0.07
4	Lavaca	Texas	1.19	76	Monroe	Alabama	-0.08
5	Austin	Texas	0.97	77	West Baton Rouge	Louisiana	-0.09
6	Washington	Texas	0.91	78	Harrison	Mississippi	-0.10
7	East Baton Rouge	Louisiana	0.84	79	Jackson	Mississippi	-0.10
8	Citrus	Florida	0.82	80	Assumption	Louisiana	-0.10
9	Colorado	Texas	0.81	81	Taylor	Florida	-0.11
10	Monroe	Florida	0.76	82	Holmes	Florida	-0.11
11	Hernando	Florida	0.75	83	Brooks	Texas	-0.11
12	Franklin	Florida	0.73	84	Lamar	Mississippi	-0.12
13	Gulf	Florida	0.68	85	Terrebonne	Louisiana	-0.13
14	Sarasota	Florida	0.67	86	Pearl River	Mississippi	-0.13
15	Lake	Florida	0.61	87	Decatur	Georgia	-0.13
16	Baldwin	Alabama	0.55	88	Madison	Florida	-0.13
17	Refugio	Texas	0.54	89	Gadsden	Florida	-0.16
18	Lee	Florida	0.52	90	Lafayette	Florida	-0.16
19	Levy	Florida	0.50	91	Live Oak	Texas	-0.17
20	Collier	Florida	0.47	92	Calhoun	Florida	-0.17
21	DeWitt	Texas	0.47	93	Washington	Alabama	-0.17
22	Wharton	Texas	0.46	94	Ascension	Louisiana	-0.18
23	Charlotte	Florida	0.44	95	Grady	Georgia	-0.19
24	Marion	Mississippi	0.44	96	Livingston	Louisiana	-0.20
25	Covington	Alabama	0.42	97	Orange	Texas	-0.20
26	Aransas	Texas	0.34	98	East Feliciana	Louisiana	-0.20
27	Walton	Florida	0.33	99	Wilkinson	Mississippi	-0.20
28	Santa Rosa	Florida	0.32	100	Brazoria	Texas	-0.21
29	Okaloosa	Florida	0.30	101	Iberville	Louisiana	-0.21
30	Manatee	Florida	0.30	102	Gilchrist	Florida	-0.22
31	Pike	Mississippi	0.30	103	Tangipahoa	Louisiana	-0.23
32	Pasco	Florida	0.29	104	St. Mary	Louisiana	-0.25
33	Washington	Florida	0.29	105	Acadia	Louisiana	-0.26
34	Jefferson	Florida	0.28	106	Tyler	Texas	-0.26
35	Marion	Florida	0.27	107	Nueces	Texas	-0.27
36	Rapides	Louisiana	0.25	108	Pointe Coupee	Louisiana	-0.27
37	Victoria	Texas	0.25	109	Kleberg	Texas	-0.27
38	Pinellas	Florida	0.24	110	Washington	Louisiana	-0.27
39	St. Charles	Louisiana	0.24	111	Hardee	Florida	-0.29
40	Thomas	Georgia	0.23	112	Stone	Mississippi	-0.30
41	Beauregard	Louisiana	0.23	113	San Patricio	Texas	-0.30
42	St. Tammany	Louisiana	0.20	114	George	Mississippi	-0.35
43	Mobile	Alabama	0.20	115	Avoyelles	Louisiana	-0.35
44	Hillsborough	Florida	0.19	116	St. Helena	Louisiana	-0.35
45	Escambia	Florida	0.19	117	St. Bernard	Louisiana	-0.36
46	Jackson	Florida	0.17	118	St. John the Baptist	Louisiana	-0.36
47	Lafayette	Louisiana	0.16	119	DeSoto	Florida	-0.37
48	Bay	Florida	0.15	120	Cameron	Louisiana	-0.39
49	Clarke	Alabama	0.13	121	Orleans	Louisiana	-0.40
50	Hancock	Mississippi	0.12	122	Evangeline	Louisiana	-0.40
51	Calcasieu	Louisiana	0.12	123	Harris	Texas	-0.43
52	Jefferson	Texas	0.10	124	St. Landry	Louisiana	-0.43
53	Wakulla	Florida	0.09	125	Plaquemines	Louisiana	-0.46
54	Sumter	Florida	0.08	126	Jim Wells	Texas	-0.48
55	Waller	Texas	0.07	127	Liberty	Texas	-0.50
56	Suwannee	Florida	0.07	128	Hendry	Florida	-0.51
57	Jefferson Davis	Louisiana	0.06	129	Newton	Texas	-0.53
58	Matagorda	Texas	0.06	130	Kenedy	Texas	-0.54

59	Amite	Mississippi	0.06	131	St. Martin	Louisiana	-0.55
60	Walthall	Mississippi	0.02	132	Dixie	Florida	-0.55
61	Jackson	Texas	0.01	133	Bee	Texas	-0.61
62	Calhoun	Texas	0.00	134	Jim Hogg	Texas	-0.63
63	Lafourche	Louisiana	0.00	135	Glades	Florida	-0.63
64	Vermilion	Louisiana	0.00	136	Willacy	Texas	-0.80
65	Fort Bend	Texas	-0.01	137	Liberty	Florida	-0.88
66	Polk	Florida	-0.01	138	Cameron	Texas	-0.90
67	Jasper	Texas	-0.01	139	Hidalgo	Texas	-1.02
68	Escambia	Alabama	-0.01	140	Webb	Texas	-1.03
69	Galveston	Texas	-0.03	141	West Feliciana	Louisiana	-1.04
70	Geneva	Alabama	-0.03	142	Duval	Texas	-1.06
71	Jefferson	Louisiana	-0.04	143	Vernon	Louisiana	-1.07
72	Sabine	Louisiana	-0.05	144	Starr	Texas	-1.40

