2011

Temporal changes of coastal community resilience in the Gulf of Mexico region

Kenan Li
Louisiana State University and Agricultural and Mechanical College

TEMPORAL CHANGES OF COASTAL COMMUNITY RESILIENCE IN THE GULF OF MEXICO REGION

A Thesis

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Master of Science

in

The Department of Environmental Sciences

by
Kenan Li
B.S., Nankai University, 2009
December 2011

Acknowledgements

I would like to acknowledge and extend my heartfelt gratitude to my advisor professor Dr. Nina Lam, and to my committee members Dr. Margaret Reams and Dr. Vincent Wilson, for providing me with the opportunity to complete my Master program. This research was supported by two grants from the Bureau of Ocean Energy Management, Regulation and Enforcement (BOMRE) (Award number: M09AC15619 and M09AC15620). I would also like to thank my fellow student Danielle Larock in helping me collect data. Thanks for my parents and who give me support and encouragement in writing this thesis. And especially to God, who made everything possible.

Table of Contents

List of Tables

List of Figures

Abstract

The Gulf of Mexico Region is a region where coastal hazards are frequently occurring. To study the resilience of the counties along the Gulf of Mexico is of great importance to its sustainable planning and development. It also plays a huge role in coastal hazard mitigation. This study assesses the temporal changes of coastal community resilience of 132 counties along the Gulf of Mexico. The basic analytical framework to assess resilience consists of three dimensions (exposure, damage, and recovery) and two relationships (vulnerability and adaptability). Vulnerability refers to the relationship between exposure and damage, whereas the relationship between damage and recovery is termed adaptability in this study. Two important concepts were advanced in this study, which are assessing community resilience by the community's behavior before and after disturbances, and validating the results through statistical techniques. Four socioeconomic resilient systems were derived according to their behaviors before and after natural coastal hazards: susceptible, recovering, resistant, and usurper. Seven different grouping tests using k-means cluster analysis were run on the 132 counties. 28 variables from the resilience and vulnerability literature and the human development literature were examined and explored to serve as input to discriminant analysis. Factor analysis was used to find the most important variables that affected the resilience capacity.

The results show that when using population growth as a recovery indicator, the classification gains the best discriminant scores (84.8% accuracy for 2000's data, and 81.8% for the 1990's data) using the 28 variables. In general, community resilience did not change much from 1990 to 2000. A total of nine counties changed their resilience capacity during the decade. Of those, four were found to have an increase in resilience, while the remaining five had a decrease in resilience.

Chapter 1: Introduction

1.1 Problem Statement

In recent years, the concepts of resilience, vulnerability, and adaptability have been increasingly used in the literature. The concept was first introduced by Holling (1973) in the field of ecology. Despite the voluminous literature in this field, there is not yet a convincing approach to quantifying and measuring community resilience. “The difficulties are due partly to the many different definitions of resilience by different researchers, which are often confused or used interchangeably with similar concepts such as vulnerability , sustainability and adaptability” (Lam and Reams, 2009). Counties along the Gulf of Mexico were frequently affected by natural coastal hazards, and the plenty historical hazard data gives us the opportunity to study the community resilience. Study of this type can help the hazard protection and mitigation and government planning to a large extent.

The resilience of a community can be compared with the elasticity of a spring in analogy. If we talk about the elasticity of a spring, we may be concerned with how much the outside force can be on it, how much elastic force it can generate, can it rebound to the former original state, or will it be devastated by the outside force. Similarly, several factors may contribute to the community resilience, such as: how often is the county exposed to natural hazard, or how often is the system perturbed by external force; how much damage is caused by the hazards, or what is the magnitude of the disturbance; and lastly, to what degree is the county able to recover, or is the system able to bounce back to its equilibrium after disruption.

Moreover, supposed we know the elasticity of a set of springs, we may want to know what factors make the elasticity of different springs so different from each other. It may be due to

its shape, size, or materials the spring is made of. In a socioeconomic system, a lot of factors affect the behavior of a community before and after hazards. We define a community's resilience capacity according to its behavior before and after disturbance, but we are also concerned about what factors contribute to the resilience capacity, and whether communities that have different resilience capacities have different socioeconomic as well as natural structures. In order to answer this question, more research is needed to examine two areas: to find appropriate indicators to represent the community's socioeconomic and natural environmental structure, and to evaluate if communities having similar resilience capacity will have similar socioeconomic structure.

1.2 Research Goals and Objectives

Despite abundant literature in socioeconomic resilience, vulnerability, and hazards and risk assessment, there is not yet any convincing approach to quantifying and measuring community resilience. There is a critical need to create a model to measure community resilience capacity which can truly capture the causes and consequences regarding resilience, so that we can use it as a tool for hazard mitigation and disaster recovery (Lam et al., 2011).

The goal of this thesis research is to develop an empirically derived model to quantitatively measure community resilience. The study area includes 132 counties in the Gulf of Mexico region. The resilience measurement will include assessment of the state of a community before hazards happen and in the aftermath of the hazards, such as population or income change. Through the model development process, this thesis aims to identify the key factors that would increase or decrease resilience.

The development of a meaningful and practical resilience measurement model is very much needed to foster our understanding of what we mean by resilience and how it can be increased or decreased. A straight-forward model for measuring resilience that is grounded on sound theoretical principles will be very useful for sustainable planning and management and help speed economic recovery after major disaster events (Lam et al., 2011).

Specifically, the tasks in this study are four-fold: (1) to develop and refine a conceptual model to define different types of communities resilience, according to their behavior before and after disaster events; (2) to classify the 132 coastal counties into the types as defined using k-means analysis; (3) to develop indicators to measure dimensions and constructs of a socioeconomic system, and subsequently to validate the grouping results; (4) to simplify the variables by factor analysis; (5) to compare the results through the decade between 1990 and 2000 to study the possible temporal changes in community resilience.

Chapter 2: Background and Framework of This Study

2.1 Resilience Definition

The term resilience stems from a large body of literature, in which it has been defined in two different ways. Some researchers define resilience as the speed of a system returning to the original state after disruption, whereas others define resilience as the magnitude that a system could be perturbed without shifting to a different state (Holling, 1973; Holling, 1996; Walker et al. 2006). The two definitions reveal two aspects of concerns by researchers: one focuses on maintaining “efficiency” of function; and the other focuses on maintaining “existence” of function (Holling, 1996).

The first definition, and the more traditional one, concentrates on the stability near an equilibrium state, where resistance to disturbance and speed of return to the equilibrium are the normal property measurement (O’Neill, et al., 1986; Pimm, 1984; Tilman and Downing, 1994). This definition focuses on “efficiency, constancy, and predictability”, and all these attributes are at the core of engineers’ desire for fail-safe design, so this definition is termed “engineering resilience” (Holling, 1996). The second definition of resilience emphasizes the magnitude of disturbance that a system can absorb before changing its structure by changing indicator variables and processes that control behavior. This definition emphasizes conditions far from equilibrium steady state, where instability can flip the system into another regime of behavior, in other words, to another equilibrium domain (Holling 1973; Holling 1996; Walker et al., 1969). The attributes focused here include “persistence, change, and unpredictability”, all of which are embraced by biologists and ecologists. Hence, this view of resilience is called “ecological resilience” (Holling, 1996).

Norris in his paper in 2007 pointed out that despite various definitions, there is general consensus on two points: first, resilience is better conceptualized as an ability or process than as an outcome (Brown and Kulig 1996; Pfefferbaum et al., 2005); second, resilience is better conceptualized as adaptability than stability. Adaptability also takes different forms. In the "engineering resilience" case, a system returns to a predesigned state or function in the aftermath of disturbances. In the "ecological resilience" case, the system is allowed to return to many possible desirable states that match the environment (Gunderson, 2000). Therefore the second type of definition is more relevant for human communities, organizations, and societies (Holling, 2007).

Although these two types of definitions almost reveal all the concerns near equilibrium, when applied to community and its environment, both types of definitions are not sufficient to capture all the attributes. In other words, communities are not like simplified mathematical models in which we have defined equations and roots to tell us if it is deviated from equilibrium or coming back to equilibrium. In a physic or mathematic system, we have functions to measure the magnitude of disturbance, and the speed of returning back to equilibrium in the aftermath of a disturbance, but for a socioeconomic community, we need to design a theoretical framework to seek proper measurements for the system.

2.2 Vulnerability Definition

The term vulnerability is closely related to resilience in the literatures, and in some publications the two terms have been used interchangeably. Since resilience includes the capacity to increase the ability to cope with stress, in some literature vulnerability is a loose antonym for resilience (Adger, 2000). Adger and Kelly (1999) in the context of environmental

change states that it is an emerging issue to analyze vulnerability of different social groups and the institutional architecture which determines resilience.

Adger in 2000 pointed out that “the concept of resilience is clearly related to other configurations of environmental society relationships such as vulnerability”. He defined that “social vulnerability is the exposure of groups of people or individuals to stress as a result of the impacts of environmental change”. In his definition, he equates vulnerability to exposure. So a vulnerable county is the county which is more likely to be exposed to natural hazards. He realized the significance to connect resilience with vulnerability, however he did not consider the aftermath of the exposure and the internal socioeconomic construct of a community. In other words, a well prepared county may not necessarily suffer more than a poorly prepared county, even if it is more exposed to natural hazards. We cannot say the former county is more vulnerable.

Folk, et al. (2002) defined vulnerability in an ecological sense as “the propensity of an ecological system to suffer harm from exposure to external stresses and shocks”. In this definition, vulnerability is considered as a “propensity” to take the internal construct of a system into consideration, and ignores the exposure probability.

Turner and others in 2003 stressed that vulnerability is not just exposure to hazards. It includes three elements which are “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 “sustainable science” (Turner et al., 2003; Liu J. et al. 2007). This definition of vulnerability includes resilience as an element. But in their definition, the term resilience is more like adaptability. They treated

resilience as the ability to respond and recover from disaster events. Their definition paid a proper attention to the internal sensitivity. They emphasized the sensitivity of a system to external exposure matters in assessing the resilience capacity of a system.

Cutter and Finch in 2008 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 impacts of hazards”. Cutter and Finch’s definition includes adaptability into vulnerability. This definition includes adaptability which is an essential element in resilience.

For the measurement of vulnerability, the United Nations’ Intergovernmental Panel on Climate Change (IPCC, 2001, p.995) defined vulnerability (V) as a function of exposure (E), sensitivity(S), and adaptive capacity (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 adaptability capacity is the ability of a system to adjust to climate change or to cope with its consequences. Yusuf and Francisco (2009) followed IPCC and developed a model to assess the vulnerability of sub-national areas in South Asia to Climate change.

2.3 Adaptability Definition

The introduction of the term adaptation to human systems can date back to anthropologist and cultural ecologist Julian Steward, who used “cultural adaptation” to describe the adjustment of “cultural cores” to the natural environment through subsistence activities (Butzer, 1989). Substantial literature has focused on the adaptation ability since then.

Many resilience definitions emphasized the capacity for successful adaptation in the face of disturbance, stress, or adversity (Norris, 2007). Smit and others in 2005 pointed out that the terms of resilience, vulnerability, adaptability and exposure are interrelated in concepts. Pielke (1998) depicts adaptability in climate change context as the "adjustment in individual groups and institutional behavior in order to reduce society's vulnerability to climate." Smit and others (2000) in the climate change context refer adaptation as "adjustments in ecological-socio-economic systems in response to actual or expected climate stimuli, their effects or impacts". Brooks (2003) describes adaptability as "adjustment in a system's behavior and characteristics that enhance its ability to cope with external stress".

The concept of adaptability has been used both "implicitly" and "explicitly" in social sciences (Smit et al., 2005). Some scholars employed the concepts and terminology of biophysical ecological change with the focus on flows of matter, energy and information (Odum,1970) and related concepts of resilience , equilibrium and adaptive management (Holling, 1986), while others particularly in natural hazards perspective, have focused on perception, adjustment and management of environmental hazards (Burton et al., 1978).

In natural science, adaptability broadly refers to "the development of genetic or behavioral characteristics which enable organisms or systems to cope with environmental changes in order to survive and reproduce". (Futuyama, 1979; Winterhalder, 1980; Kitano, 2002)

2.4 Economic Development and Its Measurement

Economic development is an important aspect on studying the social-economic structure of a community. A lot of previous research has been done on the measurement of economic development. Anderson (1991) argued that social indicators that measure the general areas of

finance, natural environment, and the human aspects of the economy will provide a more comprehensive and realistic measure of the overall economic development of an area. For example, the input of labor can be measured by employment, education and literacy levels. Human aspects of the economy can be measured not only by consumption of goods, but also by access to safe water, adequate nutrition and telephones in the home. Population changes or migration can indicate a stress on resources or a loss of human capital. Finally, health indicators such as infant mortality and under-5-years mortality are other sensitive human economic indicators that reflect recent changes in economic and environmental conditions that, unlike adult mortality rates, are not dependent on time lags. However in some studies these variables are viewed as outcomes of community resilience and are therefore not included in creating the index (Norris, 2010; Nicolas, 1999).

Horn (1993) argued that economic, social and technological developments interacted with each other. Thus, in his view, the measurement of economic development should include indicators of social and technological development. Indicators relating to this inclusive development measure include: infant mortality rate, life expectancy, population protein consumption, literacy, safe water access, access to telephones, newspapers, and cars, agricultural workers as a percent of the employed, steel and energy consumption, and exports/imports. Additionally, human capital indicators such as labor force participation rate and unemployment rate would also be considered. Productivity indicators could be used to measure efficiency and progress, and used as a method for comparing industries within and across defined areas of production.

The Human Development Index (HDI) uses adult literacy and mean-years of schooling to measure knowledge acquisition; life expectancy at birth to measure a healthy life; and an

adjusted gross domestic product to measure standard of living. The components of the HDI that measure knowledge and standard of living apply to our concept of Economic Development (UNDP 1990).

Shaw-Taylor (1999) developed the Social Health Index as a measure of economic development in an attempt to assess how well a community functions by taking into account the disadvantaged populations in the community. Shaw-Taylor identified five potential indicators of social disadvantage for his index—rates of unemployment, poverty, high school drop-outs, violent crime, and Medicaid recipients—and tested them with the health outcomes of infant mortality rate, low birth weight and premature mortality rate. Using state level data across three time periods, he found that poverty and violent crime were primary and consistent predictors of social health disadvantage as measured by higher rates of infant mortality, low birth weight infants and premature mortality.

2.5 Challenges and Choosing Variables

"The challenges of measuring community resilience will be enormous. The difficulties are partly due to the many different definitions of resilience by different researchers, which are often confused or used interchangeably with similar concepts such as vulnerability, sustainability, and adaptability, and partly due to the lack of empirical validation" (Lam and Reams, 2009).

A lot of work has been done by previous researchers on finding effective and appropriate variables to indicate the socioeconomic construct of a community. The effort of finding appropriate social indicators to depict resilience or vulnerability can be traced back to 1960s and 1970s. Social indicators research became a thriving topic within the social sciences from these years (Cutter, 2003). Duncan (1969, 1984), Land (1983), Spilerman (1975) and Smith (1973, 1981) have written a lot of theoretical and methodological issues. As a current research endeavor, much of the contemporary work on social and quality of life indicators is relegated to popular

rating places guides such as “The Places Rated Almanac” (Savageau, 2000), “ America’s Top-Rated Cities” (Garoogian, 1999), or “Comparative Rankings of Environmental quality” (Green Metro Index by World Resources Institute, 1993; Green Index by Hall and Kerr, 1991) (Cutter 2003).

Cutter (2003) reviewed literature and defined characteristics that influence social vulnerability. These characteristics include socioeconomic status, gender, race and ethnicity, age, commercial and industrial development, employment loss, rural or urban, residential property, infrastructure and lifelines, renters, occupation, family structure, education, population growth, medical, services, social dependence, and special needs populations. Cutter and her group collected specific variables according to these characteristics and tested them and identified 42 variables to use in their study.

Baker (2009) selected 42 variables to create an empirically derived community resilience index on the 52 coastal counties in the Gulf of Mexico Region. Nicholas (1999) according to Doyal and Gough’s 1991 theory of human need formulated 12 measurable indicators of regional development for the Lower Mississippi Delta area. The variables used in this study were basically selected from their studies.

2.6 Basic Framework of the Study

To fulfill the objectives and research goals stated in Chapter 1, a basic framework was set for the purpose of measurement. The second definition of “ecological resilience” was used to design the theoretical framework. In this framework, which was modified from the Resilience Inference Model (RIM) developed by Lam, Reams and Baker (Lam et al., 2011), community resilience is depicted as an aggregation of three key elements or dimensions and two relationships. The three dimensions applied to this study that help to explain variation in the

observed community resilience are: exposure, damage, and recovery; and the two relationships are vulnerability and adaptability. Vulnerability is the relationship between exposure and damage, and adaptability is the relationship between damage and recovery.

