CREATING AN EMPIRICALLY DERIVED COMMUNITY RESILIENCE INDEX OF THE GULF OF MEXICO REGION

A Thesis

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Abstract

As coastal areas increase in populations there is an increasing need to determine what community characteristics are most resilient to coastal disasters. This research proposes two methods to quantify community resilience. The factor analysis method results in a weighted additive index model of six variables to derive community resilience. The index places every community in the Gulf of Mexico on a scale from 0-1. The most resilient counties in the Gulf of Mexico region were found to be Hillsborough, FL, Pinellas, FL, Sarasota, FL, Hernando, FL, Okaloosa, FL, Kenedy, TX, and Jefferson, LA with a resilience score of 1. The least resilient counties in the Gulf of Mexico were found to be Cameron, TX and Willacy, TX with a resilience score of below 0.40. The six key variables used to create the resilience index were expenditures for education, median income, percent of the workforce that is female, mean elevation of the parish, percent of the population below 5 years old, and percent of the population that voted in the 2000 presidential election.

The second method is a discriminant analysis method. In this method an a priori grouping based on the number of coastal hazards, property damage, and population change for each county was derived. Twenty-four social, economic, and environmental variables were input into the discriminant analysis to determine if they can be used to explain and define resilience. The discriminant analysis results in a classification accuracy of 94.2%. Counties found to be in the most resilient group were Hancock, MS, Collier, FL, Baldwin, AL, Escambia, FL, Walton, FL, Lee, FL, Charlotte, FL, Manatee, FL, Santa Rosa, FL, Okaloosa, FL. Counties found to be in the least resilient group were Kleberg, TX, Calhoun, TX, San Patricio, TX, Jefferson, TX, Nueces, TX, Kenedy, TX, and Willacy, TX.

This study represents a preliminary attempt in quantifying community resilience. It outlines the methods that can be used to define resilience and offers a general guideline about the

variables that might contribute to a communities' ability to recover from a coastal disaster. Further refinements with the variables are necessary in future studies.

Chapter 1
Introduction

Coupled human and natural systems, or socio-ecological systems, are integrated systems in which people interact with natural components (Liu J. et al. 2007). Interdisciplinary research to study the interactions of both human and ecosystems have been increasing (Liu J. et al. 2007, Adger 2000, DeFries and Pagiola 2005). Such studies explicitly address the interactions and feedbacks between humans and the natural systems in which they live (Liu J. et al. 2007). Traditional studies examine either the effects natural events on a human system, or study the effects of humans on an ecosystem. Traditional studies have seldom addressed the complex interactions between the two. Natural systems and human systems interact in a variety of ways. They have traditionally been studied in one of two ways: either through the lens of the human system or the lens of the natural system. One type of studies of the effects of natural systems on a human system has focused on the vulnerability of human communities to natural disasters. Termed social vulnerability these studies have examined the susceptibility of social groups to natural hazards and their ability to recover from these disasters (Cutter and Emrich 2006). During the 1950s and 1960s social research that studied the social characteristics of people in a specific place emerged. These studies were used to understand how people could cope with sickness, social inequalities, and environmental equities (Cutter and Emrich 2006). This has evolved into one approach of hazard vulnerability science which uses a mix of demography, sociology, geography and natural science to understand social vulnerability to the effects of disaster events in a natural system (Cutter and Emrich 2006, Adger 2006, Cutter et al. 2000, Boruff et al. 2005).

Studies of ecosystem change originated with the work of Holling in the 1970s. These studies examined ecosystem changes after a disturbance and the ability of an ecosystem to return to its basic form and function (Ahmed 2005). These studies introduced the term resilience into the literature as a function of ecosystems after a disturbance.

In the early 2000s the studies of social and natural systems merged (Adger 2000). From this merging of the two the idea of a socio-ecological system was derived (Walker et al. 2006). Studies of socio-ecological systems gave us a definition of system resilience that included the ability to adapt to change, the ability to learn from previous experiences, and the ability to recover from a shock and still retain the system's basic form and function. These are key concepts of socio-ecological resilience that can be applied to a human system to enhance an understanding of a human system.

One interesting challenge for researchers is finding a way to quantify the theoretical concept of resilience. If vulnerability can be quantified, resilience, its inverse, can also be quantified (Adger 2000, Adger 2006). Resilience is less easily measured than vulnerability in part because resilience includes elements like adaptive capacity and institutional learning. In order to quantify resilience, concepts of vulnerability and the outputs of intuitional learning like return, regrowth and if necessary population loss in hazardous areas will need to be measured.

The research objective of this study is to use the concepts of socio-ecological resilience and vulnerability to empirically define a set of indicators that can measure elements of community resilience. This set of indicators can theoretically be applied across scales and contains elements of adaptive capacity, social capital, economic capital and measures of self governance. One way to do this is a regional approach. This study examines the Gulf of Mexico Region that includes Texas, Louisiana, Mississippi, Alabama, and Florida to compare community resilience by county. What are the variables that reflect elements of adaptive capacity, social capital, economic capital, self governance, and flood depth that are present across the Gulf States the best identify resilience.

Chapter 2 Background

Vulnerability

Folke (2002) defines vulnerability in an ecological sense as “the propensity of an ecological system to suffer harm from exposure to external stress and shocks,” while Cutter (2000) defines vulnerability within a social system as “the potential for loss” (Ahmed 2005). Adger (2006) describes vulnerability in a system where both social elements and ecological elements are considered as the susceptibility to be harmed or a system’s susceptibility to risk and its inability to cope with or absorb a shock. These distinctions between these three definitions of vulnerability are small, but they are derived from different fields of research. Each definition and its research origin provide insights into vulnerability and expands the conceptual understanding of vulnerability.

The three major dimensions of vulnerability include a) exposure to risk or shock, such as ecosystem disturbance, b) the sensitivity of people, places, institutions or ecosystems to stress or perturbations, including their capacity to anticipate and cope with stress, and c) the resilience of exposed people, places and ecosystems in terms of their capacity to absorb shocks and perturbations while maintaining functions. (Kasperson et al. 2005, Cutter et al. 2003).

Natural hazards and disasters are products of both natural variability and human-environment interactions (Kasperson et al. 2005). The extremes of environmental variability are defined as disasters when an event overwhelms local capacity to cope with a particular disturbance (Kasperson et al. 2005). Natural hazards offer a particularly dramatic view of the role of vulnerability in explaining patterns of losses among people and places (Kasperson et al. 2005). Since vulnerability research began in the 1970s greater loss of life among poorer populations has been consistently reported while larger economic damages have been reported in more affluent areas (Kasperson et al. 2005). Natural hazards and disasters have always occurred, but as human populations have grown and management practices have altered our air, water and landscapes, hazards are now less “Acts of God” and more often results of man made changes (Kasperson et al. 2005). Natural hazards research on vulnerability focuses on the physical elements of exposure, probability and the impacts of hazards (Adger 2006, Cutter et al. 2003, Boruff et al. 2005) Natural hazard approaches to vulnerability contend that all types of hazards and all types of social and political upheaval have vastly different impacts on different groups in society. Some vulnerability of the human population is based on where they reside, and the resources they have to cope (Boruff et al. 2005, Adger 2006). The impacts of natural disasters create uneven patterns of loss. There is a tendency to treat natural hazards in separate categories and to treat disasters as discrete, individual events. However, this practice limits insights into the consequences of threats from multiple hazards in one place or a sequence of disasters following one another. Over time, multiple and recurring hazards exacerbate vulnerability. In other words, vulnerability is generally greater during the recovery period, when systems are already damaged. These patterns of differential impact influence efforts to cope with the impacts of environmental variability and degradation (Kasperson et al. 2005).

While environmental changes and natural disasters are affecting increasing numbers of people, the existing knowledge of base vulnerability and resilience is highly uneven with much known about some situations and very little about others. Some of the most vulnerable peoples and places are those about which the least is known (Kasperson et al. 2005). The linkages among environmental change, development and livelihood are attracting increasing attention in building resilient communities and strengthening adaptive capacity, but existing knowledge is still uneven and not well developed (Kasperson et. al 2005). It is still difficult to precisely and adequately document the effects of different changes upon different human groups.

Research on vulnerability within a social systems focuses on the exposure of groups of people or individuals to stress as a result of the impacts of social, political or environmental change (Adger 2000). Vulnerability in a social system is the general disruption to livelihoods and loss of security (Adger 2000). These stresses are pervasive for the poor and marginalized and related to the economic and social situation of groups within a society (Adger 2006, Cutter et al. 2005, and Cutter et al. 2003). Social vulnerability results from many conditions such as exclusion of stake holders from the public policy arena, an incorrect understanding of ecosystem processes, and poor disaster management plans. Poorer households tend to live in riskier areas in urban settlements making them more vulnerable to flooding, disease and chronic stresses. Women are differentially at risk from many elements of environmental hazards including the burden or work in recovery of home and livelihood after an event (Fordham 2003, Adger 2006). Other factors that influence social vulnerability include lack of access to resources, limited access to political power and representation, the presence or absence of social networks and connections, building stock and age, the presence of frail and physically limited individuals and the type and density of infrastructure (Cutter et al. 2003). Elements of social vulnerability are age, gender, race and socioeconomic status, special needs population or those that lack normal social safety nets during disaster recovery, and the quality and density of the built environment (Cutter et al. 2003). Social vulnerability can be observed at different scales and in relation to a range of phenomena such as human induced risks or natural hazards (Adger 2000).

