2013

Community resilience to coastal hazards : an analysis of two geographical scales in Louisiana

Chi Li
Louisiana State University and Agricultural and Mechanical College

COMMUNITY RESILIENCE TO COASTAL HAZARDS:
AN ANALYSIS OF TWO GEOGRAPHICAL SCALES IN LOUISIANA

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
Chi Li
B.S., Nanjing University of Technology, 2008
M.A., SUNY-Binghamton, 2011
August 2013

Acknowledgements

I would like to acknowledge my major advisor professor Dr. Nina Lam and my committee members, Dr. Margaret Reams and Dr. Edward Laws, for providing me with the opportunity to complete my Master's program, advising me on my project research, and providing comments and suggestions for improving my thesis. I really appreciate all my committee members for devoting their time and patience with me in the two years. It was an honor to be the students of Dr. Nina Lam, Dr. Margaret Reams, and Dr. Edward Laws.

I would also like to thank my parents for their physical and emotional support. Without their love and encouragement, I could not have achieved my goals and finished my thesis work.

This research was supported by research grants from U.S. Department of Agriculture (award number: USDA 2010-6401-21312) and the National Science Foundation (award number: 1212112). The statements and findings are those of the author and do not necessarily reflect the views of the funding agencies.

Table of Contents

List of Tables

List of Figures

Abstract

Quantifying resilience is difficulties due to the different definitions of resilience, the interchangeable uses with two other terms “vulnerability” and “adaptability”, as well as the lack of consensus on what indicators should be selected to quantifying resilience.

This thesis research examined the community resilience in Louisiana by applying the Resilience Inference Measurement (RIM) model at two geographic levels: county level and zip code level. The RIM model assesses resilience by using three dimensions (exposure, damage, and recovery) and two abilities (vulnerability and adaptability). The types of coastal hazards included in this study were: coastal, flooding, hurricane/tropical storm, tornado, and severe storm/thunder storm. The study time period was 2000 to 2010. K-means clustering analysis was used to derive the resilience groups. Discriminant analysis was applied to validate the resilience rankings by using a set of indicator variables.

At the county level, discriminant analysis yielded a remarkably high 93.8% classification accuracy when population growth rate in 2000-2010 was used as a recovery indicator and 28 adaptability variables were used to characterize the counties. The accuracy at the zip-code level decreased to 80.2% when population growth rate was used as a recovering indicator. In general, the findings at two different scales are consistent; counties and zip codes with higher socioeconomic status and more resources were found to be more resilient. Interestingly, the two most potent indicators revealed at both scales were the same, which are median rent and median value of owner-occupied housing units. These findings support the use of the RIM model to further explore adaptability indicators and the underlying process leading to resilience.

Chapter 1: Introduction

1.1 Problem Statement

As a coastal state, Louisiana has been suffering from coastal hazards for a long time. The history indicates that a person has a great chance of being affected by a hurricane if he or she lives in Louisiana (Wilkins et al. 2008). The frequency and intensity of coastal hazards in Louisiana impact the safety and economic development of the state. The most serious hurricanes during the last decade were hurricane Katrina and Rita, which devastated many counties near the coast in 2005. According to Knabb et al. (2006), 1,833 people died in hurricane Katrina, and the total property damage was estimated at $81 billion. Hurricane Rita struck the state of Louisiana less than a month after Hurricane Katrina and caused $12 billion in damage to the state of Louisiana and Texas. The historical record of such major hazards combined with recent experiences have generated many studies on how communities have been able to survive the damages caused by natural disasters in the past and how they might be even better prepared for such events in the future (Lam et al. 2009a & 2012; Reams et al.2012).

Hurricane Katrina was one of the most destructive and costliest hurricanes that has ever struck the United States. Giving the threat of climate change and global warming, there may be bigger or even more destructive storms in the future (Lam et al.2009b). Katrina and Rita certainly will not be the last hurricanes to strike Louisiana (Knabb et al. 2006). A study of community resilience to coastal hazards is therefore very important and relevant to Louisiana because such a study helps the residents understand the risk they face and local governments and planners to make better decisions that will make their communities more resilient to natural hazards.

1.2 Research Objectives

There have been many studies concerned about hazards and resilience. Most of the articles in the literature, however, are very conceptual and theoretical. The number of studies that have focused on quantifying community resilience is very limited. Klein et al. (2003) and Cutter et al. (2008) pointed out that resilience remains at the conceptual level. There has been limited scope for the measurement and little agreement on how to measure them. Quantifying resilience has some complexity due to the various definitions of the concept resilience in the last thirty years. This confusion reflects the interchangeable uses of the terms “vulnerability”, “adaptability”, and “resilience”, as well as the difficulty of developing models and selecting indicators of resilience.

To measure community resilience, several collaborative studies were carried out together by students and professors in the GIS and Remote Sensing lab at Louisiana State University in the past several years (Baker 2009; Defrank 2009; Li 2011; Reams et al. 2012; Lam et al. 2013). These studies have focused on different study areas within different time spans. The main goal of this thesis research was to measure coastal community resilience in the state of Louisiana by applying the Resilience Inference Measurement (RIM) Model developed and later refined by Lam, Reams et al. (2011, 2013). In contrast to most resilience studies that have focused on large geographic scales (countries, counties), this thesis research studied community resilience at two geographical scales: county/parish level and zip code level. One purpose of studying resilience at two geographical scales was to provide more information about resilience as a basis for small-scale communities. Another purpose was to test the stability of the RIM model at different geographic scales, which would help us further refine the indicator variables.

The county level study area included all of the 64 counties/Parishes in the state of Louisiana, and the zip code study included 501 zip codes area. Specifically, the research questions to be additionally addressed in this study are:

(1) How to measure community resilience?

(2) How applicable is the RIM model in measuring community resilience to the state of Louisiana?

(3) Are the results different at the two geographical scales?

To answer these questions, the following chapters are organized as follows:

Chapter 2 defines the concepts of vulnerability, adaptability and resilience, and discusses the conceptual model (RIM model). Chapter 3 provides basic information about the study area and the rationales for selecting the study area. Chapter 4 discusses the two methods used in this research: k-means analysis and discriminant analysis. This chapter specially describes 1) how the research classified the 64 counties and 501 zip codes into resilience types by using k-means analysis; and 2) how to determine socioeconomic and environmental indicators to be used in discriminant analysis to validate the grouping results, and to understand what factors can be used to predict resilience rankings. Chapter 5 provides the results from k-means and discriminant analyses, and compares the community resilience results between the two geographic levels. Chapter 6 provides a conclusion of this thesis research.

Chapter 2: Literature Review

2.1 Resilience

The Oxford English Dictionary defines resilience as elasticity or the act of rebounding or springing back. Since the 1970s, the concept of resilience has been used to describe systems that undergo stress and have the ability to recover and return to their original state (Klein et al. 2003).

Although the literature provides many definitions of resilience, there is no consensus on how this concept should be defined (Klein et al. 2003; Lam and Reams 2009; Li 2009). In general, two basic definitions of resilience are found in the literature. Engineering resilience refers to how fast a system can return to the original state after a disturbance; ecological resilience is a measure of how far a system can be perturbed without shifting to a different state (Holling 1973, 1996). The first definition, engineering resilience, is more frequently used. It concentrates on the stability near an equilibrium steady state and the speed of return to the original state following a perturbation (Pimm 1986, Holling 1996). Engineering resilience is more concerned with efficiency, stability and predictability. In the ecology field, many ecologists have argued that ecosystems are dynamic and involve continuous response to external influences that take place on a range of different time scales (Klein et al. 2003). Therefore, ecological resilience emphasizes conditions that can be far from any equilibrium steady state, where instability can flip a system into another stability domain (Holling 1973).

Timmerman (1981) was one of the first persons who discussed resilience of society to climate change. Adger (1997, 2000) investigated some relationships between social resilience and ecological resilience. He considered social resilience as the ability of groups or communities to withstand external disturbances to their infrastructure, such as social, economic, environmental and political changes, and to recover from such perturbations (Klein et al. 2003,

Cutter et al. 2008). Later definitions of resilience extended to the concept of "the degree to which the system is capable of self-organization" (Walker et al. 2004, Adger et al. 2005, Subcommittee on Disaster Reduction 2005 cited in Cutter et al. 2008, p.2).

The forgoing reviews reveal clearly that there are various of definitions of resilience in the hazards and disasters literature. These various definitions make the measurement of resilience difficult.

2.2 Vulnerability

Vulnerability and resilience are closely related, they are both concerned with how systems respond to changes (Adger 2000, Miller et al. 2010). Adger (2000) defined social vulnerability as the exposure of groups of people or individuals to stress as a result of the impacts of environmental change. In his paper, the term resilience was considered an antonym of vulnerability. A similar concept was suggested by Folke et al. (2002), who referred to resilience as the "flip side" of vulnerability. According to Kleins et al. 2003, it was common to interpret vulnerability as the opposite of resilience until it became apparent that the contrast lent itself to a circular reasoning: a system is vulnerable because it is not resilient and a system is not resilient because it is vulnerable. Later on, Turner et al. (2003) suggested that resilience should not be considered to be the flipside of vulnerability. Instead, vulnerability should be considered to have three dimensions. Resilience is one of the dimensions; the other two are exposure and sensitivity to the hazards. For example, if a system has high exposure and sensitivity to hazards but has a high resilience, then this system is not considered to be vulnerable (Miller et al. 2010).

Cutter et al. (2008) reviewed a broad definition of vulnerability in their report on community and regional resilience. They defined vulnerability as "the pre-event, inherent characteristics or qualities of systems that create the potential for harm or differential ability to

recover following an event”. This definition is more applicable to hazards and disasters. For social vulnerability, Cutter and Finch (2008) defined vulnerability to be “a measure of both the sensitivity of a population to natural hazards and its ability to respond and recover from impacts of hazards”. This idea incorporates vulnerability and resilience with the concept adaptability, which will be analyzed as follows.

2.3 Adaptability

The term adaptability is easily confused with vulnerability and resilience because they are interrelated concepts (Smit et al.2005, Lam et al 2013). Like resilience and vulnerability, there are many definitions of adaptability in the literature. The term adaptation was originated in natural science. It was used to describe organisms or systems that had developed certain characteristics that enabled them to survive during times of environmental changes (Smit et al. 2006). Later on, terms such as adaptation, adaptive ability and adaptability were gradually introduced into the field of social science.

Adaptability was described by Pielke (1998) as the “adjustment in individual groups and institutional behavior in order to reduce society’s vulnerability to climate”. Smit et al. (2000) referred to adaptations as ‘‘adjustments in ecological-socio-economic systems in response to actual or expected climatic stimuli, their effects or impacts.” Brooks (2003) described adaptation as the “adjustment in a system’s behavior and characteristics that enhance its ability to cope with external stress”. Brooks (2003) also stated that given constant levels of hazard over a period of time, adaptation would allow a system to reduce the risk associated with those hazards by reducing its social vulnerability. In terms of the relationship between adaptability and resilience, (Walker et al. 2004, 2005) defined adaptability as the capacity of the actors in a system to influence and manage resilience. In a subsequent study, Folke et al. (2010) described

adaptability is a part of resilience. They described adaptability as the capacity of a socio-ecological system to adjust to a change of external and internal drivers, thereby allowing for its development within a stable domain.

2.4 The Resilience Inference Measurement (RIM) Model

As mentioned in Chapter one, although there have been many studies on the subjects of community resilience, hazards, and vulnerability, very few of them have focused on how to measure resilience. The greatest challenge of resilience research remains as how to quantify resilience and what indicators should be used to measure resilience.

To measure resilience, the Resilience Inference Measurement (RIM) model (Lam et al. 2013; Li 2011) was applied in this thesis research. The resilience idea used in the RIM model is ecological resilience, where the relationships between vulnerability, adaptability and resilience are explored. In the RIM model, community resilience is conceptually depicted as three dimensions and two abilities (Figures 1). The three dimensions are (1) the exposure to hazards, (2) the damage from exposure to hazards, and (3) the recovery after hazards. To be specific, the exposure to hazards could be represented by the number of times a county or zip code is hit by natural hazards in a certain period of time; the damage from exposure could be the property damage or loses of lives caused by natural hazards in the period of time; and the recovery after the nature hazards could be population return and income growth. For the two abilities, they refer to: (1) the relationship between exposure and damage, which is considered to be vulnerability, and (2) the relationship between damage and recovery, which is considered to be adaptability.

Figure 1: The Resilience Inference Measurement (RIM) Model (modified from Lam et al. 2013)

A previous study (Liu et al. 2006) suggested that the recovery patterns of an ecological system following a disturbance can be explained as four states: susceptible, resilient, resistant, and usurper (Figure 2). Using population return in Figure 2 as an example, a susceptible state refers to a state to which the population in the community cannot fully recover after a disturbance. Such a community is also characterized by a resilience rank of 1, the lowest resilience in the resilience scoring system. A resilient state (which has been renamed as recovering in Lam et al. 2013), refers to a state of a community where population can fully recover after a disturbance. The resilient (recovering) state is characterized by a resilience rank of 2, the second lowest resiliency. Similar to a recovering state, the population in a resistant community can fully come back after a disturbance. The difference is that the damage associated with this state is smaller. Therefore, a resistant state is preferable to a recovering state. It is characterized by a resilience rank of 3, the second highest resiliency. A usurper community is one whose population is able not only to fully recover after a disturbance but also to exceed the

original size of the population before the disturbance. A usurper state is therefore the best state, and is considered the most resilient.

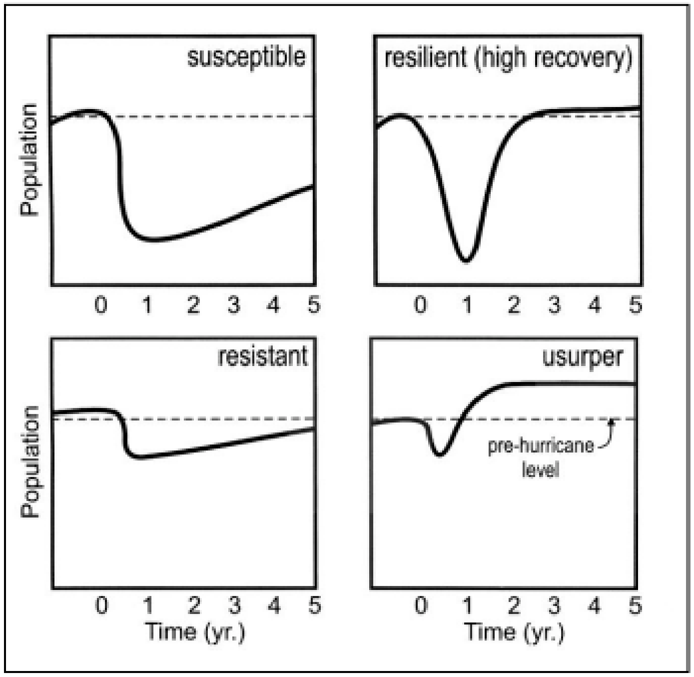

Figure 2: Patterns of the Four Recovery States in an Ecological Study (Liu et al. 2006)

Since this thesis research was a socio-ecological study, and all the hazards selected were natural hazards, the concept of the four states was therefore borrowed to evaluate community resilience. A modified version of the four typical curves was used to link the four recovery patterns of an ecological system and our resilience research (Lam et al. 2011, 2013; Li 2011). The four typical types of resilience system are named susceptible, recovering, resistant and usurper. The criterion for distinguishing the four systems is their different characteristics of exposure, damage and recovery.

Figure 3 shows how the four recovery patterns could be applied in this thesis research (Li et al. 2011). 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 county has higher than the average value in that dimension. This diagram shows how the

three dimensions and two abilities can be evaluated into the four states in the RIM model. The susceptible system has a low z-value of exposure, high z-value of damage and low z-value of recovery. This means that the system has high vulnerability and low adaptability. A susceptible system therefore has the lowest resilience. The recovering system has an even curve with average values of exposure, damage and recovery. It shows the recovering system has about the average vulnerability and adaptability. The resistant system has low vulnerability and average adaptability. If a county belongs to the resistant system, then such a county is perceived to be able to resist a disturbance. The usurper system has above average exposure, average damage and high recovery. This shows that this system has low vulnerability and high adaptability. Therefore, it is the most resilient system among the four. From susceptible, recovering, resistant , to usurper, the resiliency of the system increases.

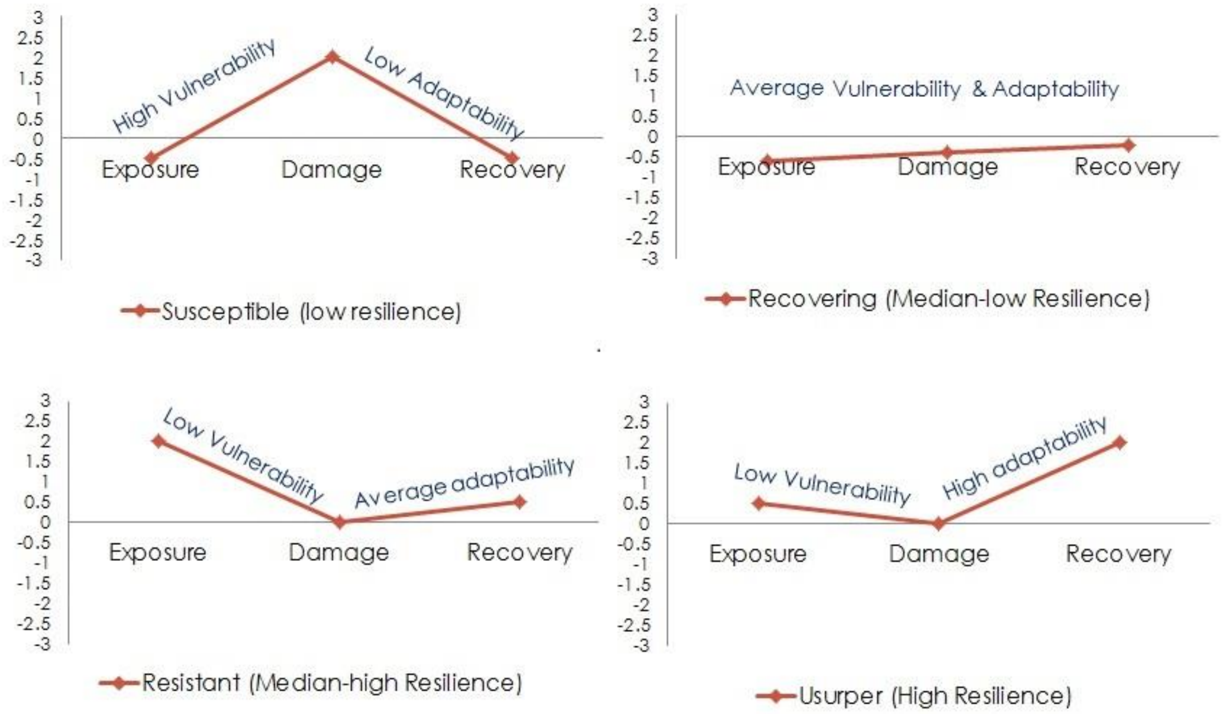

Figure 3: Four Resilience Groups Pattern (revised from Li K. 2011)

Chapter 3: Study Area and Data

3.1 Study Area

The study area was the state of Louisiana. The state of Louisiana is bordered to the west by Texas, the east by Mississippi, the north by Arkansas, and the south by the Gulf of Mexico. Louisiana has 64 parishes and a total land area of 43.203.9 square miles (Figure 4). According to the 2010 U.S. Census, the total population of Louisiana is 4,533,372. Caucasians and African-Americans are the two largest racial groups. They account for 62.6% and 32% of the total population, respectively. In contrast, Hispanics and Asians only account for 4.2% and 1.5%, respectively. The median household income is $52,762. According to the Office of Management and Budget, in 2009, Louisiana had a total of 7 combined statistical areas and 8 Metropolitan Statistical Areas (MSAs). Twenty-nine of the 64 parishes are defined as metropolitan.

Figure 4: Louisiana County Map, 2010

This study examined two different geographic scales: the county and zip code scales. All of the 64 parishes in Louisiana were included in the county-level study. For the zip code scale, the actual geographic unit used for this thesis research was ZIP Code Tabulation Areas (ZCTAs). According to the U.S. Census, USPS ZIP Codes are not areal features but a collection of mail delivery routes. The Census Bureau has used the ZIP Code Tabulation Areas (ZCTAs) to create approximates of zip codes since 2000. Because ZCTAs are the statistical geographic units that represent USPS zip codes in Census, the population data as well as shapefile boundary data needed for this study are only available for ZCTAs. ZCTAs were first introduced with the 2000 Census and continued with the 2010 Census. However, there are many differences between Census 2000 and Census 2010 ZCTAs (Table 1).

Table 1: Key Differences between Census 2000 and 2010 Census ZCTAs

Census 2000	Census 2010
Includes the U.S. and Puerto Rico	Includes the U.S., Puerto Rico, and the Island Areas
Cover the full extent of the nation - "wall-to-wall" coverage	Do not cover the full extent of the nation - "holes" exist
3-digit and 5-digit ZCTA's available	5-digit ZCTA's only
"XX" suffix used to represent large land areas such as national parks	"XX" retired - Large land areas such as national parks do not have ZCTA coverage
"HH" suffix used to represent large water bodies	"HH" retired - Large water bodies do not have ZCTA coverage

Louisiana had 542 zip codes (ZCTAs) in 2000. However, the zip code area decreased to 516 in 2010. Some zip codes existed in 2000 but not in 2010, and vice versa. A total of 492 zip codes were common to both 2000 and 2010. Zip code 70163 and 70836 existed in both years but were excluded because they were associated with no population. Zip code 70373 was also excluded because it had an extreme population increase in the 10-years period. This extreme change would

have impacted the result of k-mean groupings. Therefore, the final number of zip code included in this study was 501. Figure 5 shows the overlay of 2000 zip codes and 2010 zip codes. The areas in orange are the zip codes excluded from this study.