Resilience is defined in a large scale, and includes vulnerability and adaptability as its components, and it is the ultimate goal for measurement. Vulnerability is compared by the two dimensions of exposure and damage, whereas adaptability is compared by the two dimensions of damage and recovery.

Previously, our research team suggested that the recovery patterns of a community after a hurricane can be in four different states: susceptible, resilient, usurper, and resistant (Figure 1). The counties devastated by disturbance and unable to fully recover are called susceptible counties. Resilient counties are the ones also devastated by hazards but have the ability to recover, whereas the term usurper is used to describe counties that are somewhat influenced by disruption but exhibit growth of indicator variables in some degree. Counties which have much smaller impacts from hazards can be described as resistant (DeFrank, 2009).

Lam et al. (2011) modified the above framework and suggested four types of socioeconomic resilient systems: susceptible, recovering, resistant, and usurper. The criterion to distinguish these systems apart from each other is their behaviors on the three dimensions (Figure 2).

In order to interpret the results, four typical curves were defined for each of the socioeconomic resilient systems. The x-axis shows the three dimensions: exposure, damage, and recovery. The y-axis shows the z-scores of the three dimensions. If the z-score is higher in one dimension, it means that the system has higher value on this dimension than others.

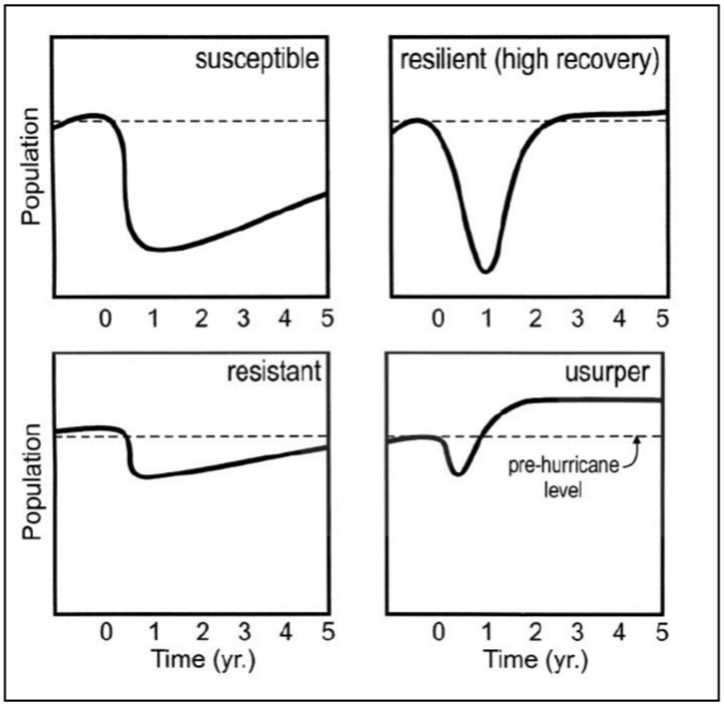

Figure 1: Four Patterns of Recovery in a Social Economical Community (Liu et al. 2006; Defrank, 2009)

The line segment connecting the exposure and damage dimensions represent vulnerability, and the one connecting damage and recovery can be considered as adaptability. For instance, in the "susceptible" graph, the upward line segment connecting exposure and damage shows that this system has more damage above the mean only despite an average exposure. This indicates that this system is much more vulnerable than the others. So an upward line segment connecting exposure and damage represents higher vulnerability. The inclination degree can also indicate the vulnerability degree. For another example, in the case of a usurper system, an upward line segment connecting damage and recovery means that the system has a very strong ability of recovering relative to its mean level of property damage. So the line segment connecting damage and recovery demonstrates the adaptability and upward means higher than average, downward means lower than average, and horizontal means average. The inclination degree shows the adaptability strength.

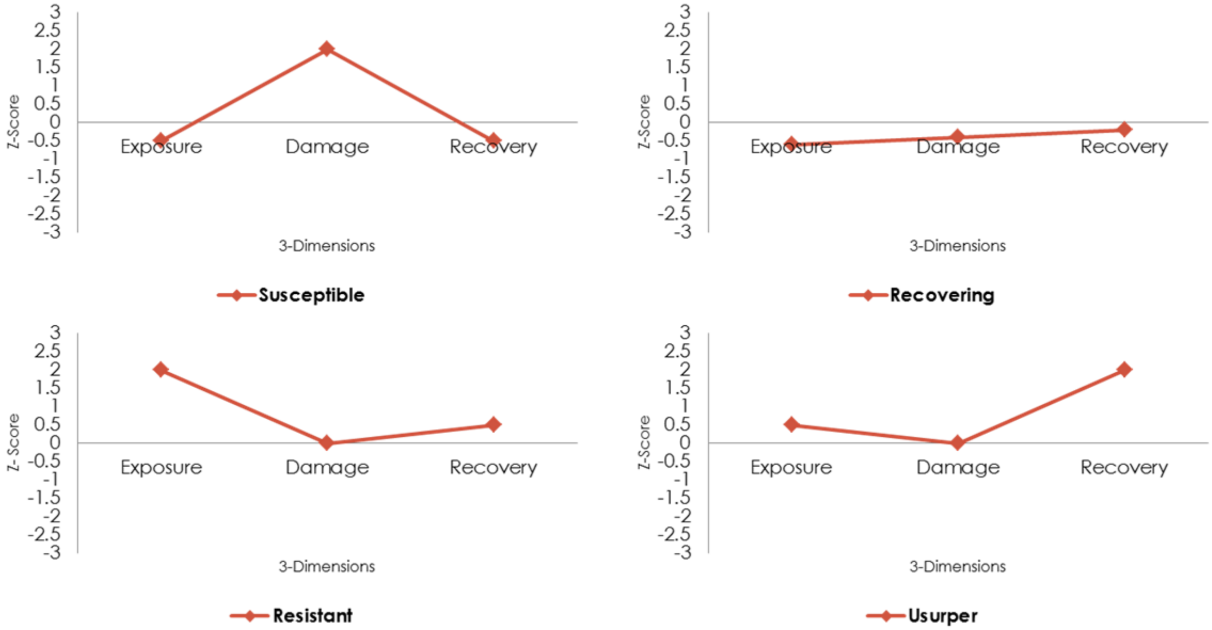

Figure 2: Resilience Curves of Four Main Socioeconomic Systems. The y-axis shows the deviation of a dimension from its mean (the nearer to zero, the less deviation from the mean).

A susceptible system is considered the lowest resilient system. It has a high probability to suffer damage from exposure. A recovering system's behavior on all the three dimensions is near the mean, none of its behavior on each one of the dimension is far above or below the mean level. Counties belonging to a resistant system have a high probability of exposure to disturbance, but they do not have significant damage above mean level. As for a usurper system, it has a high capability of self-organization. Its ability on the recovery dimension is much higher than the mean. In terms of the two relationships vulnerability and adaptability in this study: a susceptible system has high vulnerability and low adaptability; a recovering system has mean vulnerability and mean adaptability (same vulnerability and adaptability); a resistant system has low vulnerability with a mean adaptability; and a usurper system has mean vulnerability, but high adaptability. In terms of resilience ranking, susceptible is considered the lowest, following by recovering, resistant, and usurper.

Chapter 3: Study Area and Data

3.1 Study Area

The principal study area in this study is the 13 Gulf Economic Impact Areas (EIAs), which are defined by the U.S. Bureau of Ocean Energy Management, Regulation and Enforcement (BOMRE), the former U.S. Minerals Management Service (MMS), for planning and report purposes in their general, multiyear Economic Impact Statement (EIS). The study area is composed of 132 county or Parish units divided into 23 Labor Market Areas (LMAs) spreading across the five Gulf of Mexico States: Texas, Louisiana, Mississippi, Alabama, and Florida. Of the 132 counties, 52 of them share the coastline with the Gulf of Mexico directly, whereas the others are inland but still quite close to the sea.

As a comparison, the National Oceanic and Atmospheric Administration NOAA defined 142 coastal counties in the Gulf of Mexico Region by meeting one of the following criteria: (1) at least 15 percent of a county's total land area is located within the Nation's coastal watershed; (2) a portion of or an entire county accounts for at least 15 percent of a coastal cataloging unit (NOAA's List of Coastal Counties for the Bureau of the Census Statistical Abstract Series). 116 of the 132 counties are defined as coastal counties by NOAA. The 16 counties that are not defined as coastal counties by NOAA but included in the study area are: Conecuh, AL; Wilcox, AL; Alachua, FL; Bradford, FL; Broward, FL; Columbia, FL; Hamilton, FL; Miami-Dade, FL; Union, FL; Allen, LA; Greene, MS; Gonzales, TX; Hardin, TX; Montgomery, TX; Polk, TX; San Jacinto, TX. The reason to include these counties in this study is to make it easier to conduct socioeconomic impacts analysis such as oil and gas activity impacts on resilience in the Economic Impact Areas (EIAs) in the future. And although these counties are not defined as coastal counties by NOAA, they suffered coastal hazards in different degrees.

3.2 Data

The data used in the thesis comes from several data sources. Demographic and economic data were obtained from the U.S. Census Bureau 2000. Health related variables were obtained from the Bureau of Health Professions in U.S. Department of Health and Human Services: Area Resource File (ARF). The coastal hazards data were obtained from the University of South Carolina's Coastal Hazard's Lab. Finally, the mean elevation variable for each county was derived by the author by using the National Elevation Dataset (NED) available from the U.S. geological Survey (USGS) seamless map sever.

The next step is to choose the appropriate variables to indicate the three dimensions of community resilience. The choice of indicator variables for the three dimensions was inspired by Baker (2009) and Nicholas (1998). For the exposure dimension, the total number of coastal hazards from 1960 to 2006 was used to indicate how often the counties are exposed to disturbance. The types of hazards include: hurricane, tropical storm, severe thunderstorm, and coastal flooding. The per capita property damage caused by these natural coastal hazards was used to indicate the damage dimension. Three indicator variables were used and tested to indicate the recovery dimension: per capita personal income growth rate from 1969 to 1999; median income growth rate from 1989 to 2007; and total population growth rate from 1990 to 2008. Population growth and economic growth represented by income growth are the key factors on presenting recovery ability of coastal counties in this study.

A long time span for exposure (from 1960 to 2006) to study the coastal resilience was used in this study to indicate a more reliable cumulative impact. If the time period is too short, some counties may not be exposed to and impacted by any of the disturbances, hence we will not be able to assess their community resilience. With a longer time span, all of the counties in the

study area are somewhat affected by coastal hazards. This makes it possible to look at their different behaviors. The time spans for recovery variables are not exactly the same with the other two dimensions, due to data availability. Moreover, recovery should happen after disturbance, so it is reasonable to have a time lag for the variables indicating adaptability.

The indicator variables used in discriminant analysis were selected from Baker's (2009) and Nicholas' (1998) research, and they fall into six categories: demographic, social capital, governmental, environmental, economic, and health (Table 1). There are altogether twenty-eight variables to depict the social, economic and environmental (elevation) construct of a community. Both 1990's and 2000's census data for the 28 variables were used in discriminant analysis to test and compare how the counties changed between the two periods in resilience measurement.

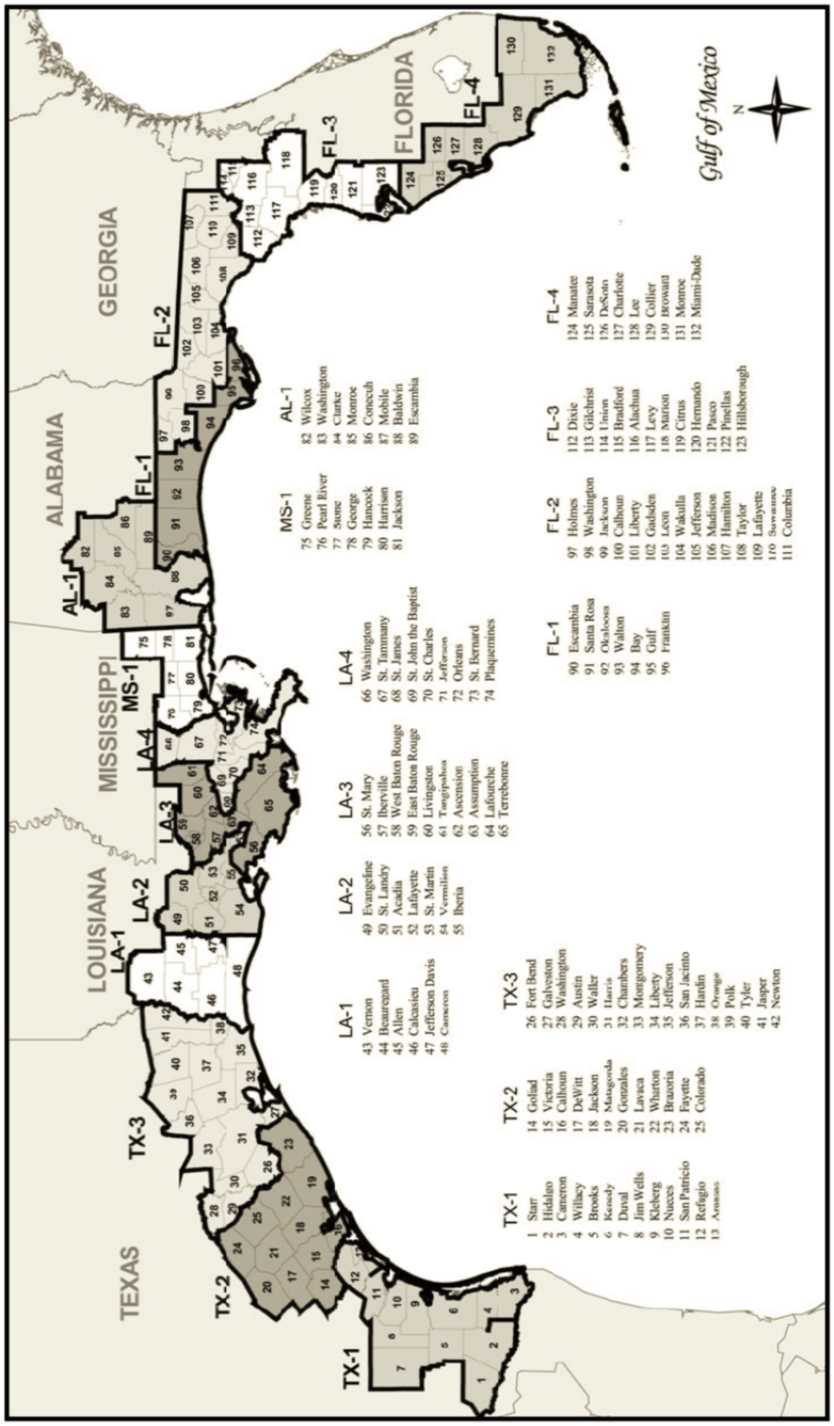

Figure 3: Study Area, the 13 Economic Impact Areas[1]

[1] Source: Minerals Management Service, (2007)

Table 1: Indicators used in Discriminant Analysis

Number	Variable	Definition
		Demographic Variables
1	PCTBLACK	Percent black (1990, 2000)
2	PCTHISPANIC	Percent Hispanic (1990, 2000)
3	PCTKIDS	Percent under 5 years old (1990, 2000)
4	PCTOLD	Percent over 65 years old (1990, 2000)
5	AVGPERHH	Average number of people per household (1990, 2000)
6	PCTFRMPOP	Percent rural farm population (1990, 2000)
		Social Capital Variables
7	FEMLBR	Percent of the workforce that is female (1990, 2000)
8	PCTFHH	Percent female-headed households (1990, 2000)
9	PCTPOV	Percent of the population living below poverty (1989, 1999)
10	PCTRENT	Percent of the population that rents (1990, 2000)
11	PCTMOBL	Percent of homes that are mobile homes (1990, 2000)
12	HOUDEN	Total housing unit per square mile (1990, 2000)
13	PCTNOHS	Percent of population over 25 with no high school degree (1990,2000)
14	PCTCVLBF	Percent of the civil workforce that is employed (1990, 2000)
		Governmental Variables
15	PCTVOTE	Percentage of population voted in the election of year (1992, 2002)
16	LGINREV	Local government finance, revenue per capita (1992, 2002)
17	GENEXPPC	Local government finance general expenditures per capita(1992, 2002)
18	EXPED	Local government finance expenditures for education (1992, 20002)
		Environmental Variables
19	MELEV	Mean elevation of the county
		Economic Variables
20	MEDRENT	Median rent (1990, 2000)
21	MVALOO	Median value of owner occupied housing (1990, 2000)
		Health Variables
22	INFMTR	5-year average infant mortality per 10000 new babies (1989-1993, 1999-2003)
23	CHILLD	3-year average chronic illness deaths per 10000 individuals(1988-1990, 1997-1999)
24	DISNWR	disabled and not working labor forces 10000 individuals (1990, 2000)
25	LBWB	3-year total low birth weight babies per 10000 new babies(1988-1990, 1997-1999)
26	HUWNF	households with no fuel used per 10000 households (1990, 2000)
27	HUWNP	households with no plumbing per 10000 households (1990, 2000)
28	MD	non-federal active medical doctors per 10000 individuals (1990,2000)

Chapter 4: K-Means Analysis

4.1 Method

This chapter documents the results from the first research task, which is to identify groups of counties that show similar character before and after disaster according to the basic framework.