Table E-2: Economic Capital Sub-index Ranking Score by County

Rank	County	State	Economic capital Score	Rank	County	State	Economic capital Score
1	Monroe	Florida	2.90	73	Beauregard	Louisiana	-0.13
2	Collier	Florida	2.59	74	Covington	Alabama	-0.14
3	Fort Bend	Texas	2.01	75	Suwannee	Florida	-0.15
4	Sarasota	Florida	1.99	76	St. James	Louisiana	-0.17
5	St. Tammany	Louisiana	1.68	77	Matagorda	Texas	-0.18
6	Lee	Florida	1.50	78	Franklin	Florida	-0.20
7	Baldwin	Alabama	1.40	79	St. Mary	Louisiana	-0.20
8	Hillsborough	Florida	1.36	80	Vermilion	Louisiana	-0.21
9	Leon	Florida	1.30	81	Clarke	Alabama	-0.23
10	Pinellas	Florida	1.24	82	Decatur	Georgia	-0.23
11	Okaloosa	Florida	1.20	83	Liberty	Texas	-0.23
12	Lafayette	Louisiana	1.19	84	Grady	Georgia	-0.24
13	Manatee	Florida	1.16	85	Jasper	Texas	-0.25
14	Jefferson	Louisiana	1.10	86	Taylor	Florida	-0.26
15	Ascension	Louisiana	1.05	87	Levy	Florida	-0.27
16	East Baton Rouge	Louisiana	1.00	88	St. Martin	Louisiana	-0.28
17	St. Charles	Louisiana	0.99	89	Geneva	Alabama	-0.31
18	Harris	Texas	0.99	90	Gulf	Florida	-0.33
19	Santa Rosa	Florida	0.98	91	Refugio	Texas	-0.33
20	Fayette	Texas	0.92	92	Washington	Florida	-0.33
21	Lamar	Mississippi	0.91	93	Gilchrist	Florida	-0.33
22	Galveston	Texas	0.90	94	Escambia	Alabama	-0.36
23	Lake	Florida	0.89	95	San Patricio	Texas	-0.36
24	Bay	Florida	0.85	96	Monroe	Alabama	-0.37
25	Austin	Texas	0.83	97	Pike	Mississippi	-0.39
26	Brazoria	Texas	0.83	98	Jefferson Davis	Louisiana	-0.39
27	Charlotte	Florida	0.82	99	Sabine	Louisiana	-0.40
28	Chambers	Texas	0.81	100	Assumption	Louisiana	-0.40
29	Walton	Florida	0.74	101	Hendry	Florida	-0.40
30	Washington	Texas	0.67	102	Gadsden	Florida	-0.41
31	Victoria	Texas	0.63	103	Washington	Alabama	-0.42
32	Wakulla	Florida	0.57	104	DeWitt	Texas	-0.45
33	Livingston	Louisiana	0.57	105	Acadia	Louisiana	-0.48
34	Harrison	Mississippi	0.52	106	Kenedy	Texas	-0.51
35	Jackson	Mississippi	0.51	107	DeSoto	Florida	-0.52
36	Polk	Florida	0.46	108	East Feliciana	Louisiana	-0.53
37	Calcasieu	Louisiana	0.44	109	Marion	Mississippi	-0.54
38	Hancock	Mississippi	0.41	110	Jackson	Florida	-0.57
39	West Baton Rouge	Louisiana	0.39	111	Sumter	Florida	-0.58
40	Pasco	Florida	0.38	112	Live Oak	Texas	-0.59
41	Waller	Texas	0.37	113	Amite	Mississippi	-0.63
42	Terrebonne	Louisiana	0.37	114	Kleberg	Texas	-0.63

43	Escambia	Florida	0.36		115	Iberville	Louisiana	-0.68
44	St. Bernard	Louisiana	0.35		116	Holmes	Florida	-0.69
45	Mobile	Alabama	0.34		117	Jim Wells	Texas	-0.70
46	Plaquemines	Louisiana	0.30		118	Glades	Florida	-0.70
47	Hernando	Florida	0.28		119	Walthall	Mississippi	-0.75
48	Marion	Florida	0.28		120	Madison	Florida	-0.76
49	Lafourche	Louisiana	0.27		121	St. Landry	Louisiana	-0.76
50	Nueces	Texas	0.26		122	Webb	Texas	-0.78
51	St. John the Baptist	Louisiana	0.26		123	Hardee	Florida	-0.79
52	Colorado	Texas	0.23		124	Vernon	Louisiana	-0.79
53	Thomas	Georgia	0.20		125	Washington	Louisiana	-0.81
54	Orange	Texas	0.18		126	Tyler	Texas	-0.83
55	Lavaca	Texas	0.17		127	West Feliciana	Louisiana	-0.83
56	Citrus	Florida	0.14		128	Lafayette	Florida	-0.86
57	Jefferson	Florida	0.10		129	Calhoun	Florida	-0.91
58	Rapides	Louisiana	0.10		130	Newton	Texas	-0.91
59	Goliad	Texas	0.08		131	Avoyelles	Louisiana	-0.93
60	Stone	Mississippi	0.08		132	Dixie	Florida	-0.94
61	Jackson	Texas	0.04		133	Liberty	Florida	-0.95
62	Wharton	Texas	0.02		134	Jim Hogg	Texas	-0.96
63	Aransas	Texas	0.02		135	St. Helena	Louisiana	-0.97
64	Jefferson	Texas	0.00		136	Cameron	Texas	-1.10
65	Calhoun	Texas	-0.03		137	Evangeline	Louisiana	-1.12
66	Cameron	Louisiana	-0.03		138	Hidalgo	Texas	-1.29
67	Tangipahoa	Louisiana	-0.05		139	Wilkinson	Mississippi	-1.49
68	Pearl River	Mississippi	-0.06		140	Bee	Texas	-1.51
69	George	Mississippi	-0.06		141	Duval	Texas	-1.51
70	Orleans	Louisiana	-0.07		142	Brooks	Texas	-1.61
71	Pointe Coupee	Louisiana	-0.10		143	Willacy	Texas	-1.85
72	Iberia	Louisiana	-0.11		144	Starr	Texas	-2.31