Vulnerability research and resilience research are often convergent. Their common elements are the shocks and stresses experienced by a system, the response of a system to a shock, and the capacity for adaptive action (Adger 2006). Risk and disturbance often define the decision making process (Adger 2006). Socioeconomic and institutional differences are major contributors to patterns of differential vulnerability (Kasperson et al. 2005). Vulnerability, however, is lessened by the elements of resilience (Adger 2006) These are the ability to absorb shocks, the autonomy of self organization, and the capability to adapt (Adger 2006, Gunderson and Holling 2002, Walker et al. 2006).

Many research traditions have tried to measure vulnerability. Vulnerability is a dynamic phenomenon that encompasses both social and biophysical processes (Adger 2006, Boruff et al. 2005, Cutter et al. 2003). Many studies have examined the biophysical elements of risk (Boruff et al. 2005). However, few have tired to quantify social vulnerability to natural hazards. In order to quantify social vulnerability Cutter et al. (2003) created a Social Vulnerability Index to define a set of variables that capture elements of social vulnerability. This index included aspects that measured age race, socioeconomic status, density of the built environment, and special needs populations. Cutter et al. have used this index to evaluate the social vulnerability of the entire United States, the coastal counties of the United States, and the relative impacts of Hurricane Katrina on the Gulf Coast (Cutter et al. 2003, Boruff et al. 2005, Cutter et al. 2005, Cutter and Emrich 2006).

Resilience

Within the ecological literature there are two types of resilience, engineering resilience and ecosystem resilience. Engineering resilience emphasizes control, consistency, efficiency and predictability. Engineering resilience retains stability near a steady state or stable condition (Gunderson and Holling, 2002). Ecosystem resilience focuses on persistence, adaptability, variability and unpredictability. Ecosystem resilience functions in multiple steady states (Gunderson and Holling, 2002). The best working definition of ecosystem resilience – termed resilience throughout this paper is composed of three characteristics: (a) the magnitude of shock a system can absorb and remain within a given state (b) the degree to which the system is capable of self organization, and (c) the degree to which the given system can build capacity for learning and adaption" (Folke 2002, Ahmed 2005). This type of resilience occurs after a disturbance and is related to the system's ability to adapt, reorganize, undergo change, and still maintain its basic structure, function, identity and feedbacks (Walker et al. 2006, Ahmed 2005). Taken from these concepts of ecological resilience our working definition of resilience used in this research is the "ability of a system to absorb a shock and return to the same structure and function through a population return or population growth experienced after a natural disaster."

Originally these concepts of resilience emerged from Holling's work in ecological systems with budworms in the northern forests (Walker et al. 2006). They have been transferred to the dynamic interactions between humans and the ecosystems they live in.

Resilience in social systems has the added capacity of humans to plan and anticipate the future. Humans are also part of the natural world and depend on the ecosystems in which they live to survive. They continuously impact these ecosystems and contribute to their structure and functions. Socio-ecological resilience then is a property of the linkages between ecosystems and human systems (Ahmed 2005, Walker et al. 2006). A socio-ecological system is not bound necessarily by the rules of ecology or by strictly social rules. Instead, a socio-ecological system runs by new rules. (Walker et al. 2006). Walker et al. (2006) argue that typical case studies show that as social systems manage ecosystems for economic gains that ecosystem becomes less able to absorb shocks, and this in turn limits the social system's ability for economic gains. When this happens it is up to the linked socio-ecological system create for itself the ability to adapt. The creation of adaptive capacity is a key feature of social-ecological resilience (Walker 2006).

To take these concepts of what humans add to socio-ecological resilience and then return them to a strictly social system is to enhance the understanding of resilience within a social system. The UN defines resilience as "the capacity of a system, community or society potentially exposed to hazards to adapt, by resisting or changing in order to reach and maintain and acceptable level of functioning and structure. This is determined by the degree to which the social system is capable of organizing itself to increase its capacity for learning from past disasters for better future protection and to improve risk reduction measures" (Ahmed 2005). Examples of social capital that are necessary for resilience include leadership, trust, and social networks within any given community (Walker et al. 2006). Examples of what happens when societal trust is missing include lack of information flow, interference with the structure of the social system, propaganda, restrictions of freedom of association, duress, and corruption (Walker et al. 2006). Examples of all of these are available from the Hurricane Katrina disaster.

One interesting challenge for researchers is finding a way to quantify the theoretical concept of resilience. If vulnerability can be quantified, resilience, its inverse, can also be quantified (Adger 2000, Adger 2006). Resilience is less easily measured than vulnerability in part because resilience includes elements like adaptive capacity and institutional learning. In order to quantify resilience concepts of vulnerability and the outputs of intuitional learning like return, regrowth and if necessary population loss in hazardous areas can be measured.

Vulnerability and resilience vary across time, spatial scales and social groups. Because these are concepts without specific, concrete measurable variables it is important to find a practical way to measure these concepts in order to increase resiliency. By making resilience measurable it is easier to manage for resilience. Developing a measurement of a system's capacity to respond to a shock will facilitate the implementation of governance structures that will allow the system to become more resilient.

One method for measuring resilience is to find quantifiable variables that are easily obtained that demonstrate resilience. Often it is only 3-5 key variables that demonstrate resilience (Walker et al. 2006). This is a reasonable and workable number. Often more complex patterns are likely to mask key patterns that demonstrate resilience (Walker et al. 2006, Yorque et al. 2002). There are two reasons for this: the first reason is humans like simplistic patters that are easily identifiable. The second reason is other empirical studies have shown that a few variables dominate observed system dynamics. (Walker et al. 2006, Yorque et al. 2002).

Given the relationship between vulnerability and resilience and Cutter et. al's method to measure vulnerability, is it possible to create a resilience index? Can we add to existing research on vulnerability to measure adaptive capacity, the ability to self-organize and the ability of a social system to undergo change and still retain the basic structure and function? Can we empirically define these variables? By knowing what variables contribute to a community's, county's or state's resilience managers will be better able to cultivate and develop these traits in order to quickly recover from disturbances.

Chapter 3 Study Area and Data

Gulf of Mexico Region

The focus of this study was the Gulf of Mexico region. This encompasses the states of Texas, Louisiana, Mississippi, Alabama and Florida. Counties selected for this study had some part of their land mass bordering the Gulf of Mexico. A total of 51 counties met this selection criterion and were used in this analysis.

Texas

From 1990 to 2000 Texas's population grew by 22.8 % (U.S. Census Bureau). The coastal counties in Texas grew on average 11% between 1990 and 2000. The county with the highest population growth was Cameron County and the county with the lowest growth was Kleberg County with a population loss of 10%. The 14 Texas coastal counties included in the study area were: Orange County, Jefferson County, Chambers County, Galveston County, Brazoria County, Matagorda County, Calhoun County, Aransas County, San Patricio County, Nueces County, Kleberg County, Kenedy County, Willacy County, and Cameron County. These counties are shown in figure 1.

Louisiana

From 1990 to 2000 Louisiana's population grew by 5.9 %. The coastal counties of Cameron Parish, Iberia Parish, Terrebonne Parish, and Vermillion Parish all grew between 7% and 8%, while Orleans Parish had a population decline of 2.5% and St. Mary Parish had a population loss of -7.9%. The 10 Louisiana coastal counties included in study area were: Cameron Parish, Iberia Parish, Jefferson Parish, Lafourche Parish, Orleans Parish, Plaquemines Parish, St. Bernard Parish, St. Mary Parish, Terrebonne Parish, and Vermillion Parish. These counties are shown in figure 2.

