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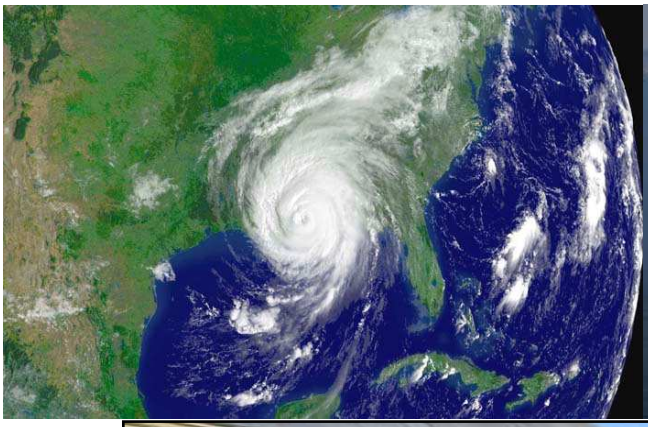
Socioeconomic Responses to Coastal Land Loss and Hurricanes: Measuring Resilience among Outer Continental Shelf-Related Coastal Communities in Louisiana



U.S. Department of the Interior
Bureau of Ocean Energy Management
Gulf of Mexico OCS Region

Cooperative Agreement
Coastal Marine Institute
Louisiana State University

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TABLE OF CONTENTS

LIST OF FIGURES vii

LIST OF TABLES vii

1. INTRODUCTION 1

2. RELATED RESEARCH 3
   2.1. Definition of Social-Ecological Resilience 3
   2.2. Measurement of Community Resilience 4

3. CALCULATION OF THE RESILIENCE INDEX FOR GULF OF MEXICO COASTAL COUNTIES AND PARISHES USING PRINCIPLE COMPONENTS ANALYSIS (PCA) METHOD 7
   3.1. Study Area and Data 7
      Gulf of Mexico Region 7
      Texas 7
      Louisiana 7
      Mississippi 9
      Alabama 9
      Florida 10
      Data 13
   3.2. Method One: Construction of the Resilience Index Using Factor Analysis Cutter's Social Vulnerability Index 13
      3.2.1. Factor Analytical Method 14

4. DEVELOPING AN ALTERNATIVE METHODOLOGY TO EXAMINE SOURCES OF RESILIENCE: APPLICATION OF DISCRIMINANT ANALYSIS (DA) TO THE COASTAL COUNTIES OF THE GULF OF MEXICO STATES 23

5. COMPARISON OF THE TWO METHODS TO CALCULATE COUNTY RESILIENCE .. 31
   5.1. Method One: County Resilience Levels Calculated by Factor Analysis 31
   5.2. Method Two: County Resilience Levels Calculated by Discriminant Analysis 32

6. EXPLORING ASSOCIATIONS BETWEEN THE RESILIENCE SCORES OF COASTAL COUNTIES AND PARISHES AND THE OIL AND GAS INDUSTRY 35
   6.1. Correlation Analyses and Results 38
   6.2. Summary 40

REFERENCES 43

APPENDIX 49

ABSTRACTS OF SELECTED THESES 49

LIST OF FIGURES

Figure 1. Reference map of Texas coastal counties. 8
Figure 2. Reference map of Louisiana coastal counties. 9
Figure 3. Reference map of Mississippi and Alabama coastal counties. 11
Figure 4. Reference map of Florida's Gulf of Mexico coastal counties. 12
Figure 5. Results of the factor analysis method for Texas and Louisiana. 21
Figure 6. Results of the factor analysis method for Mississippi, Alabama, and Florida. 22
Figure 7. Results of the discriminant analysis method for Texas and Louisiana. 29
Figure 8. Results of the discriminant analysis method for Mississippi, Alabama, and Florida. 30
Figure 9. Oil and Gas Employment among Counties within the Gulf of Mexico Region. 36

LIST OF TABLES

Table 1. Original Variables Used to Empirically Derive Factor Loadings 16
Table 2. Rotated Factor Matrix[a] 18
Table 3. Variables and Eigenvalues Used to Construct Weighted Community Resilience Index 19
Table 4. Community Resilience Index Values for All Gulf of Mexico Counties 20
Table 5. Variables Used in the Discriminant Analysis Method 25
Table 6. Rankings Used to Create *A Priori* Groupings 27
Table 6. Rankings Used to Create *A Priori* Groupings (continued) 28
Table 7. Classification of the Groups by the Discriminant Analysis Method[a] 28
Table 8. Comparing Results of the Factor Analysis and Discriminant Analysis Methods ... 33
Table 9. Data Used in the Pearson Correlation Analyses 37
Table 10. Pearson Correlation Analysis between Factor Analysis- Method Resilience Scores and Oil and Gas Employment; Oil and Gas Establishments 39
Table 11. Pearson Correlation Analysis between Discriminant Analysis-Method Resilience Scores and Oil and Gas Employment; Oil and Gas Establishments 40

1. INTRODUCTION

Since Hurricanes Katrina and Rita in 2005, scholars, policy makers, residents, and other stakeholders have raised questions about the long-term survival of coastal communities in the face of increasingly intense storms, sea-level rise and other natural hazards. Several Outer Continental Shelf (OCS) management questions relate to the overall, long-term resilience of communities in coastal Louisiana.

This research addresses the following questions.

1) How can community resilience best be measured?
2) How resilient are OCS communities to threats posed by coastal land loss and hurricanes?
3) Are OCS communities more resilient to these natural threats than coastal communities less involved in OCS activities?

These topics are relevant to BOEM and to Louisiana, given the high levels of OCS activity within the coastal areas of the State and the large-scale destruction to property, natural assets, and human life that have resulted from major hurricanes during the last few years.

Recent studies by the BOEM and others have called for more refined examinations of the social and economic impacts of OCS activities and for more innovative approaches to estimate the resilience of communities facing natural disturbances. For example, Luton and Cluck (2005) identified several limitations of the traditional Social Impact Assessment (SIA) framework in identifying the socioeconomic effects of OCS activities, given the diffuse and indirect nature of these impacts. In January 2007, the NSTC Joint Subcommittee on Ocean Science and Technology recommended giving the highest priority over the next ten years to research seeking better understanding of resilience to natural hazards and greater insight into patterns of human activity that affect the stability and sustainable use of ocean resources (NSTC, 2007).

This research involves the application of concepts from the social-ecological resilience literature to coastal communities in Louisiana and the four other northern Gulf of Mexico states: Texas, Mississippi, Alabama and Florida. The research objectives are to: 1) develop quantitative indicators of community resilience to coastal land loss and to hurricanes; 2) compile these indicators into a “resilience index”; 3) create GIS-supported maps depicting vulnerability and resilience based on these indicators; and 4) make comparisons among communities of coastal Louisiana more and less involved with OCS activities. Specifically, we investigated whether communities with more of the workforce employed in oil and gas and supporting industries tend to be more resilient to natural disasters than coastal communities with less oil and gas industry activity. Computation of the resilience index provides useful baseline information concerning the hazards facing OCS communities, the extent to which they have been able to withstand and recover from natural disturbances, and whether OCS activities may tend to enhance the overall resilience of these communities.

The residents in the study area, the coastal communities of the Gulf of Mexico region, face increasing threats to their health and safety and to the longer-term social and economic stability of their communities. Coastal hazards and threats include both large-scale, rapid-moving disturbances, such as hurricanes and storm surges, and slower-moving disturbances, such as coastal land loss, sea-level rise, and the gradual diminishment of ecosystem services over time.

While many coastal threats result from or are associated with natural processes, most are exacerbated by human activities, such as rapid population growth, inadequate infrastructure planning and investment, and unwise land-use decisions. Theorists and community stakeholders would benefit from a resilience assessment instrument that would provide them with information about their exposure to coastal hazards, their vulnerabilities to those threats, and their capacity for taking adaptive steps to make their communities safer and more likely to recover following large-scale disturbances.

Despite abundant research examining aspects of social-ecological resilience, vulnerability, hazards and risk assessment, there is yet to be a convincing approach to quantifying and measuring community resilience. There is a need to devise a quantifiable resilience index that can capture the sources and consequences of resilience and vulnerability, especially for coastal communities with significant oil and gas industry activity.

The challenges involved in developing useful resilience indices are significant (Carpenter et al., 2009; Walker et al., 2006a & b; Barnett et al., 2008). Some appear to arise, in part, due to the various definitions of resilience used by researchers. The definitions are often confused or used interchangeably with similar concepts such as vulnerability, sustainability, and adaptability. Also, the problem is exacerbated by a lack of empirical validation and evidence for the indices derived (Lam et al., 2009). Moreover, most of the literature on resilience tends to be conceptual and somewhat abstract. A straight-forward model for measuring resilience that is grounded in sound theoretical principles will be very useful for sustainable planning and management and may help speed economic assistance and recovery of communities after major disaster events.

The research seeks to quantify theoretical concepts concerning community resilience and to test associations between oil and gas industry activity levels and measures of resilience. Part of the project's theoretical foundation comes from the growing body of scholarly research concerning social-ecological resilience, hazard and vulnerability, and coupled natural and human systems (Adger et al., 2005; Cutter et al., 2003; Liu et al., 2007). In summarizing the related research in the literature below, our discussion focuses on two topics: what is community resilience and how can it best be measured?

The report is organized into the following sections: 1) related research concerning how to quantify social-ecological resilience; 2) calculation of the resilience index for the coastal Louisiana Parishes and all coastal counties in the northern Gulf of Mexico region; 3) calculation of a resilience index for the coastal parishes and counties in the GOMA region using an alternative methodology; 4) comparisons of the calculated resilience scores of Louisiana parishes most involved in OCS oil and gas activities with other parishes and counties in the Gulf of Mexico region; and 5) abstracts of theses research funded by the project.