Table E-3: Physical Capital Sub-index Ranking Score by County

Rank	County	State	Physical capital Score		Rank	County	State	Physical capital Score
1	Franklin	Florida	1.72		73	Calhoun	Florida	-0.06
2	Monroe	Florida	1.43		74	Jefferson	Louisiana	-0.09
3	Walton	Florida	0.96		75	Galveston	Texas	-0.10
4	Leon	Florida	0.75		76	Holmes	Florida	-0.10
5	Bay	Florida	0.69		77	Calhoun	Texas	-0.11
6	Sarasota	Florida	0.68		78	Matagorda	Texas	-0.11
7	Lafayette	Louisiana	0.66		79	Escambia	Alabama	-0.11
8	Collier	Florida	0.64		80	Kleberg	Texas	-0.11
9	Okaloosa	Florida	0.57		81	Pearl River	Mississippi	-0.12
10	Baldwin	Alabama	0.51		82	Orleans	Louisiana	-0.12
11	Lee	Florida	0.50		83	Lamar	Mississippi	-0.13
12	Covington	Alabama	0.49		84	Goliad	Texas	-0.13
13	Lavaca	Texas	0.46		85	St. Landry	Louisiana	-0.13
14	Pinellas	Florida	0.39		86	Harris	Texas	-0.14
15	Jim Hogg	Texas	0.36		87	Terrebonne	Louisiana	-0.14
16	Rapides	Louisiana	0.35		88	Jefferson	Texas	-0.14
17	Liberty	Florida	0.35		89	Avoyelles	Louisiana	-0.14
18	Colorado	Texas	0.34		90	Wilkinson	Mississippi	-0.14
19	Hillsborough	Florida	0.33		91	West Baton Rouge	Louisiana	-0.15
20	Thomas	Georgia	0.33		92	Tangipahoa	Louisiana	-0.16
21	Jefferson	Florida	0.33		93	Gadsden	Florida	-0.16
22	Gulf	Florida	0.33		94	DeSoto	Florida	-0.16
23	Fayette	Texas	0.32		95	Orange	Texas	-0.17
24	Lake	Florida	0.32		96	East Feliciana	Louisiana	-0.17
25	Taylor	Florida	0.31		97	Vermilion	Louisiana	-0.18
26	Manatee	Florida	0.29		98	Monroe	Alabama	-0.18
27	East Baton Rouge	Louisiana	0.28		99	Sumter	Florida	-0.18

28	Charlotte	Florida	0.26		100	Washington	Louisiana	-0.18
29	Citrus	Florida	0.25		101	Pointe Coupee	Louisiana	-0.19
30	Victoria	Texas	0.23		102	Grady	Georgia	-0.19
31	Refugio	Texas	0.22		103	Evangeline	Louisiana	-0.19
32	St. Tammany	Louisiana	0.21		104	Fort Bend	Texas	-0.20
33	Waller	Texas	0.18		105	Chambers	Texas	-0.20
34	Clarke	Alabama	0.18		106	Wharton	Texas	-0.20
35	Washington	Texas	0.17		107	Beauregard	Louisiana	-0.20
36	Aransas	Texas	0.17		108	Jim Wells	Texas	-0.20
37	DeWitt	Texas	0.17		109	St. James	Louisiana	-0.21
38	Escambia	Florida	0.16		110	Hendry	Florida	-0.21
39	George	Mississippi	0.16		111	Ascension	Louisiana	-0.22
40	Brooks	Texas	0.15		112	St. Charles	Louisiana	-0.22
41	Wakulla	Florida	0.14		113	Iberia	Louisiana	-0.23
42	Hernando	Florida	0.13		114	Amite	Mississippi	-0.23
43	Nueces	Texas	0.13		115	Dixie	Florida	-0.23
44	Austin	Texas	0.11		116	Lafourche	Louisiana	-0.24
45	Jackson	Texas	0.11		117	St. Martin	Louisiana	-0.25
46	Hancock	Mississippi	0.08		118	Acadia	Louisiana	-0.25
47	Live Oak	Texas	0.07		119	Walthall	Mississippi	-0.25
48	Santa Rosa	Florida	0.05		120	Lafayette	Florida	-0.27
49	Pasco	Florida	0.05		121	San Patricio	Texas	-0.28
50	Marion	Florida	0.05		122	Jackson	Mississippi	-0.29
51	Pike	Mississippi	0.04		123	Plaquemines	Louisiana	-0.29
52	Marion	Mississippi	0.04		124	Hidalgo	Texas	-0.29
53	Jackson	Florida	0.04		125	Washington	Alabama	-0.30
54	Polk	Florida	0.02		126	Livingston	Louisiana	-0.31
55	St. Helena	Louisiana	0.02		127	Liberty	Texas	-0.32
56	Cameron	Louisiana	0.01		128	Glades	Florida	-0.32
57	Jasper	Texas	0.01		129	Brazoria	Texas	-0.34
58	Geneva	Alabama	0.00		130	Assumption	Louisiana	-0.36
59	Calcasieu	Louisiana	-0.01		131	Cameron	Texas	-0.36
60	Jefferson Davis	Louisiana	-0.01		132	Iberville	Louisiana	-0.38
61	Decatur	Georgia	-0.03		133	Vernon	Louisiana	-0.40
62	Harrison	Mississippi	-0.04		134	Newton	Texas	-0.41
63	Mobile	Alabama	-0.04		135	Webb	Texas	-0.42
64	Suwannee	Florida	-0.04		136	St. John the Baptist	Louisiana	-0.43
65	Levy	Florida	-0.04		137	Bee	Texas	-0.44
66	Sabine	Louisiana	-0.04		138	Hardee	Florida	-0.48
67	Madison	Florida	-0.04		139	Kenedy	Texas	-0.49
68	Stone	Mississippi	-0.05		140	Duval	Texas	-0.49
69	St. Mary	Louisiana	-0.06		141	West Feliciana	Louisiana	-0.50
70	Washington	Florida	-0.06		142	Willacy	Texas	-0.51
71	Gilchrist	Florida	-0.06		143	St. Bernard	Louisiana	-0.54
72	Tyler	Texas	-0.06		144	Starr	Texas	-0.63