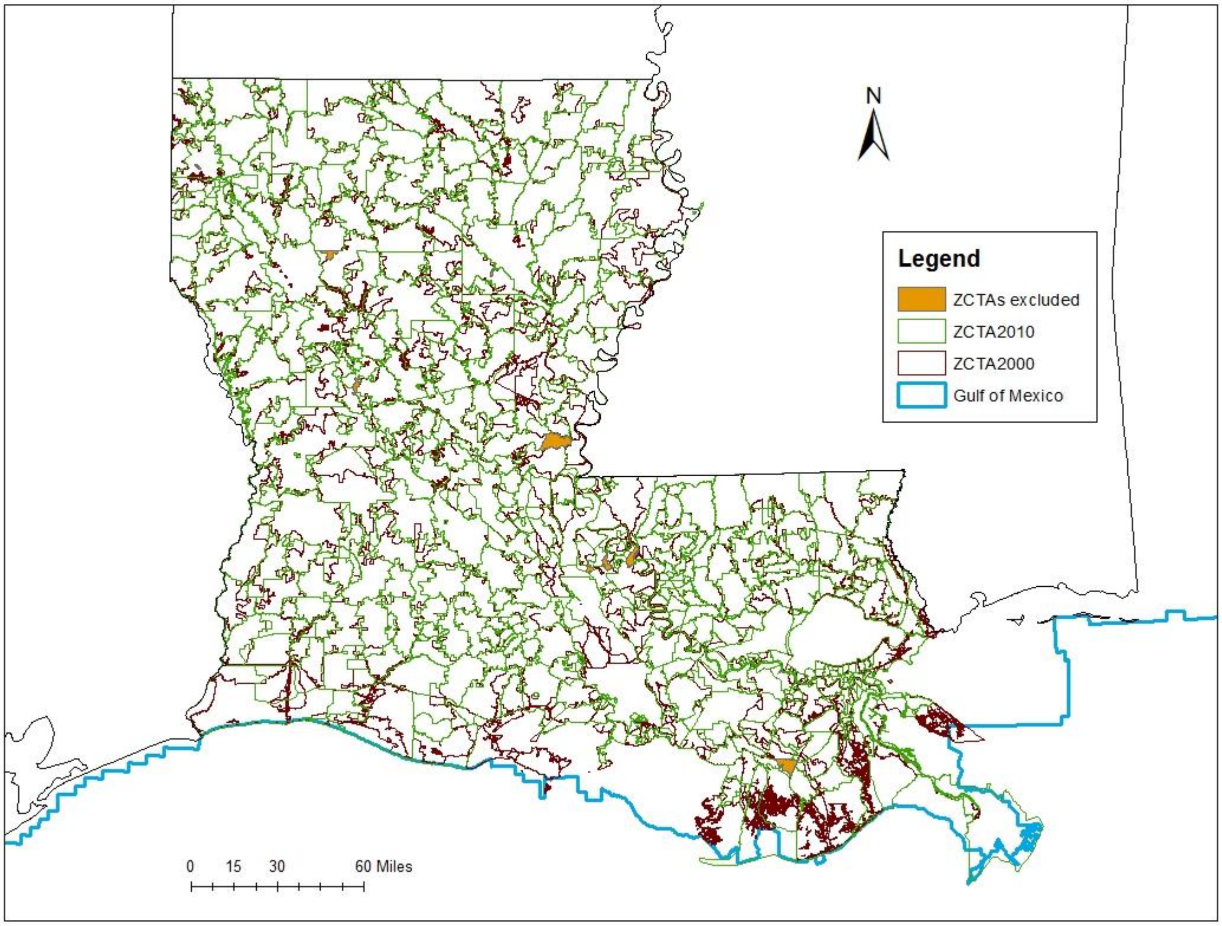

Figure 5: Overlay of ZCTA 2000 and 2010 Boundary

3.2 The Rationale of Selecting Louisiana as a Study Area

As a coastal state, 38 of the 64 parishes in Louisiana were defined as coastal counties by the Strategic Environmental Assessments Division of the National Oceanic and Atmospheric Administration (NOAA). According to NOAA's List of Coastal Counties for the Bureau of the Census Statistical Abstract Series, a county was defined as a coastal county if it meets one of the follow criteria 1) at least 15 percent of a county's total land area is located within the Nation's

coastal watershed; or 2) a portion of or an entire county accounts for at least 15 percent of a coastal cataloging unit. A coastal cataloging unit is defined by NOAA as "a drainage basin that falls entirely within or straddles an Estuarine Drainage Areas or Coastal Drainage Areas (Crowell et al. 2007).

The state of Louisiana is located between the Mississippi River deltaic plain and the Chenier Plain along the north central Gulf of Mexico. The location of the state and the long history of natural hazards make it a high risk place to live, especially for people who live in an area subsiding as sea level rises (Wilkins et al. 2008). Some of the hurricanes and tropical storms that have passed over Louisiana are among the deadliest tropical storms and hurricanes to ever hit the United States (Roth 2010). Since the mid twentieth century, major and memorable hurricanes have included Audrey (Category 4) in 1957; Betsy (Category 3 at landfall) in1965; Camille (Category 5) in 1969; Andrew (Category 3 at landfall) in 1992; and the two big recent ones, Katrina and Rita, both of which were in Category 3 at landfall in 2005 (Roth 2010). These storms devastated different parts of Louisiana, killed and left thousands of people homeless, knocked out power, blocked roadways, and destroyed and damaged many homes and businesses. Some people reacted by moving to other counties in the state; some moved out of the state. However, it is the human nature for people to love their homes. Not everyone can relocate to somewhere else, and instead many people choose to return. Coastal Louisiana is dynamic. Human endeavors cannot fix coastal Louisiana to make it static enough to be consistent with our notions of property and territory (Wilkins et al. 2008). However, we can understand the risks better and make better plans to prepare for, respond to and mitigate the damage caused by natural hazards. It is well-known that communities with resilience to the impacts of natural hazards are

not built by chance (Schwab, 2007). An accurate measurement of the community resilience to coastal hazards is therefore very essential for informing residents and planners.

3.3 Data Selection and Portrayal

The data selected for this thesis came from several different sources. Demographic, economic and governmental data were obtained from the 2000 and 2010 U.S. Census. Health-related variables were obtained from the Bureau of Health Professions in the U.S. Department of Health and Human Services: Area Resource File (ARF). Coastal hazards data were obtained from Spatial Hazard Events and Losses Database for the United States (SHELDUS), operated by the University of South Carolina. The elevation data in 30m x 30m grids were from the U.S. Geological Survey (USGS): The National Map Viewer and Download Platform. This study used ArcGIS to tabulate the average elevation values according to the county and zip code boundaries.

Community resilience to natural hazards was assessed by three dimensions: exposure, damage, and recovery. The five major types of hazards included in this study were: hurricane/tropical storm, severe storm/thunderstorm, coastal, tornado, and flooding. The coastal type used in this study included coastal flooding and storm surge. These five types of hazards were selected because they have a significant impact on Louisiana. There were also other types of natural hazards that happened in Louisiana during the ten-year period, including drought, hail, heat, wind and winter weather. During the time period 2000-2010, all hazards caused 761 total fatalities and $55.99 billion of property damage in the State of Louisiana (SHELDUS 2013). Among which, the five types of hazards selected in this study caused 715 fatalities and $55.8 billion of property damage, which accounted for the majority of the fatalities and property damage.

3.3.1 County-Level Study

To represent hazard exposure, instead of using the total number of hazards, the number of such events was adjusted by a weighting method. This idea was taken from the method used by Lam et al. (2013). The weight of an event type *i* (w_i) is derived as the ratio of the total damage of event type *i* and the total damage from all events:

$$w_i = \frac{TotalDamage_i}{TotalDamage} \quad (1)$$

The final exposure for a certain county *x* was calculated from the following equation:

$$Exposure(x) = \sum_{i=1}^{5} \sum_{j=1}^{N_{xi}} w_i(BeginDate_{ij} - EndDate_{ij}) \quad (2)$$

where N_{xi} is the number of hazards of type *i* that occurred in county x, and $BeginDate_{ij}$ and $EndDate_{ij}$ are the beginning and ending dates of hazard event *j* of type *i*, respectively (Lam et al. 2013).

To represent damage, the hazard damage used for each county is the sum of the damage from each event divided by the population of the county at the time of the event. To represent recovery, three indicators were used in this research. The three indicators were the percent of population growth between 2000 and 2010, the percent of median household income growth between 2000 and 2010, and the percentage of per capita income growth between 2000 and 2010.

A general look at the data revealed that the ranges of the data were wide, especially for exposure, and damage. Figure 6 maps the distribution of hazard exposure and damage. The upper map shows a clear pattern that the hazard exposure gradually increases from the inland counties to the coastal counties. The per capita damage map has a different pattern. It does not have a clear gradient from the north to the south as the exposure map. In general, the counties that had bigger losses were still more concentrated in coastal Louisiana, except for East Carroll parish at

the northeast corner of the state. Notably, the southeast part of the state had higher hazard damage because of the two big events, Hurricane Katrina and Rita.

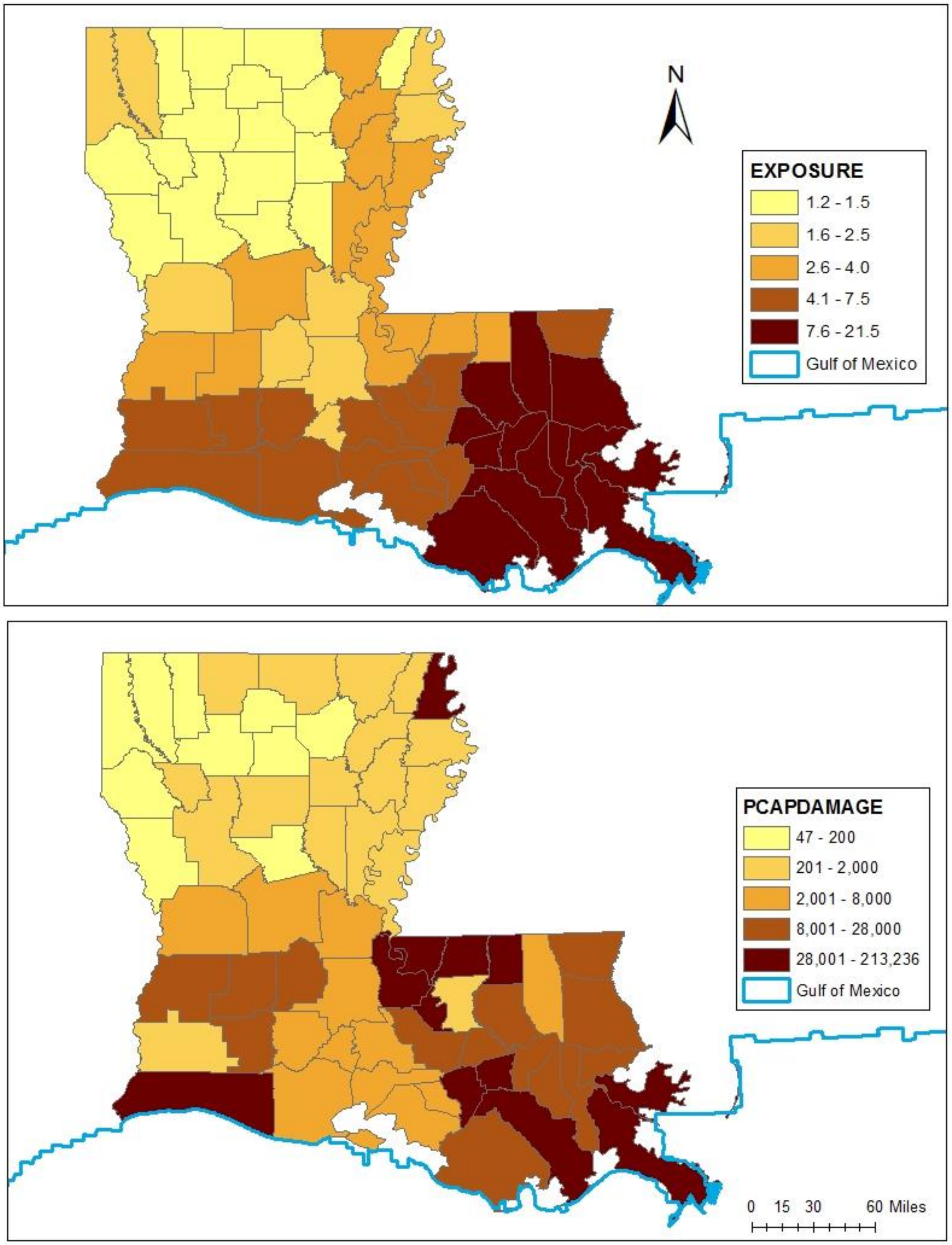

Figure 6: The Distribution of Hazard Exposure and Per Capita Damage from 2000 to 2010

Figure 7 shows the percentage population change from 2000 to 2010. The map shows that many parishes in Louisiana experienced population decline from 2000 to 2010. The number of population in Cameron, Orleans, and St. Bernard decreased by over 25% between 2000 and 2010.

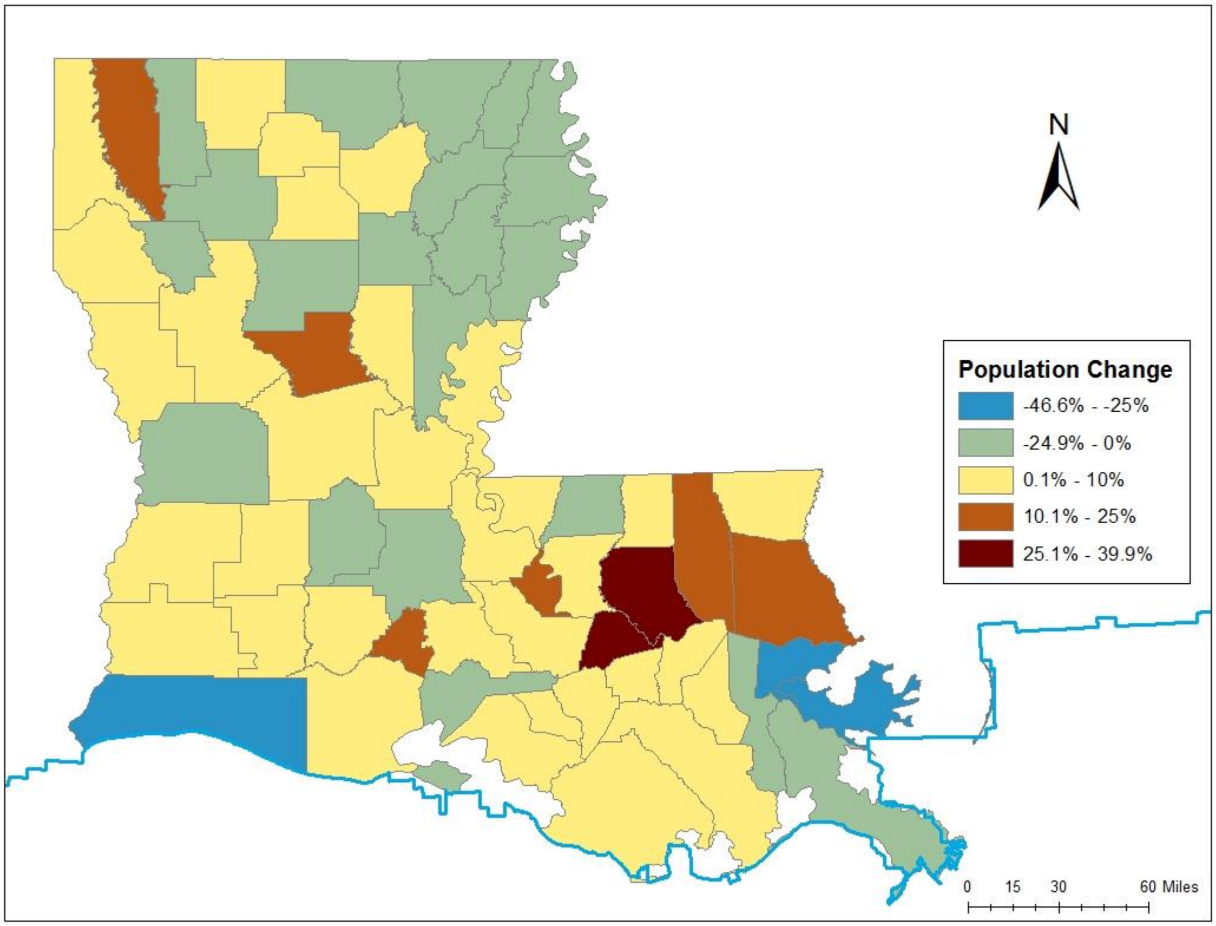

Figure 7: The Distribution of Population Change in 2000-2010

The exposure score ranged from 1.23 to 21.55; per capital damages score ranged from 46.54 to 213,236.1; population change ranged from -47% to 40%; median income change ranged from 2% to 61%; and per capita income change ranged from 9% to 67%. To get familiar with the data before doing any statistical analyses, the top 10% of the parishes that had the highest level of exposure, the highest damage, and the lowest population growth, median income growth, and per

capita income growth were tabulated (Table 2). It appeared that St. Bernard and Plaquemines parishes had the highest exposure, highest damage and lowest recovery rates. This result was not surprising because St. Bernard and Plaquemines were severely impacted by Hurricane Katrina and Rita in 2005, the two biggest events during the 10-year study period. East Carroll parish stands out in Table2. It had a low hazard exposure but very high damage, low population growth, and low median income growth. East Carroll is not a coastal county. It is actually far away from the coast. It does not have a low elevation as counties around New Orleans. The low hazard exposure shows that it is seldom hit by natural hazards. The reason for the high damage, low population growth, and low median income growth is that East Carroll has a high social vulnerability.

Table 2: Top-ranked Counties with Exposure, Damage and Recovery

Exposure	Per Capita Damage	Population Growth	Median Income Growth	Per Capita Income Growth
Jefferson [21.55]	**Plaquemines** [213236]	**St. Bernard** [-47%]	**St. Bernard** [2%]	**St. Bernard** [9%]
Plaquemines [21.47]	**St. Bernard** [93855]	Cameron [-32%]	**East Carroll** [12%]	East Feliciana [16%]
Lafourche [20.68]	**East Carroll** [86871]	Orleans [-29%]	Morehouse [15%]	West Feliciana [18%]
St. Bernard [19.36]	St. Helena [76988]	Tensas [-21%]	St. John the Baptist [18%]	Morehouse [22%]
Terrebonne [18.36]	Lafourche [66550]	**East Carroll** [-18%]	Ouachita [18%]	Jackson [24%]
St.Tammy [18.07]	West Feliciana [52121]	**Plaquemines** [-14%]	Madison [19%]	Natchitoches [24%]

Note: Exposure and damage are from the highest to the lowest, whereas population growth rate, median income growth rate, and per capita income growth rate are from the lowest to the highest

Figures 8 and 9 show the social vulnerability index values computed by the Hazards and Vulnerability Research Institute at the University of South Carolina both within a state comparison and national comparison (HVRI 2010). The maps show the East Carroll Parish has very high vulnerability. However, it is noted here that the derivation of the social vulnerability index in quite different from the RIM approach used in this thesis, as the latter incorporates all three dimensions in deriving the resilience rankings.