2. RELATED RESEARCH

2.1. DEFINITION OF SOCIAL-ECOLOGICAL RESILIENCE

Useful insight into community resilience can be derived from the large body of literature on social-ecological resilience. Some researchers define resilience as how fast a system can return to the original state after an external disturbance, while others use the term to refer to how far the system could be perturbed without shifting to a different state. The former definition is often called "engineering resilience" because it concerns the return time, whereas the latter is commonly referred to as "ecological resilience" (Holling, 2001; Walker et al., 2006a). Adger and others (2005) further stated that "Resilience reflects the degree to which a complex adaptive system is capable of *self-organization* (emphasis added), and the degree to which the system can build capacity for learning and *adaptation* (emphasis added)." They further defined resilience as "the capacity of linked social-ecological systems to absorb recurrent disturbances such as hurricanes or floods so as to retain essential structures, processes, and feedbacks". Considering the literature, we can summarize that the best working definition of resilience would include 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 adaptation (Folke et al., 2002; Ahmed, 2006; Baker, 2009).

Closely related to resilience is the concept of vulnerability. In fact, the two terms have been used interchangeably by some researchers, while others expanded the definition of vulnerability to include resilience. For example, Folke and others (2002) defined vulnerability in an ecological sense as "the propensity of an ecological system to suffer harm from exposure to external stresses and shocks", while Cutter and Finch (2008) whose work is found in the hazard literature focused on vulnerability in a social system. They defined social vulnerability as "a measure of both the sensitivity of a population to natural hazards and its ability to respond and recover from the impacts of hazards." Adger (2006) considered vulnerability in a system to include both social and ecological elements, and referred to it as the susceptibility to risk and its inability to cope with or absorb a shock. Turner and others (2003) stressed that vulnerability is not just exposure to hazards; it includes three elements: exposure, sensitivity, and resilience. They further suggested that their expanded framework of vulnerability and vulnerability analysis can be used for the assessment of coupled human and natural systems and is a key element of "sustainability science" (Turner et al., 2003; Liu et al., 2007). A similar conceptual framework is found in the work of Kasperson et al. 2005, and Cutter et al. 2003, as well.

Various factors may increase social vulnerability, including exclusion of stakeholders from the public policy arena, an incorrect understanding of ecosystem processes and risks associated with natural hazard, and inadequate plans for disaster management and response. Further, lower-income residents may tend to live in riskier areas in urban settlements, making them more vulnerable to flooding, disease, and chronic stresses. Also, women have been found to be at increased risks associated with environmental hazards, often including a disproportionate share of the work related to the recovery of home and livelihood after an event (Fordham, 2003;

Adger, 2006). Thus, potential influences on social vulnerability include 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).

2.2. MEASUREMENT OF COMMUNITY RESILIENCE

While there is voluminous literature on the conceptual frameworks, definitions, and case studies related to community resilience, very few attempts have been made to quantify resilience and/or vulnerability. There are major challenges associated with quantifying resilience. First, the numerous definitions of the terms, as discussed above, reflect how different researchers may consider and select indicators differently for measuring resilience. Thus, the selection of appropriate indicators for measurement becomes a major task. Mathematical and statistical methods will be needed to identify and evaluate the key factors iteratively, and the resultant measurement model will need to be tested and verified.

Second, there is a need to consider both social and natural aspects of resilience, and how these two systems are linked. A system that has high social resilience may have low ecological resilience and vice versa. Moreover, the interaction effects between the two systems may be exhibited at different points in time, making them difficult to measure. For example, building a levee along the Mississippi River would prevent flooding to the populated areas, hence decreasing the vulnerability of the people living in low-lying areas. However, such action may lead to increased vulnerability of the wetland ecosystem because of long-term reduction in sediment load, leading to an increase in wetland erosion. This consequence can in turn become a threat to the human system, because the loss of wetlands would reduce the buffer zone that protects the populated areas and increase the vulnerability of communities to hurricanes. This type of coupling mechanism is easy to describe but is hard to quantify, especially when useful longitudinal data are not available.

Third, of those who have attempted to measure vulnerability and resilience, the results have seldom been validated. Often, the model specification and the weights assigned to different variables were arbitrarily determined, making the resultant model difficult to apply and generalize. We present below three studies of measuring vulnerability and resilience, which will further illustrate the difficulties in measuring resilience and/or vulnerability.

Yusuf and Francisco (2009) developed a model to assess the vulnerability of sub-national areas in Southeast Asia to climate change. They followed the definition developed by the United Nations' Inter-governmental Panel on Climate Change (MaCarthy et al, 2001, p. 995), which defined vulnerability (V) as a function of exposure (E), sensitivity (S), and adaptive capacity (C):

$$V = f(E, S, C).$$

"Exposure" refers to the nature and degree to which a system is exposed to significant climatic variations, "sensitivity" means the degree to which a system is affected by climate-related events, and "adaptive capacity" is the ability of a system to adjust to climate change or to cope with its consequences. Their model is an additive weighted-average model. The weight of

each variable was assigned arbitrarily according to the literature. The results from their study are the composite vulnerability index of each sub-national region in the Southeast Asia. Their approach is straight-forward and the resultant maps are impressive, but the study suffers from the pitfalls discussed above, namely, the lack of empirical verification of model results and the arbitrariness of weight assignments.

A similar but improved approach to the above IPCC vulnerability model was used to measure the vulnerability of Australian rural communities to climate variability and change (Nelson et al., 2009a & b). The research group recognized that the concept of vulnerability is rarely converted to quantitative measures that can be used to prioritize policy interventions and evaluate their impacts. In developing their vulnerability index, they emphasized the need to include some measures of adaptive capacity to complement the existing hazard-impact modeling. An adaptive-capacity index was created using the rural livelihood analysis framework proposed by Ellis (2000) that includes indicators from the five categories of resources or "capitals": human, social, natural, physical, and financial.

The third example is the approach used and pioneered by Cutter and her research group to quantify the social aspects of vulnerability into the Social Vulnerability Index (Cutter et al., 2003; Cutter and Emrich, 2006; Cutter and Finch, 2008). The group has used the 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. To develop the index, Cutter and others selected 42 socioeconomic variables from the U.S. Census that demonstrated aspects of social vulnerability as identified by the literature. They conducted a factor analysis in the form of principal component analysis to derive 11 factors that accounted for 76.4% of variance of all the variables. The relative index of vulnerability for each county was derived by adding their factor scores, and the final index was mapped using standard deviations from the mean score to determine level of 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.

To verify the accuracy of the index, Cutter and the group correlated the number of presidential disaster declarations with the vulnerability score given to each county. The result was disappointing; they found literally no correlation (r=-0.099) between the derived vulnerability index and the political designations. Nevertheless, Cutter's approach has advanced two important concepts regarding the measurement of resilience or vulnerability, which are, the need to derive the index through statistical modeling and the need to validate the index through empirical comparisons with outcomes such as the number of disaster declarations.

There are various ways in which Cutter's method could be improved, such as applying different weighting of factor scores and better selection of factors and variables. Moreover, different statistical techniques, especially an inferential statistical modeling technique such as discriminant analysis, could be utilized to develop a mathematical model that can be inferred to other study regions. We have conducted several studies during the course of this project that have helped to refine the methodology we applied to this research. Two completed Environmental Sciences Master's theses resulted from the project and their abstracts are included in this final report.

The following sections present the results of two statistical approaches we used to create resilience measures for the coastal parishes of Louisiana and coastal counties of the five northern Gulf of Mexico states of the United States.

3. CALCULATION OF THE RESILIENCE INDEX FOR GULF OF MEXICO COASTAL COUNTIES AND PARISHES USING PRINCIPLE COMPONENTS ANALYSIS (PCA) METHOD

3.1. STUDY AREA AND DATA

Gulf of Mexico Region

The focus of this study was the northern Gulf of Mexico region, specifically the coastal counties 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, 2008). 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.