Table E-4: Human Capital Sub-index Ranking Score by County

Rank	County	State	Human capital Score		Rank	County	State	Human capital Score
1	Franklin	Florida	1.34		73	Pearl River	Mississippi	-0.04
2	Liberty	Florida	1.09		74	Lavaca	Texas	-0.07
3	Orleans	Louisiana	0.81		75	Decatur	Georgia	-0.07
4	Bay	Florida	0.73		76	DeSoto	Florida	-0.07
5	Sarasota	Florida	0.73		77	Kleberg	Texas	-0.09
6	Gulf	Florida	0.71		78	Glades	Florida	-0.09
7	Monroe	Florida	0.65		79	West Feliciana	Louisiana	-0.09
8	East Baton Rouge	Louisiana	0.64		80	Matagorda	Texas	-0.10
9	Okaloosa	Florida	0.61		81	Tangipahoa	Louisiana	-0.10
10	Walton	Florida	0.59		82	Orange	Texas	-0.10
11	Hillsborough	Florida	0.55		83	Chambers	Texas	-0.11
12	Leon	Florida	0.53		84	Colorado	Texas	-0.12

13	Jackson	Florida	0.53		85	Dixie	Florida	-0.12
14	Polk	Florida	0.49		86	Plaquemines	Louisiana	-0.12
15	Manatee	Florida	0.47		87	Covington	Alabama	-0.13
16	Collier	Florida	0.43		88	Refugio	Texas	-0.15
17	Pinellas	Florida	0.43		89	Hendry	Florida	-0.16
18	Jefferson	Florida	0.41		90	St. Mary	Louisiana	-0.18
19	Wakulla	Florida	0.40		91	Assumption	Louisiana	-0.18
20	Citrus	Florida	0.39		92	Fayette	Texas	-0.19
21	Lee	Florida	0.35		93	St. Helena	Louisiana	-0.19
22	St. Tammany	Louisiana	0.35		94	Washington	Louisiana	-0.19
23	Hancock	Mississippi	0.33		95	St. John the Baptist	Louisiana	-0.19
24	Pasco	Florida	0.32		96	Hardee	Florida	-0.19
25	Mobile	Alabama	0.32		97	Pike	Mississippi	-0.20
26	Charlotte	Florida	0.31		98	St. James	Louisiana	-0.20
27	Suwannee	Florida	0.30		99	Amite	Mississippi	-0.20
28	Gilchrist	Florida	0.29		100	Jackson	Texas	-0.22
29	Harris	Texas	0.29		101	Live Oak	Texas	-0.22
30	Jefferson	Texas	0.29		102	Geneva	Alabama	-0.22
31	Escambia	Florida	0.28		103	St. Landry	Louisiana	-0.22
32	Galveston	Texas	0.28		104	Avoyelles	Louisiana	-0.22
33	Lafayette	Louisiana	0.25		105	Vermilion	Louisiana	-0.22
34	Baldwin	Alabama	0.25		106	Lafourche	Louisiana	-0.22
35	Washington	Florida	0.25		107	Brooks	Texas	-0.25
36	Jefferson	Louisiana	0.25		108	Cameron	Louisiana	-0.25
37	Rapides	Louisiana	0.24		109	Iberville	Louisiana	-0.25
38	Hernando	Florida	0.23		110	Jefferson Davis	Louisiana	-0.26
39	Washington	Texas	0.22		111	Pointe Coupee	Louisiana	-0.26
40	Santa Rosa	Florida	0.19		112	Sabine	Louisiana	-0.27
41	Marion	Florida	0.19		113	Wilkinson	Mississippi	-0.27
42	Harrison	Mississippi	0.18		114	Acadia	Louisiana	-0.27
43	Fort Bend	Texas	0.18		115	Iberia	Louisiana	-0.28
44	Lake	Florida	0.17		116	Liberty	Texas	-0.28
45	Sumter	Florida	0.17		117	Jasper	Texas	-0.29
46	Levy	Florida	0.15		118	Stone	Mississippi	-0.29
47	Calhoun	Florida	0.15		119	Escambia	Alabama	-0.29
48	Thomas	Georgia	0.14		120	Goliad	Texas	-0.29
49	Victoria	Texas	0.14		121	Wharton	Texas	-0.29
50	Austin	Texas	0.12		122	San Patricio	Texas	-0.30
51	Taylor	Florida	0.11		123	Evangeline	Louisiana	-0.32
52	Terrebonne	Louisiana	0.09		124	Bee	Texas	-0.35
53	Gadsden	Florida	0.09		125	Clarke	Alabama	-0.36
54	West Baton Rouge	Louisiana	0.08		126	DeWitt	Texas	-0.36
55	St. Charles	Louisiana	0.08		127	Tyler	Texas	-0.36
56	Nueces	Texas	0.07		128	Jim Wells	Texas	-0.37
57	Brazoria	Texas	0.06		129	Newton	Texas	-0.37
58	Aransas	Texas	0.05		130	Washington	Alabama	-0.38
59	George	Mississippi	0.05		131	Grady	Georgia	-0.39
60	Lamar	Mississippi	0.05		132	Marion	Mississippi	-0.40
61	East Feliciana	Louisiana	0.05		133	St. Martin	Louisiana	-0.43
62	Beauregard	Louisiana	0.05		134	Vernon	Louisiana	-0.43
63	Waller	Texas	0.04		135	Monroe	Alabama	-0.44
64	Calcasieu	Louisiana	0.03		136	Webb	Texas	-0.51
65	Madison	Florida	0.03		137	Cameron	Texas	-0.52
66	Ascension	Louisiana	0.02		138	Walthall	Mississippi	-0.57
67	Calhoun	Texas	0.01		139	Jim Hogg	Texas	-0.62
68	Holmes	Florida	0.00		140	Hidalgo	Texas	-0.64
69	Jackson	Mississippi	0.00		141	Duval	Texas	-0.64
70	St. Bernard	Louisiana	-0.01		142	Willacy	Texas	-0.75
71	Livingston	Louisiana	-0.02		143	Kenedy	Texas	-0.92
72	Lafayette	Florida	-0.03		144	Starr	Texas	-0.92

