12-29-2014

Evaluating Community Resilience under Conditions of an Environmental Disaster: The Case of the Deep Water Horizon Oil Spill

Naomi W. Lazarus
University of Connecticut - Storrs, naomi.lazarus@uconn.edu

Evaluating Community Resilience under Conditions of an Environmental Disaster: The Case of the Deep Water Horizon Oil Spill

Naomi Watsala Lazarus, PhD

University of Connecticut, 2014

The impact of hazard events on human settlements reflects the complex interaction of social and physical systems that challenge the process of defining and operationalizing risks associated with environmental disasters. The objective of this research is to develop a model that examines the inter-relationships between social capital and livelihoods and to thereby estimate their impacts on levels of hazard risk. Social capital is embedded in social networks and institutional frameworks that determine the quantity and quality of resources and services available to people. In addition to addressing the physical and social dimension of hazards, this research evaluates the linkages between social capital and livelihoods and underlying spatial processes that determine levels of vulnerability and risk from a hazardous event.

The proposed hazard risk location model (HRLM) re-specifies hazard risk as a function of the hazard, exposure, and coping ability. The model is developed in two stages. First, an autoregressive model is applied to estimate the causal relationship between the dependent variable representing coping ability and variables representing social capital. Second, a threshold analysis examines the relationships between the latent variable (risk) and selected measurement variables representing the hazard, exposure, and coping ability.

The model is applied to assess the social and economic impacts of the 2010 Deepwater Horizon oil spill across coastal counties in the Gulf of Mexico. Results of the regression analysis reveal that the quantity of social capital and its contribution to coping ability are influenced by locational differences and the type of hazard event. Locational differences are observed in the

services provided by social capital across the study area and how these vary over time. Maps developed from the threshold analysis highlight spatial and temporal variation in hazard risk at the county level, and these changes are reflected in the proximity of individual counties to the spill site, population density, and the unemployment rate. In keeping with recent trends in research relating to disaster risk, the model contributes to the range of place-based assessments designed to address the impacts of environmental disasters from the perspective of community resilience.

Evaluating Community Resilience under Conditions of an Environmental Disaster: The Case of the Deep Water Horizon Oil Spill

Naomi Watsala Lazarus

B.A., Binghamton University, New York 2007

M.A., Binghamton University, New York 2009

A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

at the

University of Connecticut

2014

APPROVAL PAGE

Doctor of Philosophy Dissertation

Evaluating Community Resilience under Conditions of an Environmental Disaster: The Case of the Deep Water Horizon Oil Spill

Presented by

Naomi Watsala Lazarus, B.A., M.A.

Major Advisor

Jeffrey P. Osleeb

Associate Advisor

Samuel J. Ratick

Associate Advisor

Nathaniel Trumbull

Associate Advisor

Chuanrong Zhang

University of Connecticut
2014

Acknowledgements

I wish to thank my advisor, Dr. Jeffrey P. Osleeb, for his support and guidance that have helped me tremendously in my research at the University of Connecticut. I am grateful to my committee members, Dr. Samuel J. Ratick, Dr. Nathaniel Trumbull, and Dr. Chuanrong Zhang for their constructive criticisms that strengthened the research. I wish to thank the faculty, staff, and students of the Department of Geography for their support. I dedicate this dissertation to my family in Sri Lanka.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Overview

The process of defining hazard risk, vulnerability, and resilience has produced a range of complex theoretical frameworks that have challenged attempts to quantify the impacts of disasters. Vulnerability is defined as the likelihood of being negatively impacted by changes in the environment and is a combination of environmental and social factors (Cutter, Boruff, and Shirley 2003). The location of populations in hazard prone areas exposes them to environmental threats brought on by hazard events, such as hurricanes, floods, and industrial accidents. The social aspect of vulnerability manifests itself in the ability of people to cope with the impacts of hazard events and is determined by access to resources. These resources are in the form of income, occupation, assets, and social networks that improve peoples' ability to cope with changes in the environment. Resilience is tied to coping ability in that it defines how competent a community is to make changes that would further expedite recovery from the impacts of current and future hazard events (Manyena 2006; Cutter et al. 2008). Hazard risk is the net effect of peoples' vulnerability and resilience and is manifested in actual loss of life, damage to property, and loss of income and occupation that can occur during and after disaster events (White 1945; Cutter 2000).

Two major limitations are observed in models that attempt to operationalize risk and vulnerability. First, most vulnerability assessments address a specific problem involving a small spatial unit that may be subject to multiple hazards. While, this approach has value in terms of identifying and implementing place-based solutions to address hazard risk, it is limited in its

application across geographical space. On the other hand, some models are more generalized in their approach to quantifying vulnerability at the regional or national level raising issues relating to aggregation and scale.

The second limitation pertains to disparate definitions of vulnerability that are often employed that can be classified based on demographic, socio-economic, and institutional variables. For example, the Social Vulnerability Index (SoVI) developed by Cutter, Boruff, and Shirley (2003) adopts a weighted linear combination to identify the key factors that determine vulnerability from a collection of socio-economic and demographic variables linked to personal wealth, occupation, age, and ethnicity. Another example is the Vulnerabilities and Capacities Index (VCI), an additive model that considers the material, institutional, and attitudinal vulnerability of populations in rural and urban areas (Mustafa et al. 2011). Institutional vulnerability is linked to social capital, which takes the form of family and kinship ties, workplace relationships, membership in social institutions, and institutional frameworks that provide people access to resources. Social capital is present in formal and informal mechanisms that are built in to the social structure. Existing models consider social capital as a key factor in assessing institutional vulnerability, when in fact it has broader implications as to the socio-economic condition of populations exposed to hazard events.

Social capital underpins the concept of capabilities as articulated by Sen (1981). Capabilities are social relations or linkages embedded in social capital that support or obstruct peoples' access to resources, which in turn has an impact on livelihood security. A livelihood is a mechanism by which people engage in productive activities to meet basic needs. Livelihood security explains the stability of the mechanism that supports livelihoods and is determined by peoples' access to resources, such as assets, cash, and employment opportunities (Chambers and

Conway 1991). Therefore, the quality and quantity of social relations (capabilities) that are the foundation of social capital are intrinsically tied to the socio-economic well-being of the community. The research undertaken in this dissertation evaluates the linkages between social capital and access to resources, thereby recognizing the connection between institutional and socio-economic vulnerability.

1.2 The Problem

The objective of this research is to develop a model that examines the inter-relationships between social capital and livelihoods and to thereby estimate their impacts on levels of hazard risk. Wisner et al. (2004) propose a pseudo-equation (R = H x V) that defines risk as a product of the hazard and vulnerability. In its original form, the risk equation cannot be operationalized as it does not account for compounding and mitigating factors that determine vulnerability, and does not support a framework to address the issue of geographical scale. The impacts of hazard events vary by location, the timing of events, and the socio-economic characteristics of the exposed population. The hazards-of-place model developed by Cutter (1996) considers the biophysical and social impacts of hazards in assessing the hazard potential. In theory, the model addresses issues of geographical location, exposure, and the socio-economic condition of the population. Attempts to operationalize the hazards-of-place model, however, emphasize social vulnerability where an investigation of the socio-economic and demographic characteristics of the population is the focus of the assessment.

Vulnerability is determined by the population exposed to the hazard event and the ability of the exposed population to cope with the impacts of that event (Ratick, Morehouse, and Klimberg 2009; Ratick and Osleeb 2011). Based on the interpretation of vulnerability, this

research re-specifies the risk equation as $R = f(H, E, C)$. It deconstructs vulnerability into two sub-components, exposure (E) and coping ability (C), thereby recognizing compounding and mitigating factors that determine vulnerability as a way to operationalize the risk equation. It is hypothesized that services provided through social capital affect peoples' ability to cope during a disaster, and that coping ability, exposure, and the characteristics of the hazard vary from place to place. In addition to addressing the physical and social dimension of hazards, this research evaluates the linkages between social capital and livelihoods and underlying spatial processes that are responsible for spatial variations in levels of vulnerability and risk from a hazardous event.

1.3 The Solution

The key concepts of vulnerability, resilience, and risk are examined in the literature and discussed in Chapter 2. The relationship between vulnerability and resilience is considered from the standpoint of adaptive capacity, which emphasizes peoples' ability to cope with environmental changes (Burton, Kates, and White 1978). Coping ability is enhanced or inhibited by social capital that generates pathways for people to access resources (Sen 1981; Turner et al. 2003). The theoretical framework of the proposed risk assessment model is presented in Chapter 3 building on the inter-relationship between livelihood mechanisms and social capital as articulated in the literature. The framework is then applied to evaluate the socio-economic impacts of the Deep Water Horizon oil spill on coastal counties in the Gulf of Mexico. Chapter 4 examines the demographic, economic, and hazard profiles of the study area.

The methodology used to operationalize the re-specified risk equation is presented in Chapter 5. A regression analysis forms the first step in developing the model where the

dependent variable functions as a proxy for coping ability. A causal relationship is established between coping ability and variables representing social capital. The second component of the model is a threshold analysis the purpose of which is to examine the relationships between the latent variable (risk) and selected measurement variables representing the hazard, exposure, and coping ability as articulated in the re-specified risk equation. The threshold analysis builds on the principles of relative distance to classify and rank the spatial units in the study area on a continuum of vulnerability and risk. Chapter 6 outlines the data collection process and defines the variables used in the analyses. Data are collected at the county level. The unemployment rate is selected as the proxy variable for coping ability as it represents livelihood security. The independent variables in the regression analysis represent location quotients of services provided by social capital.

Chapter 7 examines the relationship between coping ability and social capital through an analysis of regression parameters. Tests of spatial autocorrelation are carried out to evaluate whether or not spatial processes are responsible for the spatial variation in unemployment rates and the location quotients of independent variables. The predicted unemployment rate derived from the regression analysis is incorporated into the re-specified risk equation as coping ability. The hazard component is represented by spill distance and exposure, by population density. The threshold analysis produces a ranking system to evaluate a county's measure on the hazard, exposure, and coping ability attributes. Results of the regression and the re-specified risk equation are discussed in Chapter 8.

1.4 Expected Results

The analysis is expected to yield two major results. First, factors contributing to coping ability vary across the study area and this variation is tied to the economic structure of individual counties. These variations are then reflected in the threshold analysis that ranks the risk levels of counties based on the three criteria of hazard, exposure, and coping ability. Second, variations in coping ability would determine how individual counties respond to the impacts of specific hazard events. These differences are highlighted in how services provided by social capital are positively impacted by an event in some counties, whereas in others, the event has a negative effect.

The findings are significant in that the model is able to capture the linkages provided by social capital that are responsible for the socio-economic condition of a specific location, which is representative of coping ability. In addition, the model provides a mechanism to assess hazard risk by combining coping ability, proximity to the hazard, and population density in the context of renewed interest in prioritizing the human impacts of environmental disasters. While the framework of the model in its current state focuses on social and institutional vulnerability, the analysis can be expanded to include additional variables. It is expected that changes taking place in the census data collection process will make time-specific demographic data available at the county level. Future work on the model will involve including demographic variables as a strategy to expand the scope of place-based risk assessments associated with environmental disasters.

Chapter 2

Literature Review

2.1 Introduction

Research on hazards recognizes that the impact of disasters plays out within a social-ecological continuum that requires responses that address both human and environmental concerns (White 1974; Wisner, O'Keefe, and Westgate 1977; Wisner 1993; Adger 2006; Mark et al. 2010; Birkenholtz 2012). Equal attention to these two dimensions of hazards has been addressed in several studies undertaken in different contexts (Degg and Chester 2005; Eriksen, Brown, and Kelly 2005; Valdivia et al. 2010; Conchedda, Lambin, and Mayaux. 2011). In practice, securing hazard prone environments in the form of implementing engineering projects (e.g. building stronger levees) and enforcing stricter regulations has been the focus of response and mitigation strategies. Factors that determine how people respond to changes brought on by the onset of an event and their ability to adapt to those changes have not been adequately addressed in the policy arena. These factors broadly pertain to peoples' livelihoods and their access to social capital that determine how equipped they are to cope with and recover from a disaster (Cannon 1994; Wisner et al. 2004; Lazarus 2014: 635).

Social relations that play out at the micro, macro, and meso levels that define peoples' access to resources (land, credit, employment, and information) determine to what extent they are resilient to the next event (Wisner et al. 2004; Lazarus 2014: 636). Access to social capital and its role in determining peoples' sensitivity to adverse environmental impacts have been dealt with extensively in climate change research (Eakin 2005; Birkenholtz 2009; Valdivia et al. 2010; Oluoko-Odingo 2011). In general, the resources accessible to communities through existing social relations help improve their capacity to cope with environmental stresses. Conversely,

prevailing social mechanisms may exclude specific groups from accessing social capital and increase their vulnerability (Eriksen, Brown, and Kelly 2005; Birkenholtz 2009). Furthermore, the positive and negative impacts tied to the access to social capital vary geographically and pose challenges in the assessment of risk associated with hazard events (Adams and Mortimore 1997; Eakin 2005; Eriksen, Brown, and Kelly 2005; Wilbanks and Kates 2010).

Risk is the loss that could be expected due to the onset of an event and is realized when the event negatively impacts upon peoples' resources (Kasperson, Kasperson, and Dow 2001). These events are classified as natural as in floods, earthquakes, and hurricanes or as anthropogenic, such as oil spills, chemical spills, and nuclear meltdowns. An event is translated into a disaster when the exposed population's socio-economic standing disproportionately increases its sensitivity to suffer loss (White et al. 1958; White 1974; Tobin and Montz 1997). Wisner et al. (2004) consider the "risks people face and the reason for their vulnerability" to be inter-related. Social vulnerability then is a key determinant of risk as it addresses those factors that affect peoples' capacity to cope with and recover from the adverse conditions brought on by a hazard event (Wisner et al. 2004).

2.2 Vulnerability to Hazard Events

The discussion on what constitutes a hazard in the context of human-environmental interactions has expanded since the work of Gilbert F. White in the field of flood plain management (White et al. 1958; White 1974). White argued that the occurrence of unexpected events does not always adversely impact people and is determined by the presence of vulnerable human populations and the level of *adjustments* adopted by them in a specific location (White 1974). Human adjustments in the form of engineering physical infrastructure, mitigation

policies, and emergency relief will determine the extent of an event's impact on the population. Based on this observation, a hazard is the likelihood of an event occurring with a high probability of causing loss to human life and property (Lazarus 2014: 636). Therefore, a hazard by definition is an event that poses a significant threat to society by way of its potential impact. The manifestation of this impact is dependent on location, where the presence of people in hazard prone areas such as floodplains, earthquake zones, and coastal areas exposes them to the risk of being negatively impacted by an event (Tobin and Montz 1997).

A hazard event is classified as a disaster when the potential threat to society exceeds accepted thresholds of loss of life and damage to property (Tobin and Montz 1997). These distinctions have to do with issues of scale and context. In a study on flooding in urban areas, White et al. (1958) observed that hydrographic areas typically include a number of administrative units (counties, places etc.) that posed difficulties in assigning potential losses to a specific area. In addition to the challenge of deciphering overlapping administrative boundaries, the impact of an event can produce varied results by virtue of where it occurs and the number and characteristics of the population exposed to it. A comparative analysis of the 2004 Indian Ocean tsunami with that of the Japan earthquake and tsunami highlights the relevance of scale and the scope of their impact on people. The Indian Ocean tsunami affected countries not only in Southeast Asia close to the epicenter of the undersea earthquake, but also island nations far west across the Indian Ocean, claiming a combined total of more than 200,000 lives. The Japan earthquake and tsunami affected a relatively small geographical area of Tohoku prefecture and claimed around 19,000 lives, but it resulted in multiple threats due to the damage caused to nuclear reactors in Fukushima (Winn 2012; Cronin 2005).

Building on the preceding definitions, Susman, O'Keefe, and Wisner (1983) recognize that a disaster occurs at the intersection of an extreme event and a "vulnerable human population" (264). Understanding the scope of the impact of extreme events then requires an analysis of the relationship between disasters and vulnerability. Comfort et al. (1999) argue that disasters are recreated as a community or region moves "from temporary state to temporary state" where the steps taken to restore conditions to what they were before the event result in increasing the overall vulnerability of people to the next event (41). Three major research themes address vulnerability in hazards research (Rygel, O'Sullivan, and Yarnal 2006).

(1) Vulnerability as a *pre-existing condition* that is tied to physical location – determined by the presence of human settlements in hazard prone areas and the potential loss of human life and damage caused to property (Wu, Yarnal, and Fisher 2002; Adger et al. 2004)

(2) Vulnerability tied to *coping ability* that determines how groups of people are differentially vulnerable. (Anderson and Woodrow 1991; Dow 1992; Watts and Bohle 1993; Cutter 1996; Clark et al. 1998; Wu, Yarnal, and Fisher 2002), and

(3) Vulnerability as a *hazard of place* (Cutter 1996; Wu, Yarnal, and Fisher 2002) that recognizes the importance of social and ecological factors that determine the impacts of hazard events on human populations.

Vulnerability is broadly defined as the sensitivity of a human population to be negatively impacted by a hazard event (Cutter, Boruff, and Shirley 2003; Adger 2006). The literature reveals two aspects of vulnerability. On one hand, it is manifested in hazardous landscapes (flood plains, earthquake zones etc.), which render people in these areas vulnerable by virtue of their physical location i.e. *physical vulnerability* (Cutter, Boruff, and Shirley 2003; Cardona 2004). On the other hand, it is also inherent in the social, economic, and demographic

characteristics of the population that determine how people cope with and recover from hazard events and is referred to as *social vulnerability* (Blaikie et al. 1994; Cannon 1994; Wisner et al. 2004). Physical vulnerability recognizes the environmental causes and effects of human populations exposed to hazard events and is the premise of the first theme. It takes into account the characteristics of the hazard event (its magnitude, frequency, and duration) and attempts to measure potential losses in terms of the population affected and damage to property and infrastructure (Tobin and Montz 1997; Adger 2006). The impacts of hazard events, therefore, will vary based on where they occur. As illustrated in a review of hurricanes in the Gulf of Mexico, flooding in the United Kingdom, and coastal storms in Bangladesh, the impact of these events are determined by human settlements, the level of adjustments adopted, and public policy in addressing disaster preparedness (White 1974). Vulnerability then is an outcome of the convergence of social-ecological systems in the context of extreme events (Eriksen, Brown, and Kelly 2005; Adger 2006). Based on White's (1974) interpretation of extreme events, it is the level of human adjustments, articulated in the steps taken by people to mitigate losses from a hazard event that determines overall vulnerability.

This means that disasters are the result of a process of decision-making that takes place over a period of time culminating in increased vulnerability of the population that is exposed to an event. These decisions are in the form of economic, political, and environmental policies that govern how organizational and institutional frameworks operate in a region (Comfort et al. 1999; O'Hare and Rivas 2005). The social and political environments that are shaped by these frameworks affect decisions taken by individuals and groups concerning their livelihoods and their access to social capital (Lazarus 2014: 638). These concerns are addressed in the themes of vulnerability that deal with coping ability and the significance of place. Coping ability is

recognized as the capacity for people to absorb the negative impacts of a hazard event and respond in a manner that allows them to return to normal life (Ratick et al. 2004; Manyena 2006). It highlights the steps and strategies people take to improve their ability to cope with unexpected events, which Burton, Kates, and White (1978) refer to as *adjustments*. A number of case studies focus on how communities carry out their day to day activities in different settings that assist in building coping ability over time (Burton, Kates, and White 1978). In situations where adjustments are inadequate and coping ability is compromised, people are more vulnerable as the potential threat of being harmed is greater (Tobin and Montz 1997). It is this second aspect of vulnerability that is widely recognized as *social vulnerability*.

Social vulnerability focuses on the resources available to people that determine how they are able to cope with changes following a hazard event i.e. coping ability (Adger 2000; Cutter, Mitchell, and Scott 2000; Cutter, Boruff, and Shirley 2003; Eriksen, Brown, and Kelly 2005; Adger 2006; Oluoko-Odingo 2011). Wisner et al. (2004) build on this characterization of vulnerability and define it as "the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard" (11). This definition makes reference to *characteristics* (that of socio-economic status, demographics etc.) and *situation* (access to resources and social networks) that are the determinants that characterize a disaster (Lazarus 2014: 637). This interpretation observes the relationships between the event, the population exposed to the event, and the interaction of the two that direct the transition of an event to a disaster. The physical and social dimensions of vulnerability are linked in that it is the condition of people, articulated in the social, economic, and political contexts in which their everyday lives play out that determines the extent they are

affected by environmental changes (Wisner et al. 2004; Degg and Chester 2005; Jim, Yang, and Wang 2010).

The interaction of the physical and social environments in the assessment of vulnerability is enhanced by *place*. The characteristics of the hazard (frequency, duration and areal extent), the population exposed, and the adjustments undertaken by people vary from place to place and this variation translates to levels of vulnerability (Wisner et al. 2004; Adger 2006). Place dynamics are important in understanding *hazardousness*, the increased risk of being negatively impacted by a hazard event (Tobin and Montz 1997). Cutter and Solecki (1989) propose a conceptual model that takes into account the biophysical and social aspects of how a hazard event unfolds in a given location referred to as the *hazards-of-place model*. At the outset, the model recognizes that risk and mitigation measures determine the hazard potential i.e. hazardousness. The model assumes the hazard potential to be a pre-existing condition of a specific place and its population to be negatively impacted by an event. Risk is defined as "the likelihood of occurrence (or probability) of the hazard" (536). The risk component includes frequency, magnitude, and source of hazard and has the effect of increasing the hazard potential. As such, the hazard potential is filtered through factors that influence the social and biophysical environments that determine the overall vulnerability of place.

White (1974) argues that hazards research cannot be viewed purely through the lens of environmental determinism – that people are passive and are victims of changes that occur in the environment. He also argues that human adjustments (steps taken by people to adapt to the environment) are not sufficient to completely safeguard them from adverse impacts. So in this sense, White is addressing the limitations of possibilism, which represents people as active participants in shaping their environment, and in doing so they might be able to limit adverse

impacts, but not eliminate them entirely. He acknowledges, however, that the presence of human settlements in hazard prone areas is the fundamental premise for hazards research – without humans there would not be a hazard. It follows then that the hazard of place framework (Cutter 1996) positions human vulnerability to environmental hazards along a social-ecological continuum as observed by White (1974) and by Adger (2006).

2.3 The Resilience -Vulnerability Continuum

Resilience is associated with a conscious effort on the part of society – communities, state, and local governments – to anticipate and prepare for the future. Manyena (2006) and Klein et al. (1998) recognize the role humans play in building resilience, wherein resilience is viewed as being dynamic, comprising actions taken by people to minimize the negative impacts of environmental stresses. In the context of disaster vulnerability, resilience is informed by two key elements, coping ability and adaptation. Coping ability is a concept derived from what Burton, Kates, and White (1978) refer to as *absorptive capacity*. It is defined as the ability of a vulnerable group to absorb the impacts of an environmental event by virtue of normative actions that are built in to the social structure. These actions are referred to by White et al. (1958) and Burton, Kates, and White (1978) as *adjustments*. In the case of White's work on flood plain management, adjustments refer to engineering solutions such as building levees and flood walls as well as to land use planning (White et al. 1958; White 1964). In a case study of earthquake and volcano hazards in Peru, Degg and Chester (2005) observed that rural communities developed hazard mitigation strategies that are aimed at minimizing their exposure to these events (Lazarus 2014: 637). The steps and strategies undertaken by people to reduce their vulnerability determine to what extent they are able to absorb losses in the short-term and adapt

to changes in the environment over time (Burton, Kates, and White 1978; Ratick et al. 2004; Cutter et al. 2008).

The cultural environment that is constructed by the characteristics and context of a human population determines how people are impacted by changes in the environment and the mechanisms available to cope with uncertainties. This is illustrated in the case of the Fulani tribe in the Sahel where long-established livestock management practices helped communities to survive through periods of drought (Burton, Kates, and White 1978). On the other hand, cultural changes can create the scenario for an event to be translated to a disaster. In the previous example relating to the Fulani tribe, the introduction of improved water-supply systems inadvertently heightened the risk of dislocation due to a disproportionate increase in livestock (Burton, Kates, and White 1978; Lazarus 2014: 636). Coping ability, which is the manifestation of resilience, then is linked to resources accessible to the community through livelihood mechanisms and social networks that provide the social protection necessary to withstand the adverse impacts of events.

The question then arises whether resilience is an *outcome* or a *process* (Cutter et al. 2008). Resilience is viewed as an outcome when the ability of a community to recover (or return to the pre-disaster state) can be defined. This is tied to the components of vulnerability and the characteristics that increase or decrease a community's vulnerability. Resilience is viewed as a process when the experience associated with an event leads to lessons learned and improvements in knowledge. This aspect of resilience is tied to *adaptation* as it informs future decisions on how to deal with the negative impacts of hazards thereby creating resilient communities (Cutter et al. 2008). The trajectory of the concept of adaptation can be traced back to Burton, Kates, and White (1978) where it is referred to as *cultural adaptation*. A case study that explores the

farming practices of the Kamba tribe in Kenya is cited as an example of how culture (which is a product of society and social interaction) ensures soil moisture for crops and community resilience to drought. Wilbanks and Kates (2010) advance this definition by observing that adaptation involves the participation of a broad range of stakeholders making important decisions on the sustainable use of resources in an effort to build long-term resilience. They describe how humans respond to extreme events by adopting measures to minimize the negative impact of an event. Vásquez-León et al. (2002) identify two types of adaptation strategies, *buffering* and *coping.* Buffering refers to strategies adopted over the long-term and includes technological solutions and social re-engineering that are intended to mitigate or eliminate the sources of vulnerability. Coping refers to strategies adopted in the short-term and is designed to help people return to the pre-disaster state (Adams and Mortimore 1997; Manyena 2006; Ford et al. 2008; López-Marrero 2010). In this instance, coping ability is recognized as being embedded in adaptation and distinguished as a short-term mechanism. Turner et al. (2003) define resilience as the ability of a vulnerable population to absorb the impacts of the event in the short-term, which is closely tied to Burton, Kates, and White's (1978) definition of absorptive capacity. This discussion illustrates that there is considerable overlap between the concepts of resilience, coping ability, and adaptation. Most often a combination of short-term and long-term measures is adopted to improve peoples' resilience (Lazarus 2014: 637).

White (1945) recommended the application of a comprehensive plan for community resilience (to floods) taking into account geographical, economic, and social factors to effectively manage flood plains at the local level (Lazarus 2014: 637). Human responses to hazard events are grouped under *structural* measures and *non-structural* measures. Structural measures are designed to reduce the exposure of people and property to the adverse impacts of

hazard events and include such actions as the construction of a breakwater, a seawall, a dike, or a floodgate, beach restoration and nourishment, flood-proofing structures, and building levees (Ratick et al. 2009; Randolph 2012). Non-structural measures are designed to increase people's resilience and resistance to potential threats from hazard events. Some examples of non-structural measures include flood warning and evacuation, land use management, flood insurance policies, and public acquisition of floodplains (Ratick, Morehouse, and Klimberg 2009; Randolph 2012). Comparing the structural and non-structural measures proposed by Randolph (2012) with that of White (1964), there are some important similarities and differences. In Randolph (2012), it is cited that the U.S. Army Corps of Engineers refers to structural measures collectively as *flood control*. White (1964) refers to a *system of control* beyond the structural/engineering solutions proposed, focusing on regulatory mechanisms and policies that promote flood plain management (non-structural). In both instances, a case is made for the adoption of structural and non-structural measures.

This approach was demonstrated in a case study on flooding in Shrewsbury, England (Harding and Parker 1974). Residents adopted emergency flood proofing of homes, evacuating to upper floors, and moving furniture as ways to cope with seasonal flooding of the River Severn. Long-term buffering measures, such as improving early warning systems and construction of the Clywedog Dam were undertaken by the local government. In some cases, adaptation strategies can exacerbate long-term vulnerability rather than decrease it (Harding and Parker 1974; Birkenholtz 2009, 2012). In the above case study related to Shrewsbury, the Clywedog Dam was able to decrease the flooding in towns upstream, but failed to adequately address the flooding further downstream. In another case study in the Dominican Republic, development policies designed to support commercial crops forced farming communities to

move to the highlands where woodlands and forests were cleared for cultivation, causing environmental degradation. Fishing was also undertaken by these communities as an additional source of income that resulted in overfishing and ultimately proved to be a practice that could not be sustained in the long-term (Jeffrey 1982). These examples illustrate that adaptation strategies that address livelihood concerns alone do not necessarily decrease vulnerability over time (Lazarus 2014: 637 - 638).

Furthermore, Wilbanks and Kates (2010) argue that the type of activities undertaken by people to improve resilience varies from place to place and is influenced by social, economic, and environmental factors prevalent in a given location. Adaptation is a component of resilience that goes beyond getting back to the pre-disaster setting and strives to improve peoples' capacity to cope with and recover from a disaster within a relatively short period of time with minimal assistance from outside sources (Miletti 1999; Manyena 2006; Lazarus 2014: 638). Understanding the geographical context is an important component of building resilience and is tied to the sense of place. A research theme of vulnerability expressed in the hazard of place model (Cutter 1996) addresses the sense of place in building coastal resilience, because it calls for an understanding of how the environmental impacts of an event affect people and places and how to respond effectively to them. This has important implications for research as it points to the importance of geographical context. Furthermore, Wisner (1993) argues that there are spatial and temporal dimensions to vulnerability. Previous studies (with regard to flood losses and adjustments) have addressed these spatial and temporal dimensions (White et al. 1958; White 1964).

In the last decade, the discussion on resilience has pivoted to addressing issues of sustainability. This is taken up by Turner et al. (2003) in linking community resilience to

sustainability through *coupled human-environment systems*. A coupled human-environment system takes into account the characteristics of the hazard event, human interaction with the event (exposure), and internal and external linkages that impact the human-environment system. These internal and external influences determine to what extent the system is sensitive to changes in the environment (Turner et al. 2003). The sensitivity of the system is determined by the level and quality of the interaction between human settlements and the environment. The institutional frameworks and livelihood systems place a burden on environmental resources, which in turn make the environment system more sensitive to hazard events. In Turner et al (2003), the authors develop a framework for vulnerability analysis based on coupled human-environment systems that takes into account human interaction with the natural and built environments, the dynamics of the social structure, and the role of institutions. Components of the framework are adopted in Cutter et al.'s (2008) *Disaster Resilience of Place (DROP)* model, where equal attention is given to structural and non-structural measures in building community resilience, which are concerns highlighted by White (1945) and Randolph (2012).

The conceptual frameworks proposed by Turner et al. (2003) and Cutter et al. (2008) point to the importance of the social system. The interaction between members of a prevailing social structure will determine to what extent they engage in activities that improve their ability to cope with changes in the environment. These interacting forces are an important part of the social-ecological discussion on vulnerability and resilience (Adger 2006). It emphasizes the countervailing characteristics of social vulnerability and resilience, and how these elements inform the relationships between the event, the population exposed to the event, and the interaction of the two that direct the transition of an event to a disaster. This means that disasters are the result of a process of decision-making that takes place over a period of time culminating

in increased vulnerability of the population that is exposed to an event. The cultural environment will determine what activities are undertaken within a community, which are broadly accepted within the norms that govern members of a social structure (Burton, Kates, and White 1978). The social and political environments that are shaped by these frameworks affect decisions taken by individuals and groups concerning their livelihoods and their access to social capital. Therefore, the existence of and access to social capital are key components of resilience.

2.4 Resilience Linked to Social Capital

The discussion on social capital is rooted in the concept of *capability*, which describes the mechanisms and means employed by people to maintain and improve their livelihoods (Sen 1981). Capability is determined by not only the qualities and skills an individual or group possesses, but also by access to resources (Lazarus 2014: 638). Livelihoods are tied to capabilities (Sen 1984, 1987). Capabilities determine the ability of a human population to carry out the activities necessary to maintain basic economic and social functions like acquiring food, clothing, and healthcare (Chambers and Conway 1991). The mechanisms available to acquire and manage resources are important not only for daily functions, but also to help cope with environmental changes (Sen 1981; Chambers and Conway 1991). This is tied to Burton, Kates, and White's (1978) characterization of cultural adaptation that recognizes the role of the individual and his/her relationships with the other members of the overarching social structure.

Capabilities are shaped by the provisions available to people to achieve a level of "self-protection" and "social protection" (Cannon 1994, 24). Self-protection is achieved through livelihood mechanisms that enable people to acquire resources (food, cash) and is dependent on occupation, skills, and education (WCED 1987; Bebbington 1999; Davies and Bennett 2007;

Oluoko-Odingo 2011). These qualities, skills, and resources are embedded in different forms of assets or capitals (Chambers and Conway 1991; Moser 1998; Bebbington et al. 2006). Human capital consists primarily of inherent and learned qualities of individuals such as, skills, knowledge, and health. Water and other natural resources, vegetation, and soils are some of the components of natural capital, while tools, equipment, and infrastructure make up physical capital. Financial capital consists of liquid assets, such as cash, credit, and savings (Chambers and Conway 1991; Wisner et al. 2004; Davies and Bennett 2007). Access to these assets and the way in which they are used to sustain livelihoods are dependent on the quality of social capital (Lazarus 2014: 638).

Scheffer et al. 2002 define social capital as “the value of relationships for the individuals, groups, and organizations that participate in them” (231). The term “value” refers to the resources that people are able to mobilize as a result of having access to these social networks. Horizontal or formative social capital is contained in institutions or organizations with similar goals working together to exert influence on other groups higher in the social hierarchy. Vertical or bridging social capital consists of the working relationships that are maintained among different groups across the hierarchy (community organizations, non-governmental organizations, and government officials) to achieve a common goal (Scheffer et al. 2002). Coleman (1990) observes that a social framework and the networks within the framework that allow members to access resources are pre-conditions necessary in the accumulation of social capital. Bourdieu and Wacquant (1992) characterize a social structure as a “durable network of more or less institutionalized relationships” (119) that are prevalent in family and kinships ties, workplace relationships, and membership in social institutions (Lazarus 2014: 638). Putnam (2000) discusses the inter-relationships that develop among members of religious institutions that

extend beyond their common beliefs. This "connectedness" generates a sense of community and mutual responsibility to provide social assistance to fellow members in times of need (Putnam 2000, 67). In the context of human encounters with hazards, these internal and external linkages form part of the social capital available to communities that sustains livelihoods and provides the social protection needed during periods of environmental stress (Cannon 1994; Bebbington 1997; Ford et al. 2008; Birkenholtz 2009; Mark et al. 2010; Valdivia et al. 2010; Lazarus 2014: 638 – 639).

The quality of these relationships is dependent on the aspects of *embeddedness* and *autonomy*. Embeddedness explains the relationships that exist within society through social ties, cultural practices, and political affiliations that determine what opportunities and constraints are present. Autonomy refers to the relative freedom an individual possesses that enables him/her to establish networks outside the community (Granovetter 1985). Recognizing that these two aspects of social capital are not mutually exclusive, Woolcock (1998) rephrases embeddedness and autonomy as they exist at the micro and macro levels. Embeddedness at the micro level is reflected in the integration of social networks that provides members of a group with financial and material resources (Echánove and Steffen 2005). Putnam (2000) refers to this as *reciprocity*, wherein groups of individuals are engaged in exchanging information and resources that benefit them both in the short-term and in the long-term. Autonomy allows members the freedom to establish linkages outside the social structure in order to engage in activities that supplement the benefits derived from being part of a group. At the macro level, embeddedness describes the synergistic relationship between the state and civil society that functions to serve the needs of the community. The effectiveness of this relationship is dependent on the level of accountability and transparency of government institutions, which Woolcock (1998) terms as "organizational

integrity" (168). Therefore, embeddedness and autonomy must function complementarily to generate social capital (Woolcock 1998; Lazarus 2014: 639).

The interaction of embeddedness and autonomy is heavily dependent on the prevailing social structures and norms that provide opportunities to some and pose obstacles to others. Sen (1981) highlights the role of power dynamics in a particular economic system that dictates how people manage and use their labor, assets, and production capabilities. Wisner et al. (2004) articulate this as *structures of domination* wherein individuals and groups with higher standing in the social hierarchy exercise greater agency in determining the use and allocation of resources. This is illustrated in a case study of Indonesian farmers where local government policy favors wealthier farmers in the allocation of land even though the type of crops cultivated is less profitable (Bebbington et al. 2006). In another example involving the Afar tribe in Ethiopia, participation in local social institutions and relations is a vital part of livelihood security as it creates a framework of debts and obligations wherein goods and services are exchanged. These frameworks allow the tribe to function autonomously as it tends to be marginalized from mainstream society (Davies and Bennett 2007; Lazarus 2014: 639). Political participation is one way to overcome the obstacles present within a social structure as it creates awareness and improves the agency of under-represented groups (Putnam 2000). Beatley (2009) highlights a model developed by Easton (1965) that takes a systems view on how local social and political dynamics play out. A set of complex interactions between local actors results in programs and plans being developed (outcome). Easton's model recognizes that the social and political contexts of a given location are dynamic and are influenced by competing interests of actors and stakeholders and broader macro processes.

Edwards and Foley (1997) present another dimension to the discussion on social capital by recognizing the dilemma when distinguishing what social capital *is* and what it *does*. Does social capital constitute the social frameworks that make social interaction possible? Or is it the quality of the relationships that results from these frameworks and the benefits derived from them? Or is it both? In the context of disasters, social networks can provide people the mechanism to access financial and material resources. Furthermore, the strength of linkages with government institutions increases the likelihood of peoples' demands being heard as well as the level of cooperation during the recovery process (Olson 1965; Hirschman 1970; Beggs, Haines, and Hurlbert 1996; Bebbington 1997; Mohan and Mohan 2002; Holt 2008). This seems to suggest that social capital addresses the third question put forward by Edwards and Foley (1997) that it combines the social frameworks and the benefits arising from them. A study conducted by Baker and Patton (1974) on the attitudes toward hurricanes found that awareness of peoples' rights in claiming support from the state is dependent on education levels. This was captured in the answer to a survey question by respondents with low education levels that they did not think the government or other support networks could help minimize damage from hurricanes. It addresses that component of the second query put forward by Edwards and Foley (1997) that it is the quality of social relations that exists within a given framework that aids in the development of social capital. In the context of disasters, social capital supports the overall effort expended by the affected population to recover from the impacts of the event and to adapt to similar events in the future (Lazarus 2014: 639).

Social capital can play an important role in building resilience. Wisner et al. (2004) consider social protection as the systems in place to ensure disaster preparedness. These include social relations between citizens, local government, and the broader regulatory framework that

codify the development and maintenance of infrastructure, resource flows, and services (Bebbington 1997; Mohan and Mohan 2002; Holt 2008). The linkages that result from participating in a given social structure will determine the level of adjustments undertaken by the population. Given that social capital provides the setting for other forms of capital to be used, allocated, and accessed, it is integral to developing the asset portfolio of a community. Drawing from the previous example of the Afar tribe, social frameworks provide productive linkages for purchasing staples and trading in milk products that supplement household incomes (Davies and Bennett 2007). Therefore, social capital plays an important role in how people manage levels of risk and how they cope with and adapt to changes in the environment (Lazarus 2014: 639 – 640).

The role of social capital in building resilience is connected to the broader concept of sustainability. Access to resources that strengthen and sustain peoples' livelihoods over time is tied to cultural practices and entitlements that are embedded in a given social structure (Burton, Kates, and White 1978; Sen 1981; Chambers and Conway 1991). Within the context of natural disasters, sustainability is defined as the ability to ''tolerate—and overcome—damage, diminished productivity, and reduced quality of life from an extreme event without significant outside assistance''(Mileti 1999, 4). An environment that is stressed by unsustainable practices may experience more severe environmental hazards (Mileti 1999). Sustainability is also relevant in the contexts of planning, resource management, and infrastructure development (Zheng et al. 2011; Atkinson-Palombo and Gebremichael 2012). It follows then that the sustainable use of resources acquired through social capital helps build long-term resilience. The level of resilience of a community will determine the probability of being negatively impacted by a hazard event, which is defined as hazard risk (Tobin and Montz 1997; Wisner et al. 2004).

2.5 Interpretations of Hazard Risk

Risk is defined by Kates, Hohenemser, and Kasperson (1985) as "threats to human beings and what they value" (21). This definition is associated with White's characterization of potential losses as being a measure of the social impact of a hazard event. It takes into account the cumulative effects of damage to physical property, death, economic losses (interruptions to commercial activity that affect livelihoods), and the costs involved in re-occupation and rehabilitation (White 1945; White et al. 1958; White 1964; O'Hare 2001). White (1964) later advanced the method of estimating losses through a cost-benefit analysis, comparing the change in estimated losses with adjustments to scenarios where no adjustments were undertaken. There is a general consensus that risk and the root causes of peoples' vulnerability are inter-related (Chan and Parker 1996; Cutter 1996; Adams and Mortimore 1997; Alexander 2000; Kasperson, Kasperson, and Dow 2001; Wisner et al. 2004; Ford et al. 2008). The potential source of the risk (the event), the impact of the risk itself (whether high or low), and the frequency of the event are sub-elements of risk (Miller 1981; Cutter, Michell, and Scott 2000; Lazarus 2014: 640). Wisner et al. (2004) propose a pseudo-equation, $R = H x V$ to highlight the link between the event (hazard) and peoples' vulnerability that determines the potential to sustain loss (risk). Burton, Kates, and White (1978) identify magnitude, frequency, and areal extent to be the main criteria to assess the potential risk posed by a hazard event. Measuring the magnitude of an event can vary depending on the type of hazard. For example, the physical dimensions of earthquakes as measured on the Richter scale will differ from hurricane intensity recorded on the Saffir-Simpson scale. The magnitude and frequency of an event determine not only potential losses in human and monetary terms, but also the strategies and resources deployed to respond to the event (Burton, Kates, and White 1978).

Risk is also rooted in social structures and policies that are intended to improve the livelihoods of people. The disparate power relationships that exist in a hierarchical social structure will determine how resources are allocated and who benefits (Wisner et al. 2004; Bebbington et al. 2006). Putnam (2000) observes that formal and informal relationships that develop through membership in religious institutions and political participation are dependent on the extent to which existing social frameworks allow individuals and groups to engage with others. This exchange determines what mechanisms are available to people to access resources and what strategies are adopted to sustain livelihoods in the face of environmental changes. Adaptation strategies undertaken to minimize impacts from hazard events can influence peoples' livelihoods and their access to social capital over time. These mechanisms have the effect of pushing people through periods of high and low vulnerability, which in turn perpetuates the risk of being negatively impacted by changes in the environment (Harding and Parker 1974; Comfort et al. 1999; O'Hare 2001; Holling, Gunderson, and Ludwig 2002; Turner et al. 2003; Cutter et al. 2008; Jim, Yang, and Wang 2010; Mwanukuzi 2011; Birkenholtz 2012; Lazarus 2014: 640).

Wyte and Burton (1980) state that risk assessments require analyzing the causes and effects of complex relationships within the physical and social environment. The effects of humans engaging with the environment can contribute to the risk generated by the physical characteristics of the hazard itself. For example, White's work on flood zones highlights the risk generated by people choosing to settle in flood plains (White 1945; White et al. 1958; White 1964). The probabilistic character of risk is heightened by the areal extent of the hazard event. If the impacts of an event are widespread, it is likely that peoples' experience with identifying and responding to the threat will vary from place to place, which in turn makes planning for

contingencies difficult. It filters in to the decision making process associated with determining how response and mitigation policies are formulated and implemented (Whyte and Burton 1980).

The social dimension of risk has been addressed through the formulation of frameworks that recognize the complex inter-relationships that exist among people and their livelihoods within an established social structure. The Sustainable Livelihoods Framework is designed to identify solutions to reduce poverty through a comprehensive study of social and institutional frameworks that determine how livelihood assets (different forms of capital) are used to generate productive livelihood outcomes (i.e. increased income, improved political agency, food security etc.) (Swedish International Development Cooperation Agency 2014). The *BBC* framework developed by Bogardi and Birkmann (2004) and by Cardona (1999, 2001) builds on the Sustainable Livelihoods Framework by integrating the social, economic, and environmental components of sustainable development to assess risk associated with vulnerable populations. The focus of this model is on assessing coping capacity and how an exposed population manages social, economic, and environmental assets to reduce the risk of being negatively impacted by unexpected events (Birkmann 2006). The application of the BBC model is illustrated in a case study evaluating the impacts of coastal hazards in Sri Lanka. Coping capacity is evaluated based on social networks and membership in local organizations. It was found that only a small percentage of the population is engaged in local organizations and that membership did not contribute significantly to improving disaster preparedness. In this case, the presence of informal social relations and kinship ties played a significant role in assisting people in the recovery process (Birkmann, Fernando, and Hettige 2006). These findings reveal that while frameworks oriented towards sustainability strive to understand the social and regulatory contexts that influence vulnerability, they are limited in capturing the intricate milieu of informal

relations that characterizes local communities (Swedish International Development Cooperation Agency 2014; Lazarus 2014: 640).

An attempt is made to address the impact of social relations at the local level through the Community-Based Risk Index developed by Bollin and Hidajat (2006). An additive model is proposed where risk is computed using four factors - the hazard, exposure, vulnerability, and coping capacity. A constant weighting scheme is applied to ensure each component is recognized as having equal importance. In its application, it is evident that the index is primarily concerned with the impacts of an event. For example, the indicators applied to assess coping capacity in the context of the Indian Ocean tsunami in Indonesia relate to the distribution of risk maps and the effectiveness of early warning systems (Bollin and Hidajat 2006). By taking an event-based approach, the Community-Based Risk Index supplements the long-term issues of preparedness and resilience addressed by the Sustainability Livelihoods Framework and the BBC model (Lazarus 2014: 640 – 641).

Putnam (2000) presents empirical evidence in the form of a *social capital index*, evaluating how civil liberties are related to civic engagement, which is the cornerstone of social capital. The metrics measuring civil liberties, such as income equality and gender equality, are assessed on an ordinal scale along the social capital index. It is found that states perform better on the social capital index where civil liberties are promoted and maintained than in states where inequalities exist. Social capital is also responsible in creating the conditions for improvements in income equality and tolerance, thereby emphasizing the role of embedded relationships in building community resilience (Woolcock 1998; Putnam 2000).

The role of social networks in framing peoples' *perception* of hazard events is another area that has generated interest in the sphere of vulnerability and risk assessments. Perception of

risk, in particular, is filtered through social, environmental, and psychological factors that make assessment and responses challenging (Tobin and Montz 1997). In Kasperson et al. (2005), the authors propose a conceptual framework, which they term the *social amplification of risk.* It explores how risk is communicated to the public, how it is received and interpreted, and what impacts it has at the micro and macro levels. Risk is communicated through *social amplification stations* in the form of expert knowledge, the media, social organizations, and social networks. The way in which channels of communication are used by these stations varies and has the ability to amplify or attenuate the message about the associated risk. Informal communication networks that exist between friends, family, and relatives play a part in how the information on risk is interpreted. It has to do with past experiences with similar events, cultural bias, and how members of the social network serve as reference points in shaping individual perceptions of the risk (Kasperson et al. 2005). Access to social capital and how it is used to receive and assimilate information play a key role in determining overall risk in the context of environmental disasters. Risk then is not only articulated in the potential loss of life, damage to physical property, and economic losses (White 1945; White et al. 1958; White 1964; O'Hare 2001), but also in the way in which it is perceived by a particular group of people (Kasperson et al. 2005; Lazarus 2014: 641).

Jaeger et al. (2001) identify two key elements of risk: *possibility* and *uncertainty*. Risk implies that an event or outcome is likely to occur (possibility), but its occurrence is uncertain (it cannot be predicted with certainty). Humans evaluate future outcomes based on present actions. These outcomes may be favorable or unfavorable based on individual perceptions, which in turn, affect the risk associated with the event. The level of uncertainty that is translated to risk occurs only when people have a vested interest in the outcome of a particular event that can

significantly change existing conditions. The authors re-specify the existing theory of rational action as the *rational actor paradigm (RAP)*. The RAP essentially consists of two components: a social universe (population of humans) and the social order (the social structures and mechanisms that facilitate rational action). The latter is considered normative on the assumption that the existing social order is based on sound principles. The RAP is grounded in the premise that interactions between members of a social structure strive to reach equilibrium, a state that is considered ideal as it satisfies the expectations of all actors (Jaeger et al. 2001; Lazarus 2014: 641).

Reaching such an equilibrium is challenged when risk is played out in the context of hazard events. It has already been established that risk is determined by perception and awareness (Baker and Patton 1974; Kasperson et al. 2005), which are strongly influenced by the quality of social capital circulated among the members of a group. Social capital helps build social relations, determines what information is shared, and establishes personal affiliations to place. An example of the latter is often visible in the emotional ties people have to their personal property. Based on past experiences, people are likely to weigh the costs and benefits of leaving their property unattended when faced with evacuation versus remaining in their homes and face the consequences of the impact of an event. Although the frequency of being exposed to an event is likely to create greater awareness, it is found that people are more inclined to underestimate the level of risk when personal assets and interests are at stake (Sjöberg 1987; Tobin and Montz 1997; Jaeger et al. 2001; Lazarus 2014: 641).

2.6 Place-based Assessment of Hazard Risk

Developing models that capture the multi-dimensional character of how hazards and disasters play out is challenging. Attempts to formulate models that address the biophysical and

socio-economic vulnerability of populations exposed to hazard events have met with some success. These models address the issues of livelihoods, social capital, and place in varying degrees. The *hazards-of-place model* developed by Cutter (1996) is one that attempts to incorporate the various components of vulnerability, risk, and resilience. The model recognizes that risk and mitigation strategies are countervailing forces that interact to determine the hazard potential or the potential for loss. The model also looks at vulnerability from both a biophysical and social perspective (Cutter 1996; Cutter, Mitchell, and Scott 2000). The social dimension of vulnerability is rooted in the social structures that govern peoples' day to day lives, which points to the importance of social capital. Attempts to operationalize the hazards-of-place model have focused on addressing components of the model. The Social Vulnerability Index (SoVI) developed by Cutter, Boruff, and Shirley (2003) works primarily with socio-economic and demographic variables linked to personal wealth, occupation, age, and ethnicity. As for addressing the place component, the model displays some versatility in tackling hazards affecting different geographical scales (Lazarus 2014: 641 – 642).

The *disaster resilience of place (DROP)* model addresses the impacts of hazards from the perspective of community resilience (Cutter et al. 2008). The model has four components, *antecedent conditions*, *coping responses, absorptive capacity,* and *adaptive resilience*. Antecedent conditions are tied to characteristics that are inherent in the population that determine overall vulnerability and resilience. These inherent characteristics are linked to external factors related to social systems, natural systems, and the built environment. Coping responses include the strategies in place to respond in the immediate aftermath of an event such as, evacuation, temporary shelters, and communication networks. Absorptive capacity defines the ability of a community to absorb the impacts of an event utilizing existing coping responses (Cutter et al.

2008). This is articulated as a threshold. The threshold can be exceeded when the event is catastrophic where existing mechanisms are insufficient for the community to respond or when existing mechanisms are inadequate even when the event is less catastrophic. The last component, adaptive resilience, is accomplished through improvisation and social learning (Cutter et al. 2008). The interaction of these components determines the capacity of the community to respond and is a testament to its overall resilience (Lazarus 2014: 642).

The *coupled human-environment systems* model, proposed by Turner et al. (2003), considers factors that are at play at the micro and macro levels thereby addressing vulnerability at multiple scales. Multi-scalar dynamics are embedded in the sensitivity of the system and are determined by the level and quality of the interaction between human settlements and the environment. Institutional frameworks and livelihood systems place a burden on environmental resources, which in turn makes the environment system more sensitive to hazard events. How sensitivity is addressed is tied to the response undertaken to cope with changes. These responses are either individual or collective and can comprise a combination of programs, policies, and individual action that is designed to increase the coping capacities of the human system (Turner et al. 2003). The framework adopts a comprehensive approach that considers the characteristics of the exposed population, its interaction with environmental perturbations, and the mechanisms in place to build long-term resilience. The coupled human-environment systems approach is designed to address the shortcomings of previous vulnerability models, particularly those related to place-based distinctions, feedback loops, and inter-relationships between human and biophysical systems (Turner et al. 2003; Lazarus 2014: 642).

Wisner et al. (2004) recognize that disaster risk is generated from a combination of factors involving the characteristics of vulnerable populations, the scale and magnitude of the

hazard, and environmental factors embedded in social structures and processes that produce vulnerability. Risk is articulated in the pseudo-equation, $R = H \times V$, where *H* represents the event (hazard) and *V* the number and characteristics of people affected by the event (Wisner et al. 2004). The equation not only accounts for the physical aspects of the event, but also addresses the social dimension by observing the characteristics and the presence of vulnerable populations. In this case, the definition of risk is viewed as a *condition* rather than a manifestation of physical and monetary losses sustained by the exposed population. The *Pressure and Release (PAR)* model, developed by Blaikie et al. (1994), attempts to capture the dynamics of the social and physical environment under conditions of a hazard event. Environmental conditions are assessed at the macro, meso, and micro levels in order to establish the root causes of peoples' vulnerability. The processes that generate vulnerability and the impact of the hazard event create pressure on the system that leads to varying levels of risk. In order to relieve the pressure on the system, it is necessary to consider coping mechanisms and adaptive strategies that contribute to resilience, which in turn counters the effects of vulnerability (Blaikie et al. 1994; Wisner et al. 2004; Lazarus 2014: 642 - 643).

The *Access Model* expands on the PAR model by addressing peoples' access to resources that determines resilience. It presents a framework for a detailed assessment of the social and economic processes that dictate how income, assets, and resources are distributed. By recognizing these mechanisms, the Access Model identifies components of the social system (livelihoods, social networks etc.) that determine levels of vulnerability as they are likely to change from place to place (Wisner et al. 2004). In both the PAR and Access models an analysis of livelihoods and social capital that play a part in building resilience is deemed necessary when defining the vulnerability component of the risk equation (Lazarus 2014: 643).

2.7 Conclusion

Social vulnerability is viewed as a key determinant in translating a hazard event to a disaster. It is concerned with livelihood issues relating to income, occupation, and access to resources and with social capital that provide people the means and the connectivity to sustain their livelihoods. Security of livelihoods and access to social capital are key determinants in building resilience. Resilience is articulated not only in the capacity of communities to cope with the impacts of an event in the short-term, but also in how they adapt to future changes in the environment.

Developing models that capture the multi-dimensional character of social vulnerability is challenging. Attempts to formulate models that address the biophysical and socio-economic vulnerability of populations exposed to hazard events have met with some success. These models address the issues of livelihoods, social capital, and place to varying degrees. Recent trends in research indicate a movement towards addressing resilience in how human settlements cope with and recover from the impacts of hazard events. The development of concepts related to vulnerability to risks and hazards has yet to address the complex dynamics of coupled-human environment systems. Capturing scalar dynamics in coupled human-environment systems and operationalizing them in existing compositions of vulnerability pose many challenges. The severity, cumulative and/or reversible impacts of decisions on human settlements, and the distribution of impacts both in the short-term and in the long-term need to be examined as they determine levels of vulnerability that result from human-environment interactions (Freudenburg 1999). Finding common ground in quantifying these dimensions requires the participation of stakeholders - the individuals and groups involved in the decision making process - and the relationships (linkages) among these participants. The proposed risk assessment model builds

on the inter-relationship between livelihood mechanisms and social capital as articulated in the literature. The theoretical framework of the model is discussed in Chapter 3.

Chapter 3

The Hazard Risk Location Model: A Conceptual Framework

3.1 Introduction

Understanding the social and economic impacts of disasters is integral to the development of improved mechanisms for disaster management. Vulnerability is “the susceptibility to be harmed” (Adger 2006, 269) - it describes the likelihood of a human population to be negatively impacted by a hazard event. The vulnerability of people living in hazard prone areas is determined by how extreme events interrupt the processes of everyday life that support livelihoods and social networks that are vital to human existence. Given that the impact of disasters plays out within a social-ecological continuum, equal attention to livelihood mechanisms and social networks has been addressed in several studies undertaken in different contexts (Degg and Chester 2005; Eriksen, Brown, and Kelly 2005; Valdivia et al. 2010; Conchedda, Lambin, and Mayaux 2011). The approach adopted in the implementation of structural and non-structural measures to minimize the impact of disasters has been largely event-based i.e. driven by the characteristics of the event and its damage potential. While this approach is important in minimizing loss of life and damage to property, the root causes of peoples’ vulnerability have not been adequately addressed in the policy arena. The role of livelihoods and social capital in helping people achieve a level of self-protection and social protection (Cannon 1994; Wisner et al. 2004) is an area that is relatively under-studied in hazards research. The dynamics of people and the social structures that govern their everyday lives are important aspects in the study of vulnerability and risk in the context of disasters (Burton, Kates, and White 1978; Turner et al. 2003; Wisner et al. 2004).

This research addresses the following questions (Lazarus 2014):

1. How important are safety nets to people exposed to environmental disasters?
2. How important is the quantity of social capital in minimizing the impact of an event?
3. How are individual wellbeing and social capital inter-related in determining risk associated with environmental disasters?

This research defines social capital as the mechanisms in place that build capabilities. Capabilities are the qualities that are inherent and acquired by people that enable them to carry out activities in the maintenance of livelihoods (Sen 1981; Chambers and Conway 1991). Social networks and institutional frameworks provide linkages for individuals and groups to access resources for daily functions and to cope with unexpected changes in the environment. They offer a level of social protection by way of the inter-relationships that exist within members of a community and the branches of government, social institutions, and the private sector that provide access to resources and services (Bebbington 1997; Mohan and Mohan 2002; Wisner et al. 2004). For example, participation in social institutions is a vital part of building relationships within the Afar tribe of Ethiopia as it provides the community a self-sustaining mechanism to acquire and exchange goods and services (Davies and Bennett 2007). Furthermore, the linkages that exist within a social structure help in the adoption and implementation of adaptation strategies like evacuation, public awareness, and engineering solutions to counter the impacts of hazard events as illustrated in the case study in Shrewsbury, England (Harding and Parker 1974). As these examples illustrate, social capital plays an important role in building resilience.

3.2 Model Framework

The concept of social vulnerability forms the basis for this research. A model is proposed to determine the relationships that exist between exposure, coping ability, and disaster risk. Existing frameworks, such as the Sustainability Livelihoods framework (Swedish International Development Cooperation Agency 2014) and the BBC model (Cardona 1999, 2001; Bogardi and Birkmann 2004), provide a sound conceptual basis to study the social and institutional structures in which peoples' livelihoods and resilience play out. There is, however, space for contributions to be made in evaluating the linkages between social capital and access to resources that contribute to building resilience over time. The model proposed in this study, the Hazard Risk Location Model (HRLM), focuses on the concept of capabilities as articulated by Sen (1981) where access to resources is a key indicator. The model is concerned with evaluating how social relations (linkages) embedded in social capital foster (or inhibit) access to resources, which in turn has an impact on livelihood mechanisms and outcomes. It not only addresses how people respond to and cope with events in the short-term, but also evaluates how they adapt and build resilience over time (Lazarus 2014: 643).

The framework of the HRLM links resilience to the quantity of social capital. Strategies adopted by people to build resilience are related to social and economic systems, infrastructure, institutions, and organizations that determine how flexible a community is when responding to an event (Cutter et al. 2008). In general, the resources accessible to communities through existing social relations help improve their capacity to cope with environmental stresses. In a case study conducted in the Andean region of Altiplano, the findings revealed that social institutions providing short-term loans are a valuable resource to farmers to increase and maintain yields during periods of climate variability (Valdivia et al. 2010). Conversely, social

structures may exclude some groups from accessing resources, which in turn undermine their ability to cope with environmental changes. (Eriksen, Brown, and Kelly 2005; Birkenholtz 2009). An example of this is illustrated in the social hierarchy that prevails in Rajasthan, India where access to water resources is determined by the Hindu caste system (Birkenholtz 2009).

The resources and services provided by social capital determine to what extent people are able to exploit opportunities to improve livelihoods (Sen 1981; Chambers and Conway 1991). A livelihood is a mechanism by which people engage in productive activities to meet basic needs and is tied to employment. Securing and maintaining a job improves peoples' ability to cope with changes in the environment as it provides a level of security (Cannon 1994). On the other hand, even short spells of joblessness can increase a household's susceptibility to be adversely impacted by hazard events. The network of social relations embedded in social capital provides opportunities and pathways to secure employment (Sen 1981; Chambers and Conway 1991). Therefore, the resources and services provided by social capital at the local level are reflected in unemployment patterns that play out at the macro level (Sen 1981; Mansfield 1986; Gordon 1987).

The HRLM is based on the following assumptions: (i) the impact of the hazard and the exposed population are known; (ii) coping ability (i.e. resilience) is treated as an outcome of a causal relationship with other variables, and (iii) model projections are scale dependent. The first assumption focuses on the characteristics of the event and its interaction with the human population. It also emphasizes resilience where peoples' livelihoods and social capital determine how they are impacted by an event (White 1945; Cannon 1994; Alexander 2000). These interactions are illustrated in the conceptual framework of the HRLM presented in Figure 3.1. Given that vulnerability is manifested in the interaction of a human population (B) with an

external event (C), how people adjust to the event is a measure of their resilience, reflecting a population's "social capacity to absorb and recover from the occurrence of a hazardous event" (Smith 1992, 25). The capacity to absorb and recover from unexpected events is tied to social capital (A) and the mechanisms it affords for people to improve livelihoods (Sen 1981; Chambers and Conway 1991; Moser 1998; Bebbington et al. 2006; Lazarus 2014: 643).

Opportunities available for gainful employment or the lack thereof are a product of the efficacy of social networks (linkages) embedded in social capital and are reflected in unemployment levels. Low unemployment levels are indicative of a community's ability to cope with changes in the environment, whereas high unemployment levels represent a scenario where socio-economic well-being is compromised. The presence or absence of social capital and the resources and services provided by social networks determine a community's ability to cope with changes in the environment. The arrows leading from (A) to (e) and (f) in Figure 3.1 illustrate the relationship between social capital, unemployment levels, and individual well-being that is tied to the second assumption of the HRLM, which states that coping ability or resilience is an outcome of factors that represent resources and services provided by social capital (Lazarus 2014).

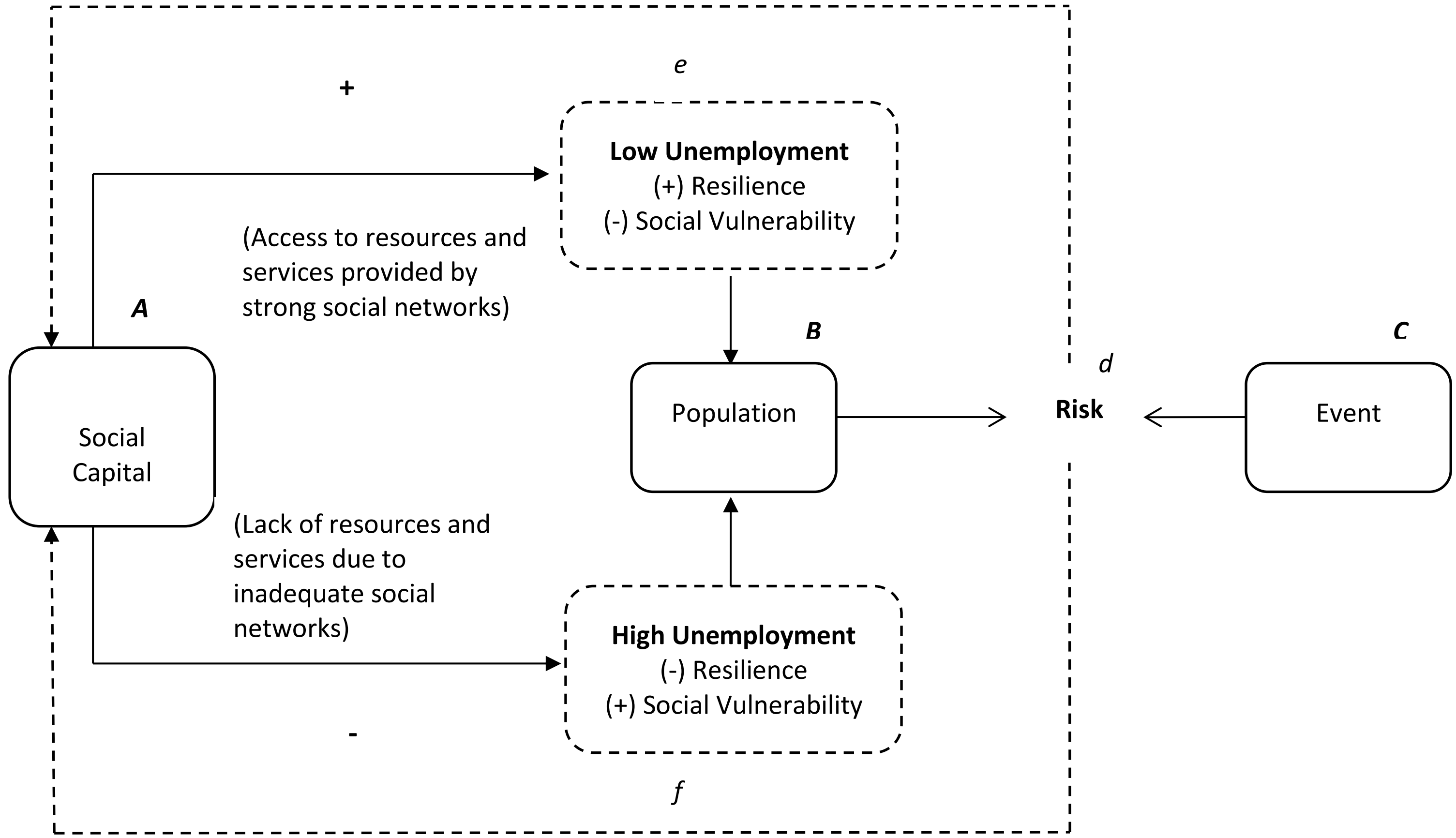

Figure 3.1 - The inter-relationships between social vulnerability, resilience, and risk (Lazarus 2014)

3.3 Hypotheses

The HRLM focuses on the socio-economic condition of the population that is reliant in part by social capital and livelihoods that determine levels of vulnerability and resilience. This is the premise of the first research question. The first research question asks, how important are safety nets provided by social capital to people exposed to environmental disasters and forms the basis of two hypotheses:

Hypothesis 1

H_0: The services provided by social capital do not have an impact on individual well-being during an environmental disaster.

H_1: The services provided by social capital affect individual well-being during an environmental disaster.

Hypothesis 2

H_0: Changes in social capital are uniform across all counties in the study area during a disaster.

H_1: Social capital varies across counties in the study area during a disaster.

The second assumption treats resilience as an outcome where the ability of a community to cope with and recover from an event is tied to factors that increase or decrease vulnerability (Cutter et al. 2008). Resilience then stands as the antithesis to vulnerability as illustrated in Figure 3.1 where increasing resilience is accompanied by decreased vulnerability (e), and diminishing resilience is linked to increased vulnerability (f). The quality of livelihood mechanisms and social capital will determine to what extent the exposed population (B) is able to respond to the impacts of the event. For example, the quantity of educational, professional, and employment services emphasizes the role of social capital through the institutional frameworks that support peoples' income earning capacity with a view to improving livelihoods (Bebbington 1997; Adger 2000; Ford et al. 2008; Holt 2008; Lazarus 2014: 643).

The experience of dealing with hazard events generates knowledge through lessons learned and may call for new and innovative strategies to sustain socio-economic conditions in the future. This feedback is illustrated in Figure 3.1 by the dotted arrows leading from (d) to (A) where risk can have a positive (+) or negative (-) effect on livelihoods and social capital. Exposure to hazard events drives communities to improve disaster preparedness by adopting improved structural and non-structural solutions and is an example of how these encounters can improve livelihood security in the long-term. On the other hand, adaptation strategies that are undertaken in response to previous exposure to events as in the case of Shrewsbury can have a negative impact on sections of the population that makes them more vulnerable to the next event. The changes made to social structures and relations that govern livelihood strategies will determine a community's adaptability over the long-term (Lazarus 2014: 644).

The second research question asks how important is the quantity of social capital in minimizing the impact of an event. The hypotheses that address these issues are as follows:

Hypothesis 3

H_0: The quantity of social capital is not a determinant in peoples' ability to cope with an event.

H_1: The quantity of social capital is a factor in determining peoples' ability to cope with an event.

Hypothesis 4

H_0: Coping ability is relatively uniform across the study area.

H_1: Coping ability varies across the study area.

The third and fourth hypotheses are tied to the assumption, which states that the model is designed to address trends within the place of assessment and therefore is limited in capturing multi-scalar dynamics. Since the HRLM is concerned with social capital and its impact on

livelihoods, the framework supports a community level assessment of resilience and risk. Like the Community Based Risk Index (Bollin and Hidajat 2006) and the BBC model (Cardona 1999, 2001; Bogardi and Birkmann 2004), it is designed to study the social and economic characteristics of a segment of the population within a specific administrative unit, such as a county, census block, or district. The HRLM focuses on the social and institutional context of the study area in which social capital is generated and utilized, thereby following a place-based approach to risk assessment. Unlike the multi-scalar model proposed by Turner et al. (2003), an analysis of interacting factors across different scales is not built into the HRLM, because it is primarily concerned with how social capital plays out at a particular scale, such as the county level. This approach focuses on the inter-relationships that exist within a social structure and how these linkages help advance peoples' ability to improve their livelihoods. The model also accommodates a comparative assessment of risk through an analysis of model results across sub-units in the study area. For example, the HRLM can be applied to census blocks or counties in a coastal region that is prone to hurricanes, and the results compared against some threshold (Lazarus 2014: 644). A threshold is a point of reference that functions as a benchmark to compare the attributes of units that fall above or below this point. By adopting this approach the HRLM avoids the problems associated with aggregated assessments (White et al. 1958; Birkmann 2007) and recognizes Tobler's rule of spatial non-stationarity (i.e. nearer things are more related than distant things) (Charlton and Fotheringham 2009).

The third research question addresses how coping ability, exposure, and the characteristics of the hazard event contribute to overall risk. The hypotheses relevant in this case are articulated as follows:

Hypothesis 5

H_0: Risk is determined by a population's ability to cope and is not related to other factors.

H_1: Risk is determined by peoples' coping ability and its inter-relationship with other factors

Hypothesis 6

H_0: The relative contribution of the impact of the hazard, the population exposed, and coping ability is uniform across the study area.

H_1: The relative contribution of the impact of the hazard, the population exposed, and coping ability varies across the study area.

The hazard component (*H)* is the distance of each county from the Deep Water Horizon (DWH) spill site representing the environmental impact of the oil spill. Exposure (*E)* is represented by population density indicative of exposure, and unemployment rate functions as a surrogate for coping ability (C) and is derived from the regression analysis. The threshold analysis builds on the principles of relative distance to establish each observation's position along a continuum. A composite index score is developed using the hazard, exposure, and coping ability measures to assess the contribution of these components to overall risk.

3.4 Model Specification

The HRLM is proposed as an alternative framework and is based on re-specification of the risk equation of Wisner et al. (2004) as follows:

$$R = f\ (H, E, C)$$

Vulnerability is deconstructed to the sub-components of exposure *(E)* and coping ability *(C)* as observed by Ratick and Osleeb (2011). The risk factor *(R)* is treated as a latent variable recognizing what Wisner et al. (2004) consider as a condition that results from the interaction of

a vulnerable human population with a hazard event. The hazard component *(H)* is represented by some measurable impact of a hazard event, such as distance-decay from an oil spill. *E* is the exposure component, which is commonly represented by population density; and coping ability *(C)* takes into account peoples' livelihoods and access to social capital that determine overall risk (Lazarus 2014: 644).

Latent variables or factors are defined as exogenous as they are not part of a causal relationship. Instead, they are representative of the interaction between several other variables. A measurement variable, on the other hand, is a variable that has an intrinsic value attached to it, and that value is drawn from an observed sample. Measurement variables are defined as free parameters as they carry a value other than zero (Hoyle 1995; Kline 2011). *H, E,* and *C* are examples of measurement variables (values are estimated from the data), and the interactions of these variables determine the value of the latent variable, *R.*

As illustrated in Figure 3.2 the model framework aims to establish a relationship between a latent variable and a specified number of measurement variables. In this case, the risk factor or *R* represents a latent variable since its definition is determined by other factors, namely the hazard, the population exposed, and coping ability. The regression analysis forms the first step in developing the HRLM where the social dimension of vulnerability is articulated in part by coping ability of the population exposed to an event. The variables represented by x_1…….x_7 in Figure 3.2 are deemed to have a causal relationship with coping ability, represented by a proxy variable, such as unemployment rate. The regression analysis deals with the importance and contribution of social capital in sustaining livelihoods that are addressed in the first and second research questions.

The second step in the HRLM is an assessment of hazard risk, which is addressed in the third question. It aims to establish the relationship between a latent variable (risk) and selected measurement variables representing the hazard, exposure, and coping ability, and is carried out using a threshold analysis. Thresholds are defined and utilized in a number of ways of which two are commonly adopted in vulnerability assessments. First, a threshold is defined as an optimal state where attributes of vulnerability are combined to assess a unit's position or rank on an ordinal scale. Data envelopment analysis or DEA is an example of an optimization technique that sets the maximum vulnerability score as 1 to ensure that the scores of all other units do not exceed this level (Ratick, Morehouse, and Klimberg 2009). Second, a threshold is defined as a point of reference where units are assessed based on their position above or below the threshold (Luers 2005). This research builds on the latter and identifies the threshold as a point of reference that varies over time and compares each unit's position along a continuum of attributes representing components of the re-specified risk equation.

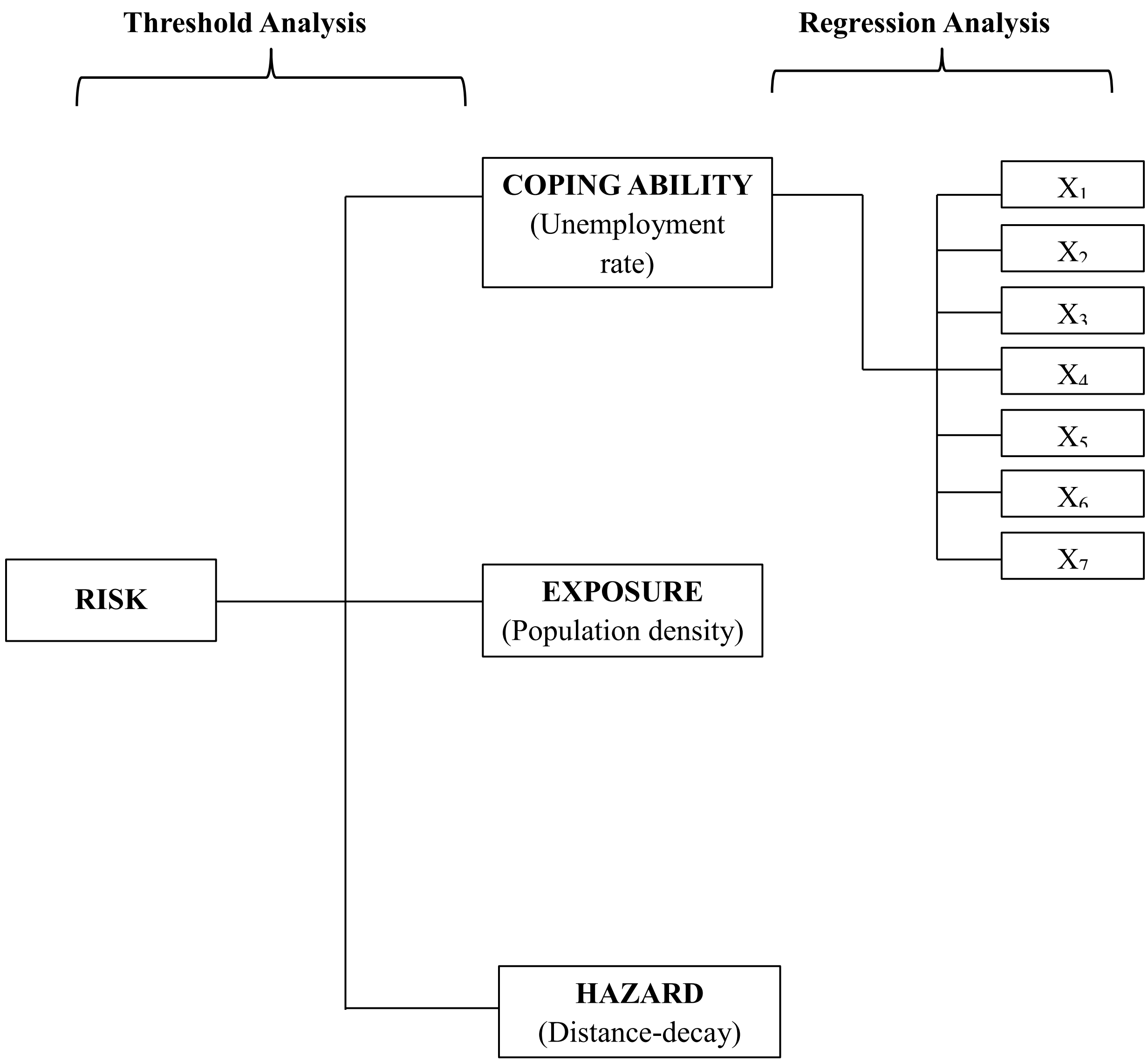

Figure 3.2 – Components of the Hazard Risk Location Model

3.5 Thresholds

A number of methods have been utilized to identify variables that represent the complexity of vulnerability. This has resulted in the development of composite indices where the variables that represent vulnerability are aggregated to provide a ranking system on which areas can be evaluated based on their vulnerability status. The inclusion of spatial data has added another dimension to vulnerability assessments that require a comparative analysis across geographical space. In a study on flooding in urban areas across the United States, White (1964) incorporated a threshold to conduct a cost-benefit analysis to measure the type of adjustments adopted to mitigate flooding. The threshold in this case was the mean annual damage sustained by a town where no adjustment was applied. The approach to developing vulnerability assessments has since paid close attention to issues of scale and weighting of variables.