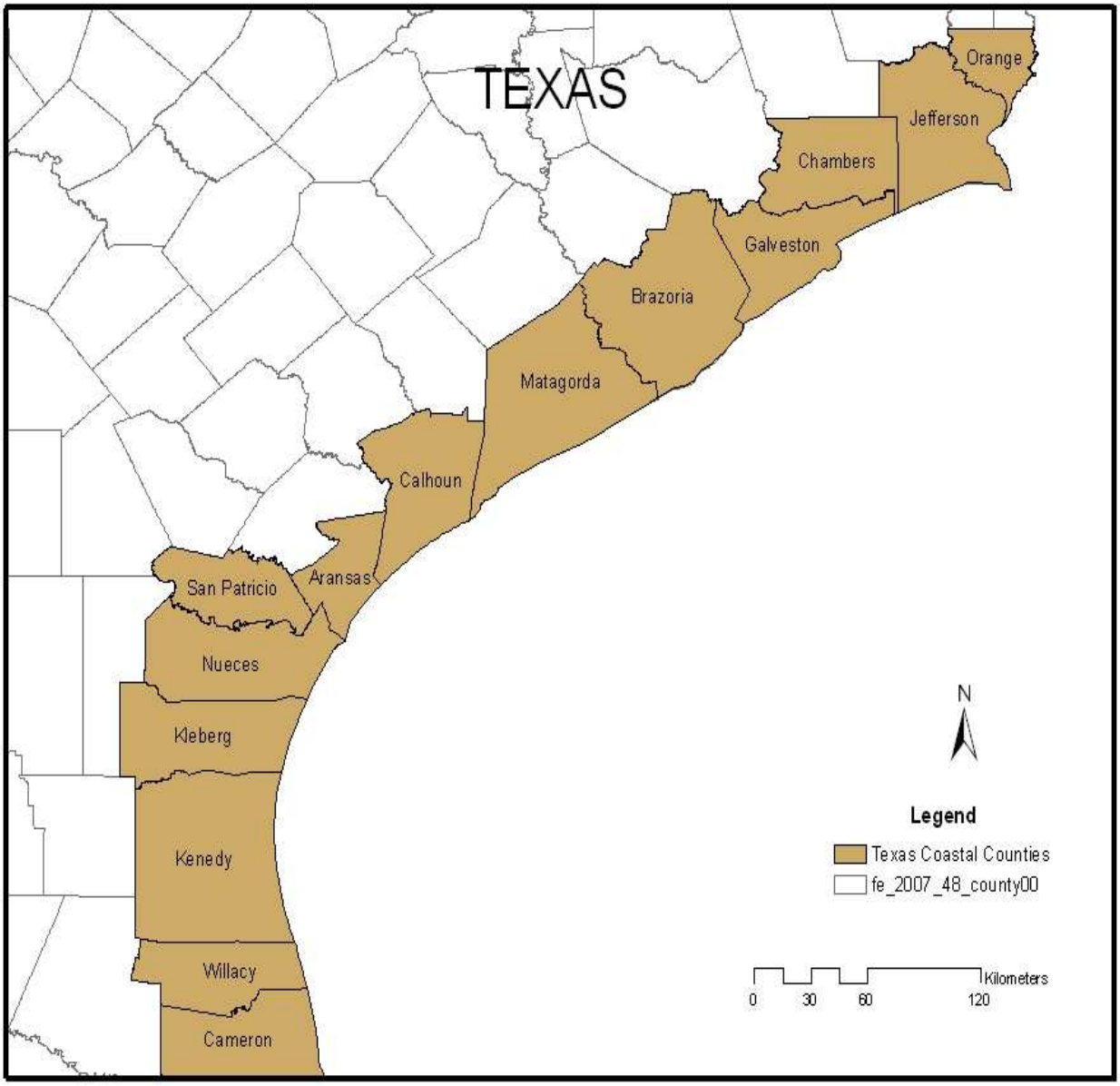

Figure 1. Reference map of Texas coastal counties.

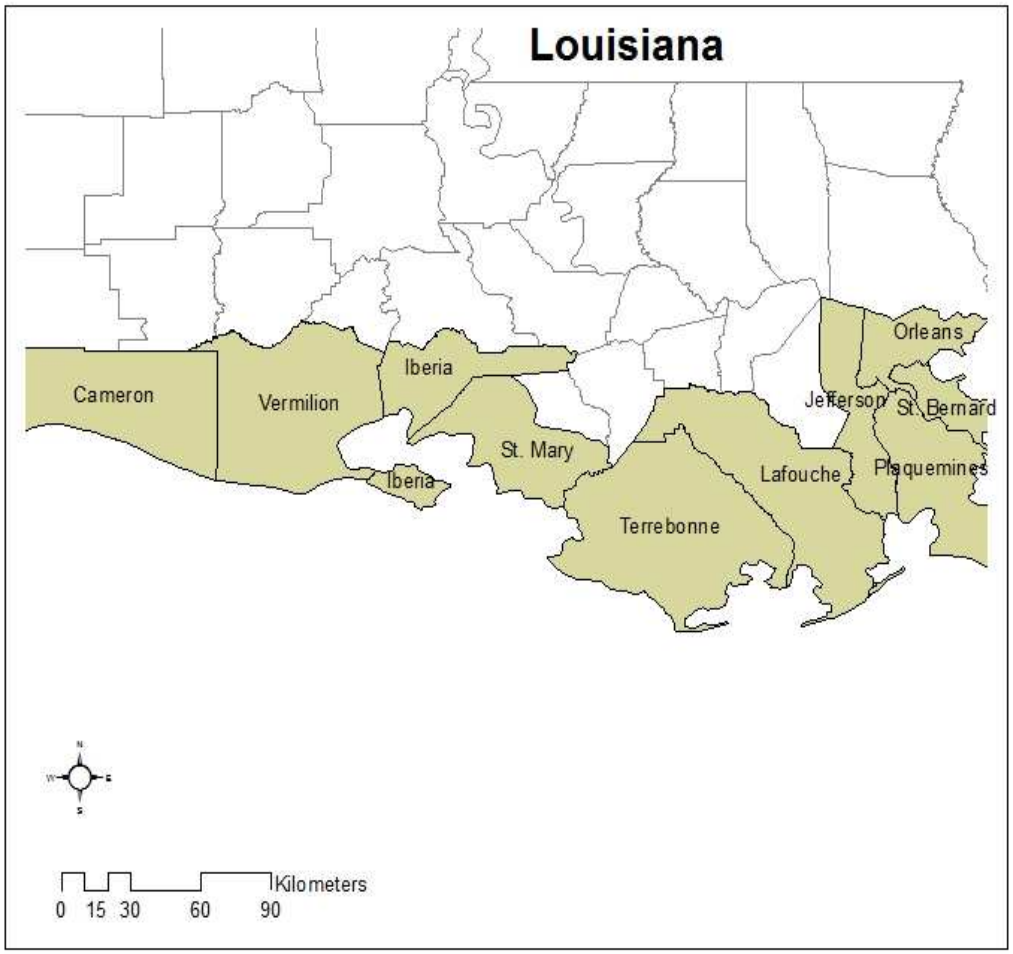

Figure 2. Reference map of Louisiana coastal counties.

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 grew by 23.5% from 1990 to 2000 (U.S. Census Bureau, 2008). 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 uninhabited 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.

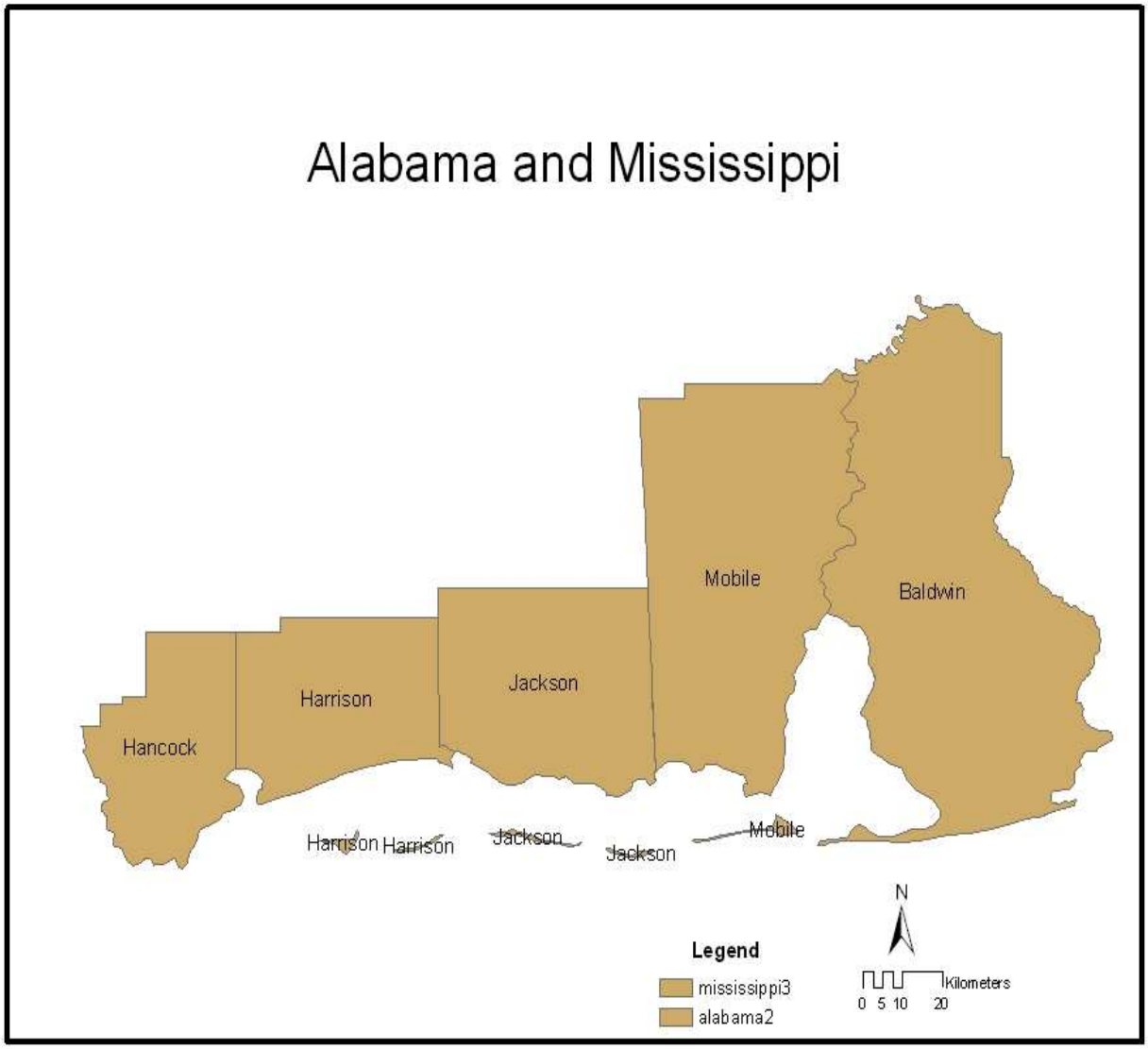

Figure 3. Reference map of Mississippi and Alabama coastal counties.

