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A COMPREHENSIVE DISASTER RISK INDEX FOR THE UNITED STATES

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ABSTRACT

Risks to life, property, infrastructure and even environmental security emanate from a variety of hazard sources. Key to reducing this risk is the ability to measure it and present it decision-makers and stakeholders in a meaningful and understandable way. Currently, there exist no comprehensive hazard risk indices for the United States that have the ability to capture and convey a contemporary conceptualization of risk to hazards. Such an index, the World Risk Index, exists at the global level. The World Risk Index serves as an analog for further research on risk at various scales.

The purpose of this dissertation is to facilitate an increased awareness of risk and the different factors that contribute to it and to provide a method for easily assessing risk at subnational scales. The following broad research questions frame this work:

a) Can the World Risk Index be customized to a subnational scale in the United States? Which indicators are appropriate for use at the state and county level in the United States?

b) Does the disaggregation of disaster risk to state and county scales provide more detailed understanding of the spatial distribution of risks and the components of risk?

c) How does the risk assessment produced by a top-down approach compare to other US risk assessments at the county scale?

To answer these questions, this dissertation is focused on the development of a risk index, the United States Disaster Risk Index (USDRI), tailored to assess risk

at various scales. The USDRI is a proof of concept, and uses the methodology and indicators of the aforementioned World Risk Index to establish a baseline for evaluating risk at the state and county level. The validity of the index is examined through exploratory spatial statistical analysis. The results are also compared to loss data in order to assess whether the USDRI explains variability in loss. In addition, the USDRI and its components are compared to existing indices to determine similarities and differences.

The results indicate that the USDRI provides new insight into risk at the state and county scale in the US. The ability to quickly tailor the index to various hazards of interest – to include potential hazards such as sea-level rise - proves to be one of its strongpoints. The USDRI, with some modification to the exposure component, shows the ability to explain variation in loss, especially at the state level. When compared to existing indices, USDRI risk and vulnerability show many similarities but also some important differences. For example, both the USDRI vulnerability component and the established Social Vulnerability Index show clusters of lower vulnerability in the Northeast US, but the USDRI shows large clusters of vulnerability in the Midwest that the Social Vulnerability Index does not. When the lessons learned are taken into consideration, the USDRI is successful in providing a baseline for the future evaluation of risk at the subnational level.

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LIST OF ABBREVIATIONS

ACS	American Community Survey
ALMI	Anselin Local Moran's I
CRED	Centre for Research on the Epidemiology of Disasters
CReSIS	Center for Remote Sensing of Ice Sheets
DRI	Disaster Risk Index
EM-DAT	Emergency Events Database
FEMA	Federal Emergency Management Agency
GDP	Gross Domestic Product
GIS	Geographic Information System
GI*	Getis-Ord GI*
GRIP	Global Risk Identification Programme
HDRI	Hurricane Disaster Risk Index
HVRI	Hazards and Vulnerability Research Institute
IBTrACS	International Best Track Archive for Climate Stewardship
IDB	Inter-American Development Bank
IHAT	Integrated Hazard Assessment Tool
IPCC	Intergovernmental Panel on Climate Change
MM	Modified Mercalli

NATHAN	Natural Hazards Assessment Network
NCDC	National Climatic Data Center
NOAA	National Oceanic and Atmospheric Administration
PREVIEW	Project for Risk Evaluation, Vulnerability, Information and Early Warning
SC	South Carolina
SHELDUS	Spatial Hazards Events and Losses Database for the United States
SIERA	Systematic Inventory for Evaluation and Risk Assessment
SoVI	Social Vulnerability Index
SPI	Standardized Precipitation Index
UN	United Nations
UNISDR	United Nations International Strategy for Disaster Reduction
UNDP	United Nations Development Programme
UNEP/GRID	United Nations Environmental Programme/Global Resource Information Database
USDRI	United States Disaster Risk Index
USGS	United States Geological Survey
WRI	World Risk Index

CHAPTER 1: INTRODUCTION

"We cannot eliminate disasters, but can mitigate the risk. We can lessen the damage. We can save more lives. Disasters caused by natural hazards are taking a heavy toll on communities everywhere — in countries rich and poor. They are outpacing our ability to respond."

UN Secretary-General Ban Ki-moon (2011)

1.1 Measuring disaster risk: establishing a baseline for progress

Indonesian President Dr. Susilo Bambang Yudhoyono recently stated that "natural disasters in all…forms have been the greatest threats to our national security and public well-being" (Yudhoyono 2012). Yudhoyono's remarks underscore the increasing recognition that natural disasters not only represent a threat to life and property but can also potentially impact state cohesiveness and function. High-impact natural hazards can cause disasters that threaten the status quo, especially in already unstable countries. These "fragile states" also suffer inordinately from climate change (Hazma and Cordena, 2012). In the extreme, natural disasters could potentially serve as triggering events for state failure (Hales and Miller 2010).

In a contemporary context, national security can be defined as "the measurable state of the capability of a nation to overcome the multi-dimensional threats to the apparent well-being of its people and its survival as a nation-state at any given time…" (Paleri 2008:52). Historically, national security was framed mainly in a military context, wherein the main idea was to protect the state from the military aggression of other states. The concept of national security has evolved, with significant debate, to recognize a variety of non-military threats to state survival, including economic, energy, and environmental threats, among others (Romm 1993).

Environmental security, put simply, examines the threats posed by environmental events at scales ranging from individual to global. Although environmental threats have existed throughout history, it was only recently that the concept of looking at human and state security through an environmental lens gained importance. Beginning in the late 1970s, scholars began to explore the notion that security could be threatened by more than military power (Brown 1977; Ullmann 1983). Since that time, a variety of approaches to environmental security have developed. These include initial efforts to place importance on the environment, the relationship between environmental concerns and conflict, the effect that conflict and militarization has on the environment, and finally, the connection between the environment and human security (Khagram et al. 2003). Sources of insecurity based on environmental concerns can include: access to and control of natural resources; the inability of systems to adapt to degrading resources, ecosystem change, natural disasters, or disease; and, environmental crime (Jasparro 2009). From the geographic perspective comes the recognition that environmental issues are complex, exist at multiple scales and across boundaries, and are not easily addressed at the international level (Wood et al. 1999). Other geographers have explored more specific topics within environmental security, such as the link between armed conflict and natural resources (LeBillion 2001). Geographer Simon Dalby has written extensively on environmental security (Dalby 2002) and critiqued approaches to the topic (Dalby 2004). Importantly, Dalby notes that new insights have shifted emphasis in the environmental security realm from topics like environmental degradation to human security and vulnerability (Dalby 2008).

Although there is a robust literature concerning environmental security, it tends to focus on large scale, slow onset issues such as resource scarcity (Homer-Dixon 1994; Kahl 2006) or, more broadly, climate change (Schubert et al. 2008). Less common are examinations of disasters as they relate to security. However, recent disasters have shown the need to examine their implications for security at multiple scales. The 2010 earthquake in Haiti caused the breakdown of an already weak state security structure (Bolton 2011). The effects of disasters may be exacerbated (i.e. the scale at which they cause insecurity increases) when they occur in less-developed countries, but developed countries also have vulnerabilities that disasters can expose. For instance, Hurricane Katrina in 2005 and the 2011 Japan earthquake and tsunami both showed that even in developed countries, the impact of natural disasters can be far reaching and, importantly, disproportionately impact vulnerable segments of a population (Futamura et al. 2011).

Underlying the concept of natural disasters and security is the inherent vulnerability present in populations that are – or could be – impacted by disasters. Recent research avenues seek to better explain the true nature of natural hazards, their effects on the human landscape, and the factors that turn natural hazards into disasters. For instance, the idea of applying the concept of resilience to natural hazards (Mileti 1999) led to efforts to develop indicators and measure the disaster resilience of places (Cutter et al. 2008). The idea that social inequality contributes to disaster (O'Keefe et al. 1976) has led to attempts to identify the causes of vulnerability (Blaikie et al. 1994) and measure social vulnerability (Cutter et al. 2003). These and other research approaches have led to the notion that disasters and disaster risk are ongoing problems rather than stand-alone events, and that human vulnerability is a central concern in the development of disaster policy (Comfort et al. 1999). These forays into the human side of natural hazards complement a robust understanding of the physical nature of hazards.

Although the understanding of vulnerability to natural disasters has greatly increased, the ability to effectively identify and measure disaster risk and apply this knowledge toward disaster risk reduction – and ostensibly contribute to better state and environmental security - is both nascent and lacking (Birkmann 2007). There have been a number of recent attempts to index disaster risk with an included vulnerability component. Most are focused on the global or regional scales; less attention has been paid to subnational scales. Even those studies that deal with individual states tend to focus on less-developed states. For the United States, although there are various risk assessments (e.g. state hazard mitigation plans), there is currently no comprehensive disaster risk index that captures contemporary understandings of risk and vulnerability at the state or county level. Such an index potentially has a variety of applications. For instance, it would provide a common frame of reference and allow for comparison of hazards, vulnerability, and risk between states and counties. This could enhance existing risk assessments by providing the comprehensive knowledge of vulnerability and risk to hazards required for emplacement of the appropriate mitigation measures and infrastructure. The multi-hazard approach of the WRI encourages risk-reduction measures that deal with more than one hazard, as opposed to reducing the risk of one hazard at the possible expense of higher risk to others (Cutter et al. 2000). More broadly, the index could be useful in assessing how well states, counties, and the US as a whole are progressing in the reduction of risk and vulnerability. One specific example of a direct contribution of a national-level risk index is to help the US meet its goals under the Hyogo Framework for Action, a 2005 plan designed to reduce disaster risk. One of the benchmarks called for in the framework is the presence of a national level risk index, something the US does not currently have.

Although there is currently no comprehensive, contemporary disaster risk index for the United States, such indices do exist at the global and regional scale. Of particular import to this study is the UN's World Risk Index (WRI). The WRI is an ambitious effort to quantify the likelihood that a country will be affected by a disaster, with the stated purpose of sensitizing the public and policymakers to disaster risk. The WRI recognizes that disaster risk is influenced by both internal (structure, process, and framework) and external (natural events and climate change) factors, highlighting the idea that there are multiple ways to reduce risk.

The WRI's indicators are found in four modular components: exposure, which accounts for the likelihood that a country will be affected by a natural hazard; susceptibility, which considers aspects such as infrastructure and economy; coping capacities, which account for indicators such as preparedness, medical services, and societal aspects; and adaptive capacities, which include education, investment, and environmental status. The WRI creators note that most global risk indices are focused on exposure; so in their index they attempt to bridge the physical-human gap at the global level that this dissertation seeks to bridge at the US national level (ADW 2012a).

1.2 Research objectives

In order to establish a baseline for understanding and acting to reduce contemporary risk at the subnational scale, it is imperative that a method for assessing that risk exists. Thus the purpose of this dissertation is to create and evaluate a disaster risk index for the United States at two administrative scales, states and by counties for a single state, with the objective of providing an easily understandable and replicable starting point for the assessment of risk at local scales. The following research questions inform this dissertation:

a) Can the World Risk Index be customized to a subnational scale in the United States? Which indicators are appropriate for use at the state level in the United States?

b) Does the disaggregation of disaster risk to 1) state and 2) county scales provide more detailed understanding of the spatial distribution of risks and the components of risk? Or, given the availability, quality, and resolution of data do the drivers of disaster risk at the subnational level merely mirror the extant pattern at the national scale?

c) How does the risk assessment produced by a top-down approach compare to other US risk assessments at the county scale? What unique value or insights can be gained from using a top down approach?

1.3 Dissertation structure

This document captures the creation and evaluation of a disaster risk index at the state and county levels in the US. Chapter Two summarizes the contemporary concept of risk as it is presented in this dissertation, and includes discussions of the four components of the USDRI: exposure, susceptibility, coping capacity, and adaptive capacity. The chapter also includes an assessment of various other methods to assess disaster risk, as well as a section on index construction.

The central focus of this work is found in Chapters Three, Four, and Five. Chapter 3 breaks down, in detail, the construction of the exposure component of the USDRI, while Chapter 4 details the same for the vulnerability component. For each, to include each subcomponent of vulnerability, the variables, weighting, and overall calculation is shown. In addition, each subcomponent is evaluated using exploratory spatial statistical techniques in order to determine the spatial patterns, they express. In Chapter Four, the overall vulnerability component is compared to an existing assessment of vulnerability, the Social Vulnerability

Index (SoVI), in order to assess whether they produce similar patterns of vulnerability at different scales and how well they relate to economic and human losses.

Chapter Five discusses the construction of the overall USDRI from the components detailed in Chapters Three and Four. As with its components, overall risk is explored visually and statistically, to include with exploratory spatial statistics in order to determine patterns and clusters of risk at both scales of analysis. One interesting feature of this chapter highlights the benefit of the modularity of the USDRI by displaying its ability to easily assess risk for individual hazards in addition to the multiple hazards compiled in the exposure component. Finally, the ability of risk at both scales of analysis to explain the variance in loss is compared to the ability of the WRI to explain variance in global losses. This provides a measure of both the efficacy of the USDRI, as well as an assessment of the success of the overall effort to downscale the WRI.

Chapter Six of this dissertation provides a summary of the findings detailed within it. The chapter includes a discussion of the shortcomings of and recommendations for improving future iterations of the index that were noted during its construction. Additionally, the final chapter explores the potential research avenues generated by this work.

CHAPTER 2: LITERATURE REVIEW

2.1 Overview

This literature review shows that in general there is both a lack of and a need for a comprehensive national disaster risk index in the US. Losses from natural hazards in the United States continue to increase. According to the University of South Carolina's Hazards and Vulnerability Research Institute, five of the top ten years for annual losses have occurred since 2002. The last year on record, 2012, saw losses of $38.6 billion ($2012 US), the third highest annual total loss ever in the US (HVRI 2014). Slowing the increasing trend in losses requires a concerted effort to decrease vulnerability and mitigate against the effects of future hazards (Gall et al. 2011). Typically, the focus of disaster risk management is short-term, concentrating on recovery immediately after an event (Cutter 2013). A key initial step in the effort to lessen the cost and other impacts of hazards and reduce overall risk over longer time frames is the ability to visualize hazard exposure and determine the factors that make populations vulnerable. The USDRI provides a new way of conceptualizing, identifying, and understanding disaster risk in the US and could help mitigate and manage said risk by incorporating current research on the concepts of vulnerability, exposure, and risk.