Composite indices are widely used as a tool to aid in decision making. The ranking system when mapped provides the decision maker with a snapshot of differential vulnerabilities across geographical space. Composite indices, however, come with inherent shortcomings that can affect the decision making process. The issue of size versus composition arises when decisions have to be made whether raw numbers or densities should be used to represent different vulnerability attributes. Ratick, Morehouse, and Klimberg (2009) and Clark et al. (1998) argue that composition of vulnerable populations as a percentage of the overall population provides a meaningful measure of vulnerability over size. For example, if two areas have the same number of vulnerable people and the total population of the first is greater than the second, focusing on composition would identify the second area as being more vulnerable than the first. When evaluated solely on size, both areas are equally vulnerable. The issue of scale also poses challenges.

Ratick and Osleeb (2011) evaluate three weighting methods, namely weighted average (WA), ordered weighted average (OWA), and data envelopment analysis (DEA). DEA is an optimization technique that assigns weights to variables that increase vulnerability and increase coping ability where a geographic area's vulnerability score is maximized so that it is less than or equal to 1. This geographic area functions as a "frontier" (Molinero and Woracker 1996; Ratick, Morehouse, and Klimberg 2009) based on which all other geographic areas are evaluated. DEA is a measure of relative vulnerability where the numerator is the weighted linear combination of attributes that increases vulnerability, and the denominator, the weighted linear combination of attributes that decreases vulnerability (increase coping ability) (Ratick, Morehouse, and Klimberg 2009). There are a number of advantages to DEA over the WA and OWA methods. First, in DEA weights are objectively assigned to the attributes by the programming formulation unlike in WA and OWA where the allocation of weights is subjective. Second, standardization is not a requirement as changing the units of measure or importance weights does not change the DEA index score (Ratick, Morehouse, and Klimberg 2009). Last, the DEA is a measure of both ranking and degree of difference (Ratick and Osleeb 2011). A disadvantage of the DEA method is that it does not account for the relative importance of the attributes, which in some cases may be a drawback when addressing the root causes of vulnerability. Another disadvantage is that the DEA index score will change if spatial units are included or as changes in the scale occur, because DEA is designed to measure relative vulnerability (Ratick, Morehouse, and Klimberg 2009).

Based on the principle of relative distance as described in DEA, the research incorporates a threshold to evaluate variables that represent vulnerability and risk across counties in the study

area. Each county's measure on an indicator is linked to the threshold by calculating its position on this continuum using the following equation,

$$\frac{x_{(j)}}{TH} - 1$$

where, *x(j)* is the observed or predicted value of the variable in question for county *j*; and *TH*, the threshold value of the variable in question. The comparison of each county's position in relation to the threshold differs from the underlying techniques employed in DEA. The DEA uses an optimization technique where the index score of a selected case is maximized and constrained to not exceed 1. The case area functions as a frontier on which the other cases are evaluated for their relative vulnerability. The threshold in the DEA, therefore, is sensitive to spatial units that are added, which contain large attribute values (Ratick, Morehouse, and Klimberg 2009; Ratick and Osleeb 2011). The threshold proposed here is a point along a continuum that is moving over time and therefore differs from the principle of optimization employed in DEA. The sensitivity of the threshold is determined by macro processes, such as demand for labor, tax policies, and government expenditure, and unlike the DEA, will not change for a specific time period as spatial units are added to the model. Examples of thresholds in this case would be the national unemployment rate and population density. Each spatial unit (county) is evaluated based on its position above or below the threshold.

3.6 Scope of the Model

The HRLM is designed to accommodate the inter-relationships that exist between the human and biophysical environments through the perspective of community resilience. It addresses the criteria associated with the research questions - the importance of social capital, the quality and scope of social mechanisms, and the inter-relationship between individual well-being and social capital. The model is built on the following premises:

- The model links social capital to individual and community wellbeing that focuses on long-term resilience;
- The model recognizes that resources generated by existing social and institutional frameworks vary across space and accommodates a place-based assessment of disaster risk across a specific scale of analysis;
- The model accommodates positive or negative feedbacks resulting from peoples' experience with an event on existing social capital.
- The model considers the impacts of a hazard event on the population exposed and how they determine community resilience over time. Therefore, the assessment is specific to a particular scenario recognizing that each hazard event is unique in its characteristics and impacts (Lazarus 2014: 645).

A community's socio-economic standing plays a vital role in building its resilience over time. In view of this, planning is an important exercise that assists in identifying the potential impacts of hazards and what strategies are feasible and workable in a given context. Beatley (2009) refers to this as economic resilience where resources generated by existing social and institutional frameworks help communities to adapt and recover from the impacts of an event. Economic resilience is tied to the diversity of sectors operating within a given area and to the

functioning of businesses. Suggested strategies for building economic resilience include diversifying the local economy, contingency planning, the sustainable use of available resources, and establishing relationships with the community. Beatley's (2009) definition of economic resilience is closely tied to the observation made by Cutter et al. (2008) that adaptive capacity is determined by mechanisms embedded in social capital. The social and institutional frameworks that facilitate the accessibility and the allocation of resources will determine to what extent communities are able to cope with unexpected changes in the environment (Lazarus 2014: 645).

3.7 Conclusion

The proposed hazard-risk-location-model (HRLM) contributes to the discussion on place-based assessments of vulnerability and disaster risk. The model provides a mechanism to assess the patterns of risk across a selected region through a re-specification of the risk equation. It recognizes the importance of livelihoods in building the resilience of communities and approaches it by linking resilience to the presence or absence of social capital. Prevailing social and institutional frameworks determine how and where resources are allocated. By focusing on the impacts of a specific hazard event on the exposed population, the HRLM attempts to address the interaction between the biophysical and human environments in a given location. The HRLM recognizes that human interactions with hazard events result in complex and varied impacts. While capturing all of the myriad inter-relationships within coupled human-environment systems is beyond the scope of the model, it provides some insights into developing improved frameworks for vulnerability and risk assessments in the future (Lazarus 2014: 645).

The next chapter introduces the study area wherein the demographic, economic, and environmental characteristics of coastal counties in the Gulf of Mexico are explored. Chapter 5

discusses the methodology adopted in operationalizing the HRLM, and tackles issues relating to model specification, components, and techniques. Chapter 6 provides details on the data used in the analysis and includes data sources and a preliminary analysis of variables. This section is followed by the analysis of the data (Chapter 7) using techniques identified in Chapter 5. Results of the data analysis are discussed in Chapter 8 in the context of the hypotheses proposed in this section. Concluding comments and prospects for future work are presented in Chapter 9.

Chapter 4

The Study Area: Gulf Coast Counties

4.1 Introduction

Fifty six US counties across the states of Florida, Alabama, Mississippi, Louisiana, and Texas border the Gulf Coast. The economy of the Gulf coast is centered on fishing, tourism, and energy production. Climatic conditions in the Gulf of Mexico make coastal counties prone to hazard events, such as hurricanes, tropical storms, and flooding. In the last decade, major hurricane events namely Katrina, Rita, and Isaac have occurred in the region. The coastal population of the region increased by eleven percent in the period 2000 to 2008, making it one of the most densely populated regions in the United States (U.S. Department of Commerce 2010). In addition to natural disasters, the Deep Water Horizon (DWH) oil spill of 2010 was a major anthropogenic hazard event that impacted coastal counties in the Gulf. The magnitude of the discharge threatened coastal ecosystems and resources tied to fishing and tourism, and tested the preparedness of federal and local authorities to respond to the crisis. This chapter provides an overview of the demographic and socio-economic characteristics of Gulf coast counties and examines the impact of the DWH oil spill in the context of building community resilience to hazard events.

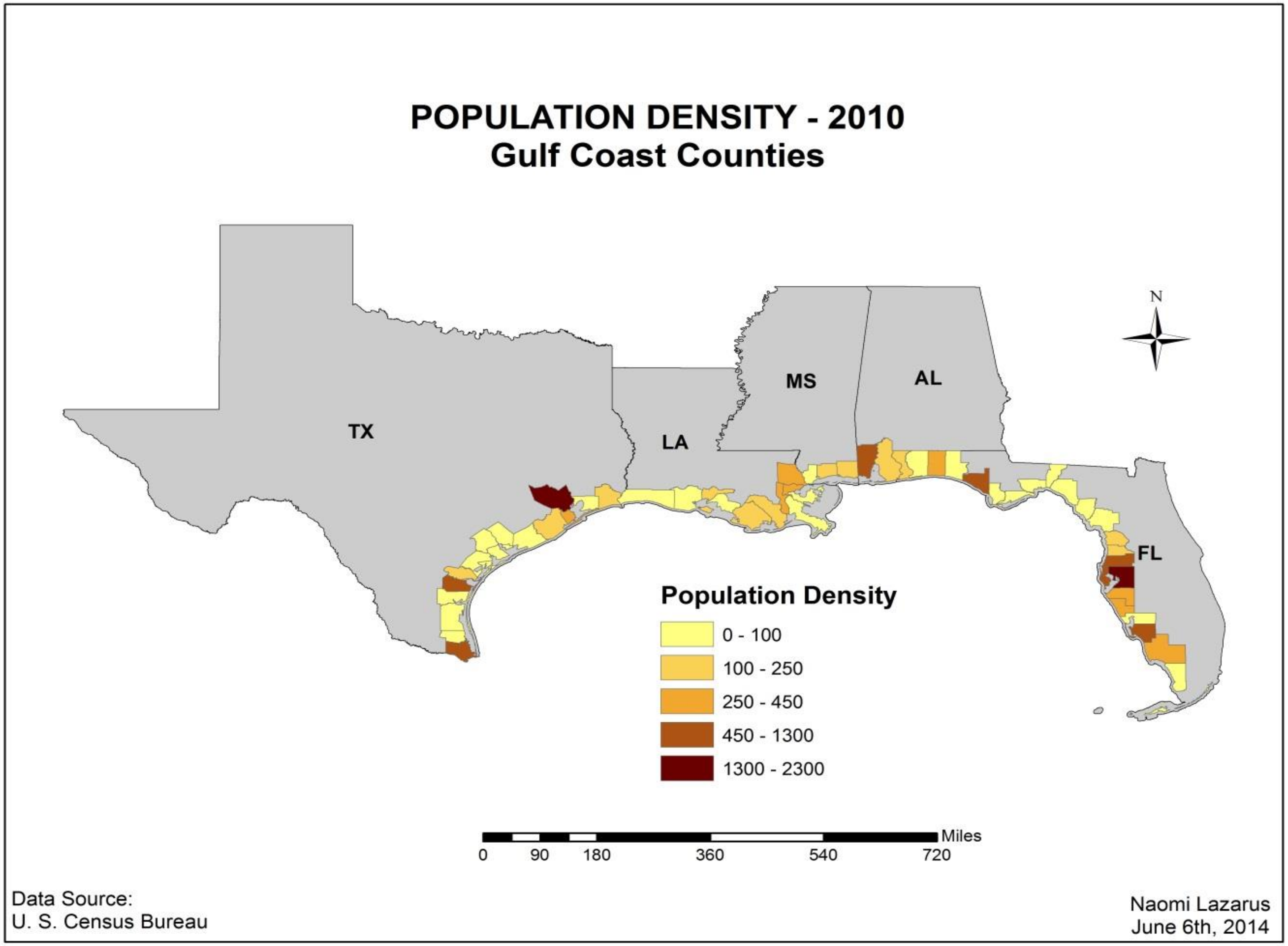

Figure 4.1 – Map of Population Density per square mile, Gulf Coast Counties

4.2 Population

The total coastal population of the United States is approximately 87 million. The Gulf Coast counties account for sixteen percent or 14.3 million (U.S. Department of Commerce 2010). Figure 4.1 illustrates that there is spatial variation in population densities within each state. Table 4.1 lists the population for the study area in 2010. Counties with large metropolitan areas tend to have higher population densities as in the case of Hillsborough County FL (Tampa), Harris County TX (Houston), and Mobile AL. Relatively high densities are also found in counties that are economically dependent on tourism such as, Orleans Parish (New Orleans) and Bay County FL (Panama City Beach).

Table 4.1 – 2010 Population Estimates for Gulf Coast Counties (Data Source: U. S. Census Bureau)

STATE	COUNTY	Total Population (2010)	Area (sq. miles)	Population Density
Alabama	Baldwin	182265	1538	118.51
	Mobile	412992	599	689.47
Florida	Bay	168852	252	670.05
	Charlotte	159978	2429	65.86
	Citrus	141236	1058	133.49
	Collier	321520	871	369.14
	Dixie	16422	764	21.49
	Escambia	297619	1387	214.58
	Franklin	11549	565	20.44
	Gulf	15863	704	22.53
	Hernando	172778	907	190.49
	Hillsborough	1229226	597	2059.01
	Jefferson	14761	694	21.27
	Lee	618754	836	740.14
	Levy	40801	598	68.23
	Manatee	322833	727	444.06
	Monroe	73090	2080	35.14

	Okaloosa	180822	512	353.17
	Pasco	464697	477	974.21
	Pinellas	916542	692	1324.48
	Santa Rosa	151372	1932	78.35
	Sarasota	379448	904	419.74
	Taylor	22570	664	33.99
	Wakulla	30776	534	57.63
	Walton	55043	1472	37.39
Louisiana	Cameron	6839	1229	5.56
	Iberia	73240	280	261.57
	Jefferson	432552	1457	296.88
	Lafourche	69318	607	114.20
	Orleans	343829	1114	308.64
	Plaquemines	23042	1051	21.92
	St. Bernard	35897	804	44.65
	St. Mary	54650	1016	53.79
	St. Tammany	233740	612	381.93
	Terrebonne	111860	642	174.24
	Vermilion	57999	1118	51.88
Mississippi	Hancock	43929	1042	42.16
	Harrison	187105	830	225.43
	Jackson	139668	1031	135.47
Texas	Aransas	23158	745	31.08
	Brazoria	313166	1794	174.56
	Calhoun	21381	478	44.73
	Cameron	406220	581	699.17
	Chambers	35096	741	47.36
	Galveston	291309	906	321.53
	Harris	4110771	1778	2312.02
	Jackson	14075	2026	6.95
	Jefferson	252273	1124	224.44
	Kenedy	416	1590	0.26
	Kleberg	32061	936	34.25
	Matagorda	36702	997	36.81
	Nueces	340223	399	852.69
	San Patricio	64804	572	113.29
	Refugio	7369	819	9.00
	Victoria	86878	889	97.73
	Willacy	22134	584	37.90

4.3 Economy

Figure 4.2 presents the gross domestic product (GDP) of coastal zone counties by region. The Gulf of Mexico region is ranked third in terms of overall GDP generating 943 billion dollars in 2013. The West Coast region recorded the highest GDP with 2,369 billion followed by the Mid-Atlantic, which contributed 2,270 billion to the local economy. The negative impact of the recession is evident in the drop in overall GDP in the Gulf and West from 2008 to 2009, whereas the Northeast, North Pacific, Mid-Atlantic, and Southeast regions remained relatively stable through this time period (NOEP 2014).

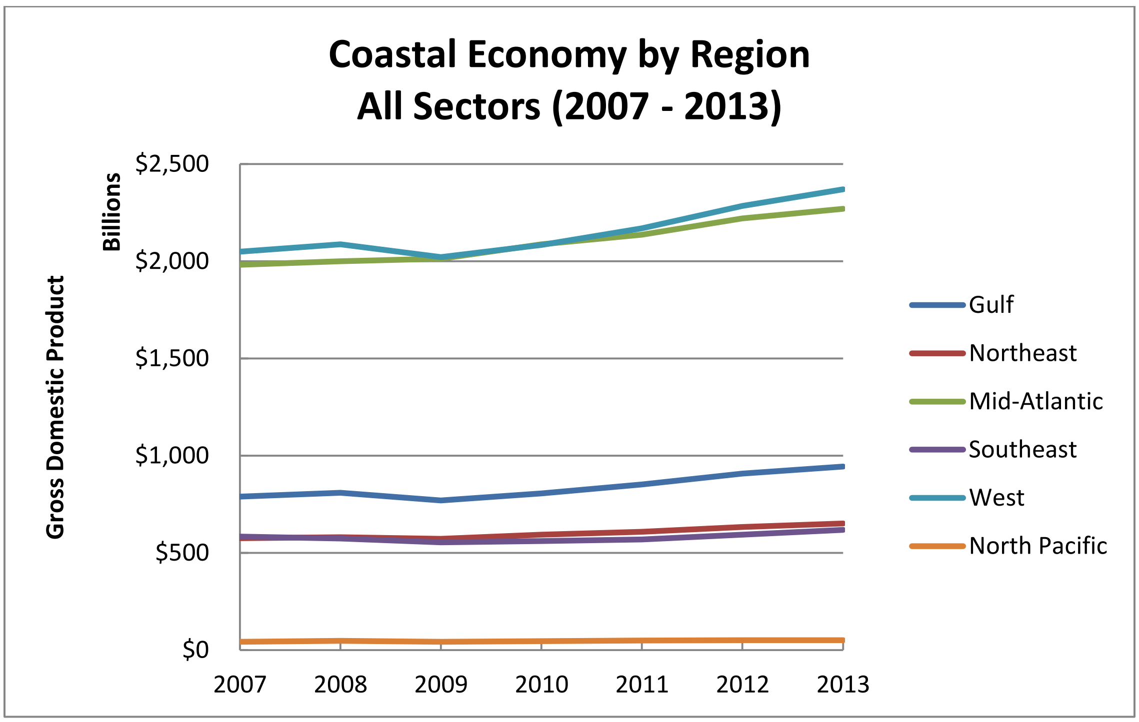

Figure 4.2 – Gross Domestic Product of Coastal Zone Counties by Region

The Gulf Coast economy is reliant on the fishing, energy, and tourism sectors. Figure 4.3 shows regional trends in natural resources and mining that include activities associated with

fishing and offshore mineral extraction. The Gulf region experienced a greater rate of recovery in marine fishing and mining activities following the recession compared to other regions as seen in the upward trend in GDP between 2009 and 2011. As a result of this growth, the Gulf contributed the highest percentage of national GDP in natural resources and mining (approximately nineteen percent) in the period, 2007 to 2013 (NOEP 2014).

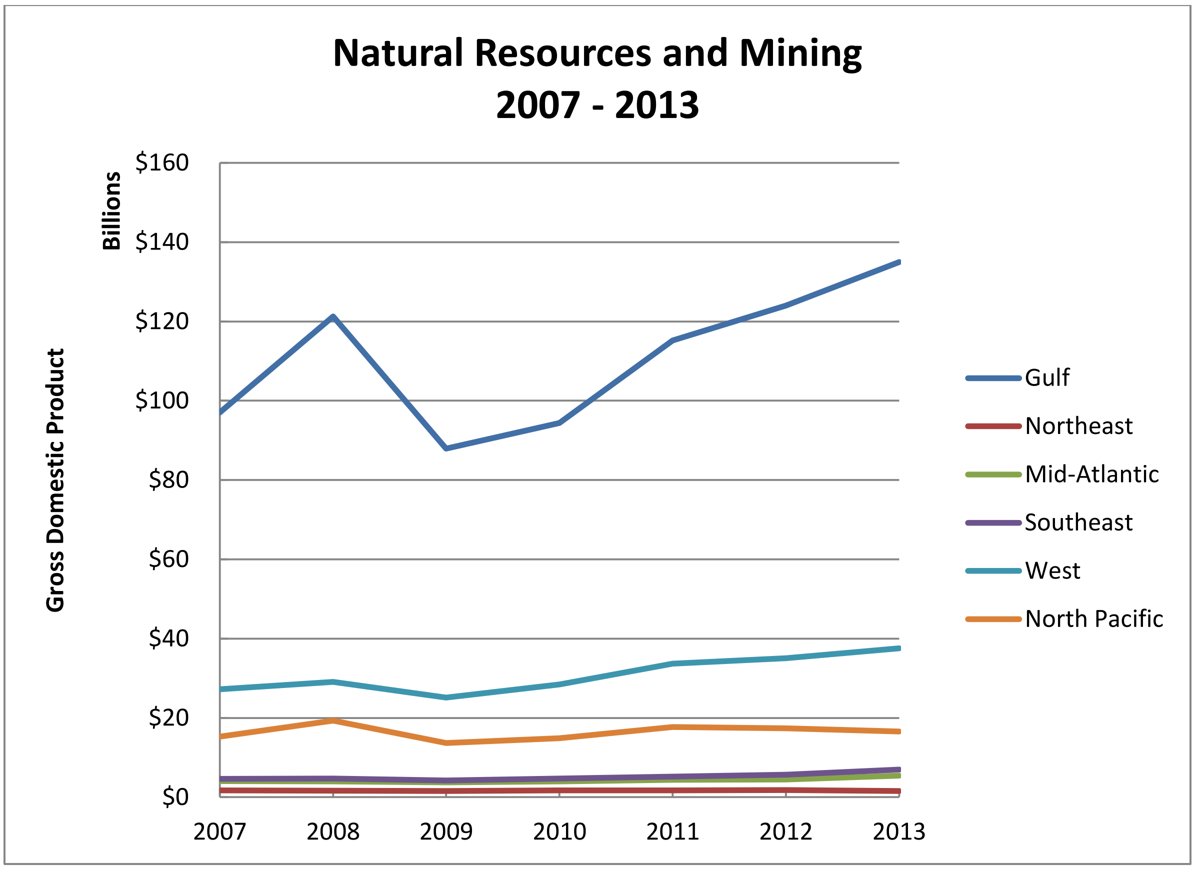

Figure 4.3 – Regional Gross Domestic Product in Natural Resources and Mining

The County Business Patterns database of the U. S. Census Bureau combines fisheries under the category of *NAICS Code 11: Forestry, Fishing, Hunting, and Agriculture Support,* which includes commercial fishery. Commercial fishery consists of activities associated with

catching, processing, and distributing fish and shellfish for sale. It accounts for large and small fisheries and recreational fishing. Recreational fishery involves fishing for personal use or sport, and is therefore, not traded for profit. The term *catch* refers to the act of extracting fish from its natural environment and applies to both commercial and recreational fishing. The catch that is brought on board a vessel and used for human consumption is referred to as *landed*. In the context of recreational fishing, fish not landed are returned to the sea although they form part of the total catch (NOAA 2006). Table 4.2 summarizes data on commercial and recreational fishing in the Gulf region.

Table 4.2 – Regional estimates of Fisheries

Commercial Fishing (2009)		
	Total catch **(tons)**	Total catch **($)**
United States	3.6 million	3.8 million
Gulf Coast	644,000	614,000
Gulf (percent share)	**18%**	**16%**
Recreational Fishing (2009)		
	Percentage of **trips**	Percentage of **catch**
Atlantic Coast	58%	51%
Gulf Coast	**31%**	**44%**

As a commercial fishery, the Gulf Coast accounts for 18 percent of the total catch (in metric tons) and the largest share of the US oyster production of 67 percent. 2.8 million fishermen in Florida, Alabama, Mississippi, and Louisiana are identified as recreational fishers. In 2009, approximately 23 million individual fishing trips were undertaken in the Gulf by commercial and recreational fishermen, many of the latter visiting from other states. The Gulf Coast accounts for 31 percent of trips made and 44 percent of the catch related to recreational

fishing and is ranked second after the Atlantic Coast making it an important source of regional income (NOAA National Marine Fisheries Service 2009).

A growing number of fishermen who are part of the informal economy are engaged in commercial and recreational fishing. The informal economy includes individuals who are self-employed or are working for employers who do not report earnings for tax purposes. These individuals typically work as manual laborers in the agricultural sector and in urban areas as domestic workers (Nightingale and Wandner 2011). Given that workers and their employers in the informal sector bypass the regulatory process, production and income related to commercial and recreational fishing in the Gulf are expected to be higher than figures published by the government.

The Gulf Coast states account for almost half of all jobs relating to oil and gas extraction in the United States. Close to four thousand private sector establishments are engaged in the industry generating more than 60,000 jobs (U. S. Census Bureau 2014a). Oil and gas extraction in the Gulf consists of exploration, production, and refining activities that take place both on-shore and off-shore. Texas leads in the number of jobs provided by the industry at 49,496 followed by Louisiana and Mississippi (Figure 4.4). Texas also has the highest number of establishments engaged in oil and gas extraction, accounting for 85 percent in the Gulf region and approximately 41 percent of the national total (U. S. Census Bureau 2014a).

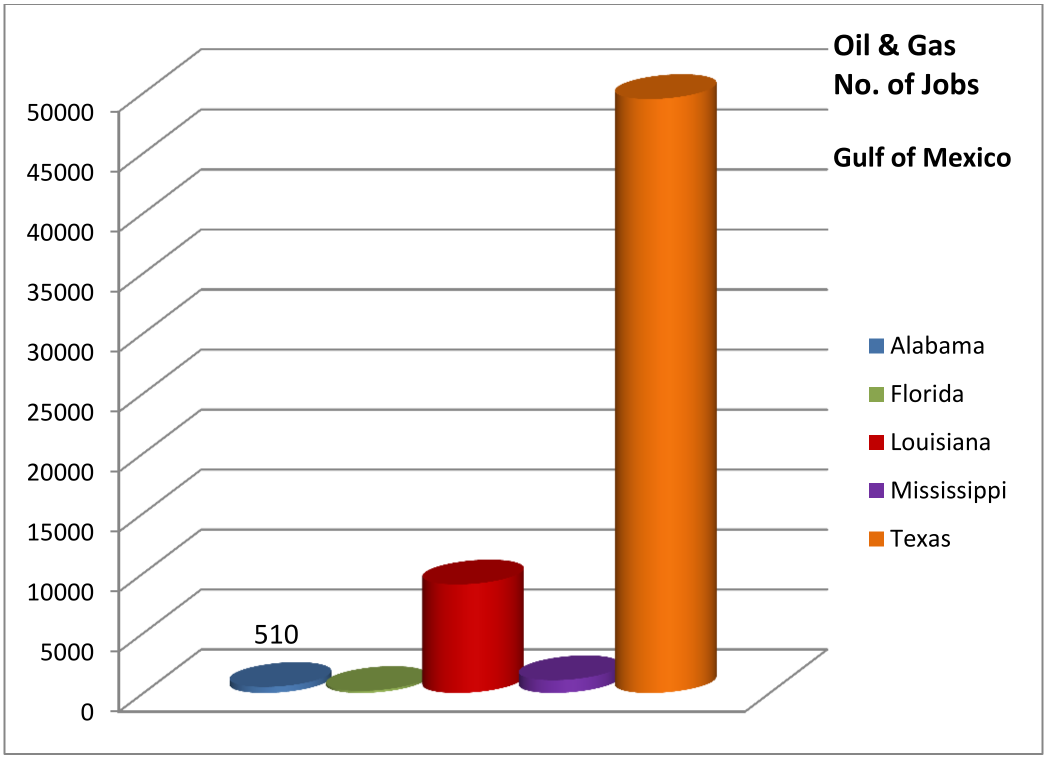

Figure 4.4 – Employment in Oil and Gas Sector, Gulf of Mexico

Recreational fishery overlaps with other sub-sectors that are linked to tourism. Based on the County Business Patterns database, tourism and recreation are embedded in two NAICS sectors. *NAICS code 71* aggregates all sub-sectors under *arts, entertainment, and recreation* (performing arts, museums, historical sites, marinas, casinos etc.), and *NAICS code 72* pertains to *accommodation and food services* (hotels, B&B, camping grounds, restaurants etc.). As such it is a challenge to extract what component is applicable specifically to *coastal tourism.* A chart showing regional trends in the leisure and hospitality industry is presented in Figure 4.5. In terms of total GDP, the Gulf Coast is in fourth place behind the West, Mid-Atlantic, and Southeast regions. However, the Gulf region recorded a higher growth rate in GDP from 2007 to 2013 i.e. 20 percent, compared to 18 percent for the West (NOEP 2014). In 2009, tourism and

recreation in the Gulf Coast accounted for 455,000 jobs and $2.2 billion in wages (United States Bureau of Labor Statistics 2009).

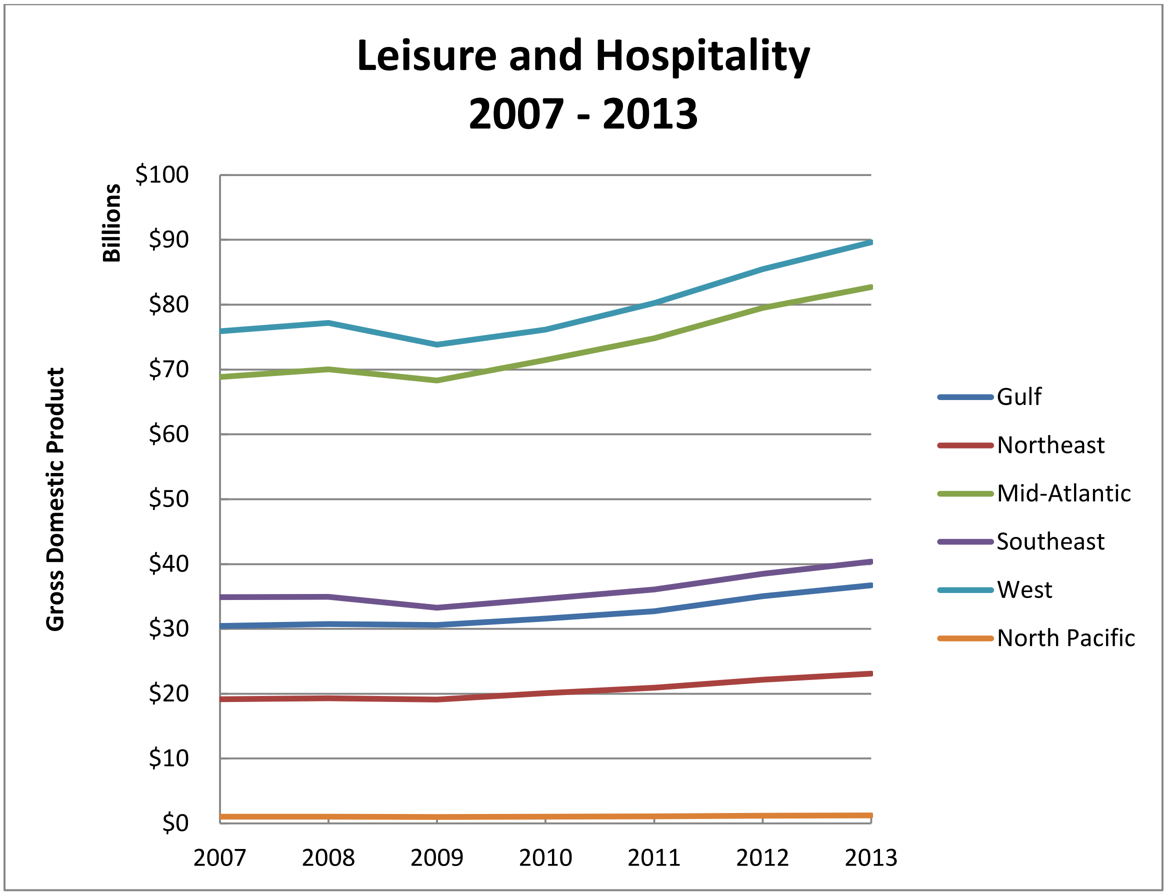

Figure 4.5 – Regional Gross Domestic Product in Leisure and Hospitality

4.4 Hazards

The Gulf Coast is subject to hurricanes, tropical storms, and flooding annually. In the period 2001 to 2011, major hurricanes have hit coastal counties resulting in damage and destruction to life and property. A timeline of events (Table 4.3) shows that the impacts of hurricanes vary depending on the magnitude and mobility of the storm. For example, Katrina, Gustav, and Ivan affected four out of five Gulf states – Louisiana, Mississippi, Alabama, and Florida. Hurricane Katrina made landfall in August 2005 and is considered the most significant

natural disaster in recent history. The category 3 storm generated wind speeds exceeding 140 mph and devastated coastal communities particularly in Louisiana. Damage to infrastructure, power outages, and travel disruptions brought economic activities to a standstill during and after Katrina (Waple 2005). The impacts were further exacerbated by shortfalls and inefficiencies in emergency preparedness and response in the aftermath of the disaster. In some cases, the prolonged implementation of disaster response and processing of claims have left local businesses and communities struggling to recover from the disaster years after the event (The Urban Conservancy 2012).

Table 4.3 – Gulf Coast States affected by Hurricanes

Year	**Hurricanes**	**States Affected**
2004	Ivan	Louisiana; Mississippi; Florida; Alabama
2005	Katrina Rita	Louisiana; Mississippi; Florida; Alabama Louisiana; Texas
2008	Ike Gustav	Louisiana; Texas Louisiana; Mississippi; Florida; Alabama

4.5 The Deepwater Horizon Oil Spill

Deep water drilling has redefined oil exploration and production in the Gulf of Mexico. Technological advances have enhanced the capabilities of drilling vessels and the quality of human capital to engage in exploration beyond the continental shelf at depths of 5,000 – 10,000

feet below sea level. In addition, drilling capacity of wells located on the ocean floor can exceed 30,000 feet. Managing and maintaining drilling equipment can only be done remotely, and risers connecting a drilling vessel to the well are exposed to strong ocean currents on the sea floor. Deep water drilling poses many challenges and is considered a high risk endeavor (National Commission 2011).

The Deep Water Horizon (DWH) was a semi-submersible drilling platform operated by British Petroleum (BP) drilling at 5,000 feet below sea level in the Mississippi Canyon's lease 252. The well depth reached 13,000 feet below the sea floor and on April 20th, 2010 the well was compromised due to an explosion on the drill platform that resulted in the discharge of more than five million barrels of oil into the Gulf (NOAA 2012a, 2012b).

The DWH oil spill has been compared to the Exxon-Valdez spill that occurred in Prince William Sound, Alaska in 1989. The Exxon-Valdez was a tanker experienced in the transportation of crude oil from Alaska to the West and Gulf coasts. Soon after leaving its port on March 23rd, 1989, the tanker ran aground as the crew redirected the vessel away from traffic lanes in an attempt to avoid sea ice. It resulted in rupturing most of the vessel's cargo tanks on board that discharged 257,000 barrels of oil into Prince William Sound. As in the case of the DWH oil spill, negligence on the part of the captain and crew, and inefficiencies in the regulatory process were cited as reasons for the Exxon-Valdez oil spill (State of Alaska 1990).

Despite similarities in the actions and processes that led to the events, there are significant differences in terms of the geography, characteristics, and impact of these two oil spills, a summary of which is presented in Table 4.4. The DWH oil spill occurred within a large water basin and under warm climate conditions. Warm surface temperatures and ocean currents in the Gulf of Mexico pushed the oil from the ocean floor east towards the Florida Keys that led

to the expansion of the areal extent of the discharge (Cleveland 2010). The Exxon-Valdez ran aground in Bligh Reef, a relatively small basin of water, and under colder climate conditions. The combination of cold surface temperatures and high pressure systems contained the oil close to the shoreline, but did not make clean-up operations any less challenging due to the uneven shoreline and rocky beaches of the reef (WWF 2009). Based on the composition of poly-aromatic hydrocarbons (PAH), the toxicity of oil discharged by the DWH was much lower than that of the Exxon-Valdez (NOAA 2010). Nevertheless, the composition of crude oil in the Mississippi Canyon decomposes into tar balls that can remain on beaches for long periods of time and travel long distances on the open seas. The geographical location, oil characteristics, and under-sea origin of the DWH oil spill posed challenges to containment and clean-up operations. The DWH continued to discharge oil for three months until the well was capped in July 2010. The total discharge of five million barrels was approximately twenty times greater than that of the Exxon-Valdez (NOAA 2012a, 2012b).

Table 4.4 – Comparative Analysis of the Deep Water Horizon and Exxon-Valdez Oil Spills (Data Source: NOAA 2012a, 2012b)

	DWH	**EXXON-VALDEZ**
Location	Gulf of Mexico 28° N 88° W	Bligh Reef in Prince William Sound, Alaska 61° N 146° W
Date	April 20th, 2010	March 24, 1989
Climate conditions	Very warm surface and atmospheric conditions – large basin of water	Very cold weather – within a small basin of water
How it happened	Compromise of well head at 5,000 ft below sea level	Tanker ran aground – to avoid ice
Oil characteristics	Light or sweet crude oil - relatively low in PAH and sulfur	Heavy crude oil – relatively high in PAH
Discharge	5 million barrels – discharged over time until well was capped - 3 months	262,000 barrels – discharged within 6 hours
Shoreline impacted	180 miles heavily or moderately oiled – impact on the sea floor still unknown	200 miles heavily or moderately oiled – diverse landscape – rock surfaces, rocky beaches – made clean-up difficult
Response	Oil Pollution Act – cooperative assessment – BP's involvement	Clean Water Act – damage assessment carried out without cooperation of Exxon

The federal investigation conducted in the aftermath of the DWH oil spill found that the risks associated with deep water drilling were largely underestimated by the oil industry and by regulatory agencies set up to monitor oil exploration and production. As a result, preventive measures such as, testing, maintenance, and accountability were inadequate to activate and deploy resources in a crisis situation. The report also emphasized the need for a comprehensive study of the environmental and human impacts of deep water drilling in coastal areas (National Commission 2011). Based on the Natural Resource Damage Assessment, an initial sum of one billion dollars was allocated by BP in 2011 for early restoration projects in coastal Louisiana, Alabama, and the Florida pan-handle. A majority of these projects pertains to the restoration of beaches and marshland. Resources were also allocated to oyster production in some counties in coastal Louisiana, namely St. Bernard, Lafourche, Plaquemines, Terrebonne, and Jefferson (NOAA 2012a). In addition, the conditions of a civil trial involving BP and its lessor, Transocean, earmark an additional $7.8 billion for private economic and medical claims (Schleifstein 2013). The planning and implementation of restoration projects and settlement of claims have been undertaken as a response to the impact of the event and not as a strategy to build resilience and long-term sustainability.

4.6 Field Trip to Study Area

A field trip was undertaken in January 2014 to observe first-hand the socio-economic impacts of the DWH oil spill. Figure 4.6 is a map showing the location of Bay County FL and Orleans Parish LA that are profiled in this section. The population in Bay County in 2010 was 168,852 and the population in Orleans Parish was 343,829. A majority of the population in both counties resides in urban areas (U.S. Census Bureau 2010). The Panama City metropolitan area is located in Bay County and the New Orleans metropolitan area in Orleans Parish. The two counties are selected based on their differentiating characteristics on exposure to hazards and the importance of offshore resource extraction, which provide a basis for comparison. Thirty four percent of the population in Bay County is located inside the floodplain zone designated by the Federal Emergency Management Agency (FEMA). In Orleans Parish, 70 percent of the population is located inside the floodplain making it more vulnerable to hazard events like floods, hurricanes, and industrial hazards (NOAA 2011). As a result of high exposure levels in the county, New Orleans was severely impacted by Hurricane Katrina in 2005, whereas Bay County was not affected by the event.

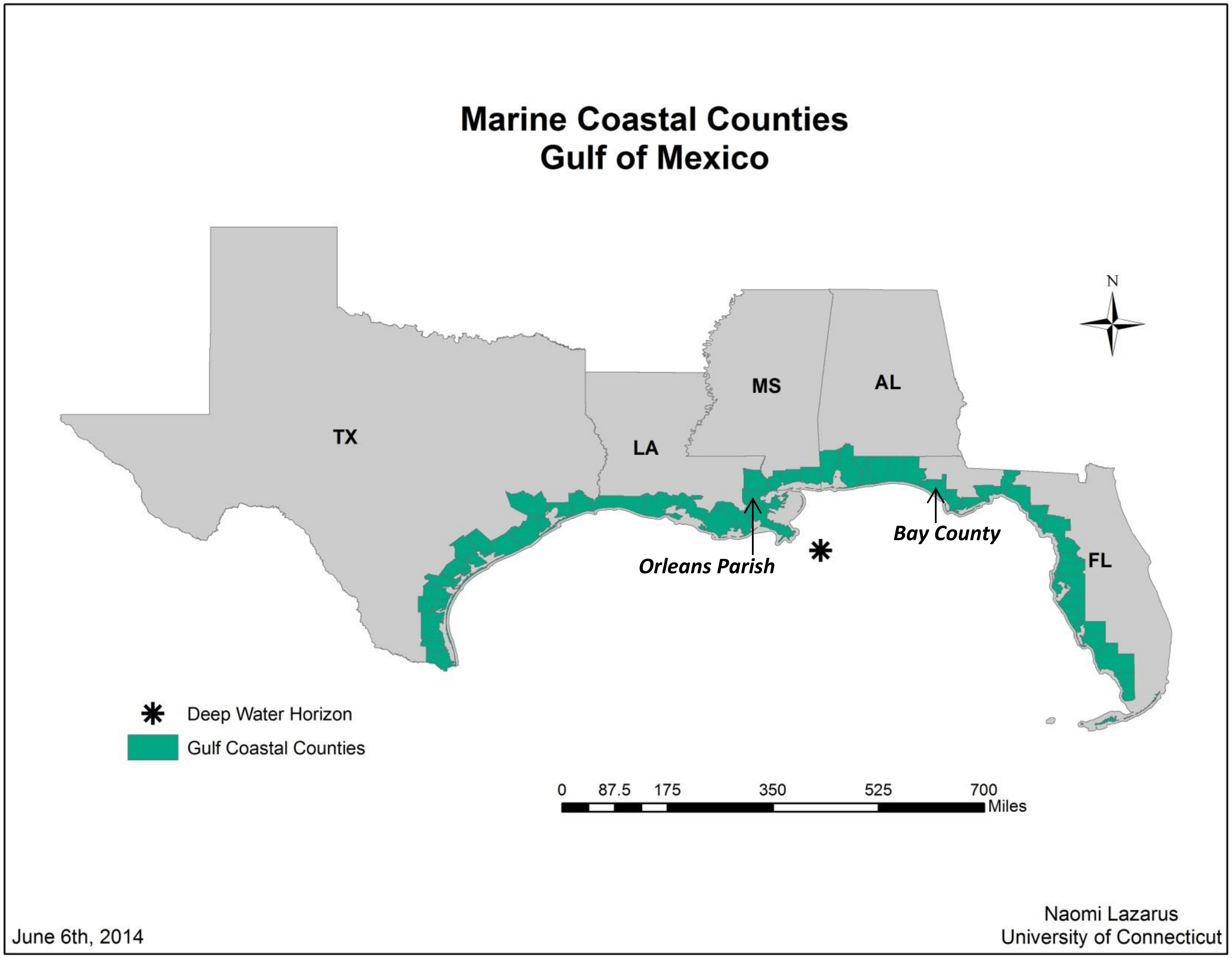

Figure 4.6 – Location of Bay County, Florida and Orleans Parish, Louisiana

In 2011, natural resources and mining contributed $25 million to GDP in Bay County of which jobs in offshore mineral extraction accounted for less than one percent of all coastal zone employment (Figure 4.7). This sector contributed approximately $3 billion to GDP in Orleans Parish and generated ten percent of all jobs related to the coastal economy (NOAA 2011; NOEP 2014). The importance of this sector in the county is indicative of the large number of drilling platforms present off the coast of Louisiana compared to offshore sites in Florida. Out of the nearly 4,000 active oil and gas platforms in the Gulf 3,359 are located off the Louisiana coast and the rest located in coastal Texas (NOAA 2012c).

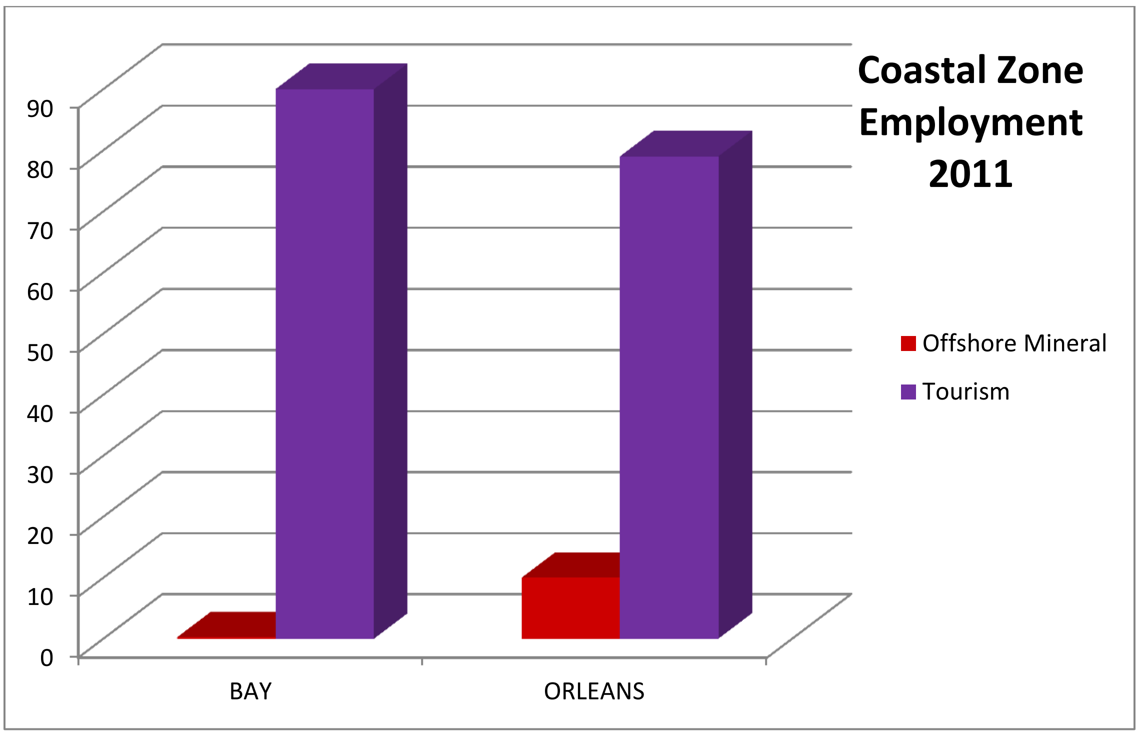

Figure 4.7 – Employment in Tourism and Offshore Mineral Extraction

The coastal economy in Bay County is composed of tourism and recreation, marine transportation, and marine construction. The tourism sector accounts for ninety percent of all jobs (NOAA 2011). Most of the economic activity is centered in the Panama City and Panama City Beach area. Tourist arrivals peak in the spring and summer months. The spring season is

dominated by visiting college students and extends from March to May depending on the timing of Spring Break. The summer months attract families on vacation. During the off season, rental properties are left vacant (Figure 4.8). Despite seasonal variation in tourism, local businesses maintain their customer-base through activities that cater to locals and the growing number of part-time residents (snowbirds) that arrive in the winter months.

Figure 4.8 – Rental Properties, Panama City Beach, Florida

While the DWH oil spill did not directly impact Bay County, the tourism sector was negatively affected due to the adverse media coverage surrounding the event. The perception of the local population about how the spill would affect the economy was a key driver that

determined peoples' response to the event. Some business owners received compensation from BP in the range of $7,000 to $35,000 while others refrained from submitting claims as they preferred to draw upon available resources to ride out the economic downturn. Economic stimulation resulted from temporary workers that came from other parts of the country to work in oil spill recovery. The high wages, $18 per hour, also attracted resident workers who had previously been employed in tourism and recreational jobs (restaurants, clubs, etc.), which further contracted business activities in this sector. Four years after the spill, tourism in Bay County is recovering steadily. Prospects for growth in tourism and recreation jobs are evident in the new rental properties that are being constructed in the Pier Park neighborhood of Panama City Beach (Figure 4.9).

Figure 4.9 – Pier Park, Panama City Beach, Florida

The economy of Orleans Parish LA is concentrated in the city of New Orleans. Tourism and recreation are the dominant economic sectors in Orleans Parish accounting for 79 percent of total jobs followed by offshore mineral extraction and marine transportation (NOAA 2011). The commercial center of New Orleans is supported by large retail stores, transportation services, and restaurants that rely on tourism. Tourism also supports small businesses in Frenchman's Market located in downtown New Orleans. The market hosts a number of small-scale vendors trading in clothing, accessories, local produce, and crafts (Figure 4.10). In the immediate aftermath of the oil spill, public concern over oil contaminating fisheries and seafood production threatened tourism in the city. However, tourist arrivals increased by 11 percent from 7.5 million in 2009 to 8.3 million in 2010 (Waller 2013). The neighborhood of Marigny located within the New Orleans metropolitan area continued to thrive economically during the spill as it mainly serves the local population. The oil industry in the Greater New Orleans area (Orleans Parish) was impacted by the spill. Offshore drilling was suspended temporarily due to the moratorium imposed by the federal government following the event. The suspension of drilling activities drastically reduced the number of oil industry jobs and contributed to an overall decline in offshore mineral extraction in Orleans Parish by 127 percent from 2005 to 2011 (NOAA 2011).

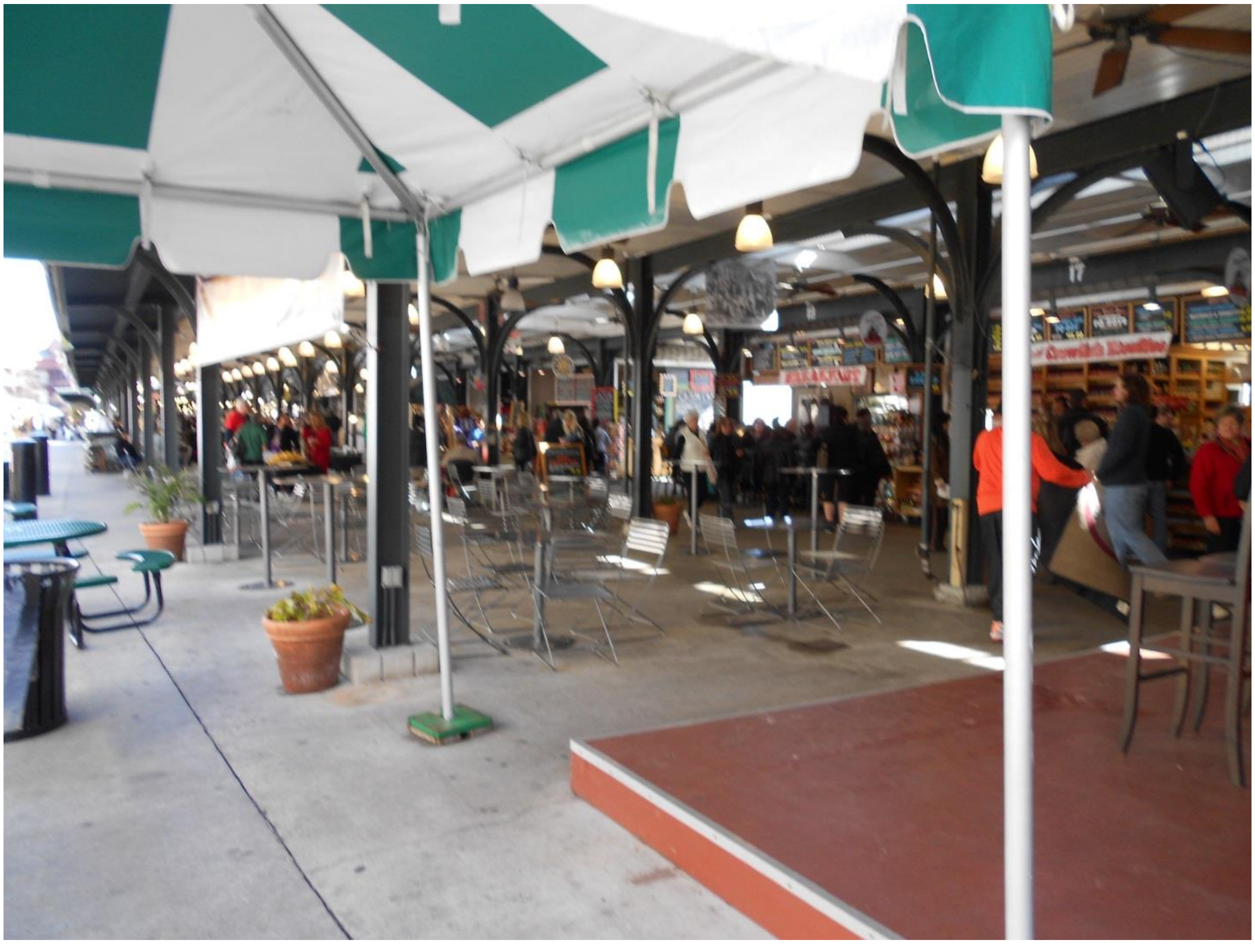

Figure 4.10 – Frenchman's Market, New Orleans

4.7 Conclusion

Vulnerability studies are concerned with evaluating the impacts of hazard events on the physical environment and on human settlements that occupy hazard prone areas. The relative location and population density of the Gulf Coast make the region sensitive to environmental disasters as was demonstrated by major hazard events that have taken place in the last decade. The DWH oil spill has broadened the discussion on the impacts of anthropogenic disasters in light of their economic importance and high environmental costs. Understanding the human impacts of oil extraction and production is important to improve community resilience to future

environmental disasters. The research explores the social and economic impacts of the DWH oil spill through an assessment of vulnerability, resilience, and risk. A model is developed to examine the differential impacts of the spill on coastal counties in the Gulf of Mexico. The components of the model are discussed in Chapter 5.

Chapter 5

Methodology

5.1 Introduction

The social dimension of hazard events is concerned primarily with the concept of vulnerability. Vulnerability is broadly defined as the sensitivity of a human population to be negatively impacted by a hazard event (Cutter, Boruff, and Shirley 2003; Adger 2006) and consists of the sub-components of exposure and coping ability (Wisner et al. 2004; Ratick and Osleeb 2011). Due to the fact that vulnerability involves evaluating environmental and social factors that increase the likelihood of sustaining losses in the form of physical damage (buildings, infrastructure), economic loss (disruption to livelihoods) (White 1945) and damage to ecosystems (Turner et al. 2003), measuring vulnerability has continued to be a challenge.

The pseudo-equation, $R = H \times V$, proposed by Wisner et al. (2004) attempts to make the link between the hazard event, vulnerability, and risk. They argue that the potential to suffer loss (risk) is not only due to the magnitude of the event in question, but is compounded by the social, economic, and political environments that determine the vulnerability of the population exposed to the event. Some issues arise in operationalizing the risk equation. First, identifying a measure for vulnerability *(V)* is challenging as it involves taking into account compounding and mitigating factors. As discussed in the hazards of place model, the overall hazard potential is determined by the biophysical environment that exposes a population to catastrophic events on the one hand, and the social environment that provides resources and strategies to deal with the impacts on the other (Cutter 1996). The model is operationalized by way of the social vulnerability index (SoVI). The SoVI is a weighted linear combination and is constructed using principal component analysis, a data reduction method that isolates components that reflect the

variance in a large number of observed variables. The variance values are used to weight each component and are referred to as factor loadings. The index accounts for a number of factors and inter-relationships within the social-ecological system as illustrated in a case study where a total of forty two variables are considered to assess vulnerability (Cutter, Boruff, and Shirley 2003; Suhr 2014).

Second, the multiplicative function of the equation is constrained by the differences in parameter values of *H* and *V*. As illustrated in the SoVI, if vulnerability is a measure of several variables then it is considered to be a composite variable as its value is derived from several other variables. The role of *H* in the risk equation is identified as some measure of the magnitude of the hazard (Alexander 2000; Wisner et al. 2004). It follows then that the differences in the inherent attributes of *H* and *V* would render the multiplicative model meaningless for the purpose of interpretation. Even if the variables are standardized, the result generated for *R* (risk) would need to be compared against a threshold in order to estimate the hazard potential of the exposed population. A threshold is a point of reference that is used to compare units on a scale of attributes identified to measure relative vulnerability (Luers 2005; Ratick, Morehouse, and Klimberg 2009).

An alternative model is proposed here with the intention of determining the relationships that exist between exposure, coping ability, and disaster risk. Existing frameworks, such as the Sustainability Livelihoods framework (Swedish International Development Cooperation Agency 2014) and the BBC model (Cardona 1999, 2001; Bogardi and Birkmann 2004), provide a sound conceptual basis to study the social and institutional structures in which peoples' livelihoods and resilience play out. There is, however, space for contributions to be made in evaluating the

linkages between social capital and access to resources that contribute to building resilience over time.

The HRLM is based on re-specification of the risk equation of Wisner et al. (2004) as follows:

$$R = f\ (H, E, C)$$

where the risk factor, *R*, is a function of the hazard *(H)*, exposure *(E)*, and coping ability *(C)*. The model framework consists of a regression analysis and a threshold analysis. First, regression is used to establish a causal relationship between the dependent variable representing coping ability *(C)* and variables representing social capital. Next, thresholds are identified for selected measurement variables representing the hazard, exposure, and coping ability to conduct an overall assessment of hazard risk. A detailed discussion of the model framework is presented in the following sections.

5.2 Regression Analysis

5.2.1 The Basic Model

The structural component of the model attempts to establish a causal relationship between coping ability and a number of independent variables that represents access to social capital. Unemployment rate is identified as the dependent variable and functions as a proxy to measure coping ability. Unemployment accounts for people without jobs who are actively looking for work. It is a key macroeconomic indicator that reflects the effect of social and institutional policies that play out at the local level (Mansfield 1986). The relationships between individuals, groups, and institutions at the local level are embedded in social capital (Scheffer et al. 2002). It

is expected that these linkages will provide people access to resources and services that increase the opportunities for employment (Sen 1981; Chambers and Conway 1991). Resources and services provided by social capital are represented by the independent variables. Examples include social assistance, employment services, utilities, and services provided by religious organizations.

Based on previous research, the relationship between access to resources (through social capital) and coping ability is assumed to be positive as illustrated in Figure 5.1. The basic regression model, therefore, would establish a positive linear relationship as indicated in the following formula:

$$Y = B_0 + B_1x_1 + B_2x_2 + \ldots\ldots\ldots\ldots + B_mx_m + e$$

where, Y is the value of the dependent variable (coping ability); B_0, the constant; and B_1, $B_{2\ldots}$ representative of parameter estimates of the respective independent variables denoted by x_1 and x_2 in a set of m number of variables, $k = 1\ldots..m$. e represents the error.

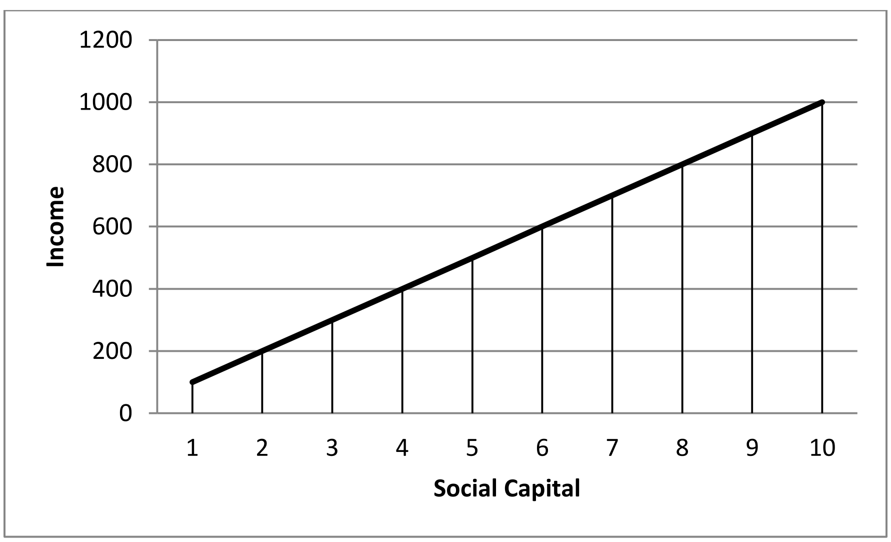

Figure 5.1 – The Trend Line of the Basic Regression Model

The assumptions of regression models include linearity, normality, homoscedasticity, and independence. The linearity assumption states that the regression equation, $y = a + bx + e$, is a linear function. In most cases, however, the relationship between the independent variable, *x*, and the dependent variable, *y*, is likely to be non-linear. A scatter plot would reveal if the linearity assumption has been violated (Kachigan 1986; Cohen et al. 2003). Violation of linearity is likely to occur in monotonic and non-monotonic relationships between *x* and *y*. In a monotonic relationship, increases or decreases in *y* is not uniform across *x* (logarithmic functions), and in a non-monotonic relationship, increases in *x* may produce either an increase or a decrease in *y* (Cohen et al. 2003). The assumption of normality states that not only are *x* and *y* normally distributed, but that the errors are also normally distributed. A normal probability plot will display how the errors are distributed across the regression line. If the distribution of errors is non-normal, it indicates the absence of independent variables and may require the model to be re-specified by adding more variables (Cohen et al. 2003).

Homoscedasticity refers to the homogeneity of variances, i.e. the variance of the errors remains constant across all values of *x* (Kachigan 1986; Cohen et al. 2003). Violation of homoscedasticity can be observed in a standardized residual plot and is referred to as *heteroscedasticity*. Heteroscedasticity will result in the standard errors of the parameters to be inflated. A number of solutions are proposed to treat heteroscedasticity, namely adding more variables, transformation, and the use of weighted least squares regression (WLS). When using WLS to treat heteroscedasticity, small weights are given to cases that fan out more from the regression line, and large weights given to cases close to the regression line (Cohen et al 2003).

Last, the assumption of independence states that residuals associated with the independent variables are independent in the population (Kachigan 1986; Cohen et al. 2003).

This assumption is violated when analyzing data over time resulting in the autocorrelation problem. For example, when considering the relationship between work experience in years *(x)* and income *(y)*, the work experience in year 2 is related to the work experience in year 1. This is known as the lag 1 autocorrelation or AR(1) in which case the assumption of independence is violated (Cohen et al. 2003). The issue of autocorrelation is addressed by incorporating an autoregressive term that recognizes the dependence of errors. In an autoregressive model, the dependent variable is estimated using the value of the independent variable in the previous time period ($t - 1$) to account for time-related autocorrelation (Maddala 1992; Hamilton 1994). The general form of the autoregressive model is as follows:

$$Y_t = c + \phi X_{t-1} + e_t$$

where, Y_t is the value of the dependent variable (coping ability) in time period, t; c is the constant; and ϕ, representative of the slope coefficient of the change in the independent variable in time period, $t - 1$. e_t is the error associated with estimating the dependent variable in time period, t. The error term is formulated as $e_t \sim IN(0,\sigma^2)$ as it is recognized as being independent (IN) with a mean of zero and the variance, σ^2. An autoregressive error model simultaneously estimates the regression parameters while correcting for the lag associated with the residuals across several time periods (Maddala 1992; Hamilton 1994; SAS Institute 2014a). This process is defined by a *lag operator*, denoted by L, and is reconstructed as follows:

$$L^j Y_t = X_{t-j}$$

where L^j is the autoregressive lag operation applied to all time periods, j; Y_t, the value of the dependent variable in time period, t, and X_{t-j} representative of the value of the independent variable, X, in the previous time period in a set of j number of time periods (Maddala 1992). The regression model is re-formulated as follows taking into account the autoregressive process:

$$Y_t = B_0 + (B_1\mathbf{L}X_1 + B_2\mathbf{L}X_2 + \ldots\ldots\ldots\ldots B_m\mathbf{L}X_m)_{\mathbf{j}} + e_t$$

where, Y_t is the value of the dependent variable (coping ability) in a given time period, t; B_0, the constant; and B_1, $B_{2\ldots}$ representative of parameter estimates of the respective independent variables denoted by X_1 and X_2 in a set of m number of variables, $k = 1\ldots..m$. The lag operator, L, represents the value of the independent variable in the previous time period ($t - 1$) in a set of j number of time periods, $t = 1\ldots..j$. e_t is the error associated with estimating the dependent variable in time period, t.

Autocorrelation is further compounded when dealing with a nested time series dataset that combines spatial data applicable across several time periods. The objective of time series analysis is to observe changes in attribute values pertaining to a specific location or observation (Singhal and Seborg 2005). For example, the basic form of time series analysis is used to observe variation in unemployment rate in County A from 1990 to 2000. A nested time series is applicable when attribute values for multiple counties are analyzed over several time periods. In this example, a nested time series dataset would consist of unemployment rates for 56 counties over a period of ten years. The combination of spatial and temporal data in regression requires addressing key issues such as:

1. Do spatial units with similar attribute values (clustering or randomness) display the same patterns over time?
2. How does the occurrence of unexpected events (hazards) impact attribute values of specific variables across geographical locations?
3. What mechanisms are available to distinguish between the changes caused by unexpected events and those related to seasonal variations in the business cycle?

These issues are discussed in the context of the spatial model, which is examined in the next section.

5.2.2 The Spatial Model

OLS regression assumes that all observations have equal weight. It is linked to *spatial stationarity*, which assumes that observations do not vary by virtue of their location. In reality, the relationship between variables may vary geographically. *Spatial autocorrelation* is observed based on the premise of Tobler's rule that near things are more related than distant things. It refutes the assumption of spatial stationarity – not only do observations vary geographically, but there may be clusters of observations in a given location that may display similarities. Geographically weighted regression addresses the problem of spatial stationarity by weighting each variable based on a significant geographical criterion, thereby assigning a parameter estimate for each location (Charlton and Fotheringham 2009). The spatial model then would display a variation in relationships between the dependent and independent variables based on the geographical location as illustrated in Figure 5.2. The data associated with a single geographical location will yield specific regression estimates that will vary from those of another location. These variations are illustrated in Figure 5.2 by the regression lines associated with locations A, B, C, and D. The re-iteration of the spatial model is presented as follows:

$$Y_{(ui)} = \beta_{0i}(u_i) + \beta_{1i}(u_i)x_{1i} + \beta_{2i}(u_i)x_{2i} + \ldots\ldots\ldots\ldots + \beta_{mi}(u_i)x_{mi} + \varepsilon_i$$

where, u_i is the geographical location of observation i; $Y_{(ui)}$ is the value of the dependent variable (coping ability) in geographical location, u_i; $\beta_{0i}(u_i)$, the constant associated with observation i; and $\beta_{1i}(u_i)$, $\beta_{2i}(u_i)_{\ldots}$ representative of parameter estimates in geographical location

u_i of the respective independent variables denoted by x_{1i} *and* x_{2i} in a set of *m* number of variables, $k = 1 \ldots.. m$. ε_i is the error associated with observation *i*.

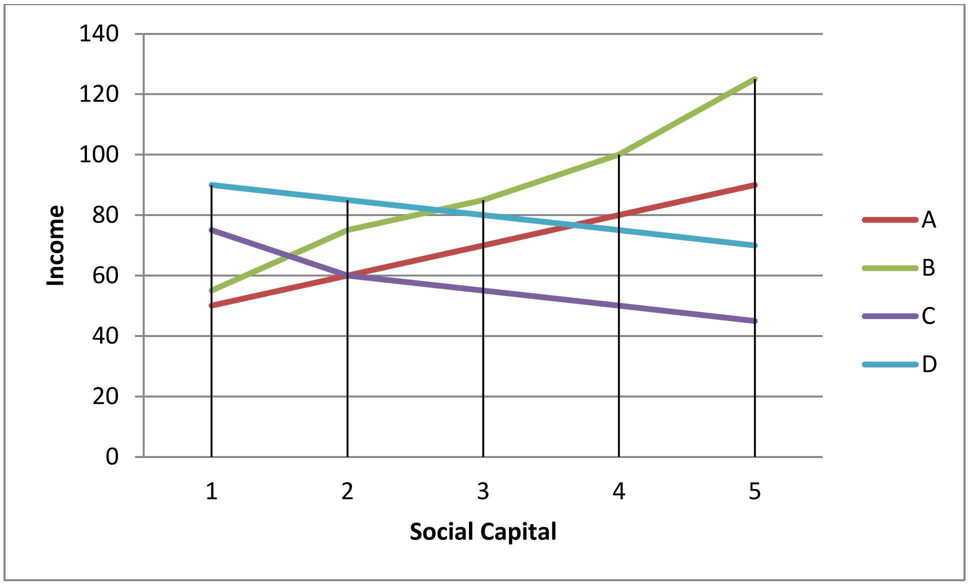

Figure 5.2 – Sample Trend Lines for Location A, B, C, and D in a Spatial Model

Spatial autocorrelation is evaluated using Moran's I, which tests the similarities of attribute values – whether they are clustered or dispersed in space. It compares the value of the variable at any one location with another relative to the mean of the variable in question. The test of spatial autocorrelation involves comparing the Moran's I statistic with the expected value, which is a coefficient indicating no spatial autocorrelation. It is computed using the formula, $E(I) = (-1)/(n-1)$, with *n* denoting the number of points in the distribution. If the calculated Moran's I is greater than the expected value, then attribute values are clustered, indicating that neighboring spatial units display similar characteristics. On the other hand, if the Moran's I statistic is less than the expected value a dispersed pattern is observed where attribute values bear no similarity across space. When the number of spatial units is large (*n* is greater than 150), the expected value, *(E(I)* approaches zero, indicative of an absence of spatial autocorrelation (ESRI 2012).

Testing the significance of the Moran's I statistic involves comparing it against the null hypothesis, which states that the spatial processes responsible for the observed pattern of the attribute in question are due to random chance. If the p-value associated with a *positive* Moran's I is statistically significant, the null hypothesis is rejected on the premise that the clustered pattern of high and/or low attribute values is likely due to underlying spatial processes. Similarly, if the p-value associated with a *negative* Moran's I is statistically significant, the null hypothesis is rejected on the premise that the dispersed pattern of attribute values is likely due to underlying spatial processes and not due to chance. If the p-value is not statistically significant it indicates that the observed spatial distribution of attribute values is due to random spatial processes that are influenced by a number of unobserved environmental factors not captured in the model (ESRI 2012).

For example, an analysis of spatial autocorrelation is applied to unemployment rates in 56 coastal counties in the Gulf of Mexico. Based on Tobler's observation that near things are more related than distant things, greater weights are assigned to counties in close proximity to each other than to those located further apart to account for spatial heterogeneity. The principle of nearest neighbor is applied when estimating the maximum radial distance within which observations display similar attributes. This distance is known as the bandwidth and is expressed in the same units as the geographical coordinates of the dataset. A fixed distance bandwidth refers to a uniform radial distance that is applied to each observation where greater weights are assigned to points inside the bandwidth than to those falling outside the neighborhood (Charlton and Fotheringham 2009). The test of spatial autocorrelation is concerned with observing local patterns of clustering (Yu 2010) and accounts for the variations in attribute values across spatial units in the study area. The attribute values are mapped and compared against the Moran's I,

which indicates the significance of the pattern of clustering or randomness that is observed. The results of the Moran's I test are reported in Chapter 8.

5.2.3 The Proposed Framework

The HRLM evaluates the variation in coping ability (represented by the unemployment rate) across spatial units in the study area over time. The framework addresses the research questions where each question is deconstructed into quantifiable units. Regression analysis is adopted to address the first and second research questions,

1. How important are safety nets to people exposed to environmental disasters?
2. How important is the quantity of social capital in minimizing the impact of an event?

The scale of analysis for this study is at the county level. In order to standardize the independent variables location quotients (LQ) are used. The location quotient is a relative measure that assesses each county in relation to the labor participation in each sector. The basic form of the location quotient is articulated as,

(1) LQ for each County / LQ for Gulf coast counties (study area)

which, when deconstructed is calculated using the formulae:

(2) $\text{LQ for each County} = \dfrac{\text{No. of workers in a sector in each county}}{\text{Total no. of workers in each county (all sectors)}}$

(3) $\text{LQ for Gulf} = \dfrac{\text{No. of workers in a sector in all counties in study area}}{\text{Total no. of workers in study area}}$

The location quotient is a ratio that measures each county's performance in a sector or industry compared to the study area as a whole. A location quotient of 1.00 for a particular

sector indicates that a county is on par with the study area in terms of its specialization and labor participation in that sector. A value greater than 1.00 indicates that a county is out-performing in that sector over other units in the study area while a location quotient between zero to 1.00 means that a sector is less important in a county relative to the study area. Location quotients provide a form of standardization wherein counties in the study area can be compared on specific attribute values. It is applicable to evaluate degree of change in services provided by social capital, which is the premise of hypothesis 1, and to analyze spatial variation in the unemployment rate i.e. coping ability as referenced in hypothesis 2. This approach is adopted with a view to address concerns over scale in the operationalization of vulnerability frameworks (Turner et al. 2003; Ratick, Morehouse, and Klimberg 2009).

Spatiotemporal analysis is a method used to analyze geographical data over time that involves parsing out a cross-section of the data to identify clusters (Knox 1964; Bilonick 1985; Amstrong, Chetboun, and Hubert 1993). The use of spatio-temporal bandwidths in GWR as proposed by Crespo, Fotheringham, and Charlton (2007) is possible when the number of spatial units is greater than or equal to 150. The study area applicable to this research contains 56 counties, which is less than the required number of spatial units for GWR. Therefore, GWR is not an appropriate model to analyze the relationships between social capital and coping ability as articulated in the research questions. For smaller sample sizes, an alternative solution would be to incorporate control variables that define distance-decay from the hazard event as well as time periods before and after the event. A control variable is one that remains fixed and is used as a measure of comparison, in this case, to observe the impact of hazard events that occur at a particular point in time (Allison 2012). The model is expanded as follows to include these additional variables:

$$Y_t = B_0 + (B_1\mathbf{L}X_1 + B_2\mathbf{L}X_2 + \ldots\ldots\ldots\ldots B_m\mathbf{L}X_m)_{\mathbf{j}} + B_T T + B_D D + B_{Tx} Tx + e_t$$

where, Y_t is the value of the dependent variable (coping ability) in a given time period, t; B_0, the constant; and $B_1, B_{2\ldots}$ representative of parameter estimates of the respective independent variables denoted by X_1 and X_2 in a set of m number of variables, $k = 1 \ldots.. m$. The lag operator, L, represents the value of the independent variable in the previous time period ($t - 1$) in a set of j number of time periods, $t = 1 \ldots.. j$. T is an interval variable controlling for time, the value of which will be set as 1 for the event year and increments of one for subsequent years. T will be zero for years before the event. B_T, therefore, is the parameter estimate of time after the event. B_D is the parameter estimate of the distance-decay variable and e_t is the error associated with estimating the dependent variable in time period, t. The control variable for distance-decay *(D)* is computed using the formula:

$$\frac{Adjusted\ Distance}{1 + T}$$

where the adjusted distance is the actual distance from the spill for the event year and is repeated for subsequent years. It will record a value of zero for time periods before the event. T is the variable previously defined as time after the event. Tx is an interaction term that assesses an estimate for each independent variable *(x)* before and after the event year, T, in a set of m number of variables, $k = 1 \ldots.. m$. B_{Tx}, therefore, is the parameter estimate of the interaction term, Tx. The inclusion of interactions terms and control variables for time and distance provides a way to assess autocorrelation and its impact on the regression model.