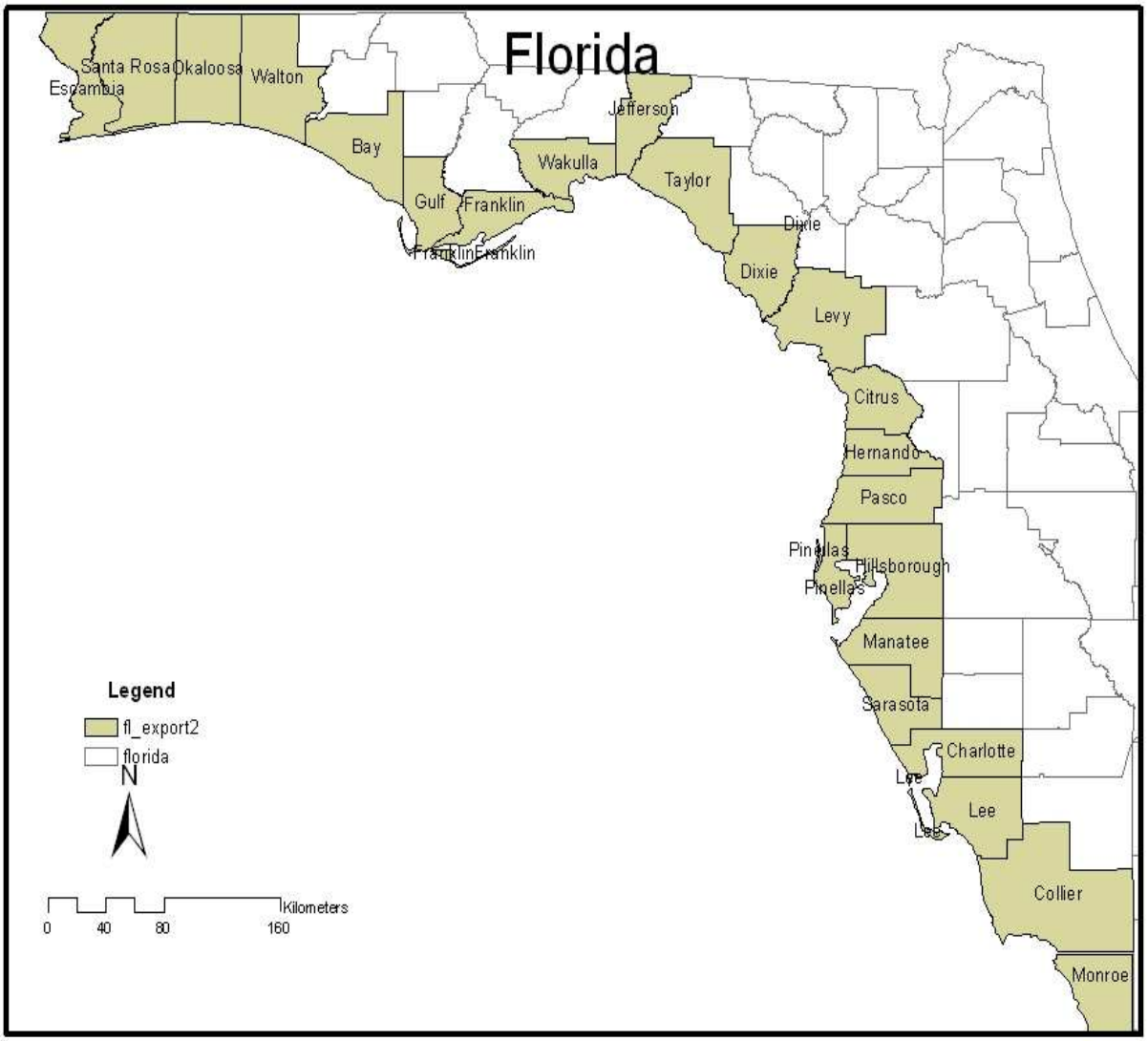

Figure 4. Reference map of Florida's Gulf of Mexico coastal counties.

Data

Demographic and economic data used in this study were gathered from the U.S. Census Bureau 2000 Census of Population and Housing, and the 1997 and 2002 Economic Census. The data were obtained from the agency's website which contains county-level information collected and reported for multiple years.

Environmental data were obtained in two different ways that will be discussed in more detail in the next section. The Toxic Release Inventory (TRI) data were obtained from the U.S. Environmental Protection Agency's website. The annual TRI tracks over 650 toxic chemicals used in manufacturing processes in the U.S. Each year, regulated facilities permitted to discharge any of these chemicals are required to report their estimated discharge amounts. Digital elevation measures were obtained from the USGS National Elevation Dataset (NED). The NED is available to the public and provides elevation values for all areas throughout the U.S. The final group of variables were taken from the coastal hazards data set made available by the University of South Carolina's Coastal Hazard's Lab. This information is available through the Spatial Hazard Events and Losses Database for the United States (SHELDUS) website and includes county-level information concerning storms and other natural hazard events from 1960-2000.

3.2. METHOD ONE: CONSTRUCTION OF THE RESILIENCE INDEX USING FACTOR ANALYSIS CUTTER'S SOCIAL VULNERABILITY INDEX

As introduced above, the social aspects of vulnerability were first quantified by Cutter et al. (2003). They developed the Social Vulnerability Index by selecting 42 socioeconomic indicators of social vulnerability and conducting a factor analysis in the form of principal component analysis (PCA) to create an index of these variables to measure social vulnerability. 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.

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. Second, 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. In other words, a principal-axis factoring method acts as a filter while a principal component analysis includes all the variables (Norusis, 2003).

Third, 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 methodology to discern which variables are most important to each dimension or factor instead of using factor scores?

Fourth, Cutter et al. (2003) 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 may be a stronger positive association between the index and some measure of recovery, like population change or presidential disaster declarations.

3.2.1. Factor Analytical Method

The methods used by Cutter et al. (2003) to create the Social Vulnerability Index were modified to create an index of community resilience. Forty-three socioeconomic variables were obtained from the 2000 Census, 36 of these variables were taken from the research of Cutter et al. (2003) and seven variables were added that measured additional aspects of vulnerability and resilience, including voting rates among residents, capacity of local government, and environmental factors. 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 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 et al., 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. Measures of the economic conditions of the area include commercial development, manufacturing density, earning density, and primary employments in an area. Supplemental Security Income (SSI) 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. The TRI reflects the estimated discharges of TRI-listed chemicals in any given area and were included because they offer insight into local environmental conditions. Elevation was used because it indicates susceptibility to flooding, a relevant consideration in coastal, hurricane-prone areas. The Toxic Release Inventory (TRI) 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, Texas, to 55,247,688 lbs in Escambia County, Florida. The median value of TRI release in the Gulf of Mexico region in the year 2000 was 283,910 pounds of toxic releases.

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
CTRFRM90	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 ($1,000) 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 $75,000 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

The variable “mean elevation” was obtained through a multistep process. First, 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 procedure was followed 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. 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 conversion 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 and seven factors explaining 69% of the variance were derived. From each factor the variable that had the highest loading was selected. The rotated factor matrix is shown in Table 2.

Table 2.
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 variables extracted from this factor matrix based on their importance within the factor are shown along with their 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:

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

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

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 to 1. Thus, the resilience index had a possible range of 0 to 1, where 0 was the least resilient; 1 was the most resilient. Table 4 shows these values.

The weighted index values for the Gulf of Mexico region had a low value of .35 in Willacy County, Texas, and seven counties had the highest possible value of 1. These counties were: Jefferson Parish, Louisiana, Kenedy County, Texas, Okaloosa County, Florida, Hernando County, Florida, Sarasota County, Florida, Pinellas County, Florida, and Hillsboro County, Florida. 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.

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

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 statistically significant correlation between the index values and population change (r= .157, s=0.000).