This chapter provides an overview of risk, exposure, vulnerability and its subcomponents, and previous attempts to describe or quantify risk. As such, this research draws from literature on natural hazards, natural hazards risk assessment, and vulnerability. All of the concepts central to creating and interpreting the USDRI have evolved over time. In particular, the definition of risk has and continues to take many forms. The World Risk Index takes a comprehensive approach to risk, defining it as the product of two main components, exposure and vulnerability. Vulnerability is further broken down into three subcomponents: susceptibility, coping capacity, and adaptive capacity. This approach provides the theoretical background for this dissertation, as well as the construct and tools needed to assess risk at the subnational scale.

2.2 Conceptual underpinnings: hazard, risk, and vulnerability

Geographer Harlan Barrow's 1923 article, "Geography as Human Ecology" is a seminal work in hazard studies. Barrows, attempting to carve out an academic and theoretical niche for geography, proposed that human ecology should be unique to it and that the discipline should be mainly concerned with the relationship between the environment and human activity (NRC 2006). Barrows understood that humans were influenced, but not governed by, the environment (Barrows 1923). Although it would take time to grow and mature, Barrows planted the seeds for the notion that aspects of the human condition caused humans to be predisposed – vulnerable – to disasters.

The work of Barrows and the influence of and interest in large disasters began to bring hazards and disaster research into focus (NRC 2006a). Early research in disasters came mainly from sociology, while hazards were the purview of geographers. However, the increasing realization of the complexity of hazards and disasters has lessened the distinction between the two; a wide variety of disciplines now inform each.

Numerous current definitions exist for the concepts of hazard and natural disaster. Broadly defined, a hazard is a threat – arising from the interaction between social, technological, and natural systems - to people and/or the things they value. The general concept of a hazard includes the probability of the event happening, as well as impact of the event on people or places (Cutter 2001b). Natural disasters occur when the impacts or effects of a natural hazard lead to increased mortality, illness, or injury and destroys/disrupts livelihoods to such a degree that it is perceived as exceptional and requiring outside help for recovery (Cannon 1994). Contemporary definitions of both hazard and disaster are presented in the 2012 report by the Intergovernmental Panel on Climate Change (IPCC), entitled *Managing the Risks of Extreme Events and Natural Disasters to Advance Climate Change Adaptation* or *SREX:*

> **Hazard:** The potential occurrence of a natural or human-induced physical event that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, and environmental resources.

Disaster: Severe alterations in the normal functioning of a community or a society due to hazardous physical events interacting with vulnerable social conditions, leading to widespread adverse human, material, economic, or environmental effects that require immediate emergency response to satisfy critical human needs and that may require external support for recovery (IPCC 2012:558-560).

The Oxford Dictionary defines risk as a situation involving exposure to danger. Table 2.1 contains other selected definitions of risk. In general, hazards

Table 2.1: Selected definitions of risk

Source	Definition
(Gunn 1990)	The expected number of lives lost, persons injured, damage to property, and disruption of economic activity due to a particular natural phenomenon, and consequently the product of specific risk and elements at risk
(Godschalk 1991)	The probability that a hazard will occur during a particular time period
(Ansell and Wharton 1992)	Likelihood x Consequence
(Petak and Atkisson 1992)	A function of the probability of the event occurring and the consequences of the event
(Cutter 1993)	The measure of likelihood of occurrence of a hazard
(Lerbinger 1997)	The probability that death, injury, illness, property damage, and other undesirable consequences will stem from a hazard
(Deyle et al. 1998)	The possibility of suffering harm from a hazard
(Schwab et al. 1998)	The potential losses associated with a hazard, defined in terms of expected probability and frequency, exposure, and consequences
(UN ISDR 2004)	The probability of harmful consequences, or expected loss resulting from interactions between natural or human induced hazards and vulnerable conditions.
(DHS 2006)	The combination of the frequency of occurrence, vulnerability, and the consequence of a specified hazardous event
(Dilley et al. 2005)	A function of hazard, exposure, and vulnerability
(Birkmann and Wisner 2006)	A function of vulnerability and hazard (**The WRI uses this definition of risk**)

risk can be thought of as either the risk of occurrence of a hazardous event (event risk) or the risk of a particular outcome from a hazardous event, or outcome risk. Outcome risk includes both the chance of occurrence and the characteristics of a system (Sarewitz et al. 2003).

In general, risk as it relates to hazards and disasters has evolved in concept from the mere probability that a hazard will occur (Godschalk 1991) to incorporate the potential outcomes of a hazard (Burton et al. 1993; Lerbinger 1997) and the underlying socio-economic conditions that highlight vulnerability, or a predisposition to be adversely affected, in the place that hazard occurs. The evolution in the concept of risk has taken it from a primarily physical construct to one that also includes societal aspects. This is in line with the development of hazards research, which has advanced from a focus that was mainly on hazards themselves to one that includes the totality of the setting in which they occur.

Recent definitions of hazard risk are even more comprehensive, including measures that - ostensibly - mitigate or lessen risk, often called coping or adaptive capacities (Birkmann and Wisner 2006). Taking coping and adaptive capacities into consideration underscores the notion that risk is not a static property. Rather, risk is a dynamic system; changes in societal characteristics and capacity – or indeed the physical characteristics of hazards – provide constant feedback to the overall evaluation of risk.

Thus the more modern ideas about risk move the concept from describing the risk of a hazard to describing the risk of a disaster. Wisner, et al. (2004)

describes disaster risk as a function of hazard and vulnerability, with the resultant risk being zero if either of these components is zero (Wolf 2012).

Figure 2.1 depicts the expanding nature of risk over time. The figure shows the evolution of the concept of risk from a relatively simple and straightforward definition based strictly on the hazard (at the bottom of the figure) to much more complex concepts that include human and environmental factors. Risk is depicted with open ended boundaries to account for future evolution of the concept. As the understanding of risk has expanded, so too has the understanding of its component parts like exposure and vulnerability.

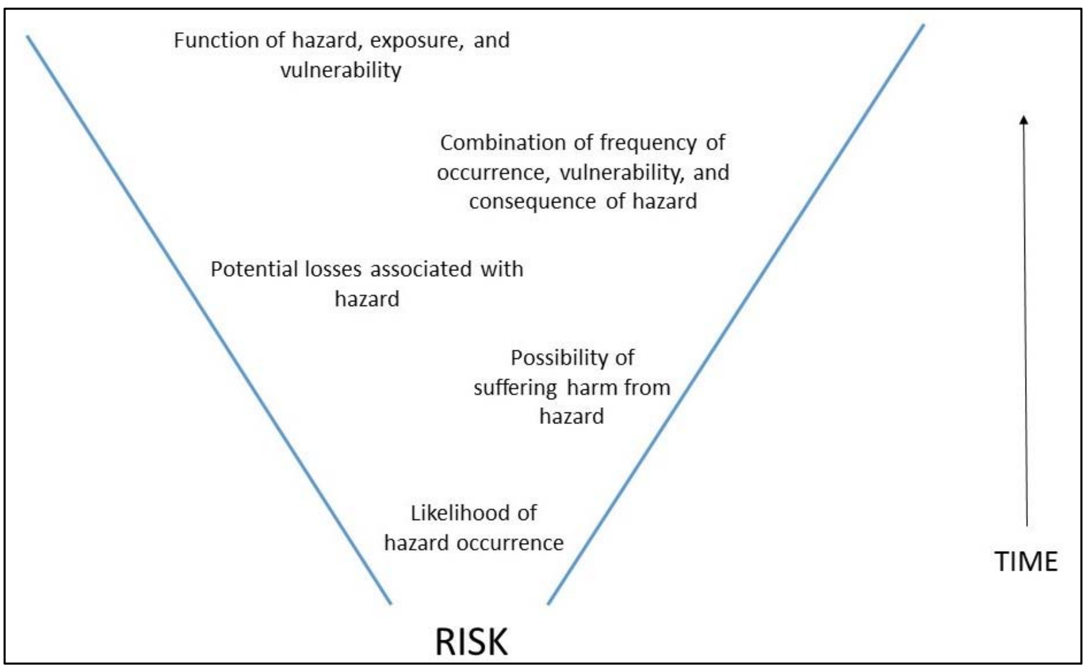

Figure 2.1: The expanding concept of risk

The IPCC SREX distinguishes the definition of disaster risk from disaster by adding the phrase “Likelihood of occurrence over a specified period of time” to its previously stated definition of disaster. In addition, the SREX notes that vulnerability and exposure are determinants of both risk and of disaster impacts

(IPCC 2012). Note that all definitions of hazard risk in some way include a probabilistic component, either explicitly or within their concept of hazard, implying that without exposure to a particular hazard there is no risk to it. Risk, then, in its modern form, can be described as a function of the interrelated concepts of hazard, exposure, and vulnerability. Hazard refers to the probability of an event at a given magnitude occurring, vulnerability the predisposition for loss to occur, and exposure the entities (e.g. humans, property, infrastructure) actually at risk (Yin et al. 2011). One way to visualize the interplay of these elements is the risk triangle (Figure 2.2), developed for insurance industry modelling. The area of the triangle represents overall risk. If any element -

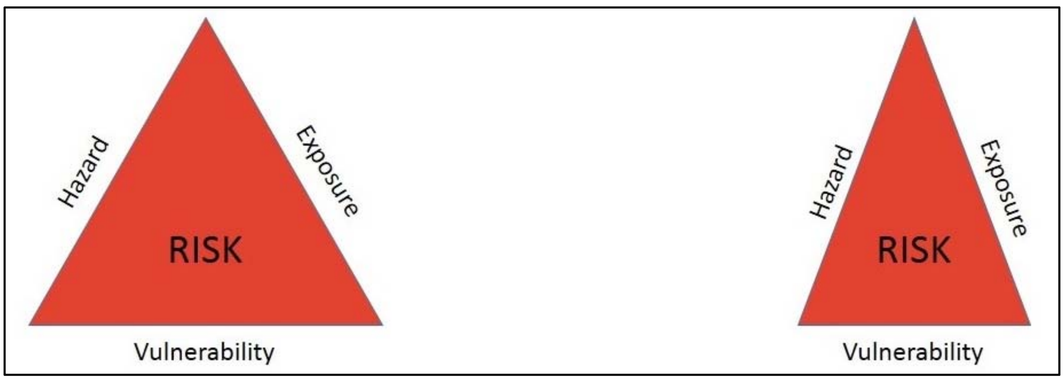

Figure 2.2: The risk triangle (left). The triangle on the right represents reduced risk (smaller area) as a result of lower vulnerability. Adapted from Crichton (1999)

represented by the legs and base of the triangle - is reduced, then the overall area of the triangle is small, representing lower risk (Crichton 1999).

Building on these concepts, the World Risk Index describes risk as "the interaction of a hazard and the vulnerability of societies." (ADW 2012) The WRI combines hazard and exposure by creating a probabilistic, annual measure of human exposure to hazard. In so doing, it simplifies and reframes risk to a function of exposure and vulnerability, while making a clear distinction between the two (Birkmann et al. 2013). This research uses the WRI's contemporary concept of risk as it replicates and downscales the WRI into a new index. Doing so allows for an exploration of the WRI's interpretation of risk at different geographic scales, and could provide new insight at those scales.

The concept of vulnerability also has a plethora of definitions and interpretations, which include the potential for loss (Mitchell 1989) threat of exposure, the capacity to suffer harm, and the differences in risk between social groupings (Cutter 1996). Vulnerability has both spatial and temporal aspects, and hazards research has long acknowledged that vulnerability to hazards results from both human / environment interactions as well as social and demographic aspects (Mileti 1999). Bohle (2001) explored this dual nature of vulnerability. To Bohle, vulnerability has in an internal aspect that concerns an entity's reaction to a hazard and an external aspect that is centered on exposure (Bohle 2001). As the definition of vulnerability has widened over time, it has come to include many internal aspects that include susceptibility to hazard, as well as the abilities to cope with and adapt to hazards. Moreover, vulnerability takes many thematic forms, including physical, social, economic, and environmental (Birkmann 2006). In general, an entity's vulnerability to some outside stress is a function of its exposure to and sensitivity to that stress (Smit et al. 2001).

As with risk, the concept of vulnerability to hazards has changed and expanded in meaning over time, moving from an internal risk factor to a multi-dimensional concept. There are three general themes in vulnerability research.

The first assumes vulnerability arises from societal factors independent of the event that exposes it, the second treats vulnerability as a function of proximity to hazards, and the third describes the hazardousness of place (Hewitt and Burton, 1971) as being a result of biophysical and social factors (Cutter 2008). Importantly, Eakin and Luers' review of the different conceptualizations of vulnerability argues that the various approaches to the topic are all ultimately necessary and even complementary (Eakin and Luers 2006).

Cutter's hazards of place model of vulnerability (Cutter 1996) expounds upon the third theme. The model includes two sources of vulnerability that have spatial outcomes: biophysical vulnerability, or the intersection of society and biophysical conditions, as well as social vulnerability, which is described as the susceptibility of social groups or society to loss. The overall vulnerability of a place is a result of both biophysical and social vulnerability (Cutter 1996). Most of the hazards research since the model was introduced (e.g. Brooks et al. 2005; Wood et al. 2010; Schmidtlein et al. 2011) have used the hazards of place concept or some offspring of it as a conceptual framework (Yorke et al. 2013).

As work on an integrated concept of vulnerability has advanced from the groundwork laid by the hazards of place model, the societal component has continued to increase in importance. Moreover, the idea of feedback has also been incorporated into vulnerability models, highlighting the ability of vulnerable groups to adjust to or cope with their vulnerability (Gall 2007). Birkmann (2005) describes the expansion and change in the concept of vulnerability as vulnerability's "key spheres". The spheres concept (Figure 2.3) shows that over time the definition of vulnerability has changed and its scope has widened, but nested within its current form are previous concepts.