The first step is how to group the 132 coastal counties into the four kinds of socioeconomic systems as defined in Chapter 2. The classification method used is k-means analysis. K-means analysis is a nonhierarchical clustering method. It aims to partition observations or cases into “k” groups, where each case is assigned to the cluster that has the nearest distance to its centroids. K-means analysis method has several advantages over traditional hierarchical clustering methods. In general, the results are less susceptible to the outliers in database, the distance measurement used, and the irrelevant or inappropriate indicator variables used (Hair et al., 1998). It also does not need a distance or correlation matrix between all pairs of cases, which is a requirement for hierarchical clustering methods.

All the raw data was changed into z-scores before inputting them into the analysis. This is a very important step, since k-means analysis calculates the similarity by simple Euclidean distance. So to have all the data in the same value scale before calculation is necessary. Otherwise, the variables that have large ranges of values will dominate the calculation of distance. Using z-scores means treating all the variables in the three dimensions equally. Another reason to use z-scores is the ease to compare the extent to which the three dimensions of a community are deviated from the mean. The final interpretation is based on an examination of

how many standard deviations an observation is above or below the mean on the three dimensions.

A basic comparison criterion for vulnerability is that: If a county's exposure's z-score is higher than its damage's z-score, it has low vulnerability; If a county's exposure's z-scoreis lower than its damage's z-score, it has high vulnerability. A basic comparison criterion for adaptability is that: If a county's recovery's z-score is higher than its damage's z-score, it has high adaptability; If a county's recovery's z-score is lower than its damage's z-score, it has low adaptability.

In terms of resilience, the comparison rule is: adaptability is treated as the first key factor to assess resilience capacity; vulnerability is treated as the second one. Since a usurper system has the highest adaptability, it ranks number one among the four, and a resistant system ranks number two due to its lowest vulnerbility. A susceptible system ranks the last because of its highest vulnerbility and lowest adaptability. So the four systems are sorted by resilience capacity from high to low as: usurper, resistant, recovering , and susceptible.

In order to see how different indicators chosen for the recovery dimension affect the grouping results, seven tests were designed using different combinations of the three indicators (per capita income growth rate, median income growth rate, and population growth rate). From test one to test three, only one variable was used to indicate the recovery dimension; for test four to five, two of them were used; and for test seven, all the three parameters were used in the analysis. The tests and the variables used in the tests are shown in Table 2:

Table 2: Indicators for the Three Dimensions: Exposure, Damage, and Recovery

Test	Exposure Indicators	Damage Indicators	Recovery Indicators
1	NUMHAZ6006	PCTDAM6006	PCTINC6999
2	NUMHAZ6006	PCTDAM6006	MEDINC8907
3	NUMHAZ6006	PCTDAM6006	POP9008
4	NUMHAZ6006	PCTDAM6006	PCTINC6999 POP9008
5	NUMHAZ6006	PCTDAM6006	MEDINC8907 PCTIN6999
6	NUMHAZ6006	PCTDAM6006	MEDINC8907 POP9008
7	NUMHAZ6006	PCTDAM6006	MEDINC8907 PCTINC6999 POP9008

Note: NUMHAZ6006 stands for the total number of hazards from 1960 to 2006. PCTDAMDAM6006 stands for the per capita property damage caused by the hazards happened from 1960 to 2006. PCTINC6999 stands for per capita personal income growth rate from 1969 to 1999. MEDINC8907 stands for the median income growth rate from 1989 to 2007. POP9008 stands for the population growth rate from 1990 to 2008.

4.2 Results

The results are shown with one line graph and one map for each test. The lines in the line-graph are the mean values of the three dimensions for each cluster based on the k-means analysis. The line graph is the basis to deduce if a group behaves in a manner similar to one of the four socioeconomic resilient systems. For each line graph, the cluster number refers to the original k-means analysis group number. The shape of the line of each cluster is compared with the four types of curves defined to determine which kind of resilience group the cluster belongs to. Then a map was drawn for each of the test. The map shows the geographic pattern of the resilience group distribution in the study area.