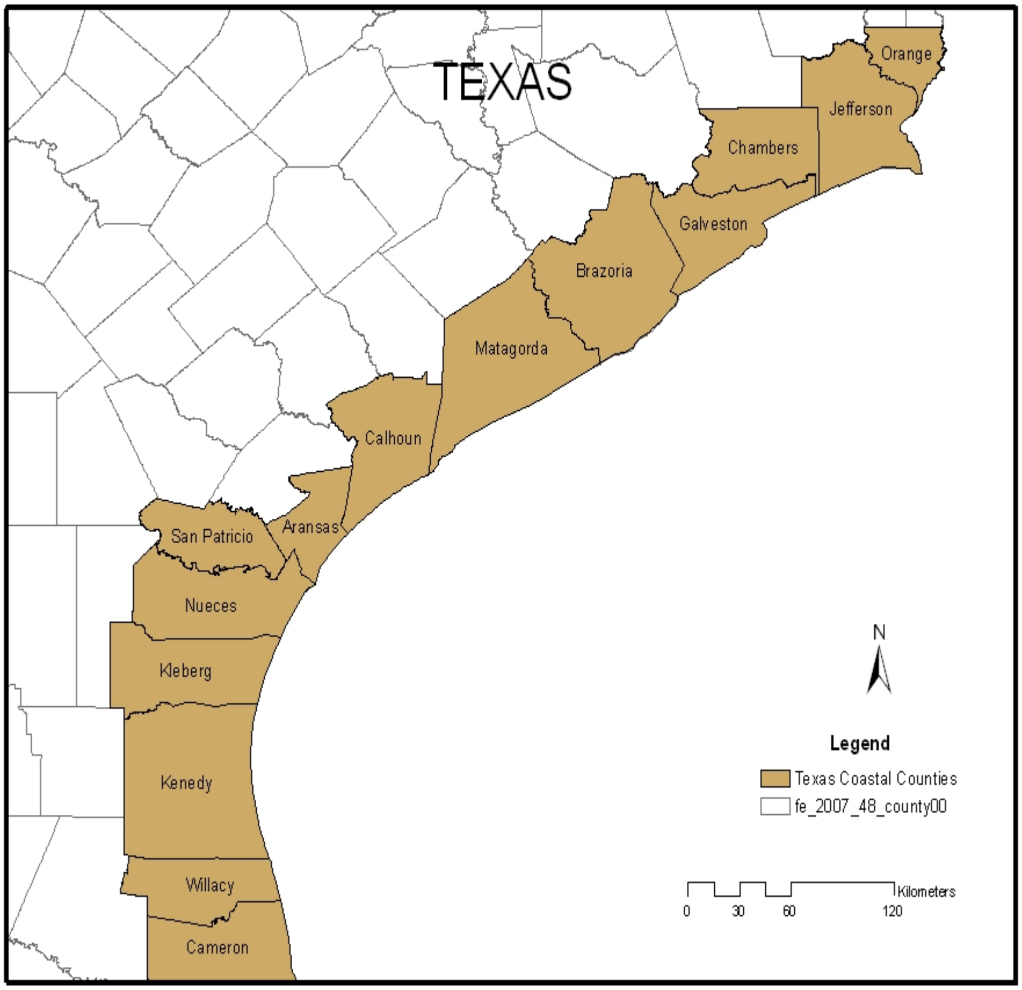

Figure 1: Reference Map of Texas Coastal Counties

Figure 2: Reference Map of Louisiana Coastal Counties

Mississippi

Mississippi experienced a population growth of 10.5% during the decade between 1990 and 2000. All three coastal counties experienced larger than average growth. Rates of change were 35.3% for Hancock County, 14.7% for Harrison County, and 14.7% for Jackson County. These three counties are shown in figure 3.

Alabama

Alabama grew 10.1% from 1990 to 2000. The coastal county of Baldwin, a suburb of Mobile, grew by 42.9% while Mobile County grew by 5.6%. These two counties are shown in figure 3.

Florida

The Florida Gulf Coast contains a mix of rural and urban areas. Florida. Florida grew by 23.5% from 1990 to 2000 (U.S. Census Bureau). Areas with large growth were the panhandle area where Santa Rosa County experienced a 44.3 % increase in population. In the same area Walton county grew by 46.3% and Wakulla County grew by 61%. In the more southern part of Florida Collier County grew by 65.3%, while its neighboring counties Lee and Charlotte grew 31.6% and 27.6% respectively. Monroe County, which is largely inhabited except for the Florida Keys grew the least at 2%. The twenty three Florida counties included in this analysis were all counties bordering the Gulf of Mexico. These were: Bay County, Charlotte County, Citrus County, Collier County, Dixie County, Escambia County, Franklin County, Gulf County, Hernando County, Hillsborough County, Jefferson County, Lee County, Levy County, Manatee County, Monroe County, Okaloosa County, Pasco County, Pinellas County, Santa Rosa County Sarasota County, Taylor County, Wakulla County, and Walton County. These counties are shown in figure 4.

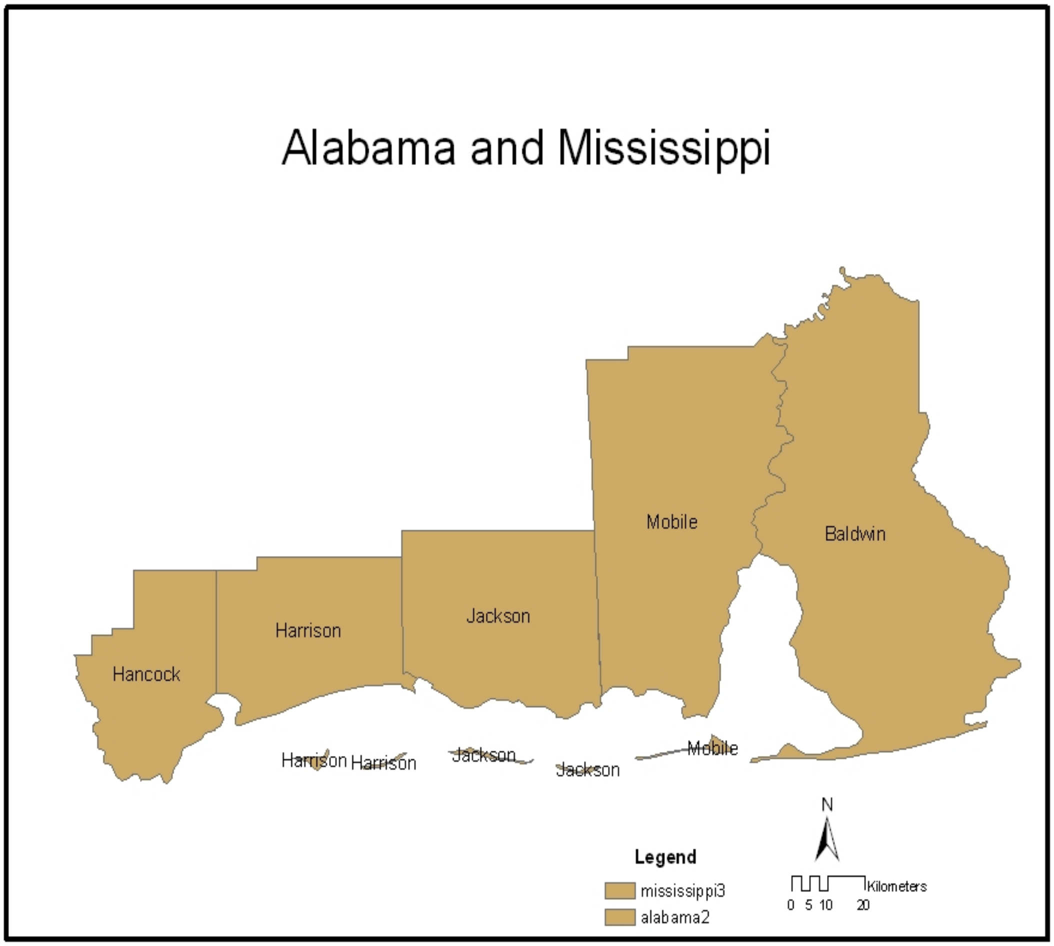

Figure 3: Reference Map of Mississippi and Alabama Coastal Counties

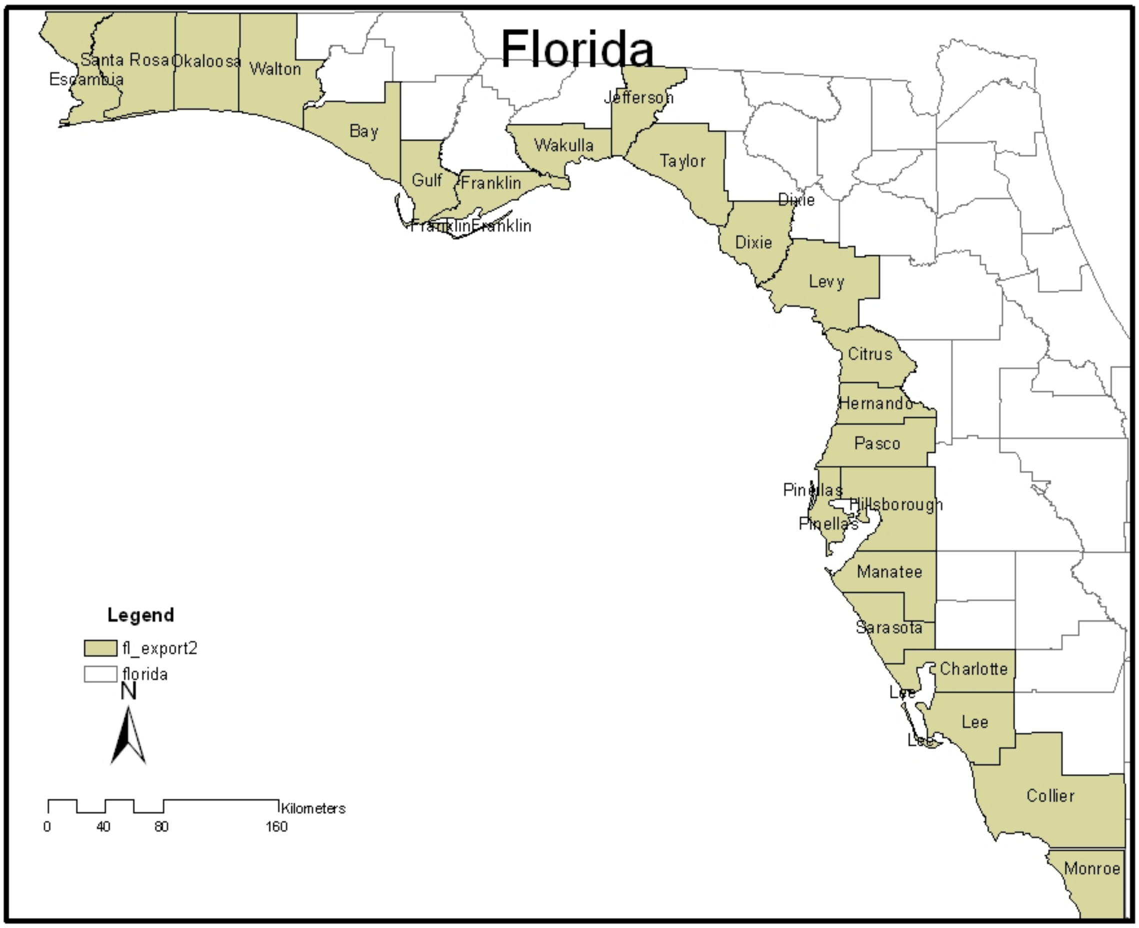

Figure 4: Reference Map of Florida's Gulf of Mexico Coastal Counties

Data

Demographic and economic data used in this study was obtained from the U.S. Census Bureau 2000 Census of Population, and the 1997 and 2002 Economic Census. This data was obtained from http://censtats.census.gov/usa/usa.shtml on February 12, 2008. Environmental data was obtained in two different ways that will be discussed in more detail in the next chapter. Toxic Release Inventory Data was obtained from the U.S. Environmental Protection Agency and was obtained from the website: http://www.epa.gov/triexplorer/chemical.htm. on June 6, 2008. Digital elevation data was available from the USGS seamless map server at the website http://seamless.usgs.gov and was obtained on June 16, 2008. The final data set used in this analysis was the coastal hazards data set made available by the University of South Carolina's Coastal Hazard's Lab. This data is available through the SHELDUS website and can be obtained at http://www.sheldus.org. This was accessed on September 8, 2008.