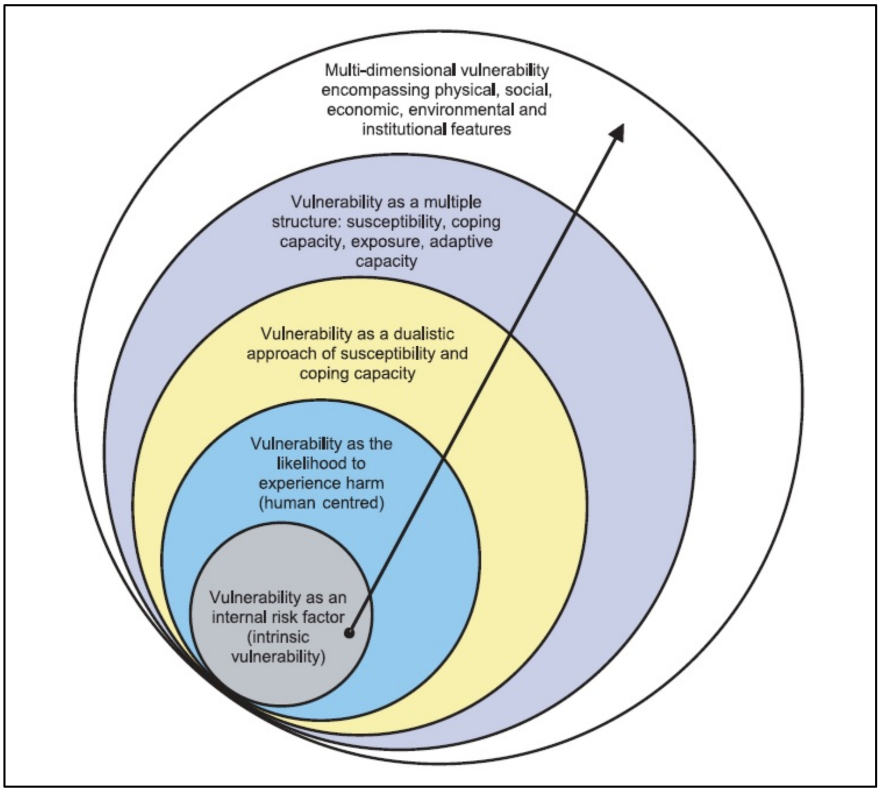

Figure 2.3: The spheres of vulnerability. Adapted from Birkmann (2005)

The WRI's understanding of vulnerability is compatible with that found in the IPCC Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation, which defines vulnerability as the propensity or predisposition to be adversely affected (IPCC 2012). The WRI capitalizes on the current expansive, multifaceted conceptualization of vulnerability by defining its vulnerability component as having three subcomponents: susceptibility, coping capacity, and adaptive capacity (Figure 2.4). The model describes the first vulnerability component, susceptibility, as "the likelihood of harm, loss, or disruption in an extreme event due to a natural hazard." (ADW 2012) As such the susceptibility component of the WRI, or those characteristics that create in a population the predisposition for loss, captures the social conditions that increase vulnerability.

The other two components, coping capacities and adaptive capacities, describe ways in which entities deal with the effects of hazards. Coping capacities describe the tools immediately available to reduce hazard effects, while adaptive capacities are the longer-term, structural measures and strategy put in place to deal with both the effects of a past hazard and future ones (ADW 2012). This expansion of the understanding of the twofold nature of vulnerability to include both aspects that increase and aspects that decrease vulnerability (Wisner 2002; Turner et al. 2003) is important.

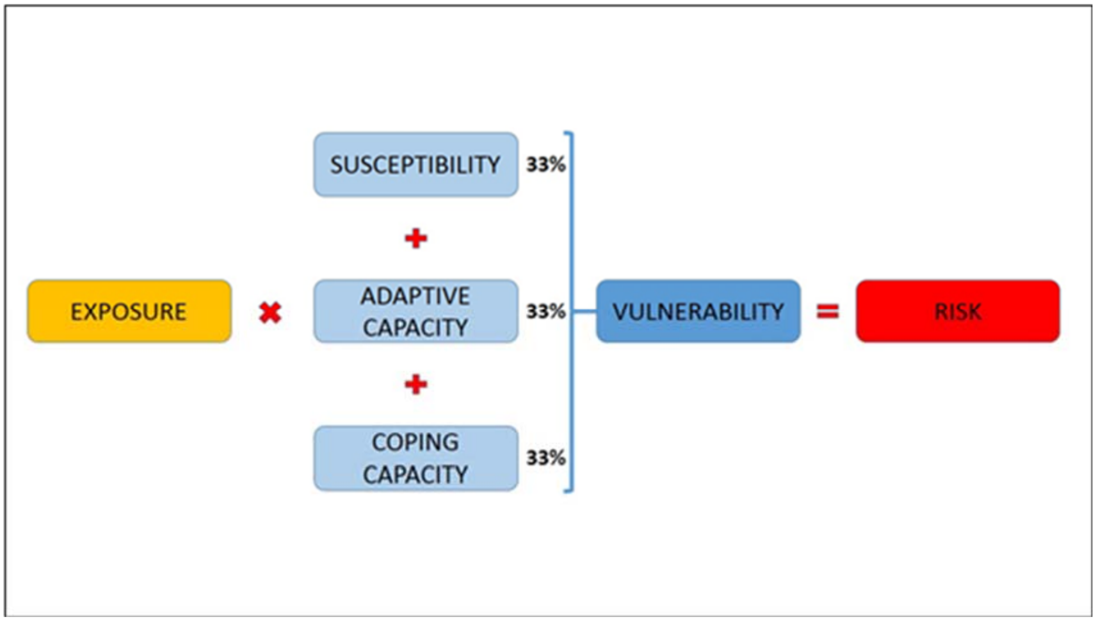

Figure 2.4: Components of the World Risk Index

Coping capacity is the ability to use available skills and existing resources (Wisner et al., 2004) to deal with adverse conditions, such as disasters (UNISDR 2009). Coping capacities are conditions inherent in people, communities, and systems and are immediately available for use should the need arise. As such coping capacities are utilized as soon as an event occurs (ADW 2012); they enable and facilitate short-term reactions to disasters. Effective coping capacity is based on factors such as the availability and effectiveness of emergency services, adequate resource allocation, and communications (Johnson and Blackburn 2014).

Adaptive capacity, complementing the shorter term nature of coping capacity, refers to long-term learning, actions and changes that result in adjustments to the potential consequences of hazards and climate change (IPCC 2012). Good adaptive capacity implies the ability to plan and implement actions that ostensibly reduce vulnerability and risk (Klein et al. 2004), implying measures that create changes in socio-ecological relations (Pelling 2010; Birkmann et al. 2011). Because of the potential for good adaptive capacity to provide informed feedback and ultimately reduce risk, it has received much focus in both the climate change adaptation and disaster risk reduction communities. There are various indicators for adaptive capacity. For example, Smit et al. (2001) identified wealth, technology, infrastructure, institutions, and skills/equity as aspects that determine adaptive capacity.

As the WRI is heavily reliant on vulnerability in its assessment of risk, it is worth noting that vulnerability, as a preexisting condition rather than an outcome, is not observable. Thus there is much uncertainty regarding the quantification of vulnerability in composite indexes. Attempts to validate vulnerability indices or those that contain vulnerability as component end up comparing pre-existing conditions to post-event outcomes, which is less than desirable (Tate 2011).

2.3 Creating a Composite Index

In general, an index compiles indicator variables into a single theoretical variable (Hinkel, 2011); in doing so they simplify complex realities and allow for comparisons in space and time (Vincent, 2004). Indices can help set standards, monitor change, and allow for the allocation of resources (Barnett et al. 2008). In the case of an index that includes vulnerability, such as the WRI, the goal is to operationalize a theoretical concept. Typically this involves the use of subcomponents in which indicator variables are aggregated (Below et al. 2012). Importantly for this study, indices that describe differences in geographic units should be replicable (Bossel, 1999). Keeping the number of indicators small, transparent, and based on widely available data helps accomplish this goal (Vincent, 2004).

Indicators are defined as “something that provides a clue to a matter of larger significance or makes perceptible a trend or phenomenon that is not immediately detectable” (Hammond et al. 1995: 1). They provide information about a variety of systems, to include physical and social systems (Farrell and Hart, 1998). Indictors are particularly adept at allowing for comparisons between similar areas, such as countries or subnational administrative units. Composite indicators, or indexes, contain a modeled compilation of indicators that ostensibly measure concepts that cannot be measured by single indicators or simpler methods (Nardo et al. 2005). There are a variety methods used to compile indices. These include deductive methods, which use a low number of normalized variables to calculate an index score; inductive methods, which reduce a larger number of variables into a small number of explanatory variables using principles components analysis; and, hierarchical methods which group variables into sub-indexes that are then aggregated to compute the index (Tate 2013). The WRI uses the hierarchical method of index construction.

When viewing and interpreting the results of an index such as the WRI it is useful to understand both the strongpoints and drawbacks of composite indexing (Table 2.2). One primary concern with index construction is data. In some cases, ideal or desired data may not be available, leading researchers to settle for poorer quality data. In others, ideal data may be available but not widely so, limiting the utility of the index it is used in. Within an index, standardization of data is typically required. A common method in vulnerability indices is to scale variables from 0 to 100 or 0 to 1. This normalization makes variables compatible,

Table 2.2: Selected pros and cons of composite indexing (from Saisana and Tarantola 2002)

Pros	Cons
-Easier to interpret than looking for trends in many separate indicators	-Can send misleading messages if poorly constructed or misinterpreted
-Facilitate ranking administrative units based on complex issues	-Can be the targets of polical challenge (especially indicators and weights)
-Can summarize complex issues	-Contain subjective judgement
-Attract public interest to the issue at hand	-Can lead to simplistic policy conclusions
-Reduce the size of an indicator list	-Require large amounts of data

but in doing so has the drawback of forcing data into linear scales (Barnett et al. 2008).

To date there are no objective means to either select variables or weight variables and components (Bohringer and Jochem 2007; Hinkel, 2011). Variables are typically weighted using expert knowledge or, lacking that, equally weighted. Both methods have their drawbacks. Equal weighting assumes that all variables contribute the same amount to the phenomena being studied, when this is likely not the case. Expert weighting depends on the availability of expert knowledge of variables (Below et al. 2012) and how they relate to the object of study, and can suffer from bias and subjectivity.

Another general concern for any index is that of validity. This concern is particularly acute when attempting to represent a complex phenomenon such as vulnerability. Indexing vulnerability is an effort to predict future outcomes; as such, indexes that assess vulnerability or that include it as a component cannot be tested or verified. Instead, vulnerability indexes can be qualitatively assessed using local knowledge to see if their results reflect reality (Barnett et al. 2008). Choices made by the index developer, to variable selection, weighting, and aggregation can introduce a large amount of uncertainty into the results of an index. For vulnerability indices in particular, as vulnerability increases, the precision of the overall index tends to decrease (Tate, 2013).

The apparent ease with which composite indicators, especially those such as the WRI that produce as an end result a single number as a metric, are interpreted in many different forums can to lead poor, uniformed conclusions about how the indicators should be used. This is an especially important consideration, as indices are often used to link science and policy (Vincent 2004). The process can be very subjective; indices can easily be manipulated to produce a desired outcome. Even so, if indexes are properly constructed and interpreted and if the limitations and biases (some are detailed in Table 2.2) of indices are understood, they can serve as valuable tools to inform policy, aid, or further research, among other things.

Literature that discusses index construction (e.g. Freudenburg 2003, Nardo et al. 2005, Nardo et al. 2008) suggest general steps to follow when creating an index. These steps include (from Nardo et al. 2008):

1) Selection of theoretical framework
2) Variable selection
3) Imputation of missing data
4) Multivariate analysis
5) Normalization
6) Weighting
7) Aggregation
8) Robustness and sensitivity.

The creation of the WRI follows these same general steps.

2.4 Frameworks for Analysis: Selected Disaster Risk Indices

Indices such as the WRI serve a useful purpose within the realm of hazards and disasters. Specifically, disaster risk indices are adept at summarizing large quantities of information, presenting that information in an understandable way to policymakers and the public, and informing risk management decisions (Davidson and Lambert 2001). The importance of indices to policy and decision making is evidenced by a drastic increase in the number of them (Nardo et al. 2005).

A variety of disaster risk indices currently exist at different scales. Indices at the national level are the most common, with prominent disaster risk indices at this scale including the United Nation Development Program's Disaster Risk Index (UNDP 2004; Peduzzi et al. 2009), Columbia University's Hotspots project (Dilley et al. 2005), and the previously discussed World Risk Index (ADW 2011). Also worth mentioning with this group is a regional project, the Inter-American Development Bank's (IDB) Indicators of Disaster Risk and Risk Management (Cardona 2006; IDB 2010). Each of these indexes provides a unique approach to the question of disaster risk. Table 2.3 provides a summary of these indices. Note that the World Risk Index is unique among the indices presented in that is combines its component parts into an overall assessment of risk, resulting in a single, comprehensive risk score that allows for comparison between countries.

The Disaster Risk Index (DRI) (Peduzzi et al. 2009), for example, calculates disaster risk at the country level. The DRI defines risk as the number of people killed per year, using cyclones, drought, flooding, and earthquakes in its model. Further, the DRI was designed for understanding past casualties, not predicting future risk (Peduzzi et al. 2009).

Table 2.3: Summary of national level risk indices

Index	Scale	Concept of Risk	Components	Hazard Used	Aggregation method
UNDP Disaster Risk Index (UNDP, 2004)	Global - risk assessed at country level	Mortality and factors that explain mortality	Relative vulnerability (exposure), Regressive determinination of vulnerability factors	Cyclones, Floods, Earthquakes	Relative vulnerability calculated based on mortality data, then regression of vulnerability factors used to explain mortality
Disaster Risk Hotspots (Dilley et al. 2005)	Global - risk assessed at 2.5 x 2.5 km grid squares	Mortality, economic loss	Mortality, direct and relative economic losses	Cyclones, Floods, Earthquakes, Drought, Landslides, Volcanoes	Risk for each component assessed, components not combined. Risk calculated for individual hazards as well as multiple hazards
Indicators of Disaster and Disaster Risk Management (Cardona 2006; IDB 2010)	Regional - risk scores at country level for	Economic, social, environmental risk	Disaster Deficit Index, Local Disaster Index, Prevalent Vulnerability Index, Risk Management Index	Avalanche, Forest Fires, Cyclones, Floods, Earthquakes, Drought, Landslides, Volcanoes	Holistic approach that assesses economic, social, environmental risk, as well as vulnerability and risk management performance. No aggregation of components
World Risk Index (ADW, 2011a)	Global - risk scores at county level	Exposure x Vulnerability	Exposure, Vulnerability (Susceptibility, Adaptive Capacity, Coping Capacity)	Cyclones, Floods, Earthquakes, Drought, Sea Level Rise	Expert weighting of variables Vulnerability components given equal weight and added Overall vulnerability and exposure multiplied to get risk

The index multiplies hazard frequency, population living in an area, and a measure of vulnerability to compute its version of risk. The use of hazard and population as exposure utilizes the same dataset, the United Nations Environmental Programme's PREVIEW data (see Chapter 3 for in-depth discussion of the PREVIEW data), as the WRI. The hazard data are modeled on a sub-national grid, while the vulnerability data are at the national level. After compilation, the DRI uses multiple regression to determine which indicators best explain mortality (UNDP 2004). The DRI approach is flexible and allows for risk comparison between countries, but does have limitations.