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		

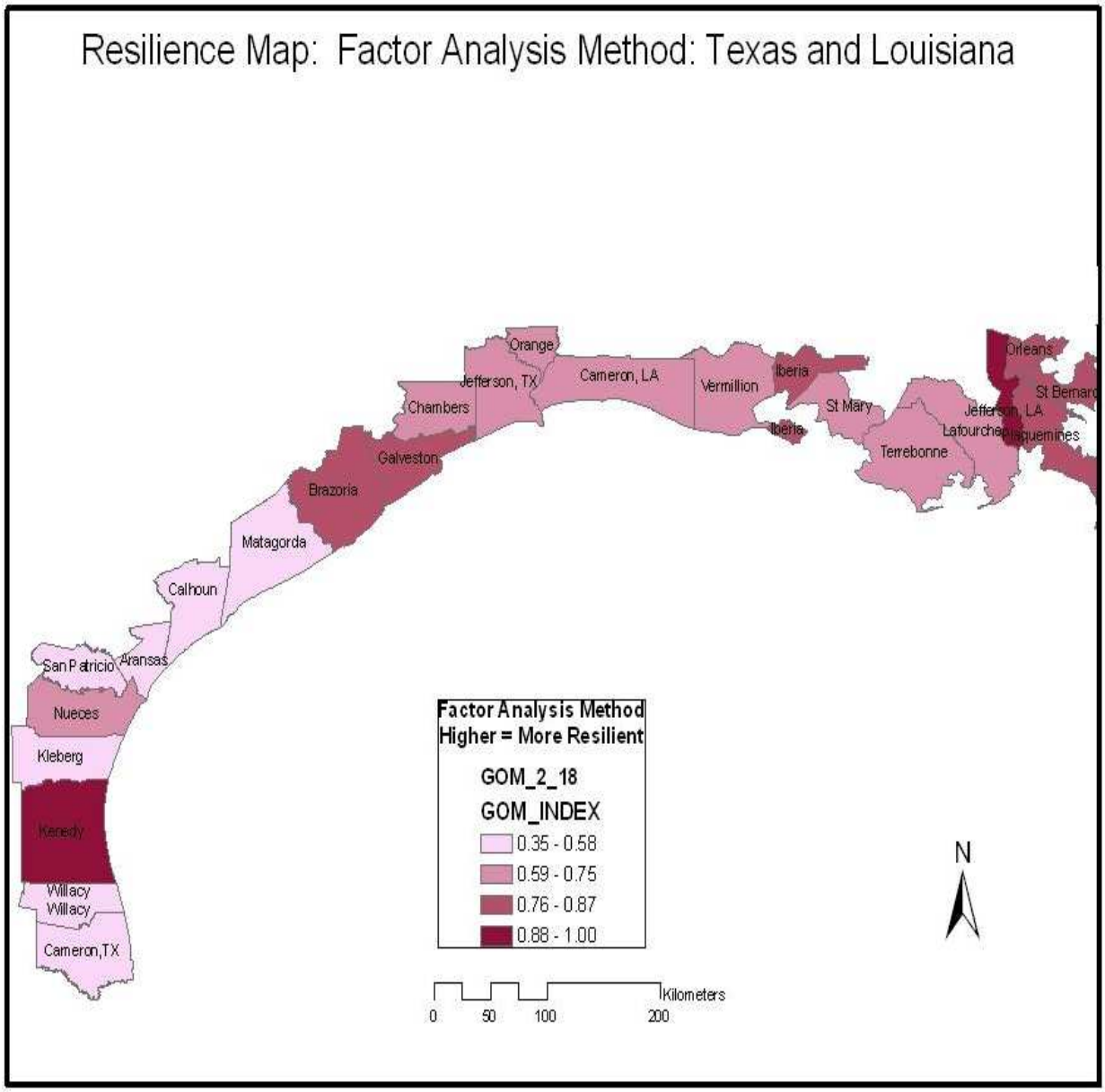

Figure 5. Results of the factor analysis method for Texas and Louisiana.

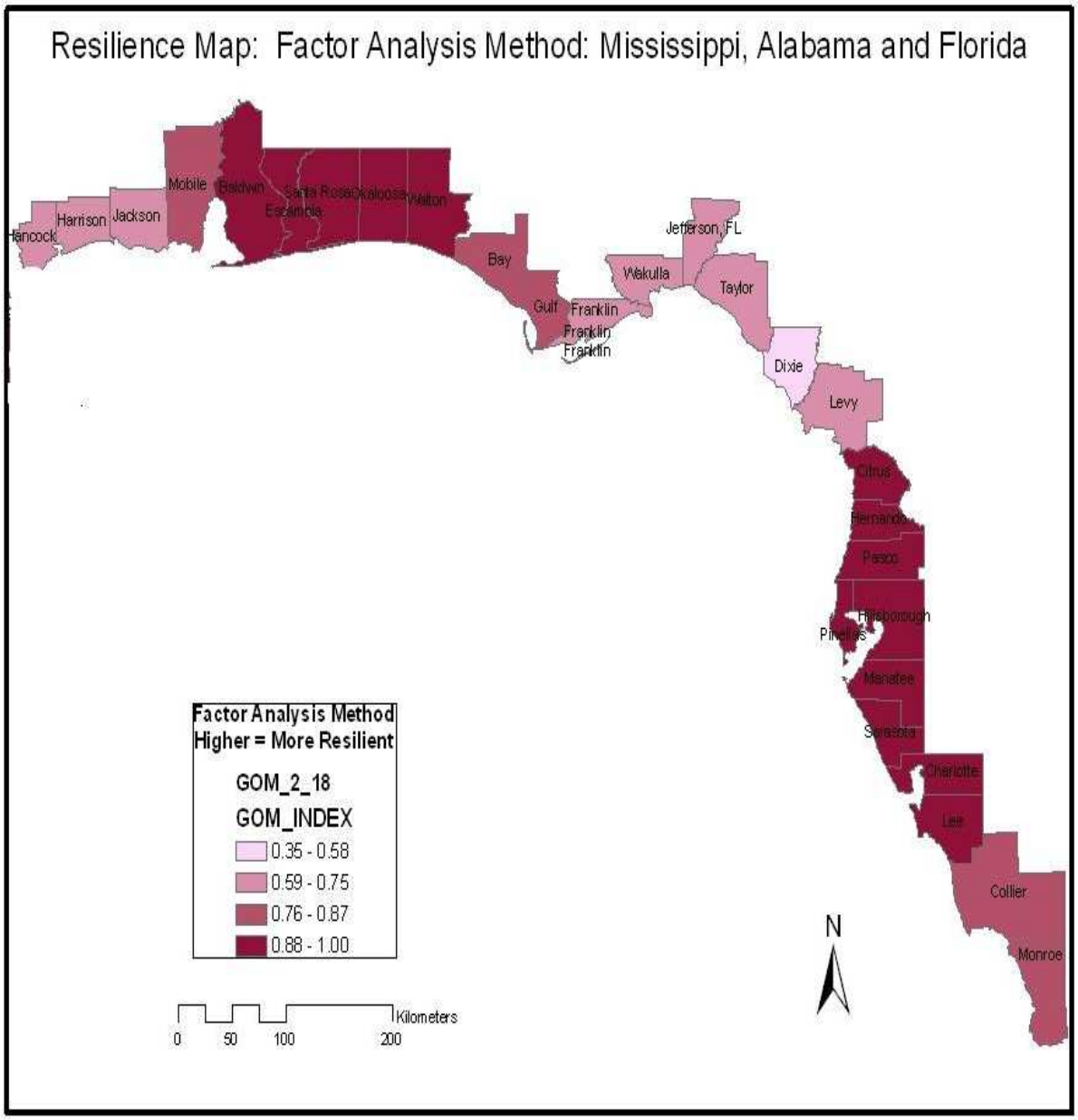

Figure 6. Results of the factor analysis method for Mississippi, Alabama, and Florida.

4. DEVELOPING AN ALTERNATIVE METHODOLOGY TO EXAMINE SOURCES OF RESILIENCE: APPLICATION OF DISCRIMINANT ANALYSIS (DA) TO THE COASTAL COUNTIES OF THE GULF OF MEXICO STATES

An alternative method to construct an index of resilience is one based on the application of discriminant analysis. This method was used by Liu and Lam (1985) to construct a zonal index of vegetation and to determine the probability of a modern analogue.

Discriminant analysis requires an *a priori* classification of samples (coastal counties in this study) into groups. The technique derives linear combinations of variables that are independent of each other (Liu and Lam, 1985; Klecka, 1980). This technique also can 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.

The variables used in the discriminant analysis were a subset of the initial variables shown in Table 1 and included several new measures of coastal storm events over time and the associated damages. 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. The population change data was obtained from the U.S. Census Bureau Census of Population and Housing Censtats Databases.

Coastal hazards included in this study were hurricanes, tropical storms, coastal flooding, storm surges, tornados, and thunderstorms. Each of these events was counted as one discrete event and was 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 a low of 8 hazards in 46 years in Orange County, Texas to a high of 60 coastal hazards in 46 years in Escambia County, Florida. 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 = fewest coastal hazards.

To create a ranking for property impacts, property damages caused by the storms and floods were pooled where 1= least property damage and 4= most property damage. The least property damage was found in San Patricio County, Texas. The residents of this county experienced 11 coastal hazard events in 46 years that totaled $9,022,930 in damages. The most property damage was found in Jefferson Parish, Louisiana, an area with 40 coastal hazard events in 46 years that resulted in $6,097,123,543 in damages.

To create the last variable, a ranking of population change, a score of 1 indicated "least growth" and 4 designated "most growth". This data ranged from a growth rate of 65% in Collier County, Florida between 1990 and 2000, to population losses of 2.5% in Orleans, Louisiana, 7.9% in St. Mary Parish, Louisiana, and 10% in Kenedy, Texas.

Once each county was given a ranking for each category described above, these rankings were combined to create a new composite ranking for each county. These values were added across the variables, so that areas with high population growth occurring in the context of high storm hazards, and high property damage were considered to be the highly resilient while areas with low growth, few hazards and lower levels of damage were considered to be least resilient. Values ranged from 3 to 12. Santa Rosa, Florida which received a 4 in all three categories finished with a rank of 12, or most resilient, while Kenedy, Texas, Kleberg, Texas, and Nueces, Texas all received "ones" in each category, resulting in rankings of 3. The rankings for each county and parish are shown in Table 6.

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

An important note is that this analytical approach using these indicators may overlook some "resilient" communities that have experience slow growth, would not identify as "resilient" any county that experienced low growth, few coastal hazards and little associated property damage over the last few decades. As a result, some resilient communities may be overlooked with this analysis. The next step in this process was to classify the groups into four categories. To do this, rankings of 3 through 12 were rescaled into values 1, 2, 3, and 4. Values of 4 were assigned to indicate the most resilient counties and parishes, while values of 1 were indicated the least resilient. The new rankings of the counties and parishes are shown in Table 6.