APPENDIX F

DISASTER PHASE'S SUB-INDEX MEAN SCORE BY COUNTY

Table F-1: Mitigation Sub-index Ranking Score by County

Rank	County	State	Mitigation Sub-index Score	Rank	County	State	Mitigation Sub-index Score
1	Monroe	Florida	1.38	73	Wharton	Texas	-0.07
2	Collier	Florida	1.28	74	Marion	Mississippi	-0.07
3	Leon	Florida	1.25	75	Pearl River	Mississippi	-0.08
4	Sarasota	Florida	1.24	76	George	Mississippi	-0.09
5	Franklin	Florida	0.89	77	Clarke	Alabama	-0.09
6	Walton	Florida	0.87	78	Sumter	Florida	-0.10
7	Lee	Florida	0.87	79	Matagorda	Texas	-0.10
8	East Baton Rouge	Louisiana	0.86	80	St. Bernard	Louisiana	-0.12
9	Baldwin	Alabama	0.86	81	Orange	Texas	-0.12
10	Hillsborough	Florida	0.79	82	Geneva	Alabama	-0.12
11	Okaloosa	Florida	0.78	83	Vermilion	Louisiana	-0.12
12	St. Tammany	Louisiana	0.77	84	Calhoun	Texas	-0.13
13	Lafayette	Louisiana	0.76	85	Tangipahoa	Louisiana	-0.13
14	Fayette	Texas	0.72	86	Jefferson Davis	Louisiana	-0.14
15	Manatee	Florida	0.69	87	Iberia	Louisiana	-0.14
16	Bay	Florida	0.63	88	Liberty	Florida	-0.15
17	Lake	Florida	0.63	89	Jackson	Florida	-0.15
18	Austin	Texas	0.62	90	St. James	Louisiana	-0.17
19	Pinellas	Florida	0.61	91	Cameron	Louisiana	-0.17
20	Fort Bend	Texas	0.61	92	St. John the Baptist	Louisiana	-0.19
21	Gulf	Florida	0.58	93	DeWitt	Texas	-0.19
22	Santa Rosa	Florida	0.49	94	St. Mary	Louisiana	-0.20
23	Charlotte	Florida	0.48	95	Amite	Mississippi	-0.20
24	Citrus	Florida	0.47	96	Gadsden	Florida	-0.21
25	Washington	Texas	0.47	97	Pointe Coupee	Louisiana	-0.21
26	Lavaca	Texas	0.43	98	Jasper	Texas	-0.21
27	Jefferson	Louisiana	0.41	99	Assumption	Louisiana	-0.22
28	Waller	Texas	0.40	100	Live Oak	Texas	-0.23
29	Hernando	Florida	0.38	101	Decatur	Georgia	-0.24
30	Jefferson	Florida	0.31	102	Escambia	Alabama	-0.26
31	Wakulla	Florida	0.31	103	Kleberg	Texas	-0.28
32	Galveston	Texas	0.31	104	St. Martin	Louisiana	-0.28
33	St. Charles	Louisiana	0.30	105	DeSoto	Florida	-0.30
34	Polk	Florida	0.29	106	Hendry	Florida	-0.30
35	Escambia	Florida	0.28	107	Sabine	Louisiana	-0.32
36	Harris	Texas	0.26	108	Monroe	Alabama	-0.32
37	Marion	Florida	0.26	109	Madison	Florida	-0.34
38	Victoria	Texas	0.26	110	San Patricio	Texas	-0.34
39	Lamar	Mississippi	0.25	111	Calhoun	Florida	-0.35
40	Pasco	Florida	0.24	112	East Feliciana	Louisiana	-0.35
41	Mobile	Alabama	0.24	113	Brooks	Texas	-0.36
42	Ascension	Louisiana	0.24	114	Liberty	Texas	-0.36
43	Aransas	Texas	0.23	115	Grady	Georgia	-0.36
44	Colorado	Texas	0.23	116	Holmes	Florida	-0.38
45	Rapides	Louisiana	0.21	117	Iberville	Louisiana	-0.39
46	Goliad	Texas	0.21	118	Acadia	Louisiana	-0.39
47	West Baton Rouge	Louisiana	0.18	119	St. Landry	Louisiana	-0.41
48	Harrison	Mississippi	0.16	120	Washington	Alabama	-0.42
49	Thomas	Georgia	0.16	121	Hardee	Florida	-0.45
50	Covington	Alabama	0.15	122	Washington	Louisiana	-0.46
51	Terrebonne	Louisiana	0.14	123	Avoyelles	Louisiana	-0.47
52	Calcasieu	Louisiana	0.14	124	Lafayette	Florida	-0.48
53	Brazoria	Texas	0.13	125	Tyler	Texas	-0.49
54	Chambers	Texas	0.11	126	Jim Wells	Texas	-0.50
55	Levy	Florida	0.09	127	Walthall	Mississippi	-0.51
56	Jackson	Mississippi	0.09	128	Glades	Florida	-0.52
57	Livingston	Louisiana	0.08	129	Dixie	Florida	-0.52
58	Hancock	Mississippi	0.07	130	Evangeline	Louisiana	-0.58

59	Jefferson	Texas	0.07	131	St. Helena	Louisiana	-0.60
60	Nueces	Texas	0.06	132	Jim Hogg	Texas	-0.61
61	Suwannee	Florida	0.04	133	Webb	Texas	-0.64
62	Washington	Florida	0.02	134	Wilkinson	Mississippi	-0.65
63	Refugio	Texas	0.01	135	West Feliciana	Louisiana	-0.67
64	Orleans	Louisiana	0.00	136	Newton	Texas	-0.67
65	Plaquemines	Louisiana	0.00	137	Cameron	Texas	-0.72
66	Lafourche	Louisiana	-0.02	138	Vernon	Louisiana	-0.77
67	Beauregard	Louisiana	-0.03	139	Hidalgo	Texas	-0.79
68	Gilchrist	Florida	-0.04	140	Kenedy	Texas	-0.79
69	Jackson	Texas	-0.04	141	Bee	Texas	-0.83
70	Taylor	Florida	-0.05	142	Duval	Texas	-1.04
71	Stone	Mississippi	-0.05	143	Willacy	Texas	-1.07
72	Pike	Mississippi	-0.06	144	Starr	Texas	-1.30