The Hotspots project (Dilley et al. 2005) is similar in method to the DRI, measuring risk in terms of exposure, mortality, and economic loss. However, Hotspots focuses on a much smaller, subnational scale, as it uses 2.5 x 2.5 square kilometer grid cells as its spatial unit of analysis (Dilley et al. 2005). Hotspots uses drought, cyclones, earthquakes, floods, landslides, and volcanoes to calculate three indices – mortality, economic losses, and proportional economic losses - of risk. Of interest in the Hotspots analysis is the delineation of the number of hazards that affect a given area. Many parts of the world are only influenced by a single hazard included in the model. This highlights the issues of data availability as this scale, as well as the need to include multiple hazards in a composite index, especially when the scale of analysis is global or regional and county comparison / ranking is an outcome. Hotspots does allow for comparison of overall risk with both population and approximated GDP (Birkmann 2007). However, the index does not specifically include a measure of vulnerability. In addition, Hotspots exposure comes from many different sources, unlike the DRI or WRI. In general, these global indices, the WRI excepted, either do not incorporate both vulnerability and coping / adaptive capacities or do so to a very limited extent.

Though a regional index, the IDB's risk project is perhaps the most comprehensive of the national scale indices, as it includes four main sub-indices. These include the Disaster Deficit Index (economic risk), the Local Disaster Index (social and environmental risk from lower level events), the Prevalent Vulnerability Index (vulnerability, socioeconomic weakness), and the Risk Management Index (actions taken to reduce vulnerability and loss). The IDB's approach is fairly complex, but it has many strengths, including that fact that it allows for the measurement and assessment of risk management over time, and the fact that is allows for the identification of risk factors that should receive priority for risk reduction efforts (IDB 2012). Moreover, the IDP concept of vulnerability is fairly consistent with that of the WRI.

The aforementioned indices outline approaches appropriate for global or national scale disaster risk assessment. There exist many efforts to frame risk at more local levels. Although the global risk indices have started to address an expanded understanding of vulnerability, subnational indices for the United States have not. For the United States, perhaps the most widely used risk assessment tool is the Federal Emergency Management Agency's HAZUS model, which estimates losses from hazards for the US at subnational scales.

Although HAZUS can be used to conceptualize vulnerability, either through exploring the implications of economic loss and / or an independent understanding of the affected population, the model does not contain a specific vulnerability component.

Although they are very few in number, there are subnational hazard risk indices for the US. One such index is the Hurricane Disaster Risk Index (HDRI), which assesses hurricane risk to US coastal counties (Davidson and Lambert 2001). The HDRI is an early attempt to comprehensively examine risk to a single hazard at the subnational level, as it includes hazard, exposure, and vulnerability components. The exposure component is multi-faceted, as is the vulnerability component, which includes socio-economic vulnerability indicators as well and well as physical ones. In addition, the index has an emergency response and recovery component, which essentially serves as a measure of coping capacity (Figure 2.5). The HDRI is a predictive index, and estimates future risk based on both economic and human losses. The measure of risk it produces for each has no units, and is scaled from 0 to 10. The as proof of concept, the HDRI was originally calculated for 15 US counties (Davidson and Lambert 2001). Though more limited in scope, the HDRI contains many of the concepts of risk and model elements that are incorporated into the WRI.

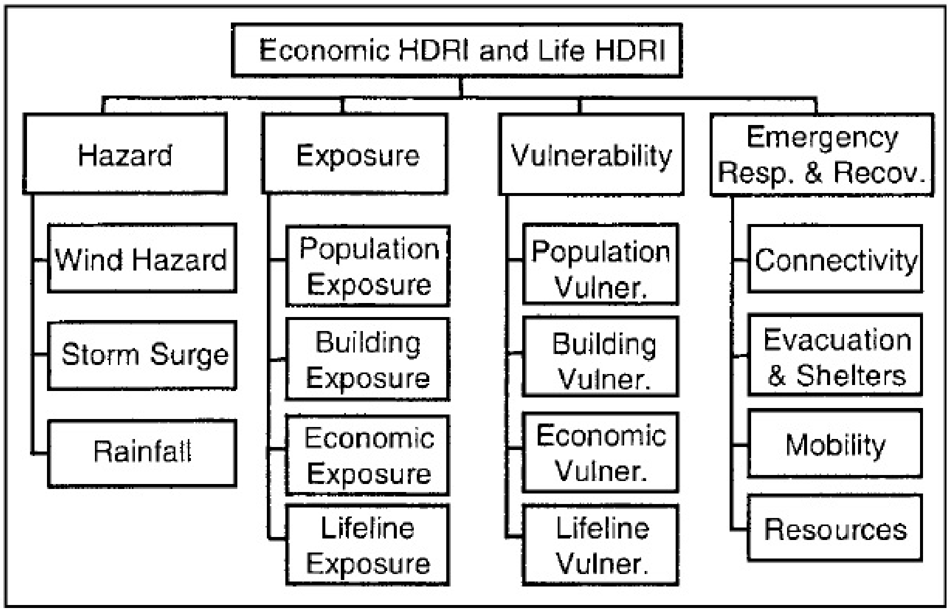

Figure 2.5: Conceptual framework of the Hurricane Disaster Risk Index
From Davidson and Lambert (2001)

There are other indices at the subnational level that assess risk or components of it. Some examine specific hazards topics such as resilience (Sempier et al. 2010; Orencio and Fujii 2013) and vulnerability (Cutter et al. 2003), while others focus on places or between places (Boruff and Cutter 2007). Many indices focus on hazard centric approaches. Some of these examine single hazards, such as earthquakes (Davidson et al. 1997); others take a multi-hazard approach in a variety of contexts (Ferrier and Haque 2003; Blong 2003; Schmidt et al. 2011).

Another category of assessments that inform both the WRI and this work are integrated hazards assessments that combine hazard exposure and vulnerability. Combining exposure and vulnerability provides a holistic approach to and adequate representation of the hazards of and among places (Cutter, 2000). Assessments utilizing this approach have focused on individual US cities

(Schmidtlein et al. 2011), counties (Cutter et al. 2000) as well as regions (Wood et al. 2010; Emrich and Cutter, 2011).

Even with the wide variety of indices and assessments that catalog or study risk, exposure, and vulnerability, there currently exists no comprehensive hazard risk index for the United States at either the state or county level. Thus implementation of the WRI for the United States fills a conceptual gap in understanding of multi-hazard risk and its comparability with more global-level indices.

2.5 Summary and conclusions

As hazard losses continue to increase, it is apparent that informed risk management is an essential element in any loss-reduction strategy. A starting point for effective risk management is a method to catalog risk as it varies over space. This allows for understanding risk as well as taking targeted actions to reduce it at the scales where reduction efforts are feasible. As this literature review has shown, the understanding of risk and its elements, to include exposure and vulnerability, has and continues to evolve. The contemporary conceptualization of risk has been applied in indices at the global level, and many risk assessments at the subnational level in the US.

Although there are a number of comprehensive risk indices at the global and regional level that present a variety of techniques for risk assessment, to this point none has been constructed for the United States. For this dissertation, the global risk index with the most potential for applicability at subnational scales, the

World Risk Index, was chosen as an analog and basis for a new disaster risk index for the United States that bridges the gap between concept and execution of risk assessment.

CHAPTER 3: CONSTRUCTING THE USDRI - EXPOSURE

3.1 Overview

This research seeks to fill conceptual gaps in the understanding of disaster risk at the subnational scale for the US. Specifically, it seeks to use a theoretical framework that defines risk as the intersection of hazard (exposure) and vulnerability, where vulnerability consists of three main subcomponents: susceptibility, coping capacity, and adaptive capacity. Capturing these essential elements of risk in a relatively straightforward manner can go a long way towards increasing understanding of risk – and, by extension, understanding hazards, mitigation, preparedness, and resilience – among policymakers and practitioners. Better knowledge of the hazards that affect subnational geographic units as well as the weak points in the social fabric of these units that leaves them more susceptible or unable to cope and adapt is crucial to informing and increasing understanding of disaster risk. The WRI constitutes a novel approach to assessing risk through the use of a weighted index that explores the different elements of it at national level, allowing for comparisons between countries. This chapter contains the conceptual framework for and explanation of the customization of the WRI to the US subnational level, as well as a complete discussion of the index's exposure component.

3.2 USDRI conceptual framework and downscaling

Taking its cue from the WRI, the US Disaster Risk Index (USDRI) calculates overall risk based on a conceptualization of it that includes both exposure and vulnerability components. Using the WRI's methodological approach and framework allows for the creation of an index that serves as a benchmark for evaluating subnational risk in the US. This, ostensibly, makes the USDRI more comprehensive than previous attempts to examine risk to hazards across the entire US.

Global hazard risk indices help explain and bring attention to complex issues, and also have the benefit of allowing for comparisons between countries. However, they lack the ability to bring out the nuances of the phenomena they are describing at subnational levels. This is even more pronounced in countries that experience a geographically disparate variety of hazards or whose populations lack homogenous socio-economic characteristics. Boiling the risk score down to one number at the country level may indicate the need for risk management measures for that country, but does little to show how risk is distributed or where it may be concentrated within that country. There is a need to downscale global hazard indices such as the WRI to subnational scales, as doing so allows for more detailed study. Moreover, it is at subnational scales where efforts to reduce vulnerability and risk are most feasible and effective.

Downscaling is a technique typically used to interpolate coarse regional or global scale data into more meaningful and actionable data at smaller scales (Wigley et al. 1990). It is widely used in the global climate change community to create local scale data from global or regional climate modeling output (Wilby and Wigley 1997; Pinto et al. 2104). In the case of the downscaling utilized in this dissertation, the end result – higher resolution data – is the same as in statistical modeling, but the way to reach that end is somewhat different. Instead of making inferences about global scale risk data, this study utilizes the same methodology as the global scale index, but uses data from the appropriate scale to complete the downscale.

3.3 Study area

To assess the viability of downscaling the World Risk Index, the index is reconstructed at the subnational scale. The analysis units in this research are the 50 states of the United States and the 46 counties in the state of South Carolina. These units were chosen for a variety of reasons. Key to this study is the ability to, as closely as possible, replicate the World Risk Index. The robustness of the data available for the United States at both the state and county level allows for use of the exact variables used in the WRI in many cases, and close proxies in others. Additionally, the USDRI is conceived as a tool for decision-makers to understand and act upon risk, so it necessarily focuses on the main subnational administration units in the US (Emrich and Cutter 2011). Finally, the United States' diverse physical and human geography presents a variety of hazards and societal conditions that provide for a comprehensive analysis of risk.

The state-level analysis (Figure 3.1) capitalizes on data availability and the diversity of US natural hazards, as it includes all five hazards used by the WRI: cyclones, earthquakes, flooding, drought, and sea-level rise. Drought and flooding occur in every state. Primary earthquake exposure occurs along the US West Coast, as well as in Alaska, Hawaii, and a large area in the middle of the country centered on the New Madrid Fault. Cyclones affect the US East and Gulf Coasts. Almost 3.7 million people living on the US coastline would be affected by a 1 meter rise in sea level.

Figure 3.1: Study area for state level USDRI

For the county-level construction of the USDRI South Carolina (Figure 3.2) is, among US states, also well suited for an effort to downscale the WRI. From an exposure perspective as it also experiences all five hazards the WRI uses. Of the five, earthquakes are the most infrequent; a destructive earthquake has not affected the state since 1886. However, the U.S. Geological Survey (USGS) National Seismic Hazard Maps show that South Carolina has the highest

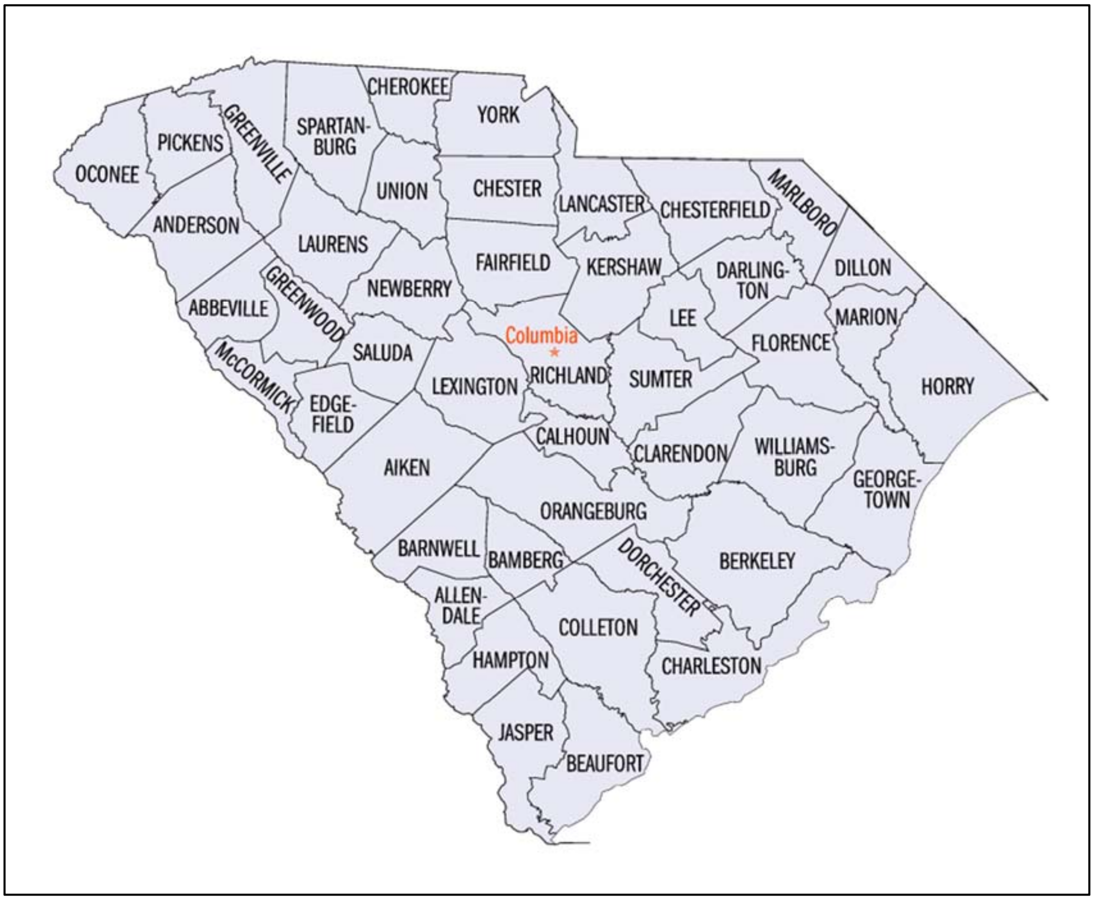

Figure 3.2: Study area for county level USDRI (Census.gov)

earthquake hazard risk among states also exposed to tropical cyclones. Among other states in the US with similar or greater earthquake risk, there is no exposure to tropical cyclones (Peterson et al., 2008). South Carolina's coastal counties allow sea level rise hazards to be incorporated at the subnational level. for this portion of the WRI to be incorporated at the sub-national level.