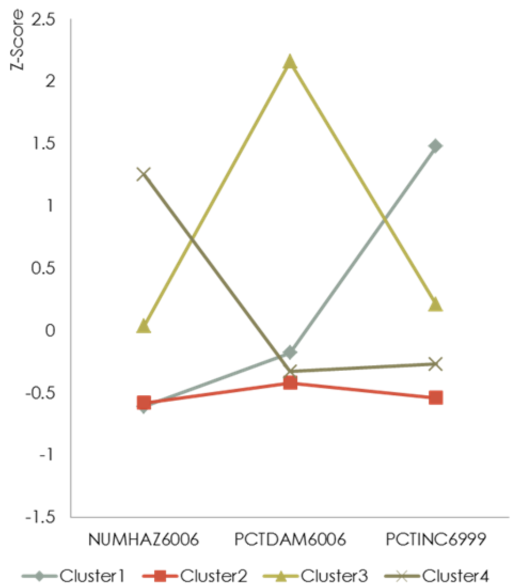

Figure 4: K-means final clusters from Test 1

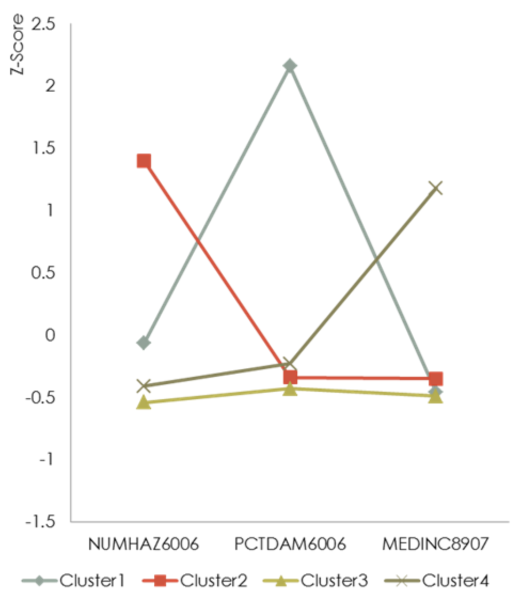

Figure 5: K-means final clusters from Test 2

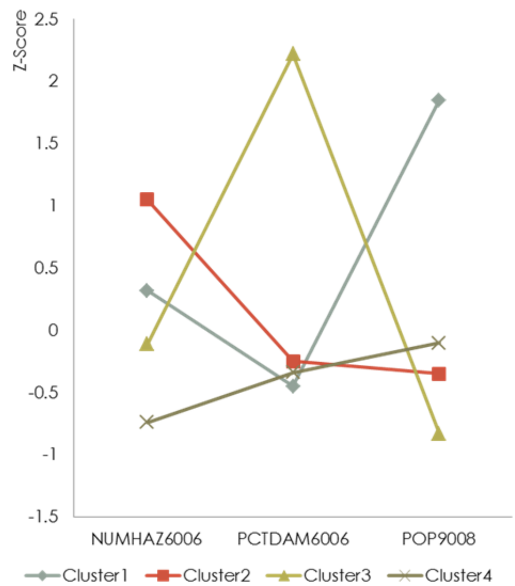

Figure 6: K-means final clusters from Test 3

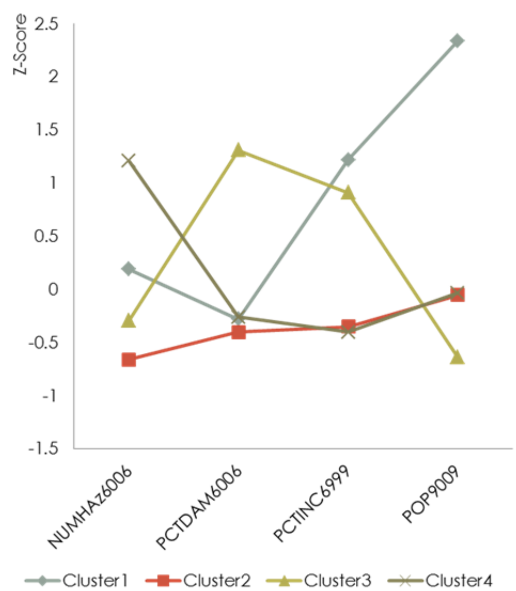

Figure 7: K-means final clusters from Test 4

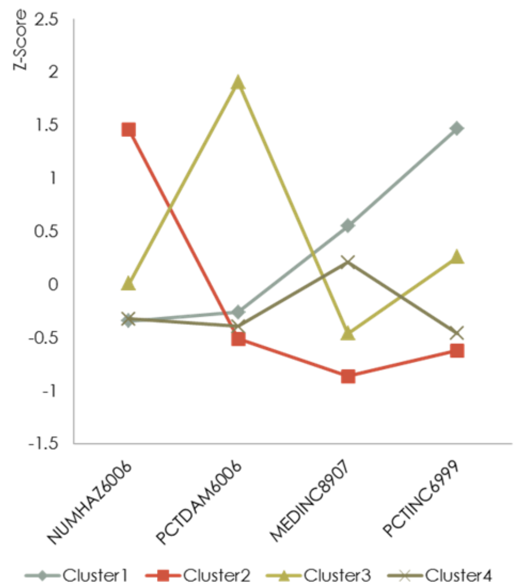

Figure 8: K-means final clusters from Test 5

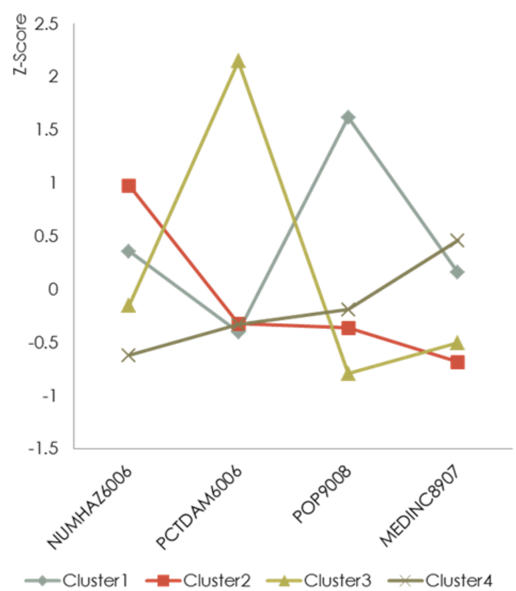

Figure 9: K-means final clusters from Test 6

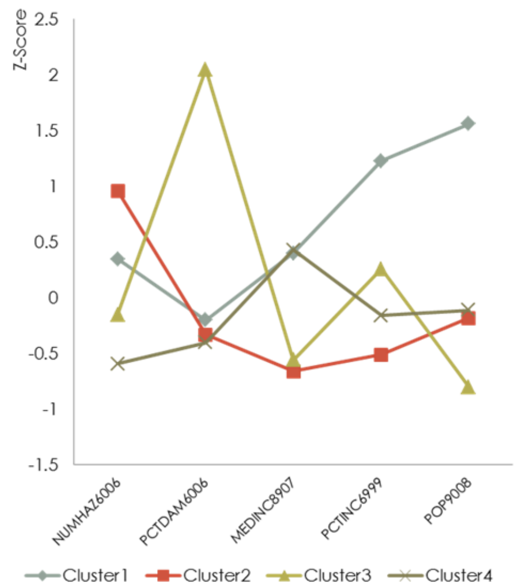

Figure 10: K-means final clusters from Test 7

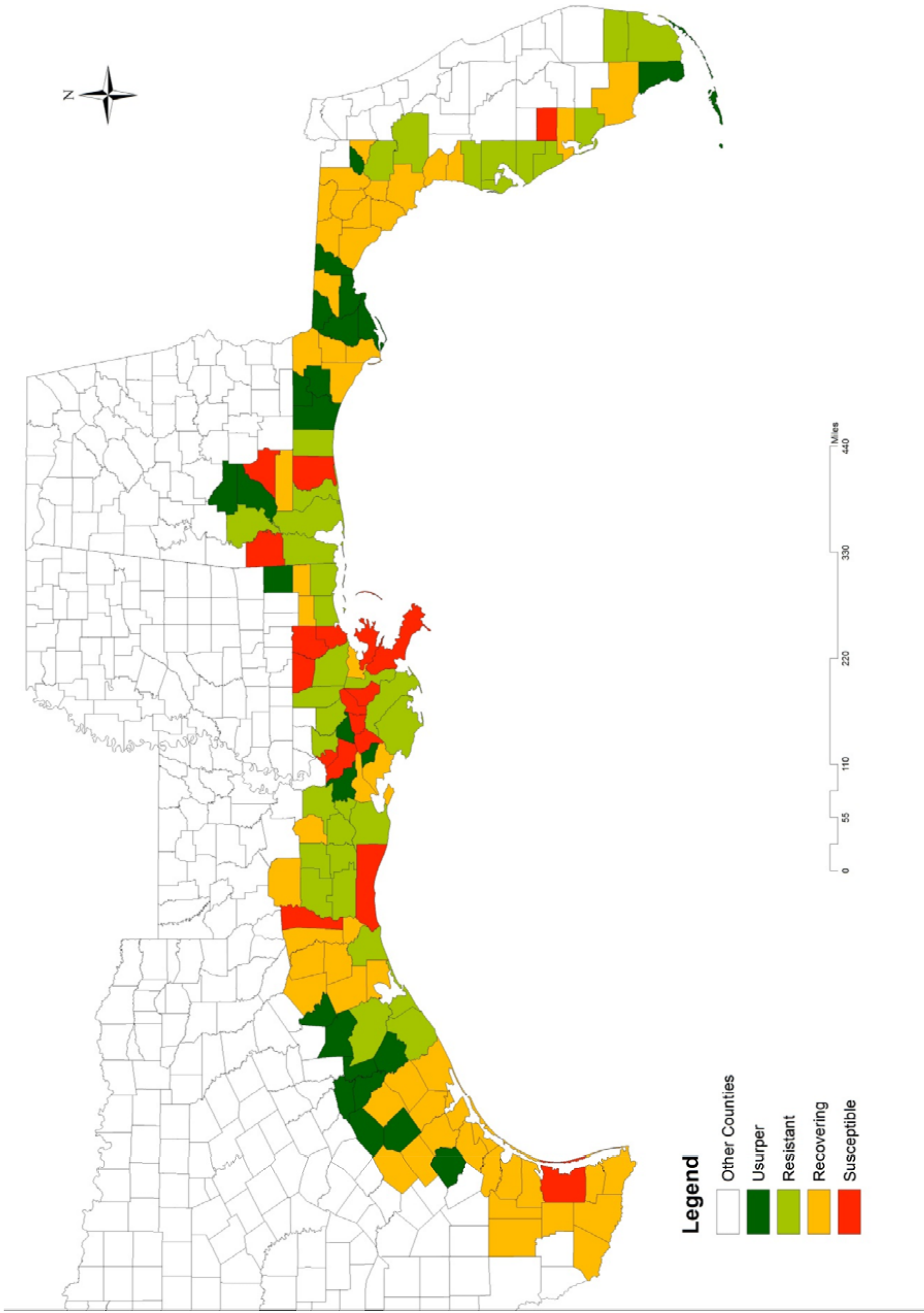

Figure 11: Test 1

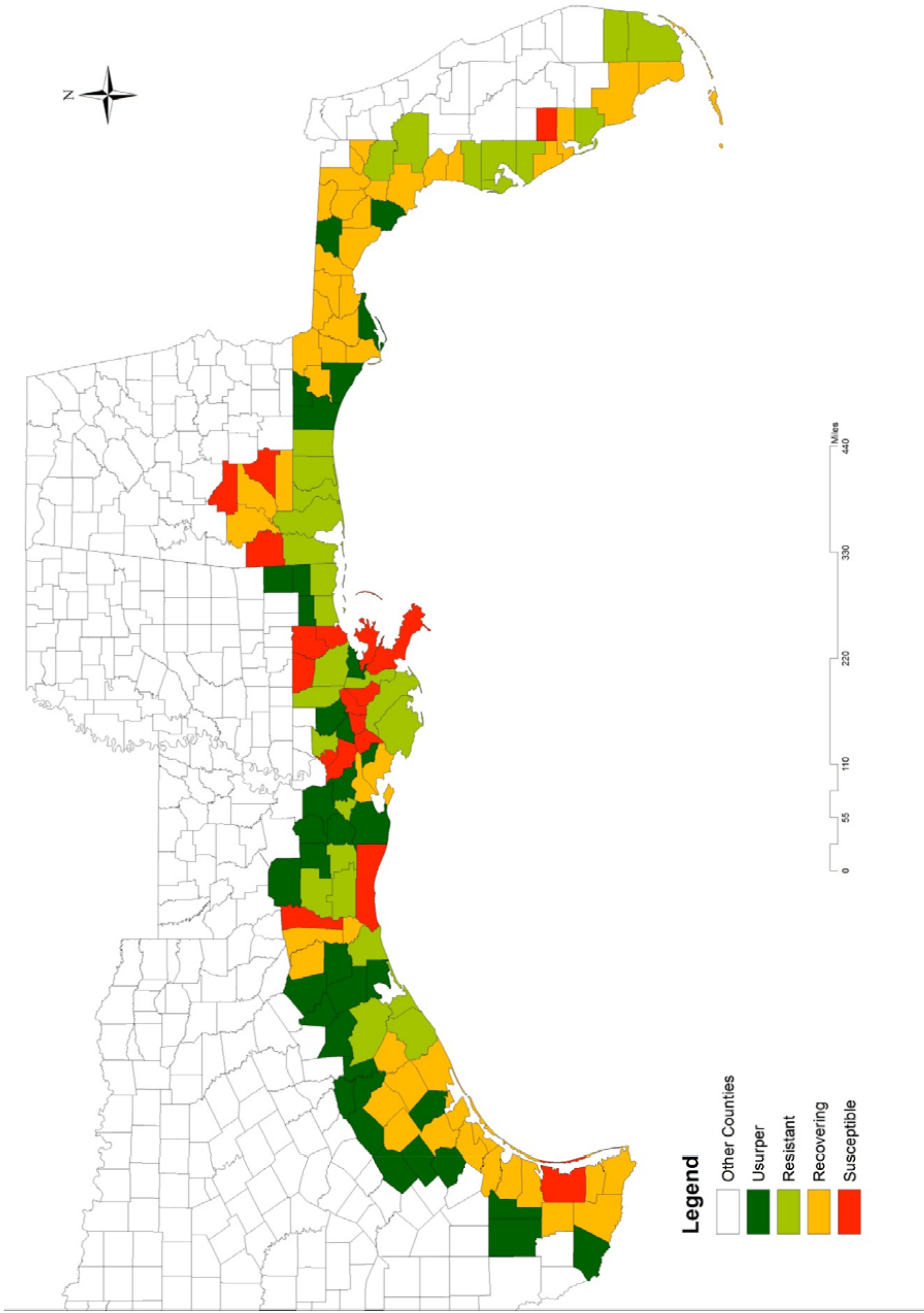

Figure 12: Test 2

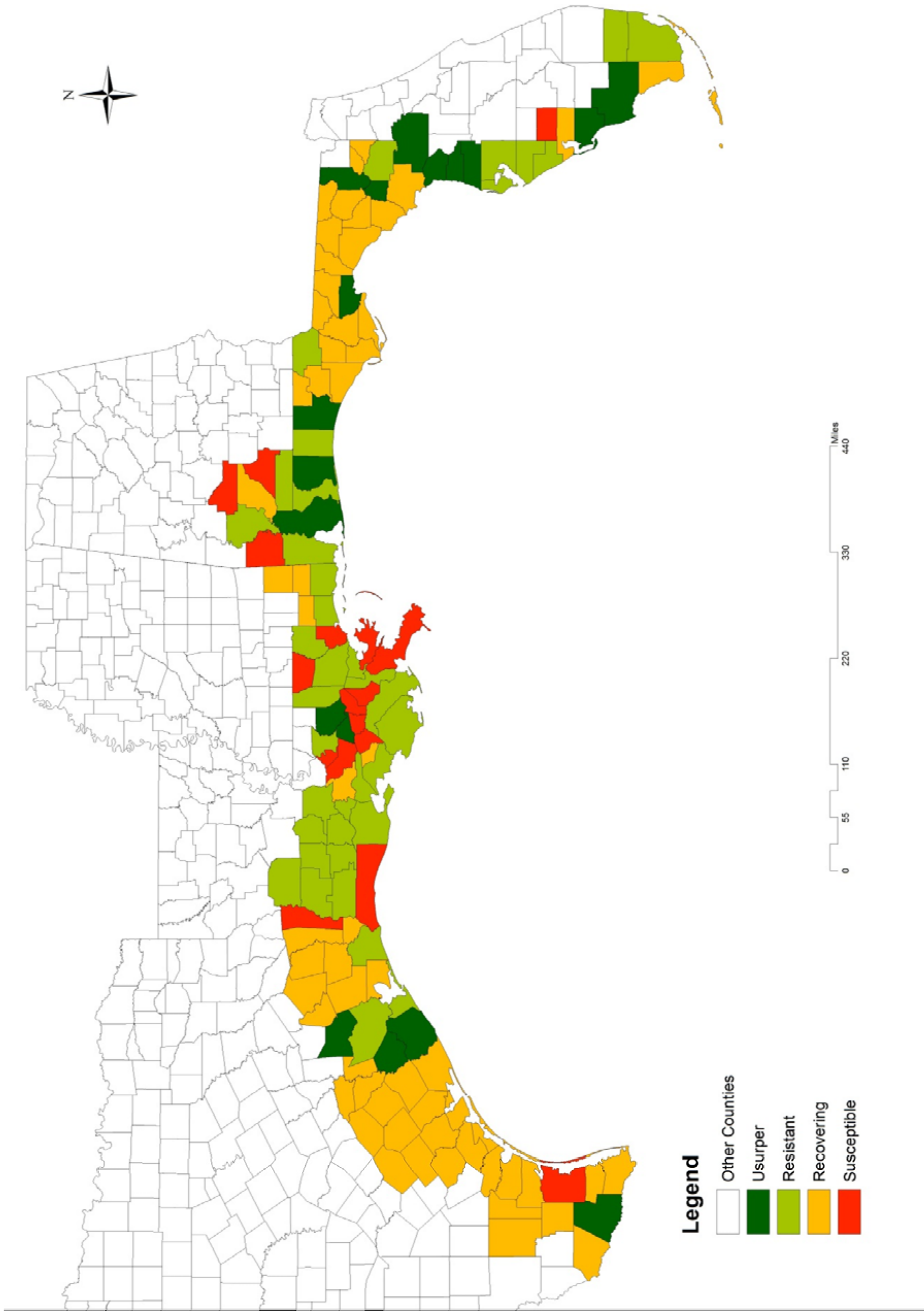

Figure 13: Test 3

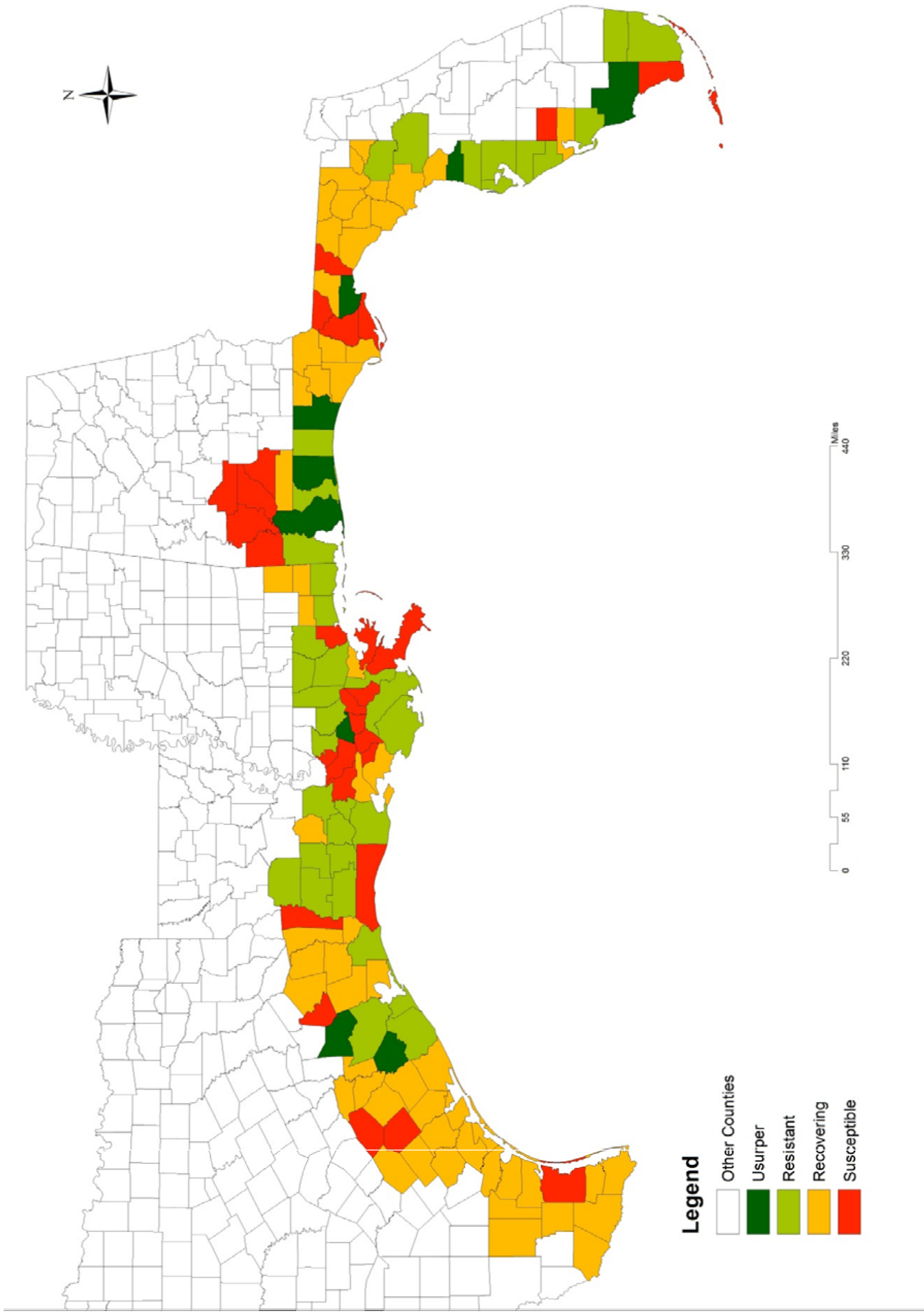

Figure 14: Test 4

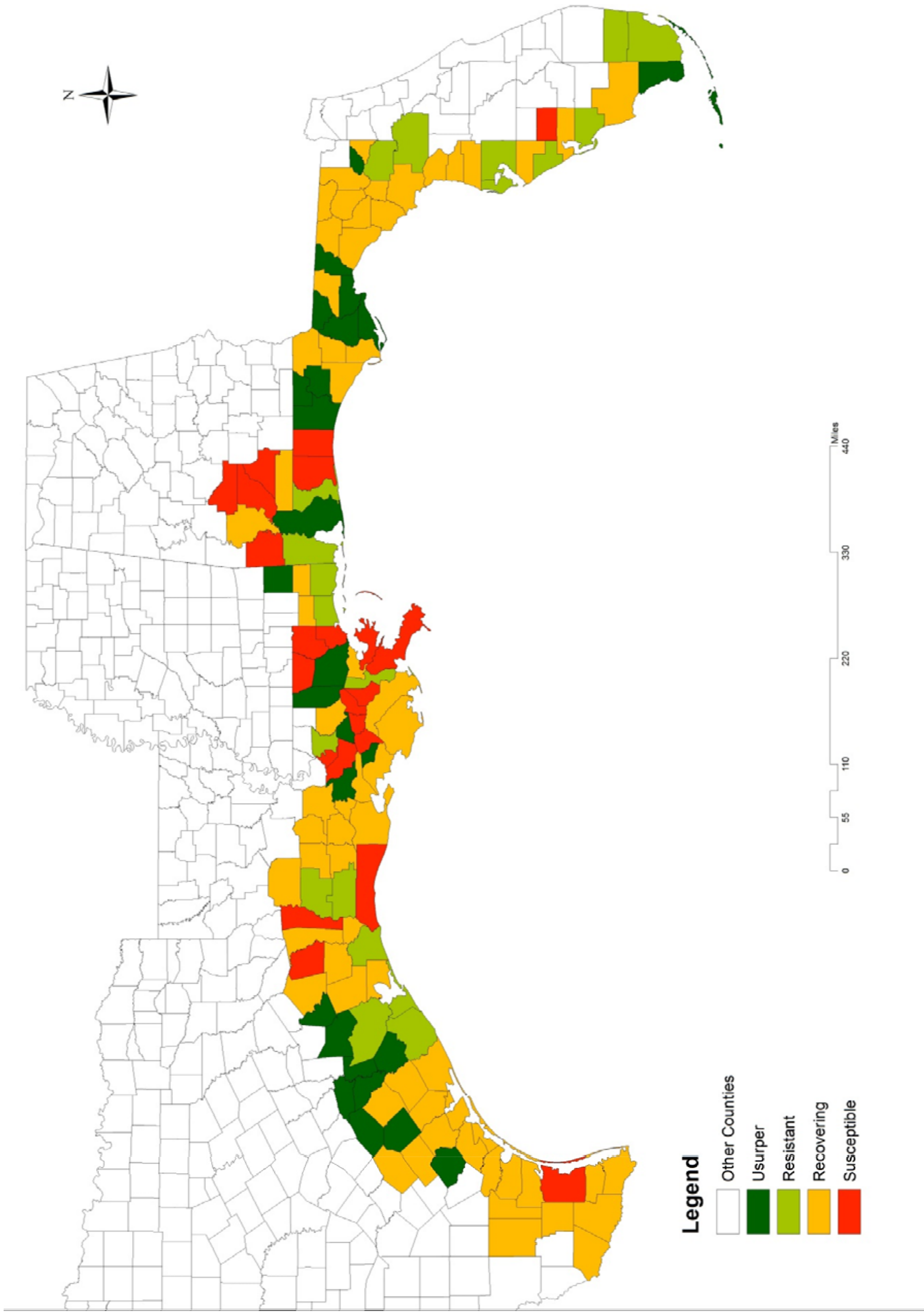

Figure 15: Test 5

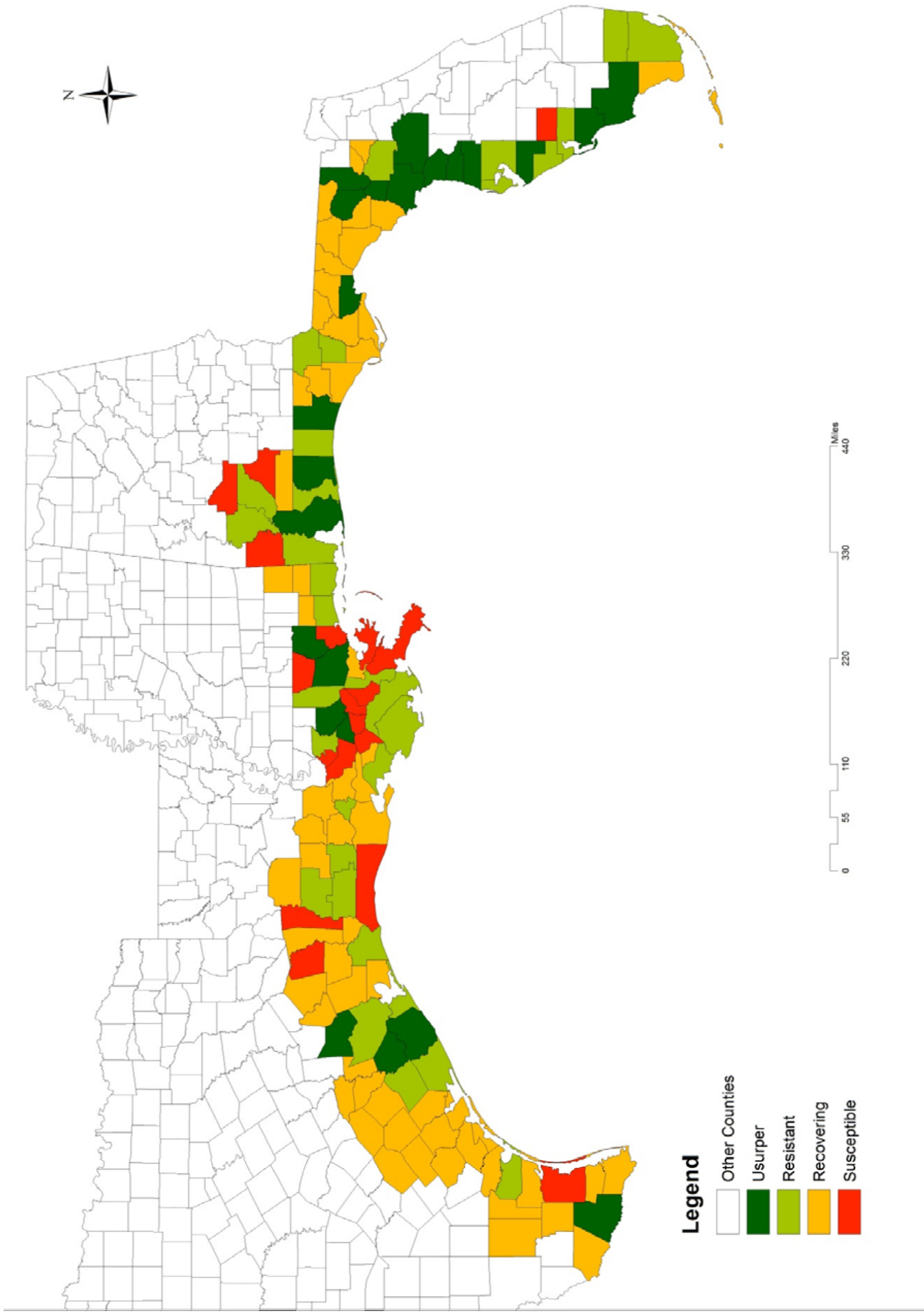

Figure 16: Test 6

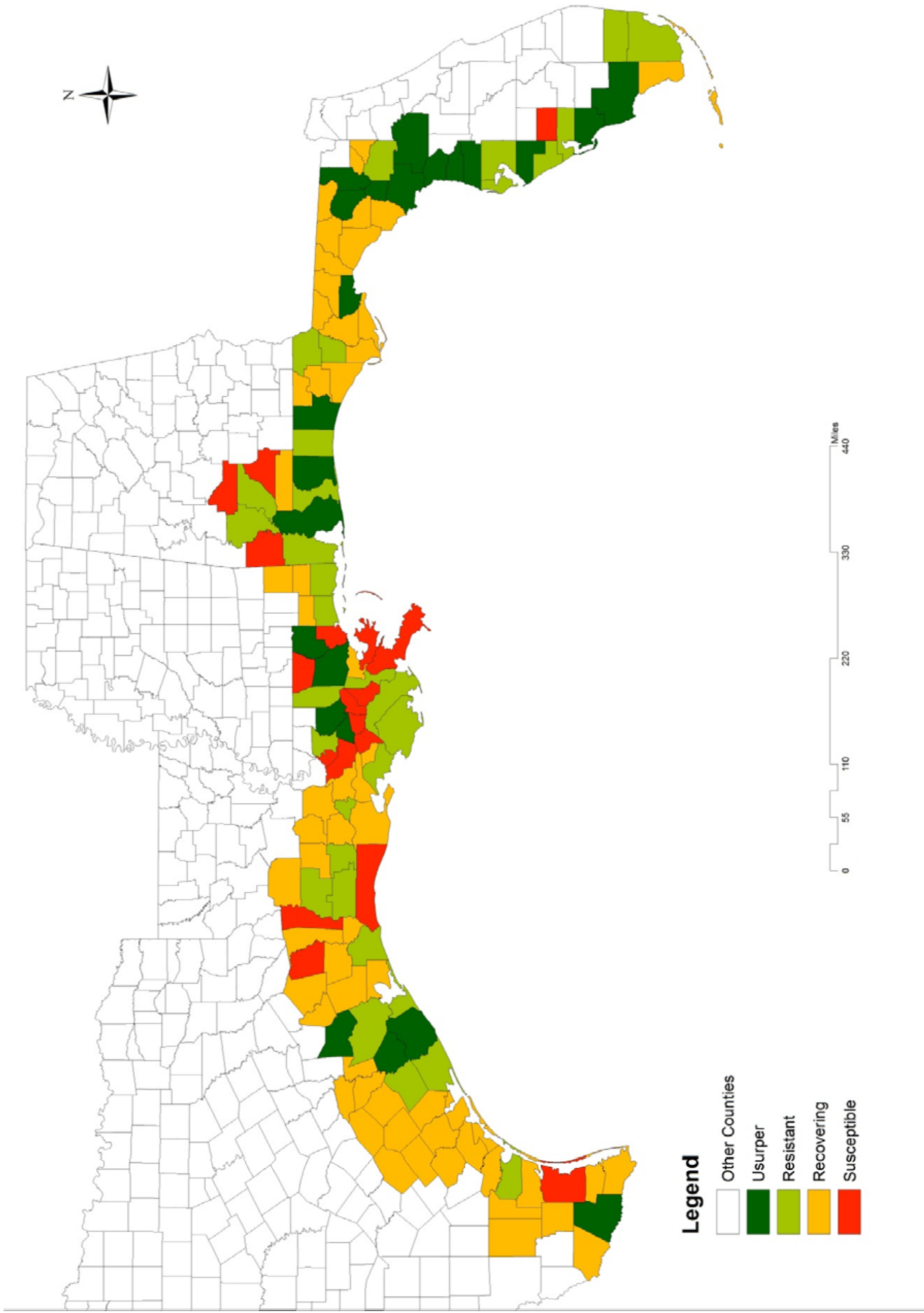

Figure 17: Test

Chapter 5: Discriminant Analysis

5.1 Method

The objective of this chapter is to see if the groups derived by the k-means analysis can be discriminated by a set of socioeconomic variables. In other words, if the groups are different, what make them differ? The main question is that do the counties, which have different resilience capacities, differentiate from each other in social-economic constructs. The social-economic construct in this chapter includes characteristics such as quality of life, economic development, and elevation. The aim is to find if these characteristics are related with community resilience as determined by k-means analysis.

Discriminant analysis is an inferential statistical technique. It is used when the dependent variable is categorical and the independent variables are interval-ratio. Discriminant analysis is applicable to any research questions with the objective of understanding group membership, where the groups comprising objects (counties in this study) that can be evaluated on a series of independent variables (socioeconomic variables in this study) (Hair et al., 1998). The results of this analysis comes with a percentage of how many cases in the cluster can be evaluated and predicted correctly by the independent socioeconomic variables, as well as a set of probabilities related to group membership.

5.2 Results

The discriminant analysis results are shown in Table 3. Among the 7 tests, test 3 which used population growth rate as a single indicator of the recovery dimension gained the highest predicted accuracy by discriminant analysis. So test 3 will be the best classification method in this study. Table 4 shows the predicted groups by discriminant analysis using the priority groups from test 3. This resilience grouping is the final result of this study.

Table 3: Discriminant Analysis Results Using 28 Social Economic Variables

Test Number	1990 Accuracy	2000 Accuracy
1	74.2%	75.0%
2	72.7%	72.7%
3	81.8%	84.8%
4	77.3%	81.8%
5	74.2%	78.0%
6	71.2%	79.5%
7	74.2%	76.5%

Table 4: Resilience Groups using the Priority Grouping Results from Test 3

COUNTY	STATE	FIPS	Test 3	Discriminant 2000s	Discriminant 1990s	Misclassification	
						2000s	1990s
Baldwin	AL	1003	Usurper	Usurper	Usurper		
Clarke	AL	1025	Resistant	Susceptible	Susceptible	*	*
Conecuh	AL	1035	Susceptible	Susceptible	Susceptible		
Escambia	AL	1053	Resistant	Resistant	Resistant		
Mobile	AL	1097	Resistant	Resistant	Resistant		
Monroe	AL	1099	Recovering	Resistant	Susceptible	*	*
Washington	AL	1129	Susceptible	Susceptible	Susceptible		
Wilcox	AL	1131	Susceptible	Susceptible	Susceptible		
Alachua	FL	12001	Resistant	Resistant	Resistant		
Bay	FL	12005	Recovering	Resistant	Resistant	*	*
Bradford	FL	12007	Recovering	Recovering	Recovering		
Broward	FL	12011	Resistant	Resistant	Resistant		
Calhoun	FL	12013	Recovering	Recovering	Recovering		
Charlotte	FL	12015	Recovering	Usurper	Usurper	*	*
Citrus	FL	12017	Usurper	Usurper	Usurper		
Collier	FL	12021	Usurper	Usurper	Usurper		
Columbia	FL	12023	Usurper	Usurper	Usurper		
DeSoto	FL	12027	Susceptible	Susceptible	Recovering		*
Dixie	FL	12029	Recovering	Usurper	Usurper	*	*
Escambia	FL	12033	Resistant	Resistant	Resistant		
Franklin	FL	12037	Recovering	Recovering	Recovering		
Gadsden	FL	12039	Recovering	Recovering	Recovering		
Gilchrist	FL	12041	Usurper	Usurper	Usurper		
Gulf	FL	12045	Recovering	Recovering	Recovering		
Hamilton	FL	12047	Recovering	Recovering	Recovering		
Hernando	FL	12053	Usurper	Usurper	Usurper		
Hillsborough	FL	12057	Resistant	Resistant	Resistant		
Holmes	FL	12059	Recovering	Recovering	Recovering		
Jackson	FL	12063	Resistant	Recovering	Recovering	*	*
Jefferson	FL	12065	Recovering	Recovering	Recovering		
Lafayette	FL	12067	Recovering	Recovering	Recovering		
Lee	FL	12071	Usurper	Usurper	Usurper		
Leon	FL	12073	Recovering	Recovering	Resistant		*
Levy	FL	12075	Recovering	Usurper	Usurper	*	*
Liberty	FL	12077	Recovering	Recovering	Recovering		
Madison	FL	12079	Recovering	Recovering	Recovering		
Manatee	FL	12081	Resistant	Usurper	Usurper	*	*
Marion	FL	12083	Usurper	Usurper	Usurper		

(Table 4 Continued)

Miami-Dade	FL	12086	Resistant	Resistant	Resistant		
Monroe	FL	12087	Recovering	Recovering	Recovering		
Okaloosa	FL	12091	Resistant	Resistant	Resistant		
Pasco	FL	12101	Usurper	Usurper	Usurper		
Pinellas	FL	12103	Resistant	Resistant	Resistant		