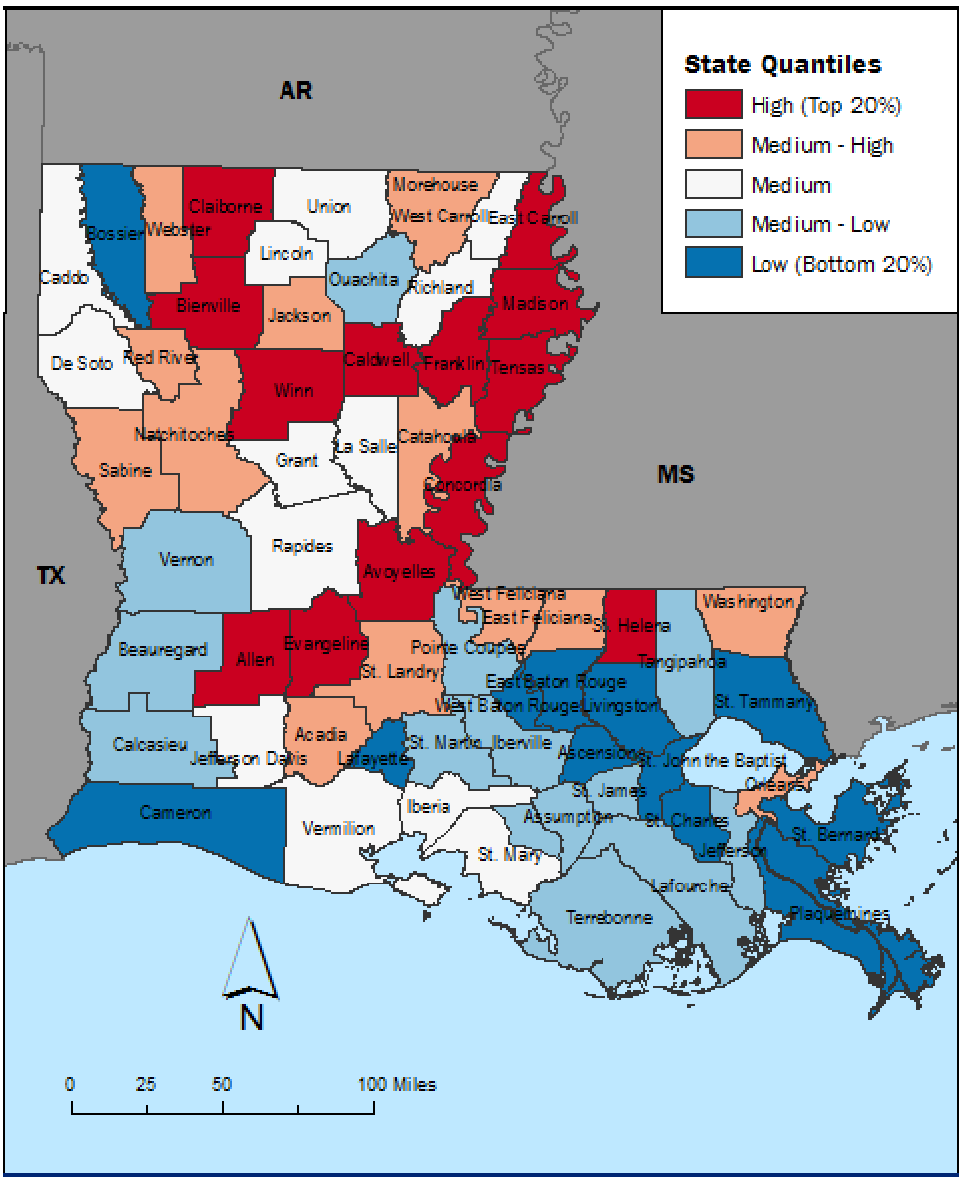

Figure 8: Sovi to Environmental Hazards, County Comparison with the State (HVRI, 2010)

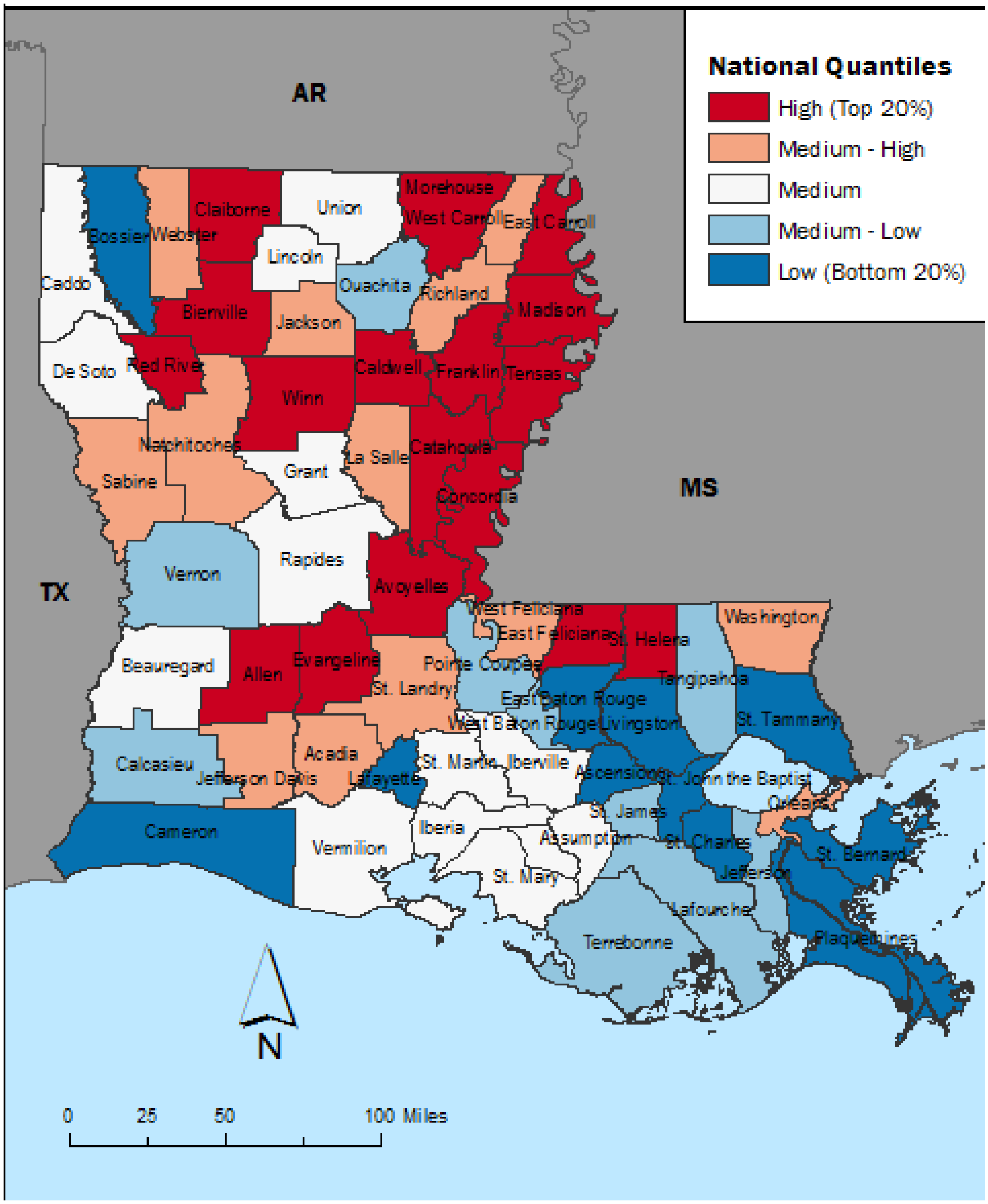

Figure 9: Sovi to Environmental Hazards, County Comparison with the Nation (HVRI, 2010)

3.3.2 Zip Code-Level Study

The hazard exposure and damage data for this thesis were obtained from SHELDUS, which originally came from NOAA. However, NOAA does not provide hazard data for small geographic regions such as zip codes. Therefore, some interpolations were done in this study to estimate hazard exposure and damage at the zip code level.

To estimate hazard exposure, Kriging was used to allocate the exposure score from the county level to the zip code level (Figure 10).). Kriging is a spatial statistical method that uses data collected from point locations to predict values in each grid cell over a spatial

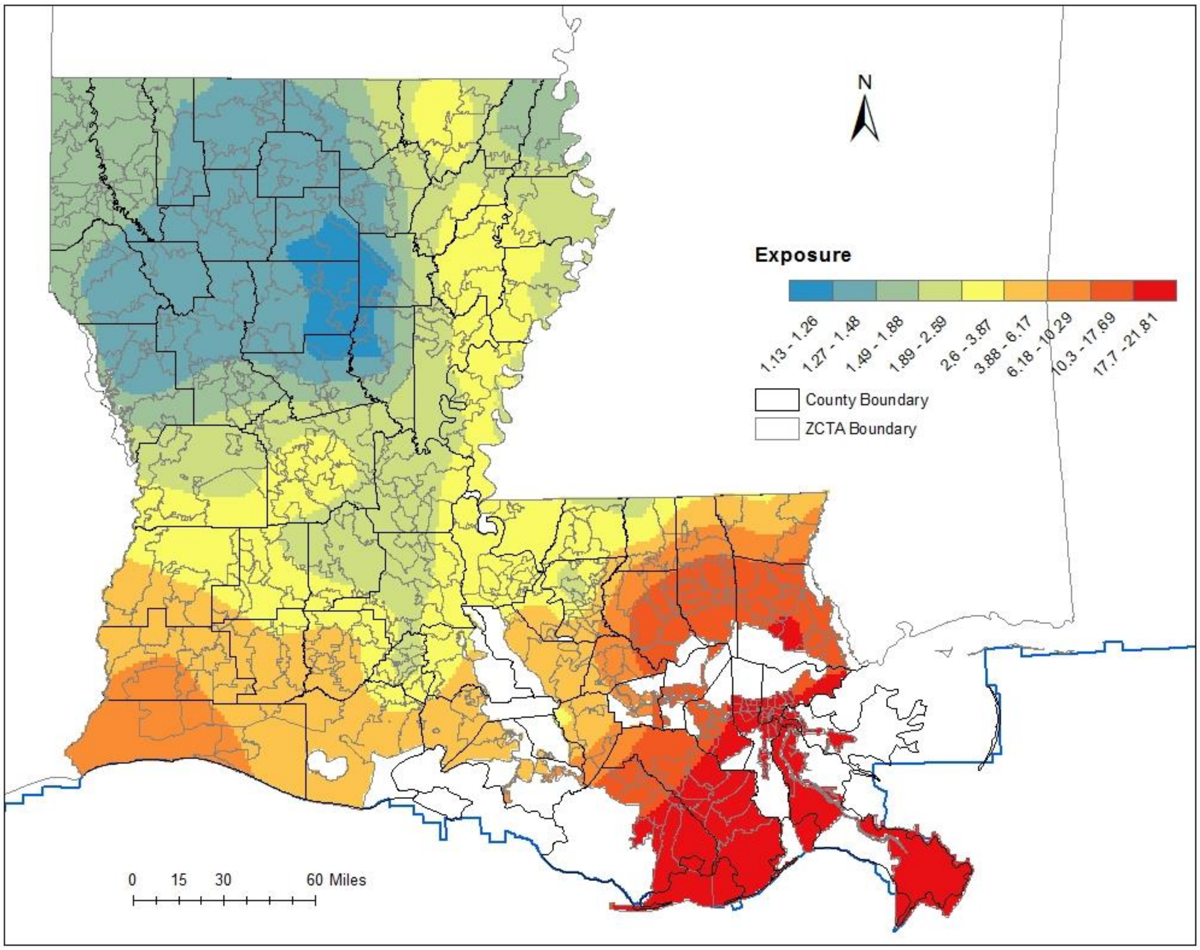

Figure 10: Redistribute Hazard Exposure from County Level to Zip Code Level

domain (Lam 1983, 2009).The rationale for using Kriging instead of other interpolation methods was its power and accuracy in predicting and creating surface (Chan et al. 2009; Margai 2010). After comparing different Kriging methods including circular, exponential, Gaussian, spherical, and stable, spherical was applied because it has the smallest average error, root mean square prediction error, and standardized mean prediction error. Furthermore, the average standard error was similar to the root mean square prediction error.

To estimate hazard damage at the zip code level, the county damage from 2000 to 2010 was divided by the number of zip codes in each county, and then divided by the zip code population in 2010.

For the recovery indictors, the same indicators were used as in the county-level study. They were 1) total population growth rate from 2000 to 2010; 2) median household income growth rate from 2000 to 2010; and 3) per capita income growth rate from 2000 to 2010.These indicators were available from the Decennial Census website (http://factfinder2.census.gov/faces/nav/jsf/pages/wc_dec.xhtml). Total population data were available for all of the zip codes in both 2000 and 2010. There were four zip codes that did not have 2010 median household income data, and one zip code lacking per capita income data in 2010.

Chapter 4: Methodology for Analyzing Community Resilience

4.1 K-Means Analysis

K-mean analysis is a clustering method that aims to partition observations into “k” groups, where each case is assigned to the cluster that has the nearest distance to its centroid (Li 2011). The equation of this method is:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \qquad (3)$$

where, $\left\| x_i^{(j)} - c_j \right\|^2$ is a chosen distance measure between a data point $x_i^{(j)}$ and the cluster center c_j .The algorithm is composed of the following steps (Erdogan and Timor 2005):

1. Place k points into the space represented by the objects that are being clustered. These points represent the initial group centroids.
2. Assign each object to the closest centroid.
3. When all objects have been assigned, recalculate the positions of the k centroids.
4. Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups based on the distance.

The purpose of using k-means analysis is to determine if the 64 counties and 501 zip codes can be grouped into four socio-resilient systems as defined in Chapter 2. Before conducting k-means analysis, all three variables (exposure, damage, and recovery) were standardized into z-scores to ensure that they were in the same dimension by using equation 4.

$$z = \frac{x - \mu}{\sigma} \qquad (4)$$

where, μ is the mean , and σ is the standard deviation of the variable. Since both the exposure and the damage variable in this dataset included several extreme values, median was used instead of the mean, and standard deviation was replaced by absolute average deviation (AAD) in this study to make the results less sensitive to outliers (Tan et al. 2005, Lam et al.2013).

K-means clustering method has some advantages over other clustering methods. The advantages include its faster speed which allows it to run with large datasets, and the fact that it tends to produce tighter clusters than hierarchical clustering (Singh et al. 2011 and Reddy et al. 2012**)**. However it also has some limitations. The main disadvantages are its sensitivity to outliers and its automatic assigned initial values can result in poor final clusters (Ghosh and Liu 2009, Singh et al. 2011). To deal with the problem of initial values, the data distribution was examined, and then the initial values for the cluster centers assigned rather than using the default initial value generated by the k-means function. Because this study focused on a time interval of only 10 years, Hurricanes Katrina and Rita stood out very much compared to other events. Therefore, the hazard exposure and damage scores were extremely high in those counties that were severely impacted by these two events. The strategy applied here was to discover the outlier counties, introduce a new cluster centroid based on the outliers, and then merge the group back to the closest centroid. Since the new cluster centroid of the outliers was very far from any other cluster centers, this procedure did not affect the other groupings.

4.2 Discriminant Analysis

Once I had the resilience grouping results from THE k-means analysis, discriminant analysis was then used to characterize the four resilient groups by a number of socioeconomic and environmental indicators. Discriminant analysis is an inferential statistical technique. It is used to determine which continuous variables discriminate between two or more naturally

occurring groups (Garson 2004). One purpose of applying discriminant analysis is to predict the prior group memberships based on a series of independent variables (Hair et al 1998, Stockburger 1998). In this study, I used it as a validation of the resilience groupings. A second purpose is to understand which variables can best be used as indicators to predict the groups (Liu and Lam 1985).

For the county level analysis, 28 variables were selected as indicators to understand the adaptability of a county. The rationale of data selection was based on several previous analyses (Baker 2009; Defrank 2009; Li 2011; Lam et al 2013) and literature reviews. The 28 variables selected fell in to six categories: demographic, social, economic, governmental, environmental, and health (Table 3). All variables were converted into either densities per square mile, per capita, or percent (Baker 2009; Li 2001; Lam 2013). For the zip code level study, only nineteen indicator variables were available for zip codes, and fewer health variables were available at the zip code level as well (Table 4).

Table 3: Indicators Used in Discriminant Analysis, County-Level

Variable	**Definition**
	Demographic Variables
PCTBLACK	Percent Black, 2000
PCTHISPANIC	Percent Hispanic,2000
PCTKIDS	Percent under 5 years old, 2000
PCTOLD	Percent over 65 years old, 2000
AVGPERHH	Average number of people per household, 2000
	Social Variables
PCTFEMLBR	Percent of the workforce that is female, 2000
PCTFHH	Percent female-headed households, 2000
PCTMOBL	Percent of homes that are mobile homes, 2000
HOUDEN	Total housing unit per square mile , 2000
PCTNOHS	Percent of population over 25 with no high school degree, 2000

(Table 3 Continued)

Variable	Definition
	Economic Variables
PCTPOV	Percent of the population living below poverty, 2000
PCTCVLBF	Percent of the workforce that is employed, 2000
MVALOO	Median value of owner occupied housing units, 2000
MEDRENT	Median rent, 2000
PCTFRMPOP	Percent rural farm population, 2000
	Government
LGFINREVPC	Local government finance, revenue per capita, 2002
GENEXPPC	Local government finance general expenditures per capita, 2002
PERVOTE	Percent of the population that voted in 2000 presidential election, 2000
EXPEDPC	Local government finance expenditures for education, 2002
	Environmental
MELE	Mean elevation of the county, 2008
	Health
INFMTR	5-year average infant mortality per 10,000 births, 1998-2002
CHILLD	3-year average chronic illness deaths per 10,000 individuals, 1998-2000
DISNWRK	Disabled and not working labor forces per 10,000 individuals, 2000
LBWB	3-year total low birth weight babies per 10,000 live births, 1998-2000
HUWNF	Households with no fuel used per 10,000 house units, 2000
HUWNP	Douseholds with no plumbing per 10,000 house units, 2000
MD	Non-federal active medical doctors per 10,000 individuals, 2000

Table 4: Indicators Used in Discriminant Analysis, Zip Code-Level

Variable	Definition
Demographic Variables	
PCTBLACK	Percent Black, 2000
PCTHISPANIC	Percent Hispanic,2000
PCTKIDS	Percent under 5 years old, 2000
PCTOLD	Percent over 65 years old, 2000
AVGPERHH	Average number of people per household, 2000
Social Variables	
PCTFEMLBR	Percent of the workforce that is female, 2000
PCTFHH	Percent female-headed households, 2000
PCTMOBL	Percent of homes that are mobile homes, 2000
HOUDEN	Total housing unit per square mile , 2000
PCTNOHS	Percent of population over 25 with no high school degree, 2000
PCTRENT	Percent population that rents, 2000
Economic Variables	
PCTPOV	Percent of the population living below poverty, 2000
PCTCVLBF	Percent of the workforce that is employed, 2000
MVALOO	Median value of owner occupied housing units, 2000
MEDRENT	Median rent, 2000
PCTFRMPOP	Percent rural farm population, 2000
Environmental	
MELE	Mean elevation of the county, 2008
Health	
HUWNF	Households with no fuel used per 10,000 house units, 2000
HUWNP	Households with no plumbing per 10,000 house units, 2000

Chapter 5: Results and Discussion

5.1 County-Level Results

5.1.1 Results from K-means Analysis

Three separate k-means analyses were conducted in this study because three recovery indicators (population growth rate, median income growth rate and per capita growth rate) were selected. Detailed information concerning the tests and variables are shown in Table 5:

Table 5: Variables Used for K-means Analysis

Test	Exposure	Damage	Recovery
1	NEXPOSURE	NDAMAGE	*NPOPCHG0010*
2			*NMEDINC9909*
3			*NPCINC9909*

Note: NEXPOSURE stands for the hazard exposure after data normalization. NDAMAGE stands for the per capita property damage after normalization. NPOPCHG0010 stands for the normalized population growth rate from 2000 to 2010. NMEDINC9909 stands for the normalized median income growth rate from 1999 to 2009. NPCINC9909 stands for per capita personal income growth rate from 1999 to 2009.

Test 1: Exposure, per capita damage and population change from 2000 to 2010

As mentioned in Chapter 4, this study has some outliers. Therefore, five clusters for k-means analysis were used. Figure 11 is a line chart that shows the k-means clustering for using five groups. A comparison of Figure 11 and Table 6 reveals that cluster 4 has some extreme values and includes only two counties in it. Cluster 4 was therefore added to cluster 1, because cluster 1 has the same line shape as cluster 4, and the center of cluster 1 is closest to the center of cluster 4.

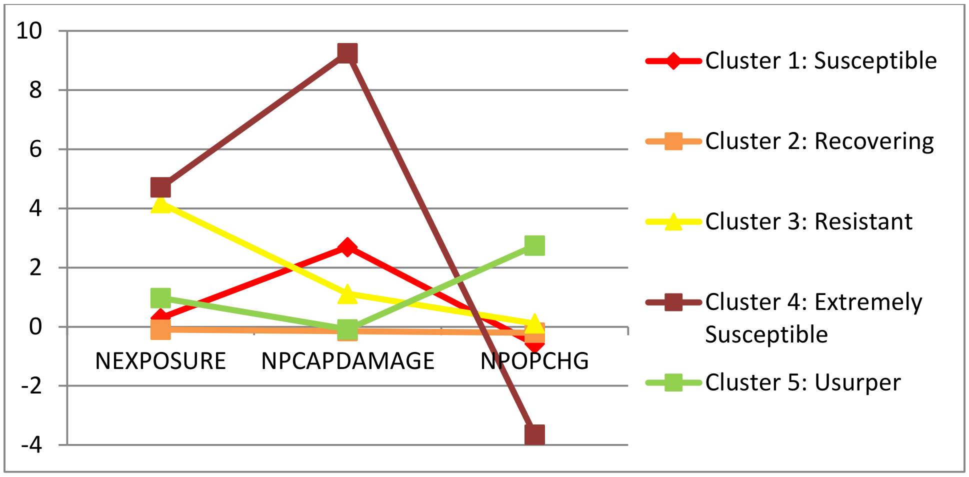

Figure 11: K-means Clusters -Five Groups, Test 1

Table 6: Number of Cases in Each Cluster

Cluster	1	9
	2	40
	3	7
	4	2
	5	6
Valid		64
Missing		0

Figure 12 shows final k-means clusters. The differences between the four groups are more apparent. Clusters 1, 2, 3, and 4 represent susceptible, recovering, resistant, and usurper counties, respectively. Figure 13 is a map showing the distribution of the k-means clusters. From this map it is apparent that the majority of the counties in Louisiana fell into the recovering category by using population change as a recovery indicator. Among the susceptible counties, eight out of nine were coastal counties, which include Cameron, East Feliciana, Plaquemines, Pointe Coupee, St. Bernard, St. Helena, St. James, West Baton Rouge and West Feliciana. Plaquemines and St. Bernard were the two additional susceptible counties. The six usurper counties were Ascension, Bossier, Grant, Lafayette, Livingston, and Tangipahoa.