3.4 The exposure component

The WRI uses four modular components - exposure, susceptibility, coping capacity, and adaptive capacity (see Figure 2.4). Exposure is described as elements (for example, people and infrastructure) present in hazard zones (UNISDR 2009). The WRI uses humans as its measure of exposure, calculating exposure by creating an average annual number of individuals exposed to hazard events, which include earthquakes, cyclones, drought, and flooding. Additionally, there is an increasing awareness that susceptibility to disasters comes not just from exposure to natural hazards, but also to other factors such as population growth and climate change (Huppert and Sparks, 2006). One of the strengths of the WRI exposure component is that is can accommodate all hazards, contingent on the calculation of a spatially referenced exposure surface. To explore the idea of including hazards that are both potential and outside of the scope of typical hazard risk assessments the WRI includes sea-level rise as an additional component of its exposure calculation.

3.4.1 Calculating exposure

The overall exposure score is the aggregate of exposure to each of the five hazards on an annual basis, by US state and by South Carolina county. Exposure is calculated by creating an exposure surface and then adding the population located within these risk zones. The population data used for this research was 2012 US population estimates found in the United States' Census Bureau's American Community Survey (ACS).

In the WRI model (Figure 3.3), exposure scores for cyclones, earthquakes, and flooding were given full weight, while drought and sea level rise were multiplied by .5, giving them half weight. Drought is a slow onset hazard that has great spatial extent. As such, it tends to expose large amounts of the population in areas that it affects, exerting undue influence on the exposure component as well as on the WRI as a whole. There is also some uncertainty in the measurement of drought exposure (Peduzzi et al., 2009). Exposure to sea-level rise, while also slow onset, has a lower spatial extent than drought. However, as the computation of sea level rise lacks a probabilistic component, it is not possible to calculate annual exposure for this hazard (ADW 2012). For this reason as well as the uncertainty involved in projecting future risk to a hazard, sea level rise also received a weight of half in the WRI exposure component. Following the WRI method, these same weights were used for the USDRI.

3.4.2. Data

Data on all of the hazards but sea-level rise comes from the United Nations Environment Programme / Global Resource Information Database's (UNEP/GRID) Project for Risk Evaluation, Vulnerability, Information and Early Warning Global Risk Data Platform (PREVIEW). PREVIEW is a web-based geographic information system that provides over 60 types of data on exposure and risk for nine different hazards, including four used in the WRI (Giulani and Peduzzi 2011). PREVIEW data, discussed in more detail later in this chapter as individual hazards are discussed, incorporates population exposed to hazards as

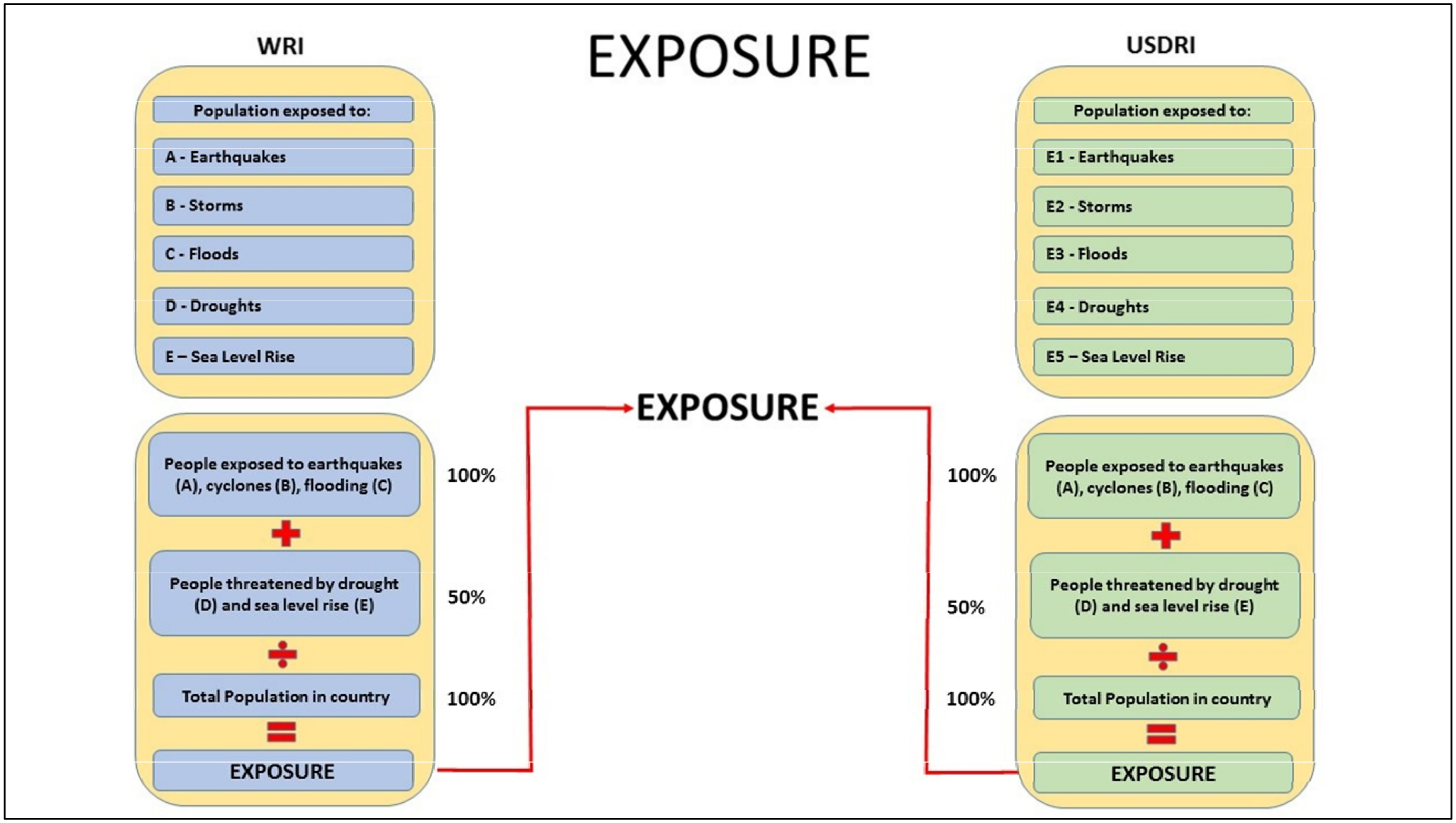

Figure 3.3: Makeup of the WRI and USDRI exposure components

well as hazard frequency and spatial extent. Thus it represents a probabilistic method of calculating exposure (Birkmann 2011).

The one hazard that PREVIEW does not cover is exposure to sea-level rise. The WRI calculates sea level rise exposure using population data from the UNEP Global Environmental Outlook Data Portal and sea level rise data from the University of Kansas' Center for Remote Sensing of Ice Sheets (CReSIS). Although the combination of these two datasets allows for an estimate of population exposed to sea-level rise, it is not feasible to include a frequency component for this hazard. Thus, it is weighted differently in the WRI exposure calculation. Additionally, there is considerable error found in geo-referencing the UNEP and CReSIS data; doing so tends to result in underestimation of exposure, especially for more sparsely populated areas (Birkmann, 2011).

To overcome this error, as well as to incorporate more recent data, the USDRI utilizes sea-level rise data from the Surging Seas sea level rise dataset, run by Climate Central. Surging Seas combines population data from the 2010 US Census as well as a tidal model to quantify human and structural exposure relative to mean high tide levels. By using mean high tide as a benchmark, Surging Seas attempts to account for the underestimation of sea level rise impact found in works that use only elevation as a guide (Strauss et al. 2012). At the time of this writing, Surging Seas data is only available for the 48 contiguous United States. Thus sea-level rise data for Alaska and Hawaii were calculated using the method detailed in the WRI. Statistical comparison of the Surging

Seas and CReSIS sea level rise data using a paired samples t-test revealed that there was no significant difference in the means of the two datasets (sig. = 439).

3.4.3 Procedures

For all of the hazards except for sea-level rise, rasterized physical exposure data was obtained from the PREVIEW data portal (Table 3.1). These rasters were then clipped, using ARCMap software, with a state map of the United States as well as a county-level map of South Carolina. To determine

Table 3.1: Variables in the exposure component

Exposure Variable (N=5)	Source	Supporting Literature
Physical exposure to cyclones	PREVEW Global Risk Data Platform	Giulani and Peduzzi (2011)
Physical exposure to earthquakes	PREVEW Global Risk Data Platform	Giulani and Peduzzi (2011)
Physical exposure to floods	PREVEW Global Risk Data Platform	Giulani and Peduzzi (2011)
Physical exposure to drought	PREVEW Global Risk Data Platform	Giulani and Peduzzi (2011)
Physical exposure to sea-level rise	Surging Seas Data Portal (48 contiguous states) CReSIS (Alaska and Hawaii)	Strauss et al. (2012)

exposure for each individual hazard, the raster values within each state were summed. For sea level rise, data were obtained directly from Climate Central for each of the US states and South Carolina counties found in the study, with the exception of Alaska and Hawaii. For these two states, rasters of UNEP population and CReSIS sea level data (1 meter increase) were clipped, and then the number of people found in areas where the population and sea-level rise rasters intersected was used as the exposure surface.

The final exposure value is the sum of the weighted populations at risk divided by the total population in the enumeration unit (state and/or county). It is expressed as a percentage, and represents the number of people in a geographic area exposed to all in the model on an annual basis.

3.5 Analysis of the exposure components

3.5.1 Cyclone exposure

Cyclone exposure for the USDRI is calculated using PREVIEW data, shapefiles for the US and South Carolina, and ARC Map software. The PREVIEW data used for calculating exposure consists of annual population exposed to both hurricane force winds and Saffir-Simpson hurricane category 1 equivalent storm surge. The wind data is comprised of data from two sources spanning the period 1969-2009. The first is the National Oceanic and Atmospheric Association's (NOAA) National Climatic Data Center (NCDC) (International Best Track Archive for Climate Stewardship (IBTrACS). IBTrACS is a compilation and, using modern techniques, a reanalysis of many different sources of cyclone track data (Knapp et al. 2010). The second is a GIS model designed by UNEP-GRID that takes into account the movement of cyclones, allowing for a determination of exposed population (Giulani and Peduzzi 2011).

PREVIEW data for cyclone surge comes from four different sources. Aside from the aforementioned UNEP-GRIP GIS algorithm, PREVIEW uses a cyclone best track dataset, a digital elevation model at 90m resolution, and a population overlay from the LandScanTM Global Population database to calculate the number of people affected by surge. Once exposure data from wind

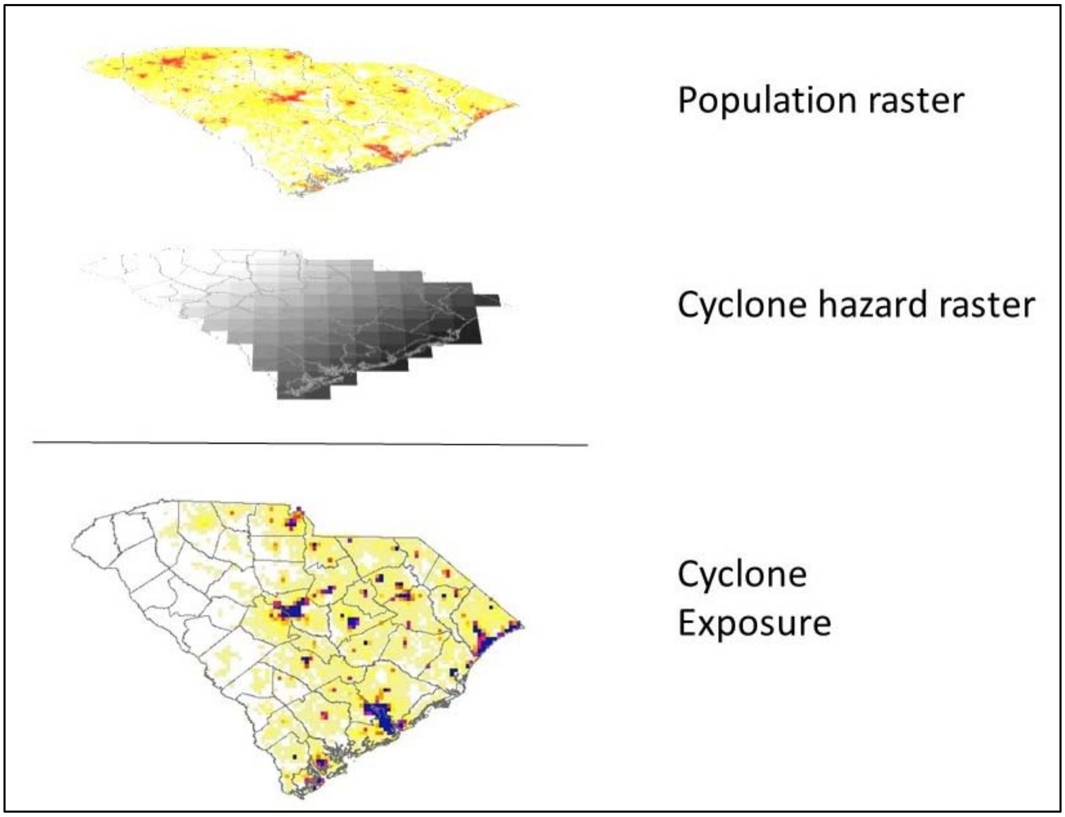

Figure 3.4: Compilation of cyclone exposure for SC counties

and surge was processed, the exposure data from the resulting rasters was combined to produce an overall cyclone exposure surface. Figure 3.4 provides a visual representation of the technique for compiling cyclone exposure. This same general process is repeated for each hazard in the exposure component.