Santa Rosa	FL	12113	Usurper	Usurper	Usurper		
Sarasota	FL	12115	Resistant	Usurper	Usurper	*	*
Suwannee	FL	12121	Recovering	Recovering	Recovering		
Taylor	FL	12123	Recovering	Recovering	Recovering		
Union	FL	12125	Recovering	Recovering	Recovering		
Wakulla	FL	12129	Usurper	Usurper	Usurper		
Walton	FL	12131	Usurper	Usurper	Recovering		*
Washington	FL	12133	Recovering	Recovering	Recovering		
Acadia	LA	22001	Resistant	Resistant	Resistant		
Allen	LA	22003	Resistant	Resistant	Resistant		
Ascension	LA	22005	Usurper	Usurper	Usurper		
Assumption	LA	22007	Susceptible	Susceptible	Susceptible		
Beauregard	LA	22011	Resistant	Susceptible	Susceptible	*	*
Calcasieu	LA	22019	Resistant	Resistant	Resistant		
Cameron	LA	22023	Susceptible	Recovering	Susceptible	*	
East Baton Rouge	LA	22033	Resistant	Resistant	Resistant		
Evangeline	LA	22039	Resistant	Resistant	Resistant		
Iberia	LA	22045	Resistant	Resistant	Resistant		
Iberville	LA	22047	Susceptible	Susceptible	Susceptible		
Jefferson	LA	22051	Resistant	Resistant	Resistant		
Jefferson Davis	LA	22053	Resistant	Resistant	Resistant		
Lafayette	LA	22055	Resistant	Resistant	Resistant		
Lafourche	LA	22057	Resistant	Resistant	Resistant		
Livingston	LA	22063	Usurper	Usurper	Usurper		
Orleans	LA	22071	Resistant	Resistant	Resistant		
Plaquemines	LA	22075	Susceptible	Susceptible	Susceptible		
St. Bernard	LA	22087	Susceptible	Resistant	Susceptible	*	
St. Charles	LA	22089	Susceptible	Susceptible	Susceptible		
St. James	LA	22093	Susceptible	Susceptible	Susceptible		
St. John the Baptist	LA	22095	Susceptible	Susceptible	Susceptible		
St. Landry	LA	22097	Resistant	Resistant	Resistant		
St. Martin	LA	22099	Recovering	Susceptible	Susceptible	*	*
St. Mary	LA	22101	Resistant	Susceptible	Susceptible	*	*

(Table 4 Continued)

St. Tammany	LA	22103	Resistant	Usurper	Usurper	*	*
Tangipahoa	LA	22105	Resistant	Resistant	Resistant		
Terrebonne	LA	22109	Resistant	Resistant	Resistant		
Vermilion	LA	22113	Resistant	Resistant	Resistant		
Vernon	LA	22115	Resistant	Resistant	Resistant		
Washington	LA	22117	Susceptible	Resistant	Resistant	*	*
West Baton Rouge	LA	22121	Susceptible	Susceptible	Susceptible		
George	MS	28039	Recovering	Susceptible	Susceptible	*	*
Greene	MS	28041	Recovering	Recovering	Recovering		
Hancock	MS	28045	Susceptible	Resistant	Resistant	*	*
Harrison	MS	28047	Resistant	Resistant	Resistant		
Jackson	MS	28059	Resistant	Resistant	Resistant		
Pearl River	MS	28109	Resistant	Resistant	Usurper		*
Stone	MS	28131	Recovering	Recovering	Recovering		
Aransas	TX	48007	Recovering	Recovering	Recovering		
Austin	TX	48015	Recovering	Recovering	Recovering		
Brazoria	TX	48039	Usurper	Usurper	Usurper		
Brooks	TX	48047	Recovering	Recovering	Recovering		
Calhoun	TX	48057	Recovering	Recovering	Recovering		
Cameron	TX	48061	Recovering	Usurper	Usurper	*	*
Chambers	TX	48071	Recovering	Recovering	Recovering		
Colorado	TX	48089	Recovering	Recovering	Recovering		
Dewitt	TX	48123	Recovering	Recovering	Recovering		
Duval	TX	48131	Recovering	Recovering	Recovering		
Fayette	TX	48149	Recovering	Recovering	Recovering		
Fort Bend	TX	48157	Usurper	Usurper	Usurper		
Galveston	TX	48167	Resistant	Resistant	Resistant		
Goliad	TX	48175	Recovering	Recovering	Recovering		
Gonzales	TX	48177	Recovering	Recovering	Recovering		
Hardin	TX	48199	Recovering	Recovering	Usurper		*
Harris	TX	48201	Resistant	Resistant	Resistant		
Hidalgo	TX	48215	Usurper	Usurper	Usurper		
Jackson	TX	48239	Recovering	Recovering	Recovering		
Jasper	TX	48241	Recovering	Recovering	Recovering		
Jefferson	TX	48245	Resistant	Resistant	Resistant		
Jim Wells	TX	48249	Recovering	Recovering	Recovering		
Kenedy	TX	48261	Susceptible	Susceptible	Susceptible		
Kleberg	TX	48273	Recovering	Recovering	Recovering		
Lavaca	TX	48285	Recovering	Recovering	Recovering		

(Table 4 Continued)

Liberty	TX	48291	Recovering	Recovering	Recovering		
Matagorda	TX	48321	Recovering	Recovering	Recovering		
Montgomery	TX	48339	Usurper	Usurper	Usurper		
Newton	TX	48351	Susceptible	Susceptible	Susceptible		
Nueces	TX	48355	Recovering	Resistant	Resistant	*	*
Orange	TX	48361	Recovering	Recovering	Recovering		
Polk	TX	48373	Recovering	Recovering	Recovering		
Refugio	TX	48391	Recovering	Recovering	Recovering		
San Jacinto	TX	48407	Recovering	Recovering	Recovering		
San Patricio	TX	48409	Recovering	Recovering	Recovering		
Starr	TX	48427	Recovering	Recovering	Recovering		
Tyler	TX	48457	Recovering	Recovering	Recovering		
Victoria	TX	48469	Recovering	Recovering	Resistant		*
Waller	TX	48473	Recovering	Recovering	Recovering		
Washington	TX	48477	Recovering	Recovering	Recovering		
Wharton	TX	48481	Recovering	Recovering	Recovering		
Willacy	TX	48489	Recovering	Recovering	Recovering		

Figures 18 and 19 show the maps of these groups. There are totally 24 counties misclassified for 1990 data, and 20 counties misclassified for 2000 data. The misclassification cases for the both 1990 and 2000 data are marked by an asterisk in Table 4 and shown in Figures 20 and 21.

5.3 Uncertainty Analysis

Since the grouping results of the seven tests have a large intersection set, discriminant analysis was also run on selected combinations of the tests. For Test 1, Test 2 and Test 3, a single indicator of the recovery dimension was used. Counties that were classified as the same group by all these tests mean that they had the same behavior on all three independent indicators. Discriminant analysis was run on the 69 overlapping counties.