Table F-2: Preparedness Sub-index Ranking Score by County

Rank	County	State	Preparedness Sub-index Score	Rank	County	State	Preparedness Sub-index Score
1	Monroe	Florida	2.01	73	Lafourche	Louisiana	-0.10
2	Collier	Florida	1.39	74	Brooks	Texas	-0.10
3	Sarasota	Florida	1.38	75	East Feliciana	Louisiana	-0.11
4	Okaloosa	Florida	1.12	76	Covington	Alabama	-0.13
5	Leon	Florida	1.10	77	Hendry	Florida	-0.13
6	Hancock	Mississippi	1.09	78	Jasper	Texas	-0.14
7	Franklin	Florida	0.90	79	Terrebonne	Louisiana	-0.15
8	Baldwin	Alabama	0.90	80	Beauregard	Louisiana	-0.15
9	East Baton Rouge	Louisiana	0.88	81	St. Bernard	Louisiana	-0.15
10	St. Tammany	Louisiana	0.84	82	Iberia	Louisiana	-0.15
11	Hillsborough	Florida	0.80	83	St. John the Baptist	Louisiana	-0.15
12	Pinellas	Florida	0.74	84	Suwannee	Florida	-0.16
13	Lee	Florida	0.72	85	Pointe Coupee	Louisiana	-0.16
14	Lafayette	Louisiana	0.72	86	Refugio	Texas	-0.18
15	Fort Bend	Texas	0.67	87	Pearl River	Mississippi	-0.18
16	Orleans	Louisiana	0.67	88	Grady	Georgia	-0.18
17	Manatee	Florida	0.64	89	Orange	Texas	-0.21
18	Bay	Florida	0.62	90	DeWitt	Texas	-0.21
19	Lake	Florida	0.61	91	Tangipahoa	Louisiana	-0.24
20	Walton	Florida	0.54	92	Jackson	Texas	-0.25
21	Gulf	Florida	0.47	93	Marion	Mississippi	-0.25
22	Santa Rosa	Florida	0.47	94	Clarke	Alabama	-0.25
23	Charlotte	Florida	0.47	95	Stone	Mississippi	-0.26
24	Wakulla	Florida	0.46	96	St. James	Louisiana	-0.26
25	Harris	Texas	0.46	97	San Patricio	Texas	-0.26
26	Pasco	Florida	0.45	98	Plaquemines	Louisiana	-0.27
27	Jefferson	Louisiana	0.44	99	Escambia	Alabama	-0.27
28	Fayette	Texas	0.41	100	West Feliciana	Louisiana	-0.27
29	Rapides	Louisiana	0.41	101	Calhoun	Texas	-0.28
30	Escambia	Florida	0.39	102	Vermilion	Louisiana	-0.30
31	Austin	Texas	0.38	103	Gadsden	Florida	-0.30
32	Gilchrist	Florida	0.37	104	Lafayette	Florida	-0.30
33	Galveston	Texas	0.36	105	Holmes	Florida	-0.32
34	Mobile	Alabama	0.36	106	Iberville	Louisiana	-0.32
35	Goliad	Texas	0.33	107	St. Mary	Louisiana	-0.33
36	Citrus	Florida	0.32	108	Monroe	Alabama	-0.33
37	St. Charles	Louisiana	0.32	109	Sabine	Louisiana	-0.34
38	Washington	Texas	0.31	110	Cameron	Louisiana	-0.35
39	Waller	Texas	0.30	111	Amite	Mississippi	-0.35
40	Harrison	Mississippi	0.27	112	Washington	Louisiana	-0.35
41	Polk	Florida	0.22	113	Calhoun	Florida	-0.37
42	Marion	Florida	0.21	114	Washington	Alabama	-0.38

43	Jackson	Florida	0.21		115	Vernon	Louisiana	-0.38
44	Hernando	Florida	0.19		116	Live Oak	Texas	-0.39
45	Aransas	Texas	0.18		117	Assumption	Louisiana	-0.40
46	Wharton	Texas	0.18		118	Liberty	Texas	-0.40
47	Ascension	Louisiana	0.17		119	St. Landry	Louisiana	-0.40
48	West Baton Rouge	Louisiana	0.14		120	Walthall	Mississippi	-0.40
49	Lavaca	Texas	0.13		121	Tyler	Texas	-0.42
50	Victoria	Texas	0.13		122	Acadia	Louisiana	-0.44
51	Brazoria	Texas	0.13		123	DeSoto	Florida	-0.45
52	Nueces	Texas	0.13		124	Avoyelles	Louisiana	-0.47
53	Madison	Florida	0.13		125	St. Martin	Louisiana	-0.50
54	Taylor	Florida	0.10		126	Glades	Florida	-0.50
55	Thomas	Georgia	0.09		127	Kleberg	Texas	-0.51
56	Calcasieu	Louisiana	0.06		128	Dixie	Florida	-0.51
57	Colorado	Texas	0.03		129	St. Helena	Louisiana	-0.51
58	Jefferson	Texas	0.02		130	Wilkinson	Mississippi	-0.51
59	Washington	Florida	0.02		131	Newton	Texas	-0.52
60	Sumter	Florida	0.02		132	Evangeline	Louisiana	-0.54
61	Jackson	Mississippi	-0.01		133	Liberty	Florida	-0.58
62	Matagorda	Texas	-0.01		134	Kenedy	Texas	-0.58
63	Lamar	Mississippi	-0.02		135	Jim Wells	Texas	-0.59
64	Livingston	Louisiana	-0.02		136	Hardee	Florida	-0.60
65	Jefferson Davis	Louisiana	-0.02		137	Bee	Texas	-0.66
66	Jefferson	Florida	-0.03		138	Jim Hogg	Texas	-0.73
67	George	Mississippi	-0.03		139	Cameron	Texas	-0.80
68	Decatur	Georgia	-0.03		140	Webb	Texas	-0.86
69	Chambers	Texas	-0.06		141	Hidalgo	Texas	-0.95
70	Pike	Mississippi	-0.06		142	Duval	Texas	-1.01
71	Geneva	Alabama	-0.07		143	Willacy	Texas	-1.07
72	Levy	Florida	-0.10		144	Starr	Texas	-1.50