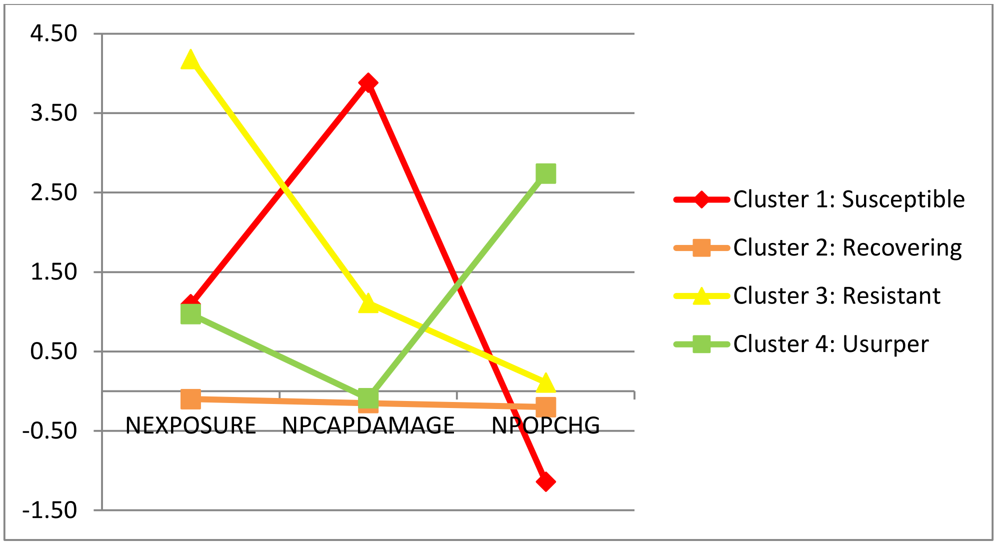

Figure 12: K-means Final Clusters from Test 1

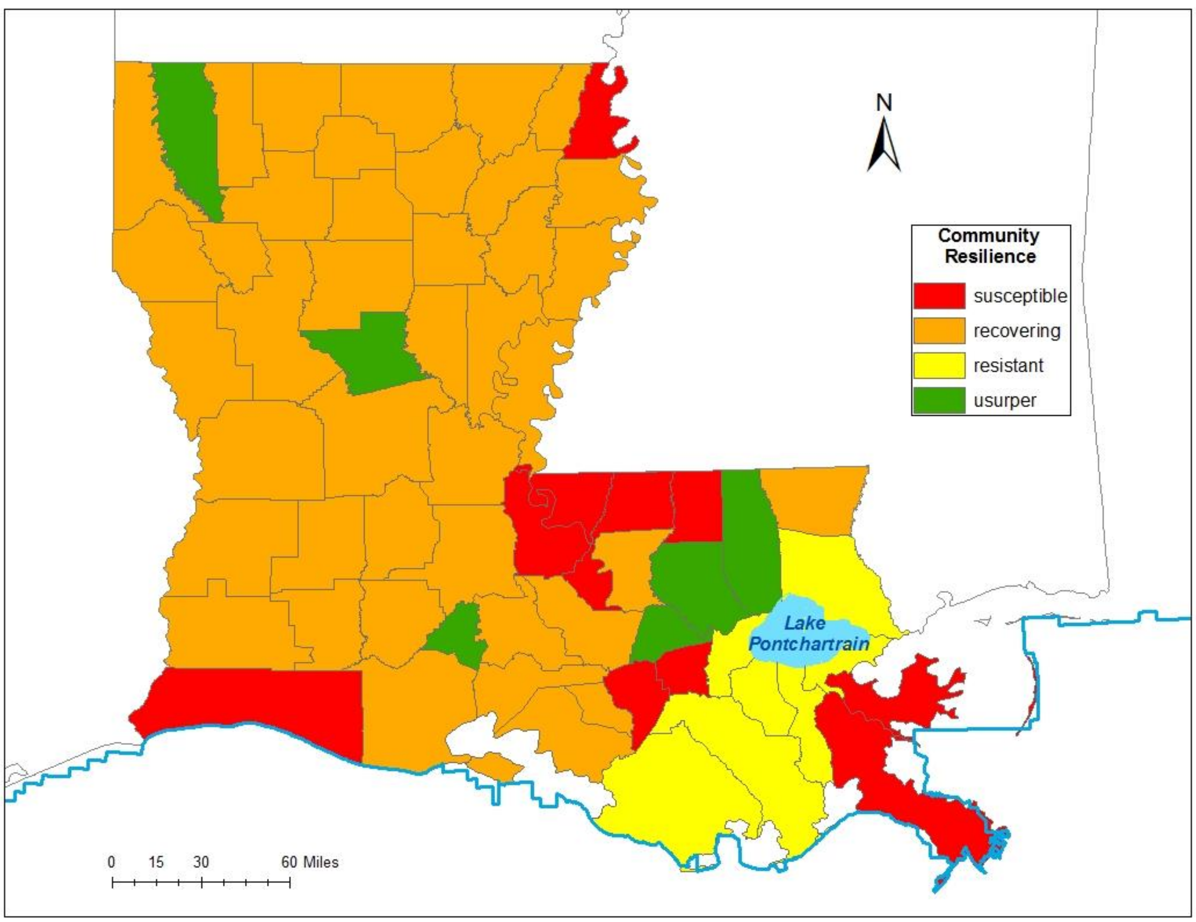

Figure 13: The Distribution of Community Resilience from Test 1

Test 2: Exposure, per capita damage and median income growth from 1999 to 2009

The same approach was used in Test 2 as Test 1. Five clusters were initially introduced for k-means analysis. The cluster with two outlier counties was combined with the cluster with the closest centroid to it. Figure 14 shows the final clusters from Test 2.

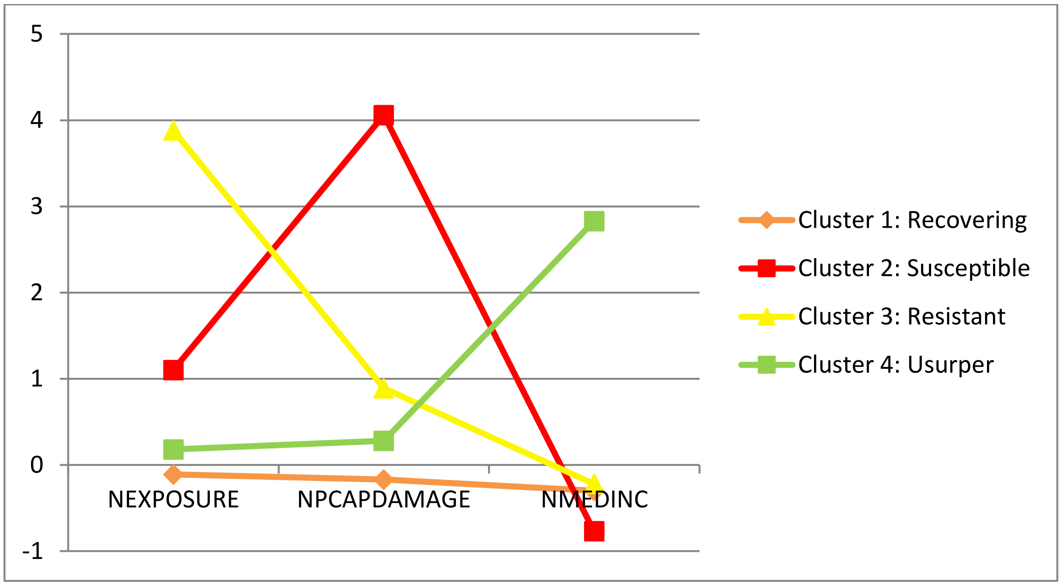

Figure 14: K-means Final Clusters Test 2

As was the case for the previous map in Test 1, the majority of the counties in Louisiana fell into the recovering category by using median income change as a recovery indicator (Figure 15). Visual inspection indicated that counties with susceptible rank did not change much from Test 1. Plaquemines and St. Bernard remained the most susceptible counties as in Test 1. These two counties had extremely high value of damage and low median income growth. The pattern of counties with high resilience changed a lot in this map. More counties appeared to be in the usurper category, including coastal counties such as Ascension, Cameron, Evangeline, Jefferson Davis, and St. Landry.

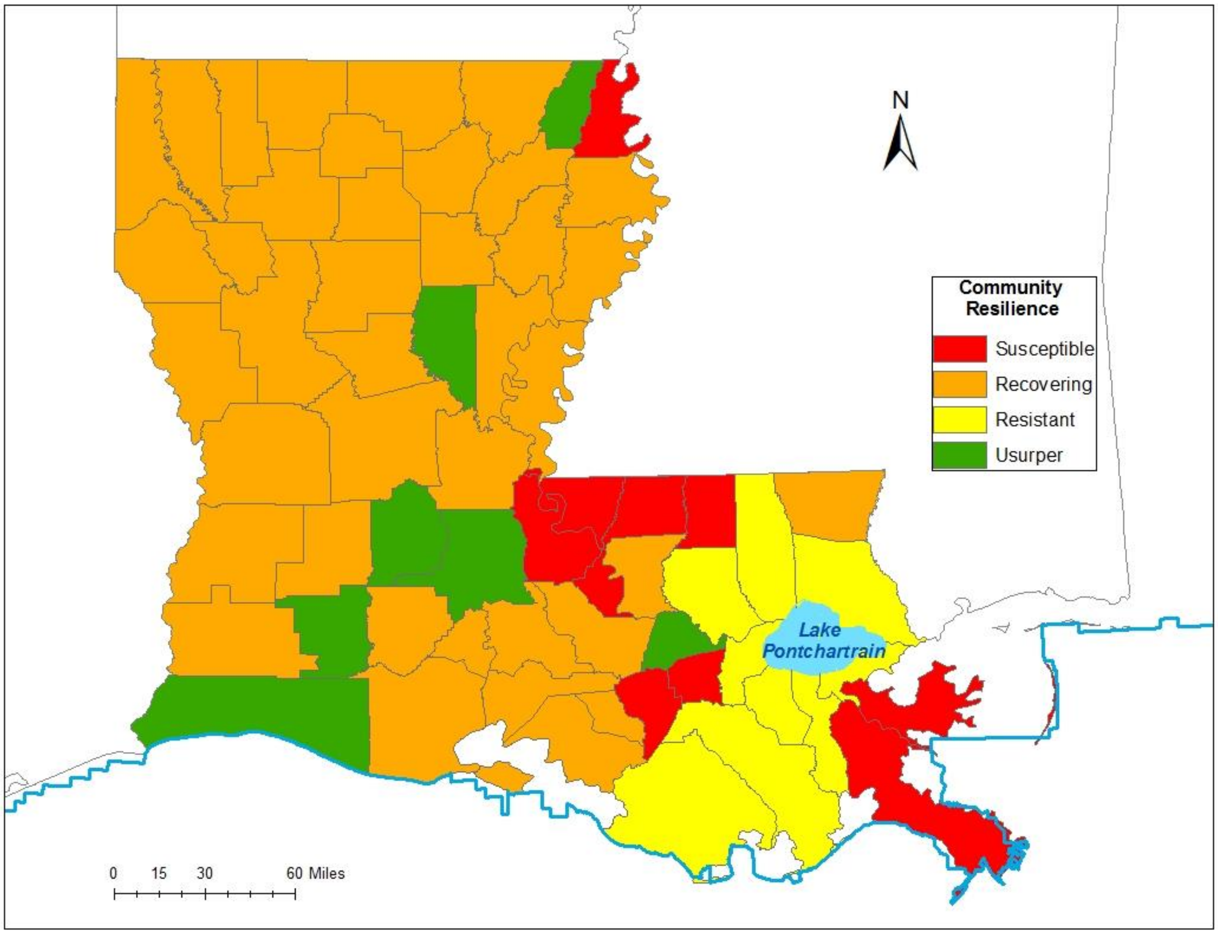

Figure 15: The Distribution of Community Resilience from Test 2

Test 3: Exposure, per capita damage and per capita income growth from 1999 to 2009

Similarly, five clusters were initially introduced for k-means analysis. The k-means clustering based on the rate of per capita income growth from 1999 to 2009 as a recovery indicator produced similar results to the result from Test 2. Figure 16 shows the final clusters. Figure 17 shows the distribution of the k-means clusters.

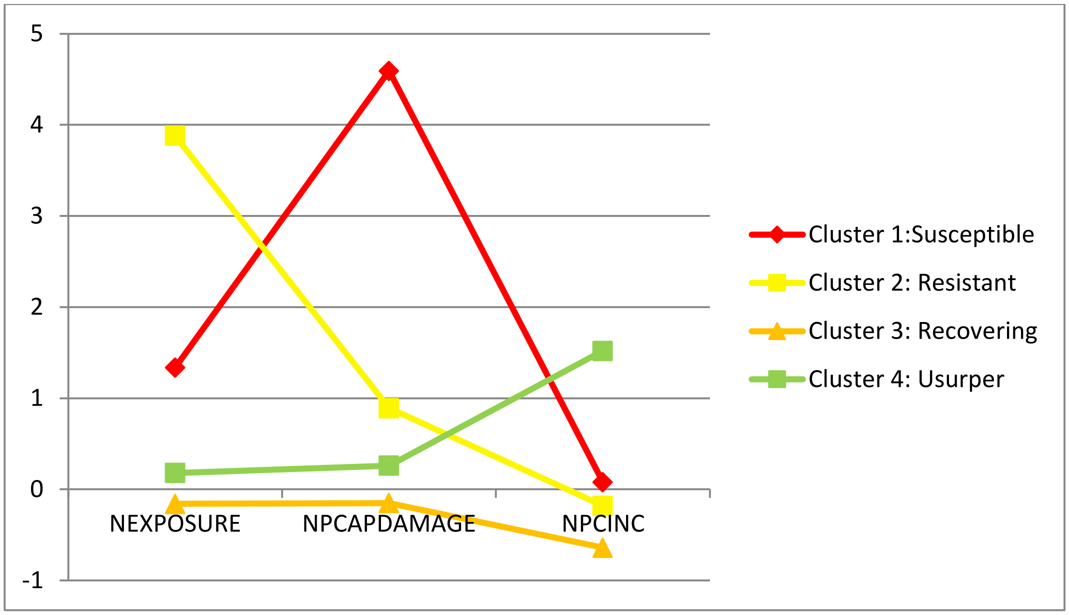

Figure 16: K-means Final Clusters Test 3

Compared to the first two tests, many more counties appeared to be usurper in this test (Figure 17). The usurper group included both inland counties and coastal counties. Compared with the k-means clustering in Test 2, which was also based on income growth, there were fewer susceptible counties in this test. St. Bernard and Plaquemines were still the two most susceptible counties. Compared with Test 2, the rank of resilience changed a lot in Assumption. It jumped from susceptible to usurper county.

Forty-one counties were found with consistent resilience rank, based on all three tests (Table 7). Appendix 2 lists more detailed information about the k-means groups for each test. Figure 18 shows the locations of the counties with the same resilience classification. It is apparent from this map that counties with the same classification of resilience tended to be geographically close to each other.

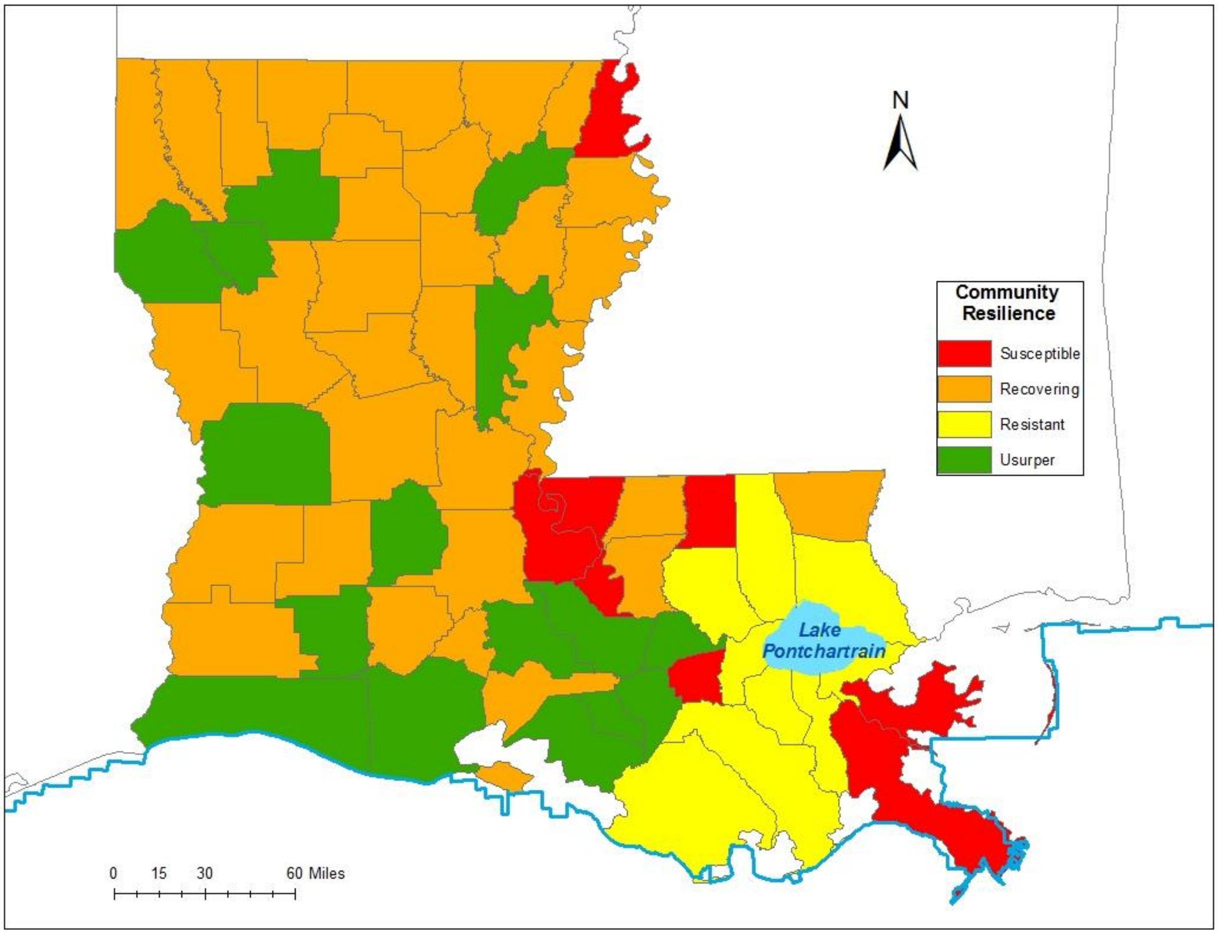

Figure 17: The Distribution of Community Resilience from Test 3

Table 7: Counties with the Same Resilience Based on All Tests

COUNTY	FIPS CODE	Test 1, 2, 3
Acadia	22001	recovering
Allen	22003	recovering
Ascension	22005	usurper
Avoyelles	22009	recovering
Beauregard	22011	recovering
Caddo	22017	recovering
Calcasieu	22019	recovering
Caldwell	22021	recovering

(Table 7 Continued)

COUNTY	FIPS CODE	Test 1, 2, 3
Claiborne	22027	recovering
Concordia	22029	recovering
East Baton Rouge	22033	recovering
East Carroll	22035	susceptible
Franklin	22041	recovering
Iberia	22045	recovering
Jackson	22049	recovering
Jefferson	22051	resistant
Lafourche	22057	resistant
Lincoln	22061	recovering
Madison	22065	recovering
Morehouse	22067	recovering
Natchitoches	22069	recovering
Orleans	22071	resistant
Ouachita	22073	recovering
Plaquemines	22075	susceptible
Pointe Coupee	22077	susceptible
Rapides	22079	recovering
Sabine	22085	recovering
St. Bernard	22087	susceptible
St. Charles	22089	resistant
St. Helena	22091	susceptible
St. James	22093	susceptible
St. John the Baptist	22095	resistant
St. Tammany	22103	resistant
Tensas	22107	recovering
Terrebonne	22109	resistant
Union	22111	recovering
Washington	22117	recovering
Webster	22119	recovering
West Baton Rouge	22121	susceptible
West Feliciana	22125	susceptible
Winn	22127	recovering

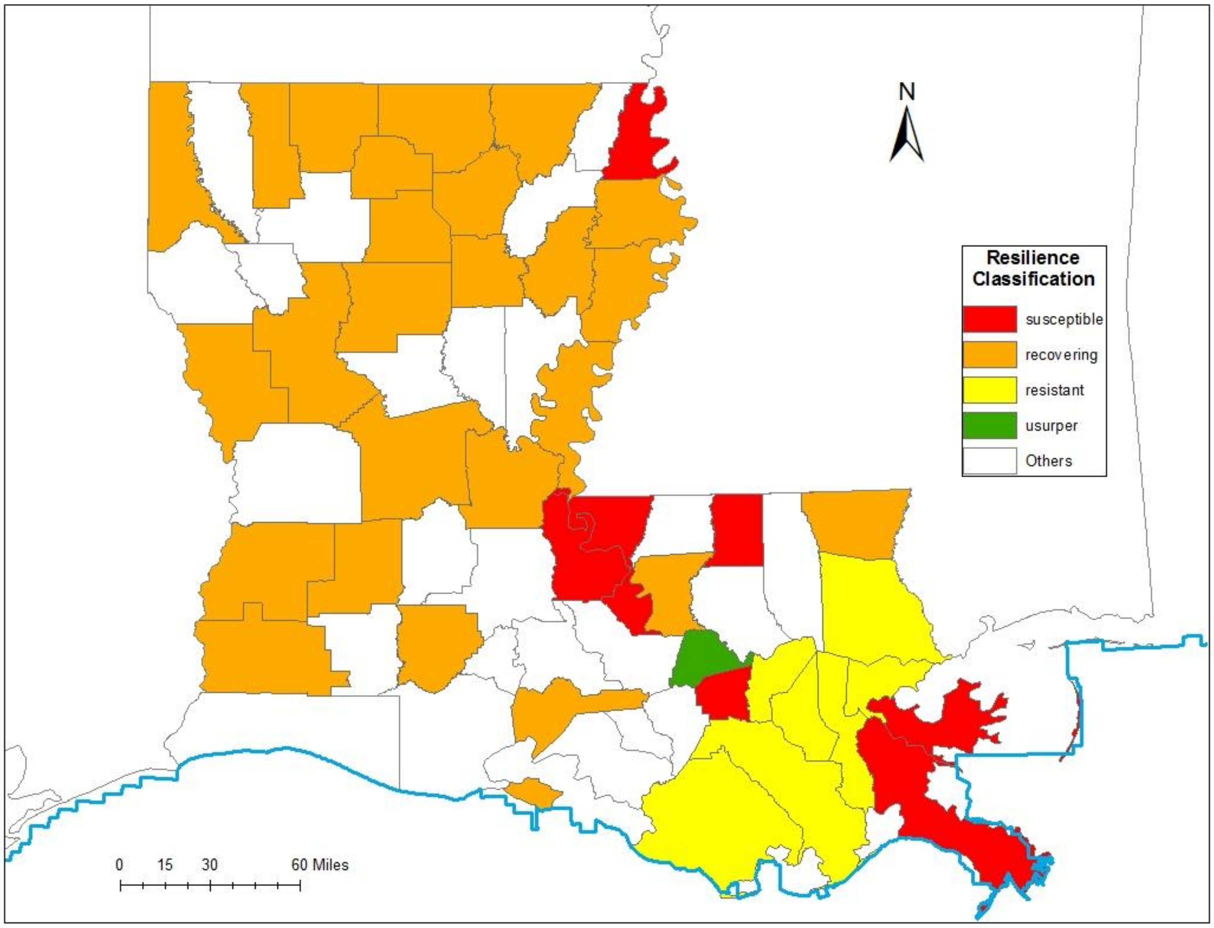

Figure 18: Counties with the Same Resilience Based on All Tests

5.1.2 Results from Discriminant Analysis

As mentioned in Chapter 4, there were two goals of applying discriminant analysis in this study: 1) to test if the group memberships derived by the k-means tests can be accurately predicted by using 28 indicator variables, and 2) to understand the relationship between group memberships and the indicator variables.