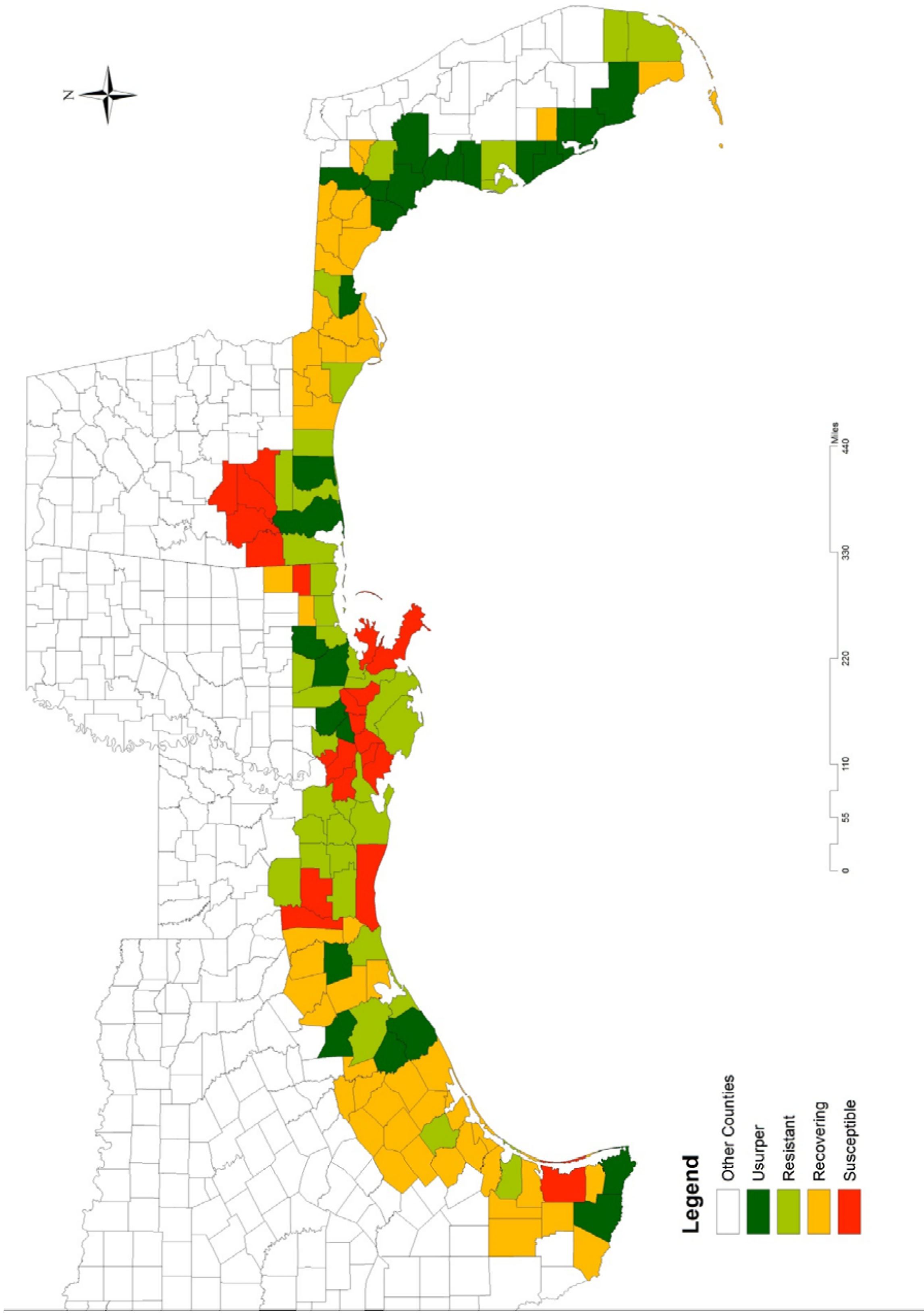

Figure 18: Discriminant Analysis Predicted Groups using 1990 data

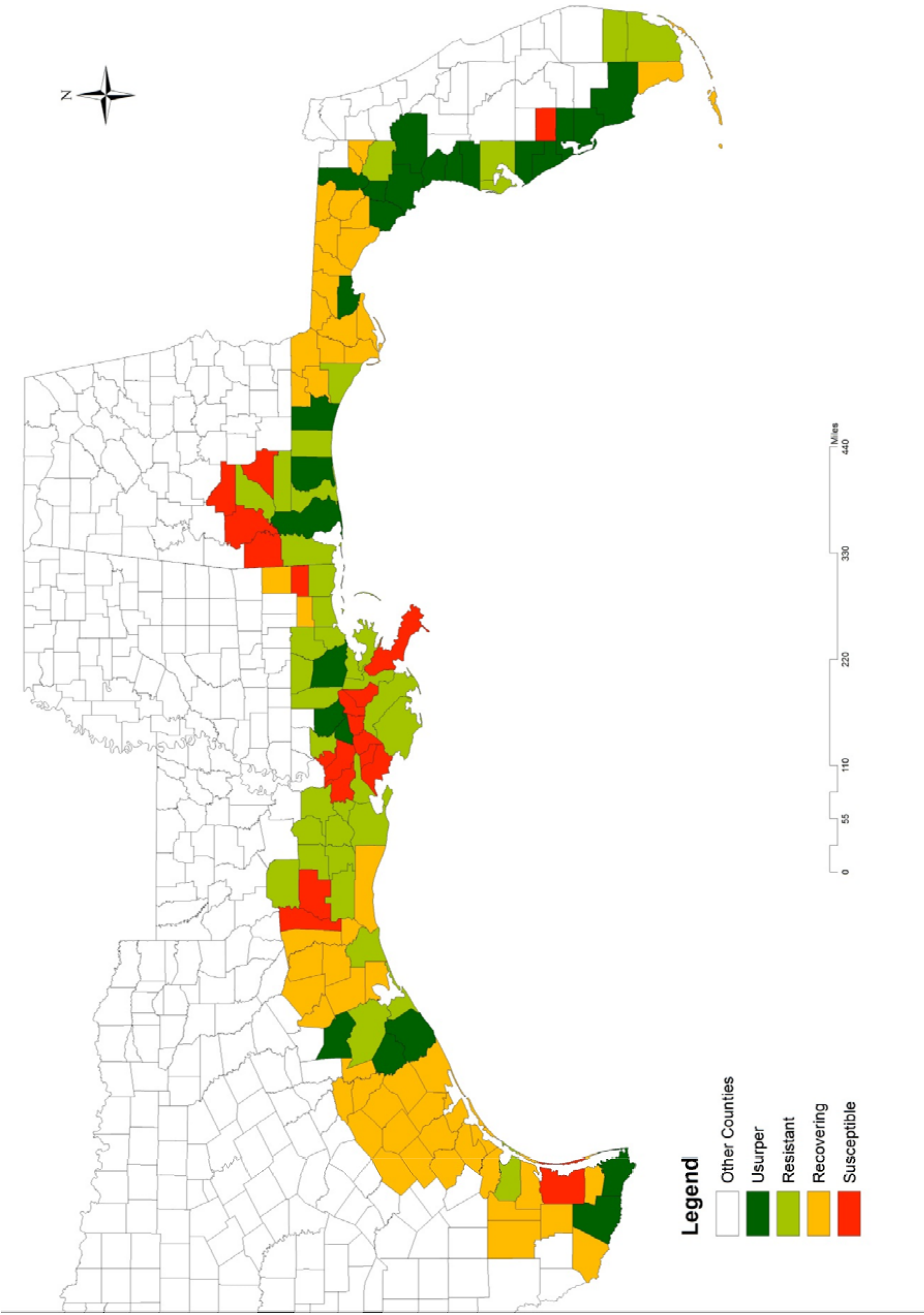

Figure 19: Discriminant Analysis Predicted Groups using 2000 data

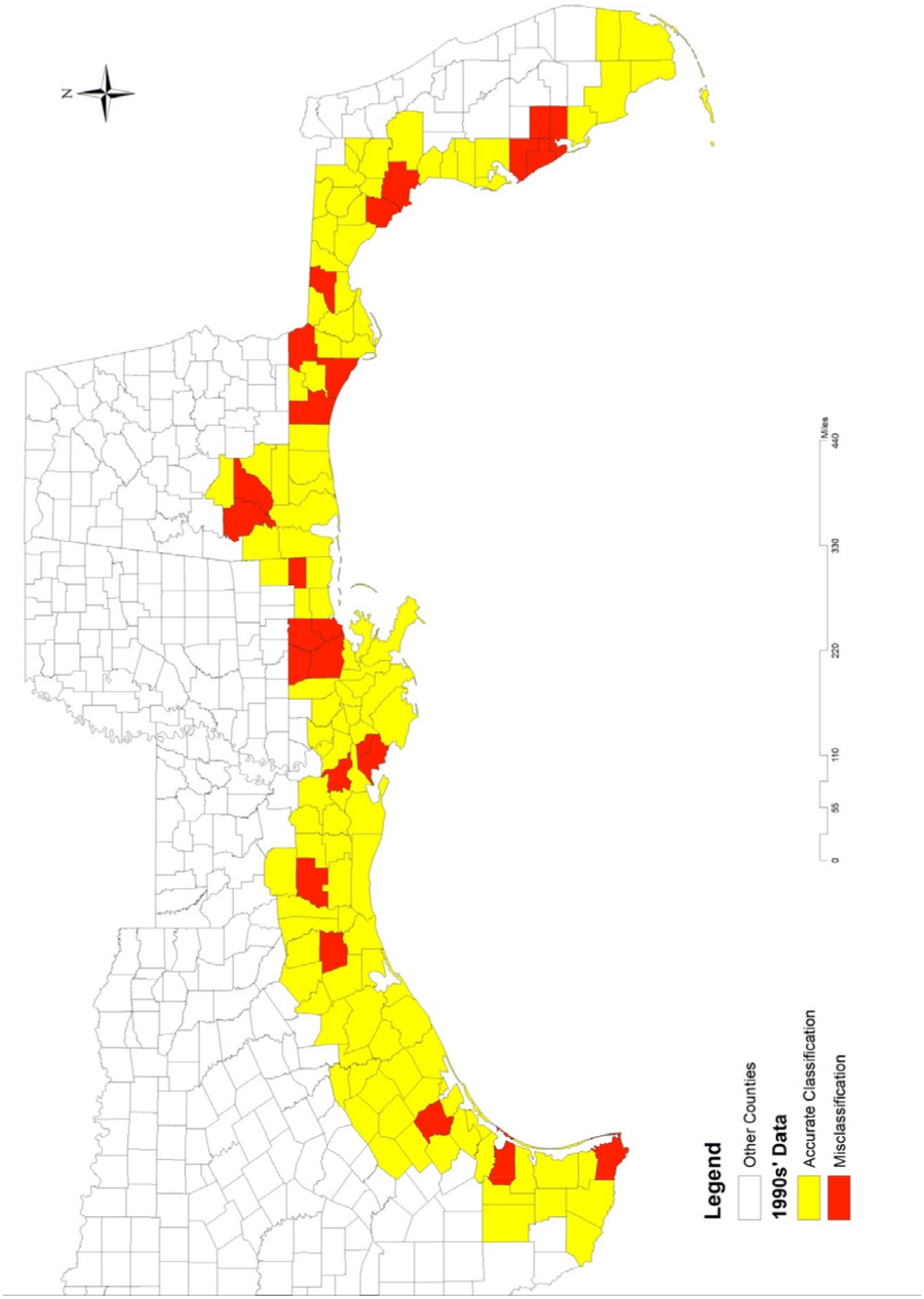

Figure 20: Misclassification part using 1990 variables

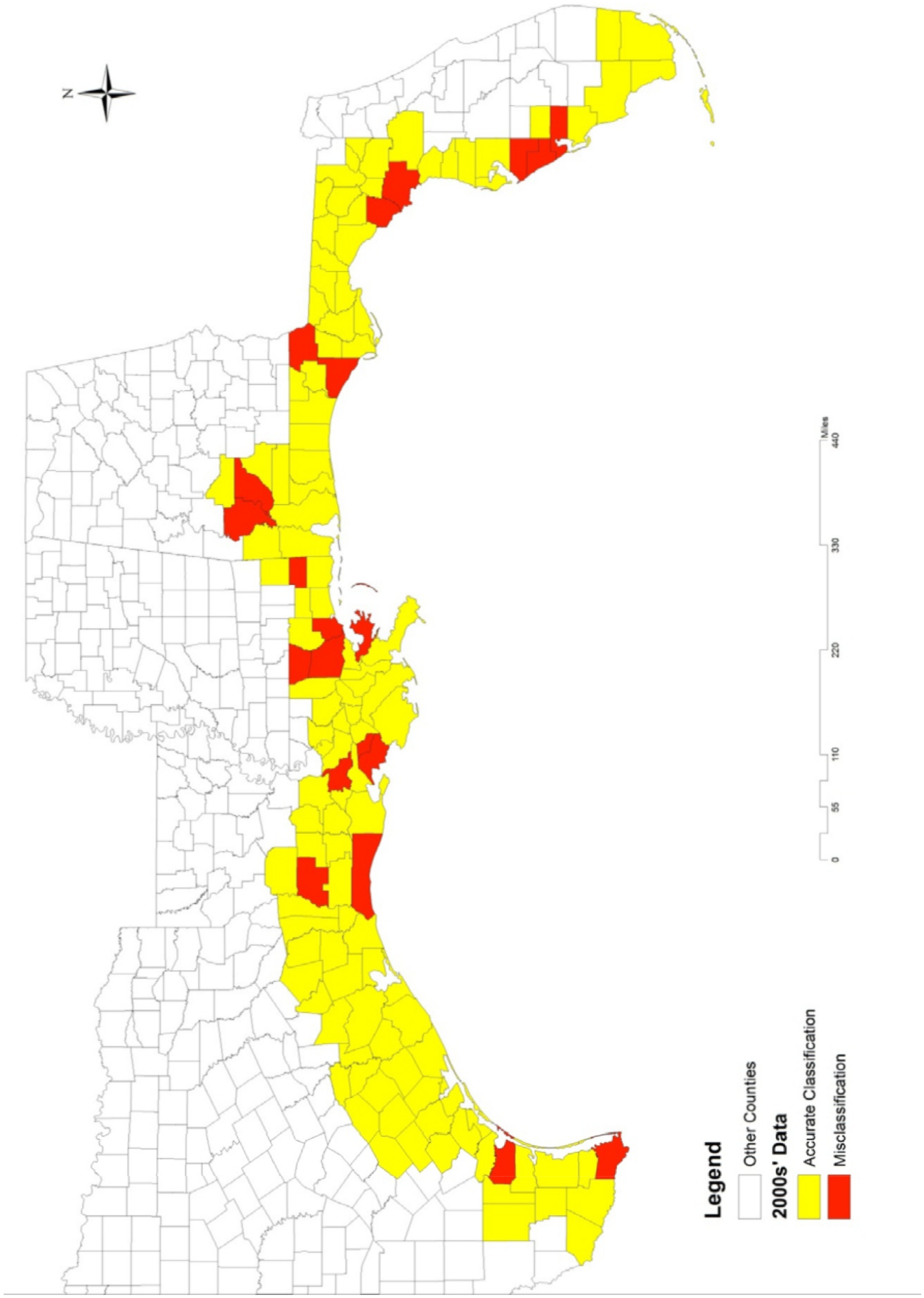

Figure 21: Misclassification part using 2000 variables

The validation results show that the accuracy is relatively lower if the indicator of "median income growth rate" (Test 2, 5, 6, and 7) is included, so it may not be a good indicator for the recovery dimension. After excluding, the discriminant analysis was run on the intersection set (totally 90 counties) of the remaining tests (Test 1, Test 3 and Test 4). Finally, discriminant analysis was run on the intersection set of all the tests (totally 53 counties). Comparison test was made for all these three discriminant analysis results. The intersection set of the selected combinations of tests are shown in Figure 22, 23 and 24, and the discriminant classification accuracy are shown in Table 5.