Table F-3: Response Sub-index Ranking Score by County

Rank	County	State	Response Sub-index Score		Rank	County	State	Response Sub-index Score
1	Monroe	Florida	1.58		73	Waller	Texas	-0.06
2	Franklin	Florida	1.24		74	Sumter	Florida	-0.06
3	Sarasota	Florida	1.07		75	Livingston	Louisiana	-0.06
4	Collier	Florida	1.03		76	Terrebonne	Louisiana	-0.06
5	Leon	Florida	1.02		77	Geneva	Alabama	-0.07
6	Lee	Florida	0.75		78	Lafourche	Louisiana	-0.07
7	Baldwin	Alabama	0.68		79	Jasper	Texas	-0.07
8	Fayette	Texas	0.64		80	Orange	Texas	-0.07
9	St. Tammany	Louisiana	0.59		81	Jackson	Texas	-0.08
10	Pinellas	Florida	0.59		82	Holmes	Florida	-0.10
11	Manatee	Florida	0.59		83	Decatur	Georgia	-0.11
12	Okaloosa	Florida	0.58		84	East Feliciana	Louisiana	-0.11
13	Walton	Florida	0.58		85	Escambia	Alabama	-0.11
14	East Baton Rouge	Louisiana	0.56		86	Lafayette	Florida	-0.11
15	Charlotte	Florida	0.55		87	Marion	Mississippi	-0.12
16	Goliad	Texas	0.54		88	Sabine	Louisiana	-0.12
17	Lake	Florida	0.53		89	Iberia	Louisiana	-0.13
18	Bay	Florida	0.51		90	Pearl River	Mississippi	-0.13
19	Lafayette	Louisiana	0.49		91	St. James	Louisiana	-0.14
20	Hillsborough	Florida	0.48		92	Gadsden	Florida	-0.15
21	Citrus	Florida	0.47		93	Stone	Mississippi	-0.16
22	Lavaca	Texas	0.42		94	St. Bernard	Louisiana	-0.17
23	Santa Rosa	Florida	0.41		95	Tangipahoa	Louisiana	-0.17
24	Fort Bend	Texas	0.40		96	St. Mary	Louisiana	-0.17
25	Washington	Texas	0.40		97	St. John the Baptist	Louisiana	-0.18

26	Gulf	Florida	0.37		98	Monroe	Alabama	-0.19
27	Hernando	Florida	0.37		99	Cameron	Louisiana	-0.19
28	Colorado	Texas	0.35		100	Calhoun	Florida	-0.19
29	Austin	Texas	0.33		101	Grady	Georgia	-0.20
30	Galveston	Texas	0.33		102	Vermilion	Louisiana	-0.20
31	Rapides	Louisiana	0.30		103	Jefferson Davis	Louisiana	-0.21
32	Thomas	Georgia	0.30		104	Tyler	Texas	-0.21
33	Jefferson	Louisiana	0.29		105	Madison	Florida	-0.22
34	Victoria	Texas	0.28		106	St. Helena	Louisiana	-0.22
35	Pasco	Florida	0.27		107	Pointe Coupee	Louisiana	-0.23
36	Escambia	Florida	0.24		108	Live Oak	Texas	-0.23
37	Jefferson	Florida	0.24		109	Liberty	Florida	-0.23
38	Wakulla	Florida	0.23		110	Walthall	Mississippi	-0.25
39	Taylor	Florida	0.22		111	Acadia	Louisiana	-0.25
40	Marion	Florida	0.21		112	Amite	Mississippi	-0.26
41	Aransas	Texas	0.21		113	Washington	Alabama	-0.26
42	St. Charles	Louisiana	0.18		114	Plaquemines	Louisiana	-0.27
43	Polk	Florida	0.16		115	Washington	Louisiana	-0.28
44	Calcasieu	Louisiana	0.16		116	Liberty	Texas	-0.32
45	George	Mississippi	0.16		117	Wilkinson	Mississippi	-0.32
46	Covington	Alabama	0.15		118	Avoyelles	Louisiana	-0.33
47	Mobile	Alabama	0.13		119	DeSoto	Florida	-0.34
48	Hancock	Mississippi	0.12		120	Assumption	Louisiana	-0.36
49	Harrison	Mississippi	0.11		121	Dixie	Florida	-0.36
50	Ascension	Louisiana	0.09		122	Iberville	Louisiana	-0.37
51	Brazoria	Texas	0.09		123	St. Landry	Louisiana	-0.37
52	Calhoun	Texas	0.09		124	Glades	Florida	-0.37
53	Jackson	Florida	0.08		125	San Patricio	Texas	-0.40
54	Levy	Florida	0.07		126	Kleberg	Texas	-0.40
55	Lamar	Mississippi	0.06		127	Brooks	Texas	-0.41
56	Refugio	Texas	0.05		128	Newton	Texas	-0.42
57	DeWitt	Texas	0.05		129	Hendry	Florida	-0.45
58	West Baton Rouge	Louisiana	0.04		130	St. Martin	Louisiana	-0.46
59	Jefferson	Texas	0.04		131	West Feliciana	Louisiana	-0.47
60	Wharton	Texas	0.03		132	Jim Wells	Texas	-0.47
61	Jackson	Mississippi	0.03		133	Kenedy	Texas	-0.49
62	Chambers	Texas	0.03		134	Jim Hogg	Texas	-0.50
63	Pike	Mississippi	0.03		135	Evangeline	Louisiana	-0.51
64	Suwannee	Florida	0.02		136	Hardee	Florida	-0.56
65	Harris	Texas	-0.01		137	Bee	Texas	-0.60
66	Washington	Florida	-0.02		138	Vernon	Louisiana	-0.62
67	Clarke	Alabama	-0.02		139	Cameron	Texas	-0.85
68	Orleans	Louisiana	-0.03		140	Webb	Texas	-0.88
69	Gilchrist	Florida	-0.03		141	Duval	Texas	-0.96
70	Nueces	Texas	-0.03		142	Hidalgo	Texas	-0.97
71	Beauregard	Louisiana	-0.03		143	Willacy	Texas	-1.03
72	Matagorda	Texas	-0.05		144	Starr	Texas	-1.55