To achieve the first goal, the classification accuracies were assessed (Table 8). Test 1 came out with a remarkably high classification accuracy of 93.8%. In other words, only 4 out of the 64 counties were misclassified. The misclassified counties were: Iberville, Lafourche, Red River ,

and St. Martin. Iberville, Red River and St. Martin were classified by k-means as recovering, but were found to have a distance closer to the centroid of susceptible group, hence they were downgraded from recovering to susceptible; Lafourche was downgraded from resistant to recovering. Tests 2 and 3 also had pretty good accuracy results, which were 92.2% and 89.1%, respectively. A comparison of Test 2 and Test 3, which were both based on income growth, showed that Test 2 had a higher accuracy. This result implies that median income was a better recovery indicator than per capita income for this model. Compared with median income, per capita income is more affected by outliers. For example, a small percentage of wealthy people can increase per capita income a lot, but not median income. That is why Test 3 included more usurper counties than Test 2 (Figures 15 and 17).

Table 8: Discriminant Analysis Accuracy Result

Test Number	**Accuracy**
1	93.8%
2	92.2%
3	89.1%

Among the 64 parishes, 4 parishes of them were misclassified in Test 1 (Table 9), 5 parishes of them were misclassified in Test 2 (Table 10), and 7 parishes were misclassified in Test 3 (Table 11). Figures 19, 20 and 21 show the locations of the misclassified parishes in each of the three tests.

Table 9: Misclassified Parishes, Test 1

Parish	Fips Code	Test 1 Cluster	Discriminant Analysis Cluster
Iberville	22047	recovering	susceptible
Lafourche	22057	resistant	recovering
Red River	22081	recovering	susceptible
St. Martin	22099	recovering	susceptible

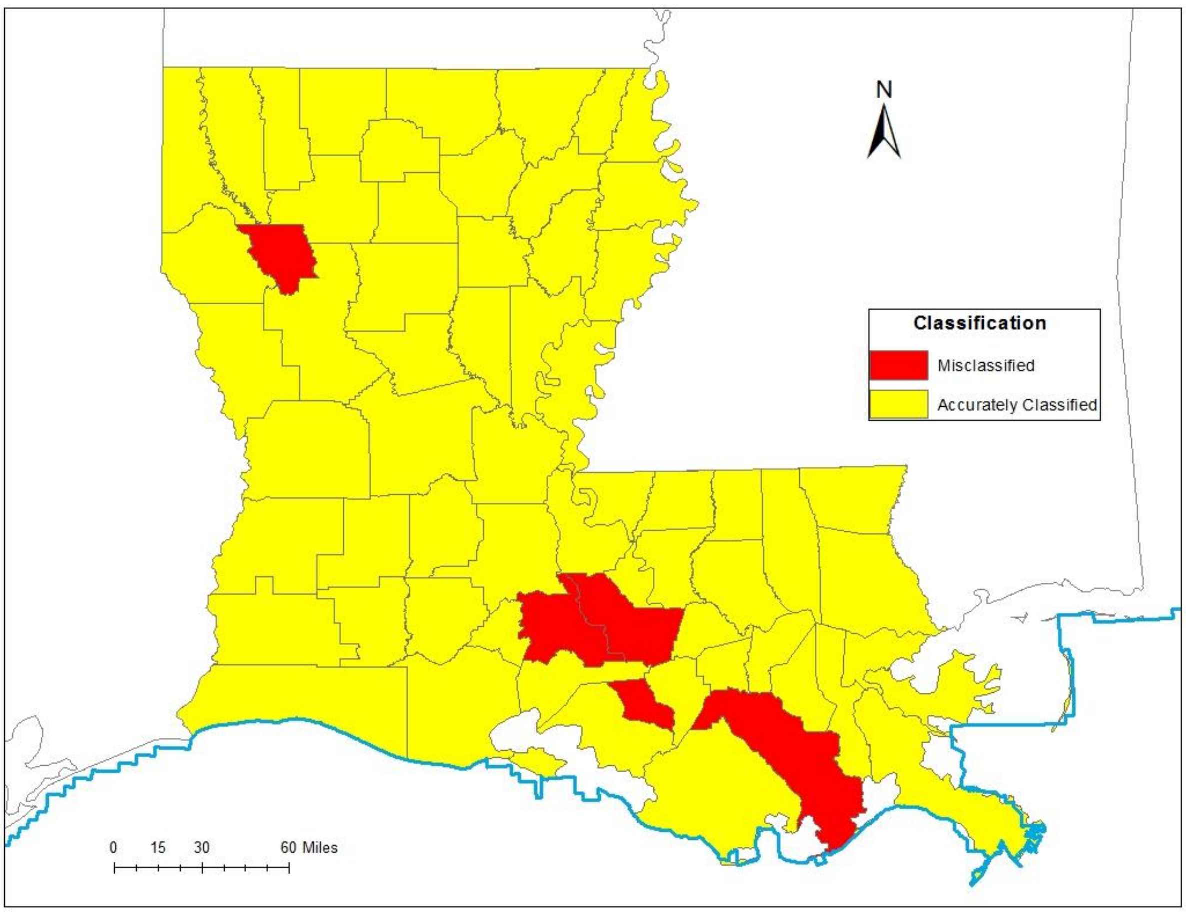

Figure 19: Misclassified Parishes, Test 1

Table 10: Misclassified Parishes, Test 2

Parish	Fips Code	Test 2 Cluster	Discriminant Analysis Cluster
Avoyelles	22009	Recovering	Usurper
Iberia	22045	Recovering	Susceptible
Iberville	22047	Recovering	Susceptible
St. Landry	22097	Usurper	Recovering
St. Martin	22099	Recovering	Susceptible

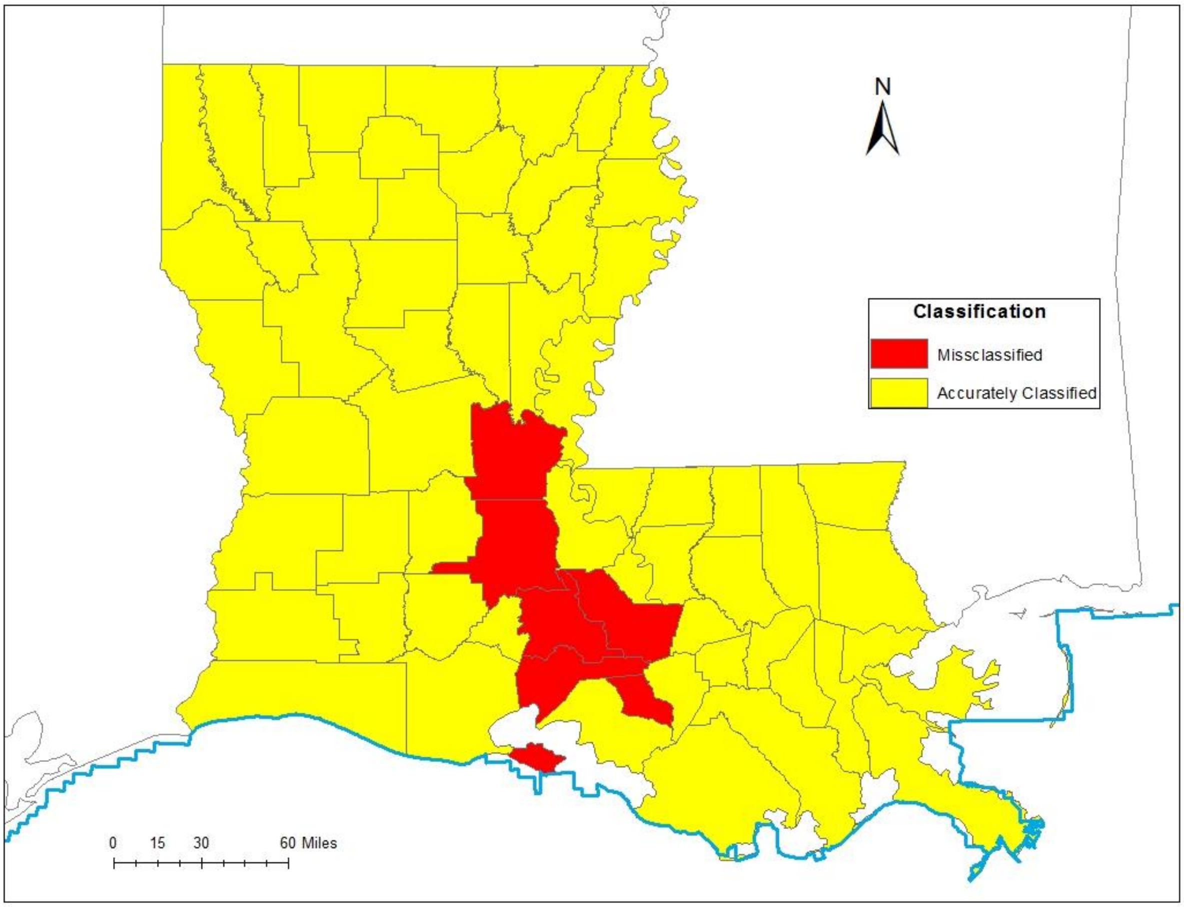

Figure 20: Misclassified Parishes, Test 2

Table 11: Misclassified Parishes, Test 3

Parish	Fips Code	Test 3 Cluster	Discriminant Analysis Cluster
Acadia	22001	Recovering	Usurper
Allen	22003	Recovering	Usurper
Bienville	22013	Usurper	Recovering
Iberia	22045	Recovering	Usurper
Jefferson Davis	22053	Usurper	Recovering
Sabine	22085	Recovering	Usurper
Vermilion	22113	Usurper	Recovering

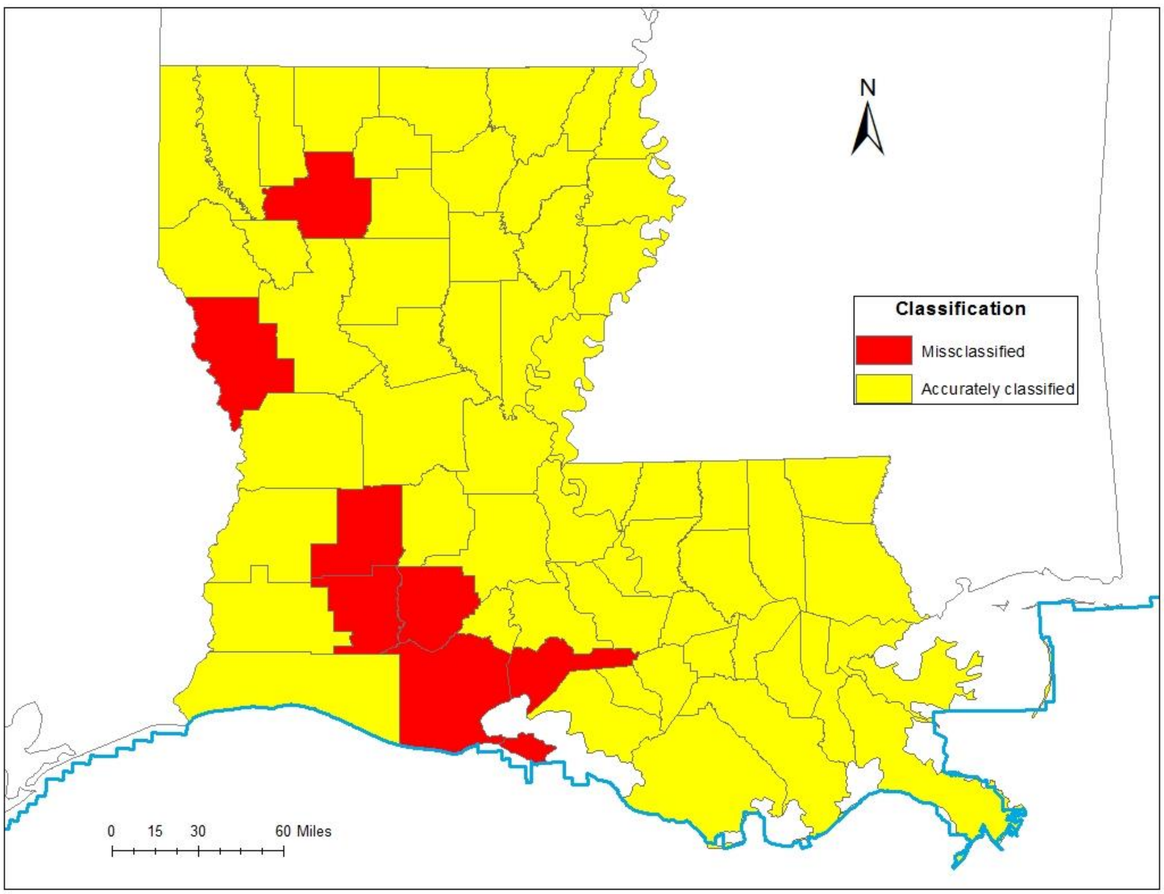

Figure 21: Misclassified Parishes, Test 3

Given the accuracy of the three tests, the next step was to explore the relationship between group memberships and the 28 variable indictors. To evaluate the power of the indicators, the potency index of each variable was calculated (Perreault et al. 1979 cited in Lam et al. 2013). The potency index of a discriminating variable is a composite, relative measure of the variable's total discriminating power across all significant discriminant functions (Lam et al. 2013). It is computed from equation (5):

$$Potency_i = \sum_{j=1}^{n} l_{ij}{}^2 * \frac{e_j}{Sum\ of\ all\ e_j} \tag{5}$$

where, $Potency_i$ is the potency index of variable i, n is the number of significant discriminant functions, l_{ij} is the discriminant loading of variable i on function j, and e_j is the eigenvalue of function j.

Tables 12, 14 and 16 show the three discriminant functions that were derived in the three tests. Two functions were found to be statistically significant in all tests (Tables 13, 15 and 17). Because the potency index is often applied when there are more than two significant discriminant functions, the potency index was therefore computed for all of the tests (Appendix 3, 4 and 5).

Table 12: Variance Explained by Discriminant Functions in Test 1

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	3.711[a]	53.0	53.0	.888
2	2.318[a]	33.1	86.1	.836
3	.971[a]	13.9	100.0	.702

Table 13: Two Significant Functions in Test 1

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1 through 3	**.032**	**161.110**	**84**	**.000**
2 through 3	**.153**	**88.266**	**54**	**.002**
3	.507	31.899	26	.196

Table 14: Variance Explained by Discriminant Functions in Test 2

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	3.099[a]	54.4	54.4	.869
2	1.705[a]	29.9	84.3	.794
3	.896[a]	15.7	100.0	.688

Table 15: Two Significant Functions in Test 2

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1 through 3	**.048**	**143.156**	**84**	**.000**
2 through 3	**.195**	**76.854**	**54**	**.022**
3	.527	30.077	26	.264

Table 16: Variance Explained by Discriminant Functions in Test 3

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	3.216[a]	56.7	56.7	.873
2	1.419[a]	25.0	81.7	.766
3	1.041[a]	18.3	100.0	.714

Table 17: Two Significant Functions in Test 3

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1 through 3	**.048**	**142.681**	**84**	**.000**
2 through 3	**.203**	**75.052**	**54**	**.031**
3	.490	33.537	26	.147

For Test 1, the two significant functions explained 53% and 33.1% of the total variance, respectively (Table 12). The mean values of the top 9 variables with the highest potency index are listed in Table 18. The statistics show that counties with higher resilience appear to be wealthier urbanized counties with higher median rent, higher median value of owner-occupied housing units, lower percentage of elderly persons, higher levels of education, lower chronic illness deaths rate, and lower percentage of rural farm population. The resistant group included some extreme values of many variables. It had extremely low percentage of rural farm population, but extremely high housing density. It also had the highest median rent, highest median value of owner-occupied housing units, lowest chronic illness deaths rate and lowest poverty rate. These characteristics are reasonable because the resistant group included wealthier urban counties around New Orleans. Although these counties are located in the low elevation areas, the social and economic resources helped these counties resist the harm from coastal

hazards. In general, the four resilience groups were well differentiated by the 9 indicator variables. The indicator “average persons per household” did not seem to be different among the four groups. It is apparent that the susceptible and recovering counties were the counties with lower socioeconomic status. In contrast, the resistant and usurper counties had higher socioeconomic status.

Table 18: Mean Values of the Top 9 Indicators in Test 1

Test1	**Susceptible**	**Recovering**	**Resistant**	**Usurper**
MEDRENT	256.4	246.7	406.5	349.0
MVALOO	76507.1	61418.4	97450	88650
PCTOLD	11.3	13.6	10.1	9.9
CHRILLD	20.7	24.3	17.4	17.6
AVGPERHH	2.8	2.6	2.8	2.7
PCTNOHS	33.5	31.5	23.0	22.6
HOUDEN	21.5	34.7	**342.8**	93.1
PCTFRMPOP	1.5	1.8	**0.1**	0.8
PCTPOV	20.8	22.5	16.2	16.2

For Test 2, the two significant functions explained 54.4% and 22.9% of the total variance, respectively (Table 14). Table 19 is tabulated with the top 9 variables with the highest potency index in the test. Six variables were also among the nine important variables in Test 1. In general, the counties with higher resilience are more likely to be wealthier counties with a significantly higher median value of owner-occupied housing units, lower percentage of African Americans, and lower infant mortality rates. The resistant group also included some extreme values of variables. It had extremely high housing density, and low median elevation. It had the highest median value of owner-occupied housing units, highest median rent, lowest percentage of old population, and lowest percentage of African Americans. In general, it appeared that the

less resilient counties were counties with lower socioeconomic status, higher African American population, and higher infant mortality rates. The more resilient counties had lower African American population, lower infant mortality rates, and higher socioeconomic status.

Table 19: Mean Values of the Top 9 Indicators in Test 2

Test2	Susceptible	Recovering	Resistant	Usurper
MVALOO	77583.3	62997.1	93900.0	61871.4
AVGPERHH	2.8	2.6	2.7	2.7
MEDRENT	259.2	256.9	383.3	241.7
PCTOLD	11.4	13.4	10.1	12.6
CHRILLD	21.0	23.9	17.2	23.5
MELEV	14.2	38.8	**6.0**	15.7
HOUDEN	27.0	43.2	**244.1**	27.0
PCTBLCK	38.7	32.1	25.9	18.7
INFMTR	879.2	1044.9	803.3	784.3

Similarly, the mean values of the top 9 important variables in the four resilience groups in Test 3 are listed in Table 20. In this test, the two significant functions explained 56.7% and 25.0% of the total variance, respectively (Table 16). Six of these variables were also among the nine important variables in Test 1 (Table 18); seven were among the nine important variables in Test 2 (Table 19). As was the case in the results from Test1 and Test 2, the resistant group stood out. The resistant group included some extreme values in this test also. The resistant counties had significantly higher numbers of medical doctors, extremely high housing density, but extremely low median elevation. Counties in the resistant group also had the highest median values of owner-occupied housing units, highest median rent, lowest percentage of chronic illness deaths rate, and lowest percentage of elderly persons. However, there are major differences between Test 1, Test 2 and Test 3 in terms of the indicators picked. For example, the usurper group had

lower median value of owner-occupied housing units, lower median rent, lower housing density, and higher chronic illness rates in both Test 2 and Test 3. Since Test 1 yielded the highest accuracy, we can consider population growth, which was used as the recovery variable in Test 1, as the most reliable for resilience measurement.