Table 5: Discriminant Analysis Results for the Intersection Set of Tests Combination

Intersection Set	Number of Counties	1990 Accuracy	2000 Accuracy
Test 1,2,3,4,5,6,7	53	98.1%	98.1%
Test 1,2,3	69	91.3%	89.9%
Test 1,3,4	90	90.0%	88.9%

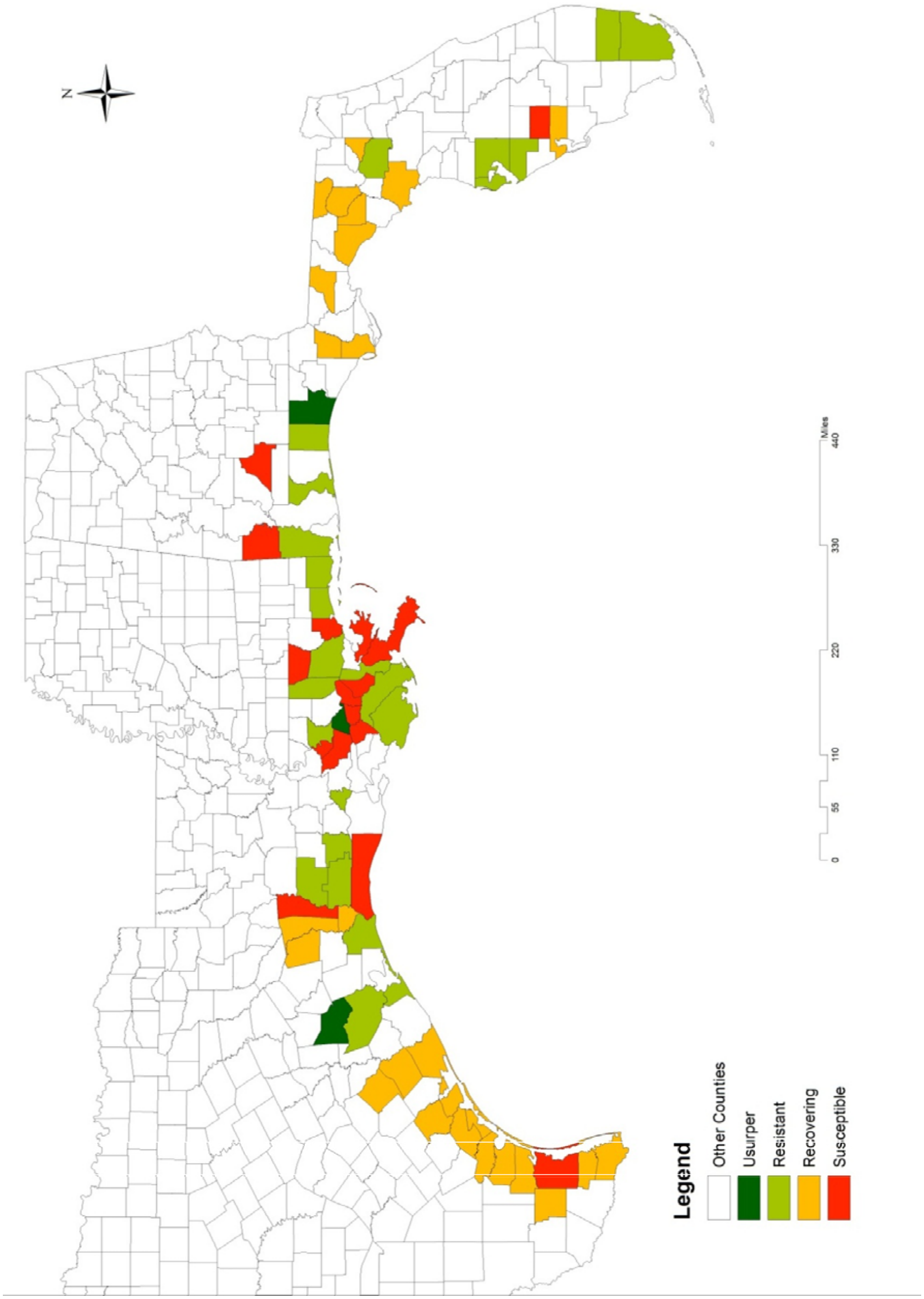

Figure 22: Intersection set of Test 1, Test 2, and Test 3

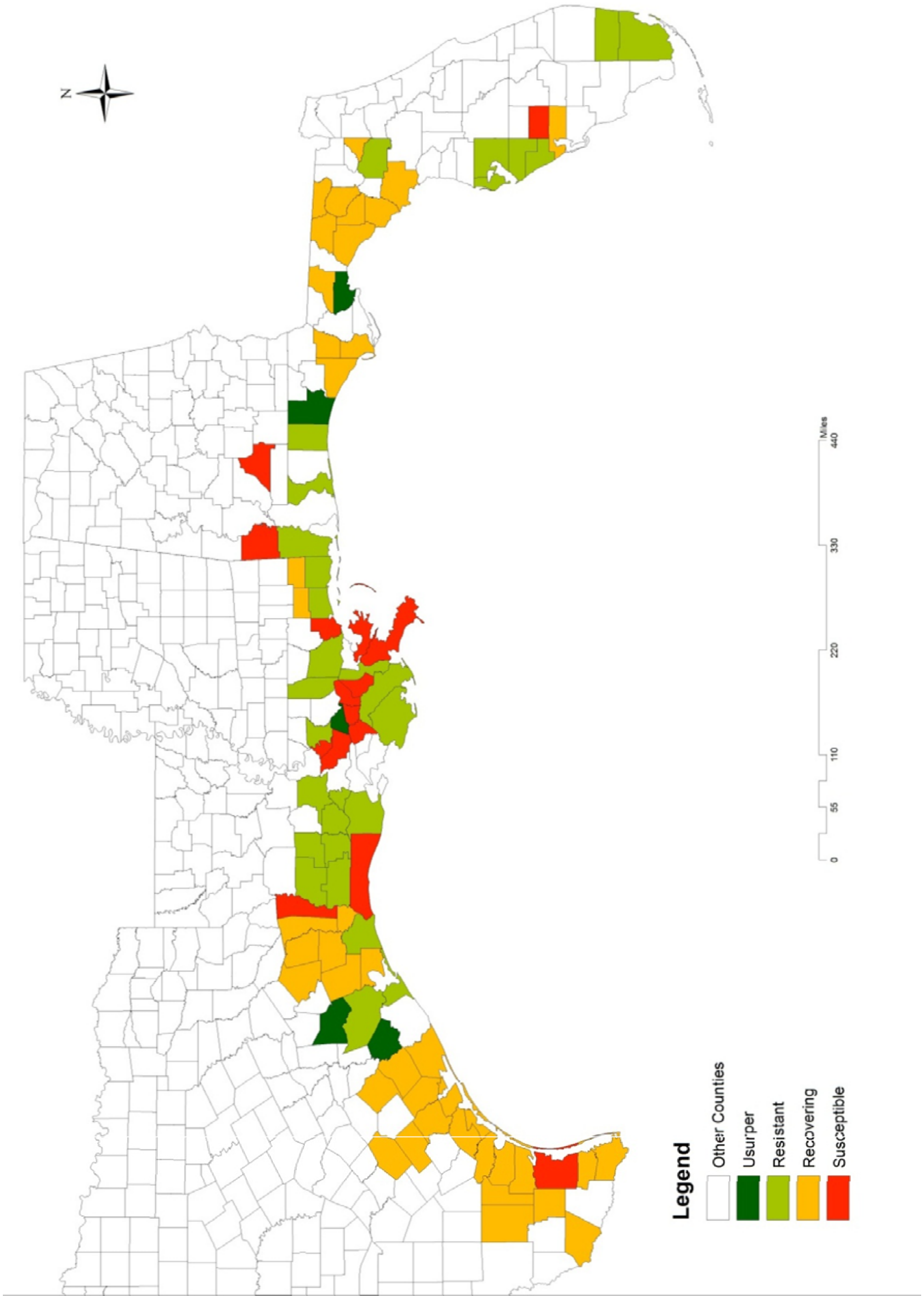

Figure 23: Intersection set of Test 1, Test 3, and Test 4

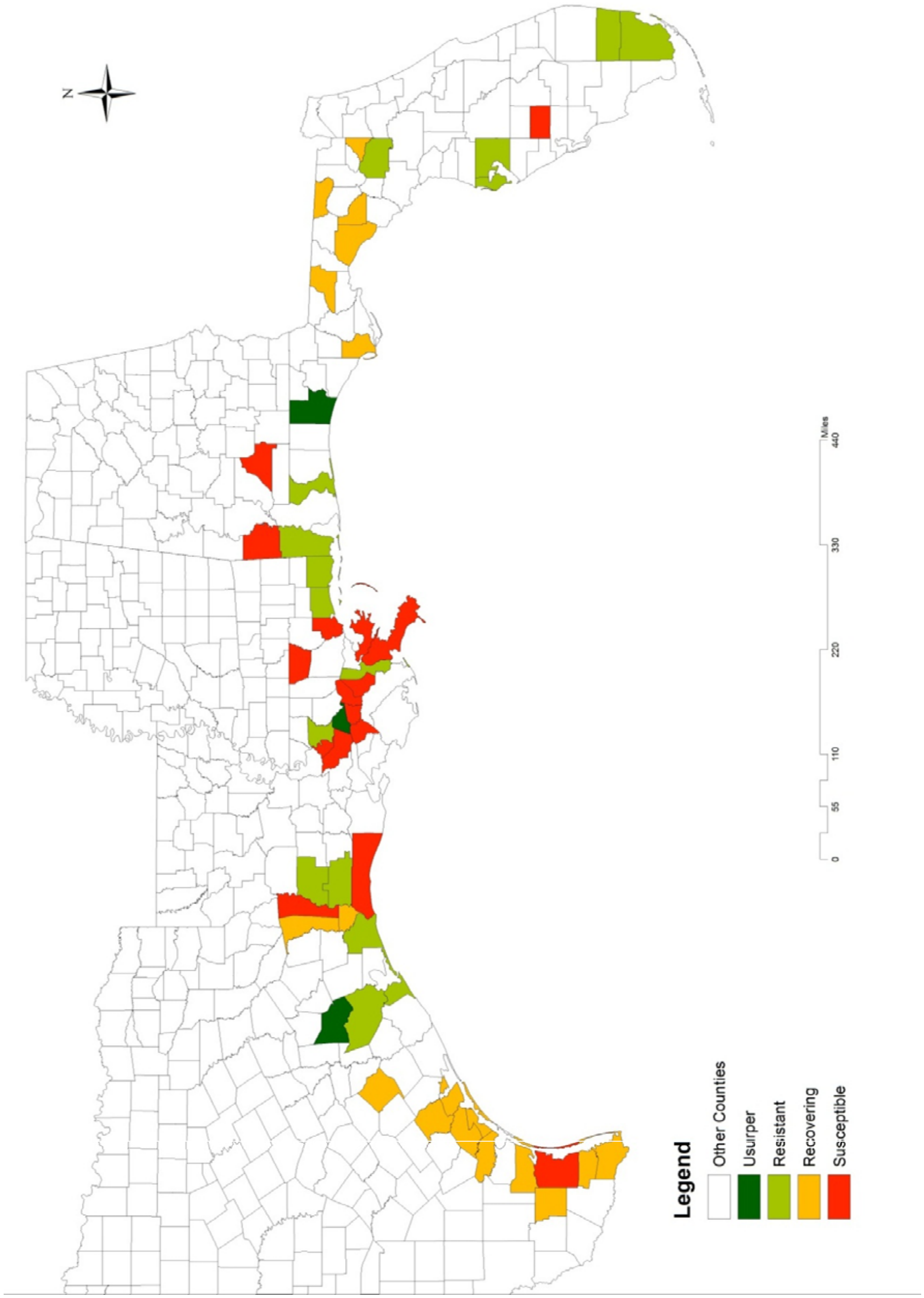

Figure 24: Intersection set of all the 7 tests

Chapter 6: Factor Analysis

6.1 Method

In this chapter, the objective is to reduce the redundancy of variables and to identify the important ones to indicate the socioeconomic structure of a county. 28 variables were picked from the literature in the last chapter for the discriminant analysis. Factor analysis was used here to reduce the redundancy and extract the most important variables.

Broadly Speaking, factor analysis is a multivariate technique that can be used to analyze the structure of interrelationships among a large number of variables by defining a set of common underlying dimensions known as factors. It can also serve as a technique to identify important variables in a data set (Hair et al., 1998). In this study, variable reduction was carried out in three steps: run the factor analysis; delete the variable that has the highest initial communality; re-run the factor analysis without the deleted one until all the remaining variables have low communalities (less than 0.5). The extracted factors were not used, since the variables themselves are more straightforward and easier to interpret the characteristics of the counties.

6.2 Results

After running the principal axis factoring method in SPSS, and looking at the variable that has the highest initial communality, the variable that has the highest initial communalities was removed step by step as shown in Table 6 and Table 7.

Table 6: Variables Removal Process for 1990 Data

	Variable Removed	Initial Communality
Step 1	PCTPOV, AVGPERHH	.933
Step 2	LGINREV	.927
Step 3	PCTOLD	.924
Step 4	MEDRENT	.918
Step 5	PCTBLCK	.889
Step 6	MVALOO	.842
Step 7	PCTNOHS	.840
Step 8	PCTKIDS	.737
Step 9	PCTRENT	.731
Step 10	HUWNP	.687
Step 11	PCTVLBF	.657
Step 12	LBWB	.562
Step 13	EXEDPC	.561
Step 14	MD	.547

Table 7: Variables Removal Process for 2000 Data

	Variable Removed	Initial Communality
Step 1	MEDRENT	.944
Step 2	PCTFHH	.935
Step 3	AVGPERHH, PCTPOV	.913
Step 4	LGFINREV	.884
Step 5	PCTHISPA	.849
Step 6	MVALOO	.817
Step 7	PCTOLD	.814
Step 8	PCTKIDS	.790
Step 9	PCTNOHS	.784
Step 10	PCTRENT	.747
Step 11	PCTCVLBF	.712
Step 12	PCTBLCK	.604
Step 13	MD	.598
Step 14	HUWNP	.548

For the 1990 data, 13 variables retained, and they are: FEMLBR, PCTFHH, PCTMOBL, PCTVOTE, GENEXPPC, DISWRK, PCTFRMPOP, INFMTR, CHRILLD, HUWNF, PCTHISPA, HOUDEN, and MELEV (Table 8).

Table 8: Variables Picked from 1990 Data

Number	Variable	Definition
1	FEMLBR	Percent of the workforce that is female
2	PCTFHH	Percent female-headed households
3	PCTMOBL	Percent of homes that are mobile homes
4	PCTVOTE	Percentage of population voted in the election
5	GENEXPPC	Local government finance general expenditures per capita
6	DISNWRK	disabled and not working labor forces
7	PCTFRMPOP	Percent rural farm population
8	INFMTR	5-year average infant mortality
9	CHRILLD	3-year average chronic illness deaths
10	HUWNF	households with no fuel used
11	PCTHISPA	Percent Hispanic
12	HOUDEN	Total housing unit per square mile
13	MELEV	Mean elevation of counties

For the 2000 data, 13 variables retained, and they are: LBWB, PCTFRMPOP, FEMLBR, PCTMOBL, HOUDEN, PERVOTE, GENEXPPC, PCTFRMPOP, MELEV, INFMTR, CHRILLD, DISNWRK, HUWNF, and LBWB (Table 9).

Table 9: Variables Picked from 2000 Data

Number	Variable	Definition
1	FEMLBR	Percent of the workforce that is female
2	PCTMOBL	Percent of homes that are mobile homes
3	HOUDEN	Total housing unit per square mile
4	PERVOTE	Percentage of population voted in the election of (year)
5	GENEXPPC	Local government finance general expenditures per capita
6	PCTFRMPOP	Percent rural farm population
7	MELEV	Mean elevation of counties
8	INFMTR	5-year average infant mortality
9	CHRILLD	3-year average chronic illness deaths
10	DISNWRK	disabled and not working labor forces
11	HUWNF	households with no fuel used
12	LBWB	3-year total low birth weight babies
13	EXPENPC	Local government finance expenditures for education Per capita

11 variables were identified by both of the two processes, and they are: FEMLBR, PCTMOBL, HOUDEN, PERVOTE, GENEXPPC, PCTFRMPOP, MELEV, INFMTR, CHRILLD, DISNWRK, and HUWNF. The discriminant results of them on Test 3's classification were: 56.8 for 2000s, and 62.1%for 1990s.

Chapter 7: Conclusions

7.1 Basic Conclusion

This study represents an attempt in quantifying the community resilience of the 132 counties in the Gulf of Mexico region. It outlines the approaches and methods that can be used to define resilience. It studies the behaviors of communities before and after natural disasters, and offers a general outline about variables that could contribute to a community's resilience capacity. It fulfilled the three objectives stated in the first chapter.

For the first objective, four types of resilience were defined, and all the 132 counties in the study area were grouped into the four types. From lowest to highest resilience, the four types are: susceptible, recovering, resistant, and usurper. Seven tests using k-means cluster analysis were run in order to find the appropriate indicator variables for the recovery dimension. The variables tested include income and population growth. The maps from the seven tests show that the counties that belonged to the same resilient type tended to geographically cluster together. We can see some regional clusters that have the same resilient type. In all the seven tests, the "resistant" counties and the "susceptible" counties are mostly distributed in the middle part of the Gulf of Mexico region (including east Texas, Louisiana, Mississippi, and Alabama, and the eastern tip of Florida).

Aiming at the second objective, discriminant analysis was run to see if the four types of counties have any differences in terms of socioeconomic construct. 28 variables were picked according to the literature to indicate the socioeconomic construct of the counties. All the seven tests were found to have an accuracy of post-classification above 71%. Test 3, which used only

population growth as the indicator for recovery, gained the best results: 81.8% accuracy for the 1990 data, and 84.8% accuracy for the 2000 data.