Chapter 4 Methods

Cutter's Social Vulnerability Index

The social aspects of vulnerability were first quantified by Cutter et al. (2003). Prior to this, previous work had examined physical vulnerability, but there was not comprehensive study that compared place based social vulnerability (Cutter et al. 2003). This is in a large part due to the difficulty of using indicators for social research, and also because social vulnerability is place based and depends largely on characteristics like urbanization, and growth rates that vary from place to place. In order to approach this concept Cutter et al. examined the social aspect of vulnerability (2003). They developed the Social Vulnerability Index by selecting 42 socio economic variables from the U.S. Census that demonstrated aspects identified by the literature as indicators of social vulnerability. They conducted a factor analysis in the form of principal component analysis to create an index of these variables in order to measure social vulnerability. The index was an additive model computed from the factor scores of 11 factors that combined these variables. These 11 factors accounted for 76.4 percent of the variance. In their analysis, Cutter et. al (2003) did not weight the factor scores in order to make no assumptions about the importance of each factor. They used the factor scores to create a relative index of vulnerability. This index was mapped using standard deviations from the mean to determine vulnerability. Those counties with the highest standard deviations from the mean were described as the most vulnerable while those with the lowest standard deviations were described as the least vulnerable.

In order to verify the accuracy of their index, Cutter et al. (2003) correlated the number of presidential disaster declarations with the vulnerability score given to each county with their index. They found literally no correlation ($r=-0.099$, $s=0.000$) between the vulnerability index and these political designations. The results from the Social Vulnerability index are inconclusive because they do not correlate with any damage from disasters, or other measures of recovery. They are in fact a suggestion about where the damage might be the highest due to socio-economic factors, but they have yet to be empirically proven.

There are a few ways in which Cutter's method (2003) could be improved. First the factor analysis method might be changed. This would presumably give different results. Instead of using a principal component analysis to create the factors a principal axis factoring method could be used. A principal component analysis seeks to explain all the common and unique variance of the variables while a principal axis factoring method seeks only to explain the common variances. Secondly, a principal component analysis is a variance based approach while principal axis factoring is a correlation focused approach. This means that in a principal axis factoring method while every variable is included in the analysis not every variable is deemed important. If you are trying to determine what is important a principal axis factoring method acts as a filter while a principal component analysis is all inclusive (Norusis 2003).

Secondly, factor scores are the sum of positive and negative values of variables around an axis for a case. They are in themselves an index of the relationship of indicators to each other. Therefore, to create an index of factor scores is to include all variables into the index, and create an index of an index. This is neither practical nor manageable. Could the factor analysis provide a rule of hand based methodology to discern what variables are important instead of using factor scores?

Thirdly, Cutter et al. made no a priori assumptions about importance. They used an additive model that did not weight the variance explained by each factor. Each factor explains a percent of the variance (i.e. eigenvalue) within the data matrix and this varies based on the relationship of the variables to each within each factor. Therefore each factor should be weighted to its relative importance, and this is statistically determined when the factors are calculated.

We suggest that after these changes are made there will be a stronger positive association between the index and some measure of recovery, like population change or presidential disaster declarations.

Liu and Lam's Discriminant Analysis Method

Another method that might be used to construct an index of resilience would be to use a discriminant analysis. This method was used by Liu and Lam (1985) to construct a vegetation zonal index and determine the probability of a modern analogue.

Discriminant analysis requires an a priori classification of samples into groups. The technique derives linear combinations of variables that are independent of each other (Liu and Lam 1985). This technique can also be used to classify groups with unknown membership into the preexisting classifications (Liu and Lam 1985). In order to run a discriminant analysis five statistical assumptions have to be met. These are: 1) the samples in each group are randomly chosen. 2) The probabilities of a sample belonging to any one group are equal. 3) The samples used to derive the discriminant functions are correctly classified. 4) The variance-covariance matrices of the groups are statistically equal. 5) The variables are normally distributed within each group.

A major difference between factor analysis and discriminant analysis is that discriminant analysis is an inferential statistical method while factor analysis is a descriptive statistical method. In other words, if the statistical assumptions are met the discriminant functions derived can be used to ascribe the resilience level of other counties.

Chapter 5 Factor Analytical Method

The method used by Cutter et al. to measure vulnerability did not correlate well with the presidential disaster declarations. But it is a valuable index that provides a conceptual framework. Resilience can be measured using the same conceptual framework. Quantification of social resilience makes management decisions less arbitrary. This research will contribute to developing a consistent set of indicators that can be used by many different managers to measure community resilience. By measuring this theoretical concept it will allow managers to determine what is important in defining and fostering resilience. This chapter reports the results of using Cutter et al.'s (2003) work on vulnerability as a framework for measuring resilience.

The methods used by Cutter et al. (2003) to create the Social Vulnerability Index were modified to create an index of community resilience. 43 Socioeconomic variables were obtained from the 2000 Census, 36 of these variables were taken from the research of Cutter et al. (2003) and 6 variables were added that measured additional aspects of vulnerability and resilience. All variables are shown in Table 1.

The variables taken from Cutter et al. (2003) were selected because they measure generally accepted aspects of social vulnerability. These aspects of social vulnerability include: lack of access to resources, limited access to political power and representation, social networks and collections, beliefs and customs, building types and age and physically limited individuals (Cutter 2003).

Specific variables that identify these measures of vulnerability are age, gender, race and socioeconomic status. Other measures of the social capital of an area are housing type and abundance, rental properties and housing values.

Table 1: Original variables used to empirically derive factor loadings

Demographic Variables	
PCTBLACK90	Percent African American
PCTINDIAN90	Percent Indian
PCTASIAN90	Percent Asian
PCTKIDS90	Percent of Population under 5years of age
PCTOLD90	Percent of Population over 65
PCTFEM90	Percent of Population that is female
PCTHISPANIC90	Percent Hispanic
MEDAGE90	Median age
AVGPERHH	Average number of people per families
BRATE90	birth rate
Social Capital Variables	
PCTF_HH90	Percent Female headed household
PCTRFRM90	percent rural farm population
PCTMOBL90	Percent of housing units that are mobile homes
PCTRENTER90	percent of housing units that are renter occupied
PCTNOHS90	percent of population over 25 with no high school diploma
FEMLBR90	percent of civilian labor force that is female
PCTVLUM91	percent civilian labor force that is unemployed
TOTCVLBF91	percent of population participating in the labor force
PCTPOV90	percent of population below the poverty level
HOSPCT03	hospitals per capita, 2003
NRRESPC90	Number of nursing home residents per capita
HOUDENUT90	Housing Density per square mile
Economic Variables	
MVALOO90	median value of owner occupied housing
MEDINCOME	Median income
RPROPDEN90	total value of all farm products sold per square mile
EARNDEN90	earnings ($1000) of all establishments per square mile
AGRIPC90	percent employed in primary extractive industries
TRANPC90	percent employed in transportation, communications and other public utilities
SERVPC90	percent employed in service occupations
PCTHH7590	percent of households earning over $75000 per year
SSBENPC90	per capita Social Security recipients
MEDRENT90	Median Rent
MAESDEN92	Number of manufacturing establishments per square mile
PCTFARM92	percent farm land as a percent of total land
SSIREC89	percent of the population that received Supplemental Security Insurance benefits
COMDEVDN92	number of commercial establishments per square mile,
Government Variables	
EXPED	Local expenditures for education
PERVOTE92	percent of population that voted in presidential election
LGFREVPERCAP	Local Government Finance, revenue per capita
PROPTACPC	Property Tax, per capita
GENEXPPC92	Direct General Expenditures per capita,
Environmental Variables	
MELE	County mean elevation above sea level
TRI	lbs of Toxic Release per county

Measures of the economics of the area are commercial development, manufacturing density, earning density, and primary employments in an area. Supplemental Security Income recipients were added as an additional measure of vulnerability. Measures of resilience in the form of local government spending were added. These are listed in the government section of Table 1.

Additional variables that measured environmental aspects were added to determine if they had any significant influence on community resilience. These variables included Toxic Release Inventory (TRI) release rates and mean elevation of the county. TRI numbers measure the amount of chemical pollutants in any given area and were included because they often indicate both socioeconomic conditions and environmental conditions. Elevation was used because it shows the flood depth or height above flood depth. This is very important in a coastal area where hurricanes can lead to storm surges and flooding, and this can lead to loss of home or life in extreme cases.