Table 20: Mean Values of the Top 9 Indicators in Test 3

Test 3	**Susceptible**	**Recovering**	**Resistant**	**Usurper**
MVALOO	82387.5	63390.3	93900.0	65693.3
MEDRENT	264.8	260	383.3	237.7
AVGPERHH	2.8	2.6	2.7	2.7
CHRILLD	20.6	24.8	17.2	21.4
PCTOLD	11.3	13.5	10.1	12.3
MD	5.6	12.1	**20.7**	6.9
HOUDEN	24.3	46.3	**244.1**	26.2
LGFINREVPC	3321.5	2506.0	3222.4	2652.9
MELEV	17.8	37.4	**6.0**	20.3

To further understand the association between the indicator variables and the four resilience groups, variables with higher potency indices in all three tests were plotted (Figures 22, 24 and 26). The counties in each resilience group were also plotted onto the first two functions to aid interpretation (Figures 23, 25 and 27).

By comparing the two plots for Test 1 (Figures 22 and 23), some relationships between resilience groups and the discriminant indictors were observed. Group 1, the lowest resilience group (susceptible), was positively associated with the average number of persons per household. Table 18 also shows susceptible group had the highest number of average persons per household . The implication is that a county with higher average number of persons per household tends to be less resilient than a county with lower average number of persons per household. The high

number of population in the household could be an obstacle for evacuating. Group 2, the second lowest resilience group (recovering), was positively associated with the percentage of old population, chronic illnesses rate, percentage of population with no high school degrees, percentage of rural farm population, and the percentage of poverty rate. The implication is that a poor rural county with a high percentage of elderly people, a high percentage of people with low levels of education, and a high percentage population with chronic illnesses tends to be less resilient to coastal hazards. Table 18 shows recovering group had the highest scores of the indicator variables except for the percentage of population with no high school degrees. Group 3 (usurper) and 4 (resistant) were the two highest resilience groups. They are positively related with the housing density, median rent, and median value of owner-occupied housing units. Again, the results were consistent with the results in Table 18 that these two groups had the highest scores of the three indicator variables.

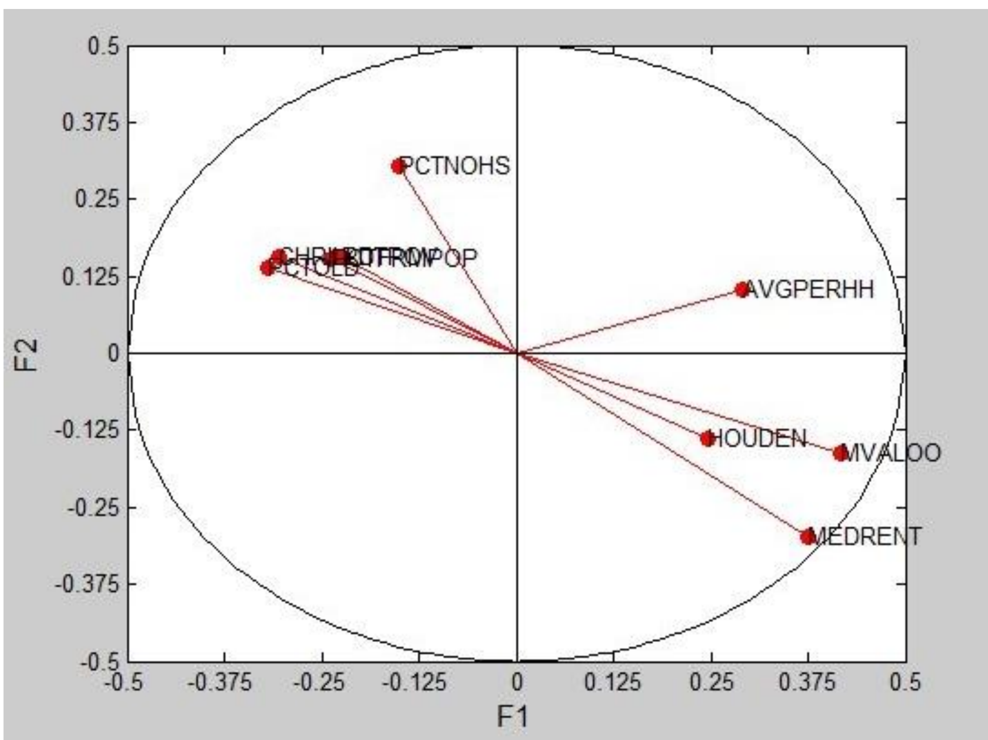

Figure 22: Discriminant Loadings on the First Two Functions, Test 1

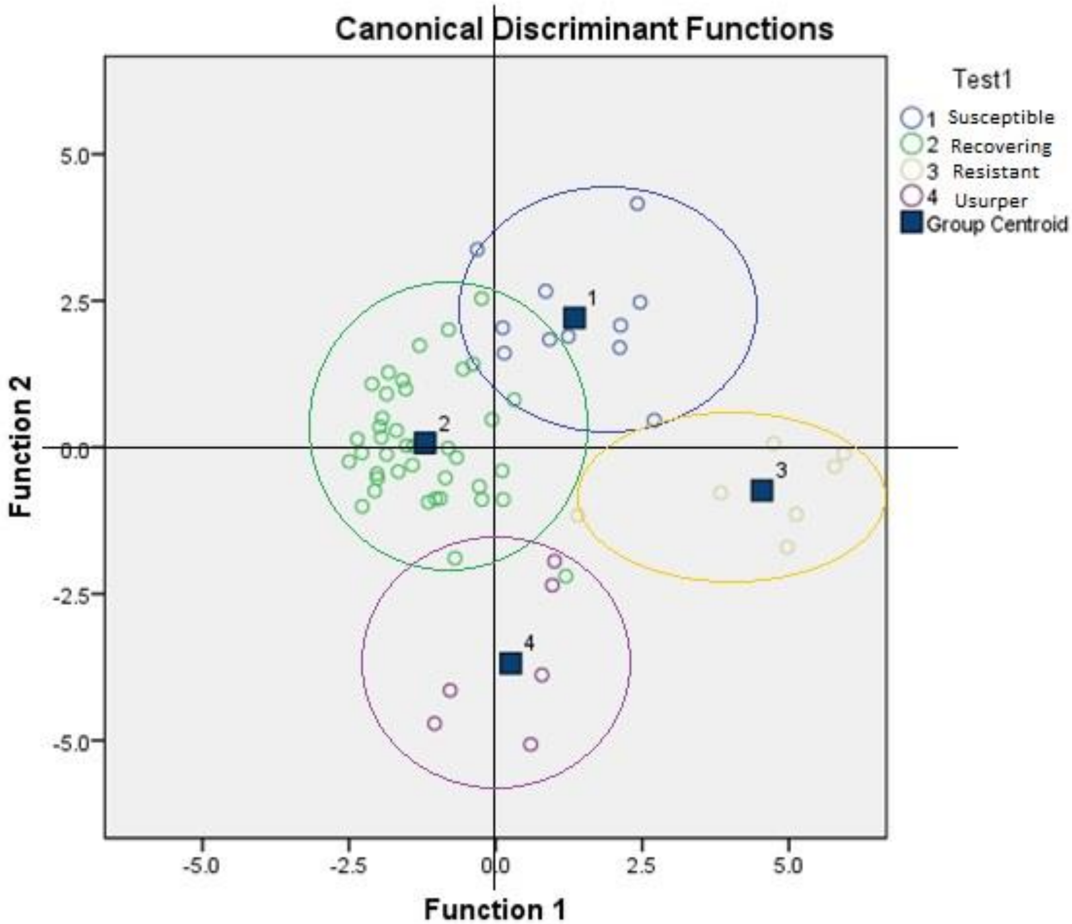

Figure 23: Plot of the Four Groups on the First Two Discriminant Functions, Test 1

Figures 24 and 25 likewise show some relationships between resilience groups and the discriminant indicators in Test 3. Figure 24 shows that group 1 counties appeared in all four quadrants. However, the majority of cases are located in quadrant 1. The recovering group was therefore considered to be positively related with the percentage of old population, median elevation, chronic illness death rate and infant mortality rate. Table 19 also shows that the recovering group had the highest percentage of old population, median elevation, chronic illness death rate and infant mortality rate. The implication is that the counties had higher percentage of elderly population, higher chronic death rate and infant mortality rate are less resilient to coastal hazards. Surprising, the high elevation didn't make these counties more resilient. Group 2, the

group with the least resilience (susceptible group) was positively related to the percentage of black population. Table 19 shows that the susceptible group had the highest percentage of black population. This result indicates that the counties with higher black population is less resilient to natural hazards. The resistant group was found to be positively associated with the average number of persons per household, housing density, median rent, and median value of owner-occupied housing units. Again, the result is consistent with statistics in Table 19. The result is also consistent with Test1. The implication is that wealthy urbanized counties are more able to resist coastal hazards.

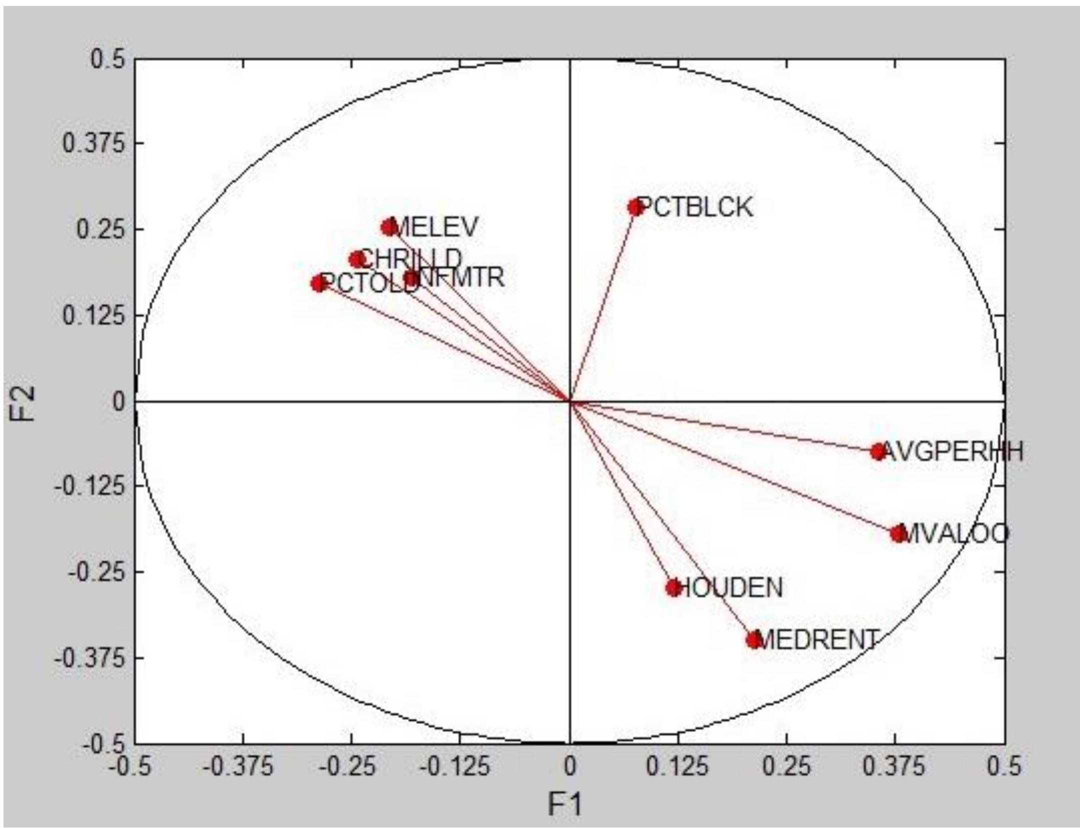

Figure 24: Discriminant Loadings on the First Two Functions, Test 2

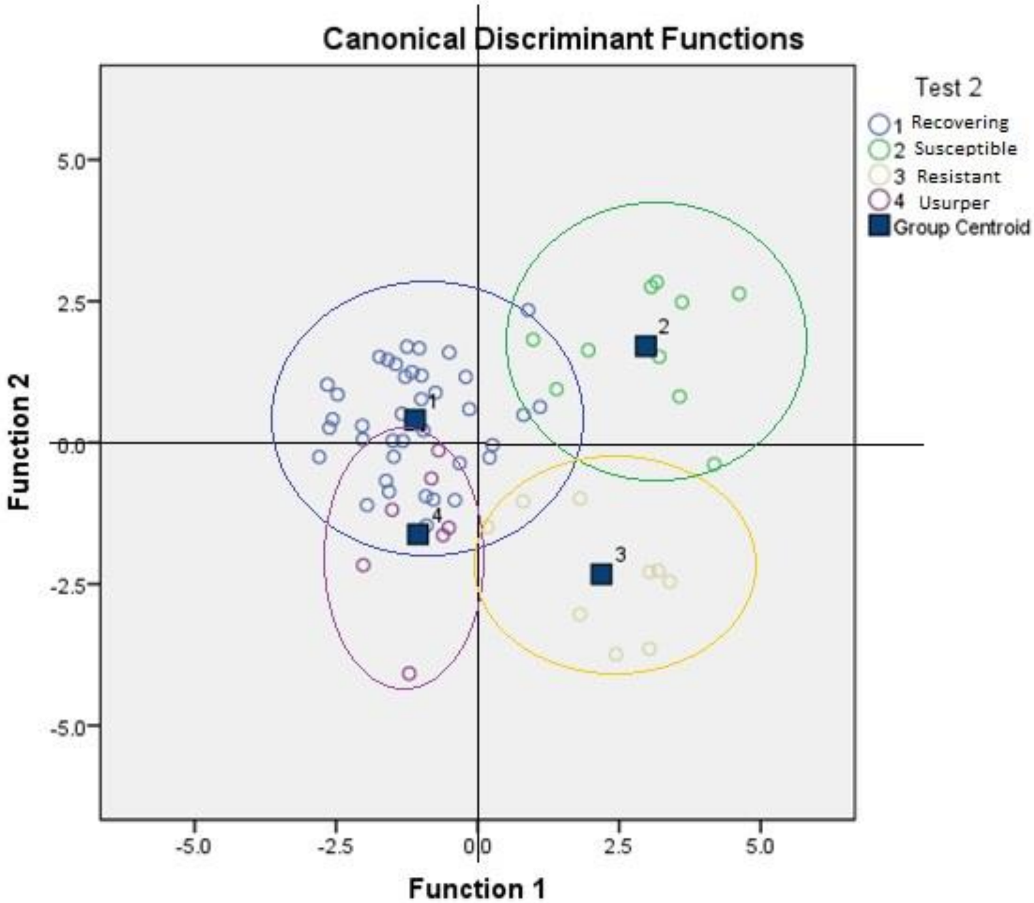

Figure 25: Plot of the Four Groups on the First Two Discriminant Functions, Test 2

Similarly, Figures 26 and 27 show some relationships between resilience groups and the discriminant indicators in Test 3. Figure 26 shows that the susceptible group was positively related to the average number of persons per household. The result is consistent with test 1.The implication is that the counties had higher number of population per household are less resilient to coastal hazards. Group 2 (the resistant group), was found to be positively related to housing density, median rent, and median value of owner-occupied housing units. In addition, it was positively associated with median number of doctors, and local government finance general expenditures per capita. Table 20 shows that the resistant counties had the highest housing density, median rent, median value of owner-occupied housing units, and median number of doctors. This result indicates that the counties the wealthier urbanized county has many

resources, and is more able to resist coastal hazards. As was the case in the results from test 2, the recovering group was positively related with median elevation, chronic illnesses rate, and percentage of old population. However, the highest resilient group was found positively associated with chronic illnesses rate, and percentage of old population. It may be due to the sensitivity of per capita income to outliers, some recovering counties were misclassified as usurper (Table 11). Since Test 1 yielded the highest accuracy, we can consider population growth, which was used as the recovery variable in Test 1, as the most reliable for resilience measurement.

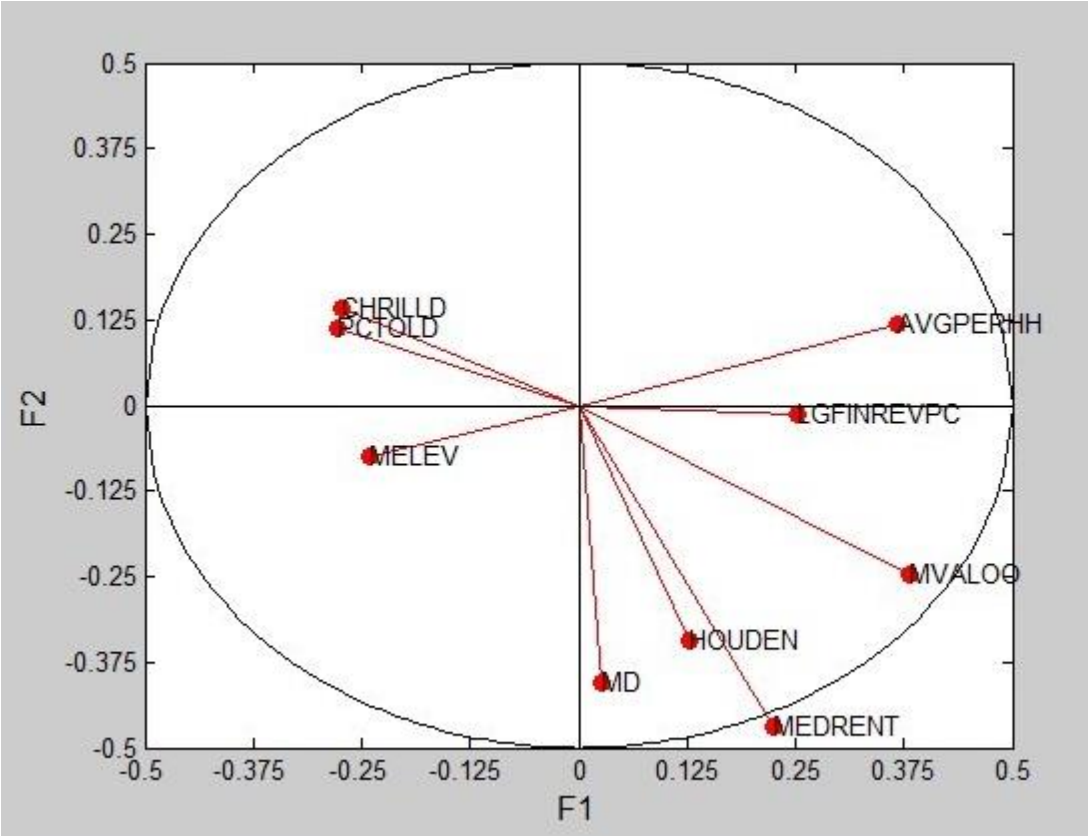

Figure 26: Discriminant Loadings on the First Two Functions, Test 3

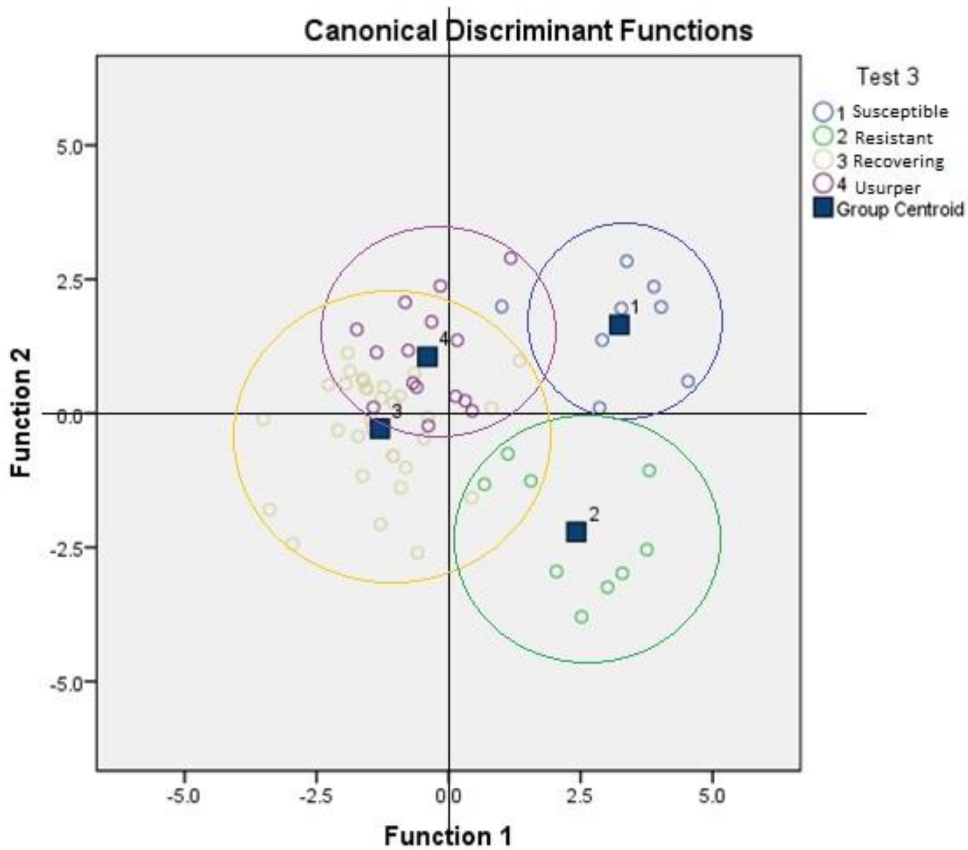

Figure 27: Plot of the Four Groups on the First Two Discriminant Functions, Test 3

5.2 Zip Code-Level Results

5.2.1 Results from K-means Analysis

Similar to the county level study, three separate k-means analysis were conducted at the zip code level study. The recovery indicators used were the same (population growth rate for Test1, median income growth rate for Test 2, and per capita growth rate for Test 3), but at the zip code level.