The proposed regression model is based on a linear trend where the impact of the event is assumed to be the same for time periods following the event year. However, it is likely that the

impacts of an event may increase in subsequent time periods and then decrease over time, which is characteristic of a quadratic trend in a situation where the regression line is non-linear as illustrated in Figure 5.3. In this case, the variable representing time after the event *(T)* is squared (T^2) and added to the model to account for the cumulative effects of the event (SAS Institute 2014b). The results of both the linear and quadratic trend models are evaluated to identify the best method to address the research questions.

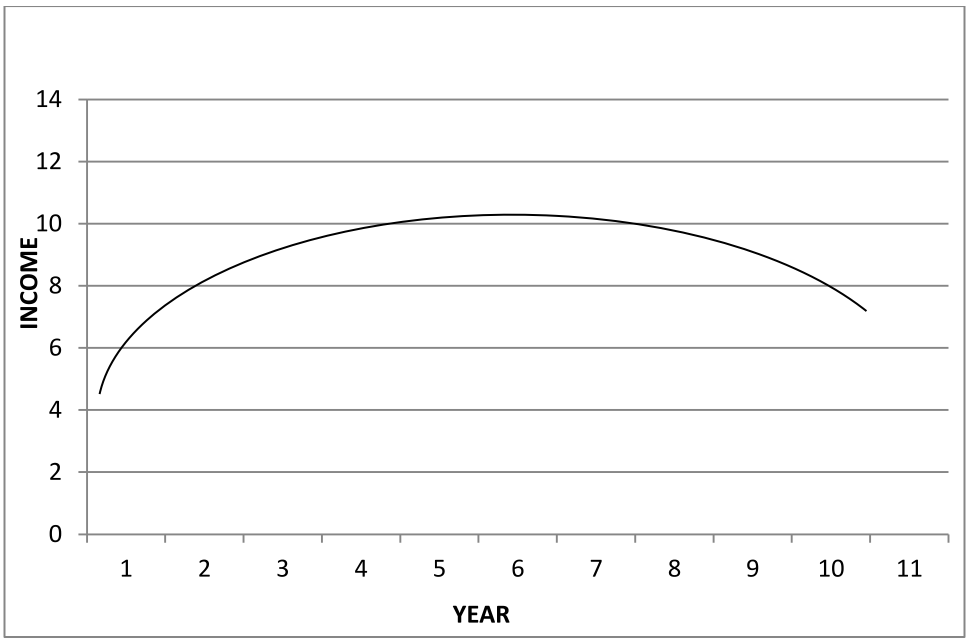

Figure 5.3 – Sample Quadratic Trend Line for a Non-linear Regression

Parameter estimates of the regression analysis address the hypotheses applicable to the first and second research questions. Hypothesis 1 states that the services provided by social capital affect individual well-being during an environmental disaster. Hypothesis 3 recognizes the quantity of social capital as a factor in determining peoples' ability to cope with an event. It is expected that changes in the independent variables will cause the unemployment rate to increase or decrease during environmental disasters. As such, the degree of change in independent variables and the time period in which these changes occur are addressed in the

regression analysis through evaluation of parameter estimates and their interaction with time after each event.

It is also likely that changes in the independent variables and the corresponding changes in the unemployment rate will vary geographically across the study area. Hypothesis 2 states that social capital is likely to vary across counties in the study area and this in turn determines spatial variation in coping ability (hypothesis 4). Maps of parameter estimates of the dependent variable and independent variables are constructed to observe these spatial patterns and supplemented with a test of spatial autocorrelation. The Moran's I test is used to evaluate whether the clustered or random pattern observed in the maps is due to spatial processes.

The dependent variable in the proposed model is the unemployment rate, which represents coping ability. Given that the unemployment rate is not a continuous variable (it is bounded between 0 and 100), its function as a dependent variable is a violation of regression assumptions. One way to address this problem is to adopt a logistic regression model. A logistic regression is used to model a binary dependent variable, where the variable value is zero or 1 (Cohen et al. 2003). This research investigates to what extent variables representing social capital are effecting a change in the unemployment rate as articulated in the hypotheses presented in Chapter 3. Given that the unemployment rate represents coping ability, treating coping ability as a dichotomous variable would simplify the problem, when in fact, the inter-relationships between social capital and livelihoods are much more complex. Therefore, a logistic regression model is not an appropriate method to address the problem in this research.

5.2.4 Limitations

The limitations associated with regression analysis are linked to multi-collinearity, model specification errors, and the effect of outliers. Multi-collinearity has a number of consequences (Kachigan 1986; Cohen et al. 2003):

1. The standard errors of the *b* parameters tend to be overestimated.
2. Parameter estimates are highly sensitive to changes in the data
3. Important variables may be omitted as they co-vary with other variables.
4. Difficulty assessing the contribution of individual variables to changes in *y*.

Multi-collinearity can be identified by calculating the VIF ($1/1-R^2_i$), where R^2 is associated with the regression of the independent variable *(i)* on all other independent variables. A VIF >10 indicates multi-collinearity. The Condition Index (CI) shows how many multi-collinearity problems exist. If the CI > 30, a test of Variance Decomposition Proportion (VDP) is carried out. If VDP > 0.5, it is indicative of multi-collinearity.

Model specification errors arise when regression assumptions are violated, particularly, homoscedasticity and independence. This also results from important variables being omitted from the analysis. If the variables in the analysis do not adequately account for the variance in *y*, the regression results are compromised. Performing a *t test* of *b* parameters is useful to assess which independent variables are important in the analysis. When the computed *t* value is greater than the value in a *t distribution* with df = n – 2, the null hypothesis (H_0: b = 0) is rejected. In this case, the *b* is likely to be greater/lesser than or not equal to zero, and is therefore important in determining changes in *y*. Model specification should be well grounded in theory so as to minimize these errors ((Kachigan 1986; Cohen et al. 2003).

Outliers can result in the assumption of normality being violated. The presence of outliers can be detected in a normal probability plot of *x* and *y* and in box plots. It can also be identified in analyzing the standardized residual values where cases with values > 3 or < -3 are considered outliers. Outliers can drastically impair regression results. The decision to remove outliers is determined by statistical tests, such as Cooke's distance and leverage. An observed Cook's distance of greater than 1.00 associated with a particular observation reveals that it is influential in determining the regression results. The co-variance ratio, in the context of regression, measures whether an observation influences the b-coefficients in a regression model similar to Cook's. Based on the formula proposed by Belsley, Kuh, and Welsch (1980), a threshold is computed to assess each observation. In general, cases with CVRs close to 1 have very little influence on the model parameters and therefore should be retained in the model.

5.3 Thresholds

5.3.1 Defining Thresholds

Re-specification of the risk equation takes into consideration the inter-relationships between three components, hazard *(H)*, exposure *(E)*, and coping ability *(C)*. The hazard component is represented by spill distance, exposure by population density, and coping ability by unemployment rate. The threshold analysis evaluates each county's attribute values on these criteria and positions them along a continuum. The formula used to calculate these values is presented below,

$$\frac{x_{(j)}}{TH} - 1$$

where, $x_{(j)}$ is the observed or predicted value of the variable in question for county *j*; and *TH*, the threshold value of the variable in question. In general, a negative result indicates that a county's attribute value on a specific variable is below the threshold, and a positive value that it is above the threshold. The description of thresholds for each variable is presented in Table 5.1. The hazard component represents the average distance from the spill. This is calculated by recording the sum of distances from the geographical centroid of each county to the spill and then dividing it by the number of Gulf coast counties. Coastal population density of the contiguous United States is used as the point of reference for exposure. This is computed for each year by dividing the estimated population in five coastal regions – Northeast, Mid-Atlantic, Southeast, Gulf of Mexico, and West – by the total areal extent of the coastal zone. A number of indices designed to measure disaster risk include mortality as an appropriate indicator of exposure, which is tied to population densities in hazard prone areas (Birkmann 2007). Therefore, population density in coastal areas is used as the threshold for exposure in the risk equation.

Table 5.1 – Thresholds for Hazard, Exposure, and Coping Ability

	Description	Threshold	Basis
H – Hazard	Average distance from the spill	324 miles	Sum of county distances from DWH / total number of Gulf coast counties
E – Exposure	Coastal population density	Will vary by each year	Total population in five coastal regions / total areal extent (209,605 sq. miles)
C – Coping ability	National unemployment rate	Will vary by each year	Persons unemployed and actively looking for work / labor force

The threshold for coping ability is linked to employment as it is indicative of peoples' ability to meet their socio-economic needs. The U.S. Bureau of Labor Statistics calculates the unemployment rate by considering people currently unemployed and who are actively looking for work as a ratio of the labor force. For the purpose of this research a low unemployment rate reflects better coping ability as it provides people the means to sustain their livelihoods by engaging in productive activities (Sen 1981; Chambers and Conway 1991). On the other hand, high unemployment rates are associated with low coping ability. A high unemployment rate is indicative of inadequate resources and services provided by social capital that, if accessible, would provide opportunities for people to secure gainful employment (Sen 1981; Chambers and Conway 1991).

The threshold formula standardizes the variables representing *H, E,* and *C* and assigns each county a position along a continuum based on the *distance* from the threshold. For this reason, the results of the threshold formula are identified as *distance measures*. The computed attribute values for selected counties are presented in Table 5.2 based on 2010 data. For example, the exposure value for Bay County, Florida is computed below. The population density of the county in 2010 is 670.05 and regional coastal population density is 503.63, which is the threshold value for the period in question. A positive measure of 0.330 indicates that the county is more exposed based on relatively high density levels.

$$\frac{670.05}{503.63} - 1 = 0.330$$

Table 5.2 – Distance Measures for Hazard, Exposure, and Coping Ability for Selected Counties

County	Hazard	Exposure	Coping
Bay County, FL	0.392	0.330	-0.052
Plaquemines Parish, LA	0.731	-0.956	0.364
Orleans Parish, LA	0.617	-0.387	0.083

When computing the attribute values for the hazard component, proximity to the oil spill is considered. *Distance from the spill* (in miles) is the variable that represents the hazard component of the risk equation, and is distinct from the *distance measures* that are computed using the threshold formula. If a county is closer to the spill, it is deemed more hazardous. The formula, however, will produce a negative value for the county in question, indicating that it is below the accepted threshold. For the purposes of interpretation, this is problematic. As such, +/- signs of the distance measures are switched to ensure uniformity with the other components of the risk equation. For example, the calculated distance measure for Plaquemines Parish is

-0.731 indicating that it is closer to the spill site compared to the threshold, which is 324 miles (see calculation below). The value is converted to 0.731 to reflect that the county is highly hazardous compared to the threshold by virtue of its proximity to the spill.

$$\frac{87.03}{324} - 1 = -0.731$$

A similar adjustment is applied when computing attribute values for coping ability. If a county's unemployment rate is higher than the threshold, the formula will produce a positive distance measure. Given that a high unemployment rate corresponds to *low* coping ability, a positive distance measure is misleading. For example, the unemployment rate in Bay County is 10.1 and the threshold applied is the national unemployment rate in 2010, which is 9.6. The result is 0.052 and is converted to -0.052 to reflect that the county is less able to cope with the impacts of hazard events by virtue of its high unemployment rate. The unemployment rate in Orleans Parish, on the other hand is 8.8, lower than the threshold. The formula produces a value of -0.083, which is converted to 0.083 indicating that the parish is better able to cope with the impacts of hazard events relative to other counties in the study area. Typically, counties with values close to zero on an attribute are closer to the threshold. Similar to the DEA, the threshold analysis is a measure of relative distance and a system of ranking counties on an ordinal scale.

5.3.2 Composite Measures

Composite indices are widely used as a tool to measure vulnerability and risk. These indices are constructed by applying differential weights to attributes that define peoples'

vulnerabilities (Cutter, Mitchell, and Scott 2000; Mustafa et al. 2011). Ratick and Osleeb (2011) evaluate three weighting methods, namely weighted average (WA), ordered weighted average (OWA), and data envelopment analysis (DEA). The WA method involves giving weights to each variable and combining the weighted measures to provide an overall measure of vulnerability. The OWA first ranks each variable from its maximum to minimum values and then multiplies it with the "order weight", which is tied to the order position of the particular observation. DEA is an optimization technique that assigns weights to variables that increase vulnerability and increase coping ability where a geographic area's vulnerability score is maximized so that it is less than or equal to 1. DEA weights are objectively assigned to the attributes by the programming formulation unlike in WA and OWA where the allocation of weights is subjective. (Ratick and Osleeb 2011).

The threshold formula in the proposed framework is used to compute distance measures for the components of the re-specified risk equation, the hazard, exposure, and coping ability. A weighted average (WA) is adopted to construct a composite measure of vulnerability and risk based on the values derived from the threshold formula. This research analyzes a nested time series dataset where each observation (spatial unit) records attribute values for each variable across several time periods. The OWA is not considered as it does not account for the variation in the order position of each observation (spatial unit) across several time periods. DEA is not selected as it is an optimization technique where the index score of a selected case is maximized and constrained to not exceed 1. The distance measure derived from the threshold formula proposed here is a point along a continuum that is moving over time and a selected case can have a value of greater or less than one at any given time.

The weighted average of attributes contributing to a composite measure of risk is calculated using the formula proposed by Ratick and Osleeb (2011):

$$I_j = \sum_{i \in A} W_i M_{ij} \quad \forall \quad j \in J$$

where, I_j is the composite weighted average for the risk index for spatial unit j; W_i, is the weight associated with attribute *i*; and M_{ij} is the attribute value *i* applicable to spatial unit j. *A* is the total number of attributes that contribute to risk and *J* is the set of spatial units in the study area.

5.4 Conclusion

The proposed hazard-risk-location-model (HRLM) provides a framework to assess the patterns of risk across a selected region through a re-specification of the risk equation. Operationalizing the model is undertaken in two stages. First, regression is used to evaluate causal relationships between variables representing social capital and unemployment rate, which functions as a proxy for coping ability. The assumption of independence of errors is of particular concern when dealing with spatial data over time as it is associated with time-related and spatial autocorrelation. These issues are addressed in statistical tests and corrections that are applied to the basic regression model to identify the best method that addresses the research questions.

The threshold analysis evaluates variations in unemployment rate, population density, and proximity to the hazard and how these variations contribute to the risk factor. The threshold analysis produces distance measures that form the basis to rank each observation on an ordinal scale. Mapping techniques are used to observe and evaluate spatial and temporal patterns of disaster risk across the study area. The HRLM recognizes that human interactions with hazard

events result in complex and varied impacts. While capturing all of the myriad inter-relationships within coupled human-environment systems is beyond the scope of the model, it provides some insights into developing improved frameworks for vulnerability and risk assessments in the future.

Chapter 6

Data

6.1 Introduction

The research is undertaken for 56 coastal counties in the Gulf of Mexico for the period, 2001 to 2012 (N = 672). The dataset combines attribute values of variables for each county across twelve time periods and is, therefore, described as a nested time series. As presented in Figure 6.1, the study area includes the states of Florida, Alabama, Mississippi, Louisiana, and Texas. Since this research is concerned with the impacts of a coastal oil spill, the counties are selected and classified as marine coastal counties having direct access to the ocean. Table 6.1 lists the variables and data sources used in this study. The data collected represent those factors that determine peoples' ability to sustain their livelihoods. The dependent variable, the unemployment rate, is representative of peoples' coping ability from the perspective of economic well-being as articulated by Sen (1981) and Chambers and Conway (1991). Since this research is concerned with social vulnerability, the unemployment rate is selected as the dependent variable as it represents income levels and peoples' ability to meet their basic needs (Cannon 1994). During a hazard event, livelihoods and social mechanisms are likely to come under stress and have a negative impact on household income creating constraints on families to manage monthly expenses. The independent variables reflect services provided by mechanisms (formal and informal) embedded in social capital that help sustain livelihoods (Cannon 1994; Wisner et al. 2004).

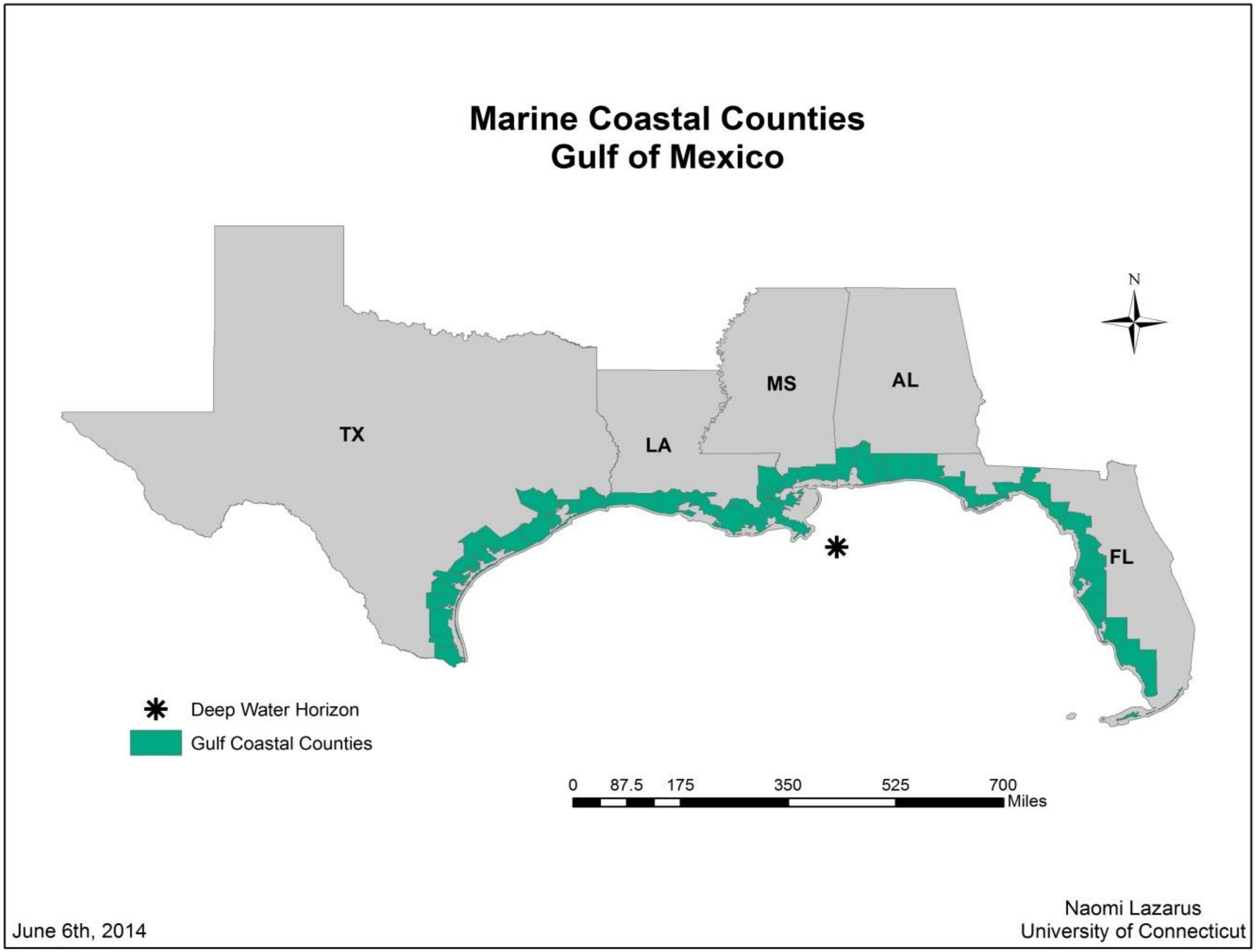

Figure 6.1 - Map of Coastal Counties in the Gulf of Mexico

6.2 Data Sources

Table 6.1 provides a summary of the variables used in the analysis. The dependent variable, unemployment rate, is obtained from the Bureau of Labor Statistics (BLS) website of the U.S. Department of Labor (http://www.bls.gov). The BLS collects data on employment and unemployment through the Current Population Survey (CPS) and the Local Area Unemployment Statistics (LAUS). The CPS database is developed from a monthly survey of 60,000 households across the United States. The LAUS program facilitates reporting of employment estimates from state agencies (BLS 2008, 2014). The information reported by state agencies is often times sporadic as some counties and localities may not have a mechanism in place to collect and report employment and unemployment figures to state agencies in a timely manner. The CPS is widely considered to be reliable as estimates are based on current trends in employment (BLS 2008, 2014). Employment is a mechanism that provides opportunities for people to build and maintain a means of living (livelihoods), which in turn increases their ability to cope with changes in the environment (Sen 1981; Cannon 1994). The unemployment rate reflects the extent to which resources and services provided by social capital are working to help build peoples' coping ability. The resources and services embedded in social capital are represented by the independent variables.

The independent variables are extracted from the County Business Patterns (CBP) website of the U.S. Census Bureau (http://www.census.gov/econ/cbp/). Data on number of workers and annual payroll are obtained from the Business Register and made available for public access. The Business Register contains information on single unit and multi-unit establishments located in the United States. The data are categorized using the North American Industry Classification System (NAICS). When dealing with a small size establishment, the

CBP provides a range with respect to the number of workers adhering to disclosure requirements articulated in the U.S. Code, Title 13, Section 9 (U.S. Census Bureau 2014b). In the case of Gulf coast counties with such disclosure restrictions, an average is calculated for the number of workers and is used in the location quotients computation.

The variables are selected based on their ability to best represent social capital. Social capital is embedded in formal and informal social relationships and networks that originate from family and kinships ties, workplace relationships, membership in social institutions, and the interaction of civil society with institutional and policy frameworks that govern the dynamics of the socio-economic context (Bourdieu and Wacquant 1992; Woolcock 1998). Social capital is rooted in the concept of *capability*, which describes the mechanisms and means employed by people to maintain and improve their livelihoods (Sen 1981). Given that individual relationships are difficult to monitor and are subject to privacy and disclosure requirements, variables representing social capital are limited. This limitation is addressed by identifying worker participation in *economic sectors* as variables representing the relationships that are embedded in social and institutional frameworks (Table 6.1). The number of people employed in each sector is indicative of the resources and services available in a given location to sustain livelihoods and to help people cope with environmental changes (Sen 1981; Chambers and Conway 1991).

Table 6.1 – List of Independent Variables and Data Sources

Variable / Code	Description	Source	Unit of Analysis
Unemployment Rate (dependent variable)	The number of people currently without work and who are actively seeking work as a ratio of the labor force	Bureau of Labor Statistics (BLS)	Percentage
Fisheries (FISH_LQ)	Number of paid employees engaged in activities described under NAICS code 1141 (all forms of marine fishing)	County Business Patterns (CBP)	Location quotients
Social assistance (SA_LQ)	Number of paid employees engaged in activities described under NAICS code 624 (services related to food, housing, and emergency services)	County Business Patterns (CBP)	Location quotients
Religious organizations (REL_LQ)	Number of paid employees working in faith-based organizations that provide services to the community - NAICS code 8131	County Business Patterns (CBP)	Location quotients
Employment services (EMP_LQ)	Number of paid employees working in agencies providing services relating to job placement, job search, and temporary work – NAICS 5613	County Business Patterns (CBP)	Location quotients
Professional services (PRO_LQG)	Number of paid employees engaged in activities described under NAICS code 54 that includes research and development, administrative services, and other business support services	County Business Patterns (CBP)	Location quotients
Utilities (UTI_LQG)	Number of paid employees engaged in activities described under NAICS code 22 (power generation, water supply, and waste disposal)	County Business Patterns (CBP)	Location quotients
Retail trade (RTL_LQ)	Number of paid employees working in sectors providing consumer goods and services, such as home goods, automobile services, supermarkets and grocery stores – NAICS code 44	County Business Patterns (CBP)	Location quotients

6.3 Variables

6.3.1 Dependent Variable

The spatial distribution of unemployment rates for 2005 and 2010 is presented in Figure 6.2 and 6.3. Unemployment rates range from 2.7 percent to 11.4 percent in 2005. Coastal counties in Louisiana, Mississippi, and Texas recorded unemployment rates higher than the national average of 5.1 percent. In general, coastal counties in Florida and Alabama reported low unemployment rates in 2005. Unemployment rates in 2010 range from 5.2 percent to 14.3 percent. In this time period, counties in Florida and Alabama experienced high unemployment rates greater than the national average of 9.6 percent. Counties in coastal Louisiana recorded low unemployment rates compared to counties in Florida and the Texas panhandle.

Counties in Florida experienced an increase in unemployment rates from 3.6 percent on average in 2005 to 12.2 percent in 2010. Unemployment rates in Plaquemines, Orleans, and Jefferson counties in coastal Louisiana and counties in Mississippi declined from 10.4% on average in 2005 to 7.7% in 2010. Marginal increases in unemployment levels were recorded in coastal Texas and Alabama during this five-year time frame.

This discussion on the distribution of unemployment rates is based on observed data. The proposed model accounts for the time lag associated with the impacts of hazard events by including control variables that represent time after the oil spill and time after Katrina. As discussed in Chapter 5, the value of the time variable is set as 1 for the event year and increments of one for subsequent years, thereby accounting for the cumulative impacts of hazard events that play out over time. The distribution of predicted unemployment rates based on the results of the proposed model is discussed in Chapter 7.

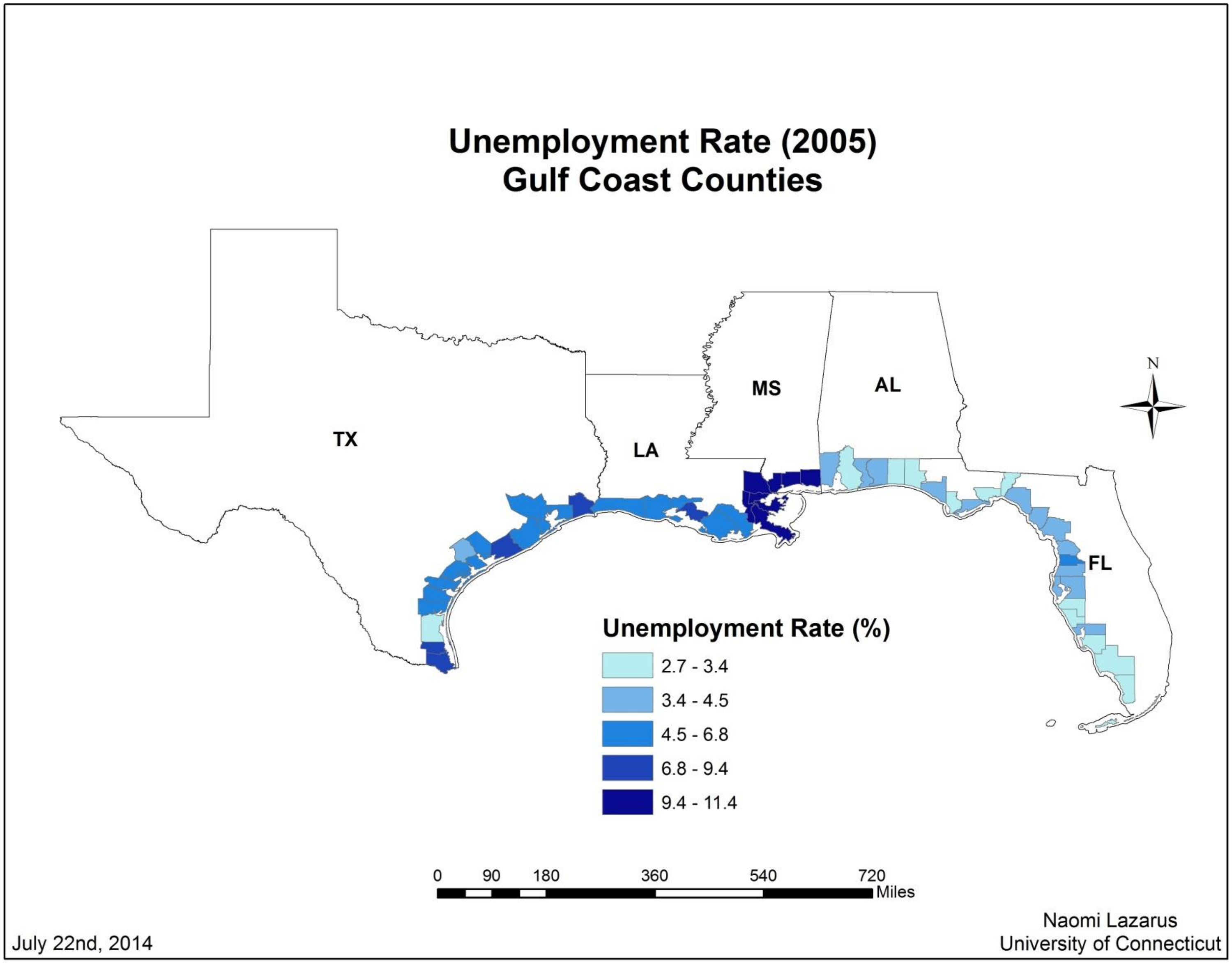

Figure 6.2 – Map of Unemployment Rate (2005)

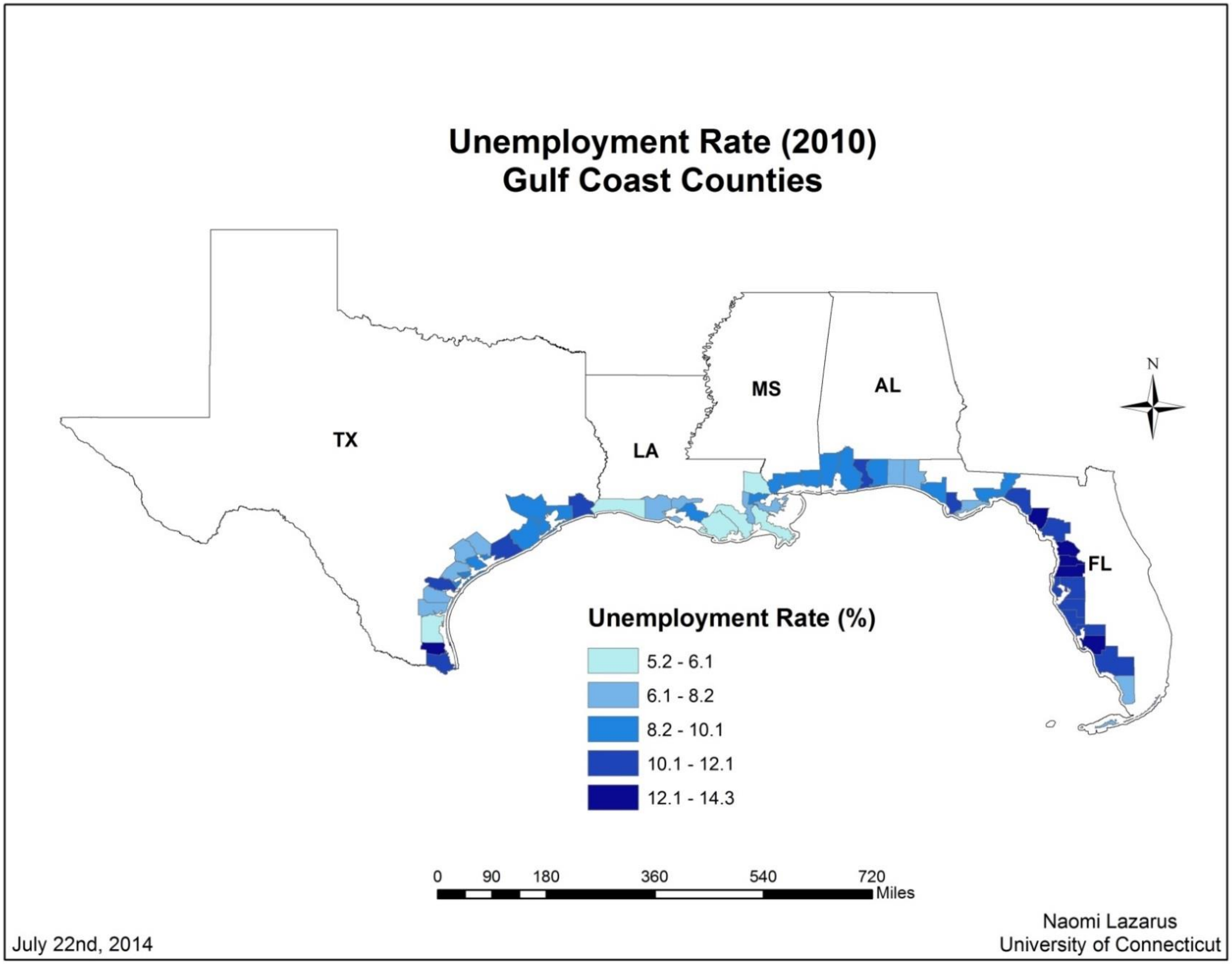

Figure 6.3 – Map of Unemployment Rate (2010)

A preliminary analysis of spatial autocorrelation in the distribution of unemployment rates is evaluated using the Moran's I test. The Moran's I statistic for unemployment rates in 2005 is 1.0177 and a value of 0.606 is reported in 2010. In both time periods the Moran's I is greater than the expected value of -0.018182 ($p = 0.000$) and is significant at $p < 0.001$. The significance of the statistic indicates that underlying spatial processes are responsible for neighboring counties to display similar attributes resulting in positive spatial autocorrelation. The clustering of high and low values is evidence that coastal counties are responding to the widespread impact of Hurricane Katrina and the DWH oil spill in similar ways despite differences in the distribution of social capital. The significance of the test of spatial autocorrelation is examined using the following examples.

In 2005, Plaquemines, Orleans, and St. Bernard counties were adversely impacted by Hurricane Katrina. These impacts are evident in the high unemployment rates of 11.4% witnessed in the counties during this time (Figure 6.2). Each county, however, adopts a different set of coping strategies as identified in the variation in location quotients. While the three counties have location quotients less than 1.00 for social assistance and high location quotients for fisheries, Orleans Parish performs better than Plaquemines and St. Bernard in sectors related to religious organizations, utilities, and professional services. In 2010, the DWH oil spill negatively impacted Hancock, Harrison, and Jackson counties in Mississippi where the unemployment rate was between 8.2% and 10.1% (Figure 6.3). All three counties displayed location quotients less than 1.00 for social assistance. Harrison County, however, recorded higher location quotients in retail, employment services, and utilities than Harrison and Jackson counties. Jackson County, on the other hand, reported higher location quotients for fisheries and religious organizations compared to the other two counties. The variation in location quotients

for specific sectors illustrates that counties adopt different coping strategies in the form of resources and services provided by social capital, but the outcome, unemployment rate, is the same indicating that counties in close proximity respond to hazard events in similar ways based on the clustering of high and low unemployment rates.

.

6.3.2 Independent Variables

The variables listed in Table 6.1 examine the spatial and temporal variations in the relationship between unemployment rates and social capital across the study area. The hypotheses presented in Chapter 3 approach the task of evaluating these relationships in two ways. First, do counties with social capital show less fluctuation in unemployment rates during hazard events than those with little access to social capital? Second, how do counties with different coping strategies fair over time under conditions of a hazard event? These queries are addressed in a preliminary examination of the variables.

The first variable used in the analysis is fisheries. As per NAICS code 1141, this sector includes finfish fishing, shellfish fishing, and other forms of marine fisheries. Given that this research is primarily concerned with the impact of oil spills in coastal communities, the fishing industry is of particular interest. It is expected that the number of people engaged in fishing will help determine to what extent livelihoods supported by the fishing industry are impacted during a maritime hazard event. In order to standardize the independent variables location quotients (LQ) are used. The location quotient is a relative measure that assesses each county in relation to the labor participation in each sector.

The basic form of the location quotient is articulated as,

(1) LQ for each County / LQ for Gulf coast counties (study area)

which, when deconstructed is calculated using the formulae:

$$\text{(2) LQ for each County} = \frac{\text{No. of workers in a sector in each county}}{\text{Total no. of workers in each county (all sectors)}}$$

$$\text{(3) LQ for Gulf} = \frac{\text{No. of workers in a sector in all counties in study area}}{\text{Total no. of workers in study area}}$$

The location quotient for fisheries compares each county's labor participation in relation to the country as a whole. Since the Gulf coast accounts for sixteen percent of the total catch, estimating the location quotients in relation to the study area would not provide an adequate measure to capture spatial variations. Therefore, the denominator in equation (1) is replaced by the location quotient for the United States and is calculated using the formula:

$$\text{(4) LQ for U.S.} = \frac{\text{No. of workers in Fisheries in U.S.}}{\text{Total no. of workers in the U.S.}}$$

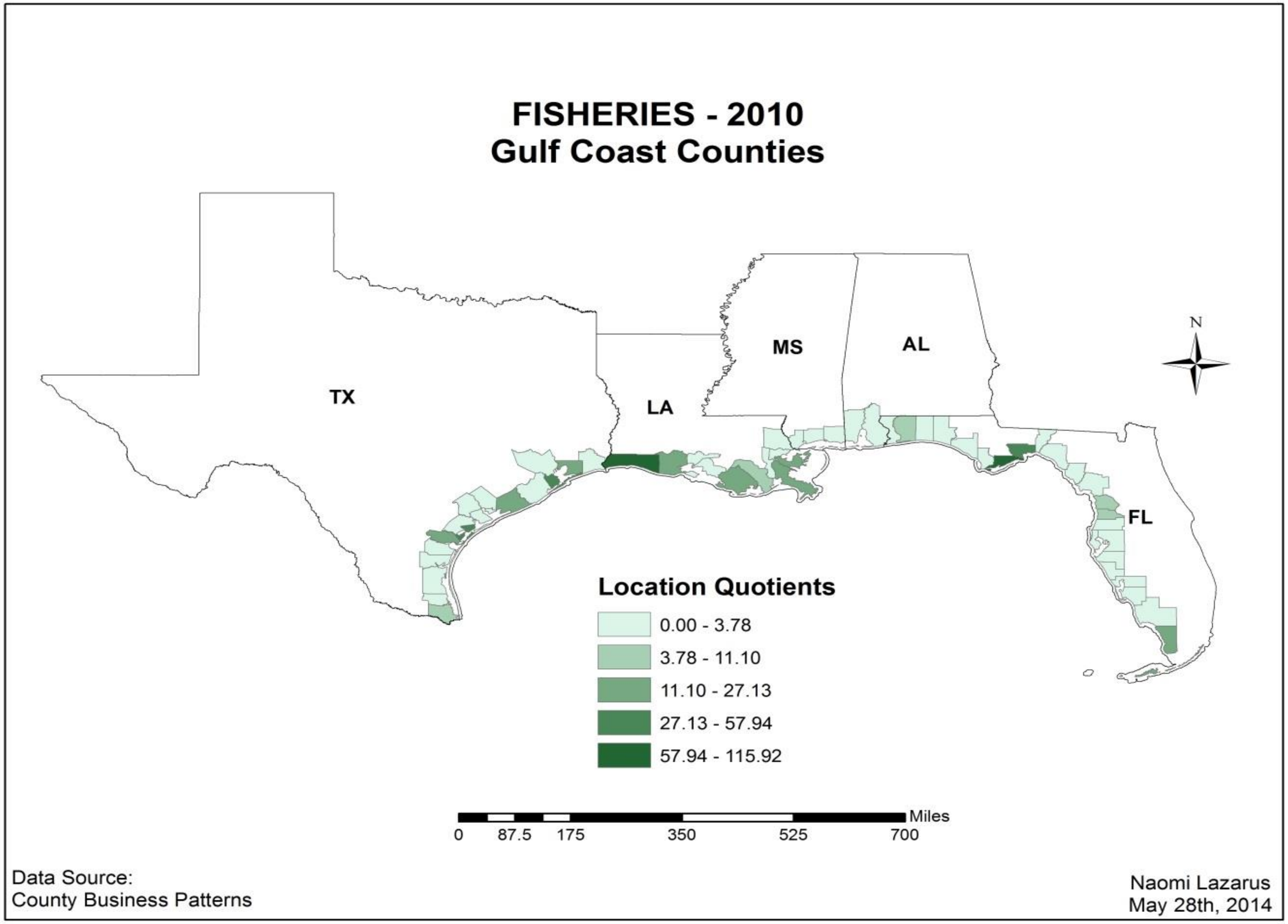

Figure 6.4 - Map of Location Quotients in Fisheries

Figure 6.4 is a map showing the distribution of location quotients for fisheries across the study area. More than half of gulf coast counties record location quotients greater than one, emphasizing the importance of commercial fisheries in the study area. Parishes in coastal Louisiana and several counties in the panhandle of Florida in particular record high location quotients in fisheries. It is expected that greater the number of people employed in the fishing industry (reflected in high location quotients), the overall unemployment rates would be lower in coastal counties in the Gulf compared to regions where the fishing industry has a relatively lower share in the local economy. During an environmental disaster, counties with high location quotients in fisheries are more vulnerable to be negatively impacted, which will cause unemployment rates to rise. Charts showing temporal variation in the unemployment rate are examined at the county level. The annual unemployment rate is used since monthly unemployment data are not available consistently at the county level. There are missing data for several months, particularly before and after Katrina and the oil spill for counties that were affected. With regard to quarterly data, the Bureau of Labor Statistics only reports employment and wages for each quarter, not unemployment rates. Given the fact that there are inconsistencies in monthly and quarterly data at the county level, changes in annual unemployment rates are discussed for selected counties.

Plaquemines Parish LA records relatively high location quotients in fisheries compared to other coastal counties in the Gulf. Figure 6.5 shows considerable variation in unemployment rates from 2001 – 2012. These fluctuations are pronounced in 2005, the year of Hurricane Katrina, when the unemployment rate peaks at 11.4 percent. There is also considerable variation in the unemployment rate before and after the DWH oil spill that occurred in 2010.

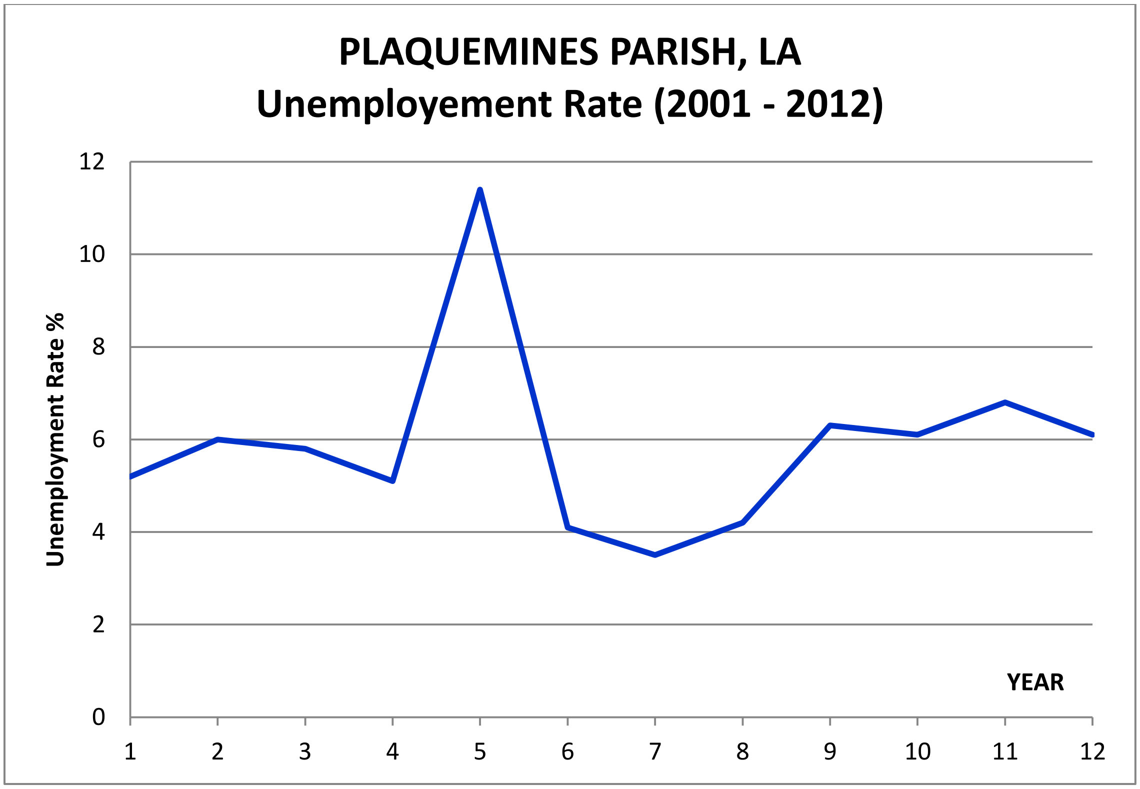

Figure 6.5 – Temporal Variation in Unemployment Rate – Plaquemines Parish, Louisiana

The second independent variable is social assistance (NAICS code: 624), which accounts for the number of employees engaged in community, food, and emergency relief services, services for the elderly and disabled, temporary shelters, child care services, and vocational rehabilitation services. These services are primarily provided by local government and therefore are subjected to budgetary restrictions at the county and state levels. The coastal counties in the study area cover five states, Alabama, Florida, Louisiana, Mississippi, and Texas. In general, states prepare annual budgets for the next fiscal year or in the case of Texas, for the next two fiscal years (NCSL 2014). Resources earmarked in the budget in the current year are utilized in the following year, which would affect the allocation of social assistance services. When computing the location quotients for social assistance, data are lagged by one year (i.e. 2009 data applied to 2008 etc.) to account for the time lag associated with the allocation of resources. In

the case of the last time period, an average three year trend (increase / decrease) in number of workers at the state level is taken to project the data for each county. The location quotient for social assistance is calculated using equations (2) and (3) modified as follows:

$$(5)\quad \text{LQ for each County} = \frac{\text{No. of workers in SA in each county (lagged)}}{\text{Total no. of workers in each county (all sectors)}}$$

$$(6)\quad \text{LQ for Gulf} = \frac{\text{No. of workers in SA in all counties in study area (lagged)}}{\text{Total no. of workers in study area}}$$

The location quotient differs from elasticity of demand commonly cited in economics. The location quotient characterizes the employment of an area into sectors and compares each sector to the employment structure of the base area. The location quotient is a relative measure that monitors the spatial variation in labor participation as it indicates the importance of a sector in a specific location. A location quotient greater than 1 indicates that the share of employment in a given sector in the local area is greater than that of the base area (Bureau of Labor Statistics 2013). The slope coefficient in the proposed model indicates the change in the unemployment rate (dependent variable) in response to a unit change in the location quotient of a particular sector. As such, the model estimates changes in the unemployment rate based on the *share* (or proportion) of a particular sector in the labor participation of the study area. Elasticity monitors the change in demand for a particular product in response to the change in price. The degree of change determines how sensitive consumer demand is when prices fluctuate. An elasticity measure greater than 1 indicates that the demand for a product i.e. quantity is highly sensitive (elastic) to small changes in price (Heakal 2014). Using the location quotient as an elasticity measure would involve measuring the change in labor participation at the county level. This would be workable if changes are monitored for a single unit (county) over a period of time.

Since this research is concerned with evaluating the spatial variation in employment and unemployment across fifty six counties in the Gulf region, treating the location quotient as a sensitivity measure like the elasticity of demand would not facilitate a spatial analysis of the problem.

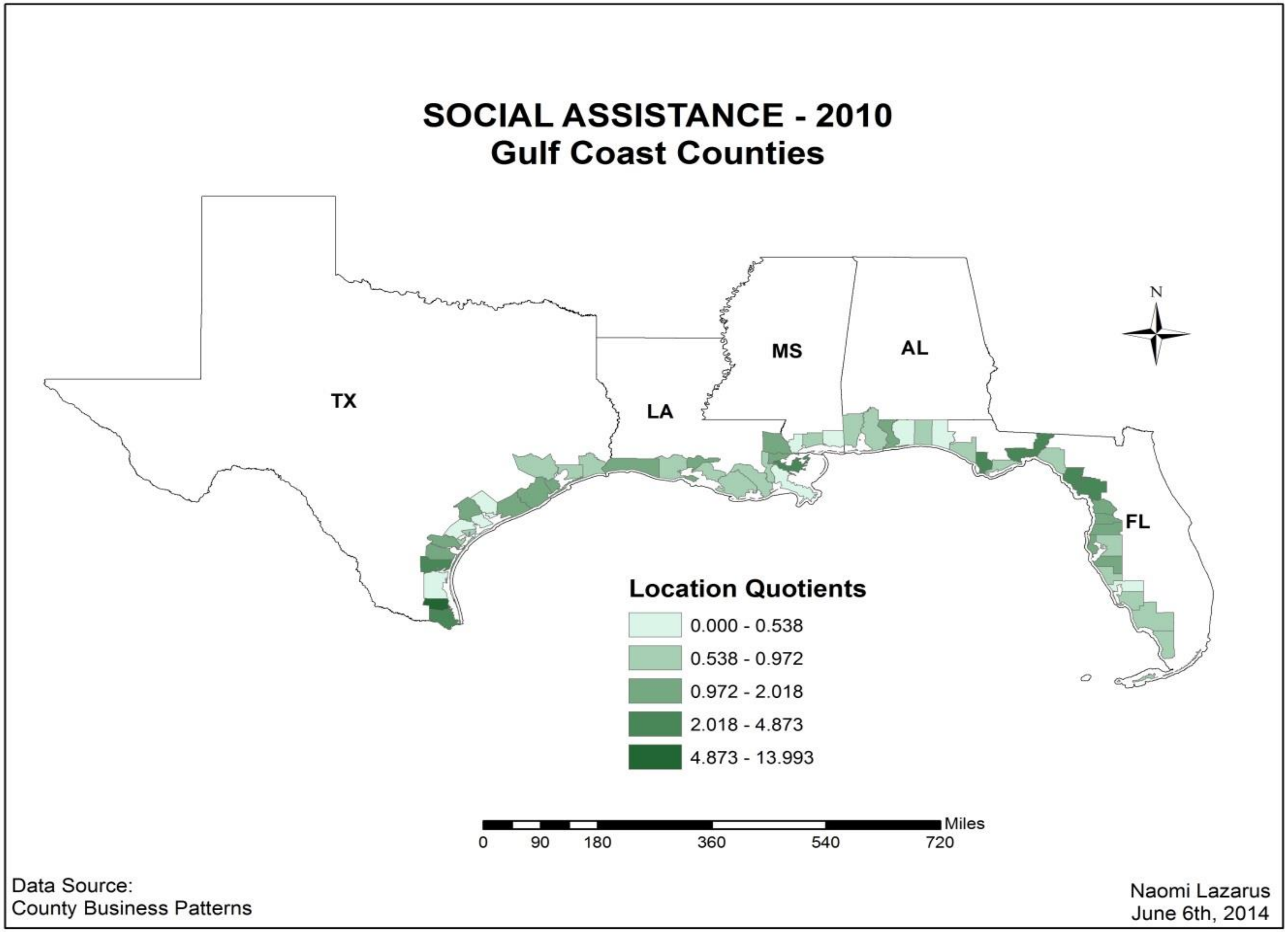

Figure 6.6 - Map of Location Quotients in Social Assistance

The spatial distribution of location quotients for social assistance is presented in Figure 6.6. The map reveals that counties across the Gulf employ a large proportion of the labor force in this sector as indicated by location quotients ranging greater than 1.00. Services provided by religious organizations are similar to the type of services classified as social assistance. Counties with a large number of workers in religious organizations are likely to provide more outreach to the community during times of environmental disasters. They form part of social capital that provides formal and informal linkages so that people can access resources to maintain livelihoods. Location quotients associated with religious organizations are calculated using the general form of the location quotient equation i.e. LQ for each county / LQ for Gulf coast counties (equation 2 and 3). The number of workers employed in religious organizations is used to calculate the location quotients and the map showing these values is presented in Figure 6.7. Counties with high location quotients linked to religious organizations are clustered in coastal Alabama, the Florida panhandle, and along the Texas coast.

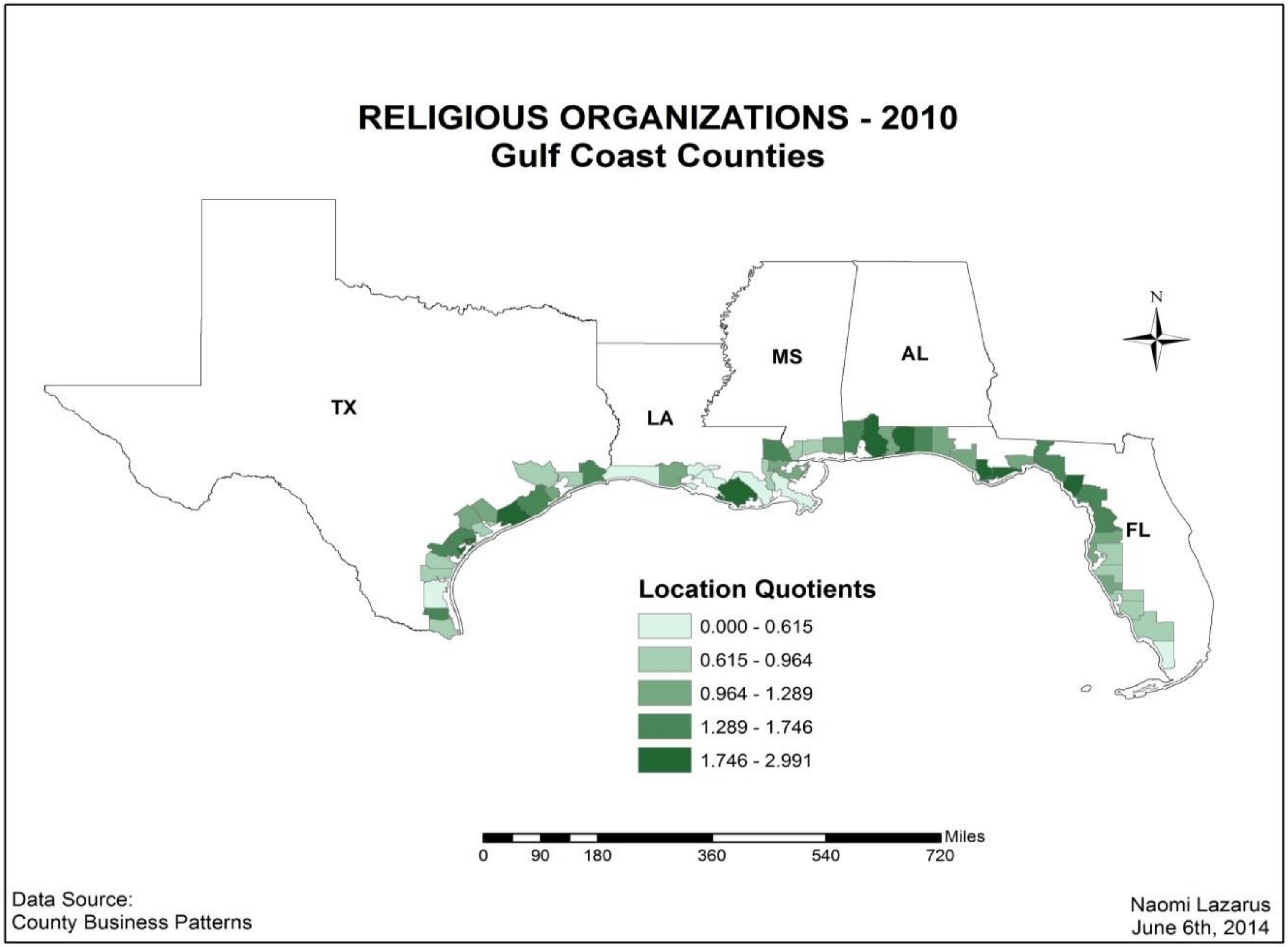

Figure 6.7 - Map of Location Quotients in Religious Organizations

It is expected that counties in the Gulf with a greater number of people employed in social assistance and in religious organizations (high location quotients) are likely to experience lower fluctuations in unemployment rates during an environmental disaster. These sectors provide an added safety net by virtue of the services they provide to the community – food, housing, emergency services, temporary shelters etc. For example, location quotients in social assistance and religious organizations are relatively high in Dixie County FL. The chart showing unemployment rates in the county (Figure 6.8) reveals that changes occur gradually over time particularly during the period, 2001 to 2007. The rapid increase in unemployment rates from 2008 to 2010 is primarily due to the recession that is driving down economic growth. In Plaquemines Parish LA, where services provided by social assistance programs and religious organizations are much lower compared to Dixie County, the fluctuation in unemployment rates over time is more pronounced as illustrated in Figure 6.5. These changes are particularly evident during hazard events like Hurricane Katrina in 2005 and the DWH oil spill in 2010.

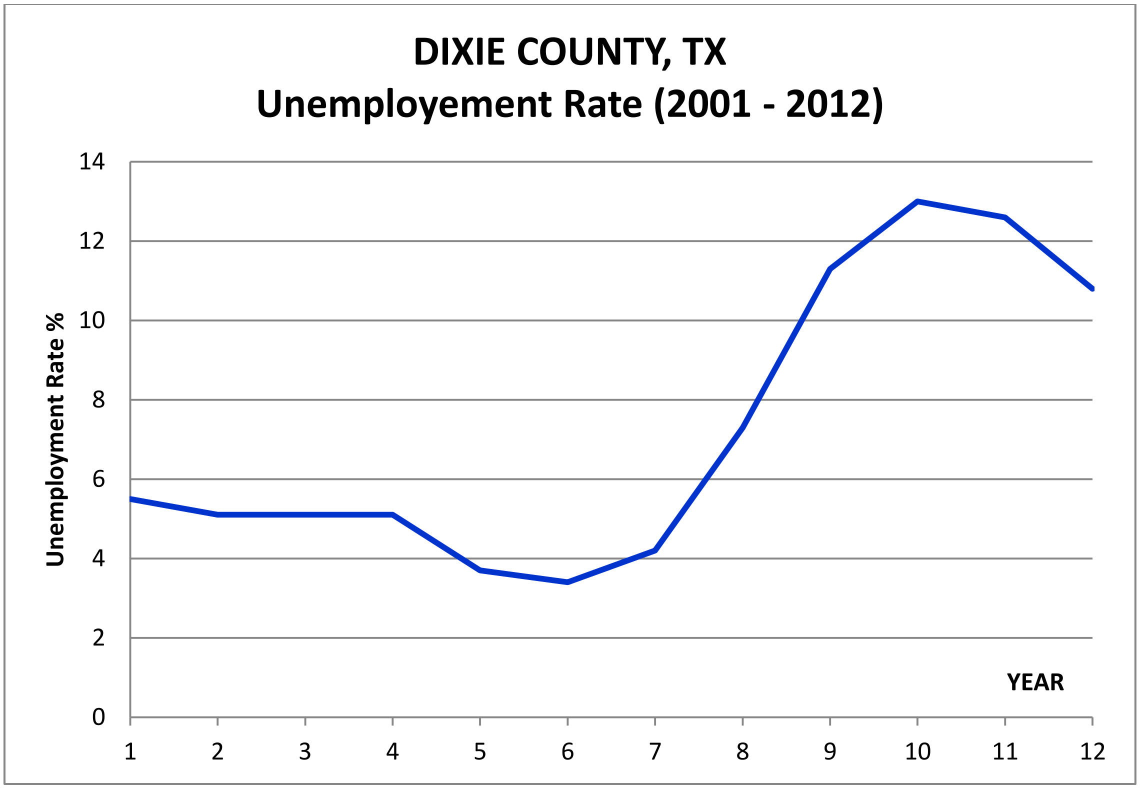

Figure 6.8 – Temporal Variation in Unemployment Rate – Dixie County, Florida

Employment services and professional services emphasize the role of social capital through the institutional frameworks that support peoples' income earning capacity with a view to improving livelihoods (Bebbington 1997; Adger 2000; Ford et al. 2008; Holt 2008). Employment services include job placement agencies, head-hunting firms, and temporary help services as classified in NAICS code 5613. Location quotients for employment and professional services are calculated using the number of workers in this sector applied to the general form of the location quotient equation i.e. LQ for each county / LQ for Gulf coast counties (equation 2 and 3).

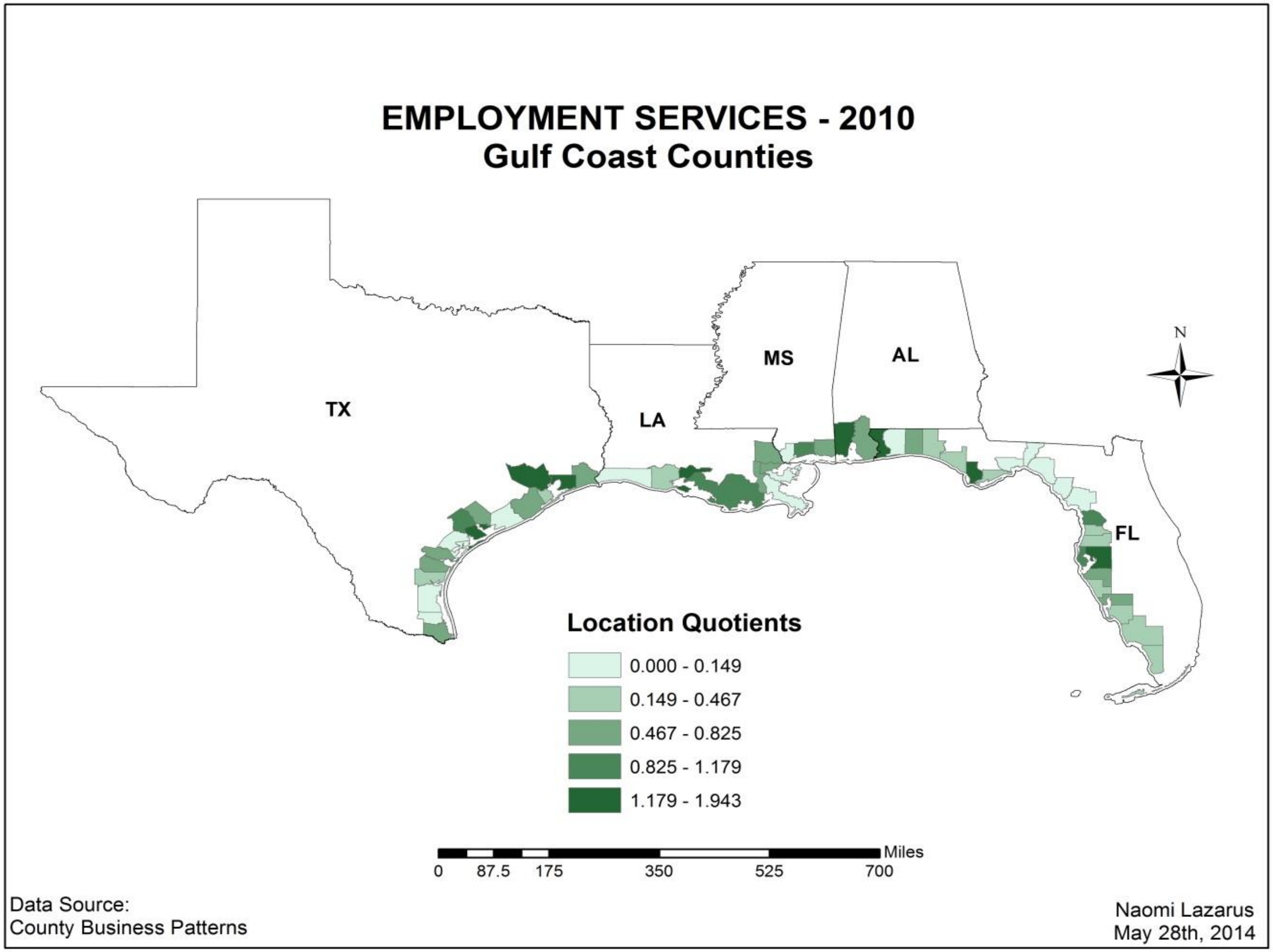

Figure 6.9 - Map of Location Quotients in Employment Services

A map of location quotients in employment services is presented in Figure 6.9. Counties with location quotients in employment services greater than 1.00 are clustered in coastal Alabama, Louisiana, and Texas. With regard to location quotients in professional services, Figure 6.10 reveals that the majority of Gulf coast counties record low values relative to the region as a whole. Examples of counties with high location quotients are Hillsborough and Pasco in southwest Florida, Harris and Galveston in Texas, and Hancock MS. Professional services consist of a wide range of services that cater to small and large businesses, such as accounting, tax preparation, research and development, management, and human resources. While employment services provide pathways or linkages for people to find and secure employment, professional services support employers in the day-to-day management and operations of small and large firms. Professional services in particular reflect a community's adaptability over the long-term in relation to unexpected changes in the environment that may call for new and innovative strategies to sustain socio-economic conditions. It is expected that counties with large numbers of workers engaged in delivering employment and professional services are better able to absorb the impacts of hazard events.

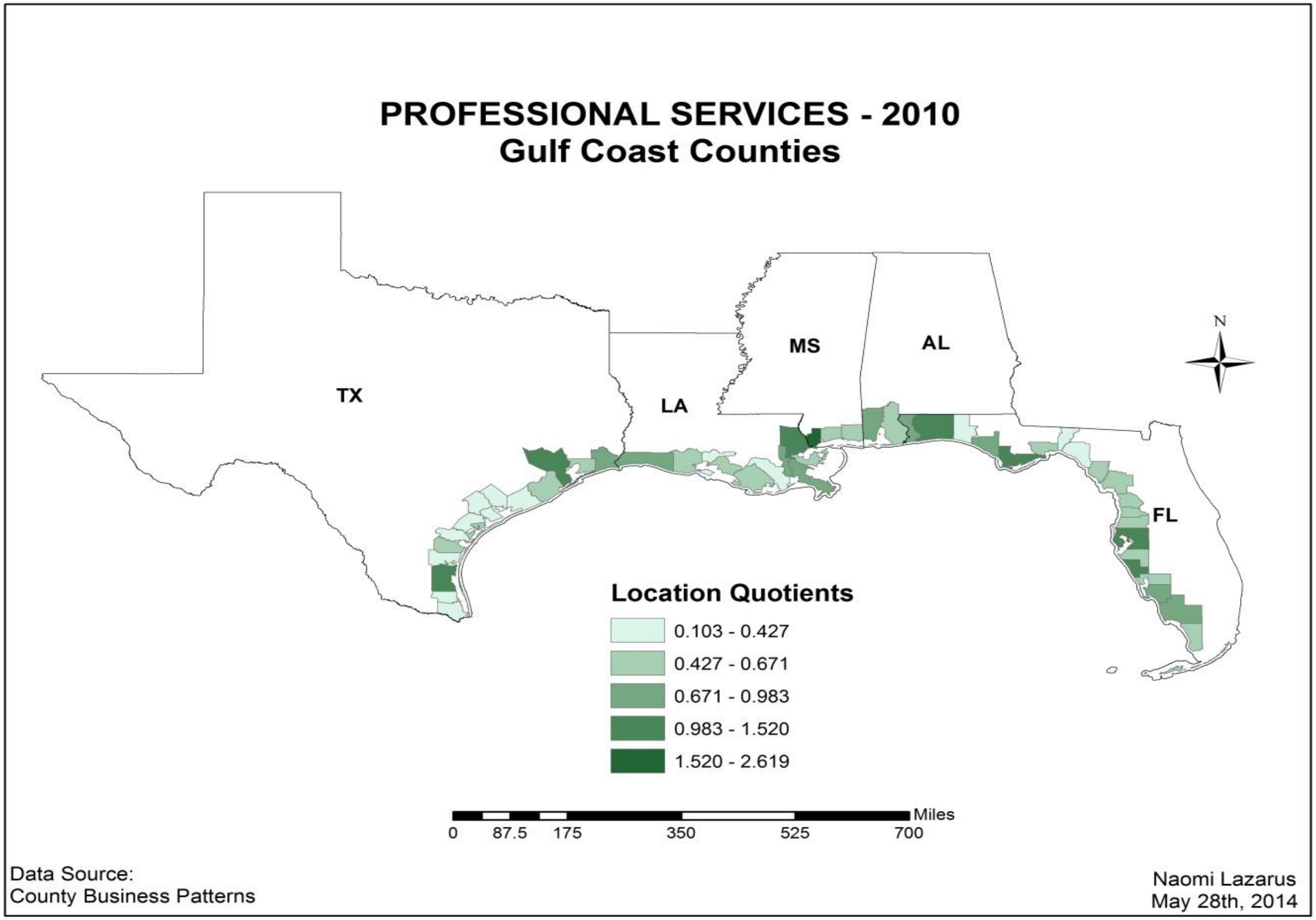

Figure 6.10 - Map of Location Quotients in Professional Services

Counties in the Gulf with a greater number of people employed in employment and professional services (high location quotients) are likely to experience much lower fluctuation in unemployment rates during an environmental disaster. These sectors provide linkages to find employment, which is a key livelihood mechanism that helps people to cope with the impacts of hazard events. For example, location quotients in employment and professional services are relatively high in Harris County TX. The chart showing unemployment rates in the county (Figure 6.11) reveals that changes occur gradually over time typically over a period of two to four years as evidenced by the decrease in unemployment rates from 2003 to 2007. The rapid increase in unemployment rates from 2008 to 2010 is primarily due to the recession that is driving down economic growth.

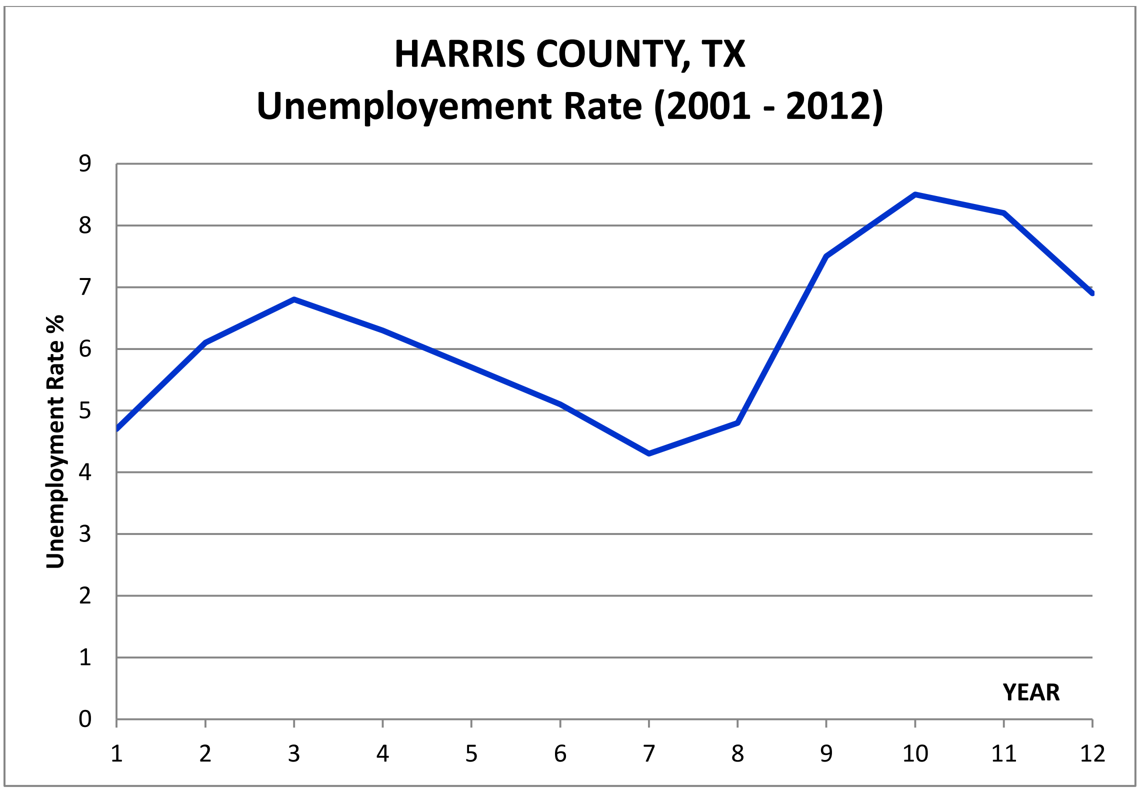

Figure 6.11– Temporal Variation in Unemployment Rate – Harris County, Texas

In Jefferson Parish LA (Figure 6.12), where services provided by employment and professional services are much lower compared to Harris County, the fluctuation in unemployment rates occurs yearly as is evident in the period 2004 to 2005 when unemployment rates increased due to the impact of Hurricane Katrina and subsequently declined over the course of the following year.

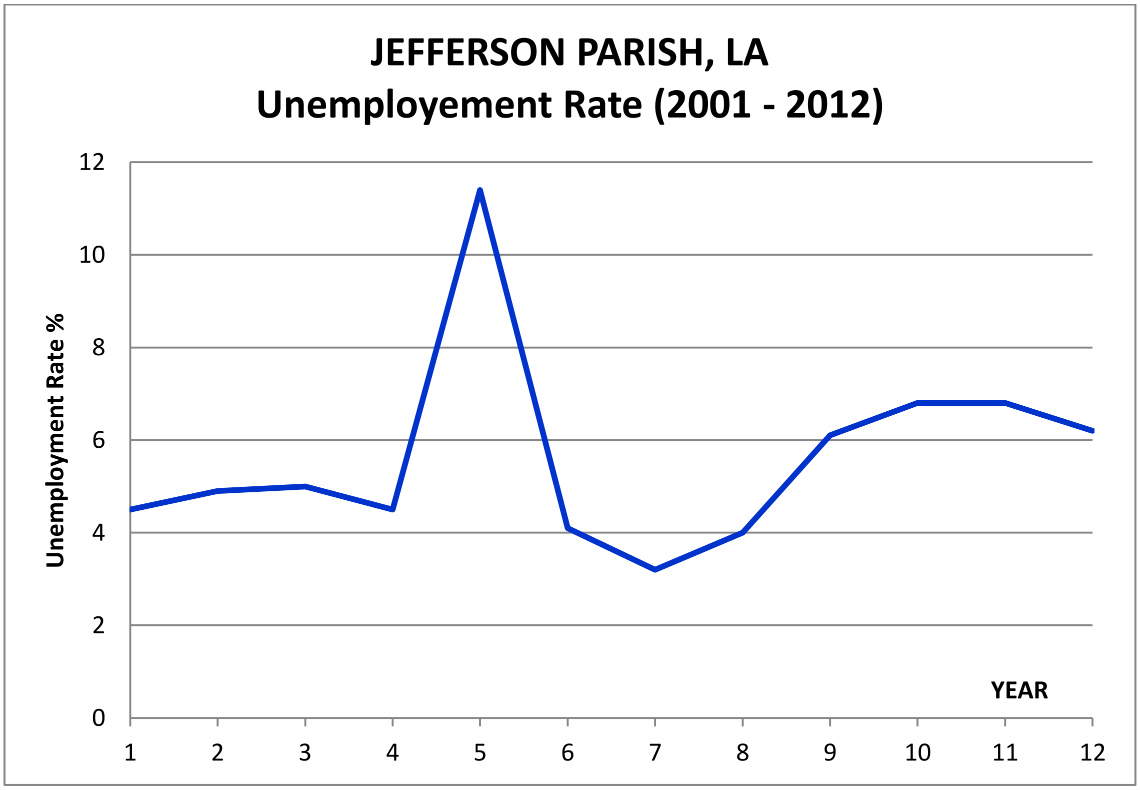

Figure 6.12 – Temporal Variation in Unemployment Rate – Jefferson Parish, Louisiana

The County Business Patterns (CBP) adopts NAICS code 44 to define retail trade as establishments engaged in the provision of consumer goods and services. These include automobiles, home furnishings, electronics, food, and apparel among others. In this research, retail trade is used as a surrogate for spending. Increase in retail spending is evidence of rising demand for goods and services, which in turn translates into an increase in jobs in the retail trade sector. The number of workers employed in retail trade is used to calculate the components of the general location quotient equation i.e. LQ for each county / LQ for Gulf coast counties (equation 2 and 3). A map showing the spatial distribution of location quotients in retail trade is presented in Figure 6.13. More than half of all Gulf coast counties record location quotients greater than 1.00 indicating that retail trade is an important part of the local economy.