The calculation of cyclone exposure for the US shows 1.68 percent of the population exposed to cyclone winds and/or surge on an annual basis. Of that total, approximately 10 percent of the exposure is due to surge, with the remainder due to wind. All of the surge exposure is along the Gulf and Atlantic coasts, while wind exposure is found in most states east of the Mississippi River.

Although the wind exposure is highest for coastal states, interior states also show some exposure based on the fact that cyclones continue to produce winds after landfall. For the states, mean exposure to cyclones is 1.48 percent, with a standard deviation of 1.93. Cyclone exposure ranges from no exposure (numerous states) to 6.24 in Connecticut (see Appendix A).

South Carolina's overall annual exposure to cyclones is 3.7 percent. Within the state, surge exposure is found in coastal counties, while wind exposure is more widespread. As expected, the highest values of overall cyclone exposure are in the coastal counties. Mean SC county exposure is 3.3 percent, with a standard deviation of 4.28. South Carolina's cyclone exposure ranges from no exposure (six counties) to 20.6 percent in Georgetown County (see Appendix A).

3.5.2 Earthquake exposure

The PREVIEW data for earthquakes gives annual exposure to earthquakes based on the Modified Mercalli intensity scale, with data from 1973-2007. The earthquake intensity data comes from the US Geological Survey's (USGS) Shakemap Atlas. Intensity information is combined with LandScanTM population data to produce the exposure surface (Giulani and Peduzzi, 2011). The USDRI uses exposure to Modified Mercalli Intensity 5 (MM5) as a benchmark to calculate exposure for the US. PREVIEW data contains exposure to both MM5 and MM9 earthquakes, but there was no MM9 exposure at the SC county level and negligible MM9 exposure at the state level.

For the United States, 1.5 percent of the population is exposed to MM5 earthquakes on an annual basis. Earthquake exposure in the US shows two distinct concentrations. States in the Pacific Rim, to include Alaska and Hawaii and the US West Coast have high exposure due to the numerous faults associated with the interaction of tectonic plates in these areas. The second exposure concentration is in the center of the US in the vicinity of the New Madrid seismic zone, which stretches across six states and is where highly populated areas exist over or near a fault system that has produced large earthquakes in the past. Mean state exposure is .41 percent, with a standard deviation of 1.69. US earthquake exposure ranges from none (16 states) to 11.61 (California). For South Carolina, earthquake exposure is negligible, as according to PREVIEW data only 58 people in the state are exposed on an annual basis. This lack of exposure is a product of the relatively short time period of the earthquake exposure surface (1973-2007), and masks the fact that South Carolina is at risk of earthquakes over the long-term, as the Charleston, SC area experienced a large, devastating earthquake in 1886.

3.5.3 Flood exposure

The PREVIEW flooding surface used in the USDRI comes from multiple sources. A GIS model is used to estimate peak flow and flooding surfaces. Observed flood data from the Dartmouth Flood Observatory for the period 1997-2009 is also included in the calculation, as is data from the UNEP-GRID flood dataset, which is used to calculate return period. These components are combined with the LandScanTM population database to produce the exposure surface (Giulani and Peduzzi, 2011).

Flood exposure exists in most US states, with .11 percent exposed annually. The highest levels of flood exposure are in the eastern US, especially in states that contain parts of major US river systems. Kentucky has the highest rate, with .5 percent of its population exposed. Within South Carolina, the PREVIEW exposure for flooding totals .03 percent, with counties along the coast as well as a small area in the northwest part of the state showing the highest values. The small exposure values for flooding are counterintuitive given knowledge of the flooding hazard in the US. This is likely a product of how the exposure surface was computed. See Section 3.5.6 for more details.

3.5.4 Drought exposure

Compared to cyclones, earthquakes, and floods, drought proves more difficult to include in the exposure component because it is a slow onset, long duration, and geographically widespread hazard. PREVIEW drought calculations are based on the Standardized Precipitation Index (SPI), which quantifies precipitation deficit over time (Guttman 1998). PREVIEW uses a GIS model of the SPI, a global precipitation dataset, and LandScanTM population data to determine drought exposure. Because of the aforementioned nature of drought, it results in exposure values that are quite high compared to the other hazards. For example, annual drought exposure for the US is approximately 78.5 million people, which is almost eight times higher than the amount of all other indexed hazards combined. Even when drought is only given half weight, as it is in the WRI, it accounts for the vast majority of exposure in the US. While this may be the case in absolute terms, the result is that drought dominates the exposure component, as well as the overall risk index, when it is calculated for the US. This phenomena is explored further in the results section of this research; the risk index is present both with and without the presence of drought.

Drought exposure exists in every US state, with areas of high exposure found on the West Coast, in the Midwest, and in the Southeast. US drought exposure has a mean of 24.89 percent, with a standard deviation of 7.34. Overall drought exposure ranges from 6.3 percent in Alaska to 30.7 percent in Wyoming. For South Carolina, every county in the state is exposed to drought, with 25.76 percent of the state's population exposed annually. County drought exposure in SC has a mean of 29.2 percent, with a standard deviation of 13.2 percent. Jasper County has the highest drought exposure, with 100 percent exposed annually (although when weighted for the USDRI, this figure drops to 50 percent). This implies that Jasper is in constant drought, which is not the case. Statistical examination of drought exposure values for SC counties shows that Jasper's value is an outlier, as is the value for Marion County (58.29 percent). The extreme value for Jasper County indicates that there could be issues with the PREVIEW drought data at the US county level, underscores the uncertainty introduced when drought is included in the USDRI. McCormick County has the lowest drought exposure in South Carolina, at 8.94 percent.

3.5.5 Sea level rise exposure

Sea level rise exposure for the USDRI was calculated using the procedure outlined in section 3.4.1, which utilizes Surging Seas data for 48 US states and CReSIS data for Alaska and Hawaii. Sea level rise exposure in the US exists in all states with a coastline. Exposure to sea level rise, among the states affected by the hazard, has a mean of .95 percent and a standard deviation of 1.68 percent. The highest sea-level rise exposure occurs in Louisiana, with 19.31 percent of the state's population exposed to a 1 meter rise.

In South Carolina, all coastal counties show exposure to a sea level rise of 1 meter. Of the counties exposed, the mean exposure is 2.71 percent and the standard deviation is 3.85. Charleston County has the highest exposure to sea level rise, with 12.85 percent of the county's population exposed to a 1 meter increase.

3.5.6 Comparing hazard exposures

The final calculation of the exposure component for the USDRI mirrors that of the WRI (Figure 3.3). Overall, 16.39 percent of the US population is exposed to hazards on an annual basis, according to the USDRI exposure calculation (Table 3.2). For South Carolina, annual exposure is 17.43 percent. In both cases, drought accounts for the majority of exposure.

Table 3.2 details the percent of the US and South Carolina population exposed annually and to each hazard. The domination of the exposure component by drought, both at the state and county levels, is evident. When drought is removed, no hazard dominates at the state level, while tropical cyclones become the dominant hazard at the county level. This underscores the more diverse and extensive hazard geography found at the US scale as compared to the SC county scale.

Table 3.2: Annual hazard exposure (USDRI calculation)

Hazard	Percent of Population Exposed Annually	
	United States	South Carolina
Cyclone	1.68	3.72
Earthquake	1.51	< .01
Flood	0.11	< .01
Drought	12.5	13.05
Sea level rise	0.59	0.66
Total	16.39	17.43

Drought accounts for over 60 percent of total hazard exposure in 49 of the 50 US states when given full weight in the exposure component, and over 90 percent of exposure in 30 states. Even with a weight of half, drought still accounts for over 60 percent of exposure in 45 of 50 states and over 90 percent of exposure in 27 of 50 states. In some states that have little exposure to other hazards in the index, drought accounts for well over 99 percent of exposure. This pattern repeats itself when exposure is examined at the county level in South Carolina. In SC, 18 of 46 counties can attribute over 90 percent of their weighted exposure to drought, while 42 of 46 counties have over 60 percent of their exposure due to drought.

Another interesting aspect of the contribution of each hazard is the relative lack of exposure to flooding at the state and county level. This is somewhat counterintuitive and in contrast to the losses that flooding actually causes in the US. In 2012, flooding accounted for nearly 60% of the monetary loss and 13% of the fatalities due to natural hazards in the US. For the period 1960-2012, flooding ranks as the second costliest hazard in the US, behind only tropical storms (HVRI 2014). A 2011 study of social vulnerability to hazards in the Southeast US used the percent of land found in the Federal Emergency Management Agency's Special Hazard Flood Area zones as a metric for exposure, finding that at the state level it ranged from 8 percent in Virginia to 48 percent Louisiana (Emrich and Cutter, 2011). It would seem as if the exposure data does not account for the physical exposure to flooding that it should. This is likely a result of two factors concerning the calculation of flood exposure. First, the relatively small window of time (12 years) over which the flood exposure is calculated does not lend itself to a complete profile of the flood hazard. More importantly, PREVIEW flood data comes from the Dartmouth Flood Observatory, which catalogs large flood events captured through remote sensing. Thus as calculated, the flood exposure surface ignores a multitude of smaller scale flooding events, which are a frequent occurrence in the US. This shows the need for careful consideration of the hazards included and the exposure calculation method for risk indexes that include natural hazards.

To explore the relationship between percent exposure of individual hazards and the overall exposure component, multiple linear regression was

Table 3.3: Beta coefficients *(β)* for exposure linear regression

Independent Variable	United States Exposure	United States Exposure (No Drought)	South Carolina Exposure	South Carolina Exposure (No Drought)
Cyclones	.423**	.603**	.512**	.868**
Earthquakes	.369**	.526**	.004**	.006**
Flooding	.026**	.037**	.006**	.007**
Drought	.805		.829**	
Sea Level Rise	.318**	.453**	.105**	.209**

(*significant at .05; **significant at .01)

conducted on the exposure component utilizing the Statistical Package for the Social Sciences (SPSS) software package (Table 3.3). In different runs of the regression, exposure and exposure with no drought were used as dependent variables, with the individual hazards as independent variables at both the state. Changes in variables that have an effect on susceptibility show as strong standardized beta coefficients (β). For the US, changes in drought (β = .805, sig = .000) have the most influence on exposure, followed by cyclones (β = .423, sig = .000). Flooding (β = .026, sig = .000) has little influence on the overall component. When drought is removed, changes in cyclone exposure (β = .603, sig = .000) have the most influence on US exposure, followed closely by earthquakes (β = .526, sig = .000) and sea level rise (β = .453, sig = .000). The pattern is much the same at the SC county level, as drought (β = .829, sig = .000) has the most influence on exposure. When drought is removed, the cyclones have the largest influence (β = .868, sig = .000), which makes sense for a state with a large stretch of Atlantic coastline.

3.6 The geography of exposure

The exposure component for the US shows its highest values in the Southeast and along the West Coast, with apparently lower exposure found along the Rocky Mountains and in parts of the Midwest (Figure 3.5). Overall state exposure for the US has a mean of 14.84 percent, with a standard deviation of 4.57. An independent samples t-test determined that mean state exposure was not significantly different than the WRI mean exposure of 14.73 (sig. = .937). State exposure ranges from a low of 7.25 percent in Alaska to 30.7 percent in Wyoming. Wyoming's high exposure value is an unexpected result, and is driven entirely by the state's drought exposure. This underscores the influence that drought has on both the WRI and USDRI, as Wyoming has no exposure to three of the five hazards used in the compilation, and only very minor exposure to earthquakes. Although Wyoming has the largest percentage of its population exposed to hazards, California has the highest total population exposed, as its 25.99 percent exposure equates to almost 9.9 million people in the state exposed to hazards annually. Alaska has the lowest exposure in the US, at 7.25 percent of its population.

South Carolina exhibits large variations in exposure, with many counties having high exposure along the coast and in the southern part of the state (Figure 3.6). Mean exposure for counties in the state is 18.18 percent, with a standard deviation of 8.36. This mean is significantly different than both the WRI mean (sig. = .024) and the USDRI mean (sig = .015). Exposure for the state's counties ranges from 4.67 percent in McCormick County to 55.3 percent in