Toxic Release Inventory data was obtained from the EPA website using the TRI Explorer tool. Release reports were selected for 2000. The data was selected by county, and total on site or offsite disposal or other releases with chemical name was used to obtain a measure of toxic pollution per county for all chemicals across all industries. These numbers were listed in of pounds. Data in the year 2000 ranged from: 0 releases of any chemical in Kleberg, TX, to 55247688 lbs in Escambia County, Florida. The median value of TRI release in the Gulf of Mexico region in the year 2000 was: 283910 lbs of Toxic releases.

The variable elevation was obtained through a multistep process. Data was downloaded from the USGS Seamless Map Server Program in a digital elevation model format (DEM) for the all coastal counties bordering the Gulf of Mexico, and the entire state of Louisiana in a NED 1 arc second data format. This data was added to a GIS using ARCMap 9.2 as a layer file and then exported into a raster file .img. Once in a raster file format this data was able to be combined into one seamless digital elevation data set. This was done for each coastal state. Once the DEMs were seamlessly processed they were added as a layer file to a GIS. Over this layer a coastal county shape file was overlayed. Coastal county data was obtained from the Census Bureau: Counties 2000 shapefile option for all coastal states. Then using the Spatial Analyst Tool, digital elevation for each county was calculated. Mean elevation for each county was selected. These attributes were then extracted and added to the Excel file containing the variables to fulfill part of the physical vulnerability requirement. Mean elevation data ranged from 0 feet above sea level in Orleans Parish the lowest county in the Gulf of Mexico region to 34.3 feet above sea level in Mobile County, Alabama.

All variables were normalized by converting into densities per square mile, per capita, or percents. The 42 socioeconomic variables were placed in a Principal Factor Analysis using the Varimax rotation option. 7 factors explaining 69% of the variance were derived. From each factor the variable that had the highest loading and best demonstrated resilience was selected. The rotated factor matrix is shown in Table 2.

The variables extracted from this factor matrix based on their importance within the factor are shown along with the eigenvalue in Table 3. Because these 6 variables only explained 69% of the variance the variance was rescaled to equal 100% of the total explained by these variables. These values are shown in Table 3. Each variable and their rescaled variances were then placed in a weighted average model to derive resilience. The formula used was:

a) $V_i = [(X - Xmin)/(Xmax - Xmin)]$

b) $I = \sum_{i=1}^{6} Vi\lambda i$

Table 2: Rotated Factor Matrix

Rotated Factor Matrix[a]

	Factor						
	1	2	3	4	5	6	7
PCTBLACK	.095	-.188	.860	.053	-.005	.036	.074
PCTKIDS	.045	-.005	-.132	.033	.896	-.064	.039
PCTOLD	-.074	-.474	.116	-.600	-.275	.313	-.337
PCTHISPANIC	.370	.285	-.253	.063	.120	-.333	-.112
MEDAGE	-.171	-.133	-.160	-.153	-.558	.336	-.546
AVGPERHH	-.250	.218	.096	.782	.224	.147	-.042
FARMPOP	-.628	-.327	-.092	-.304	-.387	.084	-.048
PCTMOBL	-.710	-.145	-.288	-.053	-.177	.188	.141
PCTRENTER	.691	-.052	.346	-.174	.262	-.449	.191
PCTNOHS	.706	.344	.118	-.156	-.035	.023	.490
FEMLBR	.303	.021	.793	-.011	-.028	.020	-.033
TOTCVLBF	.497	.569	-.379	-.030	.231	.198	.311
PCTPOV	-.090	-.699	.603	-.213	.218	.106	-.050
MVALOO	.363	.639	-.185	.489	-.045	.031	.271
MEDRENT	.599	.540	-.364	.262	.040	-.096	.241
BLDPER	.775	.308	-.053	.166	.056	.058	.110
BRATE	.112	.015	.137	.040	.853	.013	-.004
RPROPDEN	-.196	-.147	.362	-.006	.158	.304	.253
AGRIPercent	-.206	-.753	-.084	.145	-.052	.093	.093
TRANPercent	.337	-.076	-.292	.467	-.075	.086	.159
PERVOTE92	-.066	.045	.067	.186	-.074	.853	-.070
GENEXPPC	.072	.053	.091	.477	-.123	.006	.049
HOUDEN	.830	.031	.088	.093	-.058	-.064	-.054
MEDINCOME	.198	.745	-.370	.461	-.059	.024	.139
EXPED	.902	.246	-.020	.045	.033	-.048	.022
MELE	-.177	.002	.118	-.675	-.226	-.130	.221
TRI	.294	.415	.009	.208	.093	.110	-.037

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 34 iterations.

The normalized raw data of the variable *X* was scaled from 0 to 1. This was renamed *V* where *V*= normalized variable. *V* was then multiplied by the rescaled variance to create a weighted value for that variable per county. These new, weighted values were then summed to give an index value that ranged from 0-1.

The resilience index had a possible range of 0 to 1, where 0 was the least resilient while 1 was the most resilient. These values can be seen in Table 4. The weighted index values for the Gulf of Mexico region had a low value of .35 in Willacy County, TX, and seven counties had the highest possible value of 1. These counties were: Jefferson Parish, LA, Kenedy County, TX, Okaloosa County, FL, Hernando County, FL, Sarasota County, FL, Pinellas County, FL, and Hillsboro County, FL. Index values for all counties are shown in Table 4. The results of the index were mapped using a natural breaks method to visually demonstrate patterns of resilience across the Gulf of Mexico region. Figure 5 depicts the results of the factor analysis method for Texas and Louisiana while Figure 6 represents the results of the factor analysis method for Mississippi, Alabama, and Florida.

In order to determine the accuracy of our index we correlated it with the percent of population change between 1990 and 2000. There was no correlation between the index values and population change (r= .157, s=0.000).

Table 3: **Variables and eigenvalues used to construct weighted community resilience index**

Variable Name	Resiliency	% Original Variance Explained	Rescaled Variance
Expenditures for education	positive	20.13	29.18
Median Income of the parish	positive	13.53	19.61
Percent of the workforce that is female	positive	10.4	15.08
Mean Elevation of the Parish	positive	10.2	14.79
Percent of the population below 5 years old	positive	9.1	13.1
Percent of the population that voted in the last presidential election	positive	5.7	8.26

Table 4: Community resilience index values for all Gulf of Mexico counties

County	Index	County	Index
Hillsboro, FL	1.00	Cameron, LA	0.75
Pinellas, FL	1.00	Chambers, TX	0.75
Sarasota, FL	1.00	Jefferson, FL	0.75
Hernando, FL	1.00	Jackson, MS	0.75
Okaloosa, FL	1.00	Lafourche, LA	0.74
Kenedy, TX	1.00	Nueces, TX	0.74
Jefferson, LA	1.00	Vermilion, LA	0.74
Santa Rosa, FL	0.95	Wakulla, FL	0.73
Manatee, FL	0.95	St. Mary, LA	0.73
Citrus, FL	0.95	Jefferson, TX	0.72
Charlotte, FL	0.94	Franklin, FL	0.72
Lee, FL	0.93	Hancock, MS	0.69
Walton, FL	0.92	Levy, FL	0.66
Pasco, FL	0.91	Terrebonne, LA	0.65
Escambia, FL	0.90	Harrison, MS	0.65
Baldwin, AL	0.90	Orange, TX	0.64
Mobile, AL	0.87	Taylor, FL	0.62
Bay, FL	0.85	San Patricio, TX	0.58
Gulf, FL	0.84	Aransas, TX	0.58
Galveston, TX	0.84	Matagorda, TX	0.57
Orleans, LA	0.84	Dixie, FL	0.55
St. Bernard, LA	0.82	Calhoun, FL	0.55
Monroe, FL	0.82	Kleberg, TX	0.52
Collier, FL	0.80	Cameron, TX	0.40
Iberia, LA	0.79	Willacy, TX	0.35
Plaquemines, LA	0.77		
Brazoria, TX	0.77		