In counties where retail trade is an important part of the local economy, the occurrence of hazard events will likely have a negative impact on job growth in this sector and increase overall unemployment. This trend is illustrated in Figure 6.12 showing unemployment rates in Jefferson Parish, LA where location quotients in retail trade are greater than 1.00 during the period 2001 to 2012. The chart shows considerable fluctuation in unemployment rates particularly during the period 2004 to 2006, highlighting the negative impact of Hurricane Katrina on the local economy of the parish.

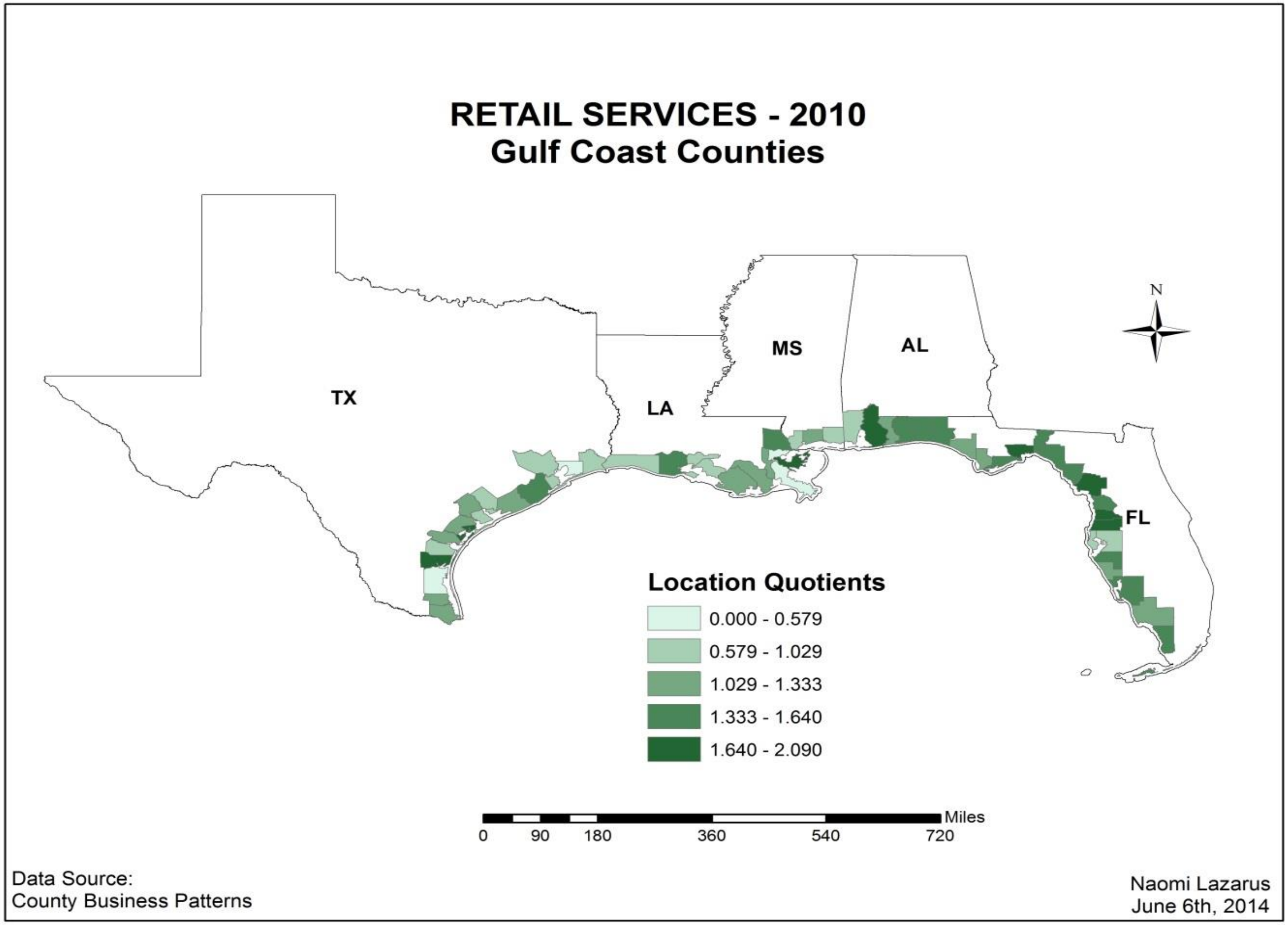

Figure 6.13 - Map of Location Quotients in Retail Trade

In counties where location quotients in retail trade are less than 1.00, as in the case of Chambers County TX (Figure 6.14), there is likely to be less variation in unemployment rates. Unemployment levels in the county are relatively stable during the period, 2001 to 2006, with minor fluctuations in 2004 and 2005. The rapid increase in unemployment rates from 2008 to 2010 is due to the overall impact of the recession that is driving down economic growth, and not specifically due to changes in the retail sector.

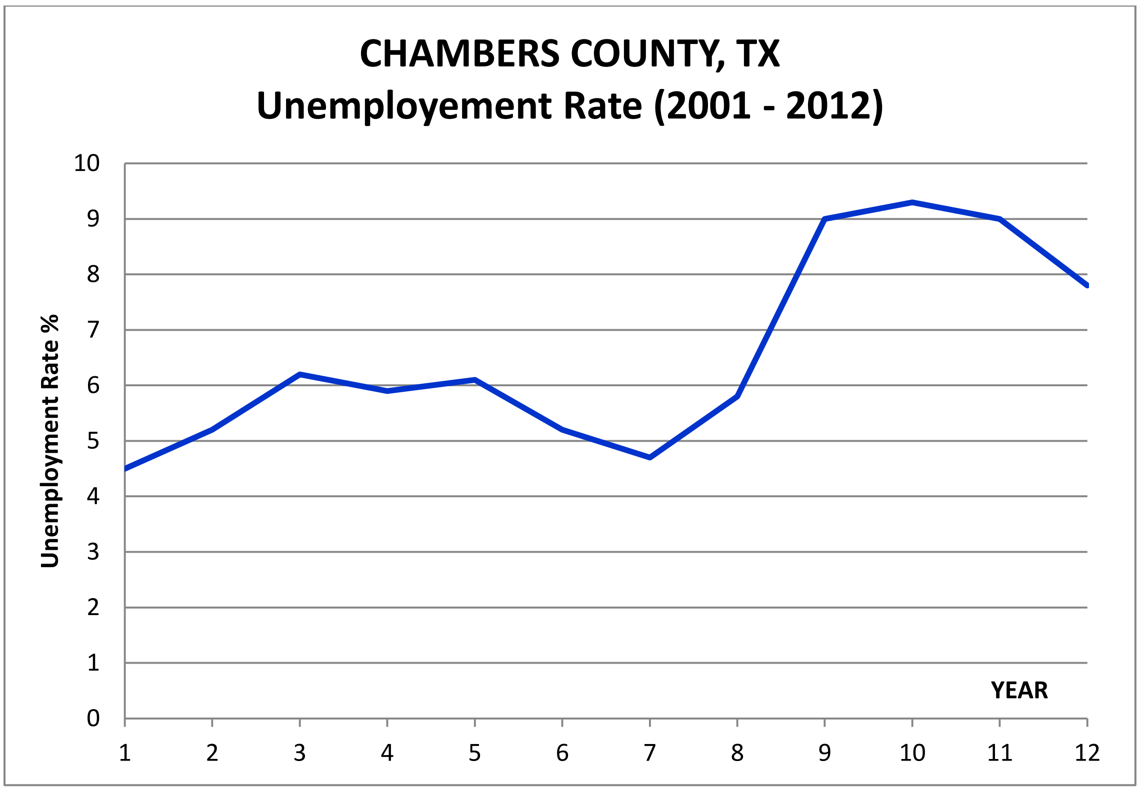

Figure 6.14 – Temporal Variation in Unemployment Rate – Chambers County, Texas

As indicated in Table 6.1, the variable identified as utilities in the County Business Patterns (CBP) consists of the number of paid employees engaged in activities linked to power generation, water supply, and waste disposal as described under NAICS code 22. In the Gulf, utility services are primarily provided by the private sector. Location quotients are calculated using the general form of the location quotient equation i.e. LQ for each county / LQ for Gulf coast counties (equation 2 and 3). A map showing the spatial distribution of location quotients in utilities is presented in Figure 6.15. Most counties in the Gulf record location quotients greater than 1.00 indicating that this sector is an important part of the local economy.

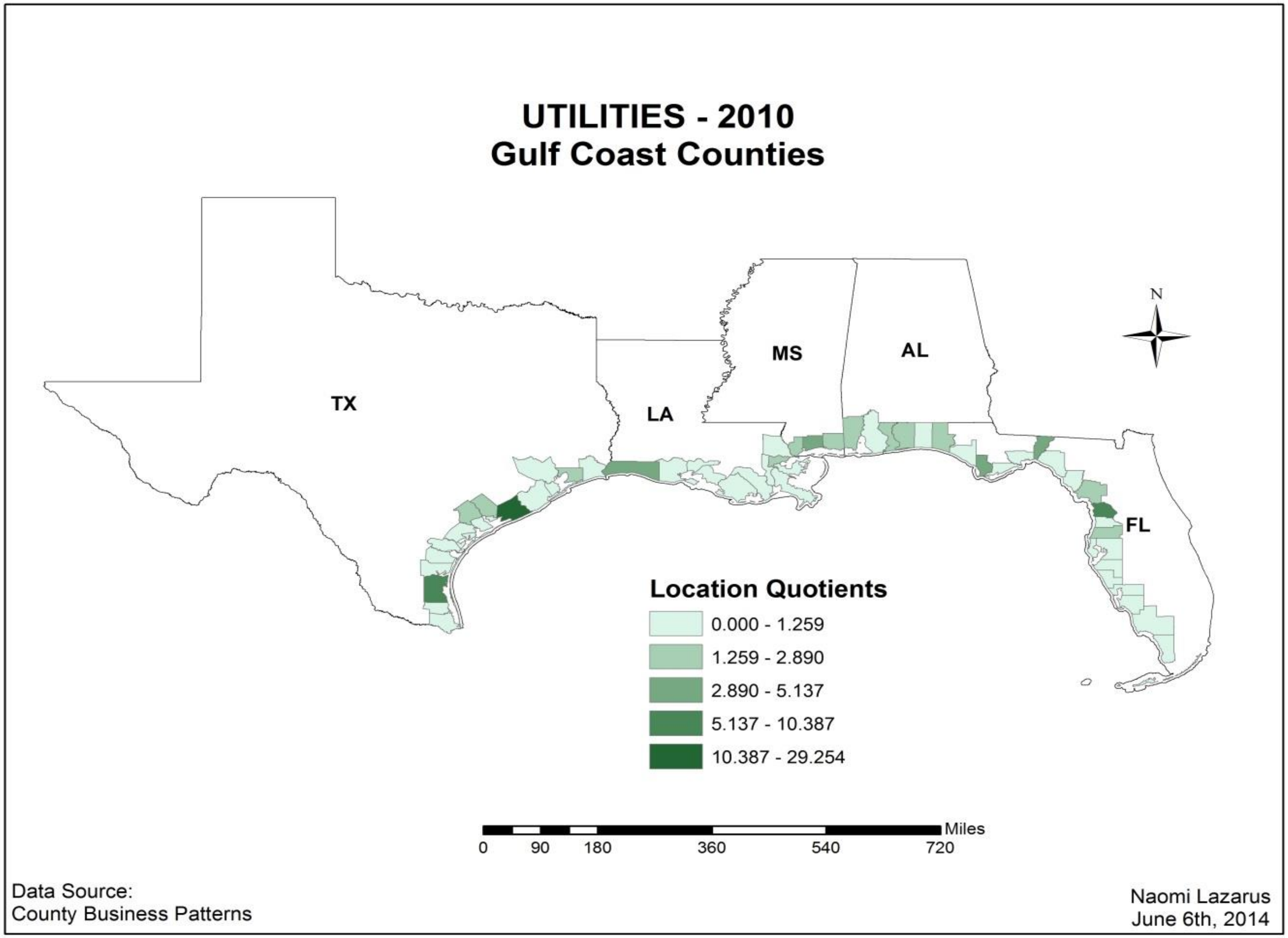

Figure 6.15 - Map of Location Quotients in Utilities

In counties where the utilities sector employs a large proportion of the labor force (location quotients greater than 1.00), there is likely to be greater variation in unemployment rates during an environmental disaster. For example, location quotients in Hancock County, MS range from 2.00 to 4.00 in the time period, 2001 to 2012. Significant variations in unemployment rates are observed in the county during this period as illustrated in Figure 6.16. An increase in unemployment rates is evident during hazard events like Hurricane Katrina in 2005 and the DWH oil spill in 2010.

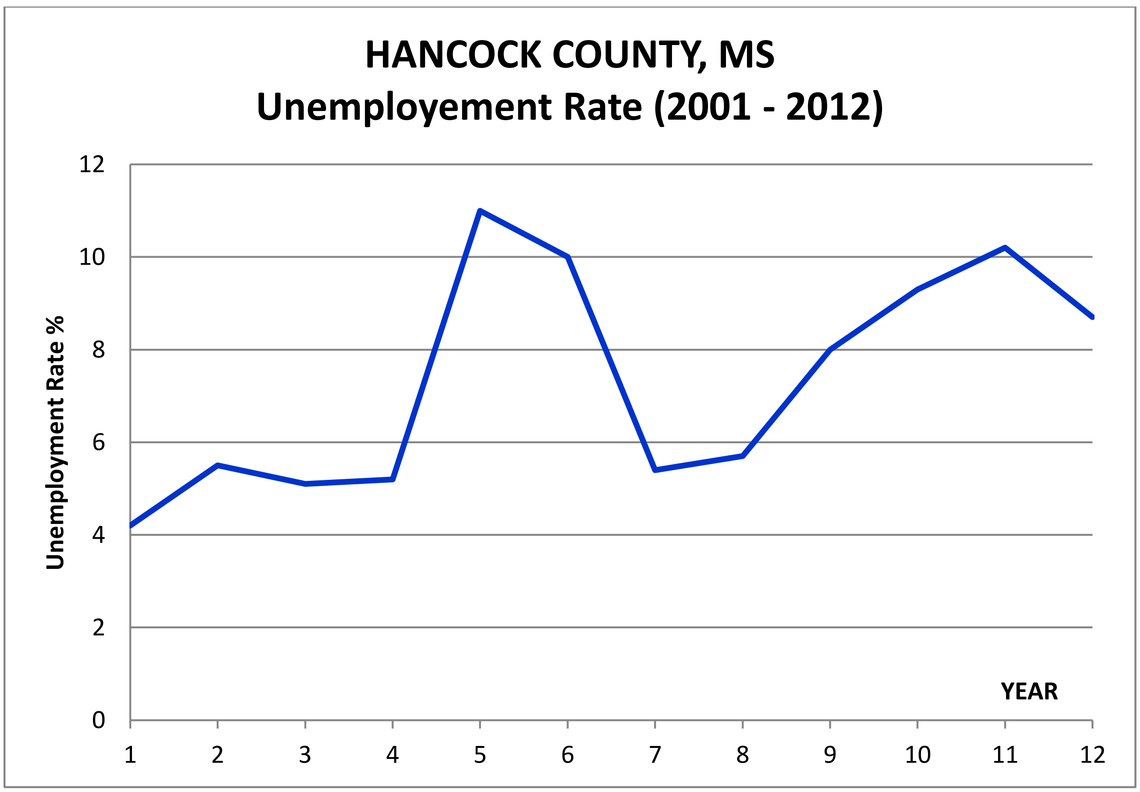

Figure 6.16 – Temporal Variation in Unemployment Rate – Hancock County, Mississippi

In counties where location quotients in utilities are less than 1.00, as in the case of Brazoria County TX (Figure 6.17), there is likely to be less variation in unemployment rates. The chart showing unemployment rates in the county reveals that changes occur gradually over time unlike the variation observed in Hancock County (Figure 6.16). The decline in unemployment rates from 2004 to 2007 accounts for the fact that Hurricane Katrina did not affect the Texas coastline as much as it impacted coastal Louisiana and Mississippi. As observed in most counties the increase in unemployment rates from 2008 to 2010 is primarily due to the recession that is driving down economic growth in the county.

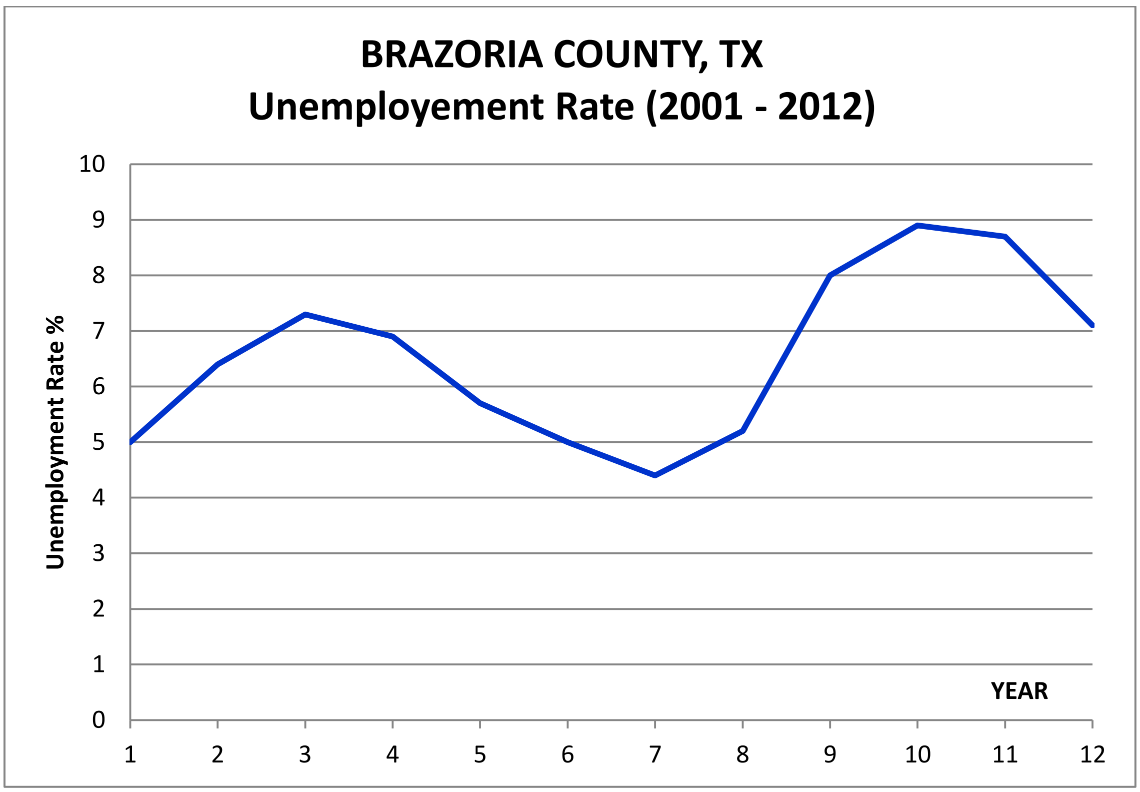

Figure 6.17 – Temporal Variation in Unemployment Rate – Brazoria County, Texas

6.3.3 Control Variables for Time and Distance-Decay

The previous section dealt with a preliminary analysis of the independent variables. The independent variables represent resources and services provided by social capital, such as social assistance and employment services that are measured as location quotients. The preliminary analysis revealed that social capital determines changes in the unemployment rate, which is representative of coping ability. Charts on unemployment rates in selected counties highlight significant fluctuations in counties affected by Hurricane Katrina and the DWH oil spill. The proposed model incorporates four control variables (Table 6.2) that are intended to capture the interaction between the variables of interest i.e. the independent variables and hazard events.

Table 6.2 – Control Variables for Time and Distance-Decay

Variable Name	**Code**	**Description**
Time after DWH oil spill	TIME_O	A variable value of 1 for the event year (2010) and increments of one for subsequent years.
Time after Katrina	TIME_K	A variable value of 1 for the event year (2005) and increments of one for subsequent years.
Time after Katrina (squared)	TIME_K_SQ	Corresponding value for TIME_K is squared
Spill distance decay	SPILL_DIST_DECAY	Distance from the spill is devalued for subsequent years after event

Variable values for TIME_O and TIME_K are set at one for the event year and increased by one for subsequent years. For example, TIME_O will have a value of one for 2010, the year

of the DWH oil spill, and a value of 2 and 3 respectively for 2011 and 2012. TIME_K will have a value of one for 2005, the year Katrina occurred, and a value of 2 and 3 respectively for 2006 and 2007. Zero values are recorded for time periods before each event. TIME_K_SQ is the squared value of TIME_K. For example, TIME_K value in 2007 is 3 and the corresponding TIME_K_SQ value is 9. This variable is included to account for a possible quadratic trend that may exist when evaluating the impacts of hazard events. A quadratic trend reflects a situation where the regression line is non-linear as it is expected that the impacts of hazard events may increase or decrease over time (SAS Institute 2014b). TIME_K and TIME_K_SQ are incorporated to address the cumulative impacts of the hazard event. A squared version of TIME_O is not included due to lack of sufficient data for time periods after 2010, the year of the DWH oil spill. The dataset contains data from 2001 to 2012, which provides a limited time window of two years after the oil spill, but a longer time period of seven years after Katrina.

The variable for spill distance is computed using the formula:

$$\frac{Adjusted\ Distance}{1 + TIME\_O}$$

where the adjusted distance is the actual distance from the spill for the event year and is repeated for subsequent years. It will record a value of zero for time periods before the event. *TIME_O* is the variable previously defined as time after the oil spill. For example, the spill distance for Mobile County AL is approximately 140 miles. The value for SPILL_DIST_DECAY in 2010 is computed using the above formula as follows:

$$\frac{140}{1 + 1} = 70$$

In 2011 and 2012, the variable values for this county will be 47 and 35, respectively, as the denominator increases by one for subsequent years after the event.

6.3.4 Model Construction

The proposed model is articulated as follows:

$$Y = B_0 + B_1x_1 + B_2x_2 + B_TT + B_DD + B_{Tx}Tx + \ldots\ldots\ldots\ldots + B_mx_m + e$$

where, Y is the value of the dependent variable (coping ability); B_0, the constant; and B_1, $B_{2\ldots.}$ representative of parameter estimates of the respective independent variables denoted by x_1 and x_2 in a set of m number of variables, $k = 1\ldots..m$. T is an interval variable controlling for time, the value of which will be set as 1 for the event year and increments of one for subsequent years. T will be zero for years before the event. The two control variables for time are TIME_K, representing time after Hurricane Katrina and TIME_O, representing time after the DWH oil spill. B_T, therefore, is the parameter estimate of time after the event. B_D is the parameter estimate of the distance-decay variable and e represents the error. Tx is an interaction term that assesses an estimate for each independent variable *(x)* before and after the event year, T, in a set of m number of variables, $k = 1\ldots..m$. B_{Tx}, therefore, is the parameter estimate of the interaction term, Tx.

The dataset combines attribute values of variables for 56 coastal counties in the Gulf of Mexico for the period, 2001 to 2012 (N = 672). The combination of independent variables, control variables, and interaction terms produces a set of 39 parameter estimates. Based on the rule of thumb for a medium effect size proposed by Cohen (1988), the minimum sample size is calculated as five observations per predictor variable, which produces 195 observations (5 x 39). Since the dataset consists of 672 observations, the requirements for a minimum sample size are satisfied.

6.4 Diagnostics

The assumptions of regression models include linearity, normality, homoscedasticity, and independence. Diagnostic tests are designed to evaluate whether the assumptions hold for the regression model, which is applied to address specific research questions. Two versions of the simple linear regression model are evaluated and the list of variables included in each are presented in Table 6.3.

Table 6.3 – Description of Variables and Variable Codes

Simple Linear Models	Category	Description	Code
Model I	Dependent variable	Unemployment Rate	UNEMP_RATE
	Independent variables	Fisheries Social assistance Religious organizations Employment services Professional services Utilities Retail trade	FISH_LQ SA_LQ REL_LQ EMP_LQ PRO_LQG UTI_LQG RTL_LQ
	Control variables	Time after oil spill Time after Katrina Spill distance	TIME_O TIME_K SPILL_DIST_DECAY
Model II	Dependent variable	Unemployment Rate	UNEMP_RATE
	Independent variables	Fisheries Social assistance Religious organizations Employment services Professional services Utilities Retail trade	FISH_LQ SA_LQ REL_LQ EMP_LQ PRO_LQG UTI_LQG RTL_LQ
	Control variables	Time after oil spill Time after Katrina Time after Katrina squared Spill distance	TIME_O TIME_K TIME_K_SQ SPILL_DIST_DECAY

Model I includes the dependent variable, unemployment rate, the location quotients of seven independent variables, and three control variables representing time after Katrina and the oil spill, and spill distance. Model II is distinguished from Model I by the addition of the squared variable for time after Katrina (TIME_K_SQ).

The linearity assumption states that the relationship between the dependent and independent variables is linear, and the assumption of normality states that not only are *x* and *y* normally distributed, but that the errors are also normally distributed. The scatter plot (Figure 6.18) and the normal probability plot (Figure 6.19) applicable to Model I reveal that the linearity and normality assumptions have been met – to a large extent, changes in *y* correspond to changes in *x* (independent variables).

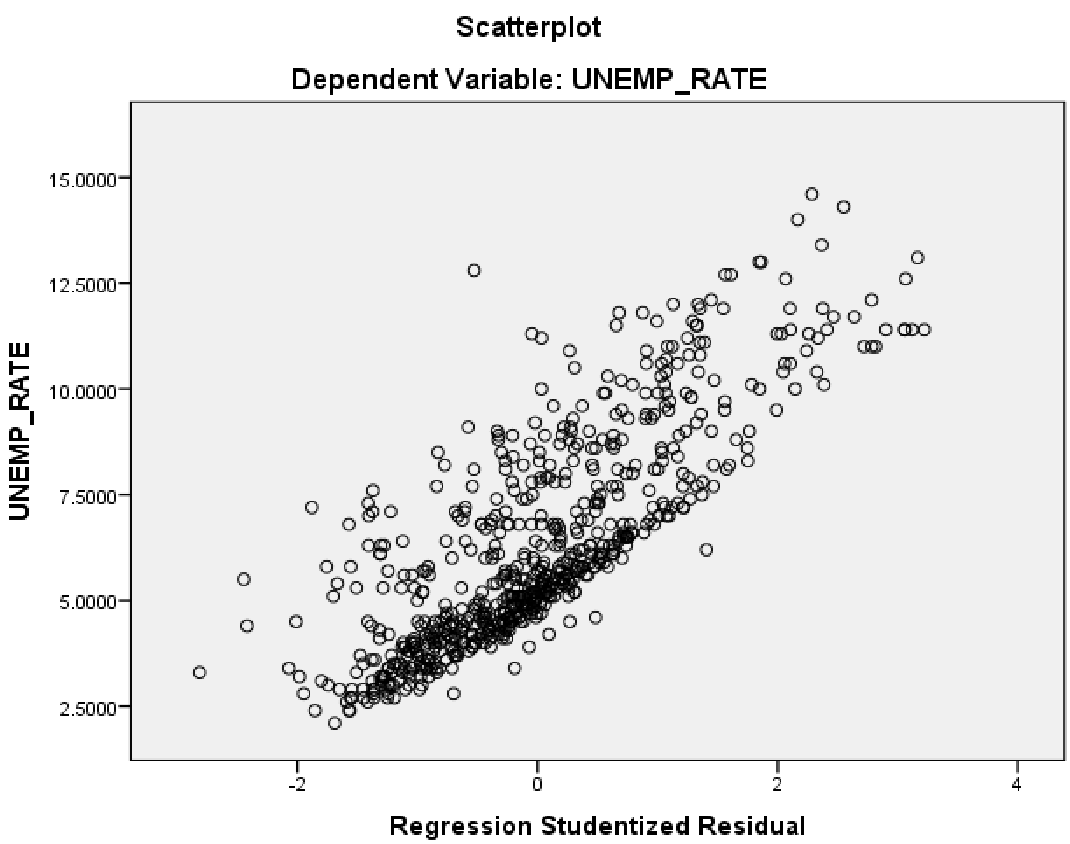

Figure 6.18 - Scatter Plot (Model I)

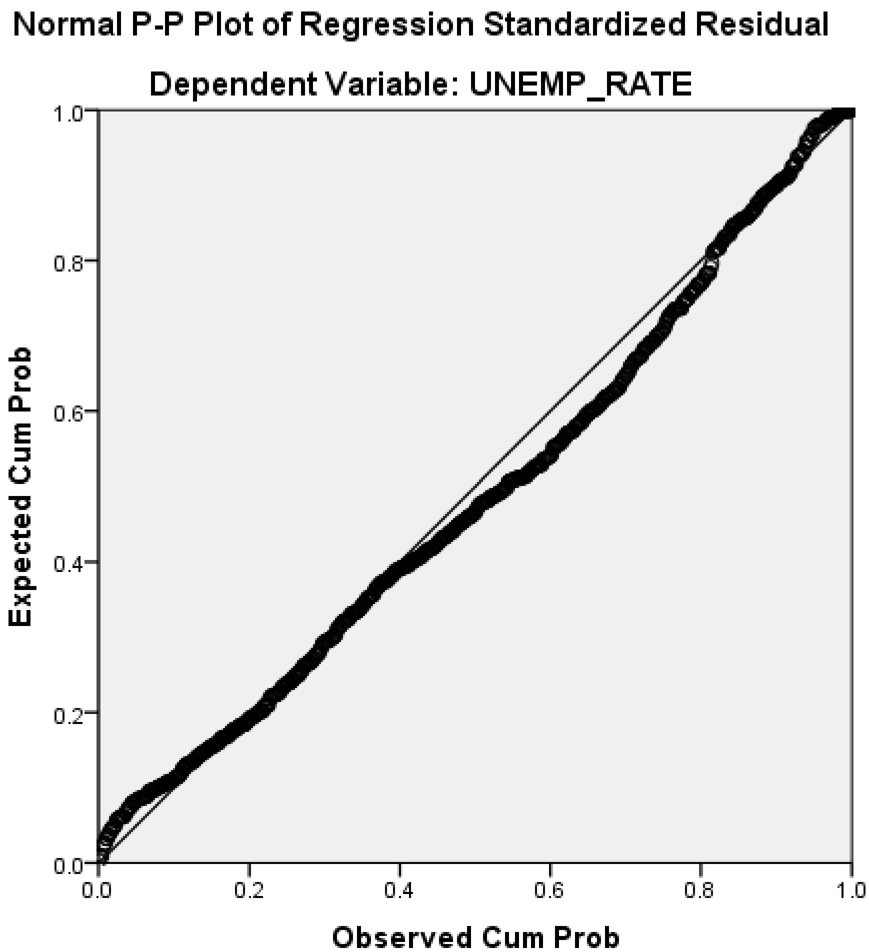

Figure 6.19 – Normal Probability Plot (Model I)

The scatter plot (Figure 6.20) and the normal probability plot (Figure 6.21) applicable to Model II when compared to those of Model I reveal that observations deviate from the regression line to some extent, but these deviations are marginal and are not sufficient to assume a violation of the assumptions. As such, it is concluded that the linearity and normality assumptions in Model II have been met.

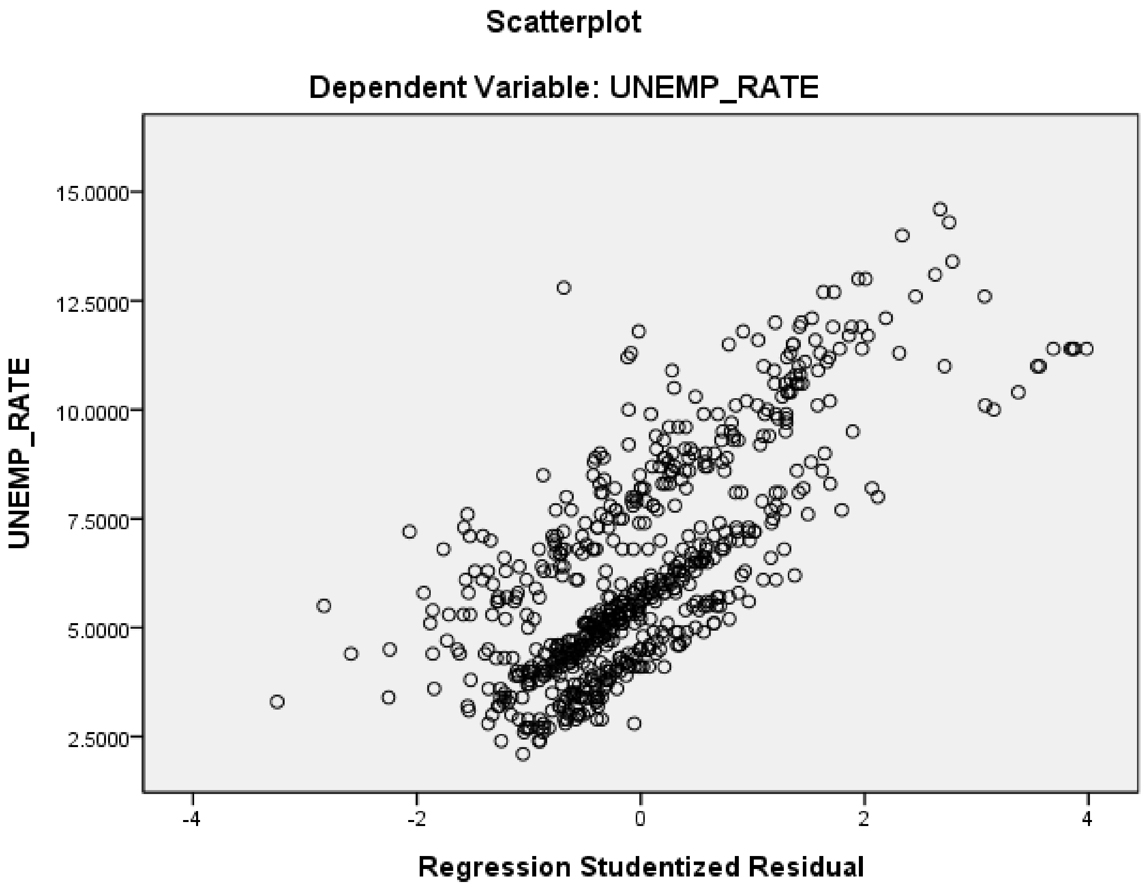

Figure 6.20 – Scatter Plot (Model II)

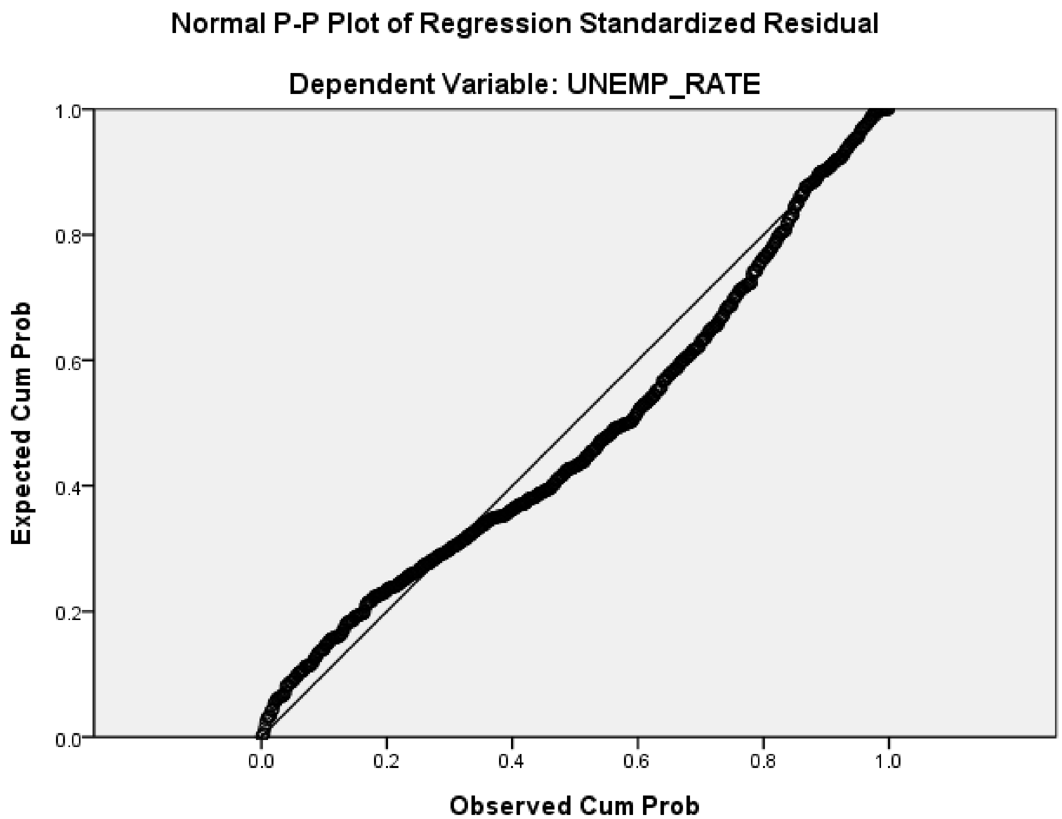

Figure 6.21 – Normal Probability Plot (Model II)

Homoscedasticity refers to the homogeneity of variances, i.e. the variance of the errors remains constant across all values of the independent variables (x). Violation of homoscedasticity is referred to as *heteroscedasticity.* Heteroscedasticity will cause standard errors of the parameters to be inflated. The standardized residual plots for Model I (Figure 6.22) and Model II (Figure 6.23) reveal that most of the error variances are spread between – 2.00 and + 2.00, and there is no visible fanning out of errors as the value of x increases.

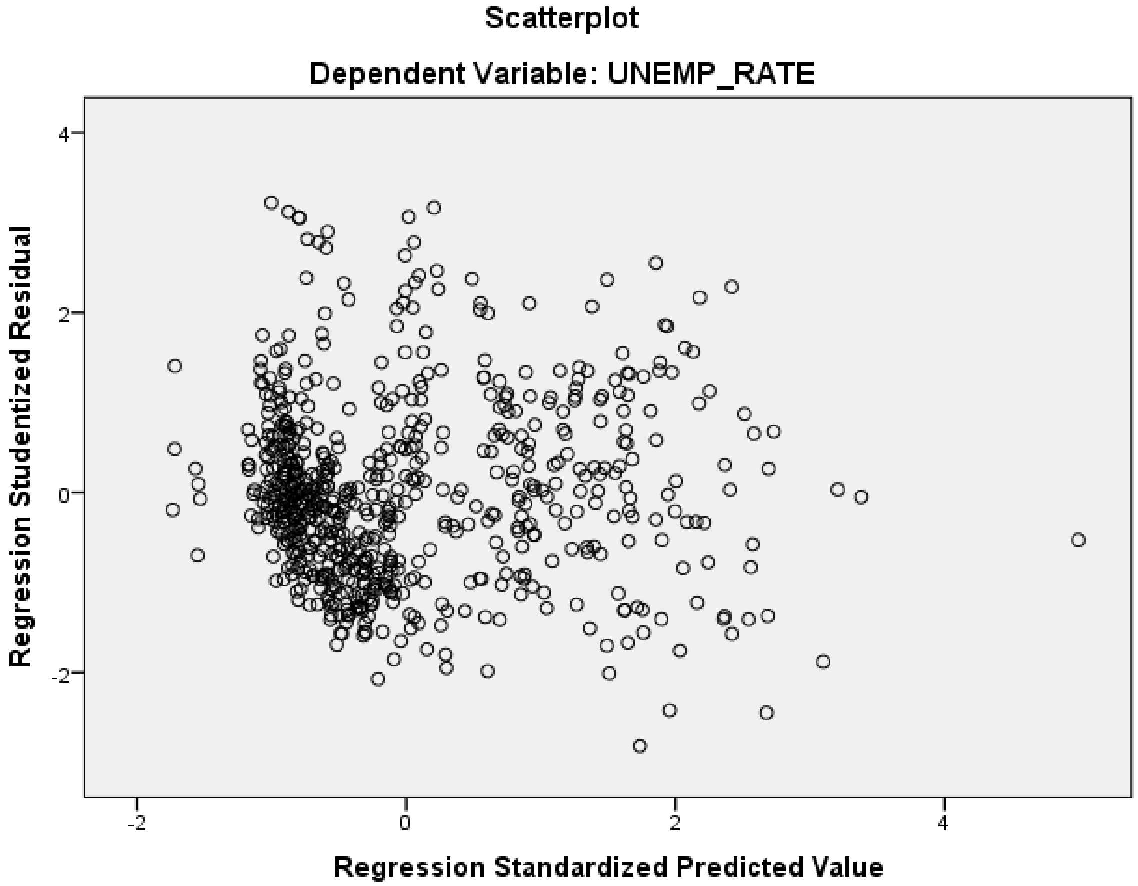

Figure 6.22 - Standardized Residual Plot (Model I)

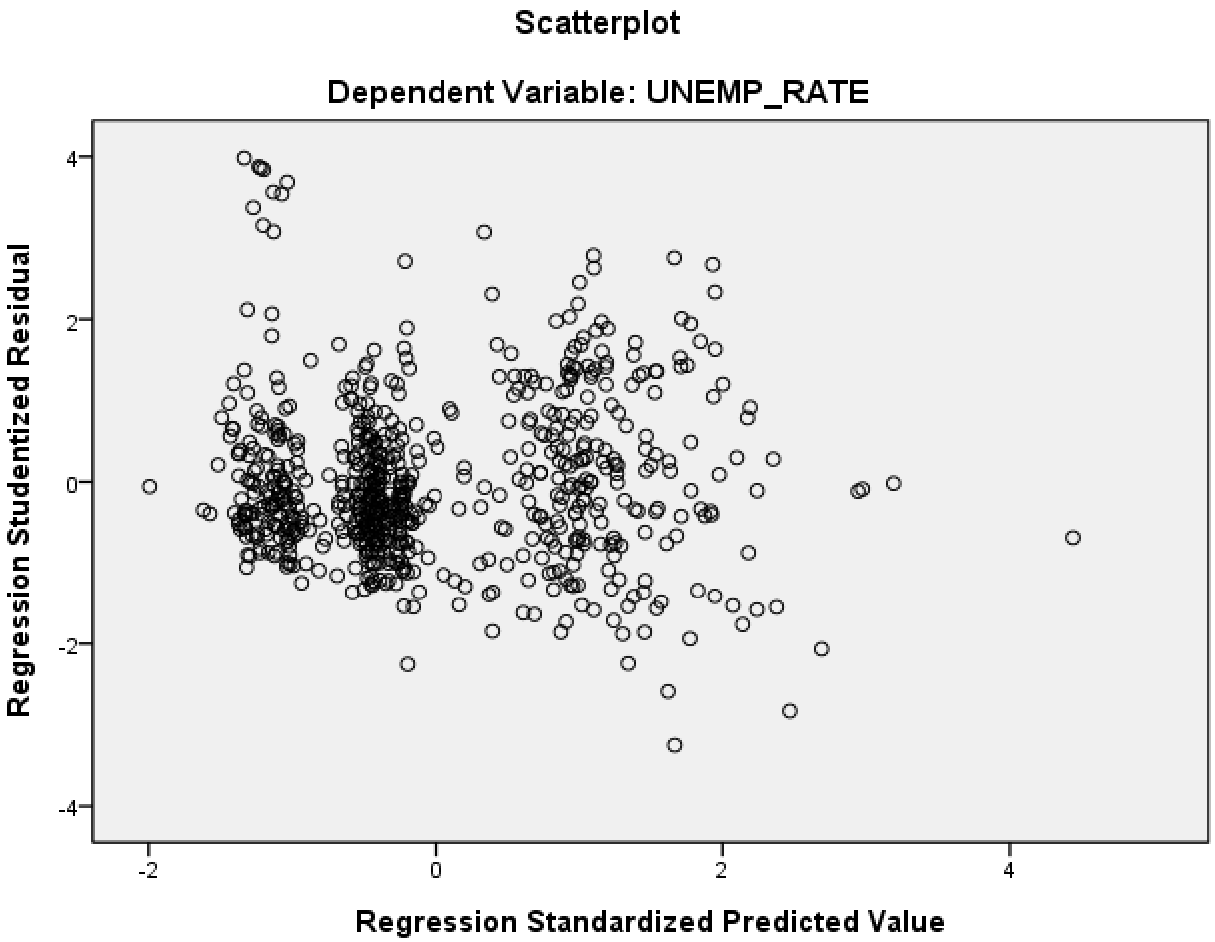

Figure 6.23 - Standardized Residual Plot (Model II)

The assumption of independence states that residuals associated with the independent variables are independent in the population. The use of a nested time series dataset results in the autocorrelation problem, which violates the assumption of independence. The Durbin-Watson (D-W) statistic is used as a benchmark to test for autocorrelation, but is inconclusive as some degree of autocorrelation is expected when working with temporal data. The D-W parameter for Model I is 0.928 and 1.096 for Model II. The significance of the statistic is tested against upper and lower bound thresholds using a D-W table. If the computed value is less than the lower

bound threshold, it confirms that autocorrelation is a problem. Zero autocorrelation is observed when the computed value is greater than the upper bound threshold. The test of D-W parameters for Model I and II is inconclusive as they fall between the lower bound threshold of 0.171 and the upper-bound threshold of 3.149. The results are significant at $p < .05$, which means that the null hypothesis (no autorcorrelation) cannot be rejected based on the conservative approach recommended by Savin and White (1977). Including interaction terms is a way to address this problem and minimize the effect of autocorrelation. The effect of interaction terms is discussed in Chapter 7.

In addition to regression assumptions, the issue of multicollinearity and the effect of outliers are addressed. Multicollinearity is indicative of the extent to which independent variables are correlated and can obstruct each variable's contribution to changes in *y*. It is assessed using the variance inflation factor or VIF. A VIF value greater than 10 indicates multicollinearity. As presented in Table 6.4, variables registered no multicollinearity (VIF < 10) for Model I. In Model II, the three time variables (TIME_K, TIME_K_SQ, and TIME_O) registered multicollinearity (VIF > 10). These function as control variables. A control variable is one that remains fixed and is used as a measure of comparison, in this case, to observe the impact of hazard events that occur at a particular point in time. An exception to the standard test of the VIF is when high values are associated with control variables (Allison 2012). Since the time variables function as controls and are used to measure interaction with the variables of interest i.e. the independent variables, multicollinearity can be ignored in this case. The VIF values of the variables of interest are less than 10, and so we can conclude that multicollinearity is not a problem in Model II.

Table 6.4 – Test of Multicollinearity – Variance Inflation Factor

Variable	**Model I VIF**	**Model II VIF**
TIME_K_SQ	---	104.521
TIME_K	3.078	40.722
TIME_O	3.026	23.502
SPILL_DIST_DECAY	1.847	1.853
SA_LQ	1.053	1.053
FISH_LQ	1.070	1.071
RTL_LQ	1.230	1.234
EMP_LQ	1.172	1.172
REL_LQ	1.127	1.127
UTI_LQG	1.031	1.032
PRO_LQG	1.096	1.096

Outliers are identified by evaluating the standardized residual values associated with each observation. Six cases in Model I and twelve cases in Model II had standardized residual values > 3.00 or < -3.00 as detailed in Table 6.5 and 6.6. The decision to retain or remove outliers is determined by a review of Cooke's distance values. An observed Cook's distance of greater than 1.00 associated with a particular observation reveals that it is influential in determining the regression results (Cohen et al. 2003). None of these cases had Cook's distance values greater than 1.00. Therefore, cases are retained in the models as they are deemed not influential in affecting the regression results.

Table 6.5 – Case-wise Diagnostics for Outliers – Model I

County	Year	Std. Residual	Cook's
Plaquemines, LA	2005	3.20127	0.01222
Hernando, FL	2009	3.14672	0.01064
Orleans, LA	2005	3.10876	0.00596
St. Bernard, LA	2005	3.05114	0.00397
Jefferson, LA	2005	3.04822	0.00385
Willacy, TX	2002	3.04069	0.0141

Table 6.6 – Case-wise Diagnostics for Outliers – Model II

MODEL II		Std. Residual	Cook's
Plaquemines, LA	2005	3.95417	0.01892
Orleans, LA	2005	3.85913	0.01017
St. Bernard, LA	2005	3.84666	0.00794
Jefferson, LA	2005	3.82803	0.00756
St. Tammany, LA	2005	3.67642	0.00542
Harrison, MS	2005	3.55253	0.00622
Hancock, MS	2005	3.49729	0.02598
Harrison, MS	2006	3.3592	0.00767
Hancock, MS	2006	3.08101	0.03983
Jackson, MS	2005	3.06705	0.00484
Willacy, TX	2002	3.04546	0.0135
Kenedy, TX	2012	-3.16725	0.04602

Maps of standardized residuals for Model I and Model II (based on 2010 data) are presented in Figure 6.24 and 6.25, respectively. High residual values are clustered in southwest Florida and in coastal Alabama and Mississippi. Coastal counties in Louisiana, Texas, and the panhandle region of Florida record low residual values. The Moran's I statistic for Model I is 0.619 and a value of 0.620 is reported for Model II. The Moran's I value for both models is greater than the expected value of -0.018182 ($p = 0.000$) and is significant at $p < 0.001$. The significance of the statistic indicates that underlying spatial processes are responsible for neighboring counties to display similar attributes resulting in positive spatial autocorrelation.

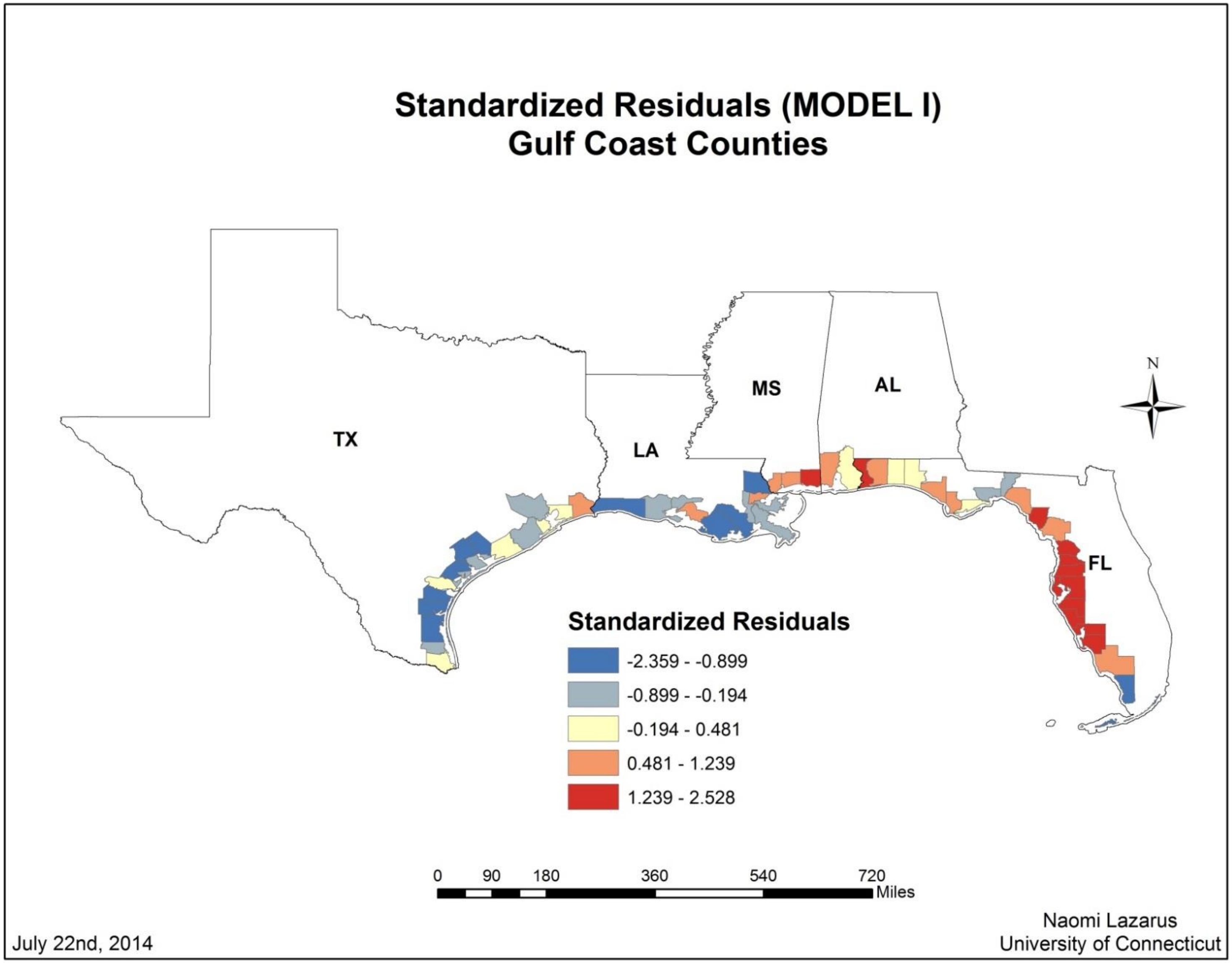

Figure 6.24 - Map of Standardized Residuals (Model I)

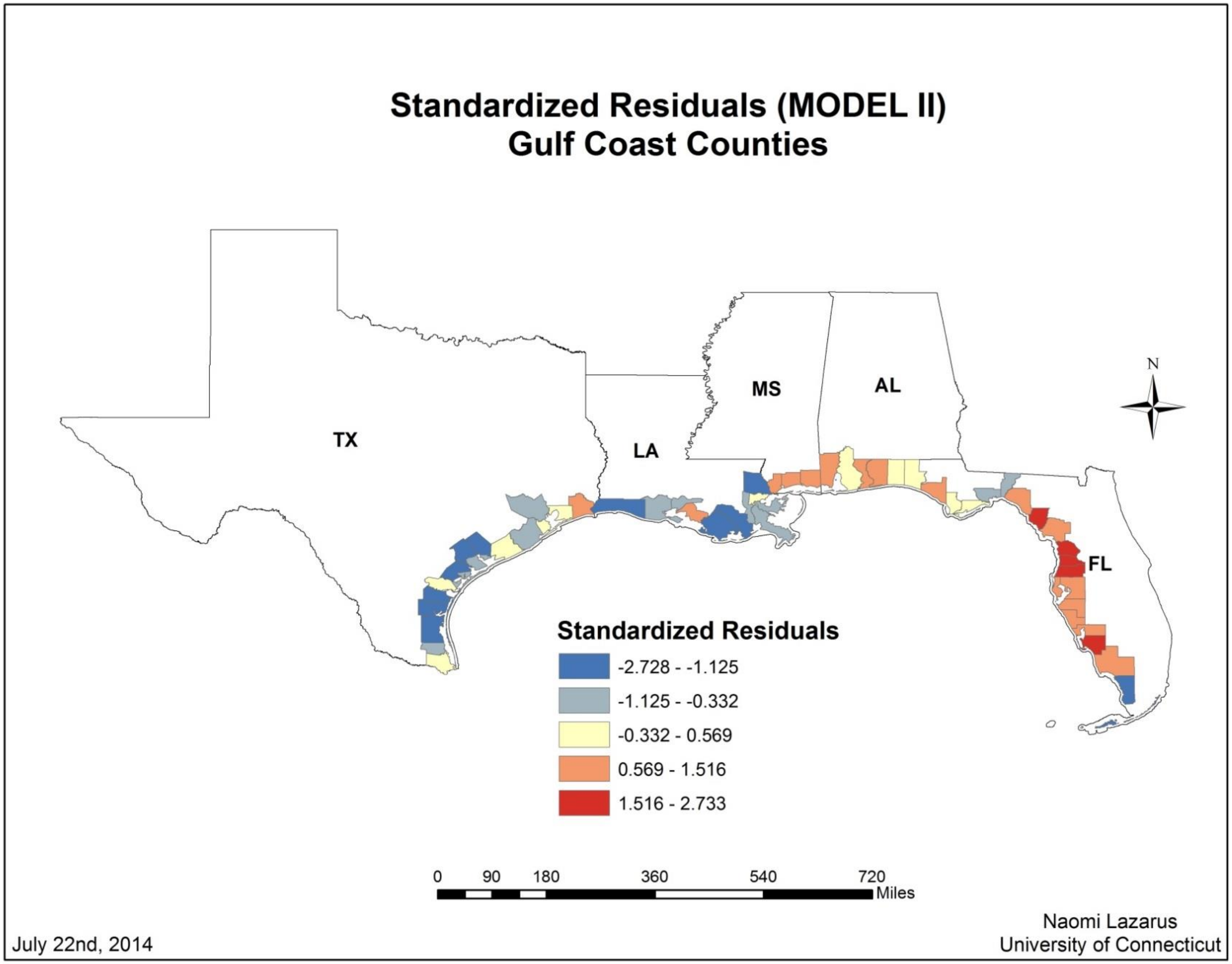

Figure 6.25 - Map of Standardized Residuals (Model II)

6.5 Conclusion

This research is concerned with establishing a causal relationship between unemployment rate and resources and services provided by social capital. Unemployment rate functions as a proxy variable for coping ability. Social capital consists of institutional and organizational frameworks that provide people with mechanisms to access resources that help build and sustain livelihoods. As such, the location quotients of sectors engaged in fisheries, social assistance, employment and professional services, religious organizations, retail, and utilities represent the independent variables.

A preliminary analysis of independent variables reveals that there are spatial and temporal variations in how social capital determines changes in overall unemployment across counties in the Gulf. Analyzing spatial and temporal patterns simultaneously using a nested time series dataset requires special attention to the assumptions in regression. Diagnostic tests are conducted for two versions of the simple linear regression model that incorporate a set of control variables. Control variables are incorporated to measure the impact of specific hazard events as they interact with the independent variables. The basic model is expanded in Chapter 7 taking into account these interactions and modified to address the issue of autocorrelation.

Chapter 7

Analysis

7.1 Introduction

The operationalization of the hazard risk location model (HRLM) is comprised of two components – a regression analysis and a threshold analysis. Regression analysis is undertaken to examine the relationships between variables representing social capital and the unemployment rate (dependent variable) to address the hypotheses presented under the first and second research questions. Unemployment rate functions as a proxy variable for coping ability and ties in with Sen's (1981) evaluation of capabilities and access to resources. Threshold analysis addresses the components of the third research question and examines the inter-relationship between coping ability, proximity to the hazard, and population density and their relative contribution in assessing risk. The threshold analysis advances the discussion by providing a mechanism to rank counties on an ordinal scale to measure hazardousness, exposure, and coping ability.

This chapter outlines the steps undertaken to operationalize the components of the HRLM. The regression analysis evaluates variations of the basic model by including interaction terms and the use of autoregressive models as a way to correct for time-related autocorrelation. This is followed by a comparative analysis of model fit and parameter estimates of independent variables, and a discussion on the clustering or dispersion of similar attribute values to observe spatial variation. The threshold analysis considers the inter-relationships between the components of the re-specified risk equation – hazard, exposure, and coping ability. The threshold formula presented in Chapter 5 is used to generate a series of distance measures for spill distance, population density, and unemployment rate to evaluate and rank each county's position along a continuum of vulnerability and risk. Distance measures are classified using the

standard deviation method and presented in maps and charts that show spatial and temporal variations in hazard, exposure, and coping levels across the study area.

7.2 Regression Analysis

7.2.1 Interaction Terms

The regression analysis constitutes the first stage in operationalizing the HRLM. It is concerned with establishing a causal relationship between the dependent variable, unemployment rate and the independent variables that represent social capital (Table 7.1). Control variables are included to assess the impacts of the Deep Water Horizon oil spill and Hurricane Katrina on the dependent variable to address to what extent services provided by social capital affect individual well-being during an environmental disaster, a key element of the first research question. The hypotheses relating to the second research question address the impact of disaster events on existing social frameworks. Interaction terms are incorporated to evaluate these relationships and to observe how each independent variable responds to hazard events.

Interaction terms are incorporated in a regression analysis to measure *interaction effects* that are observed when a time series dataset is interrupted by specific changes or events that occur at a particular time. These effects are formulated as an interaction term by multiplying input variables and using the product (term) as another variable that generates its own parameter estimate (SAS Institute 2014c). As presented in Table 7.1, the interaction terms associate each independent variable with the three time-related control variables, TIME_O, TIME_K, and TIME_K_SQ. TIME_O is used to estimate how social capital is impacted by the DWH oil spill. TIME_K and TIME_K_SQ are used to assess the impacts of Katrina. TIME_K_SQ assumes that the impacts of Katrina may increase in subsequent time periods and then decrease over time,

which is characteristic of a quadratic trend. When considering quadratic trends it is standard practice to include the lower order term, in this case, TIME_K. TIME_K is based on a linear trend where the impact of the event is assumed to be the same for time periods following the event year (SAS Institute 2014b). A squared version of TIME_O is not included due to lack of sufficient data for time periods after 2010, the year of the DWH oil spill. The dataset contains data from 2001 to 2012, which provides a limited time window of two years after the oil spill, but a longer time period of seven years after Katrina. Significant interaction terms indicate that the location quotient for a particular independent variable is significantly different for different time periods after an event. A positive parameter estimate on an interaction term indicates that the independent variable was positively affected by the disaster, and a negative estimate that the variable was negatively affected by the disaster.

Table 7.1 –Variables and Interaction Terms

Category	Description	Code
Dependent variable	Unemployment Rate	UNEMP_RATE
Independent variables	Fisheries Social assistance Religious organizations Employment services Professional services Utilities Retail trade	FISH_LQ SA_LQ REL_LQ EMP_LQ PRO_LQG UTI_LQG RTL_LQ
Control variables	Time after oil spill Time after Katrina Time after Katrina squared Spill distance decay	TIME_O TIME_K TIME_K_SQ SPILL_DIST_DECAY
Interaction Terms	Seven independent variables interacting with time after the oil spill	FISH_LQ*TIME_O SA_LQ*TIME_O REL_LQ*TIME_O EMP_LQ*TIME_O PRO_LQG*TIME_O UTI_LQG*TIME_O RTL_LQ*TIME_O
	Seven independent variables interacting with time after Katrina	FISH_LQ*TIME_K SA_LQ*TIME_K REL_LQ*TIME_K EMP_LQ*TIME_K PRO_LQG*TIME_K UTI_LQG*TIME_K RTL_LQ*TIME_K
	Seven independent variables interacting with time after Katrina squared	FISH_LQ*TIME_K_SQ SA_LQ*TIME_K_SQ REL_LQ*TIME_K_SQ EMP_LQ*TIME_K_SQ PRO_LQG*TIME_K_SQ UTI_LQG*TIME_K_SQ RTL_LQ*TIME_K_SQ

7.2.2 Model Fit

Autocorrelation is a point of concern when dealing with a nested time series dataset. It violates the regression assumption that the errors are independent. Including interaction terms is a way to address this problem and minimize the effect of autocorrelation (SAS Institute 2014b, 2014c). The Durbin-Watson statistic is used to determine the presence of autocorrelation. In the event the Durbin-Watson statistic is significant, an autoregressive model can be applied to ameliorate this problem. The autoregressive model (AR-1) assumes that the errors are correlated and simultaneously estimates the regression parameters while correcting for the lag associated with the residuals (SAS Institute 2014a).

Table 7.2 summarizes the goodness of fit and autocorrelation statistics of the regression models. Model I and Model II represent the simple linear regression models discussed in Chapter 6. Model I includes the seven independent variables and control variables associated with time after the DWH oil spill (TIME_O), time after Katrina (TIME_K), and spill distance decay (SPILL_DIST_DECAY). Model II includes the squared version of time after Katrina (TIME_K_SQ) in addition to the list of variables in Model I. Interaction terms are added to Model I and II, and results presented as Model III and IV, respectively. Last, Model V and VI represent the corresponding autoregressive versions of Model III and IV.

Table 7.2 – Model Fit Statistics of Basic and Autoregressive Models

Model	**Description**	**R^2**	**AIC**	**F**	**Sig.**	**D-W**
MODEL I	Simple Linear regression: 7 LQ variables; TIME_K; TIME_O; SPILL_DIST_DECAY	0.352	2886.11	35.83	.000	0.928
MODEL II	Simple Linear regression: 7 LQ variables TIME_K; TIME_O; TIME_K_SQ SPILL_DIST_DECAY	0.465	2758.62	52.19	.000	1.096
MODEL III	Model I with interaction: 7 LQ variables; TIME_K; TIME_O; SPILL_DIST_DECAY; 14 interaction terms	0.409	2851.42	18.68	.000	1.038
MODEL IV	Model II with interaction: 7 LQ variables; TIME_K; TIME_O; TIME_K_SQ; SPILL_DIST_DECAY; 14 interaction terms	0.524	2707.54	28.51	.000	1.281
MODEL V	Model III (AR-1): 7 LQ variables; TIME_K; TIME_O; SPILL_DIST_DECAY; 14 interaction terms	0.574	2631.34		.000	
MODEL VI	Model IV (AR-1): 7 LQ variables; TIME_K; TIME_O; SPILL_DIST_DECAY; TIME_K_SQ; 14 interaction terms	0.604	2584.70		.000	

The coefficient of determination (R^2) indicates the proportion of the variation in the dependent variable that is explained by the model. The R^2 value for the first simple linear model (Model I) is 0.352, and the R^2 value for Model II is 0.465. In the case of Model I, the R^2 value indicates that the model accounts for 35.2% of the variation in *y*, and the sum of squares unexplained by the model (SSE) is 64.8%. The variation in the dependent variable explained by Model II is 46.5% and the SSE is 53.5%. The R^2 values for the corresponding models with interaction terms (Model III and IV) are marginally higher than the basic models. The R^2 value

for Model III is 0.409 compared to 0.352 for Model I, and the coefficient for Model IV is 0.524, which is higher than 0.465 for Model II.

The F statistic evaluates the significance of the fit of the regression model and is a test of the null hypothesis, which states that the variability in the dependent variable explained by the independent variables (*x*) is zero i.e. H0: $R^2 = 0$. The F values for the simple linear models (Model I and II) are higher than the models with interaction terms (Model III and IV). The F statistic applicable to Model I is 35.83 and the corresponding value for Model II is 52.19. The results indicate that the independent variables significantly account for the variability in the dependent variable and therefore, the null hypothesis is rejected. F values for Model III and IV are lower than the simple linear models, but record higher R^2 and lower Akaike Information Criterion (AIC) values. The AIC is another estimate of model fit and is used to compare alternative models - the smaller the value, the closer it is to the actual data (Sakamoto, Ishiguro, and Kitagawa 1986). When comparing the simple linear and interaction models, Model III and Model IV are a better fit as they have lower AIC values than Model I and Model II. The AIC value for Model III is 2851.42 compared to Model I (2886.11), and the AIC value for Model IV is 2707.54, which is lower than that of Model II (2758.62).

Models V and VI are autoregressive versions of Model III and IV. As was stated above, autoregressive models are used to address the problem of autocorrelation, which violates the assumption of independence in regression. The assumption of independence of residuals states that residuals associated with the independent variables are independent in the population (Kachigan 1986; Cohen et al. 2003). This assumption is violated when analyzing data over twelve time periods resulting in the autocorrelation problem. This is known as the lag 1 autocorrelation or AR(1) (Cohen et al. 2003). The issue of autocorrelation is addressed by

incorporating an autoregressive term that recognizes the dependence of errors. In an autoregressive model, the dependent variable is estimated using the value of the independent variable in the previous time period (*t* – *1*) to account for time-related autocorrelation (Maddala 1992; Hamilton 1994). The formula of the autoregressive model is as follows:

$$Y_t = B_0 + (B_1\mathbf{L}X_1 + B_2\mathbf{L}X_2 + \ldots\ldots\ldots\ldots B_m\mathbf{L}X_m)_{\mathbf{j}} + B_T T + B_D D + B_{Tx}Tx + e_t$$

where, Y_t is the value of the dependent variable (coping ability) in a given time period, *t*; B_0, the constant; and $B_1, B_{2\ldots}$ representative of parameter estimates of the respective independent variables denoted by X_1 and X_2 in a set of *m* number of variables, $k = 1\ldots..m$. The lag operator, *L*, represents the value of the independent variable in the previous time period (*t* – *1*) in a set of *j* number of time periods, $t = 1\ldots..j$. *T* is an interval variable controlling for time, the value of which will be set as 1 for the event year and increments of one for subsequent years. *T* will be zero for years before the event. B_T, therefore, is the parameter estimate of time after the event. B_D is the parameter estimate of the distance-decay variable and e_t is the error associated with estimating the dependent variable in time period, *t*.

Prior to evaluating the autoregressive models, the simple linear regression models are tested for positive autocorrelation. The null hypothesis associated with the Durbin-Watson (D-W) test states that the autocorrelation parameter is zero. Statistical significance of the computed D-W measure is compared against upper bound and lower bound values in a Durbin-Watson table. The thresholds are identified based on the number of time periods and the number of independent variables. If the D-W parameter is *lower* than the lower bound threshold, positive autocorrelation is observed and the null hypothesis is rejected. If the D-W parameter is higher than the upper bound threshold, it is assumed that autocorrelation is zero. If the parameter falls within the upper-bound and lower-bound thresholds, the test is inconclusive. In this case, a

conservative approach is recommended to conclude that the null hypothesis cannot be rejected (Savin and White 1977).

The computed D-W measures for the simple linear models, Model I and Model II, are 0.928 and 1.096, respectively. The D-W statistic for Model III is 1.038 and the value for Model IV is 1.281. Based on the D-W table, the lower bound threshold is 0.171, and the upper bound threshold is 3.149. Since the parameters for both the simple linear and interaction models fall within the thresholds, they are not statistically significant at the $p < 0.05$. Based on a conservative approach recommended by Savin and White (1977), the test is deemed inconclusive and the null hypothesis cannot be rejected. However, inconclusive D-W results do not automatically eliminate the autocorrelation problem, and some authors suggest that the analysis be conducted assuming that serial correlation exists (Durbin 1969; University of Delaware 2014). The use of a nested time series dataset in this research increases the likelihood that autocorrelation exists, and therefore, the autoregressive models are evaluated as a way to address this problem.

Based on R^2 and AIC values, Model III and IV (interaction models) are a better fit than the simple linear models (Table 7.2). When comparing the interaction models with their autoregressive counterparts (AR-1), the autoregressive models are a better fit as they have higher R^2 and lower AIC values. The R^2 value for Model V is 0.574 compared to 0.409 for Model III, and the coefficient for Model VI is 0.604, which is higher than 0.524 for Model IV. The AIC value for Model V is 2631.34 compared to Model III (2851.42), and the AIC value for Model VI is 2584.70, which is lower than that of Model IV (2707.54). The tests indicate that Model VI is the best fit as it has the highest R^2 value of 0.604 and the lowest AIC value of 2584.70. This

model includes the seven independent variables, four control variables including TIME_K_SQ, and is corrected for autocorrelation using the AR-1 autoregressive model.

7.2.3 Analysis of parameters

In addition to the goodness of fit, model specification is evaluated by analyzing the significance of the *b* coefficients. This is undertaken by way of a t test of *b* coefficient estimates for the models. First, Table 7.3 presents parameter estimates for Model III, the simple linear model with interaction terms and its autoregressive counterpart, Model V. The direction (+/-) of the relationship of most variables does not change in the AR-1 model from the interaction model. The direction of parameter estimates for two control variables (TIME_K, TIME_O) and three interaction terms (UTI_LQG*TIME_K; REL_LQ*TIME_K; UTI_LQG*TIME_O) has changed in the AR-1 model and is not significant at $p < .05$. The results indicate that services related to utilities and religious organizations were not significantly impacted by hazard events.

Five variables are significant at $p < 0.05$ in Model III, and six variables are significant in Model V. Location quotients for social assistance, utilities, retail services, religious organizations, and employment services are significant in both models. Location quotients for fisheries are significant in Model V, but not significant for Model III. Model V is the autoregressive counterpart of Model III and corrects the lag associated with the residuals (SAS Institute 2014a). Model V, therefore, is better able to capture seasonal variation in fisheries that is time-dependent. Out of fourteen interaction terms, only four are significant of which SA_LQ*TIME_O, FISH_LQ*TIME_K, and RTL_LQ*TIME_K are common to both models. The control variable for spill distance (SPILL_DIST_DECAY) is significant in Model III and Model V, but the control variable for time after the oil spill (TIME_O) is not significant due to

the lack of sufficient data for subsequent time periods after 2010. The TIME_K variable is significant at $p < 0.05$ in Model III, but is not significant in the AR-1 model. As discussed earlier, TIME_K is a lower order interaction term that assumes the impacts of the hazard event are linear, which conforms to Model III as it is a simple linear model with interaction terms. The impacts of Katrina, however, may increase in subsequent time periods and then decrease over time, which is characteristic of a quadratic trend. Given that Model V is the autoregressive version of a linear model (Model III) it does not include a higher order interaction term to address the cumulative impacts of Katrina. As a result, the lower order interaction term (TIME_K) is not significant in Model V.

Table 7.3 – Parameter estimates of b coefficients for Model III and Model V

MODEL III Simple linear with interaction	**b**	**Sig. (p < 0.05**	**MODEL V AR-1 version of Model III**	**b**	**Sig. (p < 0.05**
TIME_K	-0.6645	.004	TIME_K	0.0538	.789
TIME_O	0.3153	.628	TIME_O	-0.2139	.706
SPILL_DIST_DECAY	0.0136	.000	SPILL_DIST_DECAY	0.00892	.000
SA_LQ	0.3313	.000	SA_LQ	0.4331	.000
FISH_LQ	-0.0009	.613	FISH_LQ	-0.00349	.011
RTL_LQ	-1.5860	.000	RTL_LQ	-0.678	.035
EMP_LQ	-0.4430	.023	EMP_LQ	-0.2957	.038
REL_LQ	-0.0598	.006	REL_LQ	-0.0535	.002
UTI_LQG	0.0678	.019	UTI_LQG	0.0749	.000
PRO_LQG	-0.5046	.128	PRO_LQG	-0.0795	.736
SA_LQ*TIME_K	-0.0444	.125	SA_LQ*TIME_K	-0.0609	.003
FISH_LQ*TIME_K	-0.00371	.007	FISH_LQ*TIME_K	-0.00206	.043
RTL_LQ*TIME_K	0.6726	.000	RTL_LQ*TIME_K	0.2414	.029
EMP_LQ*TIME_K	0.1708	.052	EMP_LQ*TIME_K	0.0931	.148
REL_LQ*TIME_K	0.01349	.672	REL_LQ*TIME_K	-0.00826	.731
UTI_LQG*TIME_K	-0.00350	.756	UTI_LQG*TIME_K	0.00015	.985
PRO_LQG*TIME_K	0.1451	.115	PRO_LQG*TIME_K	0.0160	.809
SA_LQ*TIME_O	0.24255	.021	SA_LQ*TIME_O	0.2812	.000
FISH_LQ*TIME_O	0.00877	.066	FISH_LQ*TIME_O	0.00548	.123
RTL_LQ*TIME_O	-0.8648	.032	RTL_LQ*TIME_O	-0.3314	.289
EMP_LQ*TIME_O	-0.1671	.542	EMP_LQ*TIME_O	-0.0841	.684
REL_LQ*TIME_O	0.15060	.399	REL_LQ*TIME_O	0.1150	.388
UTI_LQG*TIME_O	0.00504	.879	UTI_LQG*TIME_O	-0.00101	.967
PRO_LQG*TIME_O	0.28924	.245	PRO_LQG*TIME_O	0.2021	.268

Table 7.4 presents parameter estimates for Model IV, the simple linear model with interaction terms including TIME_K_SQ and its autoregressive counterpart, Model VI. The direction (+/-) of the relationship of most variables has not changed in the AR-1 model from the interaction model. The direction of parameter estimates for one independent variable (PRO_LQG) and five interaction terms (UTI_LQG*TIME_K_SQ; REL_LQ*TIME_K_SQ; PRO_LQG*TIME_K_SQ; UTI_LQG*TIME_O; REL_LQ*TIME_O) has changed in the AR-1 model and is not significant at $p < .05$.

Five out of seven independent variables are significant at $p < 0.05$ in Model IV, and six variables are significant in Model VI. Location quotients for social assistance, utilities, retail services, religious organizations, and employment services are significant in both models. Location quotients for fisheries are significant in Model VI, but not significant for Model IV. The control variables, SPILL_DIST_DECAY, TIME_O, TIME_K, and TIME_K_SQ are significant at $p < 0.05$ in both models. Out of fourteen interaction terms, six are significant in Model IV and five are significant in Model VI. Location quotients for social assistance, fisheries and retail services interacting with TIME_K_SQ, and location quotients for social assistance and fisheries interacting with TIME_O are common to both models.