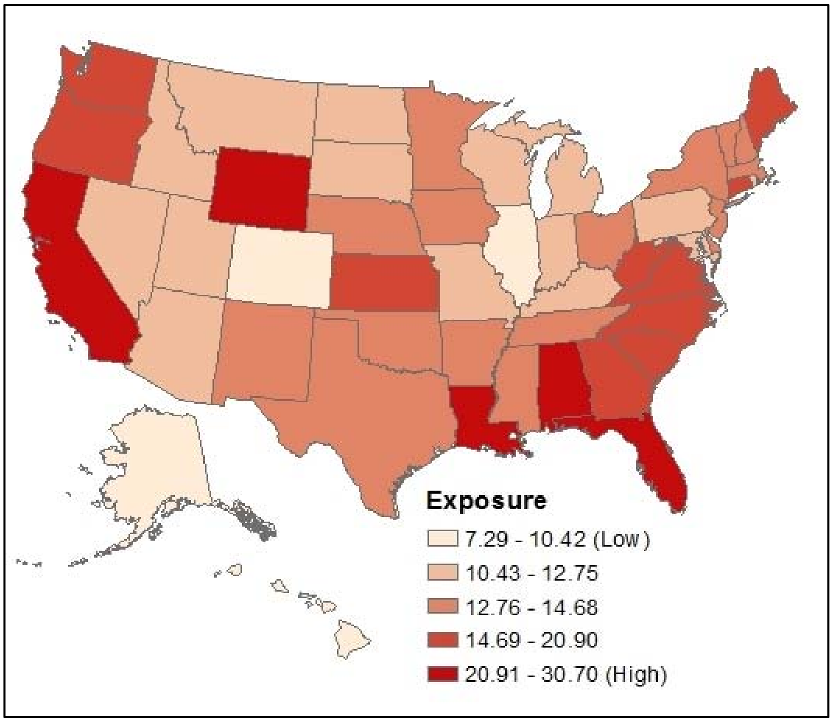

Figure 3.5: US state exposure to hazards (percent)
Data mapped using quantiles

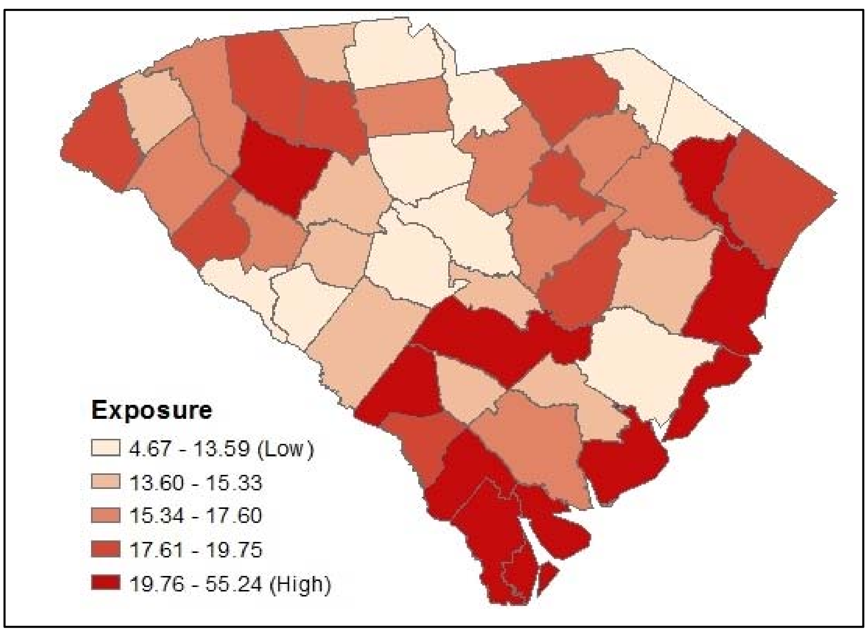

Figure 3.6: South Carolina county exposure to hazards (percent)
Data mapped using quantiles

Jasper County, near the southern tip of the state. Like Wyoming in the US analysis, the high exposure value for this county is due to the large influence of drought exposure. Charleston County has the highest population exposed annually, as its 29.48 percent exposure equates to 103,937 people.

3.6.1 Excluding drought from the exposure component

An alternate view of the hazards component of the USDRI is found by excluding drought from the exposure formula. For the reasons previously discussed in this chapter, it appears somewhat problematic to include drought in the USDRI. In a more developed country such as the US, drought represents more of an economic hazard and less of a physical one; the USDRI is an index based on physical exposure. This is not to underestimate the importance of drought as a hazard. In 2012, a total of 26 drought events – including a persistent drought in the US Midwest that caused billions of dollars – occurred globally. These droughts had far-reaching impacts, from famine in Somalia to rises in crop prices of, in some case, over 25 percent (MunichRe 2013).

Removing drought from the exposure component resulted in a much different pattern of exposure, both in the US (Figure 3.7) and in South Carolina (Figure 3.8). For the US, no drought in the component greatly decreased overall exposure from 13.22 to 3.9 percent. The largest drops in exposure at the state level were in the Midwest and Rocky Mountains. Wyoming's exposure went from 30.7 percent to less than one percent. Relatively speaking, the highest exposure values without drought are found on the West Coast and east of the Mississippi, which makes sense with knowledge of the remaining four hazards in the index. The mean exposure with no drought is 2.39 percent, with a standard deviation of

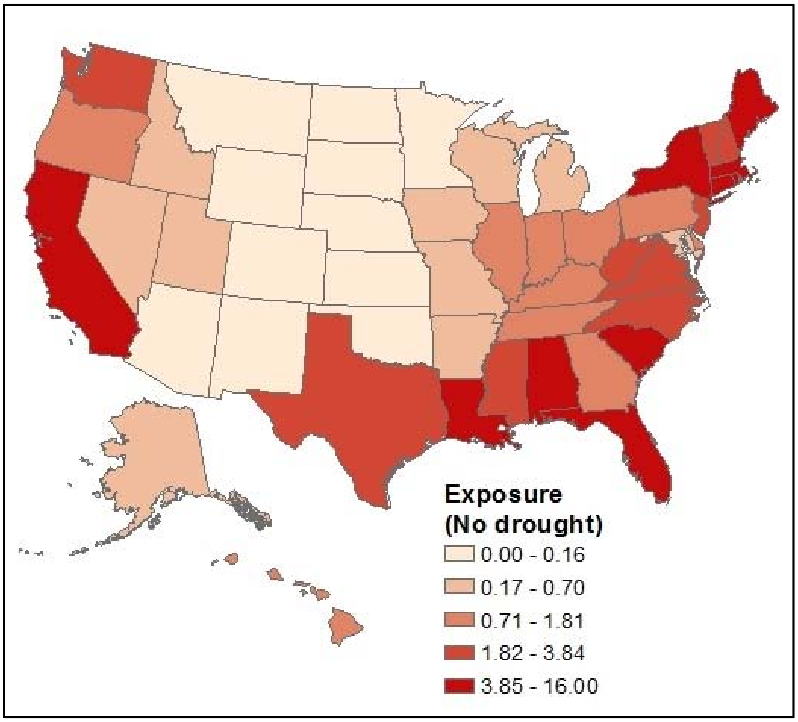

Figure 3.7: US state exposure to hazards, drought excluded

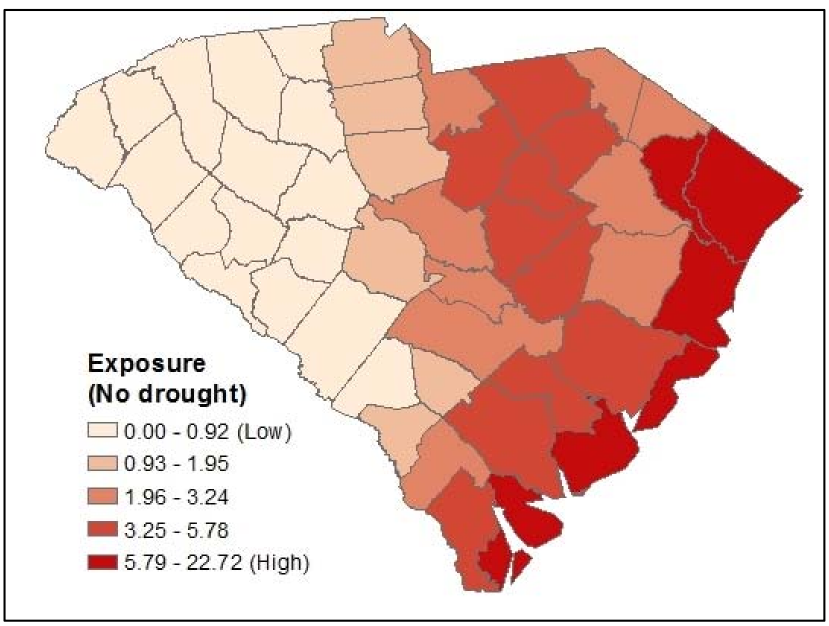

Figure 3.8: SC county exposure to hazards, drought excluded

3.2. California has the highest revised exposure figure at 12.1 percent, while numerous states have less than one percent. South Carolina's exposure with no drought also greatly decreased to 4.41 percent. Removing drought increases the influence of cyclones on the component, shifting the relatively higher exposure values into the eastern part of the state and along the coast. Mean county exposure in the state without the influence of drought is 3.62, with a standard deviation of 4.93.

3.6.2 Exploratory spatial data analysis of exposure

Exploratory data analysis helps in the recognition of patterns and relationships, as well as data description (Tukey 1977; Good 1983). However, exploratory data analysis is not particularly geared to determining spatial trends in the data. One method of examining data spatially is through exploratory spatial data analysis, which focuses on discovering spatial patterns and relationships. In general, exploratory spatial analysis can describe how data is arranged spatially, discover spatial associations (clustering), and ascertain spatial outliers (Anselin 1996). For this research, data was spatially analyzed using Anselin Local Moran's I (ALMI), which locates spatial clusters and outliers, and the Getis-Ord Gi* statistic, which determines spatial hotspots.

The oft used Moran's I statistic measures spatial autocorrelation, or the extent of dependency among spatial observations (Moran 1948). Moran's I can be calculated for a set of spatial data, with values for the statistics ranging from 1 to -1. Moran's I values closer to -1 represent dispersed (non-clustered) phenomena and values closer to 1 represent clustered phenomena. Applying

Moran's I to the results of the analysis in this dataset can help determine if there are overall aspects of the data that warrant further investigation.

One drawback of using Moran's I is that it only gives insight into the whole dataset, not its individual observations. Calculating Anselin Local Moran's I for a dataset helps gain further insight, as this statistic shows the contribution of each observation to a dataset. In particular, ALMI identifies the location of statistically significant clusters as well as outliers in a spatially referenced dataset (Anselin 1995).

Another method of exploratory spatial data analysis is through the use of Getis-Ord Gi* (Gi*) hotspot analysis. Like ALMI, Gi* shows the location of statistically significant hotspots of high or low values in a spatial dataset. Gi* also analyzes a feature and its neighbors in order to ensure that a statistically significant hotspot exists (Getis and Ord 1992).

As a first step in the spatial analysis of exposure, the Moran's I statistic was calculated for the exposure component as well as the exposure component with no drought. Note that for this calculation, and all spatial statistical calculations that follow in the work, Alaska and Hawaii were not included because they lack spatial contiguity with the rest of the US. For exposure, the Moran's I value is -.01, with a p-value of .37, and a z-score of -.71. Based on this result, the null hypothesis that the distribution of exposure is random cannot be rejected. When drought is removed from the exposure calculation, the result is a Moran's I of .23, with a p-value of .00 and a z-score of 2.62. The positive value of Moran's I along with the significant p-value (at alpha = .05) indicates a degree of clustering in the exposure score with no drought at the state level. For individual hazards in the US, only cyclones (Moran's I = .54, p = .00, z = 6.24) show significant clustering, while no hazards display significant dispersion.

The trend in spatial dependency found at the state level in the US is mirrored at the county level in South Carolina. The Moran's I statistic for the exposure component for SC counties is .12, with a p-value of .07 and a z-score of 1.83. This result again means failing to reject the null hypothesis that the exposure values are random. When drought is removed, Moran's I for the exposure component is .49, with a p-value of .00 and a z-score of 6.18. Thus without drought, the null hypothesis can be rejected at an alpha level of .05; more clustering is seen in the exposure component than would be expected. For individual hazards in SC, cyclones (Moran's I = .51, p-value = .000, z-score = 6.47) and sea level rise (Moran's I = .20, p-value = .000, z-score = 4.08) show significant clustering, with no hazards displaying dispersion.

To further investigate the spatial nature of exposure, both Anselin's Local Moran's I (ALMI) and Getis-Ord Gi* (Gi*) were calculated for the exposure component, with and without drought as part of the model (Figures 3.9 - 3.12). For the US, ALMI analysis located a statistically significant cluster of high exposure values, centered on Georgia and Florida (Figure 3.9), meaning that these states and their neighbors all exhibit anomalously high exposure. The ALMI analysis also identified Wyoming and Louisiana as a high exposure spatial outliers, meaning that these states are surrounded by states that have relatively low exposure. Wyoming's high drought exposure value accounts for its status an outlier, while Louisiana has high exposure to drought, sea level rise, and cyclones. Without drought, ALMI analysis shows a much different spatial pattern for exposure in the US. The Southeast no longer shows as a high exposure cluster, but the Northeast has one, centered on Massachusetts, Rhode Island, and Connecticut. Wyoming and Louisiana no longer show as a high outliers – Wyoming in particular has a very low exposure score without drought. Instead,

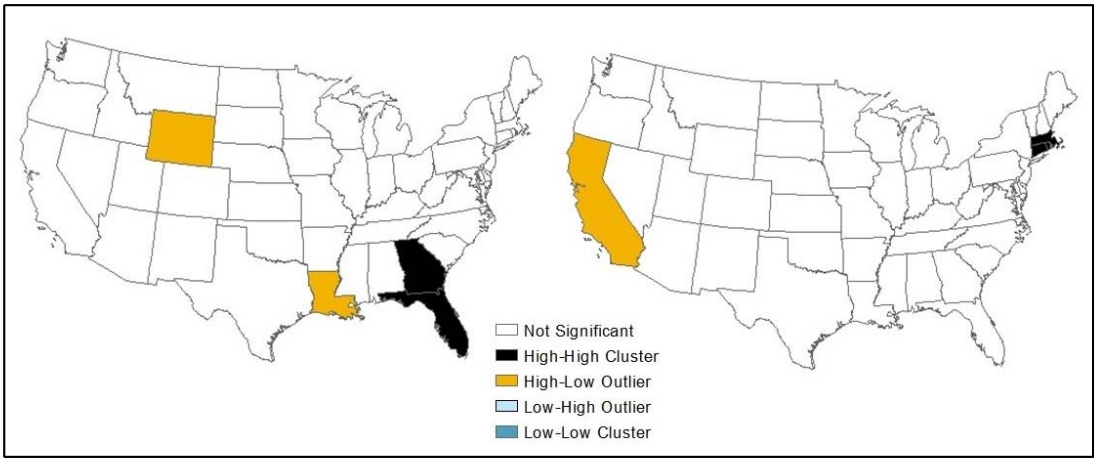

Figure 3.9: Anselin Local Moran's I for exposure (left) and exposure with no drought

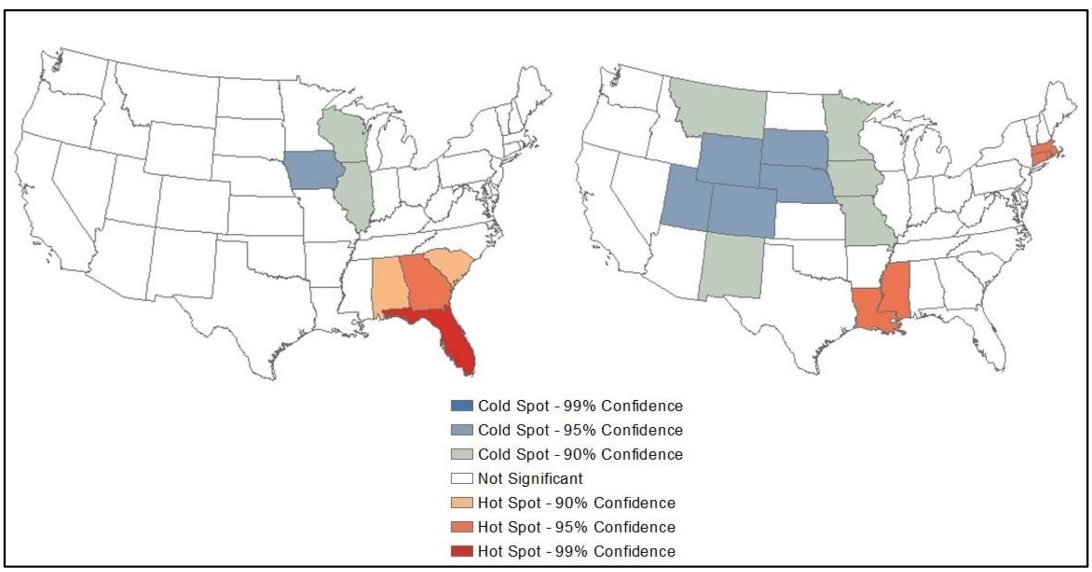

Figure 3.10: Getis-Ord Gi* for exposure (left) and exposure with no drought

California, based on earthquake exposure, has a statistically significant higher exposure value when compared to its neighbors.