Figures 28, 30 and 32 are the final cluster graphs from the k-means analysis. Figures 29, 31 and 33 show how the resilience clusters were distributed at the zip code level for each test. The results were a bit different among the three tests. There was only one usurper zip code in Test 1,

which used population growth rate as an indicator. It's zip code 70729 in West Baton Rouge. More zip codes were classified as usurper in Test 2 and Test 3. In general, the three maps show very similar patterns as the maps for the county-level study. The majority of the state was considered to be recovering in each test, the implication is that no major changes have occurred, and these zip codes were not severely impacted by coastal hazards between2000 to 2010. Zip code areas in Plaquemines were grouped as susceptible in every test. Some zip codes in Cameron, Concordia, East Baton Rouge, Lafourche, St. Landry, and St. John Baptist were considered to be susceptible in all tests. Zip codes around the New Orleans area were considered to be resistant in every test, was again consistent with the results at the county level.

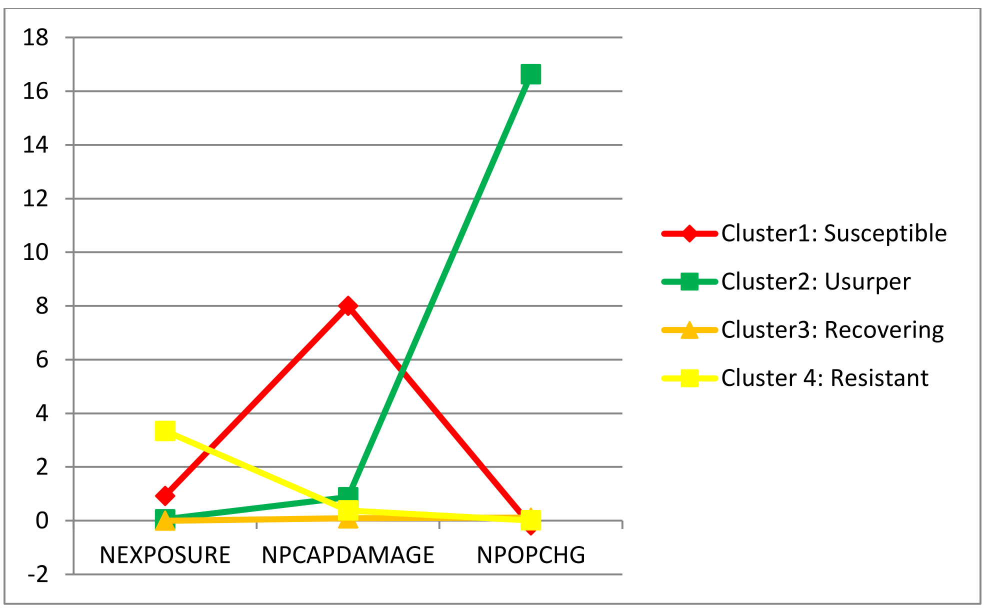

Figure 28: K-means Final Clusters for Zip Codes Test 1

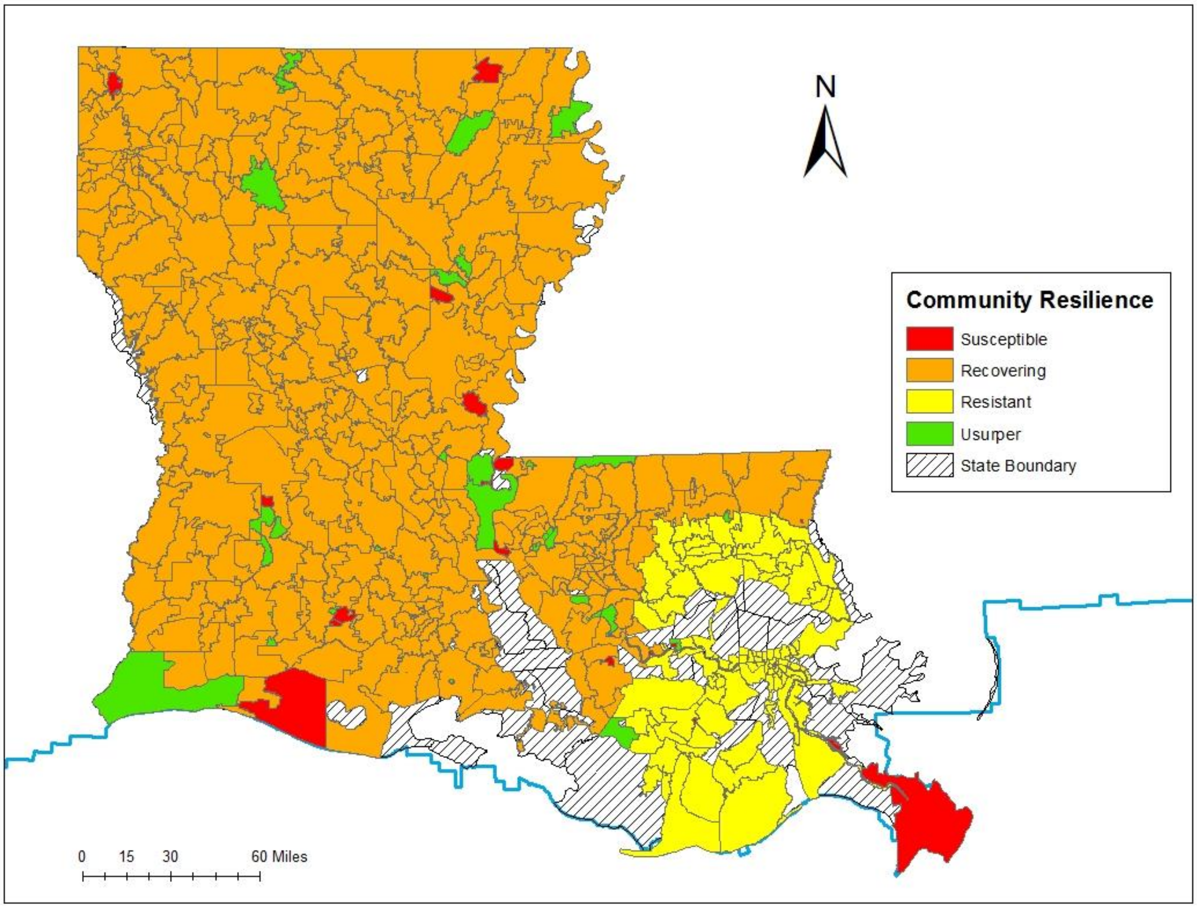

Figure 29: The Distribution of Community Resilience at the Zip Code Level from Test 1

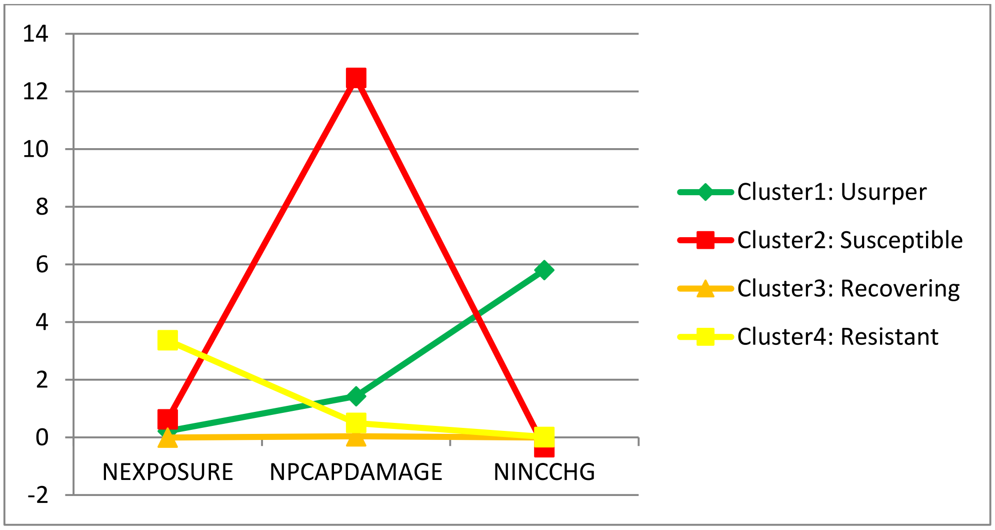

Figure 30: K-means Final Clusters for Zip Codes Test 2

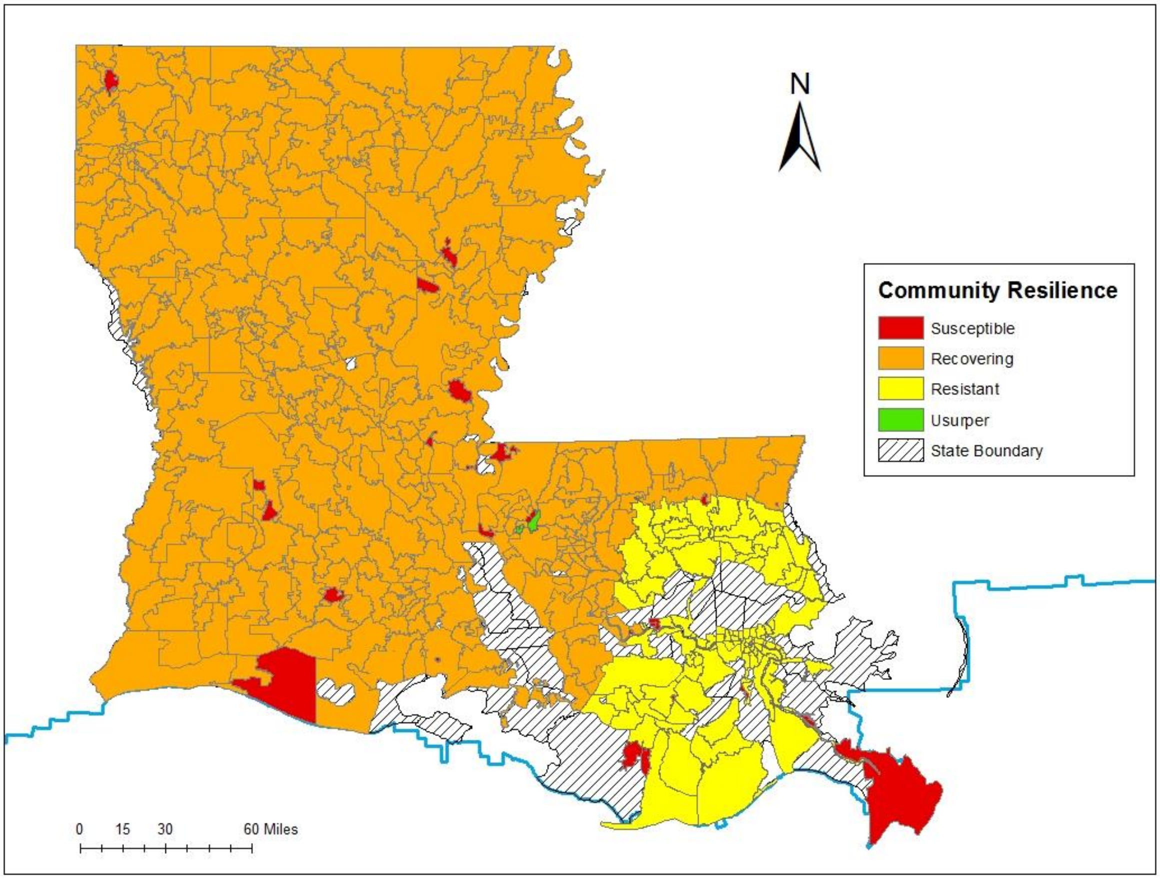

Figure 31: The Distribution of Community Resilience at the Zip Code Level from Test 2

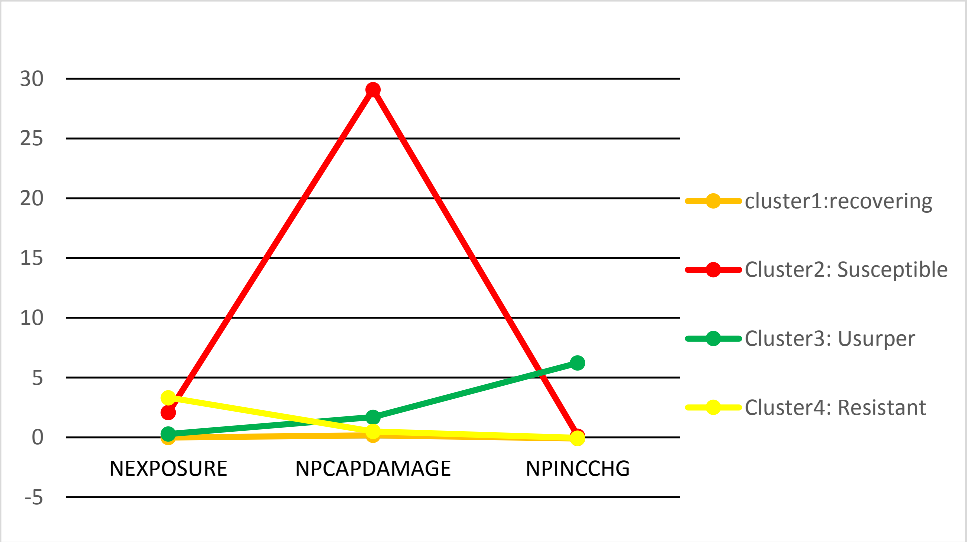

Figure 32: K-means Final Clusters for Zip Codes Test 3

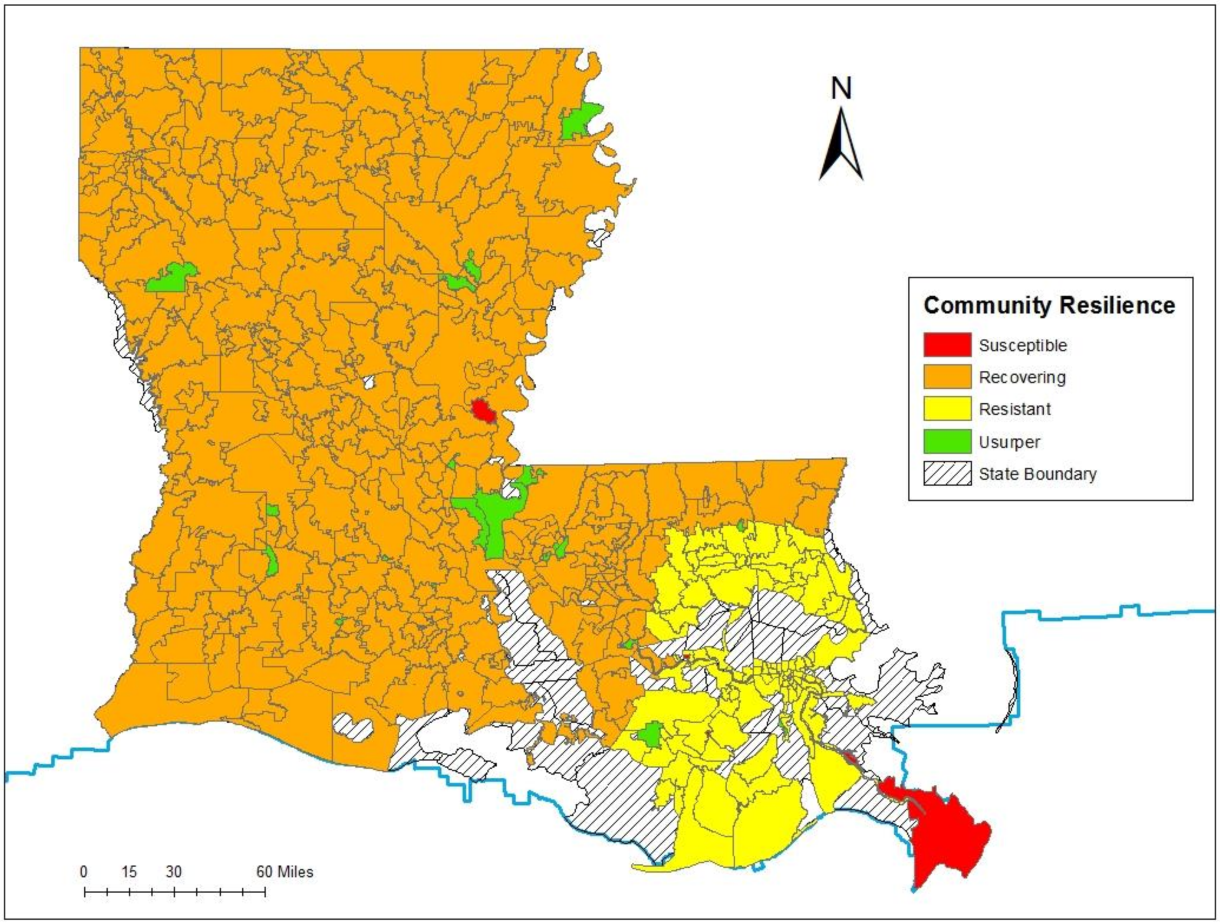

Figure 33: The Distribution of Community Resilience at the Zip Code Level from Test 3

5.2.2 Results from Discriminant Analysis

Compared with the classification accuracy at the county-level study, the accuracies of the zip code analyses were lower (Table 21). However, because of the lack of raw data of hazard exposure and hazard damage at the zip code level, the accuracies here were considered acceptable.

Table 21: Discriminant Analysis Accuracy Results for Zip Code-Level Study

Test Number	Accuracy
1	80.2%
2	74.6%
3	71%

Because Test 1 achieved the highest classification accuracy, the potency indices were calculated only for this test. However, since there was only one significant function, the mean values of the top 9 variables in function 1 were listed (Table 22).

Table 22: Mean Values of the Top 9 Indicators for the Zip Code-Level Study, Test 1

	susceptible	Usurper	recovering	resistant
HOUDEN	110.97	11.26	124.74	**849.71**
MELEV	19.52	5.32	31.21	**6.17**
MVALOO	67945.95	75500.00	67340.72	**93553.00**
MEDRENT	340.73	394.00	364.66	460.83
PCTHISPANIC	1.18	1.58	1.37	2.72
MANDEN	0.30	0.00	0.30	**1.41**
PCTMOBL	27.96	22.70	23.74	15.75
PCTFRMPOP	2.43	1.40	2.21	0.65

The statistics show that the zip codes with the highest resilience appeared to be zip codes with higher median value of owner-occupied housing units, higher median rent, higher

percentage of Hispanic population, and lower percentage of rural farm population. The resistant group also included some extreme values of a variety of variables in this test. It had extremely low median elevation, and low percentage of rural farm population, but extremely high housing density, high median value of owner-occupied housing units, and high manufacturing establishment density. In general, the four resilience groups can be differentiated by the nine indicator variables.

Chapter 6: Conclusions

This thesis research measured the community resilience to coastal hazards in Louisiana at both the county and zip code level from 2000 to 2010, using the Resilience Inference Measurement (RIM) model. There were 64 parishes and 501 zip code areas analyzed in this research.

The RIM model is composed of three dimensions and two abilities. The three dimensions are exposure, damage and recovery. The two abilities are vulnerability and adaptability. Conceptually, the RIM model connects the three important concepts in the resilience literature. Statistically, k-means analysis was used to derive the resilience groups based on the three dimensions, and discriminant analysis was able to validate the community resilience ranking based on a set of indicator variables. Twenty-eight variables were used for the county-level study, of those, 19 variables were available and used for the zip code-level study.

The purpose of studying resilience measurements at two geographic scales was to examine how geographical scale could affect the resilience measurements and the indicators. Four resilience clusters were derived from k-means analysis at both the county and zip code levels. The four groups were susceptible, recovering, resistant and usurper. In general, the study results at the two geographic levels were found to be consistent.

At the county level, a test of three different recovery variables (population growth rate, median income growth rate, and per capita income growth rate) was performed. The discriminant analysis using population growth rate as the recovery variable yielded the highest classification accuracy (93.8%), implying that population growth was the best indicator to represent the recovery dimension. The classification accuracies for the median growth and the per capita

growth rates were 92.2% and 89.1%, respectively. Hence, the results based on population growth as a recovery variable was used to summarize the findings discussed below.

At the county level, the majority of the state was considered as “recovering”, which means the majority of the state was not highly exposed to coastal hazards from 2000 to 2010. St. Bernard and Plaquemines were found to be the two most susceptible counties. Other counties around the New Orleans area with extremely low elevations were found to have higher resilience, including Jefferson, Lafourche, Orleans, St. Charles, St. John the Baptist, St. Tammany, and Terrebonne. The top two indicators were found to be median rent, and median value of owner-occupied housing units. In other words, susceptible counties were characterized by low median rent, and low median value of owner-occupied housing units, whereas resistant and usurper counties had high median rent and high median value of owner-occupied housing units. Discriminant analysis using population growth rate as the recovery variable at the county level yielded the highest classification accuracy, implying that population growth was a good indicator to represent the recovery dimension. Compared to per capita income growth rate, median income growth rate was a better indicator to represent the recovery. The result was not surprising because median income is a more robust variable than per capita income, as the calculation method makes it less sensitive to outliers.