Table 7.4 – Parameter estimates of b coefficients for Model IV and Model VI

MODEL IV Simple linear with interaction	**b**	**Sig. (p < 0.05**	**MODEL VI AR-1 version of Model IV**	**b**	**Sig. (p < 0.05**
TIME_K	-1.6014	.000	TIME_K	-1.6212	.000
TIME_K_SQ	0.2220	.000	TIME_K_SQ	0.3658	.000
TIME_O	-1.9708	.049	TIME_O	-3.8543	.000
SPILL_DIST_DECAY	0.0125	.000	SPILL_DIST_DECAY	0.0097	.000
SA_LQ	0.3223	.000	SA_LQ	0.3769	.000
FISH_LQ	-0.0018	.245	FISH_LQ	-0.0034	.012
RTL_LQ	-1.5147	.000	RTL_LQ	-0.6802	.017
EMP_LQ	-0.3813	.019	EMP_LQ	-0.298	.026
REL_LQ	-0.0627	.000	REL_LQ	-0.0541	.000
UTI_LQG	0.0708	.002	UTI_LQG	0.0711	.000
PRO_LQG	-0.2644	.307	PRO_LQG	0.0013	.995
SA_LQ*TIME_K_SQ	-0.0102	.048	SA_LQ*TIME_K_SQ	-0.0107	.012
FISH_LQ*TIME_K_SQ	-0.0009	.003	FISH_LQ*TIME_K_SQ	-0.0006	.019
RTL_LQ*TIME_K_SQ	0.1393	.000	RTL_LQ*TIME_K_SQ	0.0605	.012
EMP_LQ*TIME_K_SQ	0.0317	.079	EMP_LQ*TIME_K_SQ	0.0227	.122
REL_LQ*TIME_K_SQ	0.0159	.238	REL_LQ*TIME_K_SQ	-0.0039	.739
UTI_LQG*TIME_K_SQ	-0.0006	.789	UTI_LQG*TIME_K_SQ	0.0006	.728
PRO_LQG*TIME_K_SQ	0.0188	.295	PRO_LQG*TIME_K_SQ	-0.0018	.899
SA_LQ*TIME_O	0.3526	.007	SA_LQ*TIME_O	0.3518	.001
FISH_LQ*TIME_O	0.0182	.012	FISH_LQ*TIME_O	0.0122	.037
RTL_LQ*TIME_O	-2.0292	.001	RTL_LQ*TIME_O	-0.9214	.078
EMP_LQ*TIME_O	-0.4033	.321	EMP_LQ*TIME_O	-0.3106	.354
REL_LQ*TIME_O	-0.1811	.593	REL_LQ*TIME_O	0.2041	.486
UTI_LQG*TIME_O	0.0069	.888	UTI_LQG*TIME_O	-0.0145	.719
PRO_LQG*TIME_O	0.1911	.596	PRO_LQG*TIME_O	0.2951	.316

7.3 Spatial Autocorrelation

Spatial autocorrelation recognizes that observations vary geographically, may not be independent and may be influenced by spatial processes. This is based on Tobler's rule that near things are more related than distant things refuting the assumption of spatial stationarity, which states that observations are independent and are not influenced by spatial processes. Spatial autocorrelation not only accounts for geographical variation in attribute values, but also observes the presence or absence of clusters in attribute values that may display similarities.

While spatial autocorrelation focuses on the distribution of attributes across a single scale of analysis, the modifiable areal unit problem (MAUP) observes that correlation between attributes increases when analyzing data at larger areal units through the process of aggregation. The MAUP arises due to the *scale effect* and the *zoning effect* (Fotheringham, Brunsdon, and Charlton 2002). The scale effect is addressed by using spatially disaggregated data and is subject to data availability. As discussed in Chapter 6, the variables used in this research are extracted at the county level as availability and reliability of the data at disaggregated levels decrease due to issues of privacy, disclosure, and accuracy (BLS 2008, 2014). The zoning effect is addressed by re-aggregating the spatial units into zones that would optimize the model results (Openshaw and Rao 1995). The demarcation of zones, however, is highly subjective and the model results constrained to an arbitrary scale of analysis that would undermine the model's application in different scenarios ((Fotheringham, Brunsdon, and Charlton 2002). Due to the absence of a clearly defined set of strategies to address the MAUP, this research focuses on the discussion of spatial autocorrelation.

Spatial autocorrelation is evaluated using Moran's I, which tests the similarities of attribute values – whether they are clustered or dispersed in space. The test of spatial autocorrelation involves comparing the Moran's I statistic with the expected value, which is a coefficient indicating no spatial autocorrelation. It is computed using the formula, $E(I) = (-1)/(n-1)$, with n denoting the number of points in the distribution. If the calculated Moran's I is greater than the expected value, then positive spatial autocorrelation is observed, indicating that neighboring spatial units display similar characteristics and are clustered in a given location. On the other hand, if the Moran's I statistic is less than the expected value a dispersed pattern is observed where attribute values bear no similarity across space.

Based on the analysis of model fit and parameter estimates, the autoregressive versions of Model III and IV are considered the most objective in predicting the dependent variable, unemployment rate. Table 7.5 summarizes the models that are evaluated for spatial autocorrelation. Model III is the simple linear model with interaction terms with the time-related control variables, TIME_O and TIME_K. Model IV is the simple linear model with interaction terms including TIME_K_SQ (squared version of time after Katrina) in addition to the variables in Model III. Model V is the autoregressive version of Model III, and Model VI is the autoregressive version of Model IV.

Table 7.5 – Summary of Interaction and Autoregressive Models Tested for Spatial Autocorrelation

Model	**Type**	**Description**	**R^2**	**AIC**	**Moran's I (2005)**	**Moran's I (2010)**
MODEL III	Simple Linear with interaction terms	7 LQ variables; *TIME_K; TIME_O;* SPILL_DIST_DECAY; 14 interaction terms	0.409	2851.42	-0.0555	0.5705
MODEL IV	Simple Linear with interaction terms	7 LQ variables; *TIME_K; TIME_O; TIME_K_SQ;* SPILL_DIST_DECAY; 14 interaction terms	0.524	2707.54	-0.0175	0.530
MODEL V	Autoregressive (AR-1)	Model III (AR-1): 7 LQ variables; *TIME_K; TIME_O*; SPILL_DIST_DECAY; 14 interaction terms	0.574	2631.34	0.3909	0.5445
MODEL VI	Autoregressive (AR-1)	Model IV (AR-1): 7 LQ variables; *TIME_K; TIME_O; TIME_K_SQ;* SPILL_DIST_DECAY; 14 interaction terms	0.604	2584.70	0.3601	0.5759

Figure 7.1 is a map of predicted values for the unemployment rate generated for Model III. The Moran's I statistic for unemployment rates in 2005 is -0.0555 and is lower than the expected value of -0.018182 indicating a dispersed pattern in unemployment rates. Given that the results are not significant (p = 0.689) at p < .05, the null hypothesis cannot be rejected on the premise that the dispersed pattern of unemployment rates is attributed to random chance. The spatial distribution of unemployment rates in this case is influenced by a number of unobserved environmental factors not captured in the model (ESRI 2012).

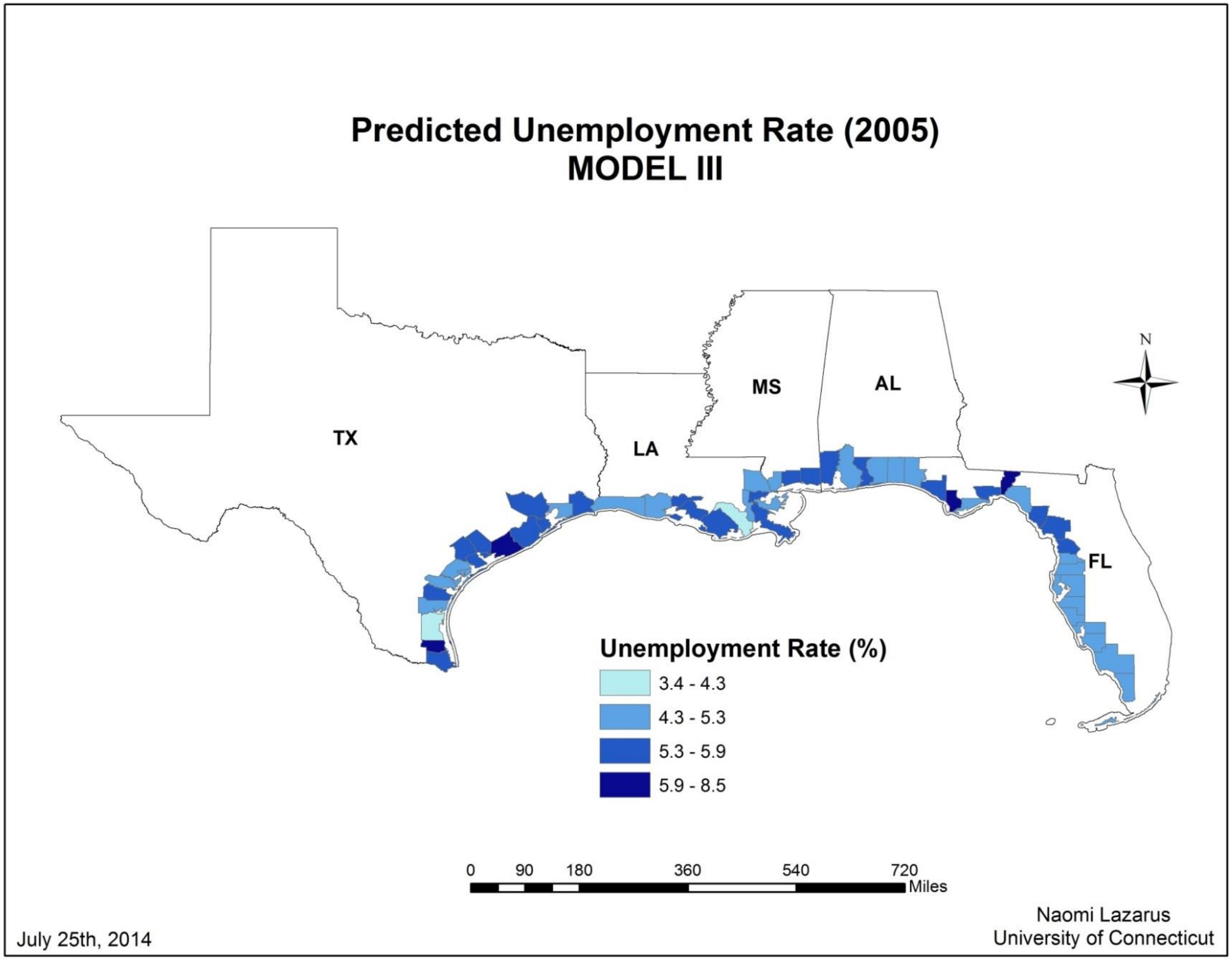

Figure 7.1 – Predicted Unemployment Rates in 2005 based on Model III Estimates

Figure 7.2 is a map of predicted values for unemployment rate generated for Model V, the autoregressive counterpart of Model III. The Moran's I statistic for unemployment rates in 2005 is 0.3909, which is greater than the expected value of -0.018182. The positive Moran's I value indicates that unemployment rates are clustered, indicating that neighboring spatial units display similar characteristics. These clusters are observed in southwest Florida, coastal Louisiana, and Mississippi. The results are significant ($p = 0.000$) at $p < .05$. The null hypothesis is rejected on the basis of the significance of the statistic, which indicates that underlying spatial processes are responsible for neighboring counties to display similar attributes resulting in positive spatial autocorrelation.

Model V estimates unemployment rates in Plaquemines, St. Bernard, and Lafourche to be in the range of 6.8% to 9.1%. These counties were adversely impacted by Hurricane Katrina. Each county, however, adopts a different set of coping strategies as identified in the variation in location quotients. While the three counties have location quotients less than 1.00 for social assistance and high location quotients for fisheries, St. Bernard Parish performs better than Plaquemines and Lafourche in sectors related to retail trade and religious organizations. Lafourche Parish recorded a location quotient of 3.65 in employment services, outperforming the other two counties in this sector. The clustering of high unemployment rates is evidence that coastal counties are responding to the widespread impact of Hurricane Katrina in similar ways despite differences in the distribution of social capital.

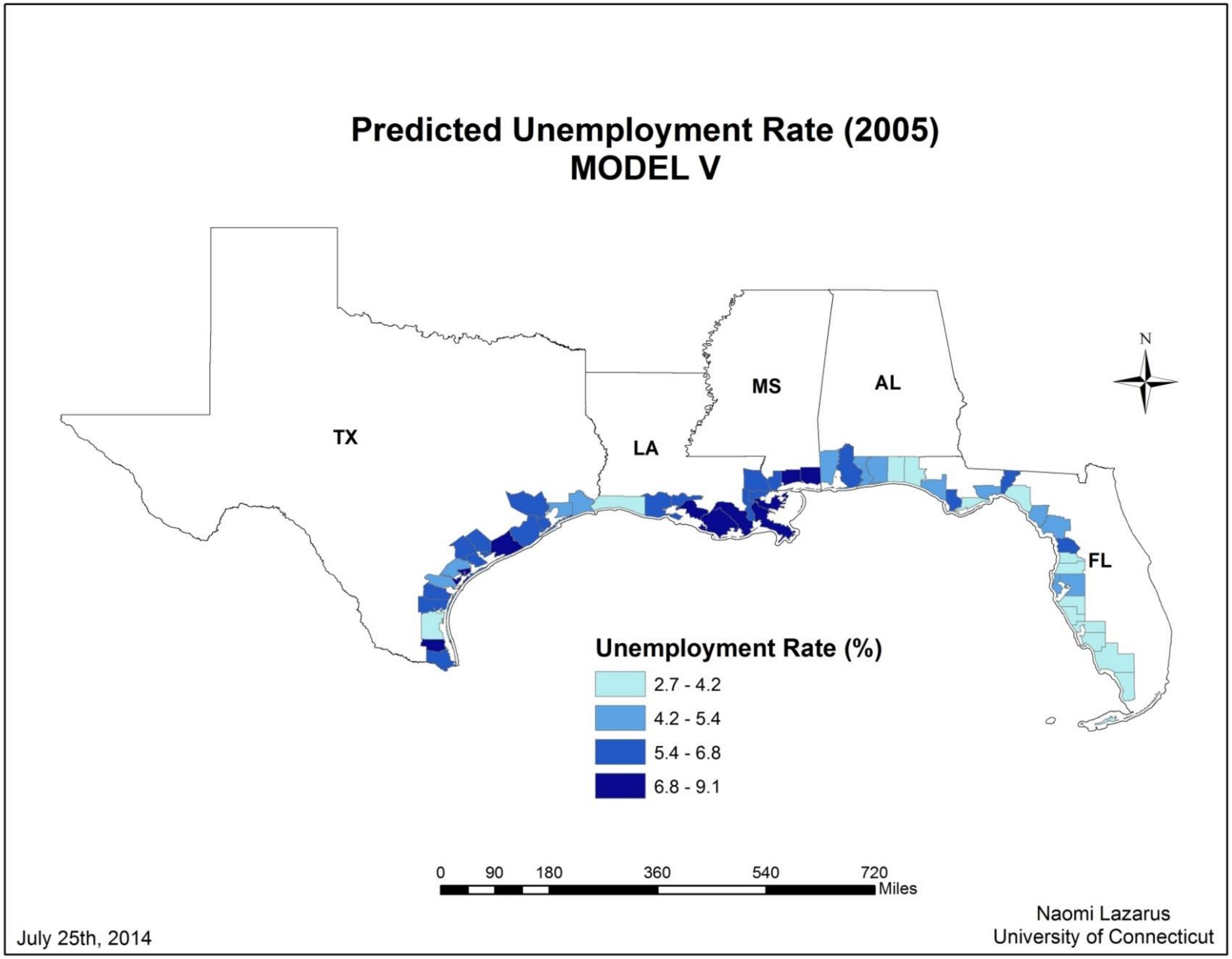

Figure 7.2 – Predicted Unemployment Rates in 2005 based on Model V Estimates

Figure 7.3 and 7.4 are predicted unemployment rates for 2010. Figure 7.3 is a map of unemployment rates generated for Model III, and Figure 7.4 are estimates generated for Model V. The Moran's I statistic for unemployment rates for Model III is 0.5705 and 0.5445 for Model V. Calculated Moran's I values for both models are greater than the expected value of -0.018182. The results are significant ($p = 0.000$) at $p < .05$. The positive Moran's I value indicates that unemployment rates are clustered, indicating that neighboring spatial units display similar characteristics. These clusters are observed in southwest Florida, coastal Louisiana, Mississippi, and Alabama. The significance of the statistic indicates that underlying spatial processes are responsible for neighboring counties to display similar attributes, and therefore, the null hypothesis is rejected.

Based on Model III estimates, unemployment rates in counties in the panhandle region of Florida are in the range of 7.6% to 9.2% (Figure 7.3). These include Bay, Walton, Santa Rosa, Okaloosa, and Escambia counties. While all five counties recorded high location quotients in retail trade and religious organizations, only Escambia County had location quotients greater than one in social assistance and employment services. Four out of the five counties recorded high location quotients for fisheries, and three counties had location quotients greater than one for utilities. These variations indicate that despite differences in the distribution of social capital these counties are responding to the impact of the DWH oil spill in similar ways as reflected in the unemployment rate.

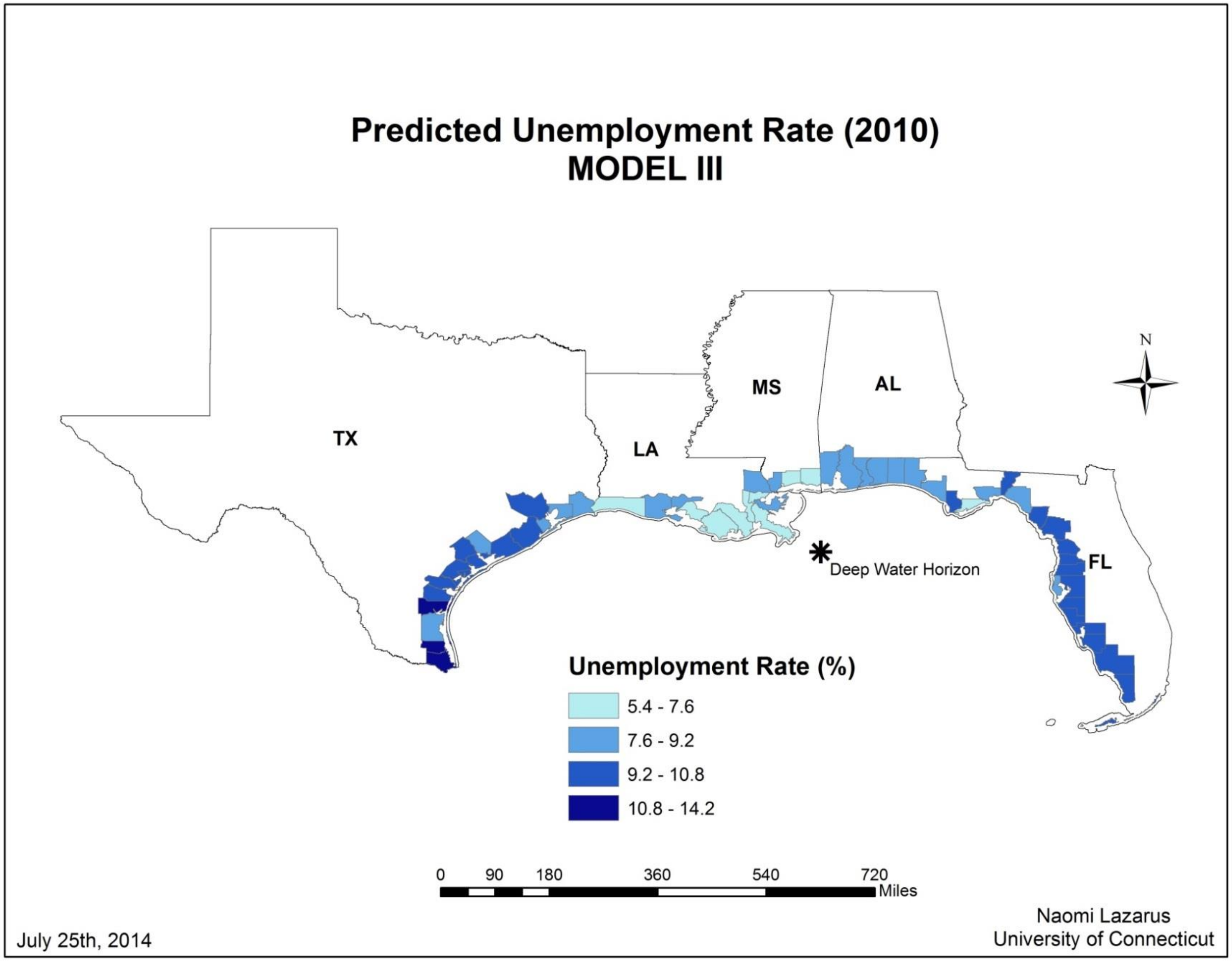

Figure 7.3– Predicted Unemployment Rates in 2010 based on Model III Estimates

In 2010, the DWH oil spill negatively impacted counties in Alabama and Mississippi where actual unemployment rates were between 8.2% and 10.1%. These include Baldwin and Mobile counties in Alabama, and Harrison and Jackson counties in Mississippi. Predicted unemployment rates based on Model V are closer to actual data than those estimated in Model III. Unemployment rates estimated by Model V are between 7.8% and 10.1% for coastal counties cited in Alabama and Mississippi (Figure 7.4), whereas predicted unemployment rates are between 5.4% and 9.2% in Model III (Figure 7.3). All four counties displayed location quotients less than 1.00 for social assistance and professional services. Mobile, Jackson, and Harrison counties recorded higher location quotients in fisheries and utilities than Baldwin, and Jackson, Mobile and Baldwin counties reported higher location quotients for religious organizations compared to Harrison. These examples illustrate that coastal counties in close proximity respond to hazard events in similar ways (clustering of high and low unemployment rates) while displaying different coping strategies in the form of resources and services provided by social capital.

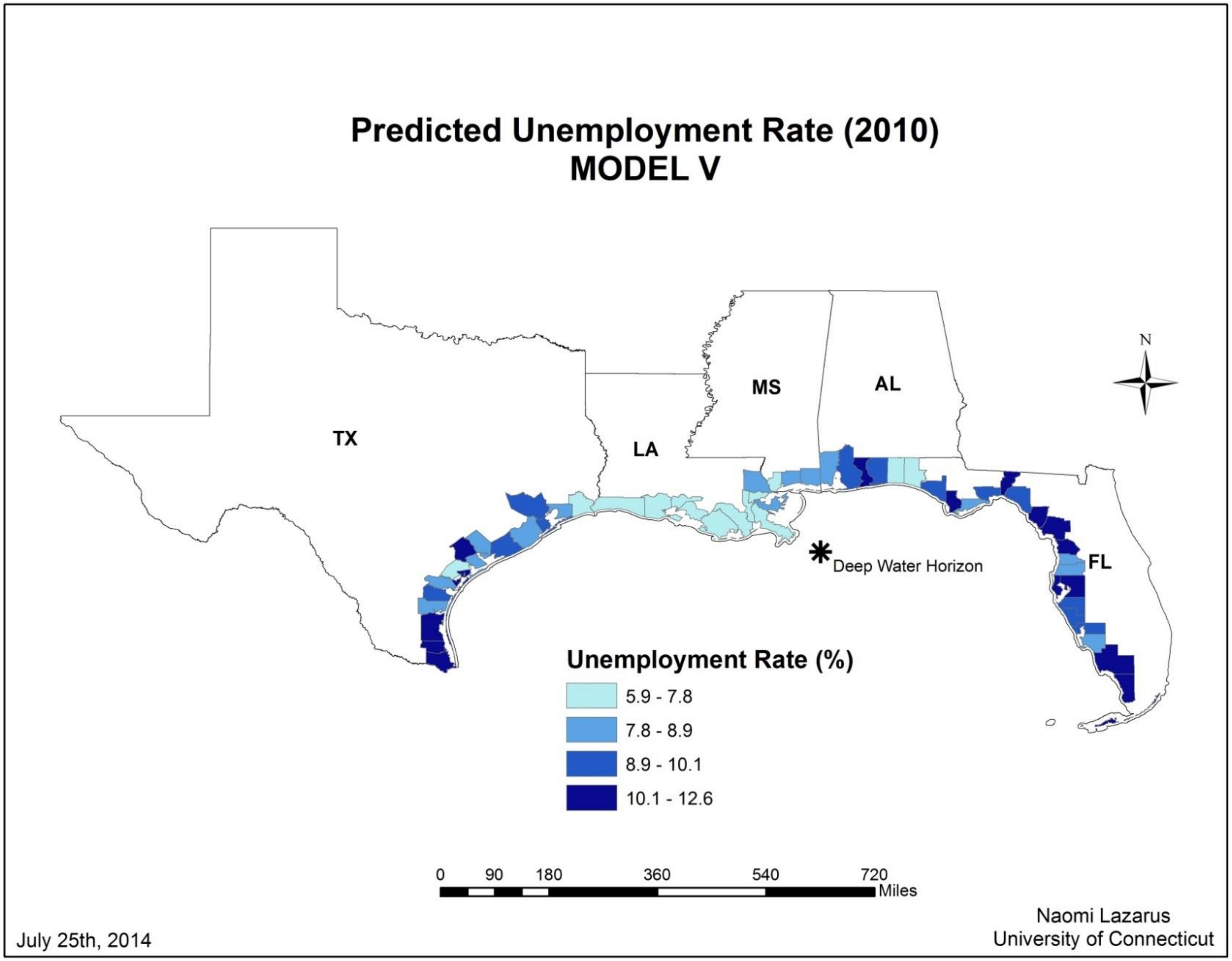

Figure 7.4– Predicted Unemployment Rates in 2010 based on Model V Estimates

The discussion on spatial autocorrelation extends to Model IV and Model VI. Model IV is the simple linear model with interaction terms with the time-related control variables, TIME_O, TIME_K, and TIME_K_SQ. Model VI is the autoregressive version of Model IV. Figure 7.5 is a map of predicted values for unemployment rate generated for Model IV. The Moran's I statistic for unemployment rates in 2005 is -0.0175 and is higher than the expected value of -0.018182 indicating a clustering of unemployment rates. Given that the results are not significant ($p = 0.994$) at $p < .05$, the null hypothesis cannot be rejected on the premise that the clustering of unemployment rates is attributed to random chance. The spatial distribution of unemployment rates in this case is influenced by a number of unobserved environmental factors not captured in the model (ESRI 2012).

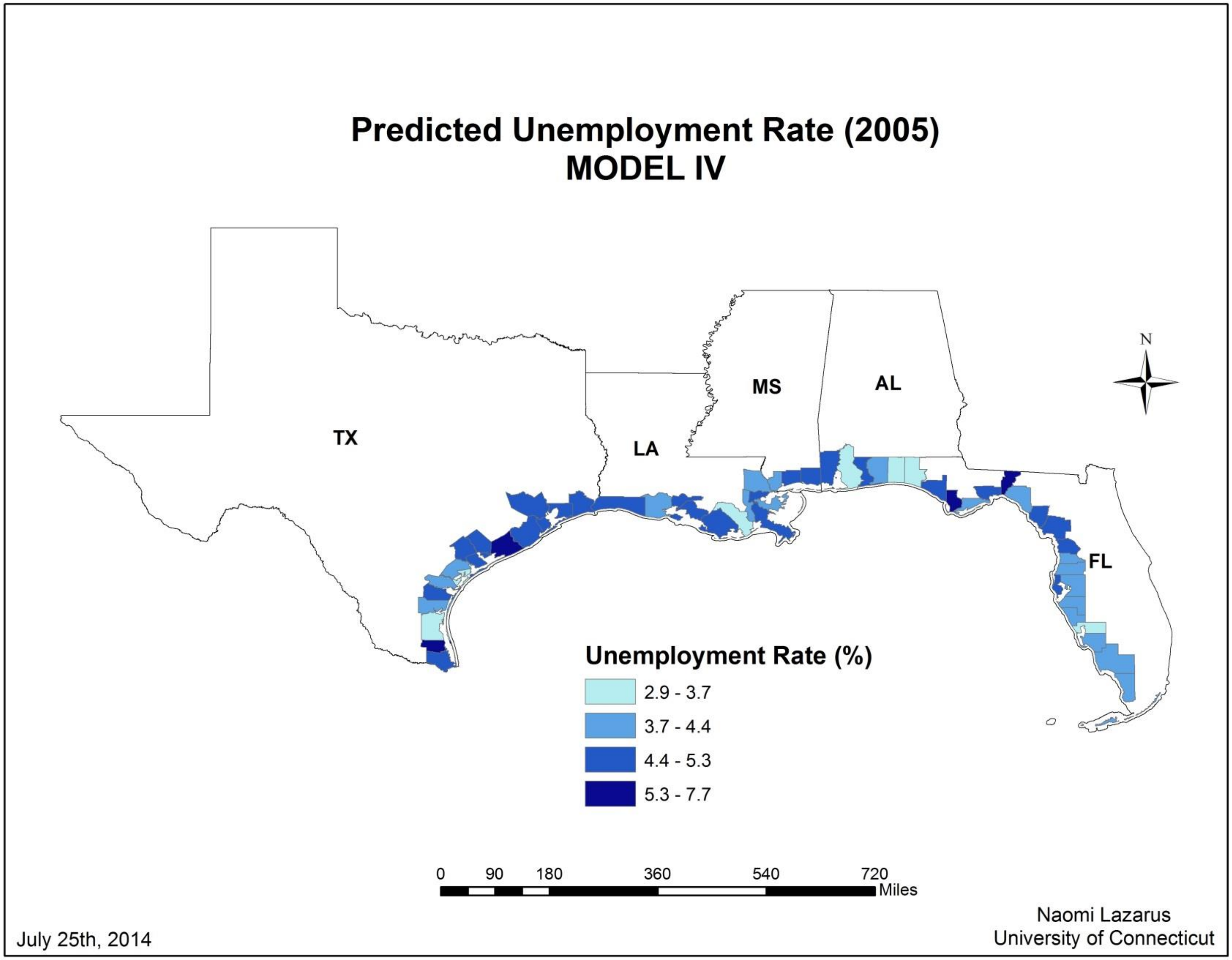

Figure 7.5 – Predicted Unemployment Rates in 2005 based on Model IV Estimates

Figure 7.6 is a map of predicted values for unemployment rate generated for Model VI, the autoregressive counterpart of Model IV. The Moran's I statistic for unemployment rates in 2005 is 0.3601, which is greater than the expected value of -0.018182. The positive Moran's I value indicates that unemployment rates are clustered, indicating that neighboring spatial units display similar characteristics. These clusters are observed in southwest Florida, coastal Louisiana, and Mississippi. The results are significant ($p = 0.000$) at $p < .05$. The null hypothesis is rejected on the basis of the significance of the statistic, which indicates that underlying spatial processes are responsible for neighboring counties to display similar attributes resulting in positive spatial autocorrelation.

Model VI estimates unemployment rates in Plaquemines, St. Bernard, and Lafourche to be in the range of 6.3% to 8.3%. These counties were adversely impacted by Hurricane Katrina. While the three counties have location quotients less than 1.00 for social assistance and high location quotients for fisheries, St. Bernard Parish performs better than Plaquemines and Lafourche in sectors related to retail trade and religious organizations. On the other hand, the model estimates low unemployment rates in coastal counties along Florida's southwest coast. These include Collier, Charlotte, Monroe, and Manatee counties where predicted unemployment rates are between 2.5% and 3.9%. All four counties displayed high location quotients in retail trade, but location quotients less than 1.00 for social assistance, employment services, utilities, and professional services. Collier, Manatee, and Monroe counties recorded high location quotients for fisheries, whereas only Charlotte and Manatee reported location quotients greater than one for religious organizations. The clustering of high and low unemployment rates is evidence that coastal counties in close proximity are responding to the widespread impact of Hurricane Katrina in similar ways despite differences in the distribution of social capital.

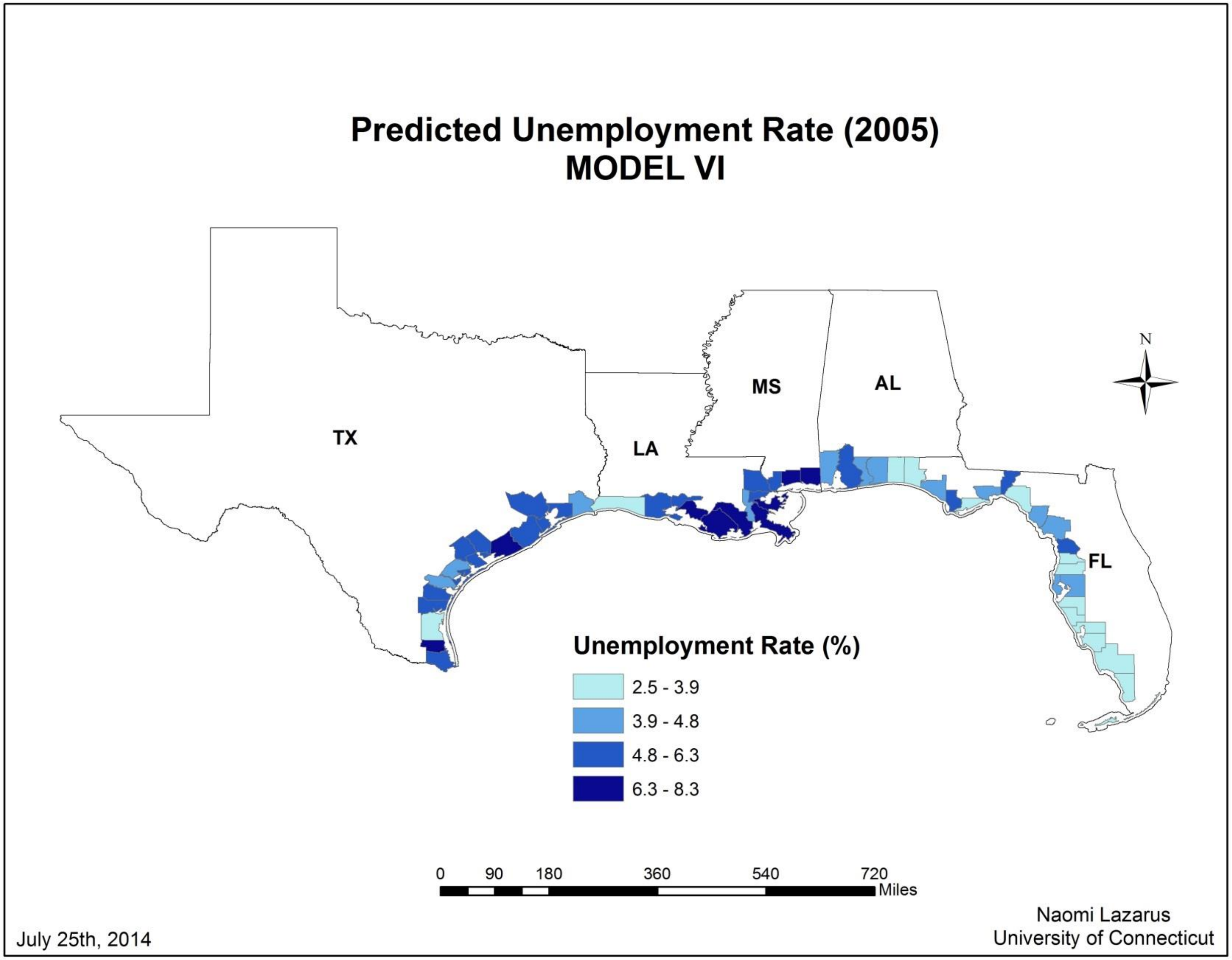

Figure 7.6 – Predicted Unemployment Rates in 2005 based on Model VI Estimates

Figure 7.7 and 7.8 are predicted unemployment rates for 2010. Figure 7.7 is a map of unemployment rates generated for Model IV, and Figure 7.8 are estimates generated for Model VI. The Moran's I statistic for unemployment rates for Model IV is 0.530 and 0.5759 for Model VI. Calculated Moran's I values for both models are greater than the expected value of -0.018182. The results are significant ($p = 0.000$) at $p < .05$. The positive Moran's I value indicates that neighboring spatial units with similar unemployment rates are clustered. These clusters are observed in the panhandle region and southwest coast of Florida, coastal Louisiana, and Alabama. The significance of the statistic indicates that underlying spatial processes are responsible for neighboring counties to display similar attributes, and therefore, the null hypothesis is rejected.

Based on Model IV estimates, unemployment rates in counties in the panhandle region of Florida are in the range of 7.9% to 9.2% (Figure 7.7). These include Bay, Walton, Santa Rosa, Okaloosa, and Escambia counties. While all five counties recorded high location quotients in retail trade and religious organizations, only Escambia County had location quotients greater than one in social assistance and employment services. Four out of the five counties recorded high location quotients for fisheries, and three counties had location quotients greater than one for utilities.

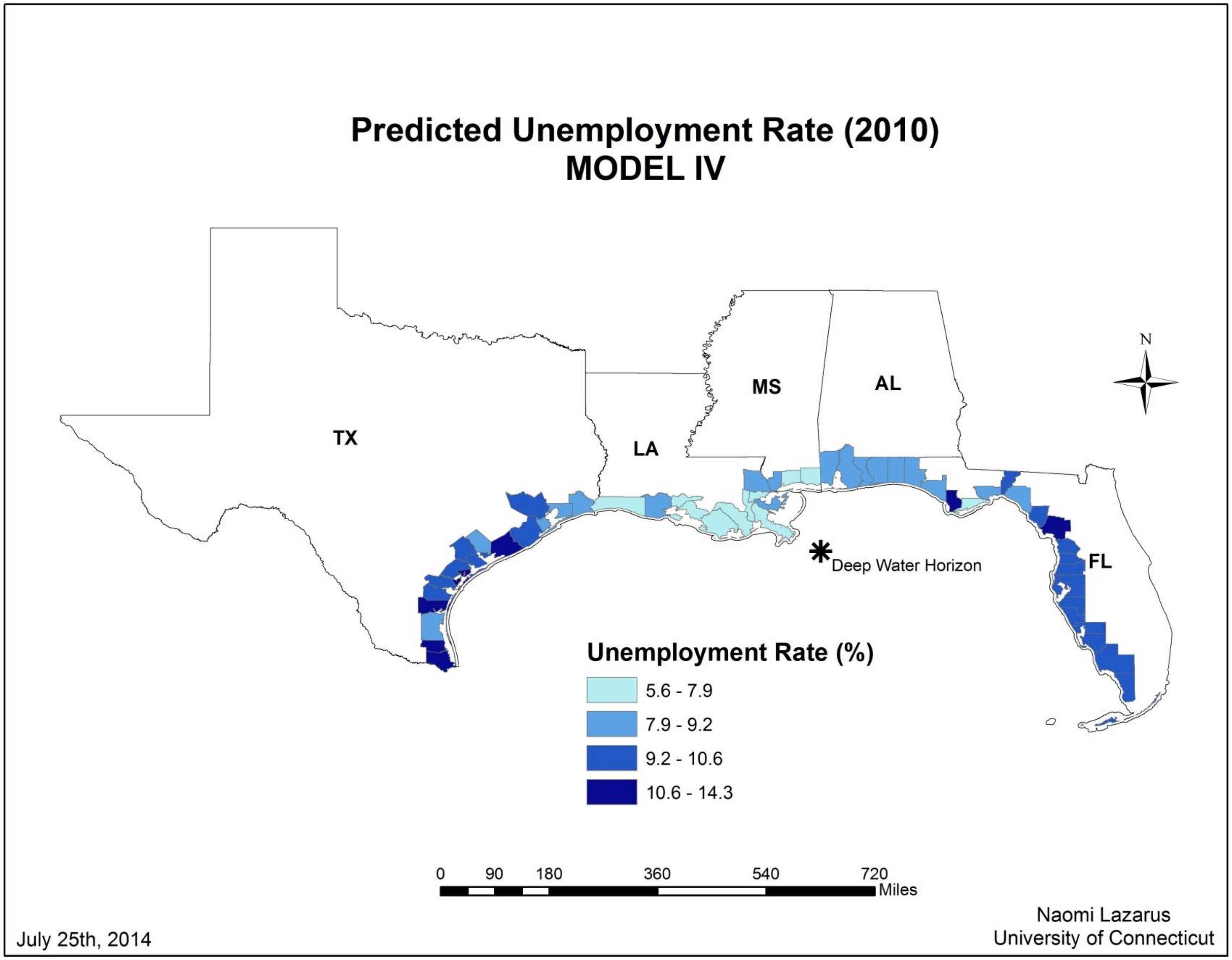

Figure 7.7 – Predicted Unemployment Rates in 2010 based on Model IV Estimates

Figure 7.8 is a map of unemployment rates pertaining to Model VI, the autoregressive version of Model IV. Model VI estimates unemployment rates in Plaquemines, Orleans, Jefferson, and Lafourche counties in coastal Louisiana to be in the range of 6.4% to 7.9%. Out of the four counties, only Orleans reported location quotients greater than 1.00 for social assistance, religious organizations, utilities, and professional services. Plaquemines and Lafourche counties had location quotients greater than one for fisheries, and Jefferson and Lafourche reported high location quotients for the retail sector. The model estimates higher unemployment rates in coastal counties along Florida's southwest coast. These include Charlotte, Manatee, and Sarasota counties where predicted unemployment rates are between 9.3% and 10.9% (Figure 7.8). All three counties displayed high location quotients in retail trade, but location quotients less than 1.00 for employment services and utilities. In addition, Sarasota County recorded high location quotients for fisheries, religious organizations, and professional services, whereas only Manatee reported location quotients greater than one for social assistance. The clustering of high and low unemployment rates is evidence that coastal counties in close proximity are responding to the widespread impact of the DWH oil spill in similar ways despite differences in the distribution of social capital.

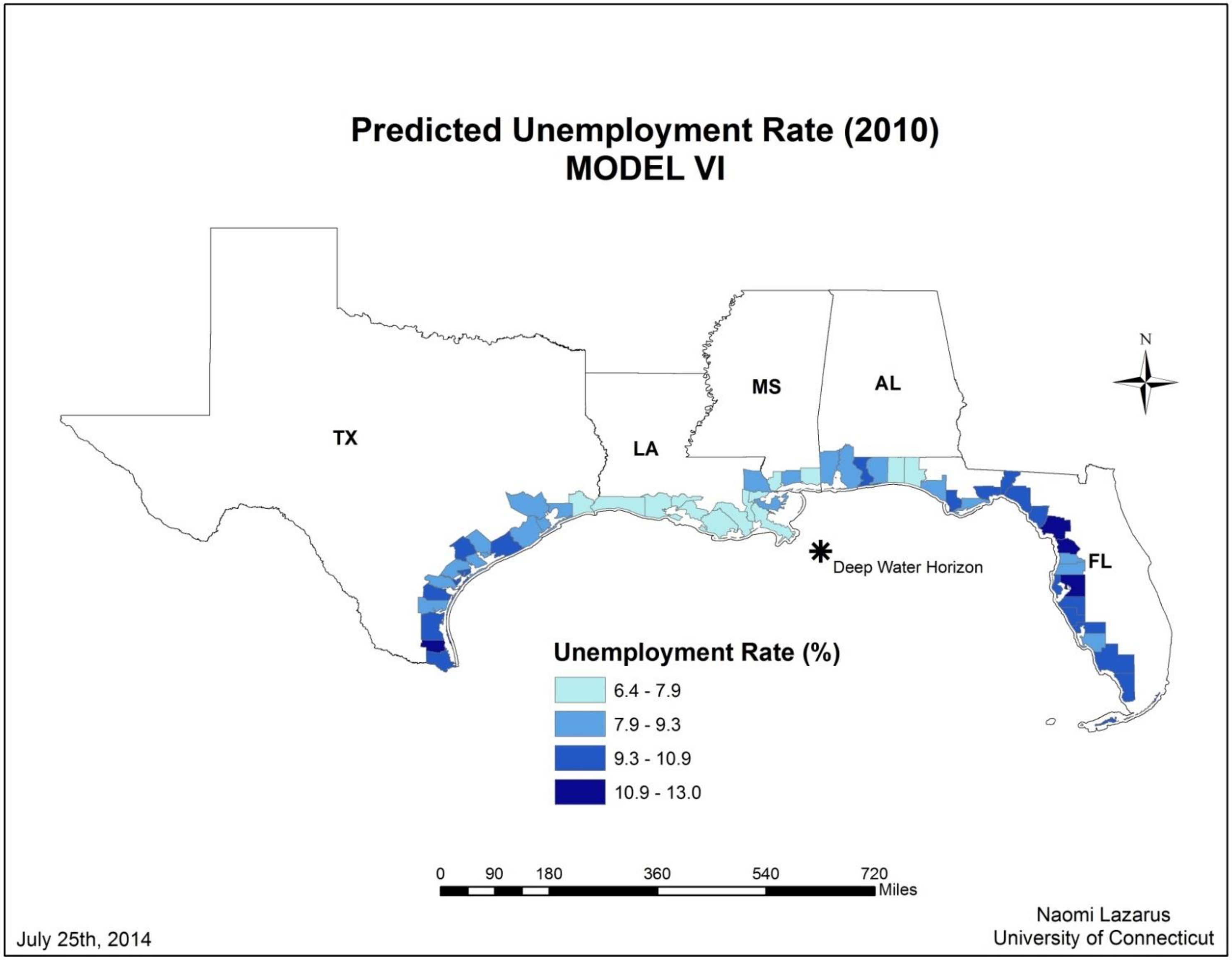

Figure 7.8 – Predicted Unemployment Rates in 2010 based on Model VI Estimates

The autoregressive model using time-related control variables, TIME_O, TIME_K, and TIME_K_SQ (Model VI) is selected as the best model for the following reasons. First, the model has the highest coefficient of determination (R^2) value of 0.604 compared to the other interaction and autoregressive models (Table 7.2), which indicates that Model VI is the best fit in terms of predicting unemployment rates (dependent variable). Second, the model records the lowest AIC value of 2584.70 relative to the other models under consideration. The AIC is another estimate of model fit. The smaller the value, the closer it is to the actual data. When comparing the AIC values of all the models, Model VI is more objective as it has the lowest AIC value.

Last, the number of significant parameter estimates for the stand-alone independent variables and interactions terms is higher in Model VI than in the autoregressive model with only TIME_O and TIME_K (Model V). The hypotheses associated with the first and second research questions are concerned with evaluating how services provided by social capital affect coping ability, which is represented by the dependent variable, unemployment rate. In order to address these questions, it is necessary to evaluate the relationships between the dependent variable and the *b* parameters of the independent variables and interaction terms. Model VI provides a comprehensive assessment of these relationships.

7.4 Threshold Analysis

7.4.1 Components of the Risk Equation

Re-specification of the risk equation takes into consideration the inter-relationships between three components, hazard *(H),* exposure *(E),* and coping ability *(C).* The hazard component is represented by spill distance, exposure by population density, and coping ability by unemployment rate. The threshold analysis evaluates each county's attribute values on these criteria by calculating a distance measure using the formula,

$$\frac{x_{(j)}}{TH} - 1$$

where, $x_{(i)}$ is the observed or predicted value of the variable in question for county *j*; and TH, the threshold value of the variable in question. As discussed in Chapter 5, the threshold for the hazard component represents the average distance from the spill across the study area. Coastal population density of the contiguous United States is used as the point of reference for exposure. The national unemployment rate represents the threshold for coping ability.

The threshold formula standardizes the variables representing *H*, *E*, and *C* and assigns each county a position along a continuum based on the *distance* from the threshold. For this reason, the results of the threshold formula are identified as *distance measures*. When computing the attribute values for the hazard component, proximity to the oil spill is considered. *Distance from the spill* (in miles) is the variable that represents the hazard component of the risk equation, and is distinct from the *distance measures* that are computed using the threshold formula.

Research on the impacts of hazards reveals that exposure is interpreted on a case-by-case basis. The context, type of hazard, and the problem addressed in each research setting are determining factors in the way in which exposure is defined in vulnerability assessments. Three overarching themes are observed in how exposure is tackled in the literature. First, exposure is characterized as the *proximity of populations* to the source of the hazard as illustrated in a case study on lead exposure in the Dominican Republic (Ratick and Osleeb 2011). Second, exposure is linked to populations coming into *contact* with a specific hazard. This approach is exemplified in a study on exposure to mercury, where a survey was conducted to identify the number of respondents who regularly consumed fish products (Ratick et al. 2004). Last, exposure is tied to the *size of the population* in a given location, which is a key aspect of physical vulnerability (Tobin and Montz 1997; Cutter, Boruff, and Shirley 2003; Cardona 2004). This approach is illustrated in a case study conducted by Ratick, Morehouse, and Klimberg (2009), where the number of people over the age of 65 and the number of people of minority descent were two variables used to develop a vulnerability assessment. This research adopts the third interpretation of exposure by incorporating population density as a component in the re-specified risk equation. Ratick, Morehouse, and Klimberg (2009) and Clark et al. (1998) argue that composition of vulnerable populations as a percentage provides a meaningful measure of vulnerability over size as it takes into account the areal extent of the study area and alleviates the problems associated with using raw numbers.

7.4.2 Classification

Classification of distance measures as *high*, *moderate*, and *low* is based on the standard deviation method. The median is identified as the central point as it accounts for the variation in the distribution of values for unemployment rate, population density, and spill distance. One standard deviation above and below the median is the cut-off point for high and low values. For example, the lower-bound threshold for distance measures associated with predicted unemployment rate in 2010 is -0.090, which is derived from subtracting the standard deviation of 0.145 from the median, 0.055. The median and standard deviation are added to obtain the upper-bound threshold of 0.200. In this case, distance measures below -0.090 are classified as *low*, and those above 0.200 are classified as *high*. Values that fall within the lower and upper bound thresholds are classified as *moderate*. This process is repeated to classify distance measures associated with population density and spill distance.

An arbitrary classification method was examined as an alternative to standard deviation where values less than -0.5 are classified as *low*, -0.5 to +0.5 as *moderate*, and values greater than 0.5 as *high*. Considerable differences in the number of counties under each category are observed between the two classification methods as presented in Table 7.6 using 2010 data. For example, the standard deviation method classifies nine counties as high and 47 counties as moderate for exposure. The number of counties in the high, moderate, and low categories as per the arbitrary method is 5, 13, and 38, respectively. With regard to coping, eleven counties are classified as high and twelve counties classified as low under the standard deviation method, whereas the arbitrary method does not include any in these categories. Marginal differences are identified in the hazard component between the two classification methods. Given that the re-specified risk equation forms the framework for assessing hazard risk based on the contribution

of hazard, exposure, and coping ability, this assessment would reflect the observed differences between the classification methods. Therefore, an objective method of classification such as standard deviation is appropriate to classify distance measures for hazard, exposure, and coping ability.

Table 7.6 – Comparison of Distance Measures based on Two Classification Methods - Standard Deviation and an Arbitrary Classification

	Hazard		**Exposure**		**Coping**	
	Std. Dev	*Arbitrary*	*Std. Dev*	*Arbitrary*	*Std. Dev*	*Arbitrary*
High	16	14	9	5	11	0
Moderate	30	30	47	13	33	56
Low	10	12	--	38	12	0

Each county's ranking on the ordinal scale provides information on its status in relation to the threshold *and* to other counties in the study area. The combination of relative distance and rank improves the narrative of analyzing the inter-relationships between levels of hazardousness, exposure, and coping ability. Figure 7.9 is a map of distance measures related to exposure i.e. population density. Spatial variation in density levels is evident particularly in coastal Florida and Texas. For example, in the panhandle of Florida, Bay County is highly exposed, whereas neighboring counties like Walton and Gulf are moderately exposed. In coastal Texas, Harris, Nueces, and Cameron counties are highly exposed while Chambers, Galveston, and Kleberg are moderately exposed.

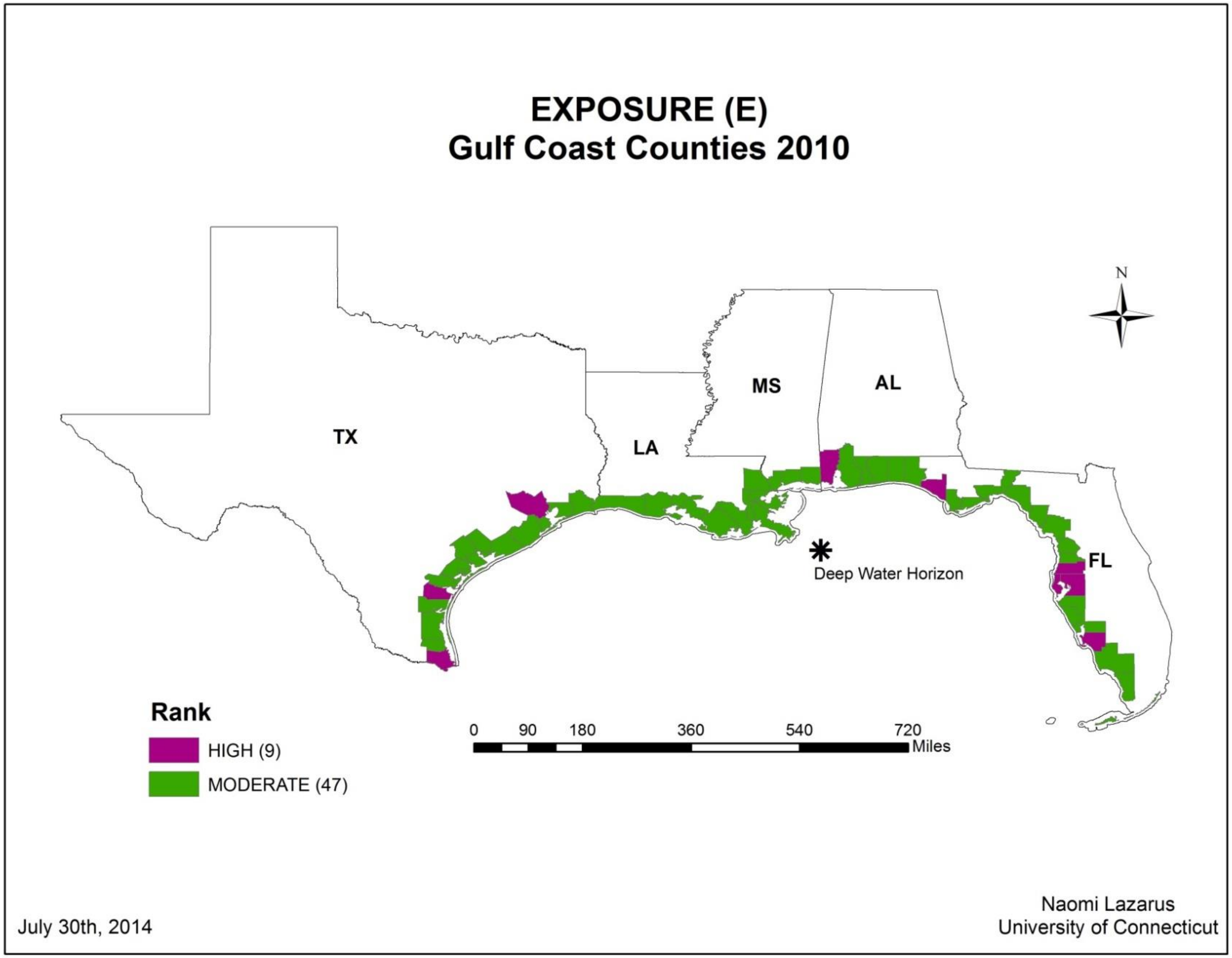

Figure 7.9 - Map of Distance Measures related to Exposure

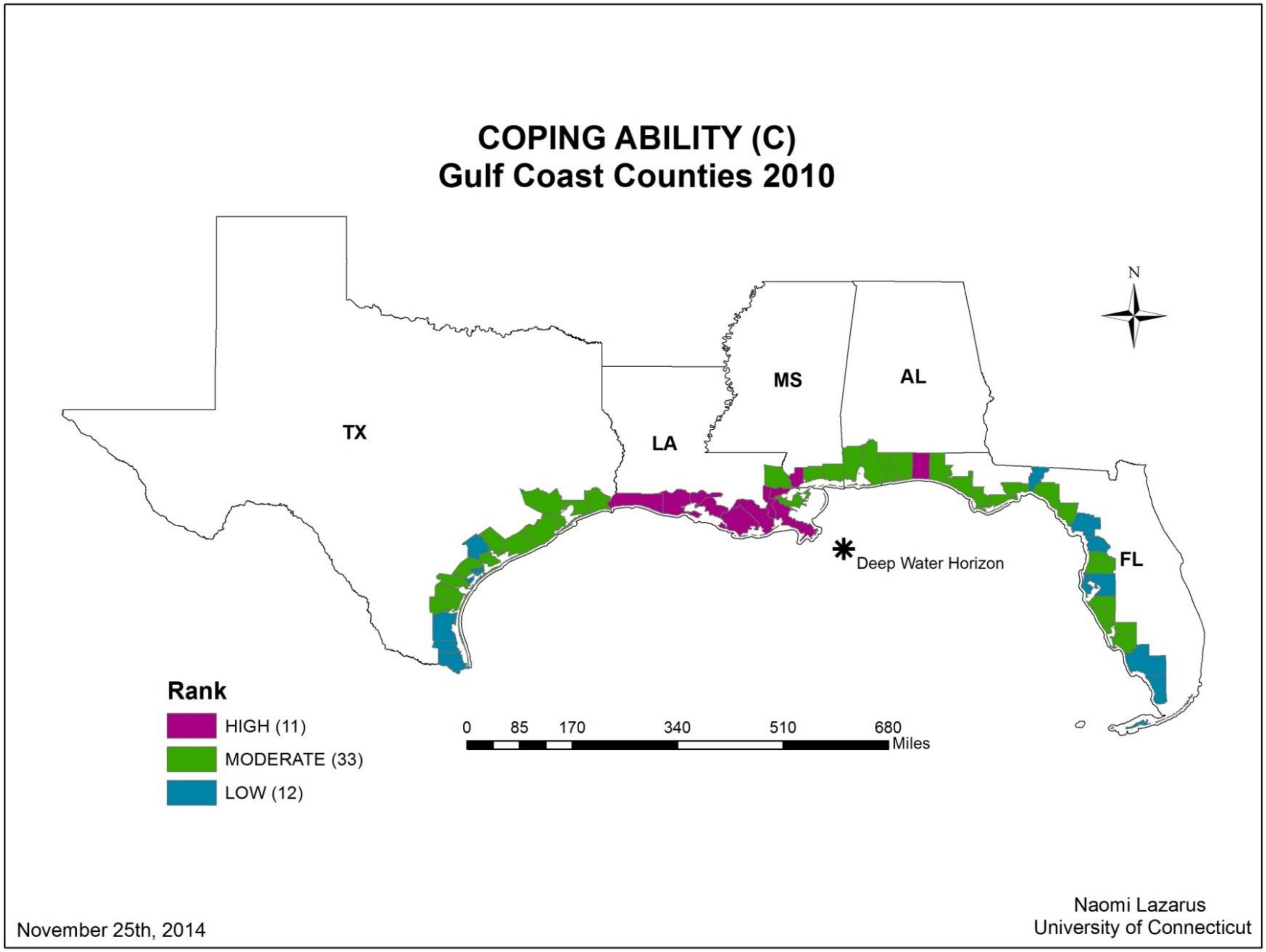

Figure 7.10 - Map of Distance Measures related to Coping Ability

In Figure 7.10, eleven counties rank high on distance measures related to coping ability, which is computed using levels of unemployment. These counties include Terrebonne, Lafourche, Orleans, and St. Tammany in Louisiana, Hancock in Mississippi, and Okaloosa in the Florida panhandle. Thirty three counties are classified as moderate on coping levels and these counties are located in the Florida panhandle, coastal Alabama, Mississippi, and Texas. Twelve counties are classified as low on coping ability and are located mostly in southwest Florida and in the Texas panhandle. Based on the number of counties classified as high and moderate, the spatial pattern reveals that most counties across the Gulf are in a better economic position (compared to the threshold) to cope with the impacts of hazard events.

Figure 7.11 is a map of distance measures related to hazard levels across the Gulf. These values are computed based on the distance of each county from the DWH spill. Counties in coastal Louisiana, Mississippi, and Alabama rank high on the hazard scale. Counties located away from this cluster, as in the case of southwest Florida and Texas, are classified as moderate or low on the hazard level. Despite these variations, most counties are better able to cope with the impacts of events as illustrated in the coping map (Figure 7.10).

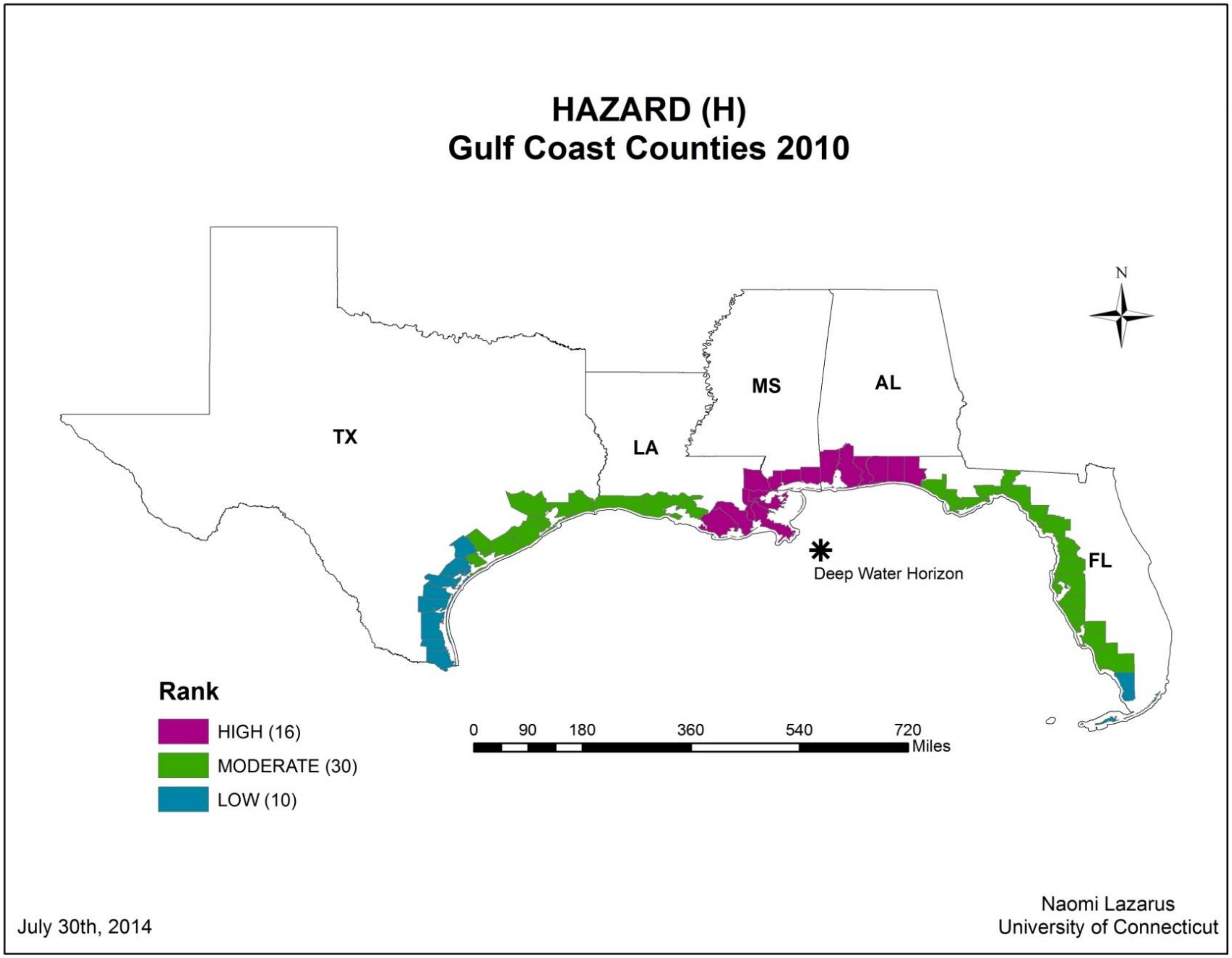

Figure 7.11 - Map of Distance Measures related to Hazard

7.4.3 Composite Risk Measure

The weighted average of attributes contributing to a composite measure of risk is calculated using the formula proposed by Ratick and Osleeb (2011):

$$I_j = \sum_{i \in A} W_i M_{ij} \quad \forall \quad j \in J$$

where, I_j is the composite weighted average for the risk index for spatial unit j; W_i, is the weight associated with attribute i; and M_{ij} is the attribute value i applicable to spatial unit j. A is the total number of attributes that contribute to risk and J is the set of spatial units in the study area. Since a uniform weighting scheme is not established to measure vulnerability, the hazard component is assigned a weight of 0.5, and exposure and coping ability are each assigned a weight of 0.25. The hazard component is given greater weight as it represents the proximity of each county to the DWH oil spill, the source of the hazard. If a county is closer to the spill, it is deemed more hazardous, and therefore, distance from the spill is a key factor in estimating overall risk under prevailing levels of vulnerability. Vulnerability is deconstructed as exposure and coping ability (Clark et al. 1998; Ratick, Morehouse, and Klimberg 2009; Ratick and Osleeb 2011), and the combined weight of these components is 0.5 (0.25 + 0.25).

The standard deviation method is used to classify composite risk index measures as *high*, *moderate*, and *low*. One standard deviation above and below the median is the cut-off point for high and low values. For example, the lower-bound threshold associated with the composite measure of risk in 2010 is -0.455, which is derived from subtracting the standard deviation of 0.328 from the median, -0.127. The median and standard deviation are added to obtain the upper-bound threshold of 0.201. In this case, distance measures below -0.455 are classified as

low, and those above 0.201 are classified as *high*. Values that fall within the lower and upper bound thresholds are classified as *moderate*.

7.5 Conclusion

The components of the hazard risk location model (HRLM) are analyzed in this chapter. First, a regression analysis is undertaken to evaluate the causal relationships between variables representing social capital and the dependent variable, unemployment rate. First, the basic model and the model with interaction terms are evaluated. The latter incorporates interaction terms to assess to what extent independent variables respond to the impacts of hazard events. The results reveal that the model with interaction terms performs better than the basic model based on the tests of model fit. Next, the autoregressive counterparts of the interaction models are evaluated. Autoregressive models address the problem of autocorrelation that is present when data are analyzed over time. Preliminary results reveal that the autoregressive models perform better in terms of model fit as they generate higher coefficients of determination and lower AIC values compared to the basic and interaction models. In addition, an evaluation of parameter estimates produced in the regression analysis reveals that the contribution of social capital to coping ability differs based on the type of hazard, indicating that the timing and characteristics of the hazard are key factors when evaluating the risk associated with hazard events.

The threshold analysis is used to assess the components of the re-specified risk equation - hazard, exposure, and coping ability. Distance measures associated with these attributes are evaluated for each county based on its position along a continuum. Maps on hazard, exposure, and coping ability reveal that there is spatial variation in the ranking of distance measures on

each attribute. In some cases, counties that are moderately exposed rank high on coping ability and hazard levels, whereas counties that rank high on exposure are only moderately able to cope with the impacts of hazard events. The assessment of hazard risk as articulated in the re-specified risk equation is expected to reflect the variations in hazard, exposure, and coping levels.

Chapter 8 provides a detailed discussion of the results. First, the parameter estimates of the selected autoregressive model are evaluated. The regression analysis addresses the underlying theme of the first and second research questions by evaluating the relationship between unemployment rate (proxy for coping ability) and variables representing social capital. Second, distance measures on hazard, exposure, and coping ability obtained from the threshold analysis are evaluated to address the third research question. This research question considers the inter-relationships between hazard, exposure, and coping ability and how they contribute to an overall assessment of vulnerability and risk.

Chapter 8

Results

8.1 Introduction

This chapter reviews the results of the regression and threshold analyses that comprise the two components of the hazard risk location model (HRLM). The regression analysis examines the relationship between unemployment rate (representing coping ability) and social capital. Social capital is represented by location quotients pertaining to fisheries, social assistance, employment services, professional services, retail, utilities, and religious organizations. Coping ability is the underlying theme of the first and second research questions. The first research question asks how important are safety nets provided by social capital to people exposed to environmental disasters. The hypotheses associated with this question evaluate how services provided by social capital affect coping ability during an environmental disaster, and how these services vary across the study area. The second research question asks how important is the quantity of social capital in minimizing the impact of an event. The reference made to *quantity* here is tied to the use of location quotients. Location quotients are a standardized measure of the number of people employed in a sector relative to the total number of people employed in a specific spatial unit. As such, the hypotheses associated with this research question examine how the quantity i.e. the location quotients of services provided by social capital affects changes in the unemployment rate, which determine coping ability.

The third research question asks how individual wellbeing and social capital are inter-related in determining risk associated with environmental disasters. It examines the inter-relationships between the components of the re-specified risk equation – hazard, exposure, and

coping ability. In this case distance to the spill represents the hazard and population density represents exposure. Coping ability is represented by the unemployment rate, which is the dependent variable in the regression analysis. The threshold analysis generates a series of values for spill distance, population density, and unemployment rate to evaluate and rank each county's position along a continuum of vulnerability and risk. Maps and charts are presented to observe spatial and temporal variations in hazard, exposure, and coping levels and how each component contributes to overall risk across the study area.

8.2 Evaluating Relationships between Social Capital and Individual Well-being

The first hypothesis examines the impact of social capital on livelihoods. The third hypothesis states that the services and resources provided by social capital are important factors in determining peoples' coping ability. These impacts are manifested in the degree of change associated with parameter estimates of the independent variables and the interaction terms used in the analysis. The interaction terms relate to two events, Hurricane Katrina and the Deep Water Horizon oil spill that occurred during the time period studied. The oil spill is the focus of the research and its impacts are evaluated in the context of previous events like Katrina.

Based on a comparative analysis of the basic, interaction, and autoregressive models presented in Chapter 7, the autoregressive model using time-related control variables, TIME_O, TIME_K, and TIME_K_SQ, (Model VI) is selected as the best model to operationalize the re-specified risk equation. The independent variables included in Model VI are the location quotients of fisheries, social assistance, employment services, retail, utilities, religious organizations, and professional services. Interaction terms are incorporated in a regression analysis to measure *interaction effects* that are observed when a time series dataset is interrupted

by specific events. Interaction terms associate each independent variable with the three time-related control variables, TIME_O, TIME_K, and TIME_K_SQ. TIME_O is used to estimate how social capital is impacted by the DWH oil spill. TIME_K and TIME_K_SQ are used to assess the impacts of Katrina. TIME_K_SQ assumes that the impacts of Katrina may increase in subsequent time periods and then decrease over time, which is characteristic of a quadratic trend. The issue of autocorrelation is addressed by incorporating an autoregressive term that recognizes the *dependence* of errors (SAS Institute 2014a). The formula of the autoregressive model is as follows:

$$Y_t = B_0 + (B_1\mathbf{L}X_1 + B_2\mathbf{L}X_2 + \ldots\ldots\ldots\ldots B_m\mathbf{L}X_m)_{\mathbf{j}} + B_T T + B_D D + B_{Tx} Tx + e_t$$

where, Y_t is the value of the dependent variable (coping ability) in a given time period, t; B_0, the constant; and B_1, $B_{2\ldots.}$ representative of parameter estimates of the respective independent variables denoted by X_1 and X_2 in a set of m number of variables, $k = 1.....m$. The lag operator, L, represents the value of the independent variable in the previous time period ($t - 1$) in a set of j number of time periods, $t = 1.....j$. T is an interval variable controlling for time, the value of which will be set as 1 for the event year and increments of one for subsequent years. T will be zero for years before the event. B_T, therefore, is the parameter estimate of time after the event. B_D is the parameter estimate of the distance-decay variable and e_t is the error associated with estimating the dependent variable in time period, t.

Model VI is selected as the best model for the following reasons. First, the model has the highest coefficient of determination (R^2) value of 0.604 compared to the other interaction and autoregressive models. Second, the model records the lowest AIC value of 2584.70 relative to the other models under consideration. The R^2 and AIC values indicate that Model VI is the best fit in terms of predicting unemployment rates (dependent variable). Last, the number of

significant parameter estimates for the stand-alone independent variables and interactions terms is higher in Model VI than in the autoregressive model with only TIME_O and TIME_K (Model V). The hypotheses associated with the first and second research questions are concerned with evaluating how services provided by social capital affect coping ability. In order to address these questions, it is necessary to evaluate the relationships between the dependent variable and the parameter estimates of the independent variables and interaction terms. Model VI, therefore, provides a comprehensive assessment of these relationships.

Table 8.1 lists the parameter estimates for Model VI. The control variables relating to time after the oil spill (TIME_O), time after Katrina (TIME_K, TIME_K_SQ) and spill distance (SPILL_DIST_DECAY) are significant at $p < .05$. When considering the seven stand-alone independent variables, six are significant and these are location quotients for social assistance (SA_LQ), fisheries (FISH_LQ), retail (RTL_LQ), employment services (EMP_LQ), religious organizations (REL_LQ), and utilities (UTI_LQG). The location quotient for professional services (PRO_LQG) is not significant. Parameter estimates of the interaction terms indicate which independent variables are impacted by the two hazard events in question, Katrina and the oil spill. Three interaction terms linked to time after Katrina (TIME_K_SQ) are significant at $p < .05$, whereas only two are significant in relation to time after the oil spill (TIME_O). Negative parameter estimates reveal that changes in social assistance and fisheries in response to Katrina (TIME_K_SQ) resulted in a decrease in unemployment rates. On the other hand, changes in location quotients for retail trade in response to Katrina resulted in an increase in the unemployment rate. Positive parameter estimates associated with TIME_O indicate that changes in social assistance and fisheries in response to the oil spill increased unemployment rates. Differences in the direction of relationships (+/-) of significant interaction terms reveal that the

timing and scope of specific hazard events have a differential impact on services provided by social capital.

The model results indicate that as the location quotients (relative importance) of social assistance (SA_LQ) increase, unemployment rates increase by 0.3769. The parameter estimate of the interaction term, SA_LQ*TIME_O is 0.3518, which is close to the estimate for the stand-alone variable. The coefficient of the interaction term reveals that social assistance did not experience a significant degree of change in response to the oil spill as unemployment rates remained largely the same for the study area as a whole. These patterns are consistent with findings in the field.

Table 8.1 – Parameter Estimates of b Coefficients of the Autoregressive Model (Model VI)

MODEL VI	**b**	**Sig. ($p < 0.05$)**
TIME_K	-1.6212	.000
TIME_K_SQ	0.3658	.000
TIME_O	-3.8543	.000
SPILL_DIST_DECAY	0.0097	.000
SA_LQ	0.3769	.000
FISH_LQ	-0.0034	.012
RTL_LQ	-0.6802	.017
EMP_LQ	-0.298	.026
REL_LQ	-0.0541	.000
UTI_LQG	0.0711	.000
PRO_LQG	0.0013	.995
SA_LQ*TIME_K_SQ	-0.0107	.012
FISH_LQ*TIME_K_SQ	-0.0006	.019
RTL_LQ*TIME_K_SQ	0.0605	.012
EMP_LQ*TIME_K_SQ	0.0227	.122
REL_LQ*TIME_K_SQ	-0.0039	.739
UTI_LQG*TIME_K_SQ	0.0006	.728
PRO_LQG*TIME_K_SQ	-0.0018	.899
SA_LQ*TIME_O	0.3518	.001
FISH_LQ*TIME_O	0.0122	.037
RTL_LQ*TIME_O	-0.9214	.078
EMP_LQ*TIME_O	-0.3106	.354
REL_LQ*TIME_O	0.2041	.486
UTI_LQG*TIME_O	-0.0145	.719
PRO_LQG*TIME_O	0.2951	.316
Model Fit		
R^2	0.604	
AIC	2584.70	

Figure 8.1 is a chart showing the temporal trend in location quotients for social assistance and unemployment rates in Bay County, FL. In the pan-handle counties of Florida (like Bay County), business owners who were legitimately affected by the downturn in tourism during the spill were collecting compensation between $7,000 and $35,000 set aside by British Petroleum (BP). There were cases where individuals and businesses collected compensation even though they were not affected. Given that these funds were administered by a private corporation, it did not reflect changes in services provided by social assistance programs as seen in the relative stability of the green trend line in Figure 8.1. These lump sum payments either acted as a cushion to cover losses or created a disincentive to work, and therefore, did not result in significant changes in the unemployment rate in 2010 (blue trend line).