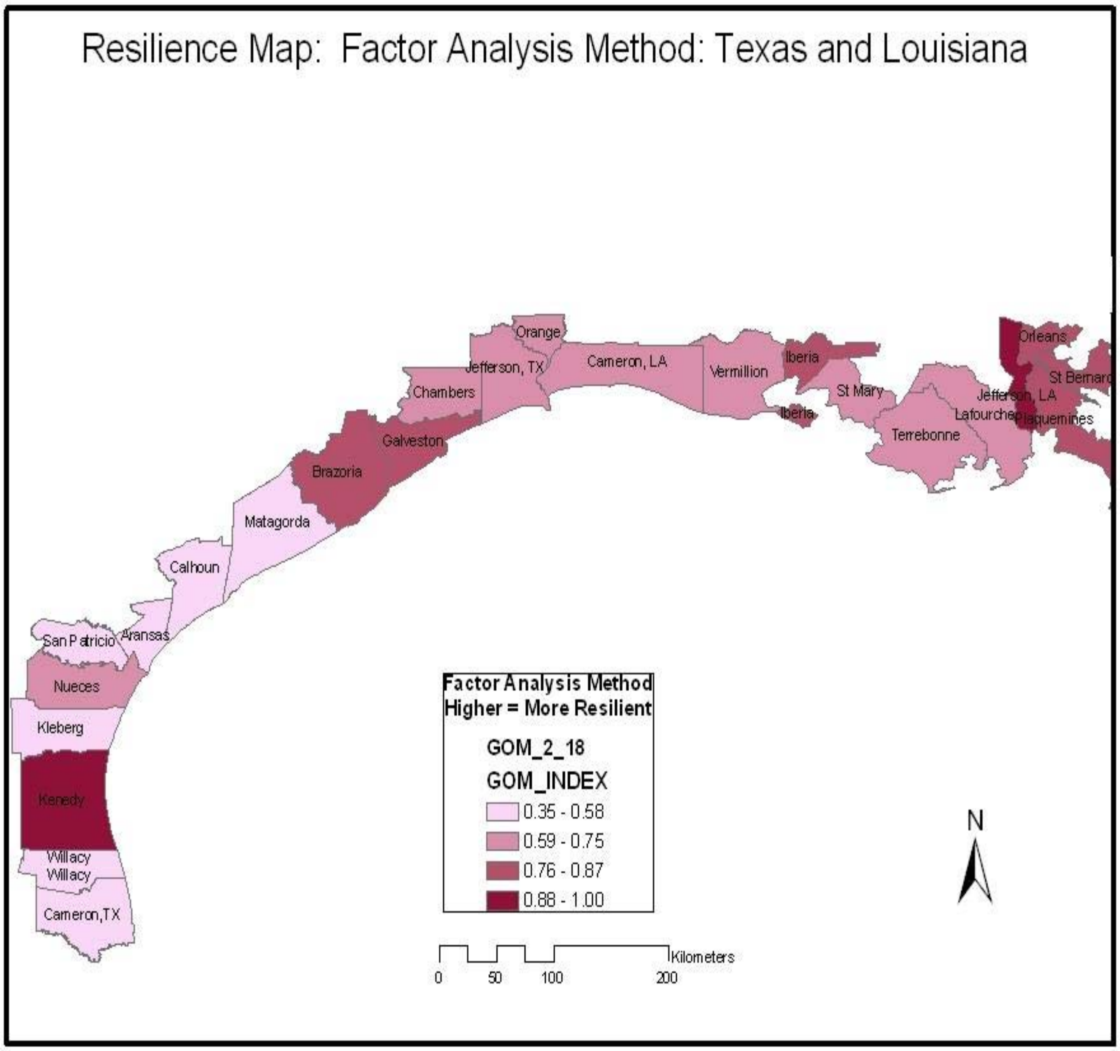

Figure 5: Results of the Factor Analysis Method for Texas and Louisiana

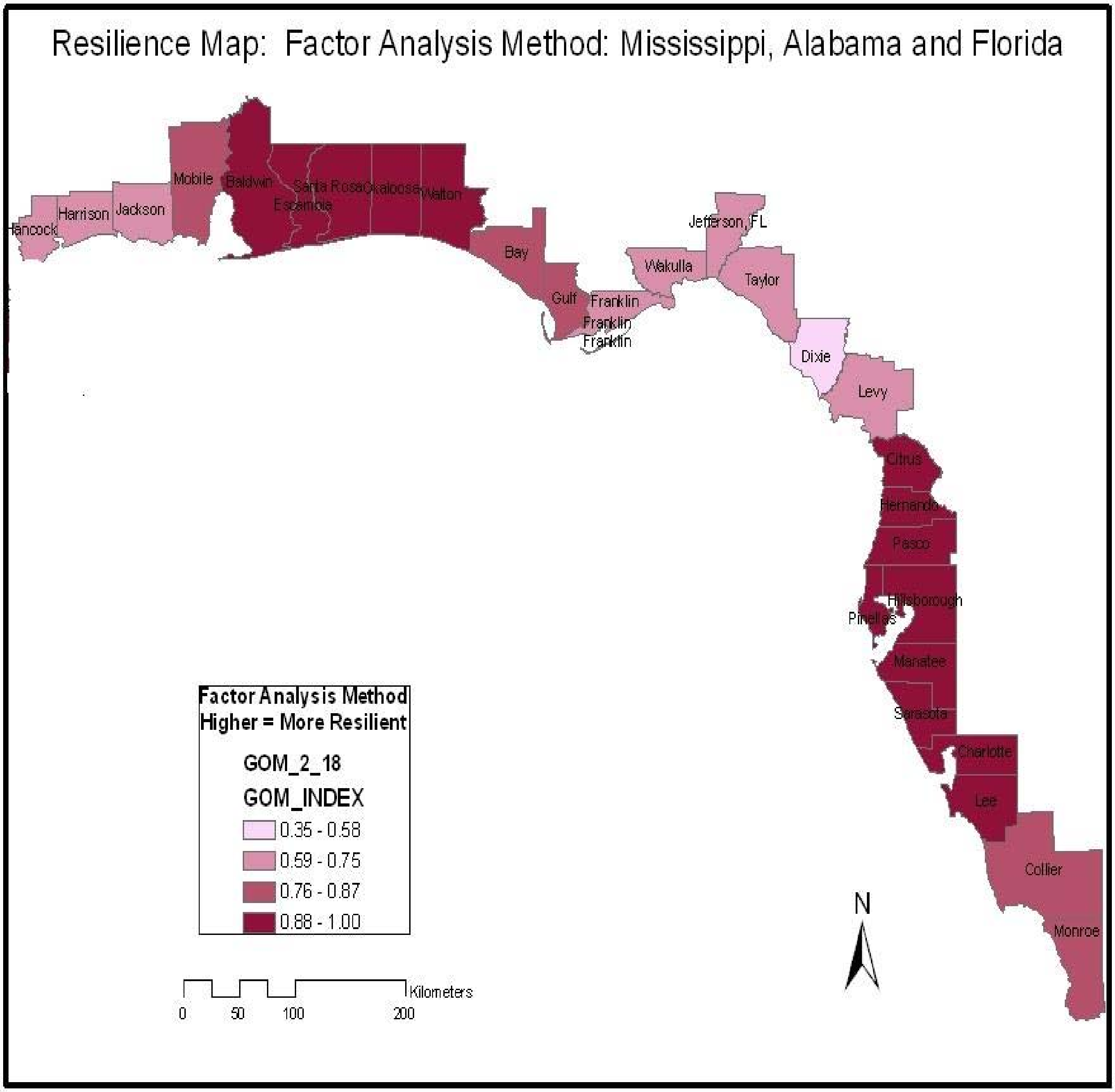

Figure 6: Results of the Factor Analysis Method for Mississippi, Alabama and Florida

Chapter 6 Discriminant Analysis Method

As an alternative method of compiling an index of resilient counties in the Gulf of Mexico we used a discriminant analysis method. A discriminant analysis allows the researcher to study 2 or more groups with respect to several variables (Klecka 1980). The variables used in this analysis were a subset of the initial variables shown in Table 1 used in to create our index. Variables were removed based on their on availability across spatial scales, and their relevance to resilience. These variables are shown in Table 5.

Four different resilience groups were utilized for this discriminant analysis. To create these groups a continuous statistical surface of disaster and impact was derived. The elements included in the measurement of resilience were the number of coastal hazards from 1960 to 2006, the number in thousands of dollars in property damage from these coastal hazards per county, and the population change from 1990 to 2000. The number of coastal hazards per county and the amount of property damage in thousands of dollars was obtained from the University of South Carolina Hazard's Lab Coastal Hazard's Database at http://www.sheldus.org. The population change data was obtained from the U.S. Census Bureau Census of Population and Housing Censtats Databases at http://www.censtats.census.gov/usa/usa.shtml.

Coastal hazards included in this study were hurricanes, tropical storms, coastal flooding, storm surges, tornados, and thunderstorms. Each of these events were counted as one discrete event and were categorized as listed by the Coastal Hazards Database maintained by the University of South Carolina Hazards Lab. Other coastal hazards like subsidence, sea level rise and coastal erosion were not addressed in this study due to the fact that they are slow insidious threats to communities that are not easily measureable.

The number of coastal hazards ranged from 8 hazards in 46 years in Orange County, TX to 60 coastal hazards in 46 years in Escambia County, FL This data was then given a rank value of 1-4. These groups were decided by dividing the number of counties by 4 to give approximately 12 counties in each group. For the ranking of coastal hazards 4= most coastal hazards, while 1 = least coastal hazards.

Table 5: Variables used in the discriminant analysis method

Demographic Variables	
PCTBLACK	percent black
PCTKIDS	percent under 5 years old
PCTOLD	percent over 65 years old
PCTHISPANIC	percent Hispanic
AVGPERHH	average number of people per household
Social Capital Variables	
PCTNOHS	percent of the population over 25 with no high school diploma
FEMLBR	percent of the workforce that is female
PCTCVLBF	percent of the workforce that is employed
PCTMOBL	percent of homes that are mobile homes
PCTRENTER	percent of the population that rents
PCTPOV	percent of the population living below poverty
HOUDEN	number of houses per square mile
Economic Variables	
MANDEN	number of manufacturing establishments per square mile
MEDINCOME	median income of the county
PCTAG	percent of the population employed by agriculture, fishing or hunting
MVALOO	median value of owner occupied housing
MEDRENT	median rent
RPROPDEN	value of all farm products sold
Government Variables	
LGFINREVPC	local government finance, revenue per capita
GENEXPPC	local government finance general expenditures per capita
PERVOTE92	percent of the population that voted in the last election
EXPED	local government finance expenditures for education
Environmental Variables	
MELE	mean elevation of the county
TRI	Toxic Release Inventory

To create a ranking for property damage damages were pooled where 1= least property damage and 4= most property damage. The least property damage was found in San Patricio

County, TX. San Patricio, TX had 11 coastal hazard events in 46 years that totaled $9,022,930 in damages. The most property damage was found in Jefferson Parish, LA, an area with 40 coastal hazard events in 46 years that resulted in $6,097,123,543 in damages.