Once these *a priori* groupings were assigned, the discriminant analysis was run in SPSS, Version 15.0. All of the socioeconomic and environmental variables were grouped together. The result was 94.2 percent of the counties were correctly placed into their assigned resilience group (from 1 to 4). Among those few counties whose group membership was not correctly predicted or assigned, Matagorda, Texas had an *a priori* classification of "2", while the discriminate analysis placed this county as a "3". Similarly, Manatee, Florida which was placed as a 4, or most resilient should have been placed in 3 or middle resilient, while Sarasota, Florida 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 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

Table 6.
Rankings Used to Create *A Priori* Groupings (continued)

County	Hazard Rank	Damage Rank	Popchange Rank	Resilience Rank	New Resilience Rank
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
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

Table 7.
Classification of the Groups by the Discriminant Analysis Method[a]

		Predicted Group Membership				
	Resilience	1.00	2.0	3.0	4.0	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	0.0	0.0	100.0
	2.00	5.6	94.4	0.0	0.0	100.0
	3.00	0.0	0.0	94.1	5.9	100.0
	4.00	0.0	0.0	10.0	90.0	100.0

Note: [a] = 94.2% of original grouped cases correctly classified.

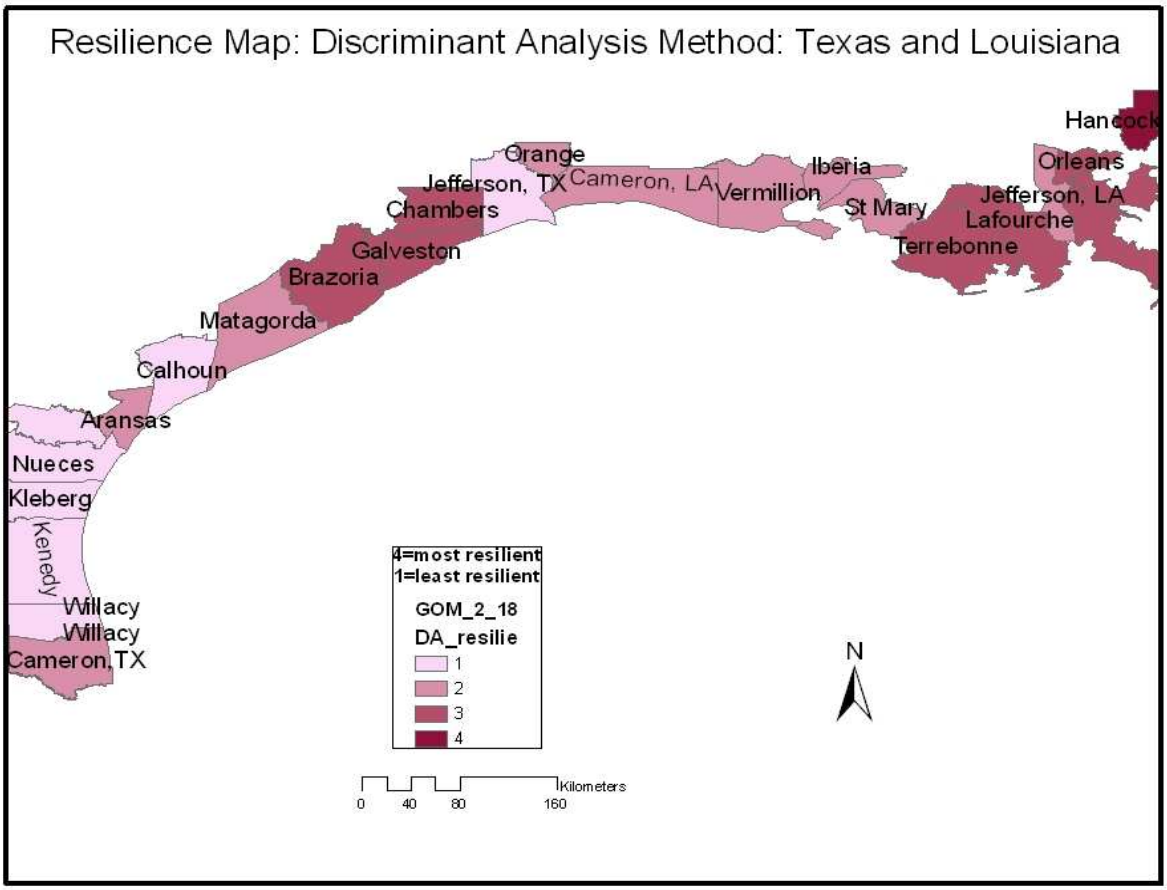

Figure 7. Results of the discriminant analysis method for Texas and Louisiana.

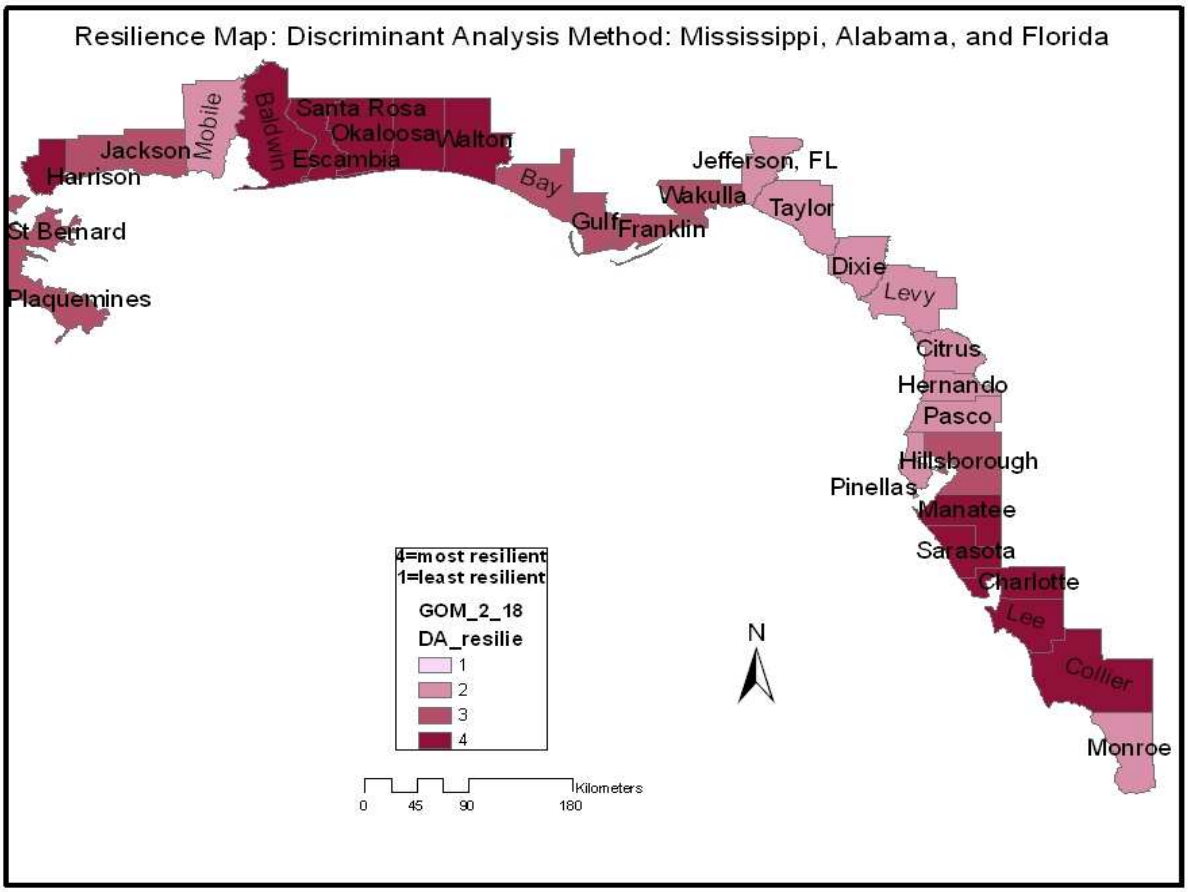

Figure 8. Results of the discriminant analysis method for Mississippi, Alabama, and Florida.

5. COMPARISON OF THE TWO METHODS TO CALCULATE COUNTY RESILIENCE

5.1. METHOD ONE: COUNTY RESILIENCE LEVELS CALCULATED BY FACTOR ANALYSIS

The counties with the lowest resilience levels according to the first methodology, the weighted resilience index derived through the Factor Analysis (FA) were: Willacy County, Texas Cameron, Texas Kleberg, Texas and Calhoun, Texas, and Dixie, Florida. With the exception of Calhoun, Texas, all these counties had median incomes below $30,000 per year. They also had relatively low voter turnout in the 2000 presidential election that ranged from 18 % in Cameron, Texas to 33 % in Dixie, Florida. Typically they had a higher percentage of the population under the age of 5 years. The percentage of children in the population of these counties ranged from 8.2% in Willacy, Texas to 5.9 % in Dixie, Florida.

Those counties estimated to be most resilient counties in the Gulf of Mexico region were centered around the suburban areas of New Orleans, and Tampa, along with the growing beach communities in Alabama and Okaloosa county in Florida. Surprisingly, Kenedy, Texas also is calculated to be 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%) and high voter turnout. Kenedy, Texas had the highest voter turnout in the Gulf region with 55%, and 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 estimated to be more resilient. These areas included the urban communities of Orleans Parish, Louisiana, Hillsborough, Florida and Pinellas, Florida. Hillsborough and Pinellas both received a score on the resilience index of 1 or most resilient, while Orleans Parish received a score of .84, placing it in the mid range of resilience.

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 in this first analysis.