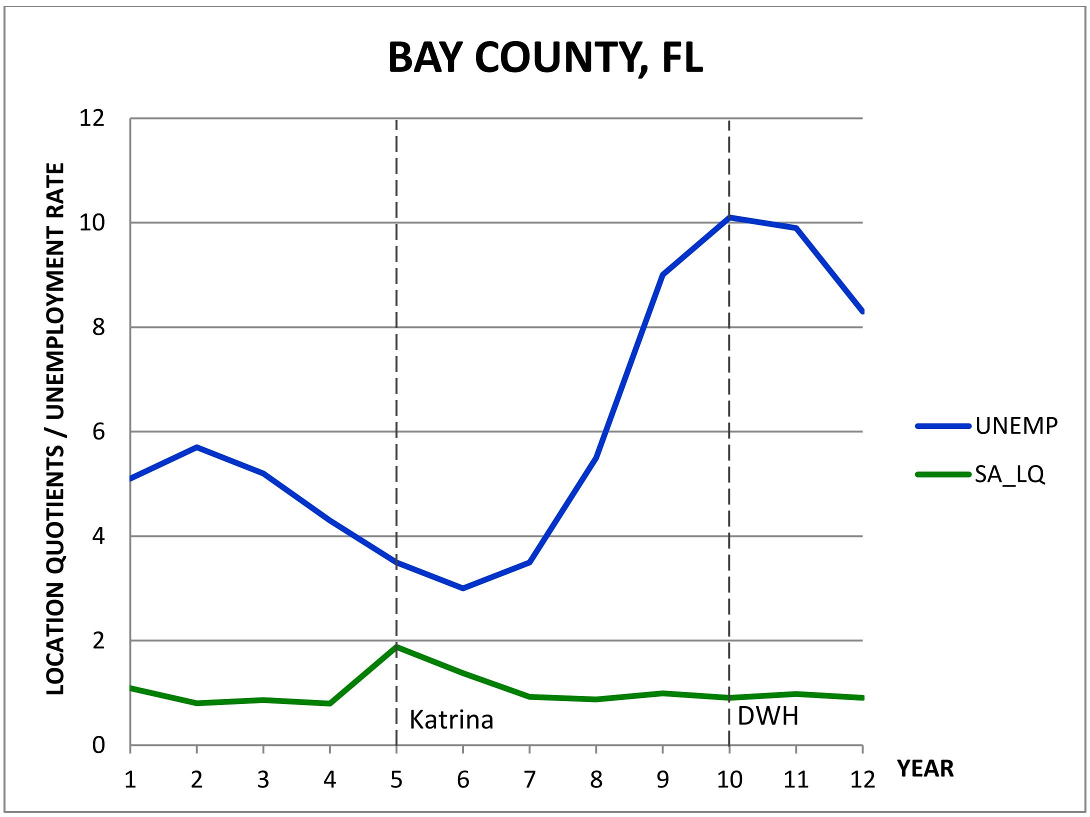

Figure 8.1 – Location Quotients of Social Assistance and Unemployment Rate – Bay County, Florida

The parameter estimate for the interaction term related to Katrina, SA_LQ*TIME_K_SQ is -0.0107. It indicates that changes in social assistance in response to Katrina resulted in a marginal decrease in the unemployment rate (Figure 8.1). Since the population exposed to the hurricane was primarily reliant on federal aid, services provided by social assistance played an important role in helping people cope with the negative impacts of the event. Additional labor employed to administer social assistance in the form of community, food, and emergency relief services, services for the elderly and disabled, temporary shelters, child care services, and vocational rehabilitation services resulted in a decrease in the unemployment rate in the short-term.

The results presented in Table 8.1 indicate that as the location quotients (relative importance) of the fishing industry increase, unemployment rates decrease for the study area as a whole. The rate of this decrease is marginal (-0.0034) and is significant at the $p < 0.05$. The interaction terms associated with fisheries reveal that changes in fisheries due to Katrina (FISH_LQ*TIME_K_SQ) resulted in a marginal decrease in unemployment rates (-0.0006). Changes in fisheries due to the DWH oil spill (FISH_LQ*TIME_O) resulted in a marginal increase in unemployment rates (0.0122). These trends are consistent with the patterns displayed in Figure 8.2 showing the temporal trend in location quotients for fisheries and unemployment rates in Hillsborough County FL. Located on the southwest coast of Florida, Hillsborough did not experience the direct impacts of Hurricane Katrina and the DWH oil spill compared to counties in coastal Louisiana and Mississippi. The unemployment rate in the county decreased in 2005 during the onset of Katrina and increased marginally in 2010, which was when the DWH oil spill occurred.

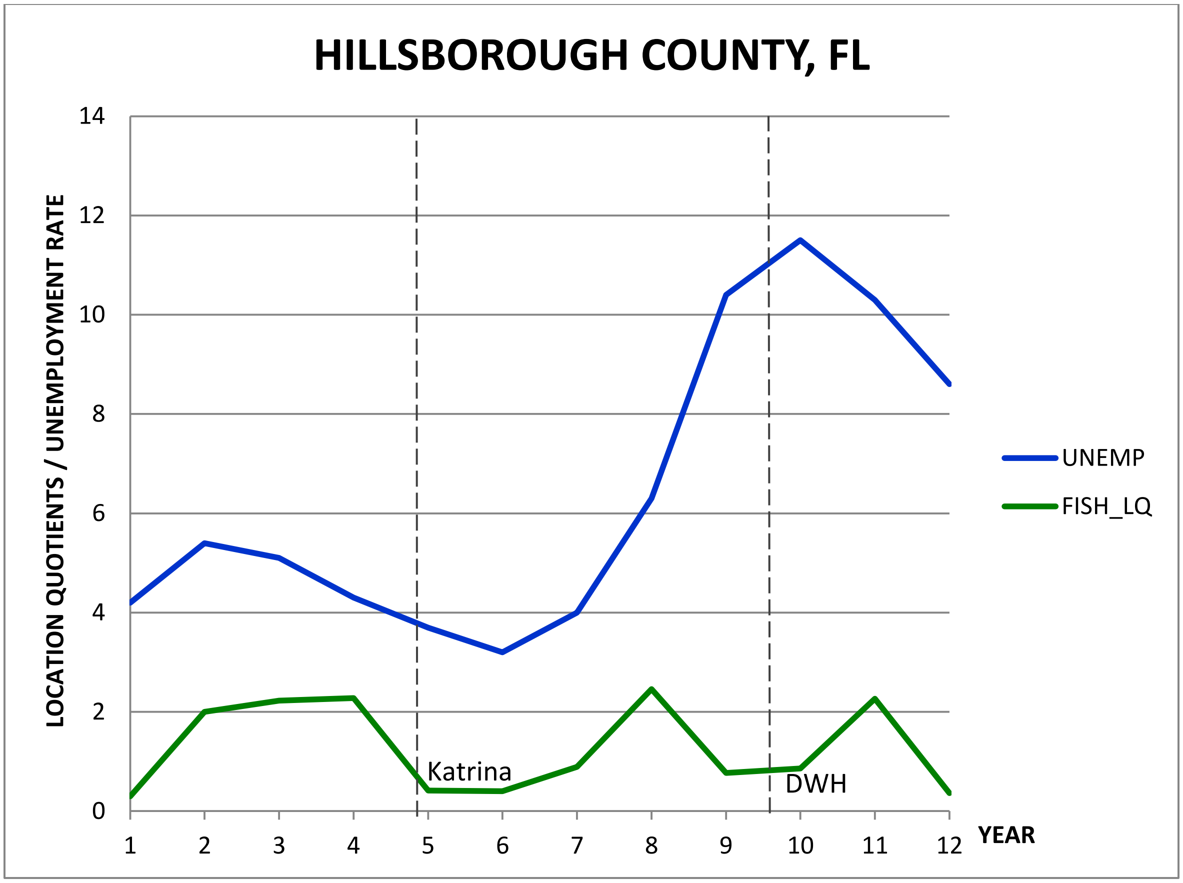

Figure 8.2 – Location Quotients of Fisheries and Unemployment Rate – Hillsborough County, Florida

There is, however, variation in the relationships between fisheries and unemployment rates at the county level. Figure 8.3 presents the temporal trend in location quotients for fisheries and unemployment rates in Plaquemines LA. The county is located along the Louisiana coast and was adversely impacted by Hurricane Katrina and the DWH oil spill. These impacts are reflected in the changes in fisheries and the unemployment rate as illustrated in Figure 8.3. The blue trend line displays greater fluctuation in the unemployment rate in Plaquemines than in Hillsborough (Figure 8.2). The differences in location quotients and the unemployment rate in Hillsborough and Plaquemines counties indicate that there are considerable spatial and temporal variations in how the impacts of hazard events play out at the county level.

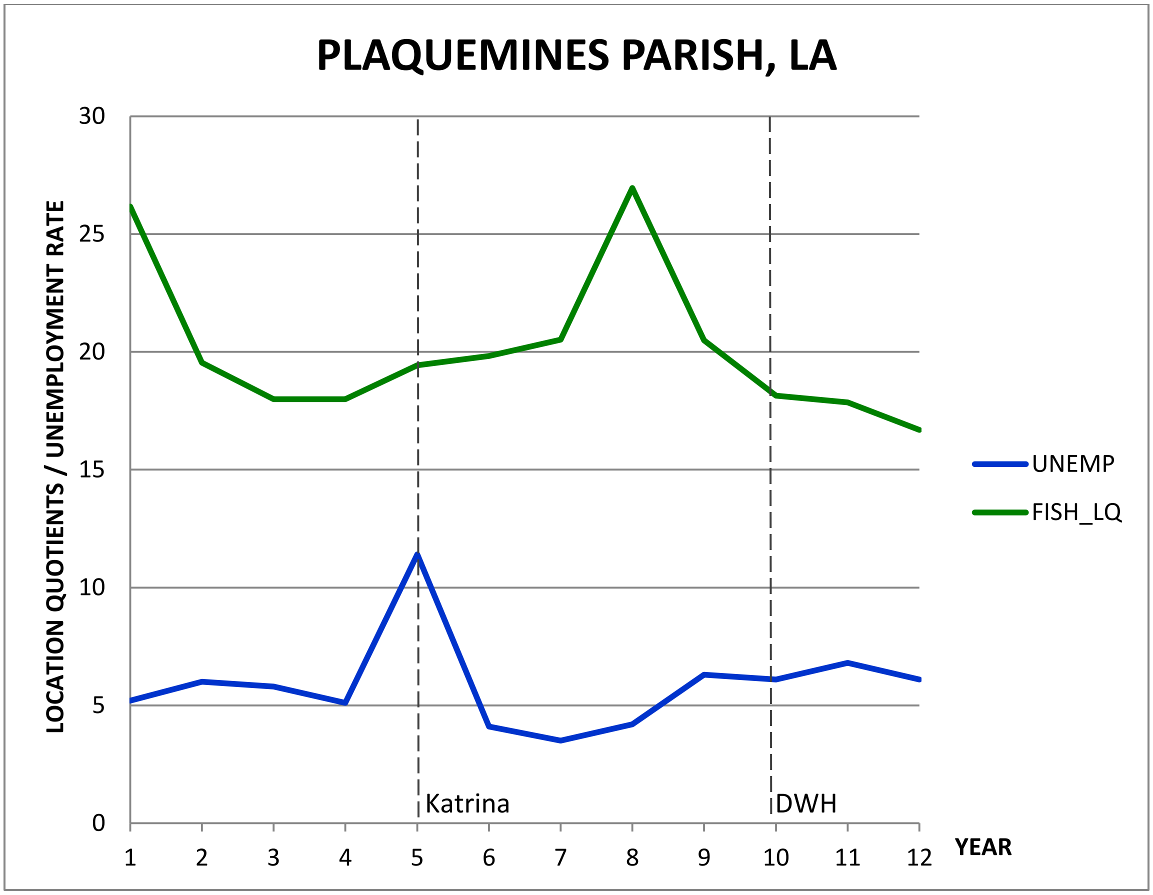

Figure 8.3 – Location Quotients of Fisheries and Unemployment Rate – Plaquemines Parish, Louisiana

The parameter estimate for retail (RTL_LQ) reveals that as the relative importance of retail services increases, the unemployment rate decreases by -0.6802 and it is significant at $p < .05$ (Table 8.1). The *b* coefficient associated with the interaction term for time after Katrina (RTL_LQ*TIME_K_SQ) shows an increase in the unemployment rate by 0.0605. This increase is indicative of the widespread impact of the hurricane and its adverse impact on the demand for goods and services provided by the retail sector. The parameter estimate for the interaction term associated with the oil spill (RTL_LQ*TIME_O) is -0.9214 and is not significant at $p < .05$. Figure 8.4 is a chart showing the temporal trend in location quotients related to retail services and unemployment rates in Orleans LA. The increase in the unemployment rate in 2005 reflects

the impact of Hurricane Katrina, whereas in 2010, the fluctuation in unemployment rates is smaller than the earlier time period. Based on observations and discussions conducted in the field, it was evident that people came from all over the country to work in oil spill recovery due to high wages. These workers stimulated the local economy with their spending (e.g. bars, restaurants, clubs etc.). Furthermore, people working in the restaurant and tourism industries left their jobs to go work in oil spill recovery as it paid well. Therefore, the oil spill did not adversely impact the retail sector as demand for goods and services was sustained to some extent by people engaged in recovery and restoration, which is reflected in the relative stability of the green trend line representing location quotients in retail services.

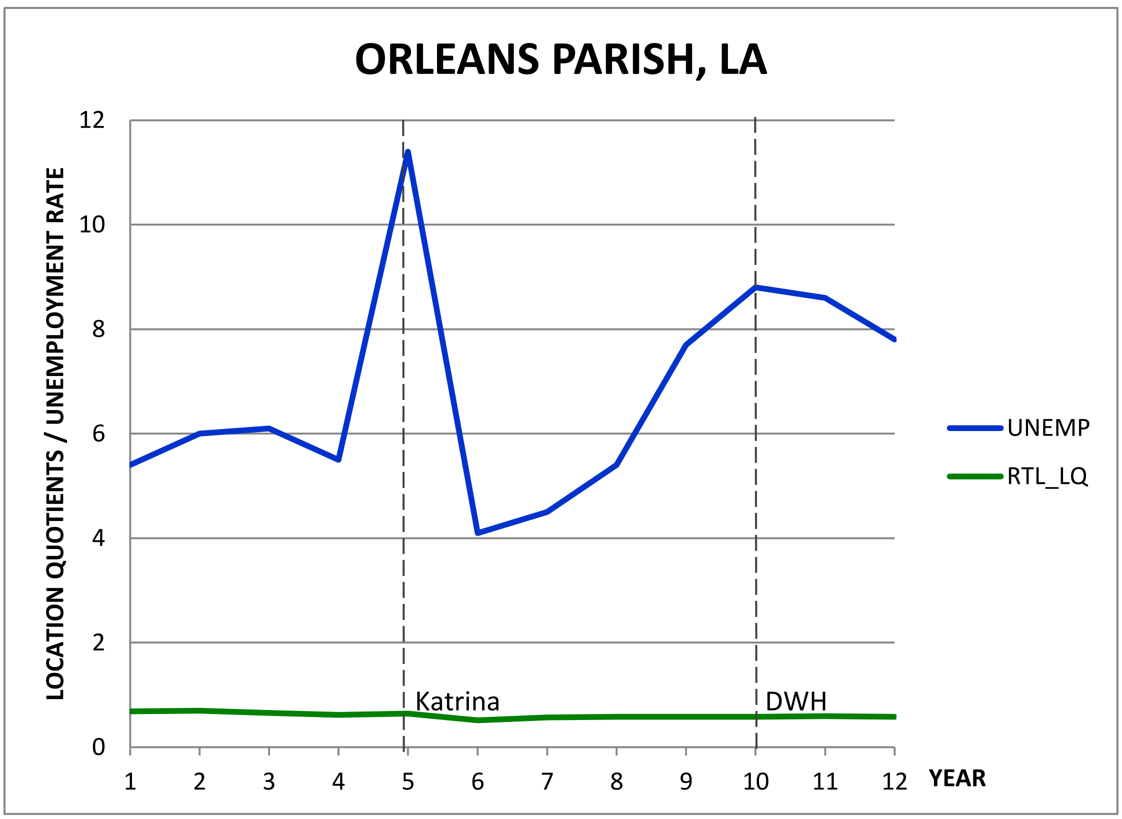

Figure 8.4 – Location Quotients of Retail Trade and Unemployment Rate – Orleans Parish, Louisiana

The results presented in Table 8.1 indicate that as the location quotients for employment services (EMP_LQ) and religious organizations (REL_LQ) increase, the unemployment rate decreases. The rate of this decrease is -0.298 for EMP_LQ and -0.0541 for REL_LQ. The results are significant at $p < .05$. The parameter estimate for utilities (UTI_LQG) is positive indicating that the unemployment rate increases by 0.0711 in response to an increase in utilities. The estimates of the interaction terms associated with employment services, religious organizations, utilities, and professional services are not significant, indicating that the services provided by these sectors are not significantly impacted by hazard events in general, and that variation in unemployment rates is likely due to other factors associated with changes in the business cycle.

The first hypothesis states that services provided by social capital affect peoples' ability to cope during an environmental disaster. The third hypothesis states that the quantity of social capital is a factor in determining peoples' ability to cope with an event. Parameter estimates of social assistance, fisheries, retail, employment services, utilities, and religious organizations indicate that changes in services provided by these sectors have a significant impact on the unemployment rate, the dependent variable that represents coping ability. As presented in Table 8.1, services and resources provided by fisheries, retail, employment, and religious organizations can bring down the unemployment rate and improve coping ability. It is expected that greater the number of people employed in the fishing and retail industries, the overall unemployment rates would be lower in coastal counties in the Gulf compared to regions where these industries have a relatively lower share in the local economy. Employment services and services provided by religious organizations form part of social capital that provides formal and informal linkages so that people can access resources to maintain livelihoods, thereby lowering the unemployment

rate. An increase in social assistance and utilities results in an increase in the unemployment rate for the study area as a whole as indicated in Table 8.1. Utilities in the form of power generation, water supply, and sewage systems are particularly vulnerable due to the damage to infrastructure caused by hazard events. Given that utilities services in the Gulf region are primarily provided by the private sector, the disruption of these services not only negatively impacts consumers, but also those employed in these sectors whose livelihoods depend on these activities. As such, unemployment rates are likely to increase as a result of damage to infrastructure and the disruption of utilities services during hazard events. On the other hand, counties with more resources allocated to social assistance are likely to experience less fluctuation in the unemployment rate during hazard events. Social assistance in the form of food, housing, emergency services etc. functions as an added safety net by virtue of the services they provide to the community. These programs create an environment where people are able to cope with the impacts of hazard events with minimal disruption in their livelihood activities (Cannon 1994; Wisner et al. 2004). The regression coefficient, however, indicates an increase in the unemployment rate in response to social assistance. Since the unemployment rate is defined as the number of people without work and who are actively looking for work as a ratio of the labor force, those who fall into this category are likely to utilize social assistance in the form of community, food, and emergency relief services. The dynamics between social assistance and unemployment rate, therefore, are much more nuanced as they are influenced by macro processes related to structural unemployment and fiscal processes. Structural unemployment is present when a decline in demand for goods and services triggers production shortfalls, which in turn drive down the demand for labor i.e. the number of skilled workers exceeds the available jobs. Fiscal processes are tied to tax policies and government expenditure that determine

resource allocations to programs, such as social assistance and infrastructure development (Mansfield 1986; Gordon 1987). As such, macro processes that trigger structural unemployment can exacerbate the adverse impacts of hazard events as resources and infrastructure provided by social assistance and utilities are often times unable to cope with the damage and destruction caused to life and property resulting in a decline in available social capital. The null hypothesis is rejected based on the degree of change in the parameter estimates of the independent variables, which highlights the fact that services provided by social capital affect peoples' ability to cope during hazard events.

As listed in Table 8.1 parameter estimates of the interaction terms indicate that social assistance and fisheries were negatively impacted by Hurricane Katrina i.e. unemployment rates declined in response to the impacts of the event on these sectors. Retail services were positively impacted and reflected in the increase in unemployment rates. The retail sector experienced a decline in the aftermath of Hurricane Katrina due to the cumulative impacts of outmigration and a decrease in tourist arrivals that undermined the overall demand for goods and services in this sector. In the case of the DWH oil spill, interaction terms associated with fisheries and social assistance were positively impacted by the event i.e. unemployment rates increased in response to the impacts of the event on these sectors. As indicated in the discussion of the stand-alone independent variables, those who are unemployed are likely to utilize social assistance in the form of community, food, and emergency relief services, although it is expected that counties with greater resources allocated to social assistance would experience less *fluctuation* in the unemployment rate. In the case of fisheries, the relationship holds as it is expected that greater the number of people employed in the fishing industry, the overall unemployment rates would increase during a hazard event in coastal counties in the Gulf compared to regions where these

industries have a relatively lower share in the local economy. Based on the analysis of significant interaction terms, the third hypothesis is conditionally accepted on the basis that changes in social capital are determined by the type of hazard event. Therefore, the null hypothesis cannot be rejected conclusively.

8.3 Evaluating Spatial Variation in Social Capital

8.3.1 Fisheries

The second hypothesis examines the spatial pattern of variables representing social capital. The principle of nearest neighbor is applied when estimating the maximum radial distance within which observations display similar attributes. This distance is known as the bandwidth and is expressed in the same units as the geographical coordinates of the dataset. A fixed distance bandwidth refers to a uniform radial distance that is applied to each observation where greater weights are assigned to points inside the bandwidth than to those falling outside the neighborhood (Charlton and Fotheringham 2009). The test of spatial autocorrelation is concerned with observing local patterns of clustering (Yu 2010) and accounts for the variations in attribute values across spatial units in the study area.

Table 8.2 summarizes the test of spatial autocorrelation for fisheries, social assistance, and retail services as these variables interact significantly with the time-related control variables linked to the DWH oil spill (TIME_O) and Hurricane Katrina (TIME_K_SQ). Based on an expected value of -0.018182 the Moran's I statistic for fisheries is positive for spatial autocorrelation (0.0629), but is not significant at $p < .05$. Testing the significance of the Moran's I statistic involves comparing it against the null hypothesis, which states that the spatial processes responsible for the observed pattern of the attribute in question are due to random

chance. If the p-value associated with a *positive* Moran's I is statistically significant, the null hypothesis is rejected on the premise that the clustered or dispersed pattern of attribute values is likely due to underlying spatial processes and not due to chance. If the p-value is not statistically significant it indicates that the observed spatial distribution of attribute values is due to random spatial processes that are influenced by a number of unobserved environmental factors not captured in the model (ESRI 2012).

Table 8.2 – Tests of Spatial Autocorrelation (Moran's I and Geary's C) for Significant Interaction Terms

Variable	**2010**			**2005**		
	Moran's I	Sig. p<.05	z score	Moran's I	Sig. p<.05	z score
FISH_LQ	0.0629	0.359	0.915	0.0335	0.501	0.673
SA_LQ	0.108	0.063	1.859	0.0343	0.479	0.707
RTL_LQ	0.0677	0.386	0.866	0.0027	0.831	0.213
Variable	**2010**			**2005**		
	Geary's C	Sig. p<.05	z score	Geary's C	Sig. p<.05	z score
FISH_LQ	0.0648	0.869	0.164	0.0610	0.983	0.021
SA_LQ	0.0614	0.917	0.104	0.0495	0.248	-1.153
RTL_LQ	0.0612	0.705	0.376	0.0603	0.953	-0.058

Table 8.2 presents an additional test of spatial autocorrelation, the Geary's C. The Geary's C analyzes local patterns of clustering and dispersion based on the null hypothesis that attribute values are randomly distributed (ESRI 2012). Unlike the Moran's I, the calculated Geary's C is compared against a constant of 1. A Geary's C greater than 1 indicates that attribute values of adjacent units are dissimilar i.e. a dispersed pattern is observed. On the other hand, a Geary's C between zero and 1 indicates a clustered pattern where adjacent units display similar characteristics. The statistical significance of the Geary's C is evaluated using the *p* value and the *z* score. The p-value tests the significance of the calculated Geary's C and compares it against the null hypothesis, which states that attribute values are randomly

distributed. The z score evaluates the level of clustering of attribute values (ESRI 2012). The Geary's C statistic for fisheries in 2010 is 0.0648 and 0.0610 in 2005, which indicates a clustered pattern. The results are not significant at $p < .05$. The z-scores close to zero indicate that the level of clustering is negligible. The tests of spatial autocorrelation reveal that patterns observed at the local level by way of the Geary's C conform to the Moran's I, which indicates that the clustered pattern of attribute values is likely due to random chance.

The Moran's I statistic reveals that the clustering of high and low location quotients for fisheries as illustrated in the maps (Figure 8.5 and 8.6) is not due to spatial processes, indicating that other factors specific to individual counties determine the spatial variation in fisheries. For example, fisheries are an important part of the local economy in Plaquemines Parish LA. In neighboring Orleans Parish LA, tourism is the primary source of job creation particularly in the city of New Orleans. The occurrence of hazard events like Katrina and the oil spill is likely to negatively impact fisheries in Plaquemines. These events could also impact New Orleans indirectly as fisheries in neighboring counties are linked to services that support the tourism sector such as, accommodation and food services. Therefore, the impacts of hazard events are not due to shared characteristics in the fisheries sector, but rather to differences in the economic composition of individual counties.

There is also spatial variation in the impact of the oil spill on fisheries as illustrated in Figure 8.5 and 8.6. The number of counties within each range of location quotients has decreased significantly in the time period, 2005 to 2010. For example, seven counties recorded location quotients in the range of 4.00 to 11.00 in 2005, and only five counties recorded similar location quotients in 2010. The decrease in location quotients reflects an overall decline in employment in the fisheries sector due to a combination of factors that included the cumulative

impacts of Hurricane Katrina, the economic recession, and fishery closures in the aftermath of the DWH oil spill (The Urban Conservancy 2012). In the parishes along the coast of Louisiana where fishing is a mainstay of the economy, fisheries were negatively impacted by the spill. For example, these impacts are reflected in the decrease in location quotients in Lafourche Parish from 48 in 2005 to 4.7 in 2010. As for counties located along the southwest coast of Florida, location quotients have not changed significantly, remaining within the range of zero to 5.0 in 2005 and 2010. The economy of these coastal counties is reliant on tourism, so fisheries would not be a significant factor in determining the impact of hazard events.

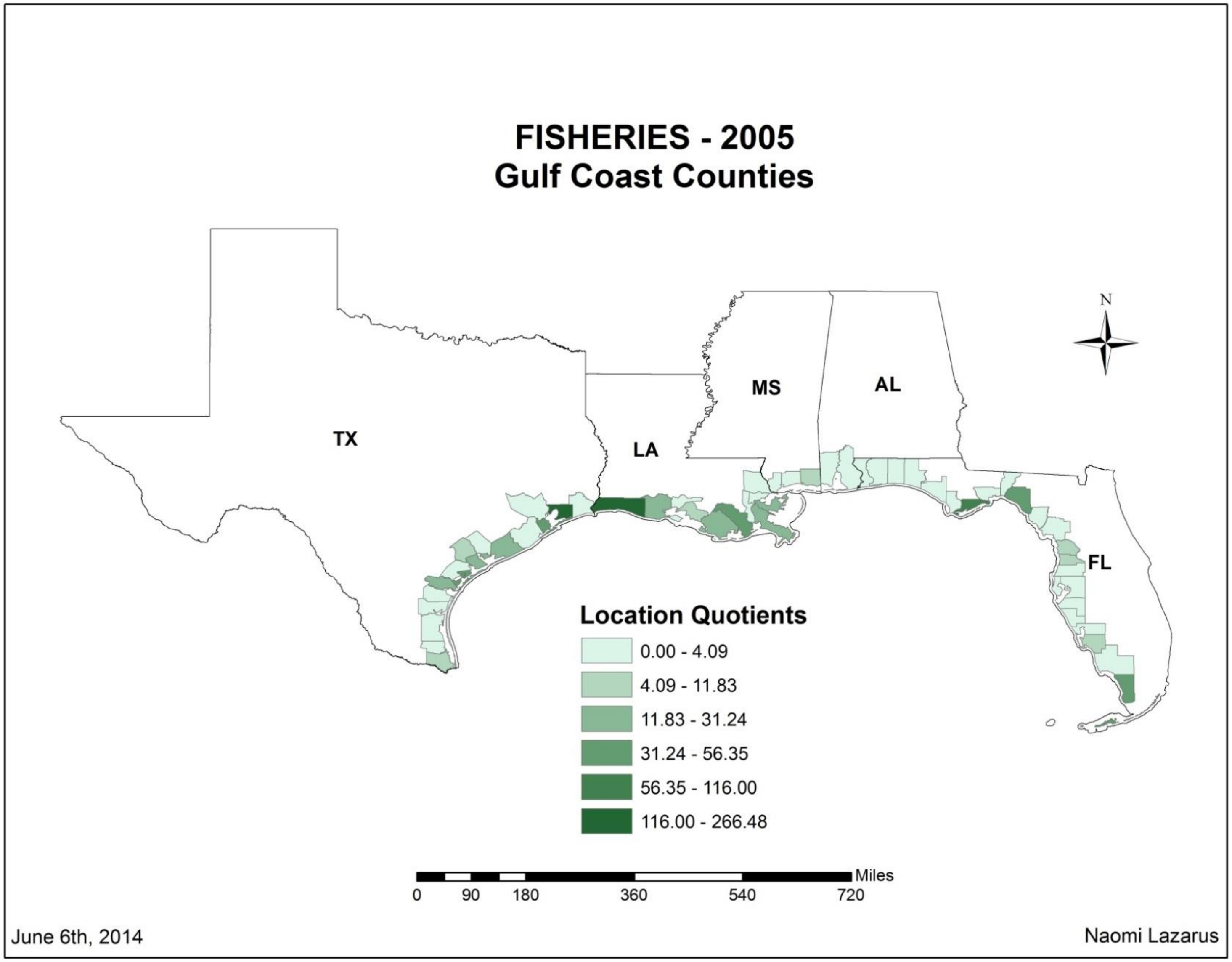

Figure 8.5 – Location Quotients of Fisheries (2005)

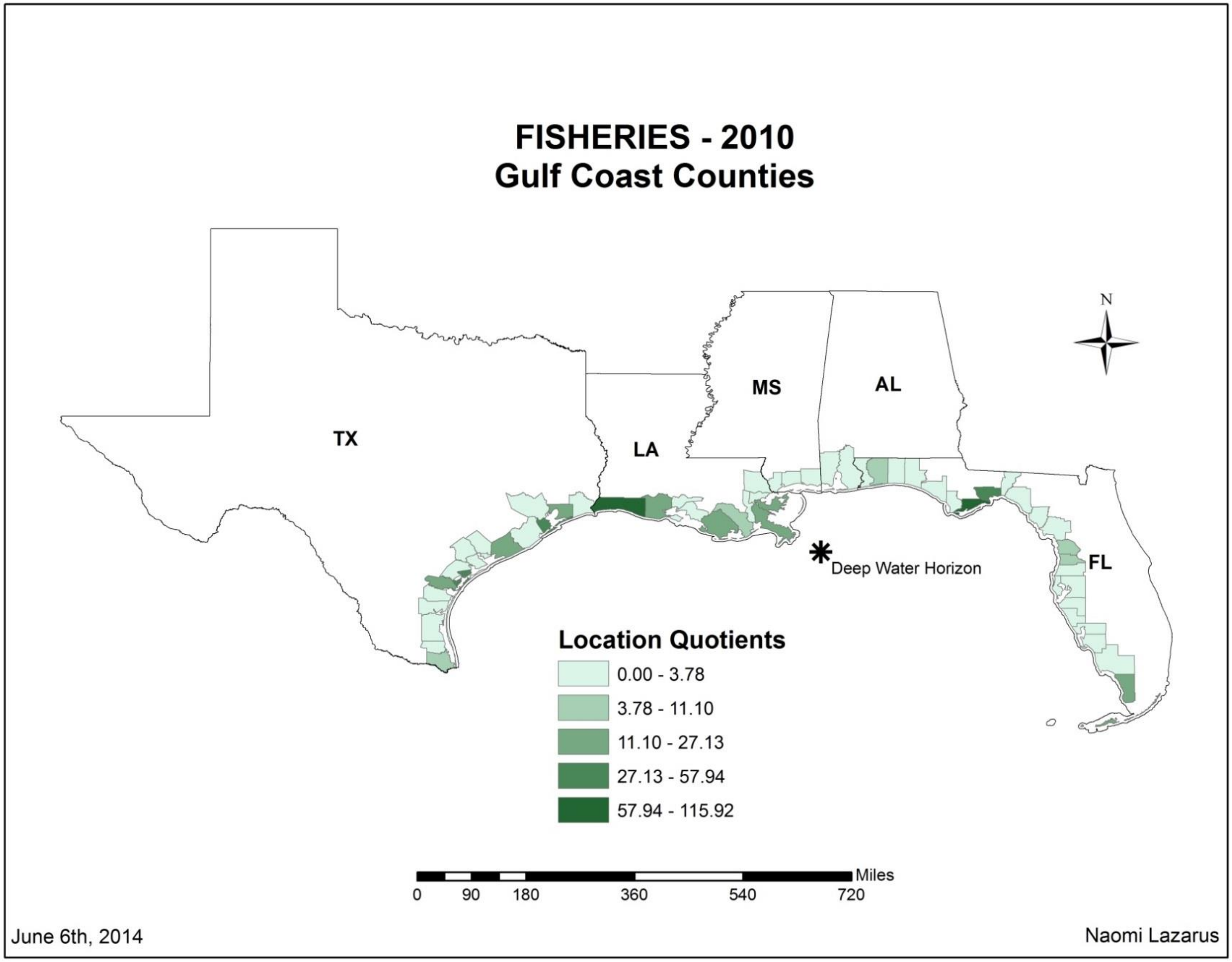

Figure 8.6 – Location Quotients of Fisheries (2010)

8.3.2 Social Assistance

The Moran's I for social assistance in 2010 is 0.108 and is above the expected value of -0.018182, indicating that attribute values are clustered (Table 8.2). However, the test is not significant at $p < .05$. Similarly, the Moran's I for social assistance in 2005 is positive (0.0343) and is not significant. Statistical significance of the Moran's I statistic involves comparing it against the null hypothesis, which states that the spatial processes responsible for the observed pattern of the attribute in question are due to random chance. If the p-value associated with a *positive* Moran's I is not statistically significant, the null hypothesis cannot be rejected. Given that the Moran's I for social assistance is not significant, it indicates that the clustering of attribute values is due to random chance and that spatial processes do not affect changes in social assistance.

The Geary's C statistic for social assistance in 2010 is 0.0614 and the results are not significant at $p < .05$ (Table 8.2). The z-score of 0.104 indicates that there is marginal clustering of high attribute values at the local level due to random chance as reflected in the global Moran's I. The tests of spatial autocorrelation reveal that patterns observed at the local level by way of the Geary's C conform to the Moran's I, which indicates that the clustered pattern of attribute values is likely due to random chance. The Geary's C statistic for social assistance in 2005 is 0.0495 and the results are not significant at $p < .05$. The z-score of -1.153 indicates that there is marginal clustering of low attribute values at the local level. Due to the high degree of variability, services provided by social assistance programs respond to hazard events in different ways. As per the parameter estimates of the interaction terms (Table 8.1), changes in location quotients for social assistance in response to Katrina are associated with a decrease in unemployment rates, and a marginal increase in unemployment rates in the time period of the

DWH oil spill. These trends are illustrated in Figure 8.1 discussed earlier where the unemployment rate in Bay County FL drops in 2005 and increases in 2010.

Figure 8.7 shows the spatial distribution of location quotients in social assistance for the period, 2005. Counties with location quotients greater than 1.00 are clustered in the panhandle and southwest coast of Florida, coastal Alabama, and Louisiana. Several counties experienced a decrease in resources allocated to social assistance in 2010 as illustrated in Figure 8.8. For example, location quotients in Bay County FL, Terrebonne LA, and Vermilion LA were between 1.00 and 1.9 in 2005 and declined to less than 1.00 in 2010.   Additional labor employed to administer social assistance in the form of community, food, and emergency relief services during Hurricane Katrina is reflected in the higher location quotients in 2005. These services are primarily provided by local government and therefore are subjected to budgetary restrictions at the county and state levels. In 2010, funds administered by British Petroleum, a private corporation, in response to the DWH oil spill were primarily targeted towards compensating business owners who had been negatively impacted by the spill and did not contribute to resources allocated to social assistance programs administered by the government. Therefore, location quotients declined or remained relatively stable during this time period.

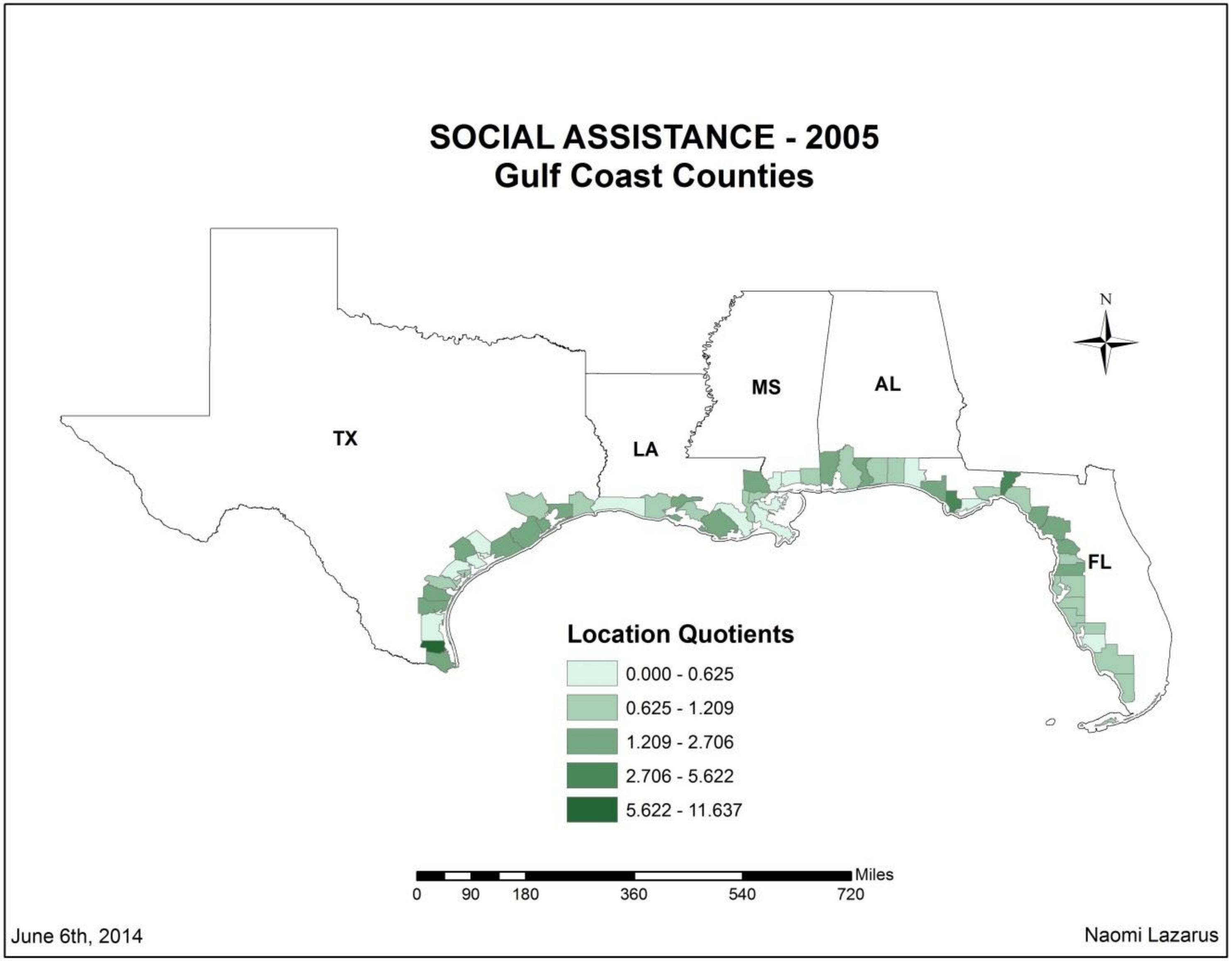

Figure 8.7 – Location Quotients of Social Assistance (2005)

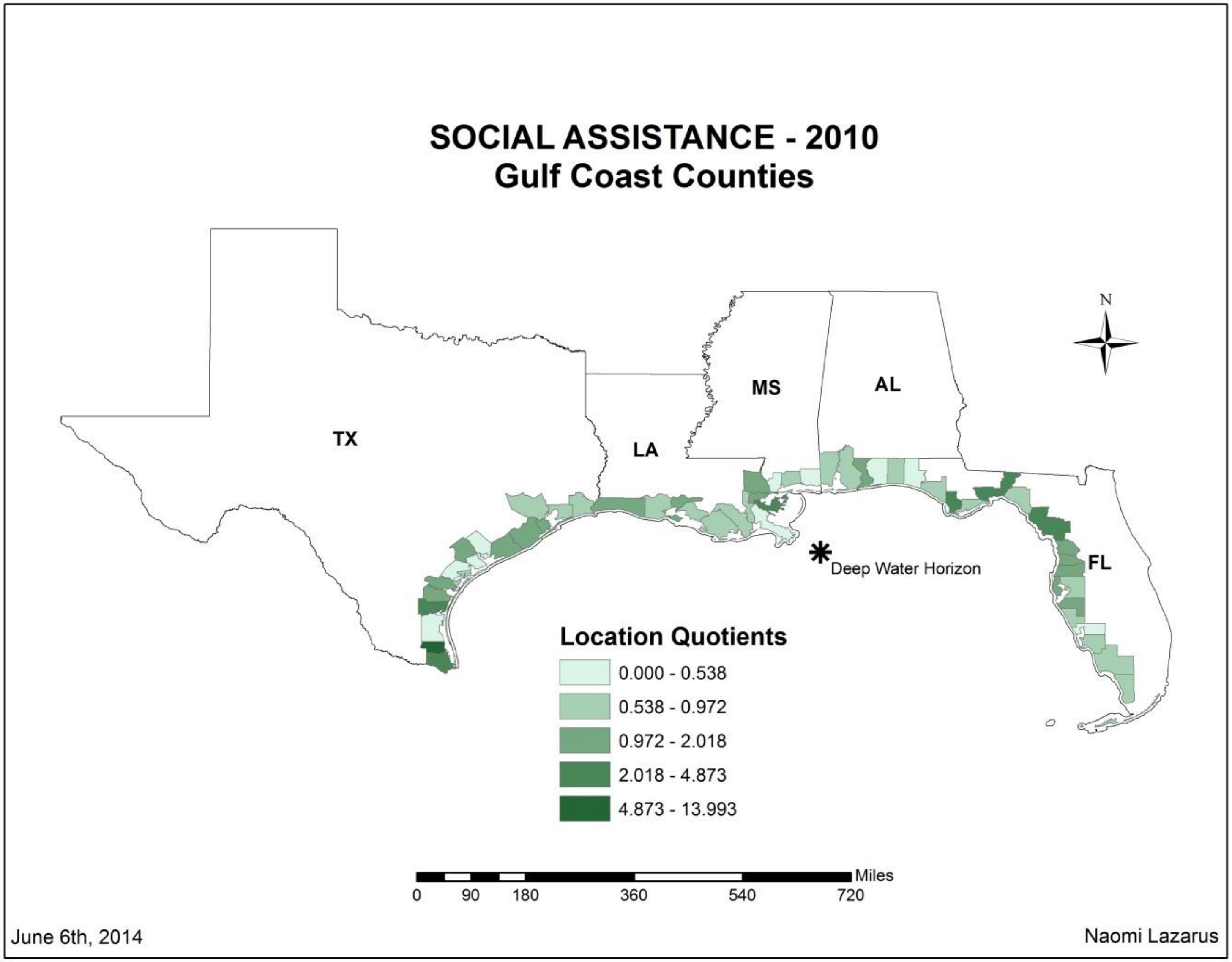

Figure 8.8 – Location Quotients of Social Assistance (2010)

8.3.3 Retail Services

The Moran's I value for the retail sector is 0.0027 in 2005 and 0.0677 in 2010 (Table 8.2). In both time periods, the Moran's I statistic is greater than the expected value of -0.018182, and is not significant at $p < .05$. The results reveal that the clustering of attribute values is not due to spatial processes, and therefore, the null hypothesis cannot be rejected. In this case, the impacts of hazard events are not due to shared characteristics in the retail sector, but rather to differences in the economic composition of individual counties. The Geary's C statistic for retail services in 2010 is 0.0612 and 0.0603 in 2005, which indicates a clustered pattern. The results are not significant at $p < .05$. The z-score of 0.376 in 2010 indicates that there is marginal clustering of high attribute values at the local level due to random chance as reflected in the global Moran's I. The z-score of -0.0583 in 2005 represents marginal clustering of low attribute values at the local level and the value close to zero indicates that the level of clustering is negligible.

Maps showing the spatial distribution of location quotients in retail services in 2005 and 2010 are presented in Figure 8.9 and 8.10, respectively. In both time periods, counties with location quotients greater than one are clustered in the panhandle of Florida, southwestern Florida, and coastal Louisiana. At the county level, location quotients in retail services remained relatively stable across the region. For example, location quotients in Pasco and Hernando counties in southwest Florida ranged from 1.5 to 2.0. In coastal Louisiana, location quotients in Cameron and Iberia counties remained in the range of 0.8 to 1.00. Demand for goods and services in the retail sector was sustained by spending tied to the tourism industry and to some extent by people engaged in recovery and restoration, which minimized the negative impacts of hazard events.

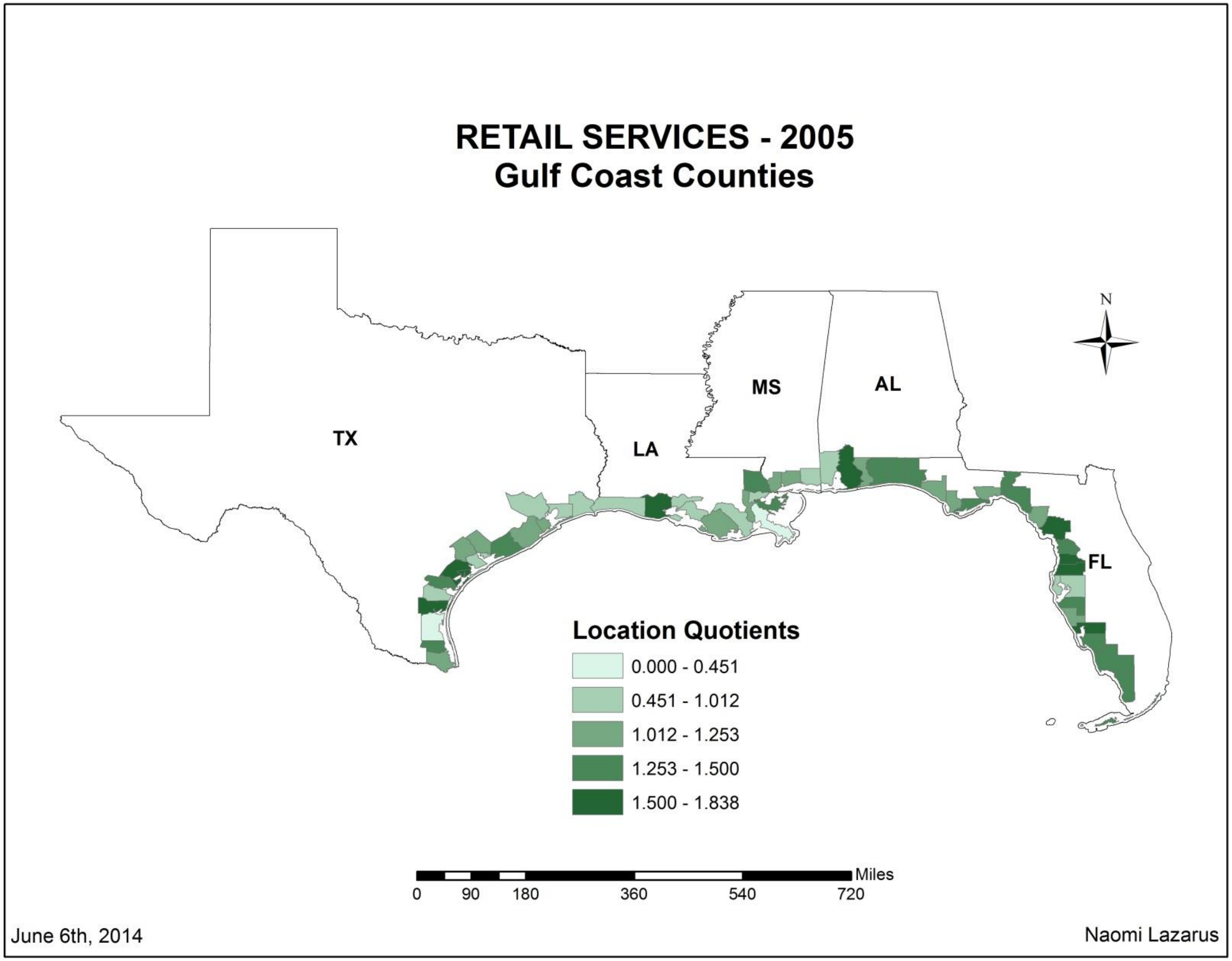

Figure 8.9 – Location Quotients of Retail Services (2005)

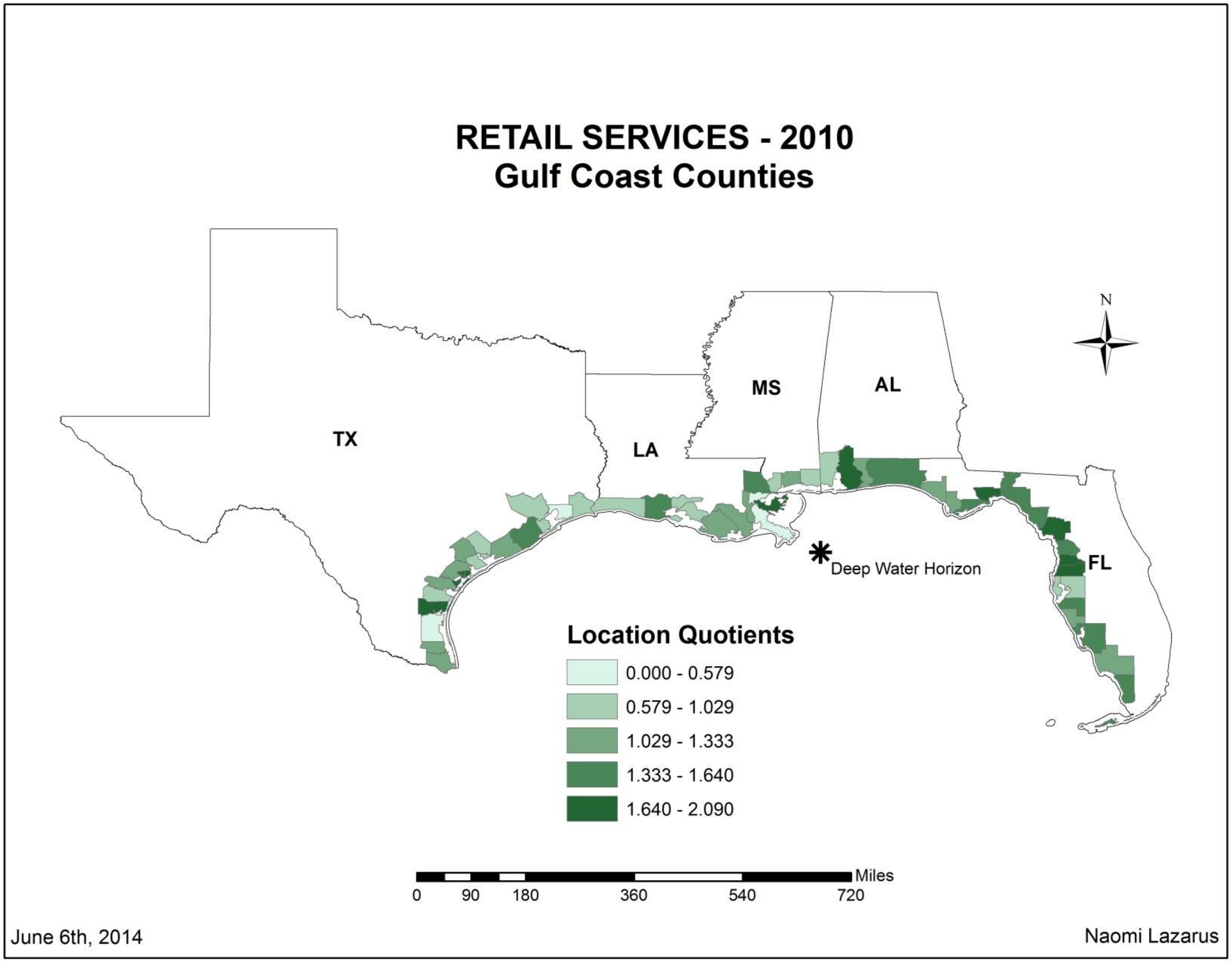

Figure 8.10 – Location Quotients of Retail Services (2010)

The second hypothesis states that services provided by social capital vary across counties in the study area during a hazard event. The spatial distribution of location quotients in significant interaction terms reveals that fisheries, social assistance, and retail services respond in different ways at the county level. Furthermore, the tests of spatial autocorrelation by way of the Moran's I and Geary's C indicate that the clustering of high and low attribute values is not due to spatial processes and that counties in close proximity are likely to respond to hazard events in different ways. As such, the null hypothesis is rejected based on the spatial pattern of location quotients, which highlights that services provided by social capital vary across counties in the study area during a hazard event.

8.4 Spatial Variation in Coping Ability

Coping ability in the re-specified risk equation is represented by the unemployment rate. The fourth hypothesis examines the variation in unemployment rate across the study area to assess whether counties with greater access to social capital experience less fluctuation in the unemployment rate than counties where social capital is constrained. Maps of predicted unemployment rates for 2005 and 2010 are presented in Figure 8.11 and 8.12. Coastal counties in Louisiana, Mississippi, and Texas record high unemployment rates in 2005 compared to counties in Florida. The unemployment rate in these counties ranged from 4.8% to 8.3%. Counties located along the southwest coast of Florida like Charlotte, Sarasota, and Manatee experienced an increase in the unemployment rate from 2.5% to 3.9% in 2005 to 9.3% to 10.9% in 2010.

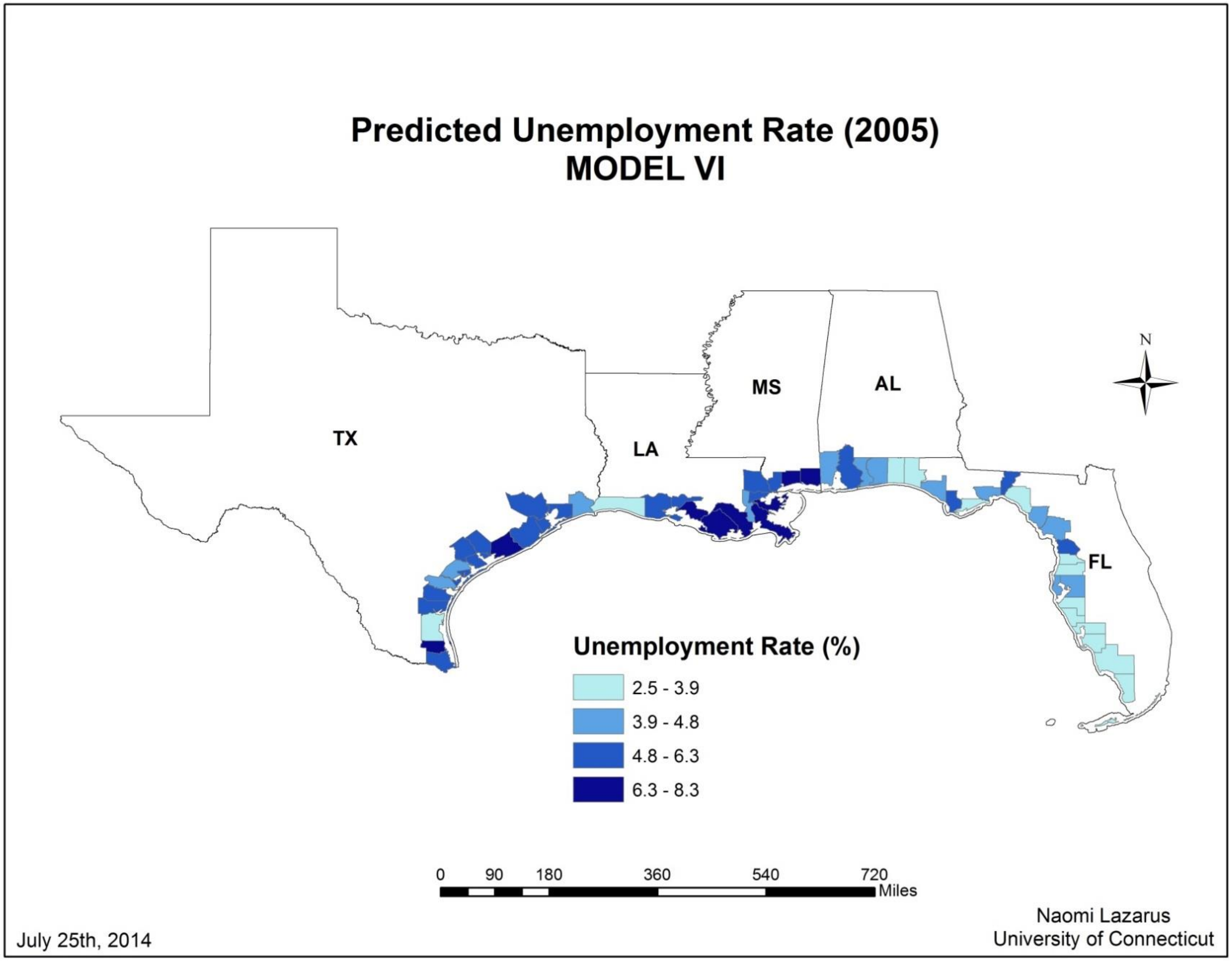

Figure 8.11 – Predicted Unemployment Rate (2005)

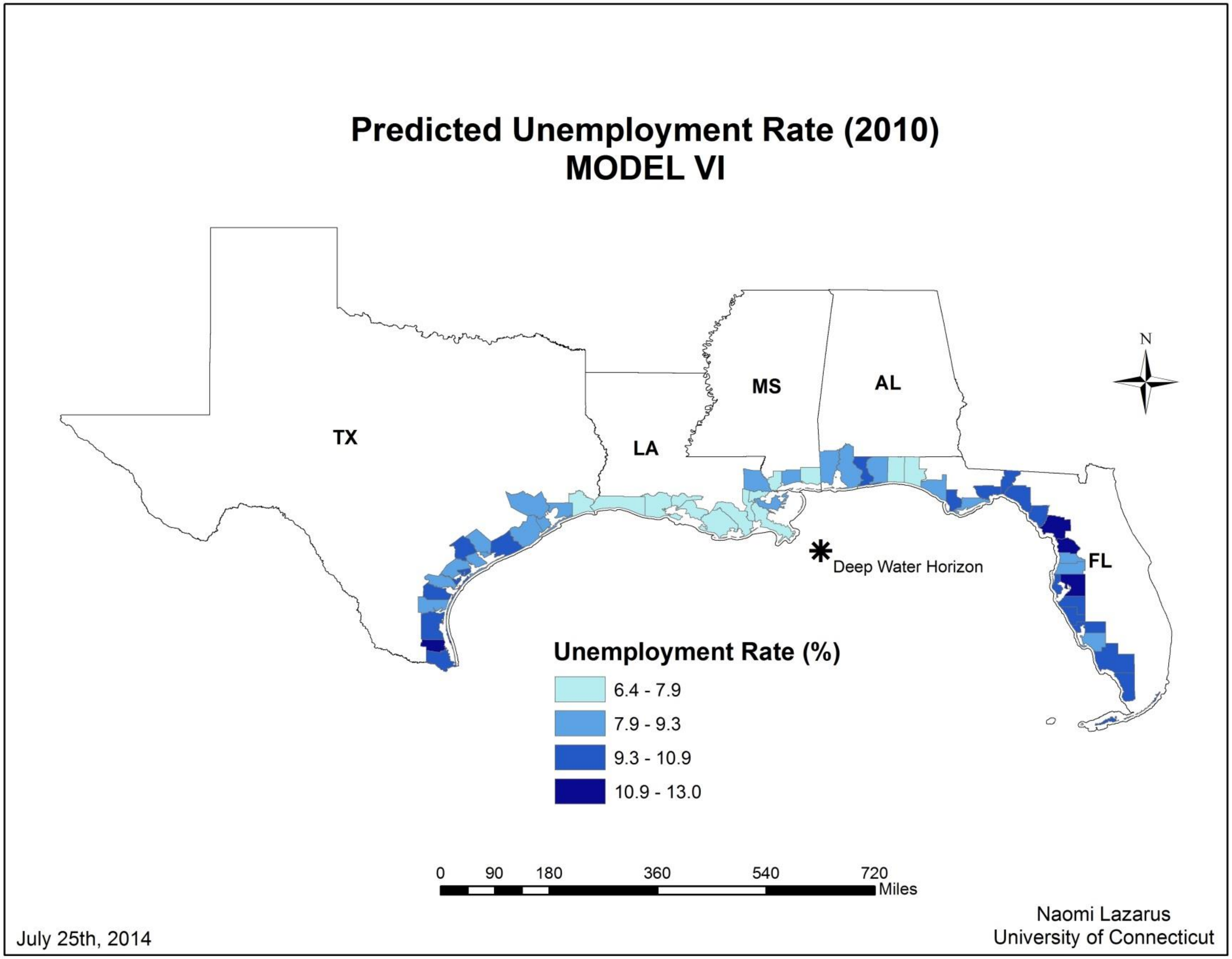

Figure 8.12 – Predicted Unemployment Rate (2010)

The Moran's I statistic for unemployment rates in 2010 is 0.5759 and 0.3601 in 2005 (Table 8.3). Calculated Moran's I values for both time periods are greater than the expected value of -0.018182. The results are significant at $p < .05$. The positive Moran's I value indicates that neighboring spatial units with similar unemployment rates are clustered. These clusters are observed in the panhandle region and southwest coast of Florida, coastal Louisiana, and Alabama. The significance of the statistic indicates that underlying spatial processes are responsible for neighboring counties to display similar attributes, and therefore, the null hypothesis is rejected. The clustering of high and low values is evidence that coastal counties in close proximity are responding to the widespread impact of Hurricane Katrina and the DWH oil spill in similar ways despite differences in the distribution of social capital.

Table 8.3 – Tests of Spatial Autocorrelation (Moran's I and Geary's C): Predicted Unemployment Rate

Variable	**2010**			**2005**		
	Moran's I	Sig. p<.05	z score	Moran's I	Sig. p<.05	z score
UNEMP_RATE	0.5759	0.000	5.948	0.3601	0.000	3.792
Variable	**2010**			**2005**		
	Geary's C	Sig. p<.05	z score	Geary's C	Sig. p<.05	z score
UNEMP_RATE	0.0596	0.397	-0.846	0.0641	0.0313	2.153

The Geary's C statistic for unemployment rate in 2010 is 0.0596, which indicates a clustered pattern. The results are not significant at $p < .05$. The z-score of -0.846 indicates that there is marginal clustering of low attribute values at the local level due to random chance as reflected in the global Moran's I. The Geary's C statistic for unemployment rate in 2005 is 0.0641, which indicates a clustered pattern. The results are significant at $p < .05$. The z-score of

2.153 represents significant clustering of high attribute values at the local level and the null hypothesis of complete randomization is rejected.

Predicted unemployment rates and location quotients in fisheries and social assistance in neighboring Orleans and Jefferson counties in coastal Louisiana are presented in Figure 8.13 and 8.14, respectively. The blue trend line showing unemployment rates follows a similar trajectory in both counties with unemployment remaining high in 2005 and 2010. On the other hand, there is considerable variation in fisheries and social assistance between the two counties as displayed in the green and red trend lines. There is greater fluctuation in location quotients related to social assistance in Orleans (Figure 8.13) than in Jefferson (8.14) particularly after 2005. A reversed trend is displayed for fisheries. Here, Jefferson experiences greater fluctuation in location quotients than Orleans. The charts emphasize the results of the Moran's I test that counties in close proximity respond to hazard events in similar ways (trend in unemployment) while at the same time they have different coping strategies as represented by changes in fisheries and social assistance.

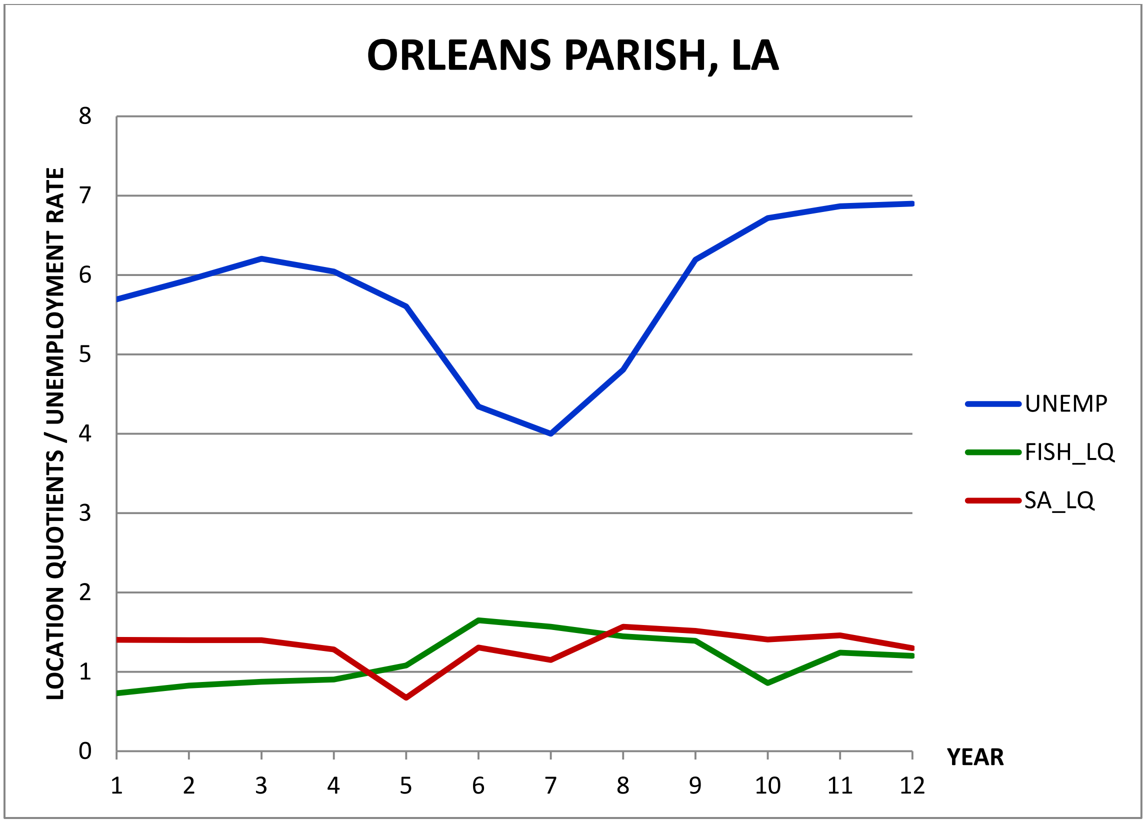

Figure 8.13 – Model VI Predicted Unemployment Rate and Location Quotients in Fisheries and Social Assistance – Orleans Parish, Louisiana

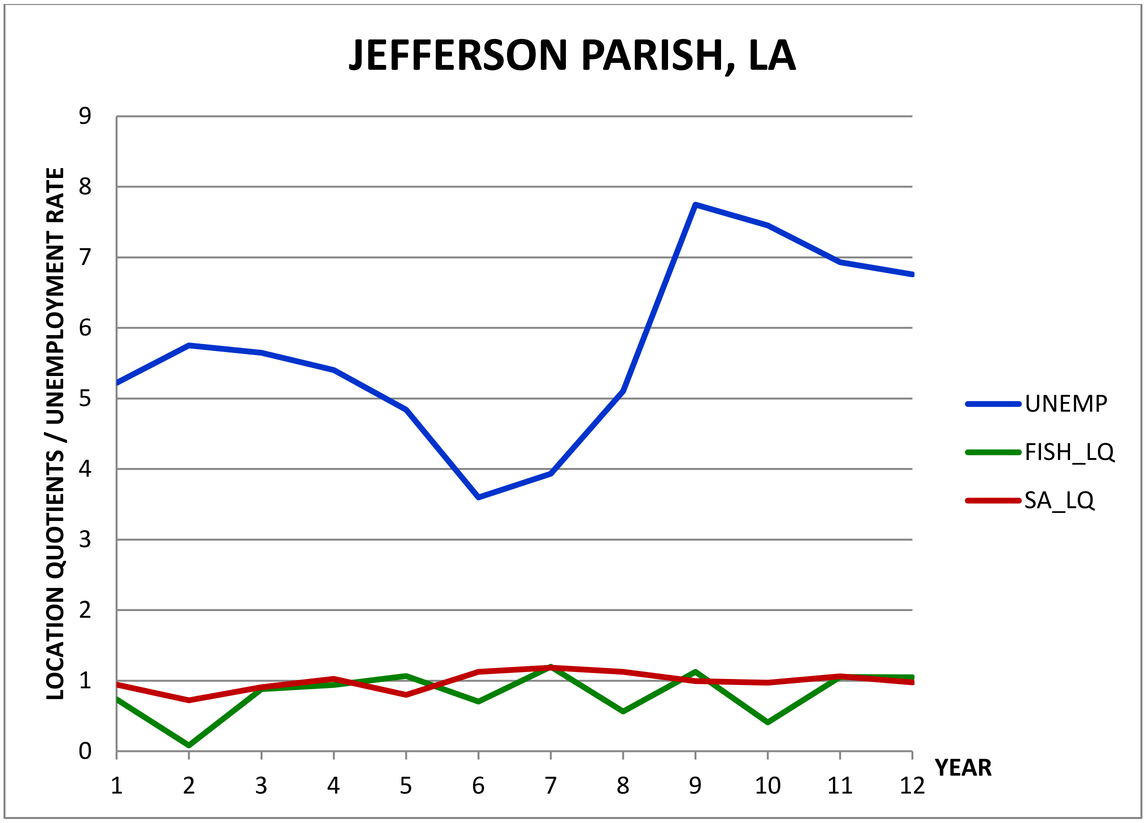

Figure 8.14 – Model VI Predicted Unemployment Rate and Location Quotients in Fisheries and Social Assistance – Jefferson Parish, Louisiana

The fourth hypothesis states that coping ability varies across the study area. The tests of spatial autocorrelation indicate that the clustering of high and low attribute values varies over time. In 2010, the period subject to the DWH oil spill, the Moran's I and Geary's C indicate that the clustering of high and low attribute values is not due to spatial processes and that counties in close proximity are likely to respond to hazard events in different ways. Therefore, the null hypothesis, which states that coping ability is relatively uniform across the study area, is rejected. When evaluating the distribution of unemployment rates in 2005, during the time of Hurricane Katrina, the Moran's I and Geary's C indicate that spatial processes are responsible for the clustering of high and low attribute values. In this case, the null hypothesis cannot be

rejected conclusively. Therefore, the fourth hypothesis is conditionally accepted on the basis that spatial variation in coping ability is determined by the type of hazard event.

8.5 Assessment of Vulnerability

The pseudo-equation, $R = H \times V$, proposed by Wisner et al. (2004) attempts to make the link between the hazard event, vulnerability, and risk. The HRLM is based on re-specification of the risk equation of Wisner et al. (2004) as follows:

$$R = f\ (H, E, C)$$

where the risk factor, *R*, is a function of the hazard *(H)*, exposure *(E)*, and coping ability *(C)*. Hypothesis 5 considers how these three factors are inter-related in counties across the study area. The distance measures generated by the threshold formula indicate each county's position in relation to the threshold and to neighboring counties. The components of the risk equation are subject to the timing and impact of specific events. Given that the research is concerned with the impacts of the Deep Water Horizon oil spill, the hazard *(H)* component is represented by each county's *distance from the spill* and is relevant to 2010 (year the spill occurred) and to subsequent time periods. When computing the attribute values for the hazard component, proximity to the oil spill is considered. *Distance from the spill* (in miles) is the variable that represents the hazard component of the risk equation, and is distinct from the *distance measures* that are computed using the threshold formula. Exposure *(E)* and coping ability *(C)* are sub-components of vulnerability (Ratick and Osleeb 2011) that underscore the social dimension of hazard events. Exposure is represented by population density and coping ability is represented

by the unemployment rate. The location of exposed populations and their coping ability will determine the risk of being negatively impacted by environmental disasters.

8.5.1 Assessment of Coping Ability

In 2005, more than half of all counties in the Gulf reported moderate levels of coping in terms of unemployment rate. Distance measures from the oil spill for these counties fall within the range of -0.242 to 0.301 and are displayed in green on the map (Figure 8.15). Six counties record high coping levels in 2005 and are indicated in purple on the map. These include several counties in southwest Florida, Walton and Okaloosa in the Florida panhandle, and Kenedy in Texas. Distance measures associated with the unemployment rate in these counties ranged from 0.320 to 0.517, which are well above the upper bound threshold of 0.301. Several counties in coastal Louisiana like Plaquemines, St. Bernard, Lafourche and Terrebonne are displayed in blue indicating low coping levels. The unemployment rate in these counties was above 7.0% in 2005, which was higher than the national average of 5.1%. An analysis of location quotients linked to social capital reveals that while the counties have high scores on retail and fisheries, location quotients for social assistance are less than 1.00. Therefore, in the absence of adequate social safety nets to address the needs of the population during a hazard event like Hurricane Katrina, these counties experienced low coping levels.