To create the last variable of a ranking of population change where 1= least growth and 4= most growth. This data ranged from a growth rate of 65% in Collier County, FL between 1990 and 2000, to population losses of 2.5% in Orleans, LA, 7.9% in St. Mary Parish, LA, and 10% in Kenedy, TX.

Once each county was given a ranking for each category described above these rankings were combined to create a new ranking for each county. These values were added across the variables, so that areas with high population growth, high storm hazards, and high property damage were considered the most resilient. While areas with low growth, low hazards and low damage were considered the least resilient. Values ranged from 3 to 12. Santa Rosa, FL which received a 4 in all three categories finished with a rank of 12, or most resilient, while Kenedy, TX, Kleberg, TX, and Nueces, TX all received 1s in every category to give them rankings of 3. These rankings are shown in Table 6Areas with low growth, low storms, and low property damage can also be resilient, but those measures of resiliency are more subtle than this analysis and may have been overlooked.

The next step in this process was to classify the groups into four categories. In order to do this rankings of 3 through 12 were rescaled into values 1,2,3, and 4. Values of 4 were the most resilient while values of 1 were the least resilient. The new rankings are shown in Table 6.

Table 6: Rankings used to create a priori groupings

County	hazard rank	damage rank	popchange rank	resilience rank	new resilience rank
Santa Rosa, FL	4	4	4	12	4
Charlotte, FL	3	4	4	11	4
Lee, FL	3	4	4	11	4
Baldwin, AL	3	3	4	10	4
Collier, FL	2	4	4	10	4
Escambia, FL	4	4	2	10	4
Hancock, MS	2	4	4	10	4
Manatee, FL	3	4	3	10	4
Okaloosa, FL	3	4	3	10	4
Walton, FL	4	2	4	10	4
Bay, FL	4	2	3	9	3
Brazoria, TX	2	3	4	9	3
Gulf, FL	4	2	3	9	3
Jefferson, LA	4	4	1	9	3
Lafourche, LA	4	4	1	9	3
Plaquemines, LA	4	4	1	9	3
Sarasota, FL	2	4	3	9	3
Terrebonne, LA	4	3	2	9	3
Wakulla, FL	3	2	4	9	3
Chambers, TX	1	3	4	8	3
Franklin, FL	3	2	3	8	3
Galveston, TX	2	3	3	8	3
Harrison, MS	2	4	2	8	3
Hillsborough, FL	3	2	3	8	3
Jackson, MS	2	4	2	8	3
Orleans, LA	3	4	1	8	3
St. Bernard, LA	3	4	1	8	3
Citrus, FL	2	1	4	7	2
Dixie, FL	1	2	4	7	2
Hernando, FL	2	1	4	7	2
Jefferson, FL	2	3	2	7	2
Levy, FL	2	1	4	7	2
Monroe, FL	4	2	1	7	2
Taylor, FL	3	2	2	7	2
Cameron, TX	1	1	4	6	2
Cameron. LA	2	2	2	6	2
Iberia, LA	1	3	2	6	2
Mobile, AL	2	3	1	6	2
Pasco, FL	2	1	3	6	2
Pinellas, FL	3	1	2	6	2
St. Mary, LA	2	3	1	6	2
Vermilion, LA	1	3	2	6	2
Aransas, TX	1	1	3	5	2
Matagorda, TX	2	2	1	5	2

(**Table 6 Continued.)**

Orange, TX	1	3	1	5	2
Calhoun, TX	1	1	2	4	1
Jefferson, TX	1	2	1	4	1
Nueces, TX	1	1	2	4	1
San Patricio, TX	1	1	2	4	1
Willacy, TX	1	1	2	4	1
Kenedy, TX	1	1	1	3	1
Kleberg, TX	1	1	1	3	1

Once these a priori groupings were made the discriminant analysis was run in SPSS. All variables were grouped together. The result was 94.2 percent of the groupings were correctly classified. Expcetions were in these counties, Matagorda, TX, which was a priori classified as a two. The discriminant analysis placed this county as a 3. Manatee, FL which was placed as a 4, or most resilient should have been placed in 3 or middle resilient, while Sarasota, FL was a priori placed as a 3 or middle resilient, but the discriminant analysis placed it as a 4 or most resilient.

The results of the discriminant analysis were mapped using a natural breaks method. Figure 7 shows the results of the discriminant analysis for Texas and Louisiana while Figure 8 shows the results of the discriminant analysis across Mississippi, Alabama, and Florida.

Table 7: Classification of the groups by the discriminant analysis method

Classification Results[a]

			Predicted Group Membership				
		resilience	1.00	2.00	3.00	4.00	Total
Original	Count	1.00	7	0	0	0	7
		2.00	1	17	0	0	18
		3.00	0	0	16	1	17
		4.00	0	0	1	9	10
	%	1.00	100.0	.0	.0	.0	100.0
		2.00	5.6	94.4	.0	.0	100.0
		3.00	.0	.0	94.1	5.9	100.0
		4.00	.0	.0	10.0	90.0	100.0

a. 94.2% of original grouped cases correctly classified.

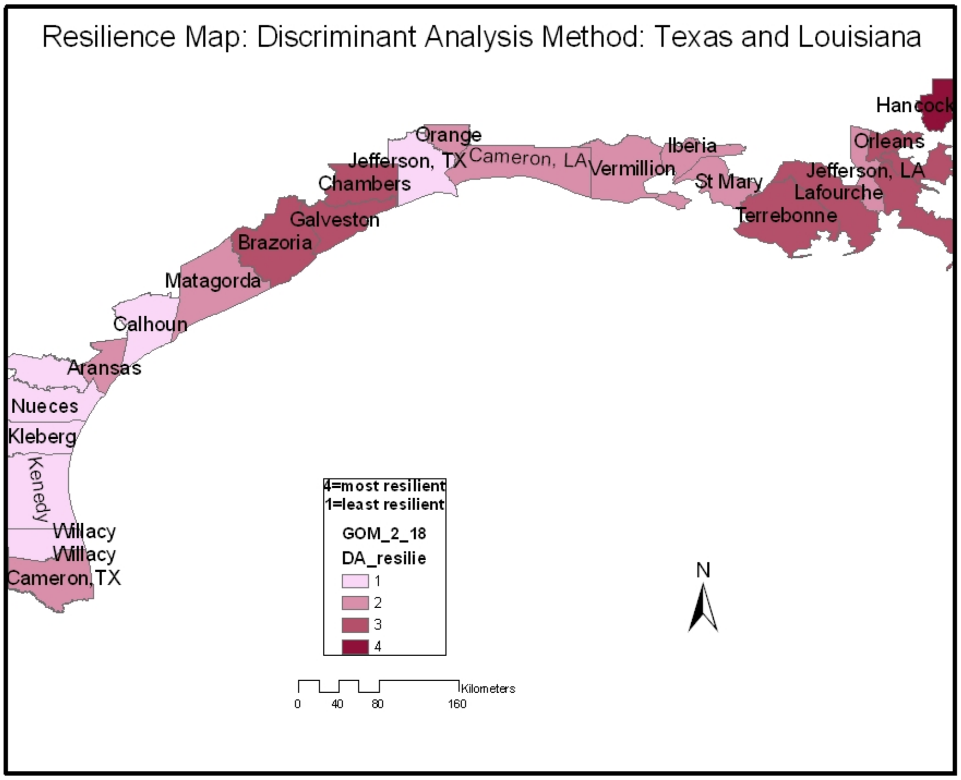

Figure 7: Results of the discriminant analysis method for Texas and Louisiana

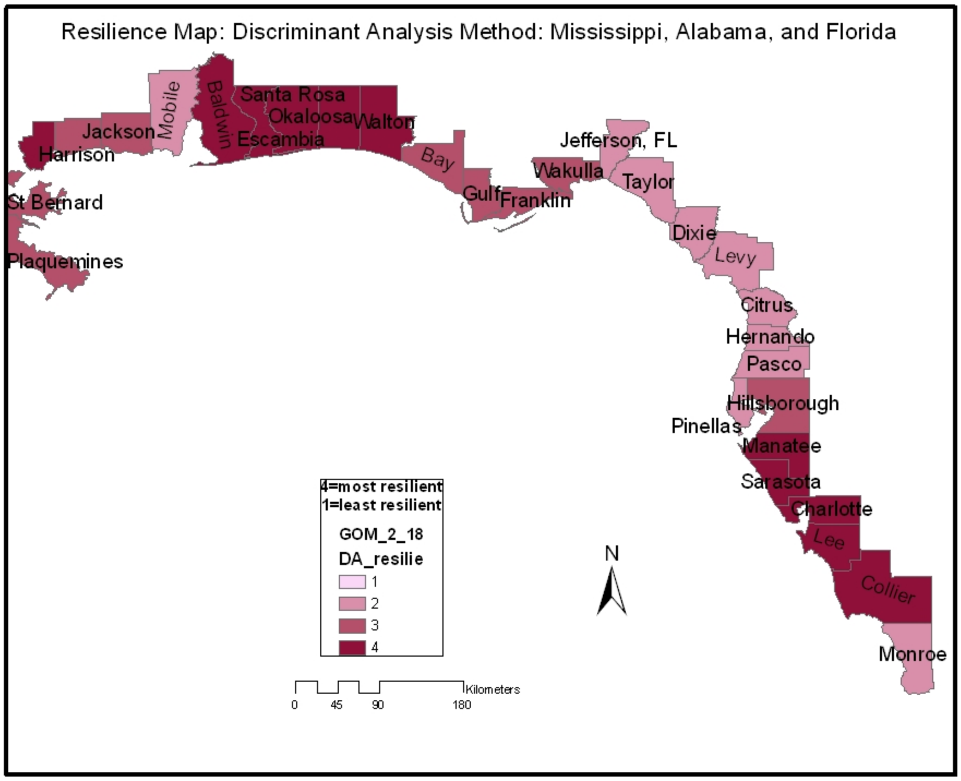

Figure 8: Results of the discriminant analysis method for Mississippi, Alabama and Florida