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, Texas, has the lowest expenditures for education in the region, a very low median income, a middle elevation, a high number of children, and the highest value of voter participation. Given the weighting method a high level of voter participation is enough to push a county into a higher level of estimated resilience, despite the presence of other factors that would suggest socioeconomic vulnerability

5.2. METHOD TWO: COUNTY RESILIENCE LEVELS CALCULATED BY DISCRIMINANT ANALYSIS

The discriminant analysis (DA) resulted in a different pattern of estimated resilience among the Gulf of Mexico coastal counties than the first method, the Factor Analysis (FA) This can be seen in Table 8, where the FA column represents the results of the first 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 (DA) 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 methods. In these counties there is a correspondence between the resilience grouping based on risk and the resilience grouping based on socioeconomic factors. Twenty-six counties in the Gulf of Mexico region have the same resilience categorization by both methods. For example, Willacy, Texas is in the least resilient category via both the Factor Analysis and the Discriminant Analyses methods, while Okaloosa, Florida is estimated to be in the most resilient category by both methods.

On the right-hand of Table 8, the counties that have a different resilience categorization as the result of FA and DA are shown. Most of these counties are categorized differently by only one resilience group. For example, Cameron, Texas is placed in group 1, or the least resilient group via the factor analysis method, but by the discriminant analysis method is placed in group 2, a slightly more resilient group. Another example is Hillsborough, Florida, which by the factor analysis method is placed into group 4, the most resilient group, but using the discriminant analysis method is placed into group 3, a slightly less resilient group. Nine counties had differences that are greater than a one-group difference. These counties are: Jefferson, Texas, Nueces, Texas, Kenedy, Texas Jefferson, Louisiana, Mobile, Alabama, Pasco, Florida, Citrus, Florida, Hernando, Florida and Pinellas, Florida. For each of these counties, the difference between the resilience scores for the two methods was two group categories.

Overall, the Factor Analysis (FA) method led to more counties being categorized in a higher, “more resilient” category than their placement as determined by the Discriminant Analysis method. This is, in part, because the Discriminant Analysis method reflects levels of relative risk present overtime within the counties, while the Factor Analysis method reflects factors such as expenditures for education and percent of the population that voted in the last presidential election, possible indicators of “adaptive capacity” within the community. Taken together, both metrics are useful for managers, and can highlight areas that are vulnerable due to high physical risks and because they have less resilient populations.

Table 8.
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

6. EXPLORING ASSOCIATIONS BETWEEN THE RESILIENCE SCORES OF COASTAL COUNTIES AND PARISHES AND THE OIL AND GAS INDUSTRY

Oil and gas activity can affect social-ecological resilience in a number of ways. For example, the oil and gas industry provided almost 2 million people with jobs and more than $800 million in revenue for Louisiana in 2000 (LOGA, 2008). The economic impacts of oil and gas industry activities can lead to a higher occurrence of affluence, a variable that theoretically strengthens social resilience and recovery from major disturbances (Folke et al., 2005). On the other hand, oil and gas production is also suspected to be associated with wetland loss through erosion and subsidence, as well as other forms of environmental degradation, problems that, theoretically, weaken ecological resilience (Austin et al., 2004).

Are social-ecological resilience and oil and gas activity associated in any way? Specifically, does this study suggest that higher levels of employment within the oil and gas industry may help make a community more resilient to natural and man-made disasters?

To address these questions, it is useful to consider patterns of employment within the oil and gas industry across the five states. The map displayed in Figure 9 depicts the county-level employment in 12 NAICS categories related to the oil and gas industry (Pulsipher, et al. 2012) and includes additional inland counties that are not part of our study of coastal counties. The map is included here to illustrate the distribution jobs in the industry throughout the region. Areas of higher oil and gas employment are evident among several coastal counties in Louisiana and Texas, and also Jackson, Mississippi and Mobile, Alabama.

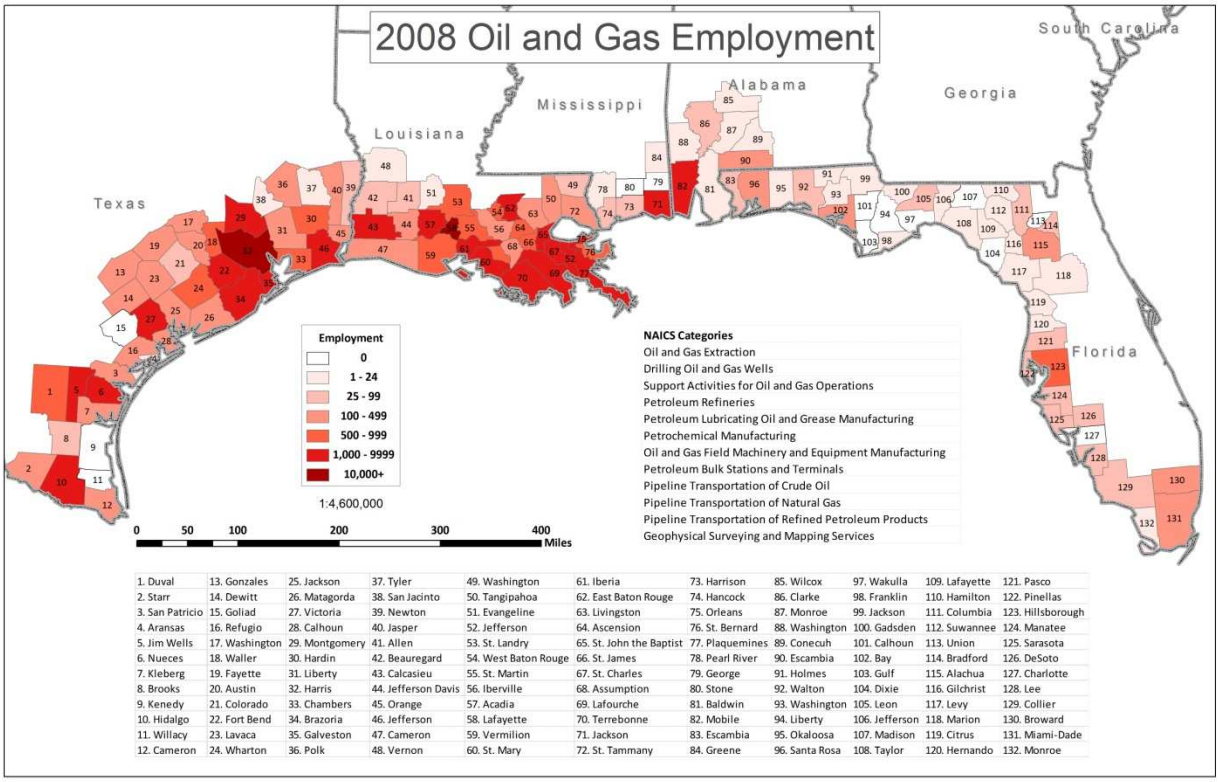

Figure 9. Oil and Gas Employment among Counties within the Gulf of Mexico Region.

To determine whether there are statistically significant associations between the presence of the oil and gas industry and the county-level resilience scores, we conducted Pearson Correlation Analyses between variables measuring industry activity and the resilience scores for each of the coastal counties in the study area. The Pearson r Correlation Coefficient ranges from 0 to 1, with values closer to 1 indicating a stronger association between two variables. The directional sign of the Pearson r indicates whether the association is inverse or positive. Also, the p value determines whether an observed association is statistically significant, with a smaller value (less than .10) signaling a more significant association (Antonius, 2003).

We used 2008 employment data from the WholeData information service, purchased and made available for this project by the LSU Center for Energy Studies. WholeData estimated employment figures from County Business Patterns (CBP) data, using iterative estimation techniques to fill in the gaps where data may have been missing in the original CBP data. The employment data reflects five oil and gas employment categories: NAICS codes 211 (Oil and Gas Extraction), 213111 (Drilling Oil and Gas Wells), 213112 (Support Activities for Oil and Gas), 333132 (Oil and Gas Field Machinery Manufacturing), and 541360 (Geophysical Surveying). We used the sum of employment and establishments for these 5 codes for each county to create two measures of oil and gas industry presence.

The data included in the Pearson Correlation Analyses are shown in Table 9. The counties and parishes are listed in alphabetical order; the ten with the largest sum of oil and gas employment are highlighted.

Table 9.
Data Used in the Pearson Correlation Analyses

County	FA Resilience Score	DA Resilience Score	Sum of O&G Employment (5 NAICS codes)	Sum of O&G Establishments (5 NAICS codes)
Aransas, TX	0.58	2	18	7
Baldwin, AL	0.90	4	2	3
Bay, FL	0.85	3	336	2
Brazoria, TX	0.77	3	751	37
Calhoun, TX	0.55	1	73	6
Cameron, LA	0.75	2	136	14
Cameron, TX	0.4	2	99	3
Chambers, TX	0.75	3	184	16
Charlotte, FL	0.94	4	0	0
Citrus, FL	0.95	2	0	0
Collier, FL	0.80	4	17	7
Dixie, FL	0.55	2	0	0
Escambia, FL	0.90	4	6	4
Franklin, FL	0.72	3	0	0
Galveston, TX	0.84	3	257	22
Gulf, FL	0.84	3	0	0
Hancock, MS	0.69	4	67	2
Harrison, MS	0.65	3	6	3
Hernando, FL	1	2	1	1
Hillsborough, FL	1	3	29	7
Iberia, LA	0.79	2	1395	57
Jackson, MS	0.75	3	26	2
Jefferson, FL	0.75	2	0	0
Jefferson, LA	1	3	2540	54
Jefferson, TX	0.72	1	517	22
Kenedy, TX	1	1	0	0
Kleberg, TX	0.52	1	110	14
Lafourche, LA	0.74	3	1491	41
Lee, FL	0.93	4	15	5
Levy, FL	0.66	2	0	0
Manatee, FL	0.95	4	3	2
Matagorda, TX	0.57	2	80	10
Mobile, AL	0.87	2	436	17
Monroe, FL	0.82	2	5	3
Nueces, TX	0.74	1	3420	178

County	FA Resilience Score	DA Resilience Score	Sum of O&G Employment (5 NAICS codes)	Sum of O&G Establishments (5 NAICS codes)
Okaloosa, FL	1	4	2	1
Orange, TX	0.64	2	232	4
Orleans, LA	0.84	3	1866	48
Pasco, FL	0.91	2	47	4
Pinellas, FL	1	2	19	6
Plaquemines, LA	0.77	3	941	41
San Patricio, TX	0.58	1	435	27
Santa Rosa, FL	0.95	4	203	6
Sarasota, FL	1	3	13	4
St. Bernard, LA	0.82	3	72	7
St. Mary, LA	0.73	2	2993	38
Taylor, FL	0.62	2	0	0
Terrebonne, LA	0.65	3	6078	89
Vermilion, LA	0.74	2	494	28
Wakulla, FL	0.73	3	0	0
Walton, FL	0.92	4	0	2
Willacy, TX	0.35	1	0	0

The two counties with the most oil and gas industry employees are Louisiana's Terrebonne Parish, with 6078 employees, and Nueces County in Texas, with 3420 workers. These counties are followed by several parishes or counties in Louisiana: St. Mary Parish (2993), Jefferson Parish (2540), Orleans Parish (1866), Lafourche Parish (1491), Iberia Parish (1395), Plaquemine Parish (941); and two in Texas: Brazoria County (751) and Jefferson County (517).