Compared to the county level study, the discriminant analysis yielded lower classification accuracy in all tests at the zip code level study. The first test using population growth rate came out with percent 80.2% discriminant classification accuracy, which was acceptable. The map also showed a similar pattern as the map for the county-level study, using population growth as a recovery indicator. Zip codes around Plaquemine County were grouped as susceptible, and zip codes around the New Orleans area were considered to be resistant. Similar to the county-level

results, the top two indicators were found to be median rent and median value of owner-occupied. The more resilient zip code areas were found to be areas with high median rent and median value of owner-occupied housing unit, and the less resilient zip code areas were found to be areas with low median rent and median value of owner-occupied housing units.

There are some limitations and difficulties of using zip codes as a study area. First and formost was the data availability issue. There were no natural hazard data available at the zip code level. The hazard exposure and damage were therefore derived from interpolations, which made the data less reliable. There were also no governmental variables available and fewer health-related variables at the zip code level. Second, there were some zip codes that existed in 2000 but not in 2010, and vice versa. This fact created some difficulties in calculating population changes as well as income changes. Third, the U.S Census started to use ZCTAs as an alternative to zip codes after 2000. ZCTAs boundaries of Louisiana changed a lot during the 10 years. In some cases the changes could be quite big, for example, the land area of zip code 70036 increased from 4.38 square miles to 46.8 square miles from 2000 to 2010. In most cases the boundary changes were small and acceptable to work with.

In summary, this thesis research examined the community resiliency to coastal hazards that occurred in 2000-2010 in Louisiana at the county and zip-code level. This is the first that the RIM model has been applied at the zip code level within a large region. The more resilient counties/zip codes were found to be associated with higher socioeconomic status, including higher housing density, higher median rent, higher owner-occupied housing value, lower percentage of old population, lower average number of persons per household, and lower chronic illnesses rate, whereas the less resilient counties/zip codes were found to be the less

wealthy counties with lower housing density, but higher average number of persons per household, higher percentage of old population, and higher chronic illnesses rate.

Bibliography

Adger, W.N. 1997. Sustainability and Social Resilience in Coastal Resource Use. *CSERGE Working Paper Series*, Centre for Social and Economic Research on the Global Environment, University of East Anglia, Norwich and University College London, UK.

Adger, W.N. 2000. Social and Ecological Resilience: Are They Related? *Progress in Human Geography* 24 (3), 347–364.

Adger W.N., Hughes T.P., Folke C., Carpenter S.R., Rockstrom J. 2005. Social-ecological Resilience to Coastal Disasters. *Science* 309: 1036-1039

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.

Brooks N. 2003. Vulnerability, Risk and Adaptation: A Conceptual Framework. Working Paper38. Tyndall Centre for Climate Change Research. Norwich: University of East Anglia.

Chan T.C., Chen M.L., Lin I.F. et al., 2009. Spatiotemporal Analysis of Air Pollution and Asthma Patient Visits in Taipei, Taiwan. *International Journal of Health Geographics* 8:26.

Crowell M., Edelman S., Coulton K., and McAfee S. 2007. How Many People Live in Coastal Areas? *Journal of Coastal Research* 23(5):3-6.

Cutter, S. L., Barnes L., Berry M. et al. 2008. *Community and Regional Resilience: Perspectives from Hazards, Disasters, and Emergency Management.* CARRI Research Report 1. Oak Ridge National Lab: Community and Regional Resilience Initiative.

Cutter, S. L., and Finch C. 2008. Temporal and Spatial Changes in Social Vulnerability to Natural Hazards. *Proceedings US 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.

Erdogan S.Z. and Timor M. 2005 .A Data Mining Application in a Student Database. *Journal of Aeronautics and Space Technologies* 2 (2): 53-57.

Folke, C., Carpenter, S., Elmqvist, T., et al. 2002. Resilience and Sustainable Development: Building Adaptive Capacity in a World of Transformations. *Environmental Advisory Council to the Swedish Government*, Stockholm, Sweden.

Garson G.D. 2004. *Discriminant Function Analysis*. Retrieved from: http://www2.chass.ncsu.edu/garson/pa765/discrim.htm

Ghosh J. and Liu A. 2009. *The Top-ten Algorithms in Data Mining*. pp. 21-36 X. Wu and V. Kumar (Eds).

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

Holling, C. S. 1996. *Engineering Resilience versus Ecological Resilience*. Pages 31–44 in P. Schulze, editor. Engineering within ecological constraints. National Academy, Washington, D. C., USA.

HVRI. 2010. Social Vulnerability to Environmental Hazards State of Louisiana. Retrieved from: http://webra.cas.sc.edu/hvri/products/sovi2010_img/PDF/Louisiana_0610.pdf

Klein R., Nicholls R., and Thomalla F. 2003. Resilience to Natural Hazards: How useful is this Concept? *Environmental Hazards* 5, 35–45.

Knabb, R.D., Rhome J. R., Brown, D.P. 2006. Tropical Cyclone Report: Hurricane Katrina. National Hurricane Center. Retrieved from http://www.nhc.noaa.gov/pdf/TCR-AL122005_Katrina.pdf.

Lam N.S.1983. Spatial Interpolation Methods: A Review. *The American Cartographer* 10 (2): 129-149.

Lam N.S. 2009. Spatial Interpolation. In Kitchin R, Thrift N(eds) *International Encyclopedia of Human Geography*. Volume 10, pp. 369-376. Oxford: Elsevier.

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., Pace K., Campanella R., LeSage J., Arenas H. 2009a. Business Return in New Orleans: Decision making amid post-Katrina uncertainty. *PLoS One* 4(8):e6765. doi:10.1371/Journal.pone.0006765.

Lam N.S., Arenas H., Li Z., Liu K. B. 2009b. An Estimate of Population Impacted by Climate Change along the U.S. Coast. *Journal of Coastal Research*, Special Issue 56:1522-1526.

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.

Lam N.S., Reams M., Li K. et al. 2013. A Framework for Community Resilience Measurement: The Resilience Inference Measurement (RIM) Model. Manuscript in Review.

Li K. 2011. Temporal Changes of Coastal Community Resilience in the Gulf of Mexico Region. M.S. Thesis, Department of Environmental Sciences. Baton Rouge: Louisiana State University.

Liu K.B., and Lam N.S., 1985. Paleovegetational Reconstruction Based on Modern and Fossil Pollen Data: An Application of Discriminant Analysis. *Annuals of the Association of American Geographers* 75:115-130.

Liu K.B., Lam N.S., Pace K., Platt W.J., Reams M.A. 2006. Complex Interactions between Natural and Human Systems in a Hurricane-prone Environment: Ecological Responses and Social Resilience in the Gulf Coast Region. Unpublished Research Proposal, Louisiana State University.

Margai F.M. 2010. *Environmental Health Hazards and Social Justice: Geographical Perspectives on Race and Class Disparities* (Earthscan Ltd) www.earthscan.co.uk/Portals/0/Catalogues/9781849713429.pdf

Miller F., Osbahr H., Boyed E. et al. 2010. Resilience and Vulnerability: Complementary or Conflicting Concepts? *Ecology and Society*, *15*.

NOAA's List of Coastal Counties for the Bureau of the Census Statistical Abstract Series. Retrieved from: http://www.census.gov/geo/landview/lv6help/coastal_cty.pdf

Perreault WD, Behrman DN, Armstrong GM. 1979. Alternative Approaches for Interpretation of Multiple Discriminant Analysis in Marketing Research. *Journal of Business Research* 7: 151-73.

Pielke, R.A. 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.
Reddy P.C. and Reddy R.S. 2012. K- Means Algorithm with Different Measurements in Clustering Approach. *International Journal of Engineering and Advanced Technology* 1(6).

Reams MA, Lam NSN, Baker A. 2012. Measuring Capacity for Resilience among Coastal Counties of the U.S. Northern Gulf of Mexico Region. *American Journal of Climate Change* 1:194-204.

Roth D. 2010. Louisiana Hurricane History. NOAA National Weather Service. Retrieved from: http://www.hpc.ncep.noaa.gov/research/lahur.pdf

Schwab A.K., Eschelbach K., Brower D.J., 2007. *Hazard Mitigation and Preparedness*. Wiley & Sons, Hoboken.

Singh K., Malik D. and Sharma N. 2011. Evolving Limitations in K-means Algorithm in Data

Mining and Their Removal. *International Journal of Computational Engineering & Management* 12.

Stockburger D.W.1998. *Multivariate Statistics: Concepts, Models, and Applications*. Missouri State University.

Subcommittee on Disaster Reduction (SDR). 2005. *Grand challenges for disaster reduction*. Washington D.C.: National Science and Technology Council.

Tan P.N., Steinbach M., Kumar V. 2005. *Introduction to Data Mining*. First Edition. Boston, MA: Addison-Wesley Longman Publishing Co.

The H. John Heinz III Center for Science, Economics and the Environment, 2000. The Hidden Coasts of Coastal Hazards: Implications for Risk Assessment and Mitigation. Washington, DC: Island Press.

Timmerman P. 1981. Vulnerability, Resilience and the Collapse of Society. *Environmental Monograph* 1. Institute for Environmental Studies, University of Toronto, Toronto

Walker, B. H., Holling C. S., Carpenter S. R., and Kinzig A. 2004. Resilience, Adaptability and Transformability in Social–ecological Systems. *Ecology and Society* 9(2): 5.

Walker B.H., Anderies J.M., Kinzing A.P., Ryan P. 2006. Exploring Resilience in Socio-ecological Systems through Comparative Studies and Theory Development: Introduction to the Spatial Issue. *Ecology and Society*. 11(1):12.

Wilkins J.G., Emmer R.E., Hwang D. J. et al. 2008. *Louisiana Coastal Hazard Mitigation Guidebook*. Louisiana Sea Grant College Program. Retrieved from: http://www.lsu.edu/sglegal/

Appendix 1: 38 Coastal Parishes in Louisiana

Fips Code	State	Parish Name
22001	LA	Acadia
22005	LA	Ascension
22007	LA	Assumption
22009	LA	Avoyelles
22011	LA	Beauregard
22019	LA	Calcasieu
22023	LA	Cameron
22033	LA	East Baton Rouge
22037	LA	East Feliciana
22039	LA	Evangeline
22045	LA	Iberia
22047	LA	Iberville
22051	LA	Jefferson
22053	LA	Jefferson Davis
22055	LA	Lafayette
22057	LA	Lafourche
22063	LA	Livingston
22071	LA	Orleans
22075	LA	Plaquemines
22077	LA	Pointe Coupee
22079	LA	Rapides
22085	LA	Sabine
22087	LA	St. Bernard
22089	LA	St. Charles
22091	LA	St. Helena
22093	LA	St. James
22095	LA	St. John the Baptist
22097	LA	St. Landry
22099	LA	St. Martin
22101	LA	St. Mary
22103	LA	St. Tammany
22105	LA	Tangipahoa
22109	LA	Terrebonne

Fips Code	State	Parish Name
22113	LA	Vermilion
22115	LA	Vernon
22117	LA	Washington
22121	LA	West Baton Rouge
22125	LA	West Feliciana

Appendix 2: Resilience Groupings at the County Level

Fips code	Name	State	Test1	Test 2	Test 3
22001	Acadia	LA	recovering	recovering	recovering
22003	Allen	LA	recovering	recovering	recovering
22005	Ascension	LA	usurper	usurper	usurper
22007	Assumption	LA	susceptible	susceptible	usurper
22009	Avoyelles	LA	recovering	recovering	recovering
22011	Beauregard	LA	recovering	recovering	recovering
22013	Bienville	LA	recovering	recovering	usurper
22015	Bossier	LA	usurper	recovering	recovering
22017	Caddo	LA	recovering	recovering	recovering
22019	Calcasieu	LA	recovering	recovering	recovering
22021	Caldwell	LA	recovering	recovering	recovering
22023	Cameron	LA	susceptible	usurper	usurper
22025	Catahoula	LA	recovering	recovering	usurper
22027	Claiborne	LA	recovering	recovering	recovering
22029	Concordia	LA	recovering	recovering	recovering
22031	De Soto	LA	recovering	recovering	usurper
22033	East Baton Rouge	LA	recovering	recovering	recovering
22035	East Carroll	LA	susceptible	susceptible	susceptible
22037	East Feliciana	LA	susceptible	susceptible	recovering
22039	Evangeline	LA	recovering	usurper	usurper
22041	Franklin	LA	recovering	recovering	recovering
22043	Grant	LA	usurper	recovering	recovering
22045	Iberia	LA	recovering	recovering	recovering
22047	Iberville	LA	recovering	recovering	usurper
22049	Jackson	LA	recovering	recovering	recovering
22051	Jefferson	LA	resistant	resistant	resistant
22053	Jefferson Davis	LA	recovering	usurper	usurper
22055	Lafayette	LA	usurper	usurper	recovering
22057	Lafourche	LA	resistant	recovering	recovering
22059	La Salle	LA	recovering	resistant	resistant
22061	Lincoln	LA	recovering	recovering	recovering
22063	Livingston	LA	usurper	resistant	resistant
22065	Madison	LA	recovering	recovering	recovering

Fips code	Name	State	Test1	Test 2	Test3
22067	Morehouse	LA	recovering	recovering	recovering
22069	Natchitoches	LA	recovering	recovering	recovering
22071	Orleans	LA	resistant	resistant	resistant
22073	Ouachita	LA	recovering	recovering	recovering
22075	Plaquemines	LA	susceptible	susceptible	susceptible
22077	Pointe Coupee	LA	susceptible	susceptible	susceptible
22079	Rapides	LA	recovering	recovering	recovering
22081	Red River	LA	recovering	recovering	usurper
22083	Richland	LA	recovering	recovering	usurper
22085	Sabine	LA	recovering	recovering	recovering
22087	St. Bernard	LA	susceptible	susceptible	susceptible
22089	St. Charles	LA	resistant	resistant	resistant
22091	St. Helena	LA	susceptible	susceptible	susceptible
22093	St. James	LA	susceptible	susceptible	susceptible
22095	St. John the Baptist	LA	resistant	resistant	resistant
22097	St. Landry	LA	recovering	usurper	recovering
22099	St. Martin	LA	recovering	recovering	usurper
22101	St. Mary	LA	recovering	recovering	usurper
22103	St. Tammany	LA	resistant	resistant	resistant
22105	Tangipahoa	LA	usurper	resistant	resistant
22107	Tensas	LA	recovering	recovering	recovering
22109	Terrebonne	LA	resistant	resistant	resistant
22111	Union	LA	recovering	recovering	recovering
22113	Vermilion	LA	recovering	recovering	usurper
22115	Vernon	LA	recovering	recovering	usurper
22117	Washington	LA	recovering	recovering	recovering
22119	Webster	LA	recovering	recovering	recovering
22121	West Baton Rouge	LA	susceptible	susceptible	susceptible
22123	West Carroll	LA	recovering	usurper	recovering
22125	West Feliciana	LA	susceptible	susceptible	susceptible
22127	Winn	LA	recovering	recovering	recovering

Appendix 3: Potency Index of the Indicators for the County Study, Test 1

Indicator Variables	Discriminant Loadings		Potency Index
	Function 1	Function 2	
MEDRENT	**0.374**	**-0.297**	**0.1200**
MVALOO	**0.416**	**-0.163**	**0.1167**
PCTOLD	-0.319	0.138	0.0700
CHRILLD	-0.306	0.157	0.0671
AVGPERHH	0.29	0.102	0.0558
PCTNOHS	-0.151	0.304	0.0496
HOUDEN	0.247	-0.14	0.0451
PCTFRMPOP	-0.236	0.153	0.0433
PCTPOV	-0.223	0.157	0.0401
LGFINREVPC	0.217	0.157	0.0385
MELEV	-0.239	-0.012	0.0352
GENEXPPC	0.211	0.14	0.0349
PCTHISPA	0.21	-0.089	0.0302
PCTCVLBF	0.163	-0.181	0.0289
MD	0.176	-0.156	0.0284
DISNWRK	-0.183	0.118	0.0260
PCTBLCK	-0.02	0.225	0.0197
PCTMOBL	-0.162	0.096	0.0197
HUWNP	-0.085	0.182	0.0172
PCTKIDS	0.011	-0.186	0.0134
HUWNF	0.122	0.092	0.0124
INFMTR	-0.135	-0.018	0.0113
PERVOTE	0.051	0.156	0.0110
PCTFHH	-0.008	0.164	0.0104
LBWB	-0.083	0.061	0.0057
PCTFEMLBR	-0.053	0.098	0.0054
PCTRENT	-0.007	-0.1	0.0039
EXPENPC	0.014	0.014	0.0000
Note: Bold variables are the variables with the highest potency indexes			

Appendix 4: Potency Index of the Indicators for the County Study, Test 2

Indicator Variables	Discriminant Loadings		Potency Index
	Function 1	Function 2	
MVALOO	**0.38**	**-0.193**	**0.1064**
AVGPERHH	**0.357**	**-0.074**	**0.0842**
MEDRENT	**0.214**	**-0.348**	**0.0725**
PCTOLD	-0.287	0.17	0.0634
CHRILLD	-0.242	0.207	0.0530
MELEV	-0.207	0.252	0.0502
HOUDEN	0.121	-0.273	0.0359
PCTBLCK	0.078	0.282	0.0321
INFMTR	-0.182	0.161	0.0306
PCTPOV	-0.139	0.205	0.0274
PCTFRMPOP	-0.162	0.17	0.0272
PCTFHH	0.075	0.243	0.0246
PCTCVLBF	0.053	-0.25	0.0240
LGFINREVPC	0.174	-0.112	0.0240
HUWNP	0.029	0.251	0.0229
MD	0.031	-0.243	0.0216
GENEXPPC	0.147	-0.139	0.0208
PCTMOBL	-0.018	0.233	0.0195
PCTHISPA	0.099	-0.187	0.0187
PCTFEMLBR	-0.004	0.215	0.0164
DISNWRK	-0.144	0.045	0.0141
HUWNF	0.146	-0.023	0.0139
PCTNOHS	-0.03	0.176	0.0116
PCTKIDS	-0.042	-0.132	0.0073
LBWB	-0.105	0.005	0.0071
PCTRENT	-0.072	-0.057	0.0045
EXPENPC	-0.044	-0.086	0.0039
PERVOTE	0.111	0.112	0.0000
Note: Bold variables are the variables with the highest potency indexes			

Appendix 5: Potency Index of the Indicators for the County Study, Test 3

Indicator Variables	Discriminant Loadings		Potency Index
	Function 1	Function 2	
MVALOO	**0.361**	**-0.248**	**0.1093**
MEDRENT	**0.224**	**-0.47**	**0.1024**
AVGPERHH	**0.368**	**0.118**	**0.0982**
CHRILLD	-0.274	0.143	0.0584
PCTOLD	-0.278	0.113	0.0575
MD	0.026	-0.405	0.0507
HOUDEN	0.127	-0.343	0.0472
LGFINREVPC	0.253	-0.013	0.0445
MELEV	-0.241	0.074	0.0420
GENEXPPC	0.237	-0.015	0.0390
PCTFRMPOP	-0.174	0.24	0.0386
PCTMOBL	-0.047	0.331	0.0351
PCTNOHS	-0.04	0.327	0.0338
INFMTR	-0.199	0.022	0.0276
PCTPOV	-0.137	0.213	0.0269
PERVOTE	0.133	0.212	0.0260
HUWNP	-0.006	0.287	0.0252
PCTHISPA	0.137	-0.183	0.0233
DISNWRK	-0.158	0.125	0.0221
HUWNF	0.169	0.047	0.0205
PCTCVLBF	0.102	-0.175	0.0166
PCTRENT	-0.043	-0.17	0.0101
PCTBLCK	0.045	0.159	0.0091
EXPENPC	0.018	0.148	0.0069
LBWB	-0.097	0.012	0.0066
PCTFHH	0.06	0.111	0.0063
PCTFEMLBR	-0.033	0.045	0.0014
PCTKIDS	0.005	-0.016	0.0001
Note: Bold variables are the variables with the highest potency indexes			

Appendix 6: Value of Function 1 of the Indicators for Zip Code Study, Test 1

Test 1	**Function1**
HOUDEN	**0.538**
MELEV	**-0.508**
MVALOO	**0.486**
MEDRENT	**0.407**
PCTHISPANIC	**0.351**
MANDEN	**0.329**
PCTMOBL	**-0.305**
PCTFRMPOP	**-0.245**
PCTOLD	-0.196
FEMLBR	0.137
PCTNOHS	-0.137
AVGPERHH	0.124
PCTRENT	0.122
PCTFHH	0.121
PCTBLACK	0.101
PCTPOV	-0.08
HUWNF	0.063
PCTKIDS	-0.05
Note: Bold variables are the variables with the highest function scores	

Vita

Chi Li was born and grew up in Nanjing, China. Following her graduate from high school in 2004, she attended Nanjing University of Technology (NJUT). While at NJUT, she majored in Geography Information System. After graduation, Chi came to the U.S. and enrolled in State University of New York at Binghamton to pursue a Master's Degree in Geography. She found her interests in the field of environmental health and hazard when she was conducting a thesis research on asthma disparities and environmental justices in the Bronx, NY. Then she decided to further pursue her interest in the related field by working towards a second master's in Environmental Science at LSU. While at LSU to obtain a Master's degree in Environmental Science, she has enjoyed every opportunity to learn out environmental hazard and disease analysis, spatial modeling, remote sensing, and environmental laws and policies. During the two years at LSU, Chi has been also working as a graduate assistant for her major professor Dr. Nina Lam in the remote sensing and GIS Lab. Chi will graduate in summer of 2013 with a Master's in environmental science with a focus on environmental assessment and analysis.