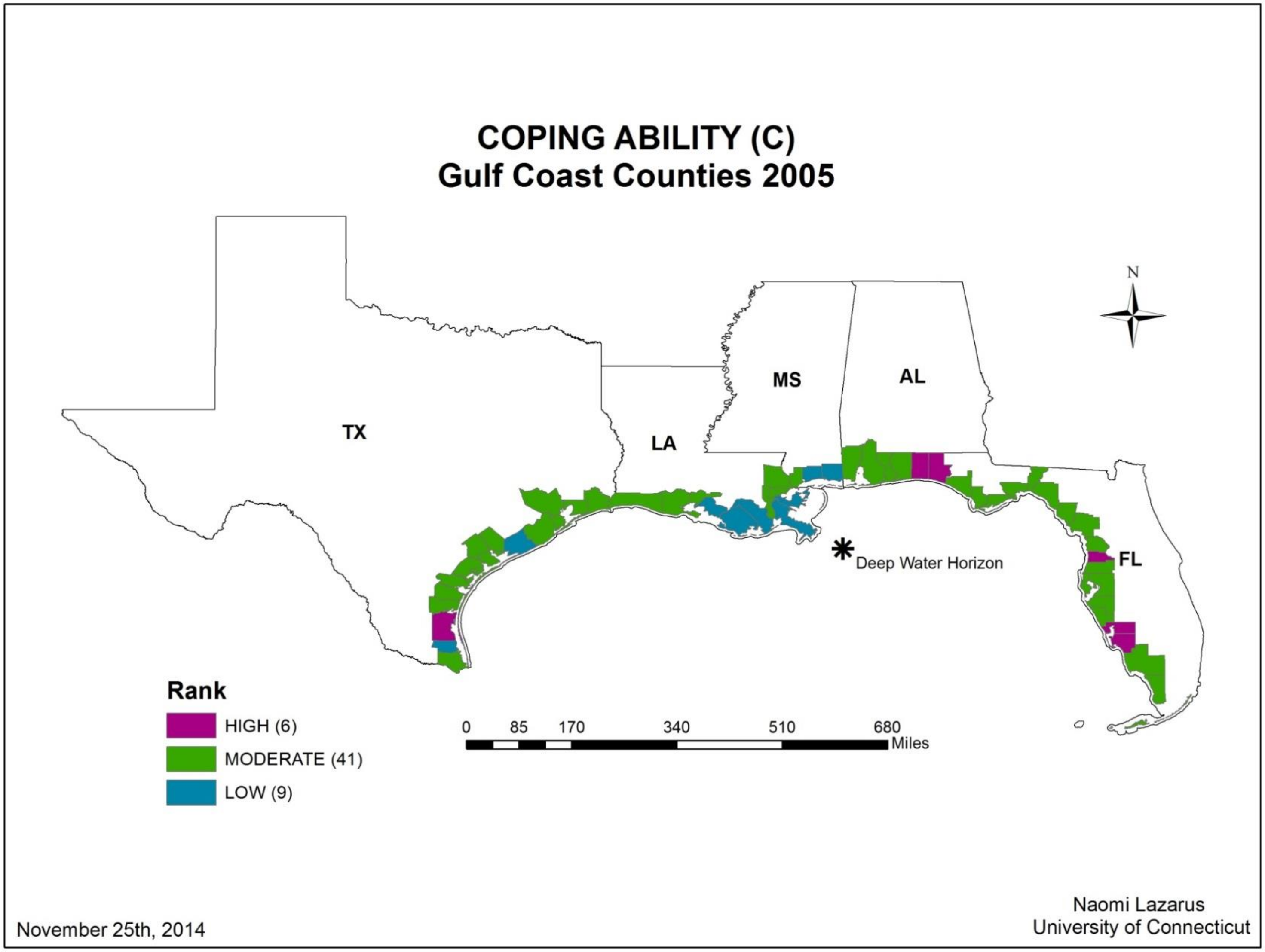

Figure 8.15 – Distance Measures for Unemployment Rate representing Coping Ability (2005)

The number of counties recording low coping levels has increased from nine in 2005 to twelve in 2010, the year of the DWH oil spill, as indicated in blue on the map (Figure 8.16). Counties in coastal Louisiana registered high coping levels despite being in close proximity to the spill. These counties were prioritized in the allocation of compensation by BP and these payments assisted small businesses to regroup, thereby reducing unemployment levels. It has been reported that business owners in Plaquemines Parish that were significantly impacted by Hurricane Katrina used oil spill payments to rebuild their operations (The Urban Conservancy 2012). Several counties in southwest Florida and the panhandle region have transitioned from high coping levels in 2005 to low or moderate coping levels in 2010. As reported by residents in Bay County FL, these changes are partly due to the real estate industry that experienced a short-lived surge in 2005 and then declined due to the onset of the recession in 2007. By 2008 the decline in real estate had dealt a heavy blow on the local economy of coastal counties in the state.

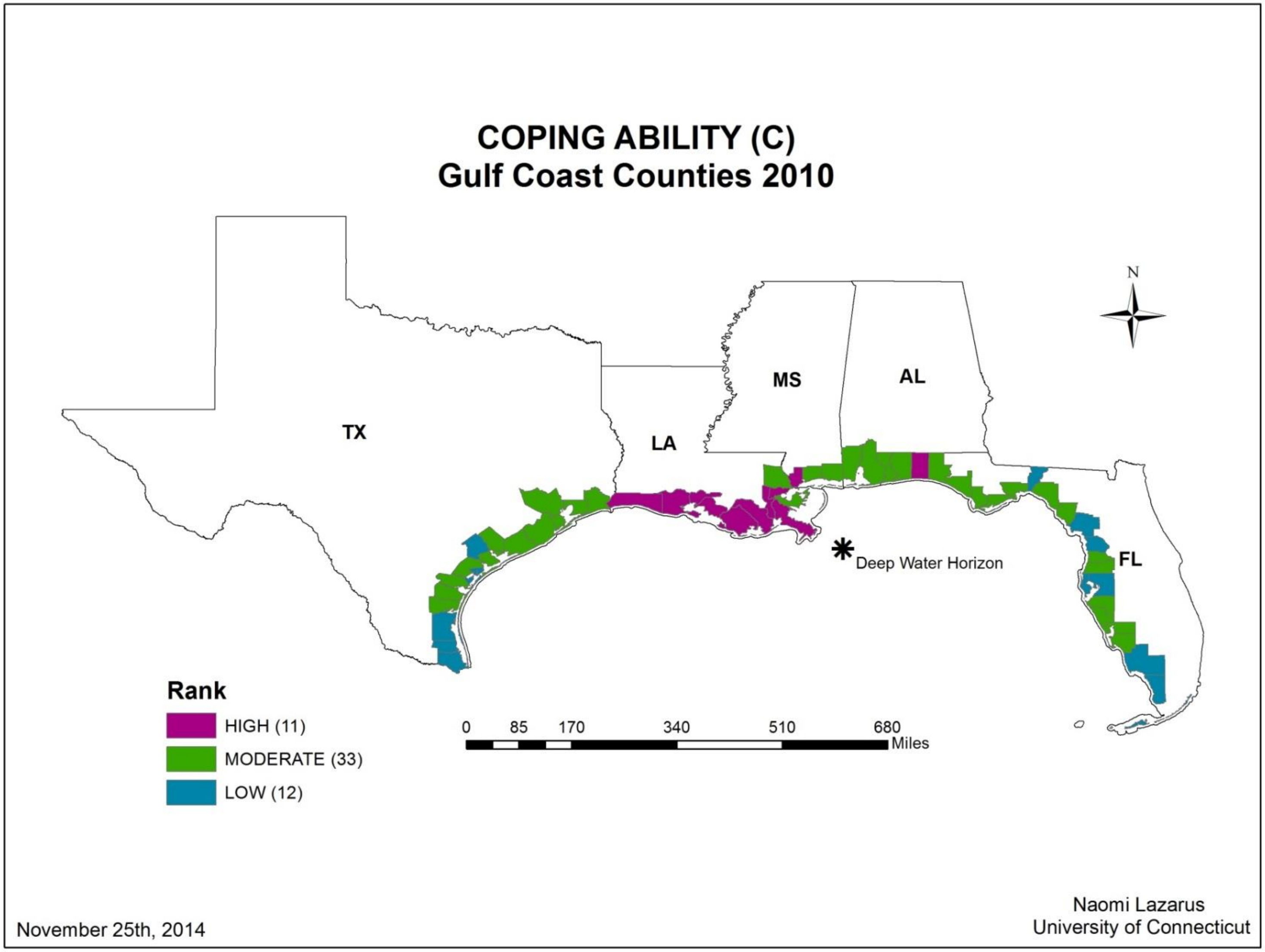

Figure 8.16 – Distance Measures for Unemployment Rate representing Coping Ability (2010)

The assessment of coping ability reveals that the impact of social capital on unemployment levels varies across counties in the Gulf. These inter-relationships position counties at different points along a coping continuum and are reflected in distance measures that vary across time and geographical space. Coping ability is also affected by broader macroeconomic processes linked to economic downturns, changes in the business cycle, and the cumulative effects of hazard events that play out over time. The analysis reaffirms that community resilience is a *process* that is subject to changes in the environment (Cutter et al. 2008).

8.5.2 Assessment of Exposure

The vulnerability component of the risk equation is made up of coping ability and exposure. Wisner et al. (2004) point out that vulnerability plays out at the intersection between human populations and hazard events. This section carries out an assessment of exposure by analyzing spatial and temporal trends in population density. The population of the United States grew by 9.7 percent in the period 2000 to 2010. Regional patterns indicate that the South region of the US, which includes the study area, experienced the highest growth rate of 14.3 percent (U. S. Census Bureau 2011). Typically, coastal regions attract large numbers of people and are densely populated as they possess natural resources that produce environmental and cultural amenities that are conducive to trade and tourism (NOAA 2013). The average coastal population density in 2008 was 155 per square mile, which is greater than the national average of 87 (USDOC 2010; U. S. Census Bureau 2011). The coastal population density is used as the threshold to compute distance measures for exposure.

As illustrated in Figure 8.17 and 8.18, counties that overlap urbanized areas rank high on the distance measure scale. Bay, Hillsborough, and Pasco counties in Florida and Mobile AL are highly exposed as they are home to densely populated areas surrounding the metropolitan areas of Panama City, Tampa, and Mobile, respectively. The major metropolitan areas of Houston, Corpus Christi, and Brownsville position Harris, Nueces, and Cameron counties in Texas high on the exposure scale. These counties record distance measures greater than 0.100 and 0.134, the cut-off points for high exposure levels in 2005 and 2010, respectively.

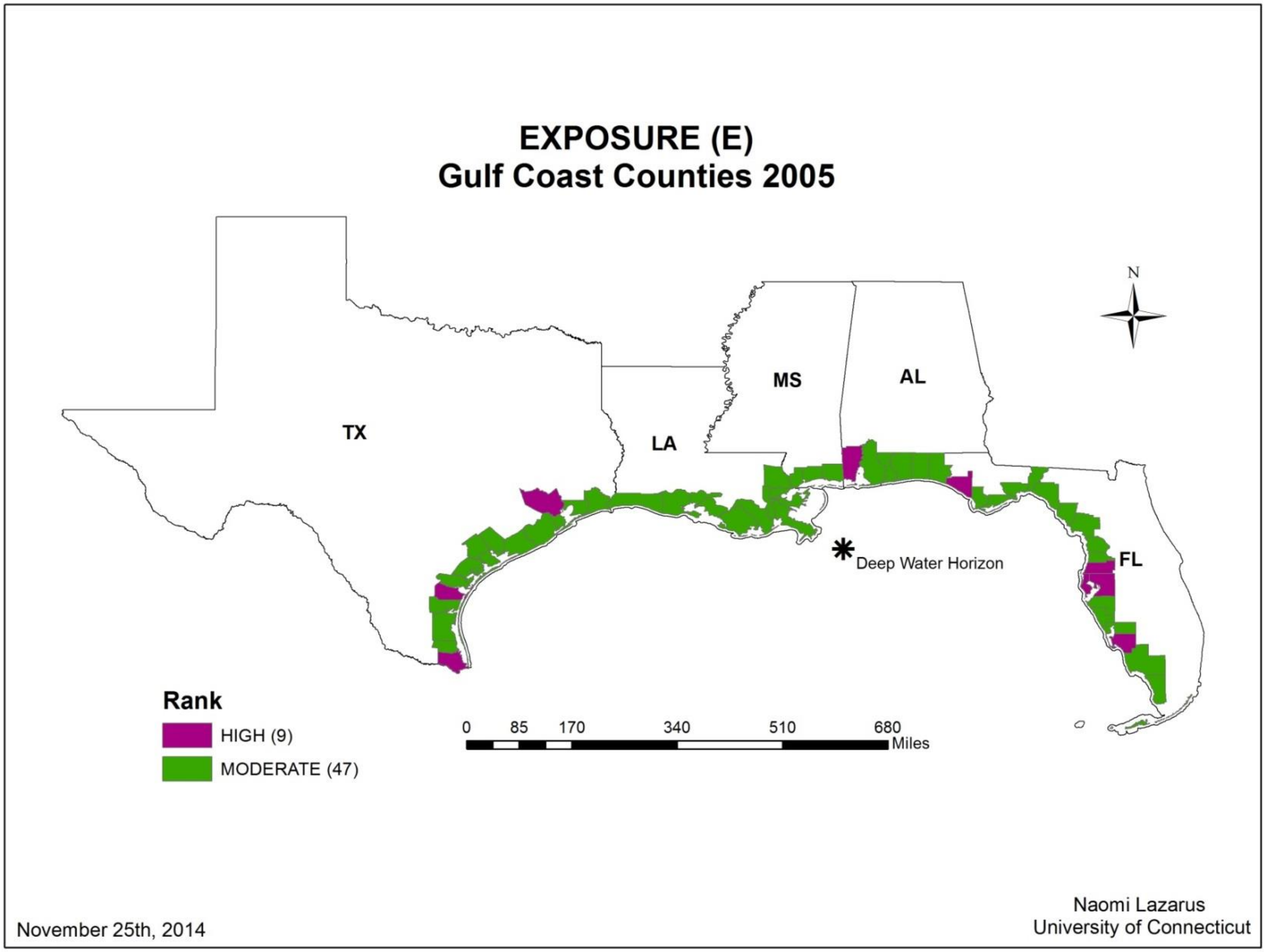

Figure 8.17 – Distance Measures for Population Density representing Exposure (2005)

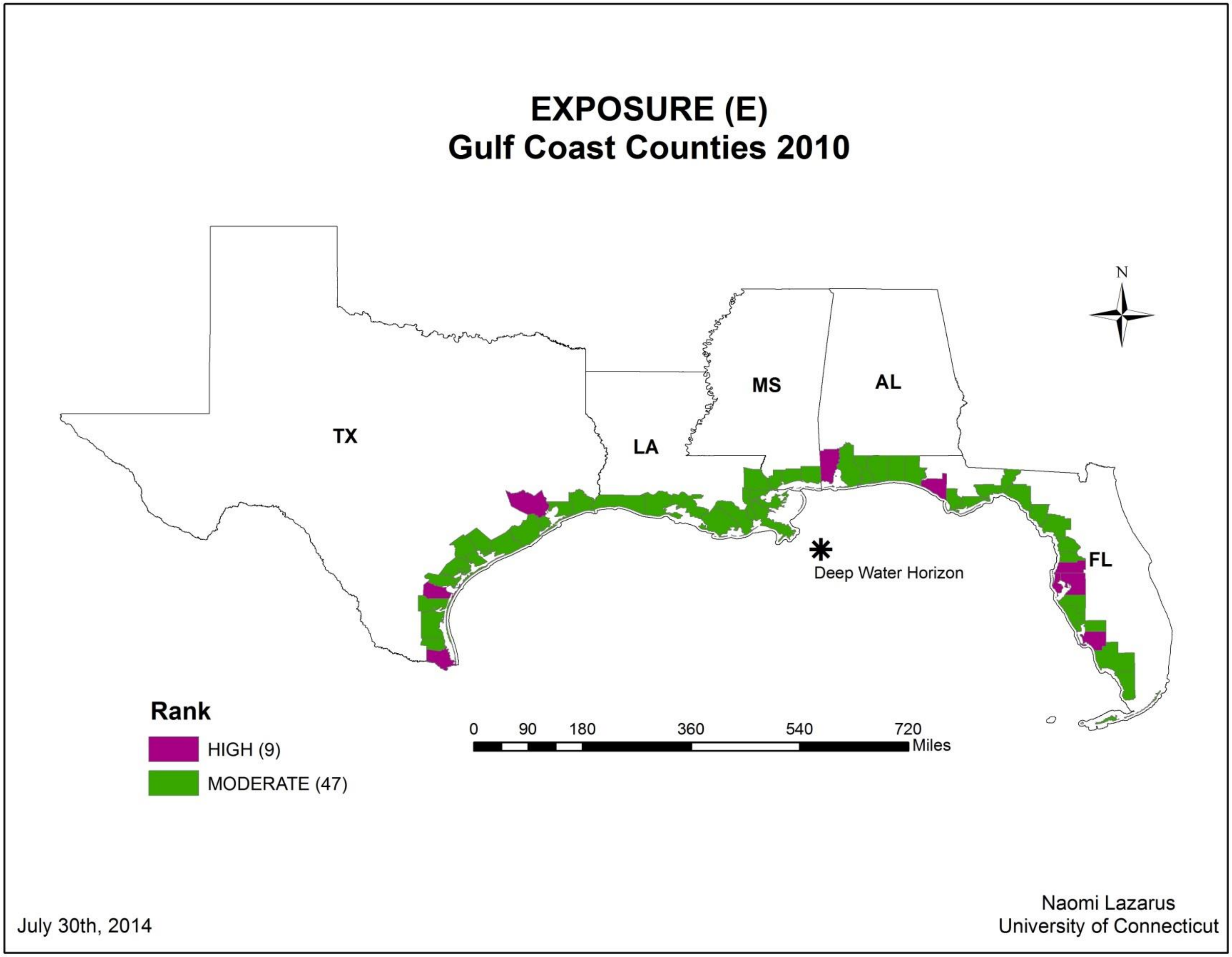

Figure 8.18 – Distance Measures for Population Density representing Exposure (2010)

Counties that experienced changes in distance measures from 2005 to 2010 are located in the panhandle of Florida, Mississippi and Louisiana (Figure 8.17 and 8.18). Santa Rosa FL experienced a marginal increase in population density as indicated in the change in distance measures from - 0.848 to -0.844. The distance measure for exposure in Orleans Parish LA dropped significantly from - 0.162 in 2005 to -0.387 in 2010. These changes are linked to the cumulative impacts of Hurricane Katrina and the oil spill that occurred within this time period.

8.5.3 Composite Measure of Vulnerability

The re-specified risk equation recognizes coping ability and exposure as determinants of vulnerability. Analyzing the spatial pattern of vulnerability across counties in the Gulf is necessary to establish which areas are at greater risk of being negatively impacted by hazard events. A spatial and temporal assessment of vulnerability considers the intersection of exposure and coping ability. The weighted average of attributes contributing to a composite measure of vulnerability is calculated using the formula proposed by Ratick and Osleeb (2011):

$$I_j = \sum_{i \in A} W_i M_{ij} \quad \forall \quad j \in J$$

where, I_j is the composite weighted average for the vulnerability index for spatial unit j; W_i, is the weight associated with attribute i; and M_{ij} is the attribute value i applicable to spatial unit j. A is the total number of attributes that contribute to risk and J is the set of spatial units in the study area. Since a uniform weighting scheme is not established to measure vulnerability, equal weights are applied to exposure and coping ability.

The standard deviation method is used to classify composite vulnerability index measures as *high*, *moderate*, and *low*. One standard deviation above and below the median is the cut-off

point for high and low values. For example, the lower-bound threshold associated with the composite measure of vulnerability in 2005 is -0.816, which is derived from subtracting the standard deviation of 0.474 from the median, -0.342. The median and standard deviation are added to obtain the upper-bound threshold of 0.132. In this case, distance measures below -0.816 are classified as *low*, and those above 0.132 are classified as *high*. Values that fall within the lower and upper bound thresholds are classified as *moderate*.

Vulnerability maps are constructed showing the intersection of exposure and coping ability for 2005 (Figure 8.19), 2007 (Figure 8.20), and 2010 (Figure 8.21). Analyzing the spatial pattern of vulnerability over time monitors county-level fluctuations in the level of vulnerability and sets the stage to assess the impacts of the Deep Water Horizon oil spill.

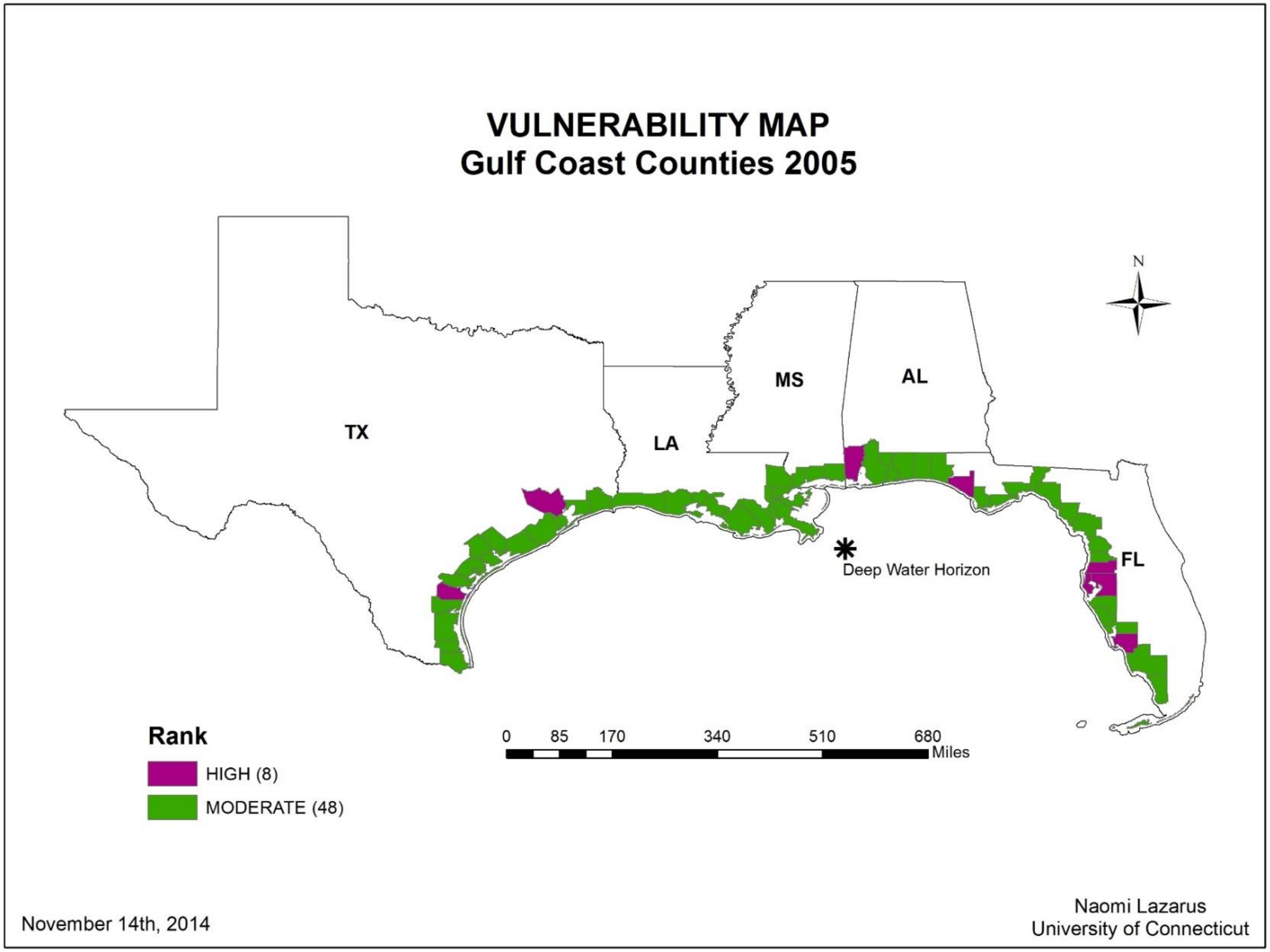

Figure 8.19 – Vulnerability Map showing the intersection of Exposure and Coping Ability Levels (2005)

In 2005, counties that were highly vulnerable are located along the southwest coast of Florida and in coastal Alabama and Texas. High vulnerability levels in these counties are largely due to population densities that rank them high on exposure. For example, population densities in Hillsborough, FL and Mobile, AL are 1,896 and 670, respectively, which are well above the threshold of 155. Furthermore, these counties are only moderately able to cope indicating that resources provided by social capital are inadequate to sustain the livelihoods of people during an environmental disaster. Moderate levels of vulnerability are observed in forty eight counties located across the panhandle region of Florida, coastal Louisiana, Mississippi and Texas. Moderate coping and exposure levels make these counties less vulnerable to hazard events than counties with very high population densities as observed in Mobile AL and Hillsborough FL.

Figure 8.20 is a map showing vulnerability levels in Gulf Coast counties in 2007. Counties in southwest Florida like Hillsborough, Pinellas, and Lee experienced a decrease in vulnerability from 2005 to 2007 and are classified as moderate in 2007. High vulnerability levels were recorded in Kleberg, San Patricio, Refugio, and Willacy counties in coastal Texas in 2007, whereas in 2005 these counties were in the moderate category. Baldwin County, AL that recorded a moderate vulnerability level in 2005 is classified as low on the vulnerability ranking in 2007 due to an increase in the county's position on the coping ability continuum from -0.040 to 0.116. Terrebonne Parish in Louisiana and Santa Rosa County in Florida experienced an increase in vulnerability levels in the two year time period from moderate to high. These changes are due in part to a decline in coping levels (increasing unemployment) coupled with moderate population densities that increase overall vulnerability in these counties.

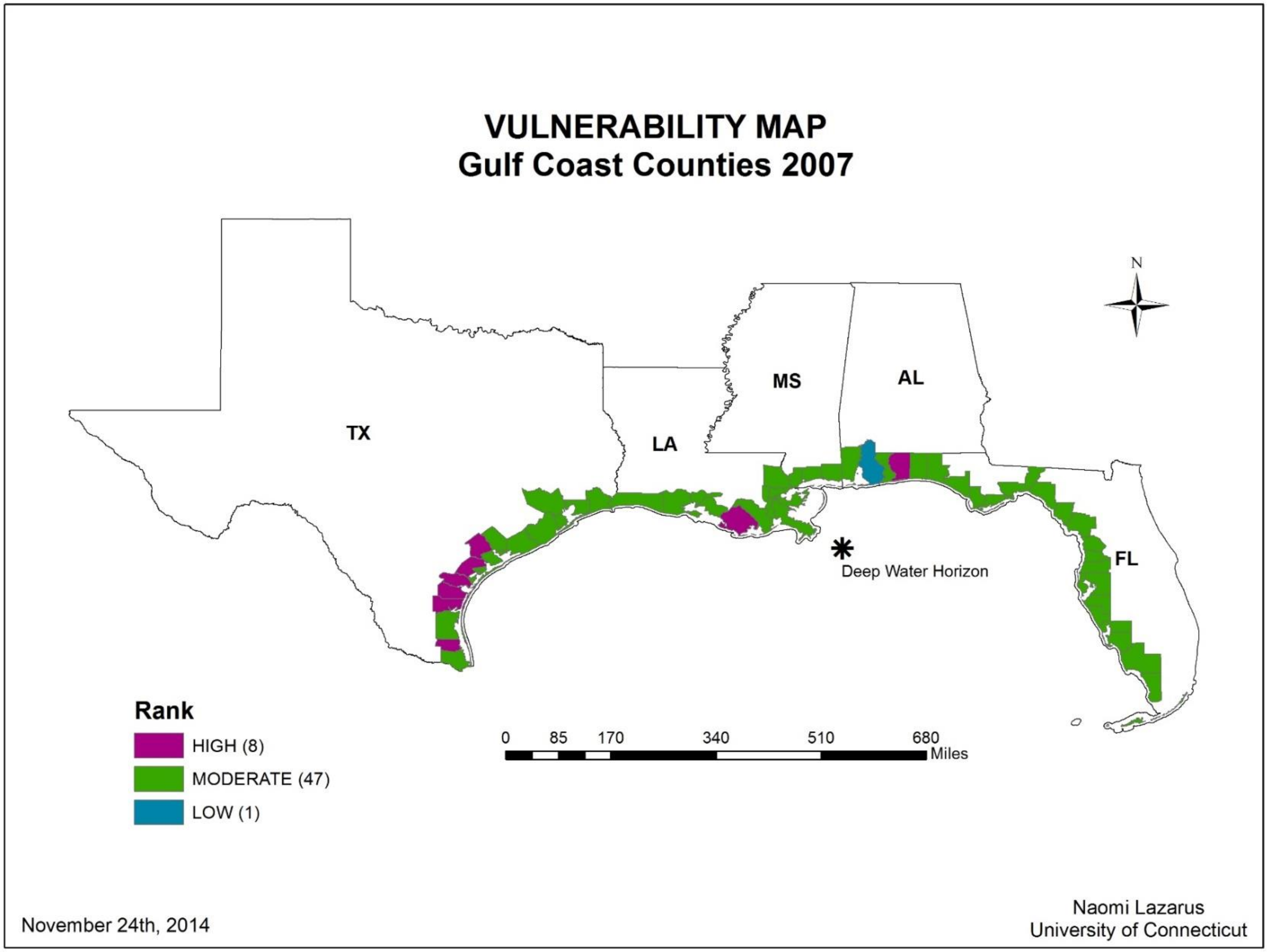

Figure 8.20 – Vulnerability Map showing the intersection of Exposure and Coping Ability Levels (2007)

Figure 8.21 presents vulnerability levels across the Gulf in 2010. Several counties in southwest Florida, Mobile AL, and Nueces and Cameron in Texas maintain high vunerability levels from 2005 to 2010. These trends are due to high population densities that increase exposure to hazard events. Kleberg, San Patricio, Refugio, and Willacy counties in coastal Texas that recorded high vulnerability in 2007 (Figure 8.20) have transitioned to the moderate category due in part to marginal improvements in coping ability.

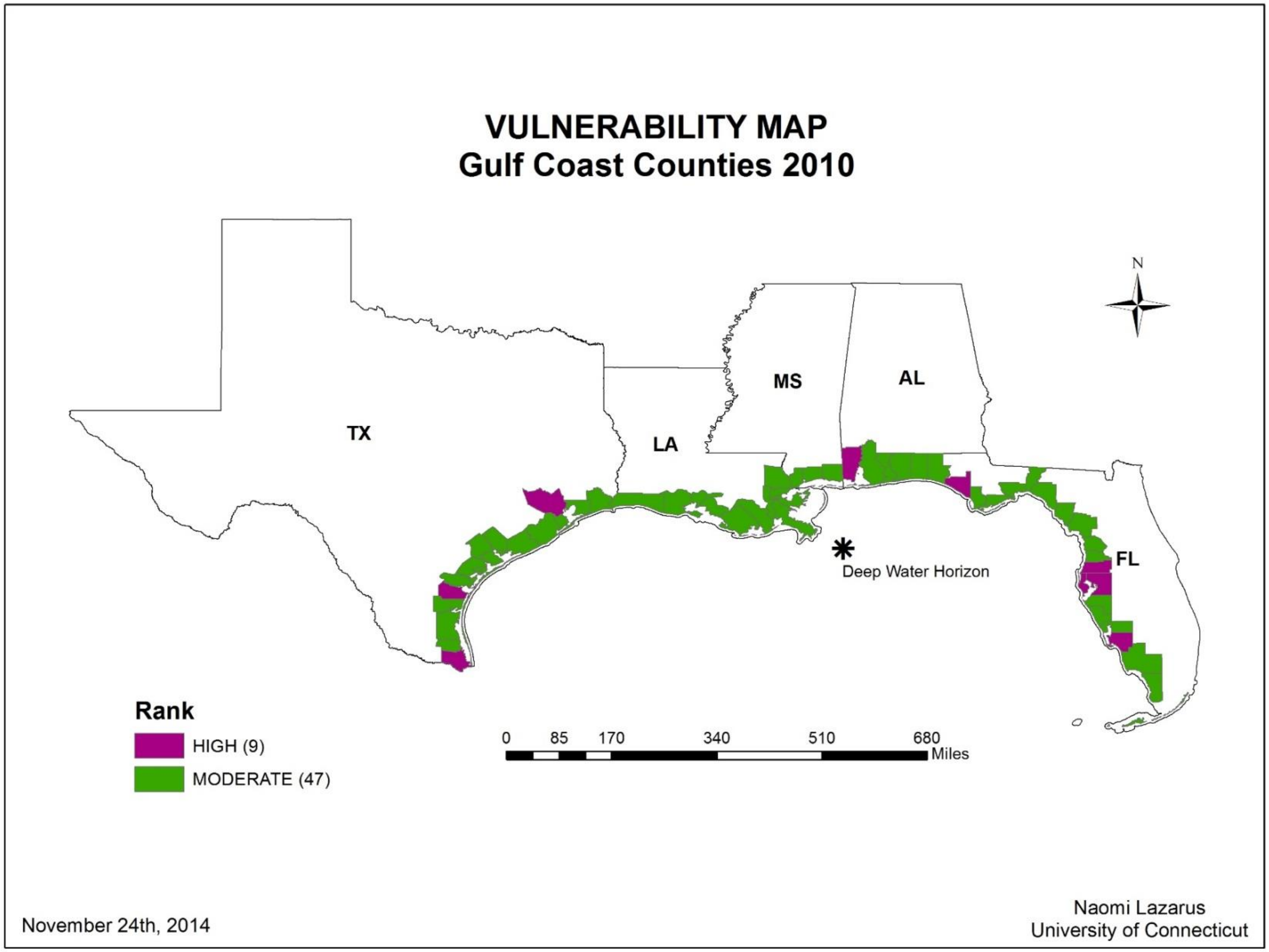

Figure 8.21 – Vulnerability Map showing the intersection of Exposure and Coping Ability Levels (2010)

Vulnerability decreased marginally in Jefferson and Lafourche in coastal Louisiana as a result of a net decrease in population density and moderate to high coping levels as illustrated in Figure 8.22 and Figure 8.23. As illustrated in the trajectory of the blue line, distance measures associated with coping in the two counties were lower than the upper-bound threshold of 0.244 in 2007 and greater in 2010. Both counties experienced increases in coping levels from 2007 to 2010 due to a corresponding decline in unemployment rates reflected in high location quotients in fisheries, employment services, and retail.

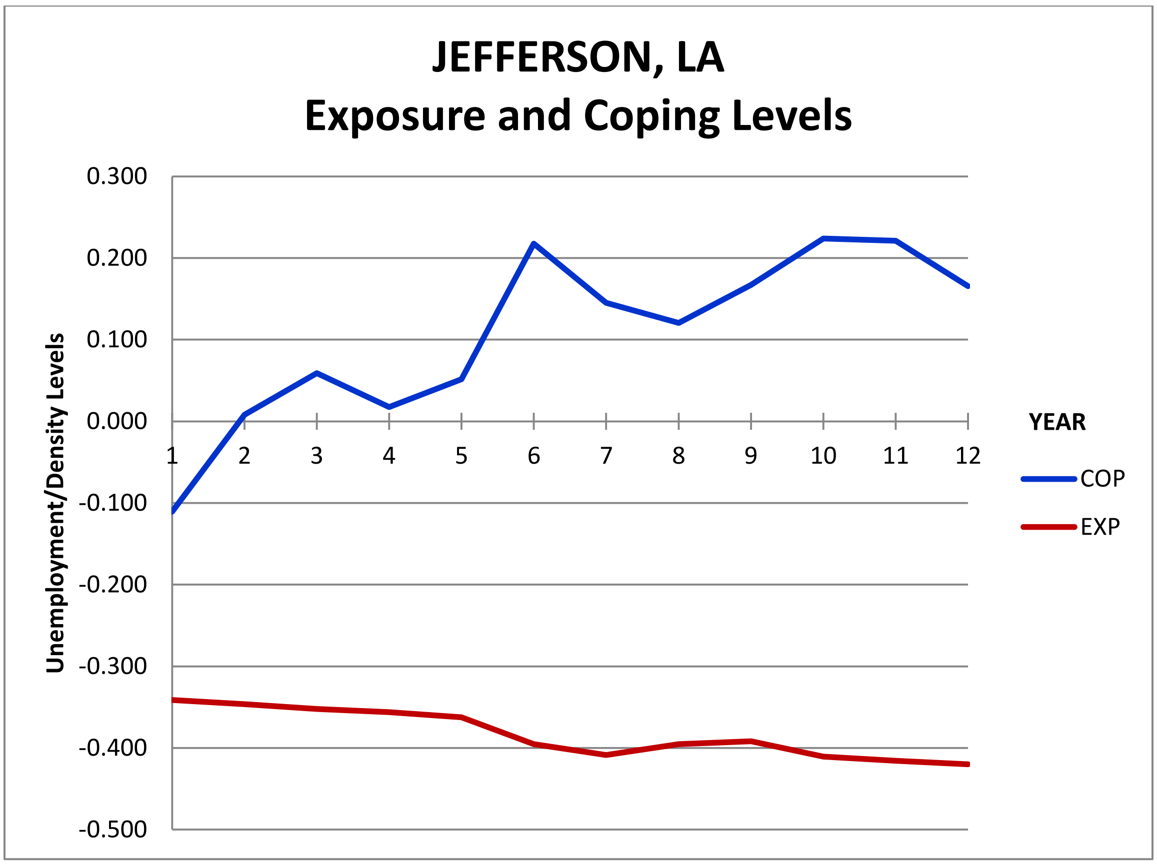

Figure 8.22 – Temporal Trend in Exposure and Coping Ability – Jefferson Parish, Louisiana

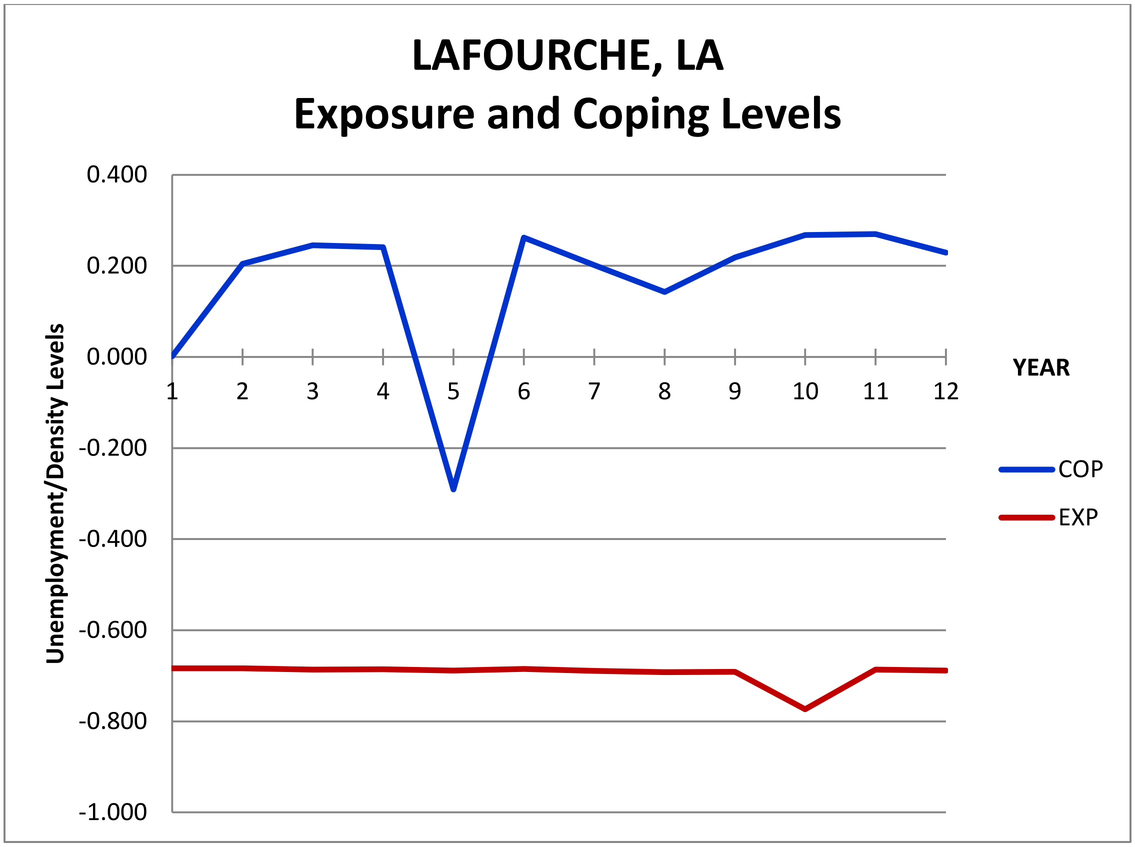

Figure 8.23 – Temporal Trend in Exposure and Coping Ability – Lafourche Parish, Louisiana

In Terrebonne Parish LA (Figure 8.24), coping levels increased dramatically from 2008 to 2010 while exposure levels were stable. The decline in unemployment is partly due to the increase in location quotients linked to fisheries and to services provided by religious organizations. Vulnerability levels shifted from high to the moderate category during this time period, because of the combination of high coping and moderate exposure levels.

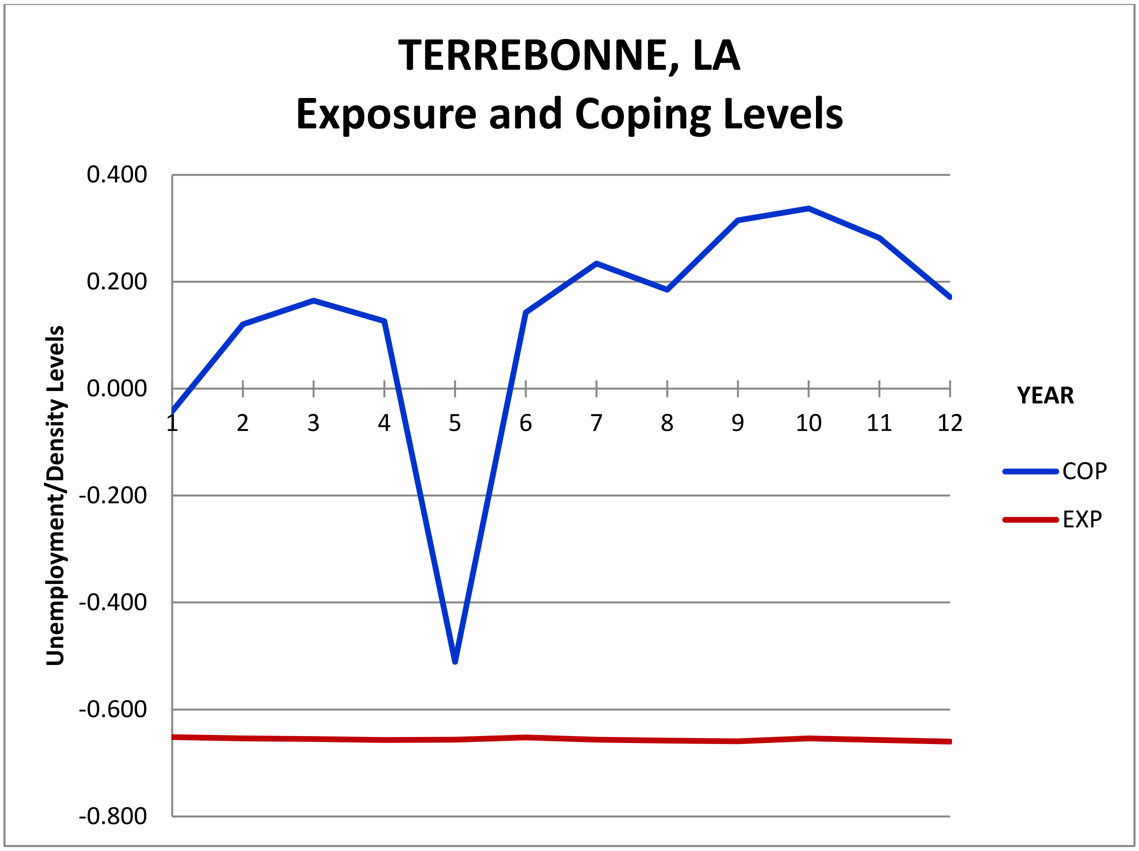

Figure 8.24 – Temporal Trend in Exposure and Coping Ability – Terrebonne Parish, Louisiana

Vulnerability levels in Lee County, FL transitioned from the moderate category to high vulnerability from 2007 to 2010. As illustrated in Figure 8.25, while exposure levels remained above the upper-bound threshold of 0.134, coping levels declined significantly from a distance measure of 0.324 in 2007 to 0.063 in 2010. The unemployment rate in Lee County was above the national average in the period 2008 to 2012. A decrease in location quotients linked to fisheries and to employment services in combination with increasing population density is contributing to increased vulnerability in the county.

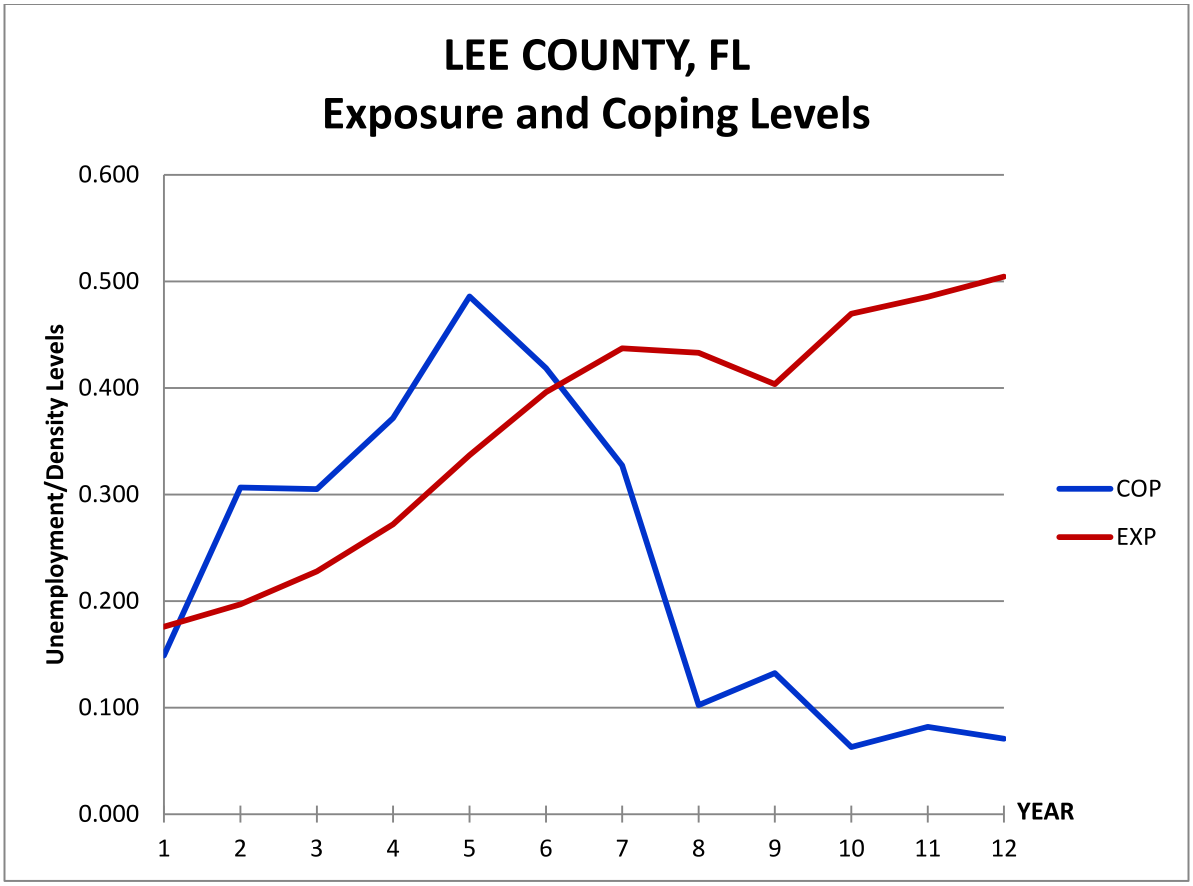

Figure 8.25 – Temporal Trend in Exposure and Coping Ability – Lee County, Florida

Spatial and temporal variations in exposure and coping levels are responsible for differences in vulnerability across the study area. The vulnerability assessment reveals that the reasons for changes in vulnerability differ even amongst counties in close proximity such as, Jefferson, Lafourche and Terrebonne in Louisiana. Location quotients of variables that represent social capital contribute to increases and decreases in the unemployment rate that is representative of coping ability. Therefore, the role of social capital determines spatial and temporal changes in vulnerability even as counties may retain similar socio-economic and demographic characteristics.

8.6 Assessment of Hazard Risk

The vulnerability assessment considered two components of the re-specified risk equation – exposure and coping ability. The objective of the HRLM is to develop and operationalize *hazard risk*. In the context of the Deep Water Horizon oil spill, the hazard component of the risk equation is represented by spill distance. As illustrated in Figure 8.26, counties in close proximity to the spill site are more hazardous as they are more likely to be negatively impacted by the event. Most of the counties are located in coastal Louisiana, Mississippi, and Alabama. Counties located at a greater distance from the spill, as in the case of southwest Florida and Texas are less likely to be impacted by the spill.

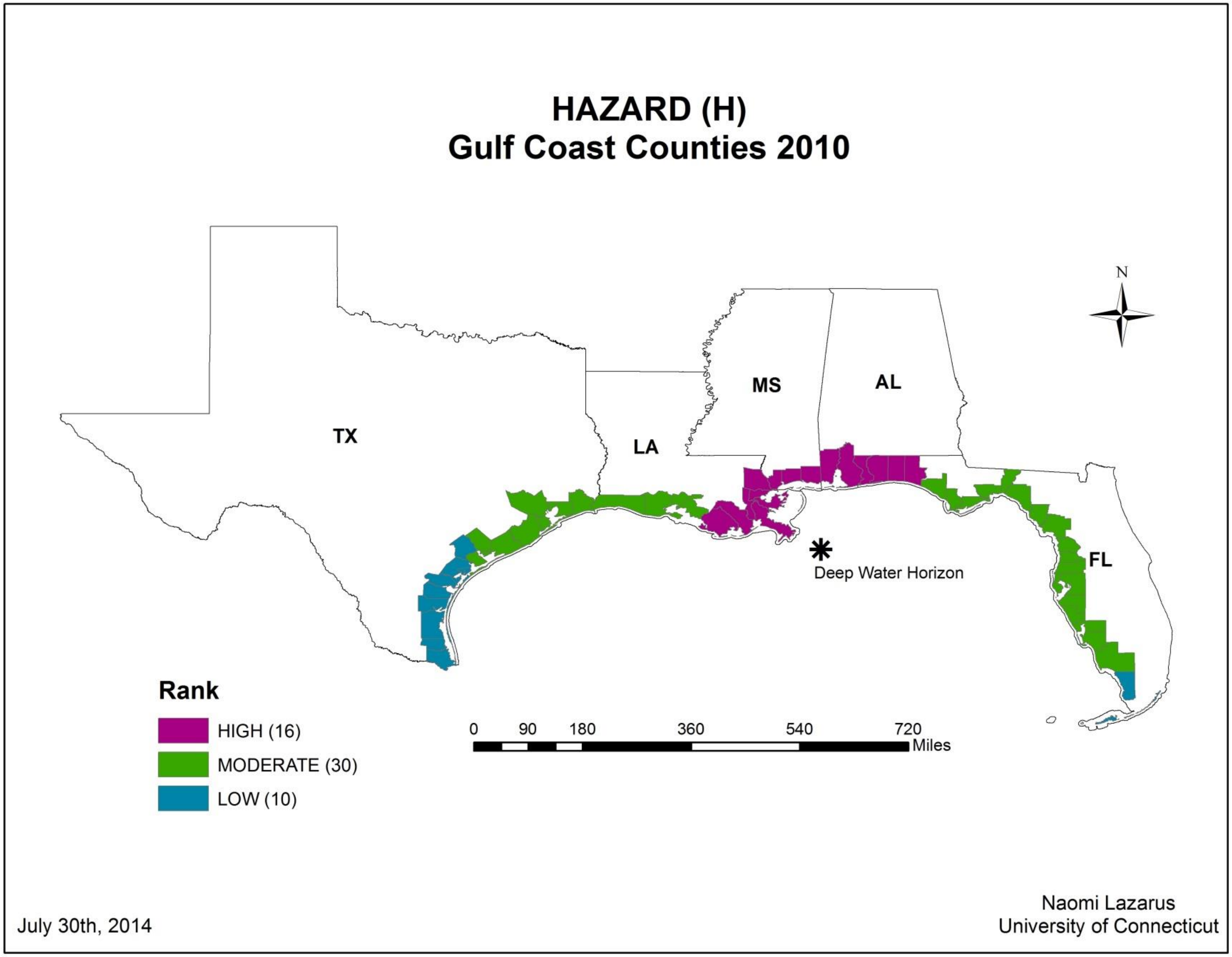

Figure 8.26 – Distance Measures for Spill Distance representing Hazard (2010)

The discussion on hazard risk builds on the vulnerability assessment and combines distance measures associated with population density (exposure), coping ability (unemployment rate), and spill distance (hazard). The weighted average of attributes contributing to a composite measure of risk is calculated using the formula proposed by Ratick and Osleeb (2011). Since a uniform weighting scheme is not established to measure vulnerability, the hazard component is assigned a weight of 0.5, and exposure and coping ability are each assigned a weight of 0.25. The hazard component is given greater weight as it represents the proximity of each county to the DWH oil spill, the source of the hazard. If a county is closer to the spill, it is deemed more hazardous, and therefore, distance from the spill is a key factor in estimating overall risk under prevailing levels of vulnerability. Vulnerability is deconstructed as exposure and coping ability (Clark et al. 1998; Ratick, Morehouse, and Klimberg 2009; Ratick and Osleeb 2011), and the combined weight of these components is 0.5 (0.25 + 0.25).

The hazard risk map for 2010 is presented in Figure 8.27. The HRLM classifies nine counties as high risk. Orleans, Jefferson, and St. Tammany in coastal Louisiana, Mobile, AL, and Okaloosa in the Florida panhandle are classified as high risk due to their high hazard and exposure levels and moderate coping ability. Thirty seven counties are moderately at risk in 2010 and are clustered in coastal Louisiana and southwest Florida. Low risk counties are concentrated in the Texas panhandle.

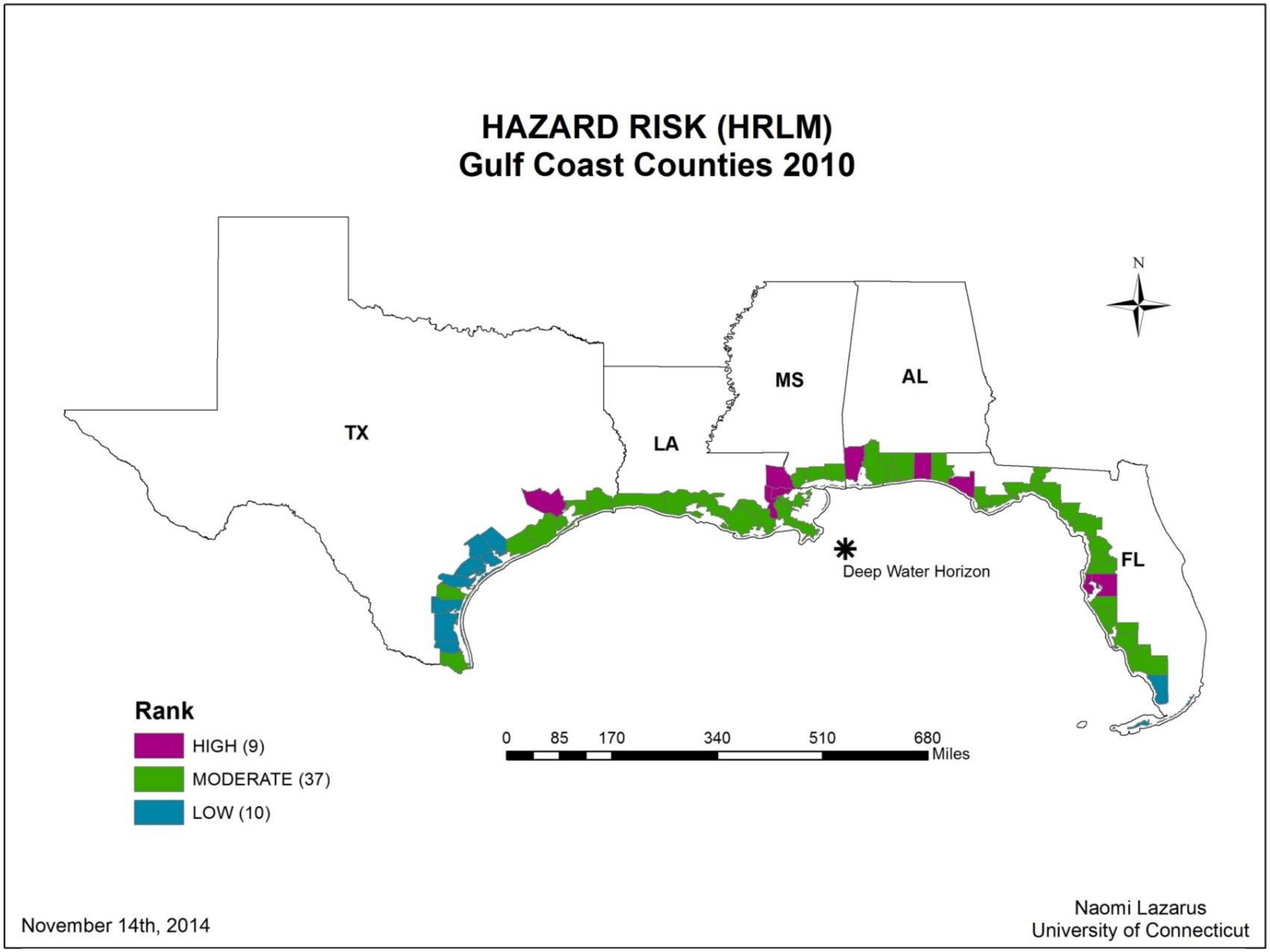

Figure 8.27 – Hazard Risk Map showing the intersection of Exposure, Coping Ability, and Hazard Levels as per the Hazard Risk Location Model (2010)

Charts showing coping, exposure, and hazard levels in selected counties are presented below. The solid blue and red lines represent the trend in coping ability and exposure, respectively. The dotted line indicates distance from the spill i.e. the hazard level. The chart on coping, exposure, and hazard levels in Orleans Parish (Figure 8.28) reveals a sharp drop in population density from 2005 to 2006 due to the impacts of Hurricane Katrina, but a recovery in the period of the oil spill (2010 to 2011). According to reports from the field, the oil spill affected fisheries in neighboring Plaquemines Parish, but did not affect tourism in New Orleans, which is the mainstay of economic activities in the city. Tourism and recreation are the dominant economic sectors in Orleans Parish accounting for 79 percent of total jobs followed by offshore mineral extraction and marine transportation (NOAA 2011). Employment in the leisure and hospitality sector grew by 7 percent from 2010 to 2011 (NOEP 2014). Furthermore, location quotients for social assistance, utilities, professional services, and religious organizations remained above 1.00, indicating that social capital contributed to jobs and livelihoods in Orleans Parish as the event was unfolding. These economic gains, however, were insufficient to minimize the county's risk of being negatively impacted by the event owing to its close proximity to the spill (high ranking on hazardousness) and its moderate exposure levels. As such, Orleans Parish recorded a high risk level in 2010 as illustrated in Figure 8.27.

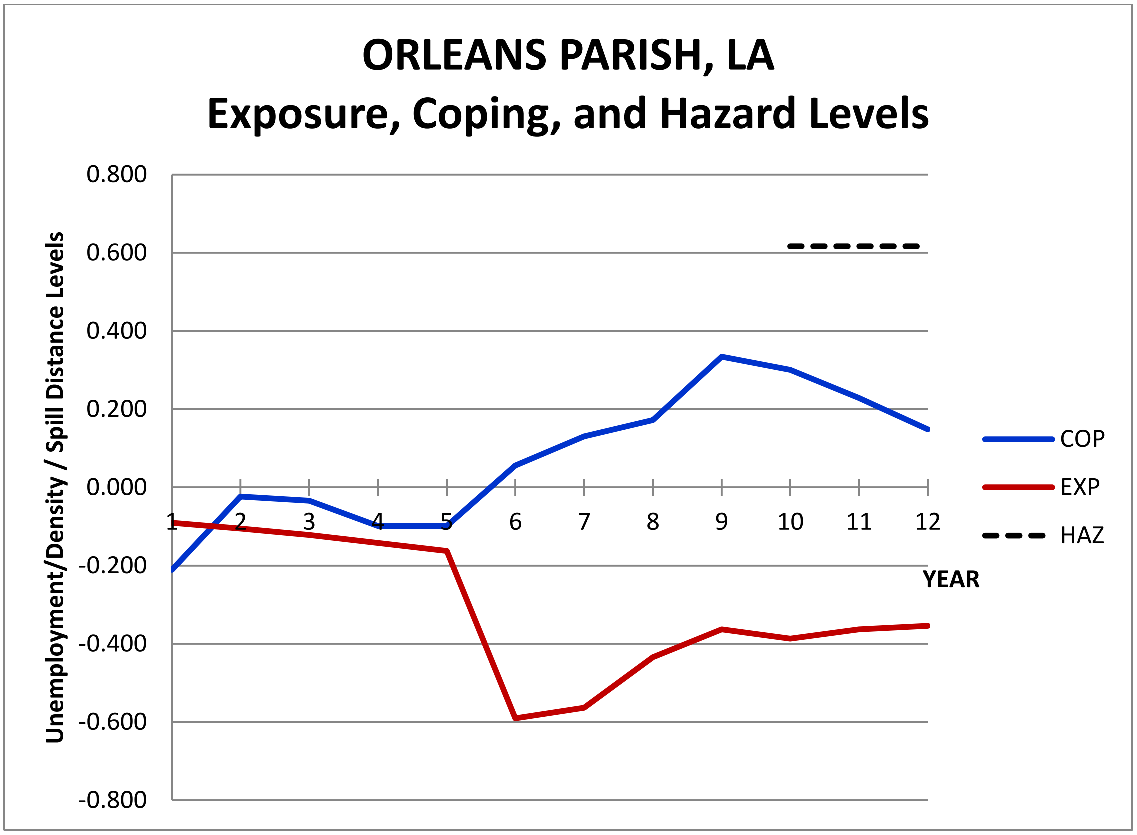

Figure 8.28 – Temporal Trend in Exposure, Coping Ability, and Hazard Levels – Orleans Parish, Louisiana

In neighboring Plaquemines Parish (Figure 8.29), the combination of high coping levels and moderate population density decreases overall risk. Despite fishery closures in the aftermath of the spill, location quotients for fisheries experienced only a marginal decline. An increase in resources allocated to utilities and professional services contributed positively to coping ability, which is reflected in a relatively low unemployment level of 7.1% in 2010 compared to the national average of 9.6%. The decline in unemployment was partly due to the presence of workers brought in for oil spill recovery efforts that stimulated the local economy. The impact of the oil spill on local businesses, however, is not reflected in the data, as post-disaster recovery waned over time. Based on findings in the field, the recovery period for local fishermen in Plaquemines Parish has been slow and difficult as they relied mostly on close relationships

among business owners for support during the recovery process (The Urban Conservancy 2012). It emphasizes how social capital, in the form of workplace relationships and social networks, helps people cope with the impacts of hazard events over time.

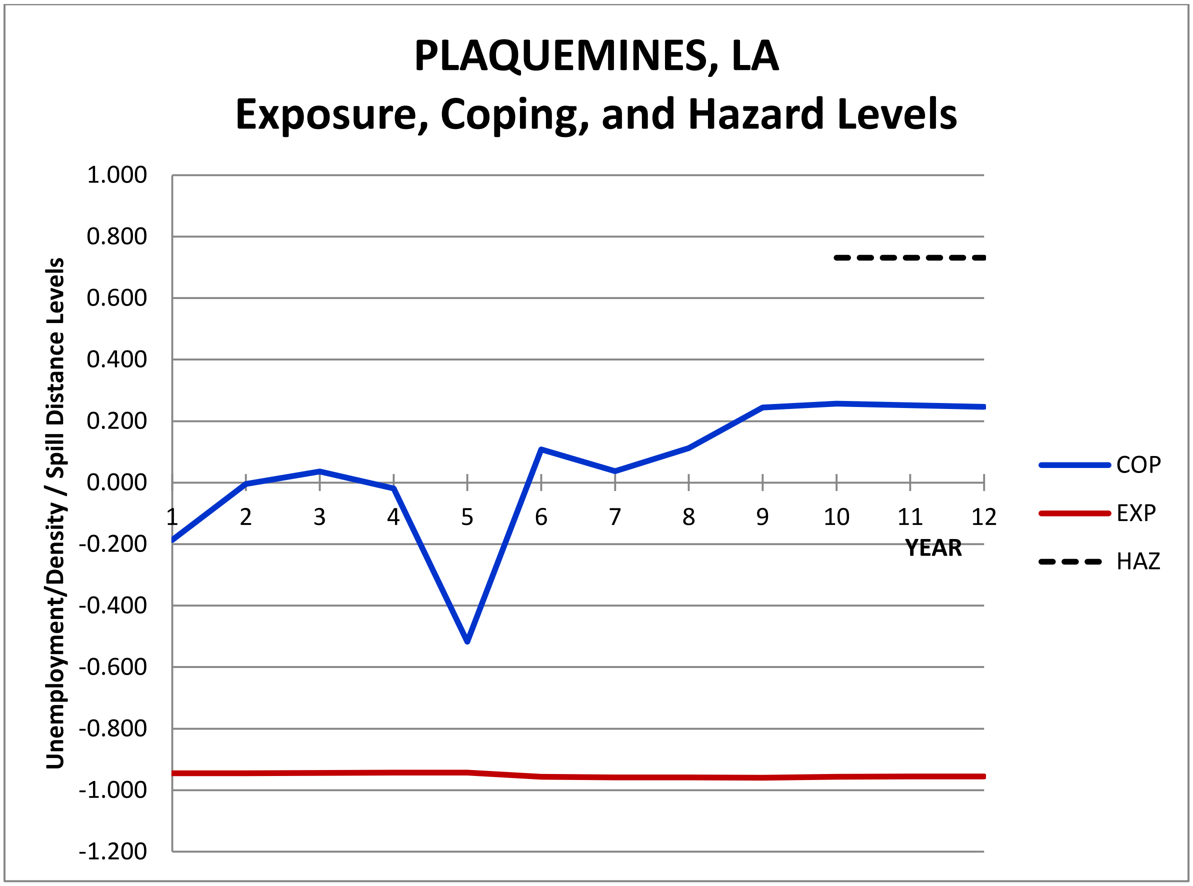

Figure 8.29 – Temporal Trend in Exposure, Coping Ability, and Hazard Levels – Plaquemines Parish, Louisiana

Coastal counties in the Florida panhandle experienced the impacts of the oil spill in different ways. Bay County FL is classified as high risk in 2010 due to very high population densities associated with urbanized areas such as, Panama City. Coping levels remained well below the upper-bound threshold of 0.200 from 2009 to 2010 and remained stable through 2011 as evidenced by the gradual recovery in tourism and recreational activities after the recession (Figure 8.30). Tourism in Bay County is seasonal with the spring and summer attracting large

numbers of visitors. Beach front rentals are mostly vacant from December to March, but the presence of snowbirds sustains the economy to some extent. Based on observations in the field, construction of new rental properties is ongoing in the Pier Park area of Panama City Beach in anticipation of a growth in tourist arrivals.

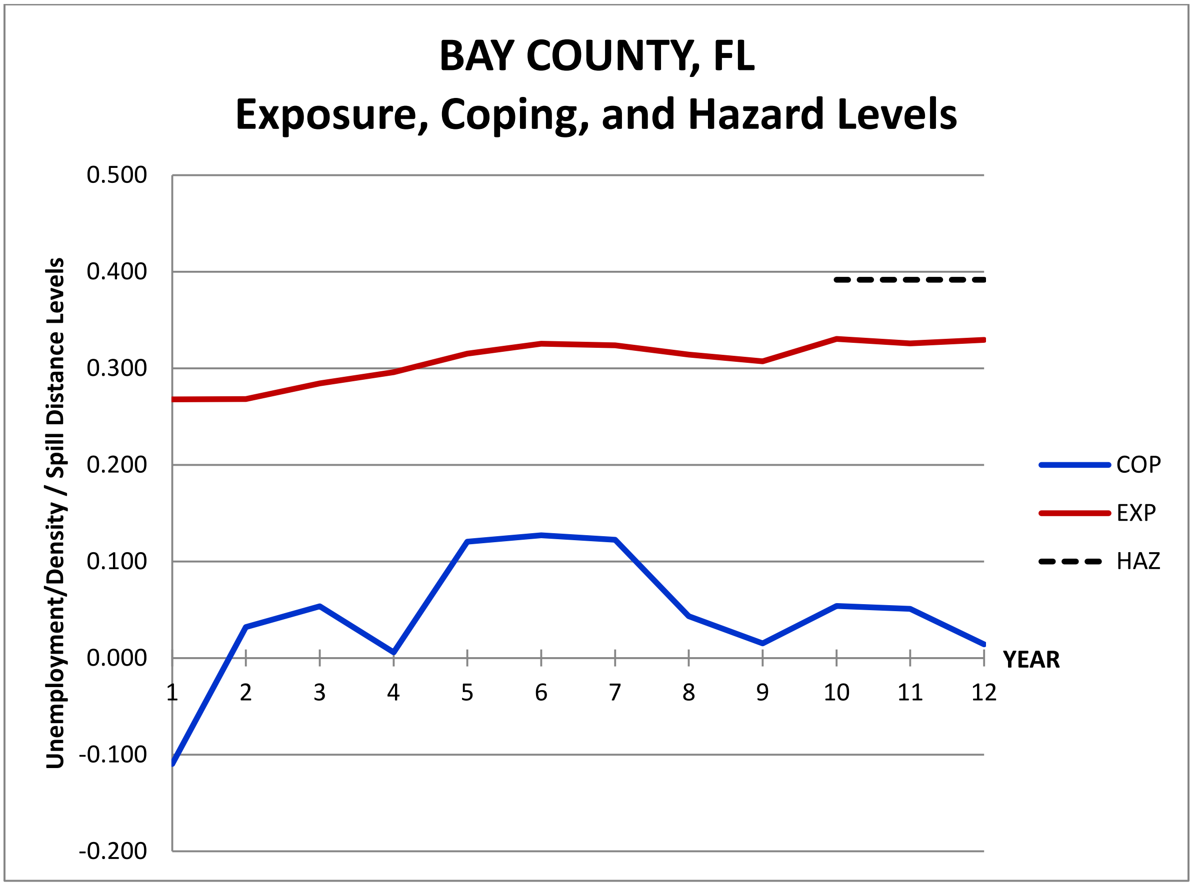

Figure 8.30 – Temporal Trend in Exposure, Coping Ability, and Hazard Levels – Bay County, Florida

Escambia County FL recorded a moderate risk level in 2010 due to a combination of moderate coping and population density levels and high exposure (Figure 8.31). Given that the Florida panhandle is heavily reliant on tourism, media reports on the oil spill played a role in keeping visitors away. The images of report streaming live from Pensacola Beach had a negative impact on businesses reliant on the tourism industry. According to reports from the field, the oil

spill had only minimal impact on the beaches in the Florida panhandle. The magnitude of the spill and the widespread media coverage did not adequately contextualize its impacts. As observed in Bay and Escambia counties, the impact of the spill was place-specific and translated to varying levels of risk across the Gulf coast counties.

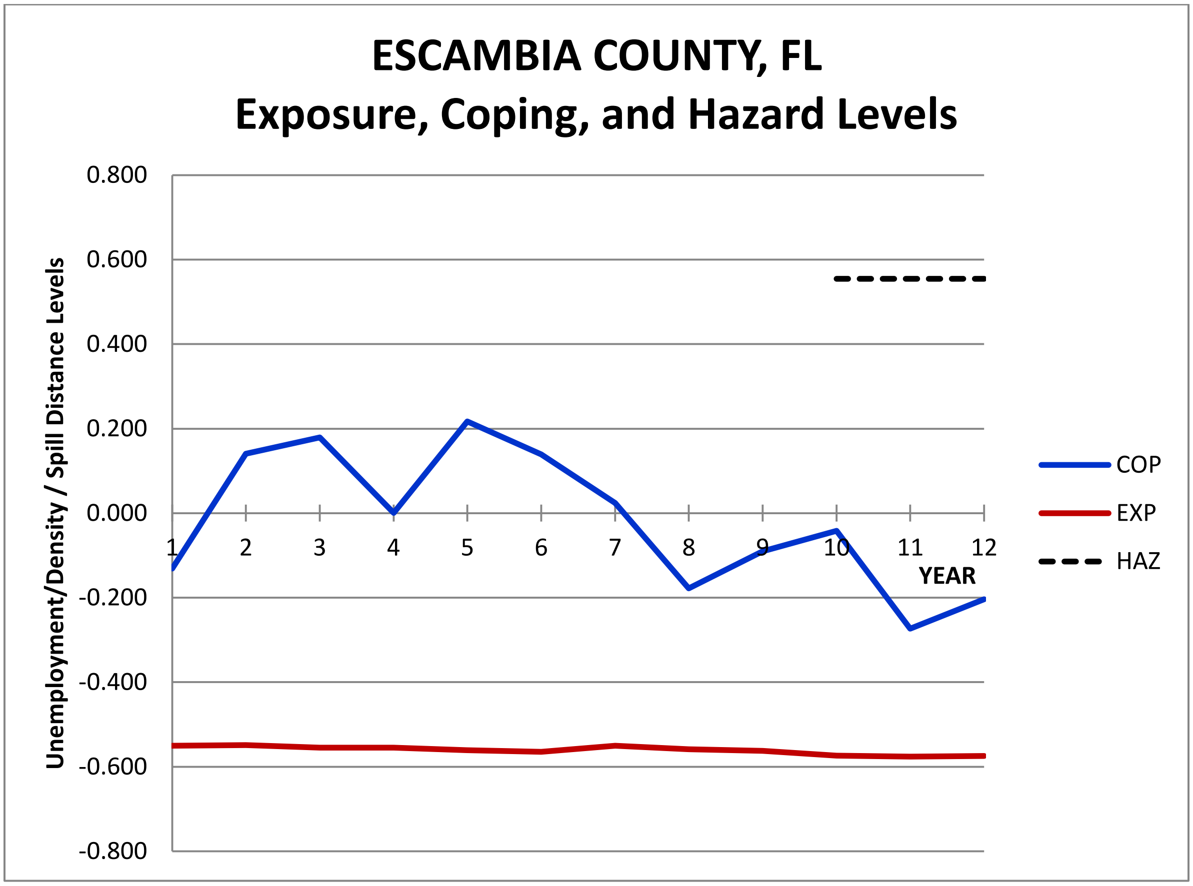

Figure 8.31 – Temporal Trend in Exposure, Coping Ability, and Hazard Levels – Escambia County, Florida

The goal of the threshold analysis is to evaluate the relative contribution of variables representing coping ability, exposure, and hazard in determining risk to address the fifth and sixth hypotheses. The fifth hypothesis states that risk is determined by peoples' coping ability and its inter-relationship with other factors, namely population density and proximity to the spill. The sixth hypothesis states that the relative contribution of the impact of the hazard, the

population exposed, and coping ability varies across the Gulf region. Vulnerability and risk levels are evaluated using maps and charts to compare the spatial pattern of risk based on distance measures predicted by the HRLM. The results show that spatial and temporal variations in one or more distance measures associated with unemployment rate, spill distance, and population density are observed across counties in the Gulf, which in turn affect how these variables determine risk across geographical space.

8.7 Verification of the Model

The HRLM is verified in two steps. First, hazard risk maps are compared against observed unemployment rates to assess how well the HRLM is able to predict vulnerability and risk over time. Next, the HRLM is verified using total employment figures as reported by the Bureau of Economic Analysis (BEA) to assess whether the model is able to capture the effect of macroeconomic processes that influence coping ability.

8.7.1 Unemployment Rate

The HRLM's version of hazard risk is based on predicted unemployment rates derived from the regression analysis. The spatial distribution of hazard risk based on the model is presented in Figure 8.27 that was discussed in the previous section. Figure 8.32 is the hazard risk map for 2010 where coping ability is derived from the *observed* unemployment rate. Predicted unemployment rates in fifty one counties conform to observed data, indicating that the HRLM is effective in accurately estimating risk levels for 91 percent of counties in the study area.