Chapter 7 Discussion and Conclusion

Discussion

The counties with the lowest resilience according to our weighted resilience index from the factor analysis were: Willacy County, TX, Cameron, TX, Kleberg, TX, Calhoun, TX, and Dixie, FL. With the exception of Calhoun, TX all these counties had median incomes below $30,000 per year. They also had extremely low voter turnout in the 2000 presidential election that ranged from 18 % in Cameron, TX to 33 % in Dixie, FL. Typically they had a higher percentage of the population under 5 years old. The percentage of children in the population of these counties ranged from 8.2% in Willacy, TX to 5.9 % in Dixie, FL.

The most resilient counties in the Gulf of Mexico region were centered around the suburban areas of New Orleans, and Tampa, along with the growing region of the Gulf Shores area in Okaloosa county. Surprisingly, Kenedy, TX is also among the most resilient counties in the Gulf of Mexico region. These counties all had a high percentage of women in the workforce (above 47 %). They also had high voter turnout. Kenedy, TX had the highest voter turnout in the Gulf region with 55%, but other counties that exhibited high resilience had above 40% voter turnout.

In our analysis expenditures for education were weighted at 29%. Areas with high expenditures for education were more resilient. These areas included the urban areas of Orleans, LA, Hillsborough, FL and Pinellas, FL. Hillsborough and Pinellas both received a score on the resilience index of 1 or most resilient, while Orleans received a score of .84 or middle resilient.

The next important variable was median income. This was given a weight of 19.6%, while percent of the labor force that was female and mean elevation of the county were both weighted at 15%. The final two variables were percent of the population under 5 years old which was weighted at 13% and percent of the population that voted in the last presidential election was weighted at 8.2%. Affluence and education account for roughly 50% of what makes a community resilient.

What is interesting however is that a combination of the other factors can easily place a county in the highly resilient category. For example, Kenedy, TX, has the lowest expenditures for education in the region, a very low median income, a middle elevation, a high number of kids, and the highest value of voter participation. Given the weighting method a high number of voter participation is enough to indicate resilience, despite other factors that would not. This indicates that the element of adaptive capacity measured by a high voter turnout can supersede other variables that might indicate higher vulnerability to allow for greater resilience.

The discriminant analysis returned a different pattern of resilience than the weighted resilience index. This can be seen in Table 8 where the FA column represents the results of the factor analysis method, the equal interval column represents the results of the factor analysis method that were mapped and divided into four groups via equal intervals, and the DA column represents the numeric results of the discriminant analysis method.

Table 8 is divided into two sections. The left hand section shows the counties that are grouped in the same resilience category by the two index methods. In these counties there is a correspondence between the resilience grouping based on risk and the resilience grouping based on socio-economic factors. On the left hand side of table 8 26 counteis in the Gulf of Mexico region have the exact same resilience categorization by both methods. For example, Willacy, TX is in the least resilient category via both the factor and discriminant analyses methods while Okaloosa, FL is in the most resilient category via both methods.

On the right hand of table 8 the counties that have a different resilience categorization based on the method used to determine resilience are shown. Most of these counties are categorized differently by one resilience group. For example, Cameron, TX is grouped in group

1, or the least resilient group via the factor analysis method, but by the discriminant analysis method is placed in group 2, which is a slightly more resilient group. Another example of this is Hillsborough, FL, which by the factor analysis method is placed in group 4 or the most resilient group. By the discriminant analysis method it is placed in group 3, a slightly less resilient group. 9 counties had differences that are larger than one group. These counties are: Jefferson, TX, Nueces, TX, Kenedy, TX Jefferson, LA, Mobile, AL, Pasco, FL, Citrus, FL, Hernando, FL and Pinellas, FL. For each of these counties the difference between the resilience scores for the two methods were two groups.

What this study found was counties were generally categorized in a more resilient grouping according to the factor analysis method than the discriminant analysis method. This is in part because the discriminant analysis method is a risk analysis method while the factor analysis method measures adaptive capacity in the form of expenditures for education and percent of the population that voted in the last presidential election. What this means is that taken together both metrics are useful for managers, and can better show managers where they can should include adaptive measures in their management plans. Combined, these two metrics can highlight areas that are vulnerable due to high physical risks and because they have less resilient populations.

Limitations and Future Research

This study represents the first attempt in quantifying community resilience. It outlines the approaches and methods that can be used to define resilience. It also offers a general guideline about the variables that might contribute to a communities' ability to recover from a coastal disaster such as hurricane strikes. However, further refinements with the variables are necessary in future studies.

Table 8: Table Comparing Results of the Factor Analysis and Discriminant Analysis Methods

Areas of Similar Resilience Groupings					**Areas of Different Resilience Groupings**			
County	FA	Equal Interval	DA		County	FA	Equal Interval	DA
Willacy	0.35	1	1		Cameron, TX	0.40	1	2
Dixie	0.55	2	2		Kleberg	0.52	2	1
Matagorda	0.57	2	2		Calhoun	0.55	2	1
Aransas	0.58	2	2		San Patricio	0.58	2	1
Taylor	0.62	2	2		Harrison	0.65	2	3
Orange	0.64	2	2		Terrebonne	0.65	2	3
Levy	0.66	2	2		Jefferson, TX	0.72	3	1
Franklin	0.72	3	3		Nueces	0.74	3	1
Wakulla	0.73	3	3		St. Mary	0.73	3	2
Lafourche	0.74	3	3		Vermilion	0.74	3	2
Jackson	0.75	3	3		Jefferson, FL	0.75	3	2
Chambers	0.75	3	3		Cameron, LA	0.75	3	2
Brazoria	0.77	3	3		Iberia	0.79	3	2
Plaquemines	0.77	3	3		Monroe, FL	0.82	3	2
St. Bernard	0.82	3	3		Hancock	0.69	3	4
Orleans	0.84	3	3		Collier	0.80	3	4
Galveston	0.84	3	3		Kenedy	1.00	4	1
Baldwin	0.90	4	4		Mobile	0.87	4	2
Escambia	0.90	4	4		Pasco	0.91	4	2
Walton	0.92	4	4		Citrus	0.95	4	2
Lee	0.93	4	4		Jefferson, LA	1.00	4	2
Charlotte	0.94	4	4		Hernando	1.03	4	2
Manatee	0.95	4	4		Pinellas	1.06	4	2
Santa Rosa	0.95	4	4		Gulf	0.84	4	3
Okaloosa	1.02	4	4		Bay	0.85	4	3
					Sarasota	1.06	4	3
					Hillsborough	1.08	4	3

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Future directions of this research could include refinements of the socio-economic factors included in the discriminant analysis model. On way to do this would be to only include the six variables used to construct the factor analytical weighted additive index in the discriminant analysis model. Another option would be to derive the a priori groups used in the discriminant analysis model from a k-means cluster analysis. Lastly, a continuous index variable for resilience can be created by using the probabilities of group membership resulted from the discriminant analysis can be constructed (as in Liu and Lam, 1985), so that the two sets of indices derived from the factor analysis and the discriminant analysis can be compared.

Other options to further this research are to conduct similar studies at the zip code and census tract levels. Another possible way to further this research that is currently ongoing is to conduct a similar study or specifically a case study in small area after a specific natural disaster. This concurrent research will further our understanding about resilience in the Gulf of Mexico.

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VITA

Ariele Baker was born in San Angelo, Texas, in 1980. Her early years instigated her love of travel, but the she settled in Jena, Louisiana, in 1989. By 1996 she was moving on to the Louisiana School for Math, Science and the Arts. She graduated from LSMSA in 1998, and received a bachelor of science degree in biology from Lyon College in 2002.

After college Ariele traveled.. She went first to Europe to bum around and then she worked as a conservation biologist on endangered Hawaiian avifauna in Volcano National Park, Hawai'i She then moved to Baton Rouge and worked for the Louisiana Department of Wildlife and Fisheries for a few years. Following this, and wanting to work towards public outreach, Ariele began teaching science enrichment classes to kids ages 3-12. This led to a job conducting surveys of fishermen and their perceptions of the sport of fishing for the State of Florida. While in lovely south Florida Ariele also hung out, and gave kayak tours. This fostered the thought that public perception is very important for management of scientific issues. Science must be met with a political will, and information must be disseminated clearly and understandably. This led Ariele to return to graduate school for her master's in environmental science. Upon completion of this master's degree she would like to work in public outreach and with development issues.