Table F-4: Recovery Sub-index Ranking Score by County

Rank	County	State	Recovery Score		Rank	County	State	Recovery Score
1	Collier	Florida	1.29		73	Stone	Mississippi	0.03
2	Monroe	Florida	1.27		74	Gilchrist	Florida	0.01
3	Walton	Florida	1.18		75	Orange	Texas	0.01
4	Sarasota	Florida	1.13		76	Lafourche	Louisiana	0.00
5	Leon	Florida	1.08		77	Beauregard	Louisiana	-0.02
6	Lee	Florida	0.96		78	Wharton	Texas	-0.03
7	Baldwin	Alabama	0.91		79	Jasper	Texas	-0.04
8	East Baton Rouge	Louisiana	0.87		80	Jefferson Davis	Louisiana	-0.04
9	St. Tammany	Louisiana	0.79		81	Liberty	Florida	-0.06
10	Okaloosa	Florida	0.78		82	Tangipahoa	Louisiana	-0.09
11	Fayette	Texas	0.75		83	Clarke	Alabama	-0.13
12	Lake	Florida	0.74		84	Geneva	Alabama	-0.14

13	Austin	Texas	0.74		85	Pearl River	Mississippi	-0.14
14	Lafayette	Louisiana	0.72		86	Live Oak	Texas	-0.15
15	Bay	Florida	0.66		87	St. Mary	Louisiana	-0.16
16	Fort Bend	Texas	0.63		88	Orleans	Louisiana	-0.18
17	Manatee	Florida	0.59		89	Assumption	Louisiana	-0.19
18	Santa Rosa	Florida	0.59		90	Calhoun	Florida	-0.20
19	Hillsborough	Florida	0.58		91	DeSoto	Florida	-0.20
20	Washington	Texas	0.57		92	Taylor	Florida	-0.22
21	Pinellas	Florida	0.50		93	Gadsden	Florida	-0.22
22	Wakulla	Florida	0.50		94	Vermilion	Louisiana	-0.22
23	Charlotte	Florida	0.49		95	Pointe Coupee	Louisiana	-0.22
24	Franklin	Florida	0.48		96	San Patricio	Texas	-0.23
25	Colorado	Texas	0.45		97	Matagorda	Texas	-0.24
26	Covington	Alabama	0.45		98	Sumter	Florida	-0.24
27	Lavaca	Texas	0.44		99	Iberia	Louisiana	-0.24
28	Ascension	Louisiana	0.41		100	St. John the Baptist	Louisiana	-0.24
29	Waller	Texas	0.40		101	Escambia	Alabama	-0.25
30	Citrus	Florida	0.39		102	Liberty	Texas	-0.26
31	Jefferson	Louisiana	0.38		103	Pike	Mississippi	-0.27
32	Goliad	Texas	0.37		104	Decatur	Georgia	-0.28
33	St. Charles	Louisiana	0.35		105	Holmes	Florida	-0.29
34	Galveston	Texas	0.34		106	St. Bernard	Louisiana	-0.29
35	Refugio	Texas	0.33		107	Sabine	Louisiana	-0.30
36	Jackson	Texas	0.31		108	Grady	Georgia	-0.30
37	Gulf	Florida	0.30		109	Washington	Alabama	-0.32
38	Hernando	Florida	0.30		110	St. James	Louisiana	-0.34
39	Lamar	Mississippi	0.29		111	Kleberg	Texas	-0.34
40	Chambers	Texas	0.29		112	St. Martin	Louisiana	-0.36
41	Marion	Florida	0.28		113	East Feliciana	Louisiana	-0.38
42	Escambia	Florida	0.26		114	Madison	Florida	-0.42
43	Victoria	Texas	0.25		115	Iberville	Louisiana	-0.42
44	Harris	Texas	0.25		116	Acadia	Louisiana	-0.44
45	Washington	Florida	0.25		117	Amite	Mississippi	-0.44
46	Brazoria	Texas	0.24		118	Monroe	Alabama	-0.45
47	George	Mississippi	0.22		119	St. Landry	Louisiana	-0.45
48	Plaquemines	Louisiana	0.21		120	Tyler	Texas	-0.46
49	Pasco	Florida	0.18		121	Hendry	Florida	-0.46
50	Mobile	Alabama	0.18		122	Avoyelles	Louisiana	-0.50
51	Rapides	Louisiana	0.17		123	Washington	Louisiana	-0.51
52	Polk	Florida	0.17		124	Walthall	Mississippi	-0.52
53	Calcasieu	Louisiana	0.17		125	Newton	Texas	-0.54
54	Livingston	Louisiana	0.15		126	Glades	Florida	-0.56
55	Aransas	Texas	0.14		127	Jim Wells	Texas	-0.57
56	Hancock	Mississippi	0.14		128	Lafayette	Florida	-0.58
57	Thomas	Georgia	0.13		129	St. Helena	Louisiana	-0.61
58	Terrebonne	Louisiana	0.13		130	Dixie	Florida	-0.61
59	Jefferson	Florida	0.12		131	Bee	Texas	-0.64
60	Calhoun	Texas	0.12		132	Hardee	Florida	-0.67
61	Levy	Florida	0.12		133	Wilkinson	Mississippi	-0.68
62	Jim Hogg	Texas	0.12		134	Evangeline	Louisiana	-0.68
63	Harrison	Mississippi	0.11		135	West Feliciana	Louisiana	-0.77
64	West Baton Rouge	Louisiana	0.10		136	Vernon	Louisiana	-0.81
65	Jefferson	Texas	0.09		137	Webb	Texas	-0.88
66	Jackson	Mississippi	0.07		138	Cameron	Texas	-0.90
67	DeWitt	Texas	0.05		139	Kenedy	Texas	-0.94
68	Marion	Mississippi	0.05		140	Hidalgo	Texas	-0.95
69	Cameron	Louisiana	0.05		141	Brooks	Texas	-0.97
70	Suwannee	Florida	0.04		142	Duval	Texas	-1.11
71	Jackson	Florida	0.03		143	Willacy	Texas	-1.27
72	Nueces	Texas	0.03		144	Starr	Texas	-1.60

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