6.1. Correlation Analyses and Results

We ran bi-variate correlation analyses between the two measures of oil and gas industry activity (total employment of the five NAICS categories and number of establishments) and the resilience scores (calculated by the two methods) for the coastal counties within the study area. The analyses were conducted in SPSS version 15.0.

The first analysis between the resilience score generated through the Factor Analysis method for the 52 counties and the oil and gas activity variables resulted in no statistically significant correlations between resilience scores and industry activity. The Factor Analysis Method Resilience Score (FASCORE) and EMPLOY yielded a Pearson r coefficient of -.059, p=.680. Similarly, the FASCORE and ESTAB resulted in a Pearson r of -.050 and a p value of .756. The results of these correlation analyses are shown below in Table 10.

Table 10.
Pearson Correlation Analysis between Factor Analysis- Method Resilience Scores and Oil and Gas Employment; Oil and Gas Establishments

Correlations

		FASCORE	EMPLOY	ESTAB
FASCORE	Pearson Correlation	1	-.059	-.050
	Sig. (2-tailed)	.	.680	.726
	Sum of Squares and Cross-products	1.342	-534.262	-12.174
	Covariance	.026	-10.476	-.239
	N	52	52	52
EMPLOY	Pearson Correlation	-.059	1	.811**
	Sig. (2-tailed)	.680	.	.000
	Sum of Squares and Cross-products	-534.262	6.2E+07	1350741
	Covariance	-10.476	1216834	26485.116
	N	52	52	52
ESTAB	Pearson Correlation	-.050	.811**	1
	Sig. (2-tailed)	.726	.000	.
	Sum of Squares and Cross-products	-12.174	1350741	44677.308
	Covariance	-.239	26485.116	876.026
	N	52	52	52

**. Correlation is significant at the 0.01 level (2-tailed).

Next, we conducted a Pearson Correlation Analysis using the resilience scores calculated through the Discriminant Analysis (DA) method. We found no significant correlation between these resilience scores and industry employment or the number of oil and gas establishments within the county. The DA Method Resilience Score (DASCORE) and number of employees yielded a Pearson r coefficient of -.072, p=.611. Similarly, the DASCORE and the number of establishments variable resulted in a Pearson r of -.199 and a p value of .157. The results of this analysis are shown in Table 11.

Table 11.
Pearson Correlation Analysis between Discriminant Analysis-Method Resilience Scores and Oil and Gas Employment; Oil and Gas Establishments

Correlations

		DASCORE	EMPLY	ESTABLIS
DASCORE	Pearson Correlation	1	-.072	-.199
	Sig. (2-tailed)	.	.611	.157
	Sum of Squares and Cross-products	46.692	-3882.385	-287.462
	Covariance	.916	-76.125	-5.637
	N	52	52	52
EMPLY	Pearson Correlation	-.072	1	.812**
	Sig. (2-tailed)	.611	.	.000
	Sum of Squares and Cross-products	-3882.385	6.2E+07	1358447
	Covariance	-76.125	1197914	26123.971
	N	52	53	53
ESTABLIS	Pearson Correlation	-.199	.812**	1
	Sig. (2-tailed)	.157	.000	.
	Sum of Squares and Cross-products	-287.462	1358447	44932.113
	Covariance	-5.637	26123.971	864.079
	N	52	53	53

**. Correlation is significant at the 0.01 level (2-tailed).

6.2. SUMMARY

The calculation of the resilience scores for the coastal counties and parishes yielded information about the relative socioeconomic conditions among coastal jurisdictions and the extent to which the coastal communities have held on to populations over time in light of exposure to storms and other large-scale disturbances. The two methods employed, the Factor Analysis method and the Discriminant Analysis method, produced slightly different rankings or scores for parishes and counties. For example, using the FA method to calculate the resilience scores resulted in Terrebone Parish, Louisiana being placed in the third quartile of resilience among the coastal counties and parishes (Figure 5), while the DA method placed it in the second quartile (Figure 6).

The DA method may be considered a more refined approach in that it includes the exposure to hurricanes and other natural disturbances over time in the calculation of the resilience score. In that sense, it provides a method to compare areas that have been similarly affected by disturbances when evaluating their resilience or ability to maintain and increase their population over time.

The Pearson Correlation Analyses yielded no evidence of statistically significant associations between either of the calculated resilience scores and the measures of oil and gas industry activity within the counties and parishes. However, even in light of these findings, the study is a first step in operationalizing key theoretical concepts from the social-ecological resilience literature that are relevant to considerations of how industry presence may influence the socioeconomic conditions of communities. We have aggregated a range of socioeconomic and environmental variables so that comparisons can be made among coastal communities, demonstrating a useful approach for the more systematic examination and comparison of exposure, vulnerability and capacity for resilience among these coastal areas.

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APPENDIX:
ABSTRACTS OF SELECTED THESES

A.1. LAUREN DEFRANK, RESILIENCY OF NEW ORLEANS FOLLOWING HURRICANE KATRINA: A STUDY OF COMMUNITIES THREE YEARS AFTER THE STORM

In late August 2005, Hurricane Katrina and subsequent levee failures produced catastrophic flooding in New Orleans, Louisiana, killing roughly fifteen-hundred residents, and forcing the evacuation of most of the local population. Over four years later, many areas of the city had not recovered in terms of housing, business operations, infrastructure, or population. The authors examine patterns of repopulation within Orleans Parish as an indicator of community resilience to large-scale external disturbances. They pose two central research questions: To what extent do patterns of recovery observed in natural-systems after large disturbances yield insight into the recovery patterns of human communities? Also, what factors may account for variation in the resilience of coastal cities like New Orleans? The researchers analyzed mail-delivery data at the zip-code and Census-tract levels in Orleans Parish before, and at monthly intervals after the storm, as an indicator of returning population. Cluster Analysis yielded three distinct recovery patterns–"resilient", "resistant" and "susceptible"–similar to those of natural systems. Then, they used Discriminate Analysis to examine the 181 Census tracts of Orleans Parish and to estimate the relative influence of socioeconomic and environmental factors of the neighborhoods on the rates of population return. They found that three factors – higher Katrina flood depths, greater percentage of African-American residents, and lower educational attainment –predicted patterns of population return for over 75% of the 181 Census Tracts within Orleans Parish. Of these three factors flood depth was, by far, the most important predictor of returning population, indicating that among those who experienced flooding of ten feet or more, even residents with sufficient economic resources to rebuild largely have opted not to do so.

A.2. ARIELE BAKER, CREATING AN EMPIRICALLY DERIVED INDEX OF COMMUNITY RESILIENCE FOR THE GULF OF MEXICO REGION

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 to 1. The most resilient counties in the Gulf of Mexico region were found to be Hillsborough, Florida, Pinellas, Florida, Sarasota, Florida, Hernando, Florida, Okaloosa, Florida, Kenedy, Texas, and Jefferson, Louisiana with a resilience score of 1. The least resilient counties in the Gulf of Mexico were found to be Cameron, Texas and Willacy, Texas 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 five 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, Mississippi, Collier, Florida, Baldwin, Alabama, Escambia, Florida, Walton, Florida, Lee, Florida, Charlotte, Florida, Manatee, Florida, Santa Rosa, Florida, Okaloosa, Florida. Counties found to be in the least resilient group were Kleberg, Texas, Calhoun, Texas, San Patricio, Texas, Jefferson, Texas, Nueces, Texas, Kenedy, Texas, and Willacy, Texas.

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.

The Department of the Interior Mission

As the Nation's principal conservation agency, the Department of the Interior has responsibility for most of our nationally owned public lands and natural resources. This includes fostering the sound use of our land and water resources, protecting our fish, wildlife and biological diversity; preserving the environmental and cultural values of our national parks and historical places; and providing for the enjoyment of life through outdoor recreation. The Department assesses our energy and mineral resources and works to ensure that their development is in the best interests of all our people by encouraging stewardship and citizen participation in their care. The Department also has a major responsibility for American Indian reservation communities and for people who live in island communities.

The Bureau of Ocean Energy Management

The Bureau of Ocean Energy Management (BOEM) works to manage the exploration and development of the nation's offshore resources in a way that appropriately balances economic development, energy independence, and environmental protection through oil and gas leases, renewable energy development and environmental reviews and studies.