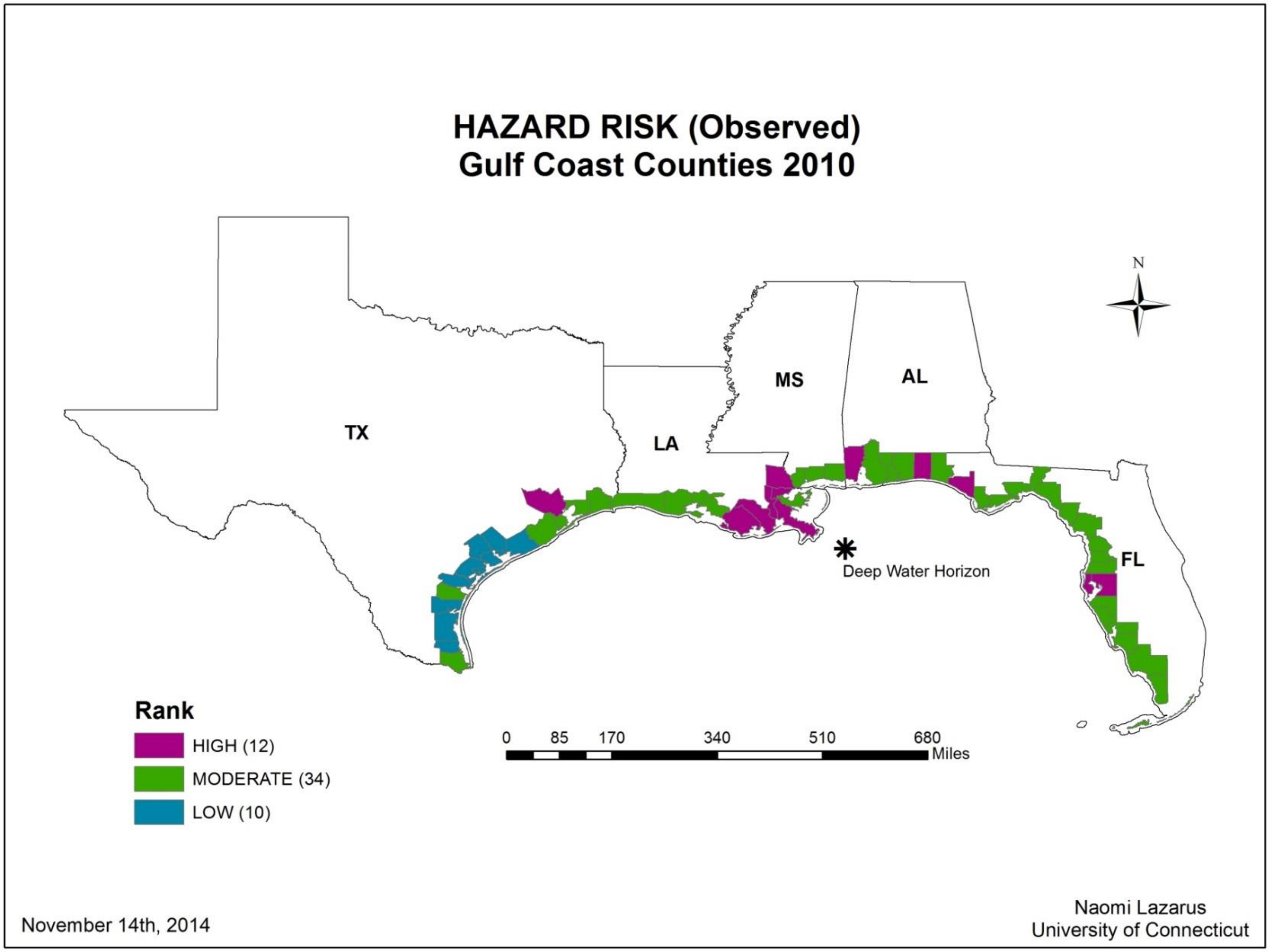

Figure 8.32 – Hazard Risk Map showing the intersection of Exposure, Coping Ability, and Hazard Levels as per Observed Data (2010)

The differences between observed and predicted risk levels are reflected in several counties that switched between the moderate and high risk categories. Plaquemines, Lafourche, and Terrebonne in coastal Louisiana recorded moderate risk levels based on the model, but are classified as high risk as per observed data. Monroe County in southwest Florida recorded a low risk level in 2010 as per the HRLM, but was moderately at risk based on observed data. The risk level in Matagorda County in coastal Texas on the other hand was classified as moderate as per the HRLM when the county recorded a low risk level based on observed data (Figure 8.32).

Charts showing coping, exposure, and hazard levels for Orleans and Plaquemines in coastal Louisiana are presented in Figure 8.33 and 8.34. The solid blue line represents distance measures for coping ability based on the HRLM, whereas the dashed blue line tracks distance measures as per observed data. The difference between predicted and observed coping ability is marginal for Orleans Parish in 2010, the year of the DWH oil spill. As a result, the risk level is classified as high for both the model and for observed data as illustrated in the risk maps (Figure 8.27 and 8.32). In Plaquemines Parish (Figure 8.34) the coping line for observed data (dashed blue line) records a moderate distance measure of 0.365 in 2010, which is lower than the upper-bound threshold of 0.370, and therefore the risk level is categorized as high on the risk map (Figure 8.32). Significant differences are observed between predicted and observed coping levels in both counties in 2005, the period in which Hurricane Katrina occurred. It is indicative that the event represents an anomaly by virtue of its magnitude and the scope of its impact across the Gulf region.

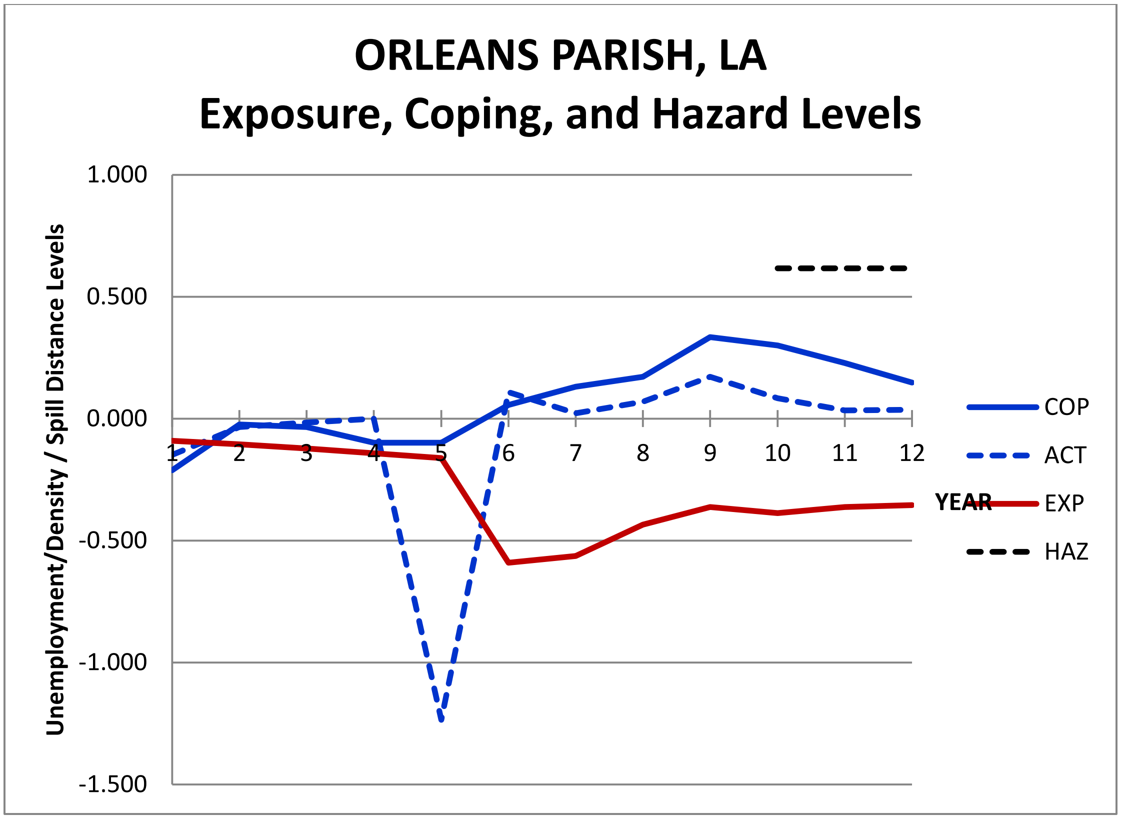

Figure 8.33 – Temporal Trend in Exposure, Coping Ability, and Hazard Levels – Orleans Parish, Louisiana

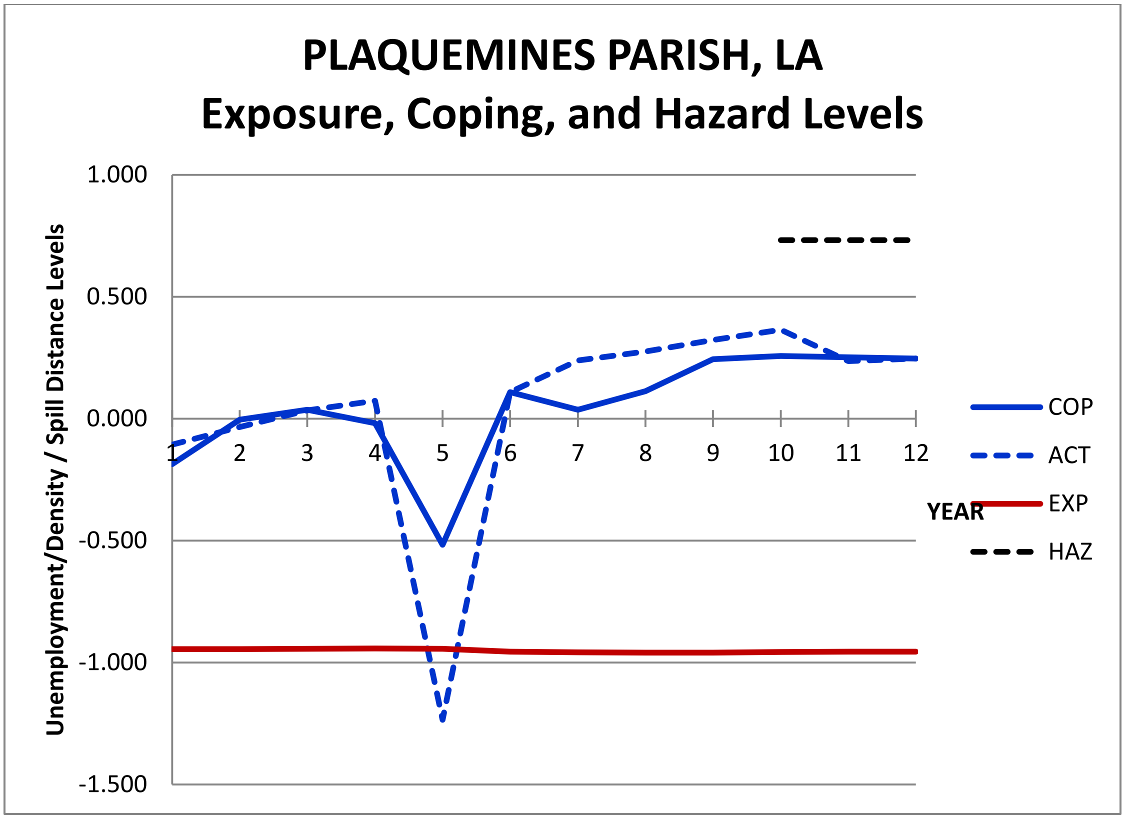

Figure 8.34 – Temporal Trend in Exposure, Coping Ability, and Hazard Levels – Plaquemines Parish, Louisiana

8.7.2 Employment

The HRLM is verified using total employment figures as reported by the Bureau of Economic Analysis (BEA). As defined by the BEA, total employment includes estimates of the number of full-time and part-time jobs in all sectors classified under the North American Industrial Classification System (NAICS). Total employment is selected as an appropriate indicator for the following reasons. First, gainful employment is considered an outcome of linkages embedded in social capital that provide people access to resources, one of which is job security. Job security forms part of the portfolio of capabilities that sustains livelihoods and improves peoples' ability to cope with changes in the environment (Burton, Kates, and White 1978; Sen 1981; Chambers and Conway 1991; Cannon 1994; Cutter et al. 2008). Second,

employment is a key macroeconomic indicator that reflects the effect of social and institutional policies that play out at the local level (Mansfield 1986). The relationships between individuals, groups, and institutions at the local level are embedded in social capital (Scheffer et al. 2002). It is expected that these linkages will provide people access to resources and services that increase the opportunities for employment (Sen 1981; Chambers and Conway 1991). The independent variables used in the regression analysis are location quotients of variables representing social capital sectors. Location quotients are relative measures of employment that compare each county's contribution in a given sector. Total employment, therefore, confirms whether the variables representing social capital in the HRLM are an accurate representation of a county's ability to cope with hazard events. Counties were sampled from the HRLM's hazard risk map for 2010 (Figure 8.27) to evaluate whether risk levels coincided with total employment patterns.

A high risk level is recorded for Bay County, FL and Baldwin County, AL is classified as moderately at risk in 2010. Moderate or high risk levels indicate that a county's coping ability is inadequate to respond to the impacts of a hazard event based on existing exposure (population density) and hazard (spill distance) levels. Charts on total employment for Bay County (Figure 8.35) and Baldwin County (Figure 8.36) reveal a sharp drop in the number of jobs from 2008 as evidence of the economic downturn, and this downward trend continues through 2010. The decrease in employment levels is reflected in a decline in coping ability that increases risk levels in these counties.

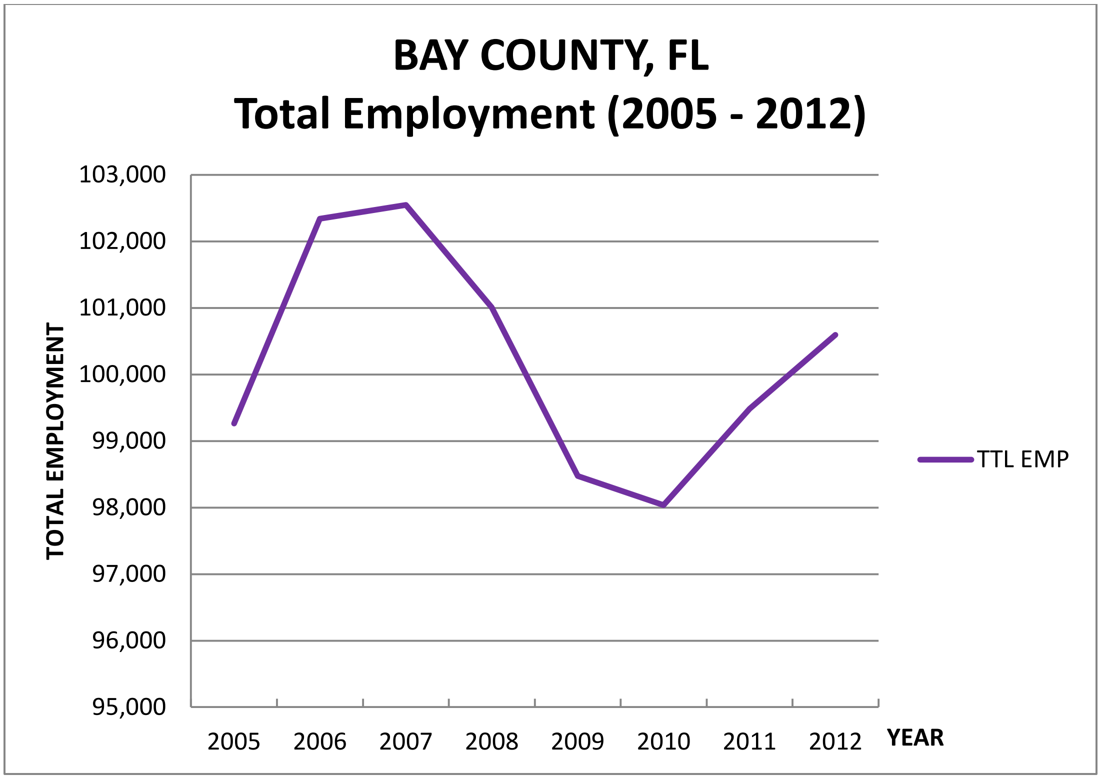

Figure 8.35 – Temporal Trend in Total Employment – Bay County, Florida

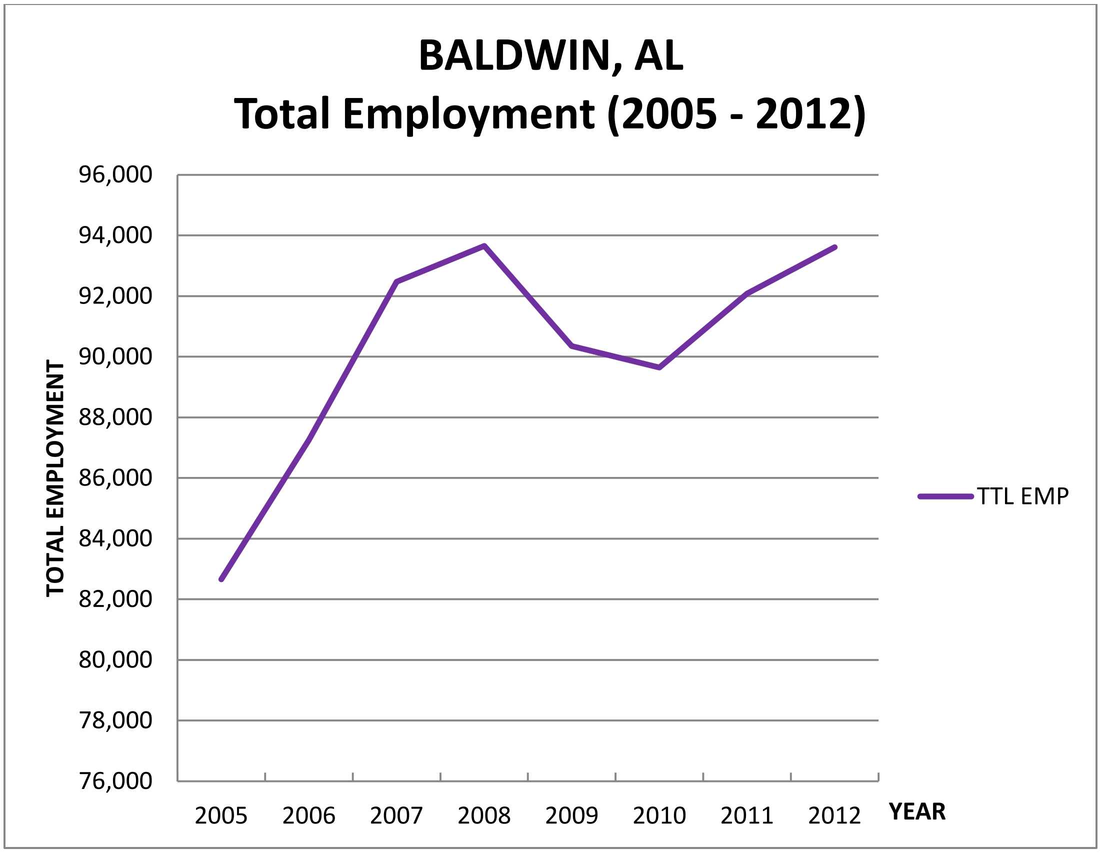

Figure 8.36 – Temporal Trend in Total Employment – Baldwin County, Alabama

Risk levels in Monroe FL and Jackson TX are classified as low in the hazard risk map. Low risk levels indicate that a county's coping ability is high or is increasing, and therefore that county is in a better position to respond to the impacts of a hazard event. The chart showing total employment in Monroe (Figure 8.37) highlights a significant increase in the number of jobs beginning 2009, which decreases the risk level of the county in 2010 as presented in the hazard risk map. The increase in total employment in Jackson County, TX (Figure 8.38) is gradual from 2008 to 2010 compared to the trend in Monroe County, but the county did not experience a significant drop in the number of jobs during the recession as was seen in Monroe County. The

overall stability in employment trends in Jackson County has the effect of improving job security and coping ability (low risk).

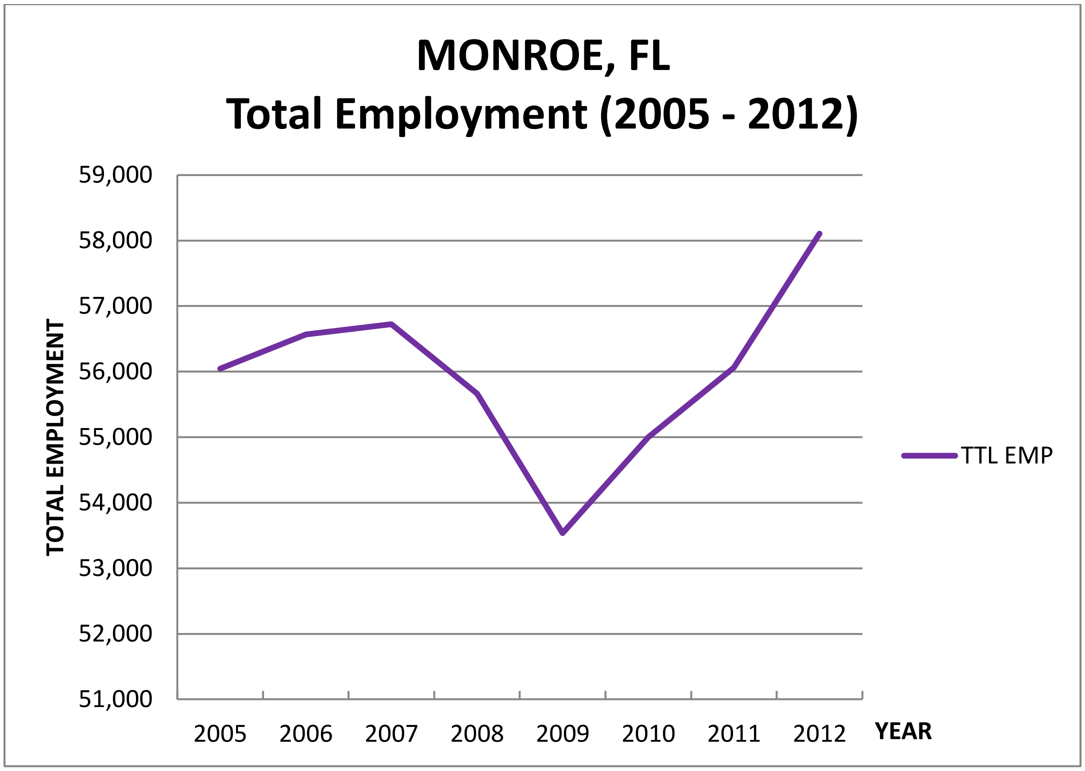

Figure 8.37 – Temporal Trend in Total Employment – Monroe County, Florida

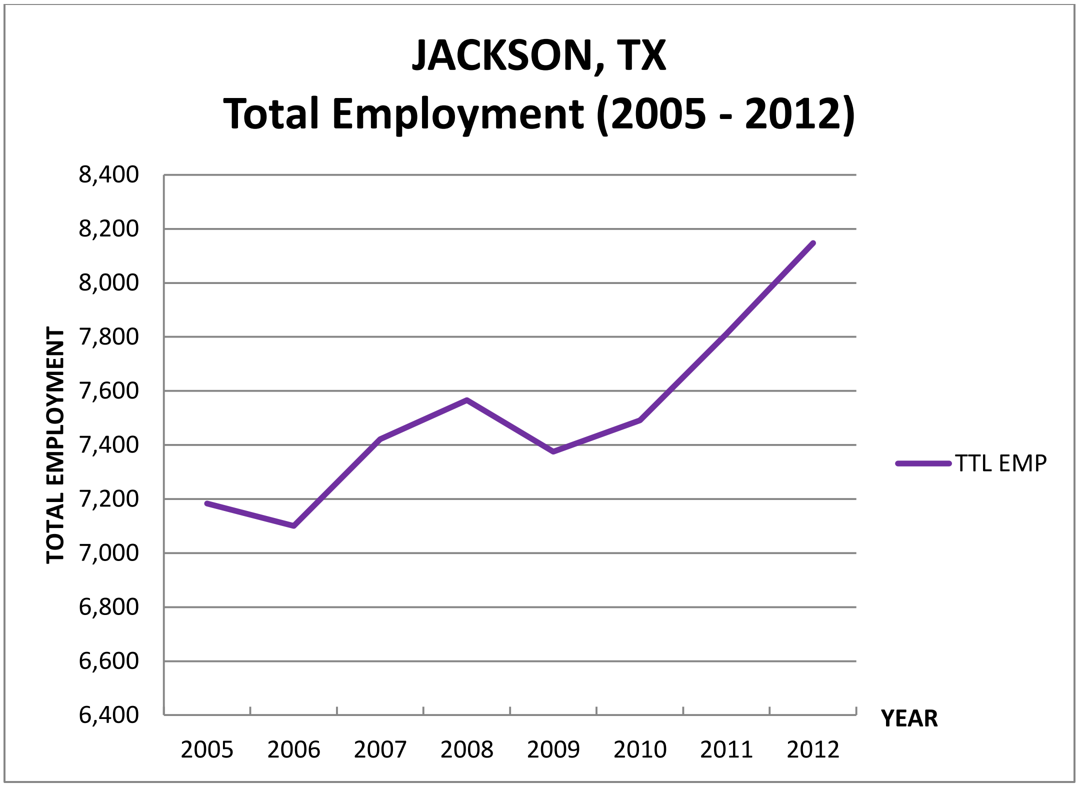

Figure 8.38 – Temporal Trend in Total Employment – Jackson County, Texas

Plaquemines and Orleans in coastal Louisiana were located in close proximity to the spill, but recorded varying levels of risk. A moderate risk level is recorded for Plaquemines and Orleans is classified as high risk in 2010 (Figure 8.27). As illustrated in Figure 8.39, total employment in Plaquemines Parish is increasing in the period, 2009 to 2011, which positively impacts incomes and livelihood security and moderates the risk level in the county. The increase in total employment in Orleans (Figure 8.40) is gradual from 2008 to 2012 compared to the variation in Plaquemines and is inadequate to respond to the impacts of a hazard event as moderate exposure (population density) and high hazard (spill distance) levels increase overall risk in the county.

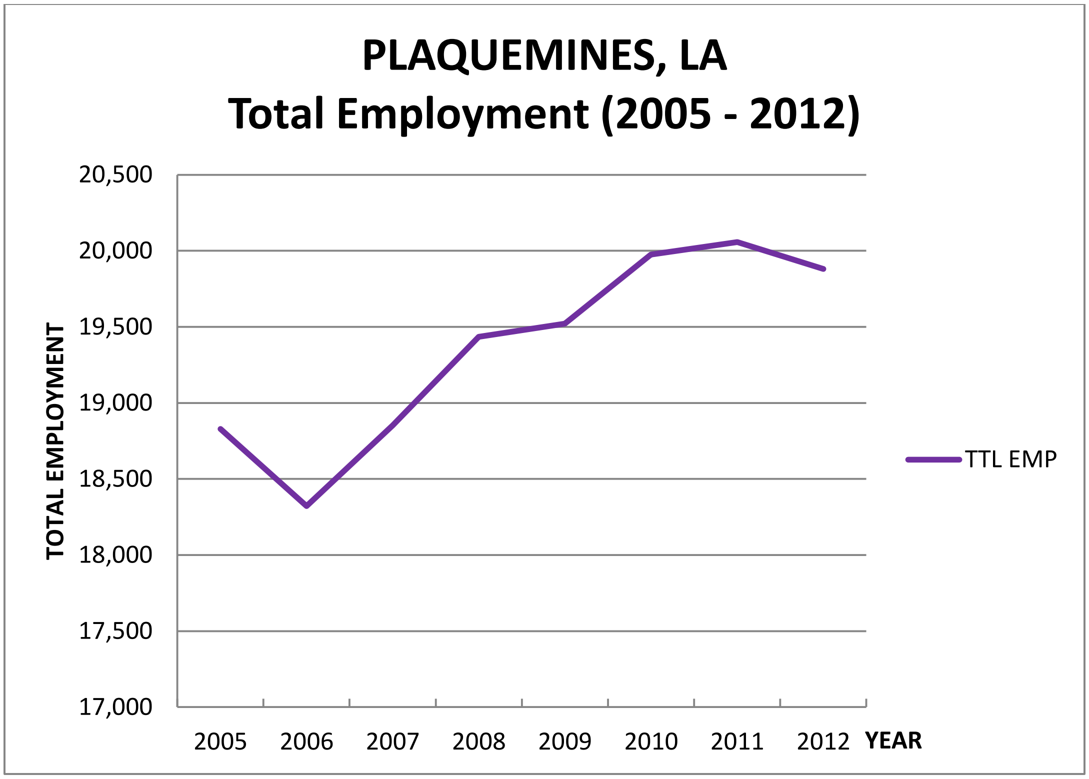

Figure 8.39 – Temporal Trend in Total Employment – Plaquemines Parish, Louisiana

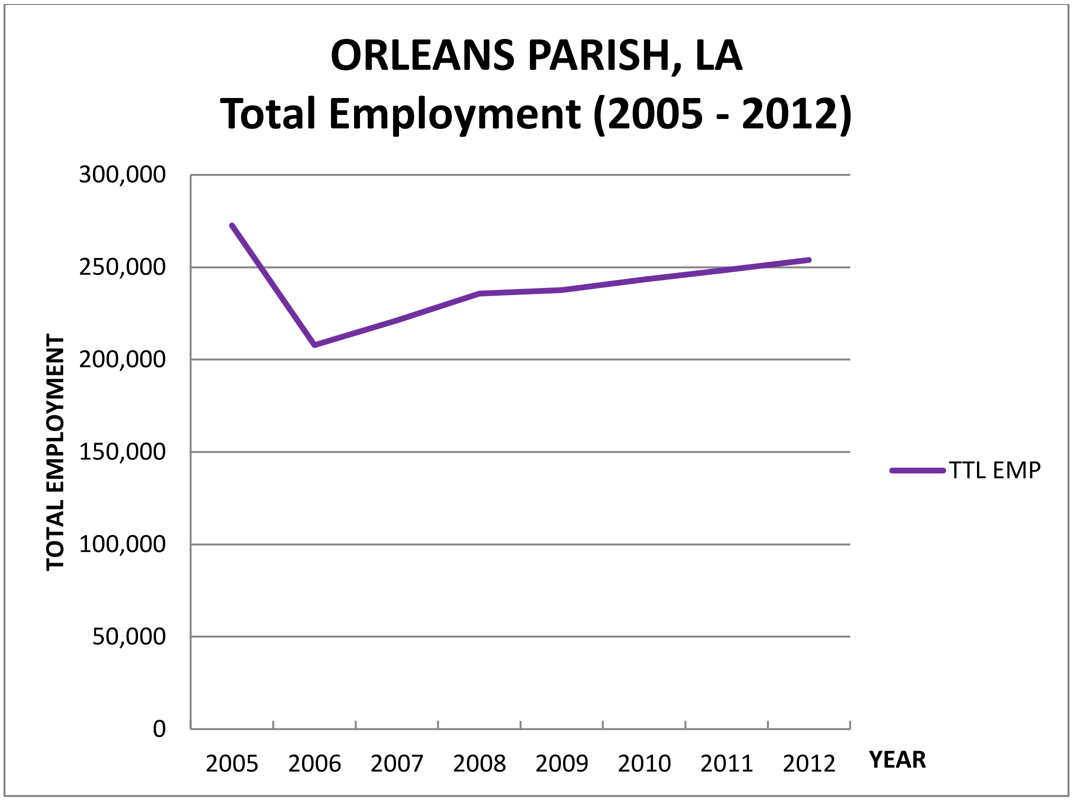

Figure 8.40 – Temporal Trend in Total Employment – Orleans Parish, Louisiana

8.8 Conclusion

This chapter presented a detailed assessment of the steps undertaken to operationalize the HRLM. The regression analysis tackles the components of the first and second research questions wherein the relationships between variables representing social capital and unemployment rate are evaluated. The relative contribution of independent variables to the change in unemployment rate and the significance of these variables are important directions in addressing how social capital impacts individual well-being. Results of the regression analysis reveal that the quantity of social capital and its contribution to coping ability are influenced by locational differences and the type of hazard event. Locational differences are observed in the clustering of high and low values of independent variables across the study area. In some

counties, the impacts of Hurricane Katrina and the DWH oil spill are inter-related reaffirming the time lag of impacts that is experienced after an event.

The third research question is addressed in the threshold analysis, which builds on the principle of relative distance to rank counties on an ordinal scale of hazard risk. The results reveal that the contribution of social capital in effecting changes to the unemployment rate (coping ability) determines overall risk. Based on observed patterns, there is considerable spatial and temporal variation in hazard risk at the county level, and these changes are reflected in the proximity of individual counties to the spill site, population density, and the unemployment rate. These spatial and temporal variations warrant the application of the HRLM to a county-level assessment of hazard risk, which will be the subject of future work. Chapter 9 provides an overview of how this research will be expanded in the future.

Chapter 9

Conclusion

9.1 Introduction

This research examined the social and economic impacts of the Deep Water Horizon (DWH) oil spill in coastal counties in the Gulf of Mexico. It addressed the inter-relationship between livelihood mechanisms and social networks that determines peoples' ability to cope with the impacts of the event. The research builds on the concepts of vulnerability and resilience to develop a model that attempts to identify what factors contribute to peoples' coping ability in the face of changes brought on by hazard events.

The proposed Hazard Risk Location Model (HRLM) builds on the concept of capabilities as articulated by Sen (1981) where access to resources is a key indicator. The model evaluates how social relations or linkages embedded in social capital determine access to resources, which in turn has an impact on livelihood mechanisms and outcomes. The conceptual framework of the model recognizes that coping ability and vulnerability are countervailing forces that determine peoples' overall risk of being negatively impacted by hazard events. The HRLM re-specifies the original risk equation of Wisner et al. (2004) as $R = f\ (H, E, C)$, where risk is a function of the hazard, exposure, and coping ability. Regression is adopted as the basis for the model's framework to examine the relationship between variables representing social capital and coping ability. Results of the regression analysis reveal that the quantity of social capital and its contribution to coping ability are influenced by locational differences and by the cumulative impacts of hazard events that occur over time.

The threshold analysis is the next step in the development of the model and evaluates variations in spill distance, population density, and unemployment rate that represent the

components of the risk equation – the hazard, exposure, and coping ability. The results reveal that there is considerable spatial and temporal variation in hazard risk at the county level, and these changes are reflected in each county's attributes in relation to its proximity to the spill site, population density, and the unemployment rate.

9.2 Future Work

9.2.1 Overview

The application of the HRLM in this research has focused on the socio-economic impact of the DWH oil spill. The future direction of the research is aimed at expanding the model to include demographic variables. The use of demographic data in vulnerability assessments has been applied to case studies in the past. For example, Cutter, Mitchell, and Scott (2000) utilized variables related to gender, race, and age to assess the social vulnerability of populations in Georgetown, South Carolina. In another case study, Ratick, Morehouse, and Klimberg (2009) used variables related to minority populations and age structure to develop an index of relative vulnerability to coastal storms in Boston, Massachusetts.

Incorporating demographic variables in the analysis provides another dimension to assess the impacts of the DWH oil spill in Gulf Coast counties and forms the basis for the following additional research questions:

(1) How does the demographic composition of the population determine access to social capital?

(2) How are demographics and social capital inter-related in determining risk associated with environmental disasters?

Building on previous case studies, the demographic variables included in the HRLM are related to race and age structure. These variables are presented in Table 9.1 and are highlighted in bold font. The variables examined are percentage of the White population, percentage of

African American, percentage of Hispanic, percentage of American Indian, percentage of Asian, percentage of the population under 5 years, and percentage of the population over 65 years. The table also lists the original variables in the analysis – the location quotients of the independent variables representing social capital and the control variables associated with time after Katrina (TIME_K; TIME_K_SQ), time after the DWH oil spill (TIME_O), and spill distance (SPILL_DIST_DECAY).

Table 9.1 – Variables included in the Expanded Model

Category	**Description**	**Code**
Dependent variable	Unemployment Rate	UNEMP_RATE
Independent variables	Fisheries Social assistance Religious organizations Employment services Professional services Utilities Retail trade	FISH_LQ SA_LQ REL_LQ EMP_LQ PRO_LQG UTI_LQG RTL_LQ
Control variables	Time after oil spill Time after Katrina Time after Katrina squared Spill distance decay	TIME_O TIME_K TIME_K_SQ SPILL_DIST_DECAY
Demographic variables	**Percent White** **Percent African American** **Percent Hispanic** **Percent American Indian** **Percent Asian** **Percent under 5 years** **Percent over 65 years**	**PCT_WHITE** **PCT_BLACK** **PCT_HISP** **PCT_AMER** **PCT_ASIAN** **PCT_5YR** **PCT_65YR**

9.2.2 Preliminary Results

The preliminary analysis of demographic variables uses data from the decennial census of 2000 and 2010. Table 9.2 compares goodness of fit and autocorrelation statistics of the original model presented in this research with that of the expanded model that includes demographic variables. Results are presented for the simple linear model, the simple linear model with interaction terms, and the autoregressive model with interaction terms. Interaction terms are incorporated in a regression analysis to measure *interaction effects* that are observed when a time series dataset is interrupted by specific events that occur at a particular time. These effects are formulated as an interaction term by multiplying the location quotients and demographic variables with the time-related control variables, TIME_O and TIME_K_SQ that represent the DWH oil spill and Hurricane Katrina, respectively. An autoregressive model is used to address the problem of autocorrelation, which violates the assumption of independence in regression. The autoregressive term, $L^j Y_t = X_{t-j}$ recognizes the *dependence* of errors and is used to correct the lag associated with the residuals (Maddala 1992; Hamilton 1994; SAS Institute 2014a). The formula of the autoregressive model is as follows:

$$Y_t = B_0 + (B_1\mathbf{L}X_1 + B_2\mathbf{L}X_2 + \ldots\ldots\ldots\ldots B_m\mathbf{L}X_m)_{\mathbf{j}} + B_T T + B_D D + B_{Tx} Tx + e_t$$

where, Y_t is the value of the dependent variable (coping ability) in a given time period, t; B_0, the constant; and B_1, $B_{2\ldots}$ representative of parameter estimates of the respective independent variables denoted by X_1 and X_2 in a set of m number of variables, $k = 1.....m$. The lag operator, L, represents the value of the independent variable in the previous time period ($t - 1$) in a set of j number of time periods, $t = 1.....j$. T is an interval variable controlling for time, the value of which will be set as 1 for the event year and increments of one for subsequent years. T will be zero for years before the event. B_T, therefore, is the parameter estimate of time after the event.

B_D is the parameter estimate of the distance-decay variable and e_t is the error associated with estimating the dependent variable in time period, *t*.

The coefficient of determination (R^2) indicates the proportion of the variation in the dependent variable that is explained by the model. The R^2 value for the simple linear model with demographic variables is 0.538, which is higher than the R^2 value of the original model, 0.465. Similarly, the R^2 values for the corresponding models with interaction and autoregressive terms are higher than the original models. This research adopted the autoregressive model with interaction terms that recorded a R^2 value of 0.604. When demographic variables are included in this model, the R^2 value improves significantly to 0.697. Therefore, based on the preliminary analysis, the model with demographic variables accounts for 70% of the variation in *y*, and the sum of squares unexplained by the model (SSE) is 30%.

Table 9.2 – Model Fit Statistics of the Original and Expanded Versions of the Regression Analysis

Description	**Original Models**					**Models including Demographic Variables**				
	R^2	**AIC**	**F**	**Sig.**	**D-W**	**R^2**	**AIC**	**F**	**Sig.**	**D-W**
Simple Linear regression: 7 LQ variables TIME_K; TIME_O; TIME_K_SQ SPILL_DIST_DECAY	0.465	2758.62	52.19	.000	1.096	0.538	2673.74	42.31	.000	1.094
With interaction terms: 7 LQ variables; TIME_K; TIME_O; TIME_K_SQ; SPILL_DIST_DECAY; 14 interaction terms	0.524	2707.54	28.51	.000	1.281	0.655	2532.57	25.88	.000	1.427
Autoregressive (AR-1): 7 LQ variables; TIME_K; TIME_O; TIME_K_SQ; SPILL_DIST_DECAY; 14 interaction terms	0.604	2584.70		.000		0.697	2446.93		.000	

The F statistic evaluates the significance of the fit of the regression model and is a test of the null hypothesis, which states that the variability in the dependent variable explained by the independent variables is zero i.e. H0: $R^2 = 0$. F values for the simple linear and interaction models with demographic variables are lower than the original models, but record higher R^2 and lower Akaike Information Criterion (AIC) values. The AIC is another estimate of model fit and is used to compare alternative models - the smaller the value, the closer it is to the actual data (Sakamoto, Ishiguro, and Kitagawa 1986). The autoregressive model records the lowest AIC value of 2446.93 and is selected as the best model to assess the relationships between the dependent and independent variables. The R^2 and AIC values of the autoregressive model indicate that the independent variables significantly account for the variability in the dependent variable and therefore, the null hypothesis is rejected.

The results of the preliminary analysis indicate that including demographic variables can significantly improve the HRLM to address the relationships between the demographic composition of the population and their access to social capital, which is the premise of the first research question. Based on the results of the regression analysis, distance measures for coping ability may be computed using predicted unemployment rate to conduct the risk assessment. The risk assessment addresses the second research question and examines the contribution of coping ability, population density (exposure), and distance from the spill (hazard) to assess how demographics and social capital are inter-related in determining risk associated with environmental disasters. It is expected that changes to the American Community Survey that are currently underway will make time-specific demographic data available at the county level, which will be included in the next stage of the analysis.

9.2.3 County Level Comparison

The fieldtrip to Bay County, Florida and Orleans Parish, Louisiana will be the basis for a county level assessment of hazard risk where the inter-relationships between demographics and social capital can be examined at the local level. The two counties vary significantly in terms of their economic and demographic profiles. The coastal economy in Bay County is composed of tourism and recreation, marine transportation, and marine construction. The tourism sector accounts for ninety percent of all jobs and is linked to other sectors like retail and real estate (NOAA 2011). Most of the economic activity in the county is centered in the Panama City and Panama City Beach area. The economy of Orleans Parish LA is concentrated in the city of New Orleans. Like Bay County, tourism and recreation are the dominant economic sectors in Orleans Parish, but unlike Bay County, the parish also engages in offshore mineral extraction (NOAA 2011).

Differences in the demographic characteristics of the population in the two counties are presented in Table 9.3. The percentage of the White population in Bay County is 66%, which is more than twice that of the White population in Orleans Parish. On the other hand, the percentage of African American in Orleans Parish is 44%, whereas in Bay County, this group comprises only 8% of the total population. The percentage of Hispanic and Asian is marginally higher in Orleans Parish compared to Bay County. In terms of the age structure, both counties have a similar proportion of the population below 5 years, while Bay County has a higher percentage of people above the age of 65 compared to Orleans Parish. The differences in the demographic profile of the counties provide an opportunity to explore how race and age determine access to social capital in specific locations and how these relationships affect the coping ability of different groups in the context of hazard events.

Table 9.3 – Demographic Profiles of Bay County, Florida and Orleans Parish, Louisiana

County	Total Population	Percent White	Percent Black	Percent Hispanic	Percent American Indian	Percent Asian	Percent below 5 years	Percent above 65 years
Bay County, FL	168,852	66%	8%	3%	< 1%	2%	6%	15%
Orleans Parish, LA	343,829	30%	44%	4%	< 1%	4%	6%	10%

9.3 Concluding Remarks

The proposed hazard-risk-location-model (HRLM) provides a framework to assess the patterns of risk across a selected region through a re-specification of the risk equation. The model identifies hazard risk as a function of the hazard, exposure, and coping ability. The conceptual framework of the model recognizes coping ability and social vulnerability as countervailing forces that determine peoples' risk of being negatively impacted by a hazard event. It is concerned with livelihood issues that determine access to resources and with social capital that provides people the means and the connectivity to sustain their livelihoods.

Operationalizing the HRLM is undertaken in two stages. First, regression is used to evaluate causal relationships between variables representing social capital and unemployment rate, which functions as a proxy for coping ability. By focusing on causality, the HRLM differs from existing models that use factor analysis to develop additive and multiplicative risk assessments. Second, the threshold analysis evaluates variations in unemployment rate, population density, and proximity to the hazard and how these variations contribute to the risk

factor. Building on the principles of data envelopment, the threshold analysis evaluates each observation's attribute values on these criteria and positions them along a continuum.

The HRLM is applied to a case study that evaluates the social and economic impacts of the Deep Water Horizon oil spill in Gulf Coast counties. The model uses time-related spatial data to analyze temporal and spatial variations in the relationship between social capital and unemployment rates across the region. The use of spatiotemporal modeling to assess hazard risk is still at its infancy and existing models are limited in their application due to stringent specifications that favor large datasets. Since the DWH oil spill affected a relatively small geographical area comprising 56 counties, the application of a spatiotemporal model would produce results with a high margin of error and cause problems in interpretation. The framework of the HRLM provides a mechanism to evaluate the impacts of hazard events that occur within a relatively small geographical area. While the HRLM is limited in capturing all of the inter-relationships within the socio-ecological context of hazard events, it provides some valuable insights into developing improved frameworks for vulnerability and risk assessments in the future.

References

Adams, W. M., and M. J. Mortimore. 1997. Agricultural intensification and flexibility in the Nigerian Sahel. *The Geographical Journal* 163 (2): 150 – 60.

Adger, W. N. 2000. Social and ecological resilience: Are they related? *Progress in Human Geography* 24 (3): 347 – 64.

Adger, W.N., N. Brooks, G. Bentham, M. Agnew, and S. Eriksen. 2004. New indicators of vulnerability and adaptive capacity. In *Tyndall Centre Technical Report 7*. Norwich, United Kingdom: Tyndall Centre for Climate Change Research. http://www.tyndall.ac.uk/content/new-indicators-vulnerability-and-adaptive-capacity (last accessed 11 March 2014).

Adger, W. N. 2006. Vulnerability. *Global Environmental Change* 16 (3): 268 – 81.

Alexander, D. 2000. *Confronting catastrophe: New perspectives on natural disasters*. New York: Oxford University Press.

Allison, P. 2012. *When can you safely ignore multicollinearity?* Statistical Horizons. http://www.statisticalhorizons.com/multicollinearity (last accessed 18 July 2014).

Anderson, M.B. and P. J. Woodrow. 1991. Reducing vulnerability to drought and famine: Developmental approaches to relief. *Disasters* 15 (1): 43 – 54.

Armstrong, M., G. Chetboun, and P. Hubert. 1993. *Kriging the rainfall in Lesotho.* In *Geostatistics Tróia '92, Vol. 2*, ed. A. Soares, 661 – 72. Dordrecht, The Netherlands: Kluwer Academic Publisher.

Atkinson-Palombo, C., and M. Gebremichael. 2012. Creating a north-south learning organization to promote sustainable water resources management in Ethiopia. *Journal of Sustainability Education* 3: Special Issue - The Geography of Sustainability.

Baker, E. J., and D. J. Patton. 1974. Attitudes toward hurricane hazard on the Gulf Coast. In *Natural hazards: Local, national, global,* ed. G. F. White, 30 – 6. New York: Oxford University Press.

Beatley, T. 2009. *Planning for coastal resilience: Best practices for calamitous times*. Washington, DC: Island Press.

Bebbington, A. 1997. Social capital and rural intensification: Local organizations and islands of sustainability in the rural Andes. *The Geographical Journal* 163 (2): 189 – 97.

Bebbington, A. 1999. Capitals and capabilities: A framework for analyzing peasant viability, rural livelihoods and poverty. *World Development* 27 (12): 2021 – 44.

Bebbington, A., L. Dharmawan, E. Fahmi, and S. Guggenheim. 2006. Local capacity, village governance, and the political economy of rural development in Indonesia. *World Development* 34 (11): 1958 – 76.

Beggs, J. J., V. A. Haines, and J. S. Hurlbert. 1996. Situational contingencies surrounding the receipt of informal support. *Social Forces* 75 (1): 201– 22.

Belsley, D. A., E. Kuh, and R. E. Welsch. 1980. *Regression diagnostics: Identifying influential data and sources of collinearity.* New York: John Wiley & Sons.

Bilonick, R.A. 1985. The space-time distribution of sulfate deposition in the northeastern United States. *Atmospheric Environment* 19 (11): 1829 – 45.

Birkenholtz, T. 2009. Irrigated landscapes, produced scarcity, and adaptive social institutions in Rajasthan, India. *Annals of the Association of American Geographers* 99 (1): 118 – 37.

Birkenholtz, T. 2012. Network political ecology: Method and theory in climate change vulnerability and adaptation research. *Progress in Human Geography* 36 (3): 295 – 315.

Birkmann, J. 2006. Measuring vulnerability to promote disaster-resilient societies: Conceptual frameworks and definitions. In *Measuring vulnerability to natural hazards: Towards disaster resilient societies,* ed. J. Birkmann, 9 – 54. Tokyo: United Nations University Press.

Birkmann, J., N. Fernando, and S. Hettige. 2006. Measuring vulnerability in Sri Lanka at the local level. In *Measuring vulnerability to natural hazards: Towards disaster resilient societies,* ed. J. Birkmann, 329 – 56. Tokyo: United Nations University Press.

Birkmann, J. 2007. Risk and vulnerability indicators at different scales: Applicability, usefulness and policy implications. *Environmental Hazards* 7 (1): 20 – 31.

Blaikie, P., T. Cannon, I. Davis, and B. Wisner. 1994. *At risk: Natural hazards, people's vulnerability, and disasters*. London: Routledge.

Bogardi, J., and J. Birkmann. 2004. Vulnerability assessment: The first step towards sustainable risk reduction. In *Disaster and society – from hazard assessment to risk reduction,* eds. D. Malzahn and T. Plapp, 75 – 82. Berlin, Germany: Logos Verlag Berlin.

Bollin C., and R. Hidajat, R. 2006. Community-based risk index: Pilot implementation in Indonesia. In *Measuring vulnerability to natural hazards: Towards disaster resilient societies,* ed. J. Birkmann, 271 – 89. Tokyo: United Nations University Press.

Bourdieu, P., and L. J. D. Wacquant. 1992. *An invitation to reflexive sociology*. Chicago, IL: The University of Chicago Press.

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

Cannon, T. 1994. Vulnerability analysis and the explanation of 'natural' disasters. In *Disasters,development and environment,* ed. A. Varley, 14 – 30. New York: J. Wiley.

Cardona, O. D. 1999. Environmental management and disaster prevention – two related topics: A holistic risk assessment and management approach. In *Natural disaster management,* ed. J. Ingelton, 151 - 3. London: Tudor Rose.

Cardona, O. D. 2001. *Holistic seismic risk estimation using complex dynamic systems.* Techinical University of Catalonia, UPC, Barcelona. http://www.desenredando.org/public/varios/2001/ehrisusd/index.html (last accessed 8 January 2014.

Cardona, O. D. 2004. The need for rethinking the concepts of vulnerability and risk from a holistic perspective: A necessary review and criticism for effective risk management. In *Mapping vulnerability: Disasters, development, & people,* eds. G. Bankoff, G. Frerks, and D. Hilhorst, 37 – 51. London: Earthscan.

Chambers, R., and G. R. Conway. 1991. Sustainable rural livelihoods: Practical concepts for the 21st century. *IDS Discussion Paper 296. Institute of Development Studies.* http://opendocs.ids.ac.uk/opendocs/bitstream/handle/123456789/775/Dp296.pdf?sequence=1 (last accessed 12 December 2013).

Chan, N. W., and D. J. Parker. 1996. Response to dynamic flood hazard factors in peninsular Malaysia. *The Geographical Journal* 162 (3): 313 – 25.

Charlton, M., and A. S. Fotheringham. 2009. *Geographically weighted regression*. Maynooth, Co Kildare, Ireland: National University of Ireland.

Clark, G. E., S. C. Moser, S. J. Ratick, K. Dow, W. B. Meyer, S. Emani, W. Jin, J. X. Kasperson, R. E. Kasperson, and H. E. Schwarz. 1998. Assessing the vulnerability of coastal communities to extreme storms: The case of Revere, MA., USA. *Mitigation and Adaptation Strategies for Global Change* 3 (1): 59 – 82.

Cleveland, C. J. 2010. *Deepwater horizon oil spill*. The Encyclopedia of Earth. http://www.eoearth.org/view/article/161185/ (last accessed 23 July 2014).

Cohen, J. 1988. *Statistical power analysis for the behavioral sciences.* New Jersey: Lawrence Erlbaum Associates.

Cohen, J., P. Cohen, S. G. West, and L. S. Aikin. 2003. *Applied multiple regression/ correlation analysis for the behavioral sciences.* New York: Taylor and Francis.

Coleman, J. 1990. *Foundations of social theory*. Cambridge, MA: Harvard University Press.

Comfort, L., B. Wisner, S. Cutter, R. Pulwarty, K. Hewitt, A. Oliver-Smith, J. Wiener, M. Fordham, W. Peacock, and F. Krimgold. 1999. Reframing disaster policy: The global evolution of vulnerable communities. *Environmental Hazards* 1 (1): 39 – 44.

Conchedda, B., E. F. Lambin, and P. Mayaux. 2011. Between land and sea: Livelihoods and environmental changes in mangrove ecosystems of Senegal. *Annals of the Association of American Geographers* 101 (6): 1259 – 84.

Crespo, R., A. S. Fotheringham, and M. E. Charlton. 2007. Application of geographically weighted regression to a 19-year set of house price data in London to calibrate local hedonic price models. *Proceedings of the 9th International Conference on Geocomputation 2007.* Maynooth, Ireland: National University of Ireland. www.geocomputation.org/2007/5C-Spatial_Statistics_2_GWR/5C3.pdf (last accessed 13 June 2014).

Cronin, J. 2005. Rebuilding livelihoods after the tsunami. *British Broadcasting Corporation (BBC).* http://news.bbc.co.uk/2/hi/business/4528332.stm (last accessed 15 February 2014).

Cutter, S. L., and W. D. Solecki. 1989. The national pattern of airborne toxic releases. *Professional Geographer* 41 (2): 149 – 61.

Cutter, S. L. 1996. Vulnerability to environmental hazards. *Progress in Human Geography* 20 (4): 529 – 39.

Cutter, S. L., J. T. Mitchell, and M. S. Scott, M. S. 2000. Revealing the vulnerability of people and places: A case study of Georgetown County, South Carolina. *Annals of the Association of American Geographers* 90 (4): 713 – 37.

Cutter, S. L., B. J. Boruff, and W. L. Shirley. 2003. Social vulnerability to environmental hazards. *Social Science Quarterly* 84 (2): 242 – 61.

Cutter, S. L., L. Barnes, M. Berry, C. Burton, E. Evans, E. Tate, and J. Webb. 2008. A place-based model for understanding community resilience to natural disasters. *Global Environmental Change* 18 (4): 598 – 606.

Davies, J., and R. Bennett. 2007. Livelihood adaptation to risk: Constraints and opportunities for pastoral development in Ethiopia's Afar region. *Journal of Development Studies* 43 (3): 490 – 511.

Degg, M. R., and D. K. Chester. 2005. Seismic and volcanic hazards in Peru: Changing attitudes to disaster mitigation. *The Geographical Journal* 171 (2): 125 – 45.

Dow, K. 1992. Exploring differences in our common future(s): The meaning of vulnerability to global environmental change. *Geoforum* 23 (3): 417 – 36.

Durbin, J. 1969. Test for serial correlation in regression analysis based on the periodogram of least-squares residuals. *Biometrika* 56 (1): 1 – 15.

Eakin, H. 2005. Institutional change, climate risk, and rural vulnerability: Cases from Central Mexico. *World Development* 33 (11): 1923 – 38.

Easton, D. 1965. *A systems analysis of political life*. New York: John Wiley and Sons.

Echánove, F., and C. Steffen. 2005. Agribusiness and farmers in Mexico: The importance of contractual relations. *The Geographical Journal* 171 (2): 166 – 76.

Edwards, B., and M. Foley. 1997. Social capital and the political economy of our discontent. *American Behavioral Scientist* 40 (5): 669 – 78.

Environmental Systems Research Institute (ESRI). 2012. How spatial autocorrelation (global moran's I) works. ArcGIS Resource Center. http://help.arcgis.com/en/arcgisdesktop/10.0/help/index.html#//005p0000000t000000 (last accessed 24 March 2014).

Eriksen, S., K. Brown, and P. M. Kelly. 2005. The dynamics of vulnerability: Locating coping strategies in Kenya and Tanzania. *The Geographical Journal* 171 (4): 287 – 305.

Ford, J. D., B. Smith, J. Wandel, M. Allurut, K. Shappa, H. Ittusarjuat, and K. Qrunnut. 2008. Climate change in the Arctic: Current and future vulnerability in two Inuit communities in Canada. *The Geographical Journal* 174 (1): 45 – 62.

Fotheringham, A. S., C. Brunsdon, and M. Charlton. 2002. *Geographically weighted regression: The analysis of spatially varying relationships*. West Sussex, England: John Wiley and Sons.

Freudenburg, W. R. 1999. Tools for understanding the socioeconomic and political settings for environmental decision making. In *Tools to aid environmental decision making*, ed. V. H. Dale and M. R. English, 62 – 93. New York: Springer-Verlag.

Gordon, R. J. 1987. *Macroeconomics*. Glenview, IL: Scott, Foresman and Company.

Granovetter, M. 1985. Economic action and social structure: The problem of embeddedness. *American Journal of Sociology* 91(3): 481 – 510.

Hamilton, J. D. 1994. *Time series analysis*. Princeton, New Jersey: Princeton University Press

Harding, D. M., and D. J. Parker. 1974. Flood hazard at Shrewsbury, United Kingdom. In *Natural hazards: Local, national, global,* ed. G. F. White, 43 – 52. New York: Oxford University Press.

Heakal, R. 2014. Economics basics: Elasticity. *Investopedia.* http://www.investopedia.com/university/economics/economics4.asp (last accessed 12 November 2014).

Hirschman, A. 1970. *Exit, voice, and loyalty: Responses to decline in firms, organizations, and states*. Cambridge, MA: Harvard University Press.

Holling, C. S., L. H. Gunderson, and D. Ludwig. 2002. In quest of a theory of adaptive change. In *Panarchy: Understanding transformations in human and natural Systems,* eds. L. H. Gunderson and C. S. Holling, 3 – 22. Washington, DC: Island Press.

Holt, L. 2008. Embodied social capital and geographic perspectives: Performing the habitus. *Progress in Human Geography* 32 (2): 227 – 46.

Hoyle, R. H. 1995. *Structural equation modeling: Concepts, issues, and applications.* Thousand Oaks, CA: Sage Publications.

Jaeger, C. C., O. Renn, E. A. Rosa, and T. Webler. 2001. *Risk, uncertainty, and rational action*. London: Earthscan.

Jeffrey, S. E. 1982. The creation of vulnerability to natural disaster: Case studies from the Dominican Republic. *Disasters* 6 (1): 38 – 43.

Jim, C. Y., F. Y. Yang, and L. Wang. 2010. Social-ecological impacts of concurrent reservoir inundation and reforestation in the Three Gorges region of China. *Annals of the Association of American Geographers* 100 (2): 243 – 68.

Kachigan, S. K. 1986. *Statistical analysis: An interdisciplinary introduction to univariate & multivariate methods.* New York: Radius Press.

Kasperson, R. E., J. X. Kasperson, and K. Dow. 2001. Vulnerability, equity, and global environmental change. In *Global environmental risk,* eds. J. X. Kasperson and R. E. Kasperson, 247 – 72. United Kingdom: The United Nations University.

Kasperson, J. X., R. E. Kasperson, N. Pidgeon, and P. Slovic. 2005. The social amplification of risk: Assessing 15 years of research and theory. In *Social contours of risk,* eds. J. X. Kasperson and R. E. Kasperson, 202 – 29. London: Earthscan.

Kates, R. W., C. Hohenemser, and J. X. Kasperson. 1985. *Perilous progress: Managing the hazards of technology*. Boulder, CO: Westview Press.

Klein, R. J. T., M. J. Smit, H. Goosen, and C. H. Hulsbergen. 1998. Resilience and vulnerability: Coastal dynamics or Dutch dikes? *The Geographical Journal* 164 (3): 259 – 68.

Kline, R. B. 2011. *Principles and practice of structural equation modeling*. New York: The Guilford Press.

Knox, E.G. 1964. Epidemiology of childhood leukaemia in Northumberland and Durham. *British Journal of Preventive and Social Medicine* 18 (1): 17-24.

Lazarus, N. W. 2014. Re-specifying disaster risk: Concepts, methods, and models. *GeoJournal* 79 (5): 635 – 48.

López-Marrero, T. 2010. An integrative approach to study and promote natural hazards adaptive capacity: A case study of two flood-prone communities in Puerto Rico. *The Geographical Journal* 176 (2): 150 – 63.

Luers, A. L. 2005. The surface of vulnerability: An analytical framework for examining environmental change. *Global Environmental Change* 15 (3): 215 – 23.

Maddala, G. S. 1992. *Introduction to econometrics*. New York: Macmillan Publishing Company.

Mansfield, E. 1986. *Principles of macroeconomics*. New York: W. W. Norton and Company.

Manyena, S. B. 2006. The concept of resilience revisited. *Disasters* 30 (4): 433 – 50.

Mark, B. G., J. Bury, J. M. McKenzie, A. French, and M. Baraer. 2010. Climate change and tropical Andean glacier recession: Evaluating hydrologic changes and livelihood vulnerability in the Cordillera Blanca, Peru. *Annals of the Association of American Geographers* 100 (4): 794 – 805.

Miller, K. J. 1981. The international Karakoram project, 1980: A first report. *The Geographical Journal* 147 (2): 153 – 63.

Miletti, D. 1999. *Disasters by design: A reassessment of natural hazards in the United States*. Washington, DC: Joseph Henry Press.

Mohan, G., and J. Mohan. 2002. Placing social capital. *Progress in Human Geography* 26 (2): 191 – 201.

Molinero, C. M., and D. Woracker. 1996. Data envelopment analysis: A non-mathematical introduction. *OR Insight* 9 (4): 22 – 8.

Moser, C. O. N. 1998. The asset vulnerability framework: Reassessing urban poverty reduction strategies. *World Development* 26 (1): 1 – 19.

Mustafa, D., S. Ahmed, E. Saroch, and H. Bell. 2011. Pinning down vulnerability: From narratives to numbers. *Disasters* 35 (1): 62 – 86.

Mwanukuzi, P. K. 2011. Impact of non-livelihood-based land management on land resources: The case of upland watersheds in Uporoto Mountains, South West Tanzania. *The Geographical Journal* 177(1): 27 – 34.

National Commission on the BP Deepwater Horizon Oil Spill and Offshore Drilling. 2011. Deep water: the Gulf oil disaster and the future of offshore drilling. Report to the President. http://www.oilspillcommission.gov/final-report (last accessed 14 February 2011).

National Conference of State Legislatures (NCSL). 2014. State tax actions: 2013. http://www.ncsl.org/research/fiscal-policy/2013-state-tax-actions.aspx (last accessed 24 March 2014).

National Oceanic and Atmospheric Administration (NOAA). 2006. NOAA fisheries glossary. http://www.st.nmfs.noaa.gov/st4/documents/FishGlossary.pdf (last accessed 10 June 2014).

_______. 2010. Deepwater Horizon oil: characteristics and concerns. http://www.noaa.gov/deepwaterhorizon/publications_factsheets/documents/OilCharacteriOilCh.pdf (last accessed 6 June 2014).

________. 2011. Coastal county snapshots. http://www.csc.noaa.gov/snapshots/ (last accessed 6 June 2014).

________. 2012a. Natural resource damage assessment April 2012: Status update for the Deepwater Horizon oil spill. http://www.gulfspillrestoration.noaa.gov/wp-content/uploads/FINAL_NRDA_StatusUpdate_April2012.pdf (last accessed 7 November 2014).

_________. 2012b. Ocean explorer. http://oceanexplorer.noaa.gov/edu/guide/welcome.html (last accessed 7 November 2014).

_________. 2012c. Ocean explorer. http://oceanexplorer.noaa.gov/explorations/06mexico/background/oil/media/platform_600.html (last accessed 7 November 2014).

_________. 2013. National coastal population report: Population trends from 1970 to 2020. http://stateofthecoast.noaa.gov/features/coastal-population-report.pdf (last accessed 19 September 2014).

National Oceanic Economics Program. 2014. Coastal economy data. http://www.oceaneconomics.org/Market/coastal/coastalEcon.asp (last accessed 23 July 2014).

Nightingale, D. S., and S. A. Wandner. 2011. Informal and nonstandard employment in the United States: Implications for low-income working families. *The Urban Institute.* http://www.urban.org/UploadedPDF/412372-informal-nonstandard-employment-in-us.pdf (accessed 23 July 2014).

NOAA National Marine Fisheries Service. 2009. Fisheries of the United States. http://www.st.nmfs.noaa.gov/Assets/commercial/fus/fus09/fus_2009.pdf (last accessed 6 June 2014).

O'Hare, G. 2001. Hurricane 07B in the Godavari Delta, Andhra Pradesh, India: Vulnerability, mitigation and the spatial impact. *The Geographical Journal* 167 (1): 23 – 38.

O'Hare, G., and S. Rivas. 2005. The landslide hazard and human vulnerability in La Paz City, Bolivia. *The Geographical Journal* 171 (3): 239 – 58.

Olson, M. 1965. *The logic of collective action: Public goods and the theory of groups*. Cambridge, MA: Harvard University Press.

Oluoko-Odingo, A. A. 2011. Vulnerability and adaptation to food insecurity and poverty in Kenya. *Annals of the Association of American Geographers* 101 (1): 1 – 20.

Openshaw, S., and L. Rao. 1995. Algorithms for re-engineering, 1991, census geography. *Environment and Planning A* 27: 425 – 46.

Putnam, R. D. 2000. *Bowling alone: The collapse and revival of American community*. New York: Simon and Schuster.

Randolph, J. 2012. *Environmental land use planning and management.* Washington D. C.: Island Press.

Ratick, S., S. Capoccia, A. Dichter, R. Goble, D. Golding, D. Hattis, and J. Tanguay. 2004. *Determining the vulnerability of populations to mercury.* Worcester, MA: Clark University.

Ratick, S. J., H. Morehouse, and R. K. Klimberg. 2009. Creating an index of vulnerability to severe coastal storms along the north shore of Boston. In *Financial modeling application and data envelopment applications, applications of management science,* eds. K. D. Lawrence and E. Kleinman, 143 – 78. Bingley, United Kingdom: Emerald Group Publishing limited.

Ratick, S. J., and J. P. Osleeb. 2011. Measuring the vulnerability of populations susceptible to lead contamination in the Dominican Republic: Evaluating composite index construction methods. *GeoJournal* doi:10.1007/s10708-011-9414-x.

Rygel, L., D. O'Sullivan., and B. Yarnal. 2006. A method for constructing a social vulnerability index: An application to hurricane storm surges in a developed country. *Mitigation and Adaptation Strategies for Global Change* 11 (3): 741-764.

Sakamoto, Y., M. Ishiguro, and G. Kitagawa. 1986. *Akaike Information Criterion Statistics*. Dordrecht, The Netherlands: D. Reidel Publishing Company.

SAS Institute Inc. 2014a. Regression with autocorrelated errors. http://support.sas.com/documentation/cdl/en/etsug/63348/HTML/default/viewer.htm#etsug_autoreg_sect003.htm (last accessed 16 July 2014).

______. 2014b. Time trend curves. http://support.sas.com/documentation/cdl/en/etsug/66840/HTML/default/viewer.htm#etsug_tffordet_sect039.htm (last accessed 16 July 2014).

_____. 2014c. Intervention models and interrupted time series. http://support.sas.com/documentation/cdl/en/etsug/66840/HTML/default/viewer.htm#etsug_arima_gettingstarted31.htm (last accessed 24 July 2014).

Savin, N. E. and K. J. White. 1977. The Durbin-Watson test for serial correlation with extreme sample sizes or many regressors. *Econometrica* 45 (8): 1989 – 96.

Sen, A. 1981. *Poverty and famines: An essay on entitlement and deprivation.* New York: Oxford University Press.

Sen, A. 1984. *Resources, values, and development.* Oxford, United Kingdom: Basil Blackwell.

Sen, A. 1987. *The standard of living. The Tanner Lectures.* Cambridge, MA: Cambridge University Press.

Scheffer, M., F. Westley, W. A. Brock, and M. Holmgren. 2002. Dynamic interaction of societies and ecosystems – linking theories from ecology, economy, and sociology. In *Panarchy: Understanding transformations in human and natural systems,* eds. L. H. Gunderson and C. S. Holling, 195 – 239. Washington, DC: Island Press.

Schleifstein, M. 2013. Oil spill trial begins for BP, Transocean, other companies: Blame game marks the first day. *The Times-Picayune.* http://www.nola.com/news/gulf-oil-spill/index.ssf/2013/02/oil_spill_trial_begins_for_bp.html (last accessed 10 June 2014).

Singhal, A., and D. E. Seborg. 2005. Clustering multivariate time-series data. *Journal of Chemometrics* 19 (8): 427–438.

Sjöberg, L. 1987. The study of risk in social systems: An anthropological perspective. In *Risk and Society*, ed. L. Sjöberg, 239 – 43. London: Allen and Unwin.

Smith, K. 1992. *Environmental hazards: Assessing risk and reducing disaster.* London: Routledge.

State of Alaska. 1990. Spill: The wreck of the exxon valdez. Final Report, Alaska Oil Spill Commission. *Exxon Valdez Oil Spill Trustee Council.* http://www.evostc.state.ak.us/index.cfm?FA=facts.details (last accessed 23 July 2014).

Suhr, D. 2014. Principal component analysis vs. exploratory factor analysis. http://www2.sas.com/proceedings/sugi30/203-30.pdf (last accessed 7 November 2014).

Susman, P., P. O'Keefe, and B. Wisner. 1983. Global disasters, a radical interpretation. In *Interpretations of calamity from the viewpoint of human ecology*, ed. K. Hewitt, 263 – 83. Australia: Allen and Unwin.

Swedish International Development Cooperation Agency. 2014. Sustainable livelihoods framework. *Advanced Training Program on Humanitarian Action.* http://www.atha.se/thematic-areas/sustainable-livelihoods-framework (last accessed 8 January 2014).

The Urban Conservancy. 2012. *My heart is tied up in this place: Impacts of the Deepwater Horizon oil spill on Plaquemines Parish's local businesses.* New Orleans, LA: The Urban Conservancy.

Tobin, G. A., and B. E. Montz. 1997. *Natural hazards: Explanation and integration.* New York: The Guilford Press.

Turner, B.L., R. E. Kasperson, P. A. Matson, J. J. McCarthy, R. W. Corell, L. Christensen, N. Eckley, J. X. Kasperson, L. Luers, M. L. Martello, C. Polsky, A. Pulsipher, and A. Schiller. 2003. A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences, U.S.A*, 100: 8074-8079.

United States Bureau of Labor Statistics (BLS). 2008. Local area unemployment statistics http://www.bls.gov/lau/ (last accessed 15 November 2014).

______. 2009. Gulf coast leisure and hospitality employment and wages. http://www.bls.gov/cew/gulf_coast_leisure_hospitality.htm (last accessed 6 June 2014).

______. 2013. Location quotient calculator. http://www.bls.gov/help/def/lq.htm (last accessed 12 November 2014).

______. 2014. Geographic profile of employment and unemployment, 2013. http://www.bls.gov/opub/gp/laugp.htm (last accessed 15 November 2014).

United States Census Bureau. 2010. Population estimates. http://www.census.gov/popest/data/historical/2000s/index.html (last accessed 6 June 2014).

______. 2011. Population distribution and change: 2000 to 2010. http://www.census.gov/prod/cen2010/briefs/c2010br-01.pdf (last accessed 13 June 2014).

______. 2014a. County business patterns. http://www.census.gov/econ/cbp/ (last accessed 6 June 2014).

______. 2014b. County business patterns. http://www.census.gov/econ/cbp/methodology.htm. http://www.census.gov/econ/cbp/ (last accessed 11 June 2014).

United States Department of Commerce (USDOC). 2010. *Coastal population trends in the United States: 1960 to 2008.* Washington D. C.: U.S. Census Bureau.

University of Delaware. 2014. Time series regression. *Department of Political Science and International Relations*. http://www.udel.edu/htr/Statistics/Notes816/class20.PDF (last accessed 18 July 2014).

Valdivia, C., A. Seth, J. L. Gilles, M. García, E. Jiménez, J. Cusicanqui, F. Navia, and E. Yucra. 2010. Adapting to climate change in Andean ecosystems: Landscapes, capitals, and perceptions shaping rural livelihood strategies and linking knowledge systems. *Annals of the Association of American Geographers* 100 (4): 818 – 34.

Vásquez-León, M., C. West, B. Wolf, J. Moody, and T. Finan. 2002. Vulnerability to climate variability in the farming sector: A case study of groundwater dependent agriculture in southeastern Arizona. *CLIMAS Report CL1-02.* Tucson, AZ: Institute for the Study of Planet Earth. http://climas.arizona.edu/pubs/CL1-02.html (last accessed 30 April 2012).

Waller, M. 2013. New Orleans hits second-highest all-time visitor count, 9.01 million in 2012, tourism officials announce. *The Times-Picayune.* http://www.nola.com/business/index.ssf/2013/03/new_orleans_hits_second-highes.html (last accessed 23 July 2014).

Waple, A. 2005. Hurricane Katrina. Asheville, NC: NOAA National Climatic Data Center. http://www.ncdc.noaa.gov/extremeevents/specialreports/Hurricane-Katrina.pdf (last accessed 13 June 2014).

Watts, M.J., and H-G Bohle. 1993. The space of vulnerability: The causal structure of hunger and famine. *Progress in Human Geography* 17 (1): 43 – 67.

White, G. F. 1945. *Human adjustment to floods*. Chicago, IL: University of Chicago.

White, G.F., W. C. Calef, J. W. Hudson, H. M. Mayer, J. R. Sheaffer, and D. J. Volk. 1958. *Changes in urban occupance of flood plains in the United States*. Chicago, IL: University of Chicago Press.

White, G. F. 1964. *Choice of adjustment to floods*. Chicago, IL: University of Chicago.

White, G. F. 1974. Natural hazards research: Concepts, methods, and policy implications. In *Natural hazards: Local, national, global,* ed. G. F. White, 3 – 16. New York: Oxford University Press.

Whyte, A. V. and I. Burton. 1980 *Environmental risk assessment*. Chichester, United Kingdom: John Wiley and Sons.

Wilbanks, T. J., and R. W. Kates. 2010. Beyond adapting to climate change: Embedding adaptation in responses to multiple threats and stresses. *Annals of the Association of American Geographers* 100 (4): 719 – 28.

Winn, P. 2012. Tsunami lessons learned. *Global Post*. http://www.globalpost.com/dispatch/news/regions/asia-pacific/indonesia/120203/tsunami-lessons-japan (last accessed 15 February 2014).

Wisner, B., P. O'Keefe, and K. Westgate. 1977. Global systems and local disasters: The untapped power of peoples' science. *Disasters* 1 (1): 47 – 57.

Wisner, B. 1993. Disaster vulnerability: Scale, power, and daily life. *GeoJournal* 30 (2): 127 – 40.

Wisner, B., P. Blaikie, T. Cannon, and I. Davis. 2004. *At risk: Natural hazards, people's vulnerability and disasters.* London: Routledge.

Woolcock, M. 1998. Social capital and economic development: Toward a theoretical synthesis and policy framework. *Theory and Society* 27 (2): 151 – 208.

World Commission on Environment and Development (WCED). 1987. *Food 2000: Global policies for sustainable agriculture, a report of the advisory panel on food security, agriculture, forestry, and environment to the World Commission on Environment and Development.* London: Zed Books Ltd.

World Wildlife Fund (WWF). 2009. Lessons not learned: 20 years after the Exxon Valdez disaster little has changed in how we respond to oil spills in the Arctic. https://wwf.fi/mediabank/983.pdf (last accessed 23 July 2014).

Wu, S.Y., B. Yarnal, and A. Fisher. 2002. Vulnerability of coastal communities to sea-level rise: A case study of Cape May county, New Jersey, USA. *Climate Research* 22 (3): 255–270.

Yu, D. 2010. Exploring spatiotemporally varying regressed relationships: The geographically weighted panel regression analysis. In *The international archives of the photogrammetry, remote sensing and spatial information sciences, Vol. 38, Part II,* eds. E. Guilbert, B. Lees, and Y. Leung, 134 – 9. The Netherlands: The International Society for Photogrammetry and Remote Sensing.

Zheng, J., C. Atkinson-Palombo, C. McCahill, R. O'Hara, and N. W. Garrick. 2011. Quantifying the economic domain of transportation sustainability. *Transportation Research Record: Journal of the Transportation Research Board* 2242: 19 – 28.