To test the uncertainty of the results, discriminate analysis was also run on the intersection set of the seven tests. Overall, the accuracy is much higher than before, with all of them above 88.9% and the highest being 98.1% (Table 4). There were totally 53 counties classified into the same resilient groups by all of the tests, and they are shown in Table 10.

From the discriminant analysis, the accuracy is not significantly changed between 1990s and 2000s, and the accuracy of 2000s is a little bit higher. This means that the four types of communities are a little bit more different in 2000s than 1990s in terms of socioeconomic status. This can mean two things: first, the variables of 2000s can depict the characteristics of the resilient groups better; second, if the communities behaved differently to disasters, their socioeconomic constructs tended to differentiate from each other in decades.

For the third objective, 11 variables were identified in the factor analysis part as the basic characteristic indicators of the counties, as shown in table 7 and table 8. These variables are identified as the ones that can represent the socioeconomic construct of a community with not too much redundancy.

7.2 Temporal Changes

There are a total of nine counties that changed from one resilience group to another from 1990 to 2000. Four of them changed to a more resilient group, and five of them changed to a less resilient group. These counties are shown in Table 13. The rows in Table 13 show which resilient group these counties belonged to in 1990, and the columns show which resilient group they belonged to in 2000.

Table 10: Temporal Changes of the Resilience Grouping between 1990 and 2000

	Susceptible (2000)	Recovering(2000)	Resistant(2000)	Usurper(2000)
Susceptible (1990)		Cameron, LA	Monroe, AL St. Barnard, LA	
Recovering (1990)	DeSoto, FL			Walton, FL
Resistant (1990)		Leon, FL Victoria, TX		
Usurper (1990)		Hardin, TX	Pearl River, MS	

In general, the resilient groups did not change much during the decade from 1990 to 2000. The change of the 11 indicators picked by factor analysis for each of the 9 county is shown in Table 11.

Table 11: Value Change of the 11 Indicators for the 9 Counties

		FEMLBR	PCTMOBL	HOUDEN	PCTVOTE	GENEXPPC	MELEV	PCTFRMPOP	INFMTR	CHRILD	DISNWRK	HUWNF
DeSoto	↓	-6.16	2.23	6.64	-4.57	413.00	0.00	-0.72	-60	-27.65	37.39	65.82
Leon	↓	4.82	-1.05	75.45	-4.31	893.00	0.00	-0.05	130	-3.65	210.15	-6.90
Hardin	↓	3.54	4.00	3.67	-1.85	728.00	0.00	0.36	-260	10.34	206.22	7.02
Victoria	↓	4.22	2.38	4.03	-1.07	1003.00	0.00	0.38	-240	-6.84	198.75	15.93
Pearl River	↓	4.05	4.60	5.71	-3.41	741.00	0.00	-0.80	-110	-10.23	384.23	20.33
Cameron	↑	7.92	-0.91	-1.07	-4.81	1889.00	0.00	-0.71	-410	-4.64	322.66	31.86
Monroe	↑	26.89	6.79	1.58	-3.53	1198.00	0.00	-2.03	-280	0.32	344.85	4.41
St. Bernard	↑	2.53	-1.60	-39.12	-6.54	512.00	0.00	-0.03	130	-0.49	228.00	-6.85
Walton	↑	2.85	0.46	5.78	0.74	674.00	0.00	-0.72	-640	-11.27	215.96	18.09

From Table 11, it is difficult to use just one indicator to show what made a county more or less resilient. There is a need to have a detailed analysis of all 28 variables and their relative increase or decrease in order to interpret the numbers in Table 11 more accurately.

7.3 The 53 Counties

There are totally 53 counties that were classified into the same resilience type by all the seven tests. Discriminant analysis yields 98.1% accuracy for the 1990 and 2000 data sets, respectively. This means that these counties were assigned the same resilience type, no matter which indicator variables were chosen for the recovery dimension. Thus, an evaluation of these counties in terms of social economic characteristics should shed light on resilience. The 53 counties' names and their resilient types predicted by discriminant analysis are listed in Table 12, and mapped in Figure 24. Only one county in each time period was misclassified. For the 1990 data, Bradford, FL was post-classified by discriminant analysis from "recovery" to "usurper". For the 2000 data, Beauregard Parish was post-classified from "resistant" to "susceptible".

Table 13 lists the mean values of the 28 social-economic indicators of the four groups. To make the interpretation easier, only the 11 variables picked from Chapter 6 were summarized. For the 1990 data set, the percentage of female labor force, 5-year average infant mortality, 3-year average chronic deaths rate, and the percentage of people voted in election did not have much differences among the four groups. The "Resistant" group had the lowest rate of mobile homes, and the percentage of mobile homes was similar for the other three groups. This is reasonable, since mobile homes are likely to suffer damages from hazards. The house density per square mile displayed a big difference between the "Resistant" group and the others. This group tended to include unban counties. The local general finance expenditure per capita was about the same except for the "Usurper" which was a little lower. Mean elevation was low for the "Susceptible" and "Resistant" Counties, and higher for "Recovering", and much higher for and "Usurper". Disabled and not working labor force rate of the "Susceptible" group was the highest,

which means that these counties lacked labor force to recovery in comparison with the other three.

Table 12: Counties Classified into the Same Resilient Groups by All Tests

	Usurper	Resistant	Recovering	Susceptible
Texas	Montgomery	Galveston, Harris, Jefferson	Aransas, Brooks, Calhoun, Cameron, Colorado, Jasper, Kleberg, Orange, Refugio, San Patricio, Victoria, Willacy	Kenedy, Newton
Louisiana	Ascension	Beauregard*, Calcasieu, East Baton Rouge, Jefferson		Assumption, Cameron, Iberville, Plaquemines, St. Bernard, St. Charles, St. James, St. John the Baptist, Washington, West Baton Rouge
Mississippi		Harrison, Jackson		Hancock
Alabama		Mobile		Conecuh, Washington
Florida	Walton	Alachua, Broward, Escambia, Hillsborough, Miami-Dade, Pinellas	Bradford*, Gulf, Hamilton, Lafayette, Leon, Taylor	Desoto

*For the 1990 data, Bradford, FL was post-classified by discriminant analysis from “recovery” to “usurper”. For the 2000 data, Beauregard Parish was post-classified from “resistant” to “susceptible”

Table 13: Mean Values of the 11 Indicators for the Four Types of Resilience Counties (1990)

	Susceptible	Recovering	Resistant	Usurper
FEMLBR	37.66	41.50	43.04	41.31
PCTMOBL	20.59	19.04	8.42	20.88
HOUDEN	24.81	27.75	425.91	53.68
PCTVOTE	44.76	37.92	37.90	42.84
GENEXPPC	1935.31	2059.11	2087.50	1786.00
MELEV	18.33	23.42	15.95	35.07
PCRFRMPOP	2.23	2.51	0.42	1.45
INFMTR	942.50	864.44	995.63	893.33
CHRILLD	66.97	64.66	68.63	59.01
DISNWRK	412.11	329.53	299.38	368.25
HUWNF	18.96	21.46	56.91	12.56

Table 14: Mean Values of the 11 Indicators for the Four Types of Resilience Counties (2000)

	Susceptible	Recovering	Resistant	Usurper
FEMLBR	44.62	45.32	46.97	44.47
PCTMOBL	22.79	20.96	8.98	22.21
HOUDEN	21.01	31.07	262.30	74.84
PCTVOTE	41.33	33.12	36.01	40.51
GENEXPPC	2817.13	2953.33	3155.50	2586.33
MELEV	18.33	23.42	15.95	35.07
PCRFRMPOP	2.09	1.62	0.36	0.91
INFMTR	771.25	785.56	840.63	666.67
CHRILLD	57.64	65.81	61.28	52.23
DISNWRK	712.20	626.49	584.37	540.73
HUWNF	58.35	50.26	78.94	30.57

For the 2000 data set, the percentage of female labor force, 3-year average chronic deaths rate, and the percentage of people voted in election also did not have much differences among the four groups. The 5-year average infant mortality was a little bit higher for the "Resistant" group, and a little bit lower for the "Usurper" group. "Resistant" group still had the highest housing density per square mile, and it still had the lowest rate of mobile homes. Mean elevation was the same as the 1990 data set. The local general finance expenditure per capita was also about the same, except for the "Usurper" group which was a little lower and the "Resistant"

group which was a little bit higher. Disabled and not working labor force rate of the “Susceptible” group was still the highest.

Future studies may be focused on choosing and testing indicator variables on the three dimensions, and on the socioeconomic and environmental structure of counties. More studies will be needed to test the model in different study areas and at different spatial scales.

7.4 Implication for Planners

This study outlines a promising framework for defining and measuring resilience of the 132 coastal counties along the Gulf of Mexico. Four resilience rankings were assigned to the 132 counties. The final grouping results and the indicators identified from this study will help the planners to determine the ability of a county to resist hazards, and its ability to recover in the aftermath. This study shows that in general coastal counties along the eastern part of the Gulf of Mexico (Florida and Alabama) had higher resilience than the western part of the Gulf (Texas, Louisiana, and Mississippi). So the western part of the coast would probably need more resources and better planning and strategies for hazard mitigation. Elevation does not seem to be a dominant factor for community resilience, some resistant counties and susceptible counties may have the same elevation. However, such values were determined for the entire counties, and the scale problem may affect the findings in this study. Urban counties seem to be more resistant than rural areas, and a low rate of mobile house does increase the resistance of a county. In general, usurper counties are more suitable for human habitation, with more protective housing and low chronic illness death rate. All these information will be useful to the planners and decision makers to develop adaptability planning for each county.

References

Anderson, V. 1991. *Alternative economic indicators*. New York: Routledge.

Adger, W.N. 2006. Vulnerability. *Global Environmental Change*. 16: 268-281.

Area Resource File (ARF). 2008. US Department of Health and Human Services. Rockville, MD: Health Resources and Services Administration, Bureau of Health Professions.

Brown, B., Perkins, D. 1992. *Disruptions in place attachments*. In I. Altman & S. Low (Eds.), Place attachment 279-304. New York: Plenum Press.

Brooks, N. 2003. Vulnerability, Risk and Adaptation: A Conceptual Framework. Working Paper 38. Tyndall Centre for Climate Change Research. Norwich: University of East Anglia.

Burton, I., Kates, R.W., White, G.F. 1978. *The Environment as Hazard*. New York: Oxford University Press.

Butzer, K.W., 1989. *Cultural ecology*. In: Gaile, G.L., Willmott, C.J. (Eds.), Geography in America. Columbus: Merrill Publishing Co..

Baker, A. 2009. *Creating an Empirically Derived Community Resilience Index of the Gulf of Mexico Region*. M.S. Thesis, Department of Environmental Sciences. Baton Rouge: Louisiana State University.

Cutter, L.S., Boruff, B.J., Shirley, W.L. 2003. Social Vulnerability to Environmental Hazards. *Social Science Quarterly* 84(2): 242-261.

Cutter, S.L., Finch, C. 2008. Temporal and Spatial Changes in the Social Vulnerability to Natural Hazards. *Proceedings of the national Academy of Sciences*. 105(7):2301-2306.

Defrank, L. 2009. *Resilience of new Orleans Following Hurricane Katrina: A Study of Communities Three Years after the Storm*. M.S. Thesis, Department of Environmental Sciences. Baton Rouge: Louisiana State University.

Doyal, L., Gough, I. 1991. *A Theory of Human Need*. New York: The Guilford Press.

Folke, C., Carpenter, S., Elmqvist, T., Gunderson, L. Holling, C.S.,Walker, B. 2002. Resilience and Sustainable Development: Building Adaptive Capacity in a World of Transformation. *Ambio*. 31: 437-440.

Futuyama, D.J. 1979. *Evolutionary Biology*. Sunderland: Sinauer.

Gunderson, L. 2000. Ecological resilience-in theory and application. *Annual Review of Ecology and Systematics*. 31: 425–429.

Hair, J., Anderson, R., Tatham, R., Black, W. 1998. *Multivariate Data Analysis*. Upper Saddle River, NJ: Prentice Hall Press.

Holling, C.S. 1973. Resilience and Stability of Ecological Systems. *Annual Review of Ecology and Systematics*. 4:1-23.

Holling, C.S. 1986. *Resilience of ecosystems: local surprise and global change*. In: Clark, W.C., Munn, R.E. (Eds.), Sustainable Development and the Biosphere. Cambridge: Cambridge University Press,.

Holling, C.S. 1996. Engineering Resilience versus Ecological Resilience. In Schelze P, eds. *Engineering within Ecological Constraints*, pp. 31-34. Washington DC: National Academy Press.

Horn, R. V. 1993. *Statistical indicators for the economic and social sciences*. Cambridge: Cambridge University Press.

IPCC (Inter-governmental Panel on Climate Change). 2001. Macarchy, J., Canziani, O., Leary, N., Dokken, D., White, K., eds. *Climate Change 2001: Impacts, Adaption, and Vulnerability*. Cambridge, UK: Cambridge University Press.

Kitano, H., 2002. Systems biology: a brief overview. *Science.* 295: 1662-1664.

Lam, N.S., Reams, M. 2009. Development of an Empirical Model for Measuring Community Resilience. Proposal Submitted and Funded by UDPA/NSF.

Lam, N.S., Reams, M., Baker, A. 2011. An Approach to Measuring Community Resilience: An Example Using Counties along the Gulf of Mexico in the United States. Manuscript in Review.

Nicholas, D. 1998. *Measuring Development in the Lower Mississippi Delta: An Integrated Environmental Approach*. M.S. Thesis, Department of Environmental Sciences. Baton Rouge: Louisiana State University.

Odum, H.T. 1970. *Environment, Power and Society*. New York: Wiley.

O'neil, R.V. DeAngelis, D.L., Waide, J.B., Allen, T.F.H. 1986. A Hierachical Concept of Ecosystem Structure and Function. Proceeding of 1987 Crawford Symposium, Oikos. 57:25-41.

Pfefferbaum, B., Reissman, D., Pfefferbaum, R., Klomp, R., & Gurwitch, R. 2005. *Building resilience to mass trauma events.* In L. Doll, S. Bonzo, J. Mercy, & D. Sleet (Eds.), Handbook on injury and violence prevention interventions. New York: Kluwer Academic Publishers.

Pielke, R.A.J., 1998. Re-thinking the role of adaptation in climate policy. *Global Environmental Change.* 8: 159–170.

Pimm, S.L. 1984. The Complexity and Stability of Ecosystems. *Nature*. 307:321-326.

Smit, B., Burton, I., Klein, R., Wandel, J. 2000. An anatomy of adaptation to climate change and variability. *Climatic Change* .45: 223–251.

Shaw-Taylor, Y. 1999. *Measurement of Community Health: The Social Health Index*. New York: University Press of America, Inc.

Sherrieb, K., Norris, F.H., Galea, S. 2010. Measuring Capacities for Community Resilience. *Social Indicator Resilience*. 99:227-247.

Tilman, D., Dawning, J.A. 1994. Biodiversity and Stability in Grasslands. *Nature*. 367:363-365.

Turner, BL., Kasperson, RE., Matson, PA., McCathy, JJ., Corell, RW., Christensen, L., Eckley, N., Kasperson, JX, Luers, A., Martello, ML., Polsky, C., Pulsipher, A., Schiller, A. 2003. Science and Technology for Sustainable Development Special Feature: A Framework for Vulnerability Analysis in Sustainability Sciences. *Proceedings of the National Academy of Sciences*. 100(14): 8074-8079.

United Nations Development Program. 1990. *Human Development Report*. New York: Oxford University Press.

U.S. Census Bureau. 2000. USA Counties Database. Washington, DC: U.S. Census Bureau. http://censtats.census.gov/usa/usa.shtml

Walker, BH., Anderies, JM., Kinzing, AP., Ryan, P. 2006a. Exploring Resilience in Socio-ecological Systems through Comparative Studies and Theory Development: Introduction to the Spatial Issue. *Ecology and Society*. 11(1):12.

Winterhalder, G. 1980. Environmental analysis in human evolution and adaptation research. *Human Ecology* . 8: 135–170.

Ysuf, AA., Francisco, H. 2009. Climate Change Vulnerability Mapping for the South Asia. Singapore: Economy and Environmental Program for Southeast Asia (EEPSEA).

Vita

Kenan Li was born and grew up in the northeast of China. Following his graduation from high school in 2005, he was matriculated by Nankai University that year. While at Nankai, he majored in environmental science with a minor in applied mathematics. Kenan Li finished his bachelor's degree at Nankai and graduated in June 2009.

After graduation, Kenan came to the U.S. and enrolled in Louisiana State University to continue his academic endeavor in the fall of 2009. Kenan has been working as a graduate assistant for Dr. Nina Lam in her remote sensing and GIS Lab, assisting the lab in ensuring that projects, duties and responsibilities were carried out in a responsive and professional manner. Kenan will graduate in fall of 2011 with degree of Master of Science in environmental science.