The Getis-Ord Gi* analysis (Figure 3.10) for exposure shows an area of high exposure in the Southeast US, with significant values found in Georgia and Florida. Gi* also identifies an area of low exposure in the Midwest, centered on Iowa, Illinois, and Wisconsin. When drought is removed from the exposure component, the area of low exposure in the Midwest remains but shifts west - centered on centered on Nebraska, South Dakota, Colorado, Wyoming, and New Mexico – and expands. Significant hotspots with no drought are found in the South, centered on Louisiana and Mississippi, and in the Northeast, centered on Massachusetts and Connecticut.

ALMI analysis for South Carolina identifies a significant cluster of high exposure in the southern part of the state (Figure 3.11), centered on Jasper and Beaufort counties. Jasper has the highest exposure value for the state at 55.3 percent, while Beaufort has the fourth highest at 25.7 percent. Another area of high exposure is centered on Georgetown County in the eastern part of the state. Removing drought from the exposure component leaves SC with a single significant cluster of high exposure that runs along the coast from Charleston County northeast to Horry County. This cluster is due mainly to exposure to tropical cyclones.

Gi* analysis shows much the same pattern for exposure with drought included, highlighting Beaufort, Jasper and Hampton counties as one significant hotspot, with another that includes Georgetown and Horry counties. (Figure

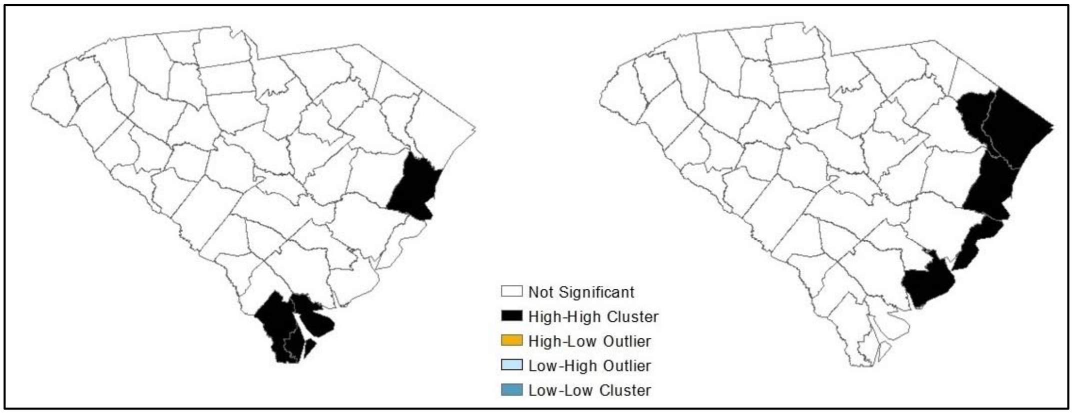

Figure 3.11: Anselin Local Moran's I for exposure (left) and exposure with no drought

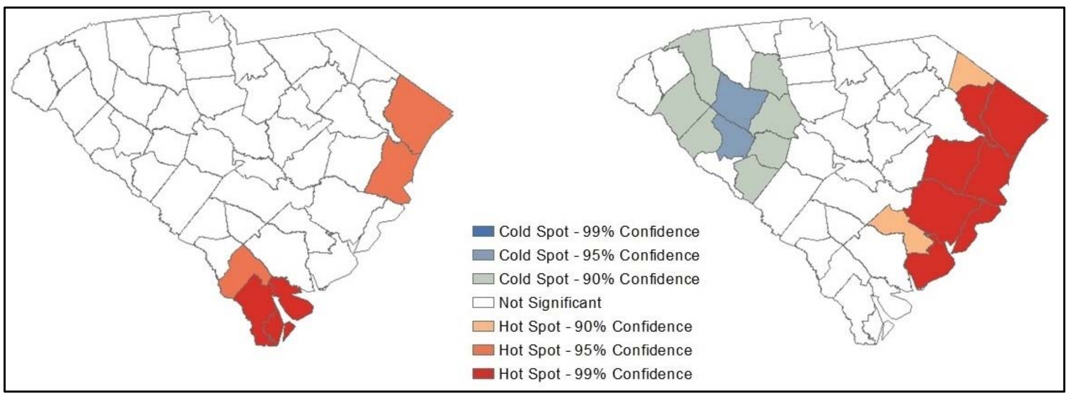

Figure 3.12: Getis-Ord Gi* for exposure (left) and exposure with no drought

3.12). Without drought, Gi* underscores a much different pattern in the state. The analysis shows a hotspot including eight counties along or near the SC coast, running from Charleston to Horry County. Six of these counties are significant at the 95% level. Additionally, a large cluster of nine low exposure counties emerges in the northwest part of the state, centered on Laurens and Greenwood counties. Removing drought, which is more of an areal hazard than any other included in the index, brings out spatial differences in exposure that are masked when it is included. It is clear, for both the US and SC, that drought has a large influence on the exposure component and the USDRI writ large.

3.7 Summary and conclusions

This chapter has detailed the overall construction of the USDRI as well as its exposure component. The USDRI is a downscaled version of the World Risk Index, thus its construction and variable choices mimic the WRI whenever possible. Overall, like the WRI, the USDRI calculates risk as the product of exposure and vulnerability for a given place.

The USDRI exposure component consists of the same five hazards – tropical cyclones, floods, earthquakes, drought, and sea level rise – found in the WRI. The component is calculated in the same manner as the WRI, which gives only half weight to drought and sea level rise. Once exposure is determined for individual hazards, the scores are added together. The resulting number assigned to the exposure component for a state or county represents the number of people in that geographic area exposed annually to the suite of hazards in the model.

At the US level, state exposure values are highest in the Southeast and along the West Coast. Central areas of the country have generally lower scores, but there are also some states with higher exposure scores here, including Wyoming, the state with the highest exposure score. For SC counties there is a large range of exposure, with many of the most exposed counties occurring in the southern part of the state and along the coast. Spatial analysis showed much the same patterns. At the US level, clusters of high exposure were noted along the Gulf Coast, while a cluster of lower vulnerability (according to ALMI analysis) occurs in the Midwest. For South Carolina, high exposure clusters are found along the coast.

The large influence of drought on the overall exposure component is evident, as at both the state and county level approximately 75% of the exposure is due to drought. Thus drought, which has caused no recorded deaths or injuries in the US since 1960, has an undue influence on an index that describes risk to hazards using human exposure. For this reason, the exposure component was calculated without drought. This drastically changed the nature and pattern of exposure at the state and county level. Overall exposure scores were much lower at both scales. For the US, removing drought from the component definitely established areas west of the Mississippi River (especially the Atlantic and Gulf Coasts) as well as the West Coast as areas of high exposure. For South Carolina, counties along the coast showed the highest values for exposure, and exposure tends to decrease in the state from the coast inland. Spatial analysis of exposure clusters and hotspots confirms these observations at both scales.

CHAPTER 4: CONSTRUCTING THE USDRI - VULNERABILITY

4.1 Overview

The complementary component to exposure in the WRI is vulnerability. The concept of vulnerability used in the WRI generally conforms to the 2009 UNISDR definition, which describes vulnerability as "the characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard." While many contemporary conceptualizations of vulnerability include an entity's exposure, this definition separates it (UNISDR 2009). The vulnerability component of the WRI attempts to capture this broad concept of vulnerability by using three individually calculated subcomponents: susceptibility, coping capacity, and adaptive capacity (Figure 4.1).

This initial effort to downscale the WRI attempts to use the same indicators, where feasible, as the original WRI. In some cases, many due to data availability at smaller scale, the indicators could not be directly replicated, so close proxies were utilized.

4.2 The susceptibility subcomponent

Susceptibility refers to the predisposition of infrastructure, humans, and the environment to be affected by the impacts of a hazard. Susceptibility can be physical or societal; the latter refers to the intrinsic conditions within a society that make it possible that, once impacted, the society will suffer great harm (IPCC 2012).

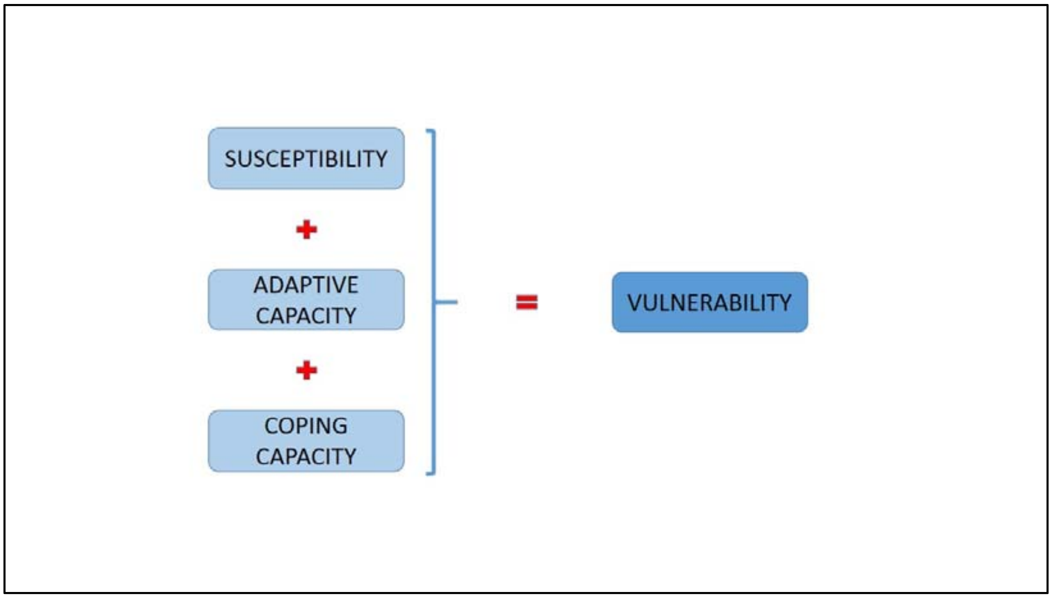

Figure 4.1: Vulnerability in the WRI

4.2.1 Variables

To capture the susceptibility within a society, the WRI uses five categories: public infrastructure, housing conditions, nutrition, poverty and dependencies, and economic capacity and income distribution (Figure 4.2). The WRI variables used to assess susceptibility (as well as adaptive capacity and coping capacity) were selected through participatory methods, and vetted by experts and practitioners in order to determine their relevance to the concept. Additionally, advice from those surveyed resulted in the weights applied to each of the groupings of variables in the sub-indices (Birkmann 2011). One category, housing conditions, was not included in the final calculation of the WRI susceptibility component, as suitable, uniform data to assess housing at the global level does not currently exist. For this reason, housing conditions were also omitted from this initial attempt to downscale to the USDRI, although data exist at the subnational level.

4.2.2 Data

The indicators used in the USDRI susceptibility component come from four different data sources (Table 4.1). The primary data source is the US Census Bureau's American Community Survey (ACS) 2012 data release. The

Table 4.1: Indicators for USDRI Susceptibility

Susceptibility Indicator (N=6)	Source	Supporting Literature
	Public Infrastructre	
Households without bathrooms	US Census American Community Survey (2008-2012)	Brooks et al. 2005
	Nutrition	
Access to healthy foods	Robert Wood Johnson Foundation County Health Rankings and Roadmaps	Ahern et al. (2011); Von Grebmer et al. (2010); UNSCN (2010)
	Poverty and Dependencies	
Dependency Ratio	US Census American Community Survey (2008-2012)	Cutter et al. (2003); Schneiderbauer (2007)
Poverty level	US Census American Community Survey (2008-2012)	Ravallion et al. (2008); UNDP (2007); World Bank (2008)
	Economic Capacity and Income Distribution	
GDP per capita	US Department of Commerce Bureau of Economic Analysis	Peduzzi et al. (2009); UNDP (2004); Schneiderbauer (2007); Ash et al. (2013)
GINI coefficient	US Census American Community Survey (2008-2012)	Gini (1921); Anand and Segal (2008); Norris et al. (2008)

ACS samples approximately 2.5 percent of the US population each year. This produces a sufficient sample size for areas of higher population, but not for sparsely populated areas (ACS, 2009). To account for the entire US population, the USDRI utilizes the ACS five-year (2008-2012) estimate, which is its most comprehensive estimate.

Data for the nutrition component is taken from the Robert Wood Johnson Foundation County Health Rankings and Roadmaps. This dataset, available online at http://www.countyhealthrankings.org/, is a collaboration between the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute. The dataset contains both rankings and raw data that look at various factors for each US county used to assess overall health. The rankings themselves are calculated within a state, meaning that comparing ranks across counties for different states is not possible. However, the USDRI utilizes only the raw data used to compile the rankings, which allows for comparison between states and counties.

Finally, data for Gross Domestic Product (GDP) comes from two different sources. State level GDP is drawn from the US State Department Bureau of Economic Analysis. This GDP data is an inflation-adjusted measure of state production, based on average US prices for goods produced within a state (BEA, 2014). The county GDP data is estimated by taking state GDP and multiplying that by the percentage of the state's employees that each county has (Ash et al. 2013).

4.2.3 Procedures

Once all variables were collected, the susceptibility subcomponent was compiled using the weights assigned to the original WRI components (Figure

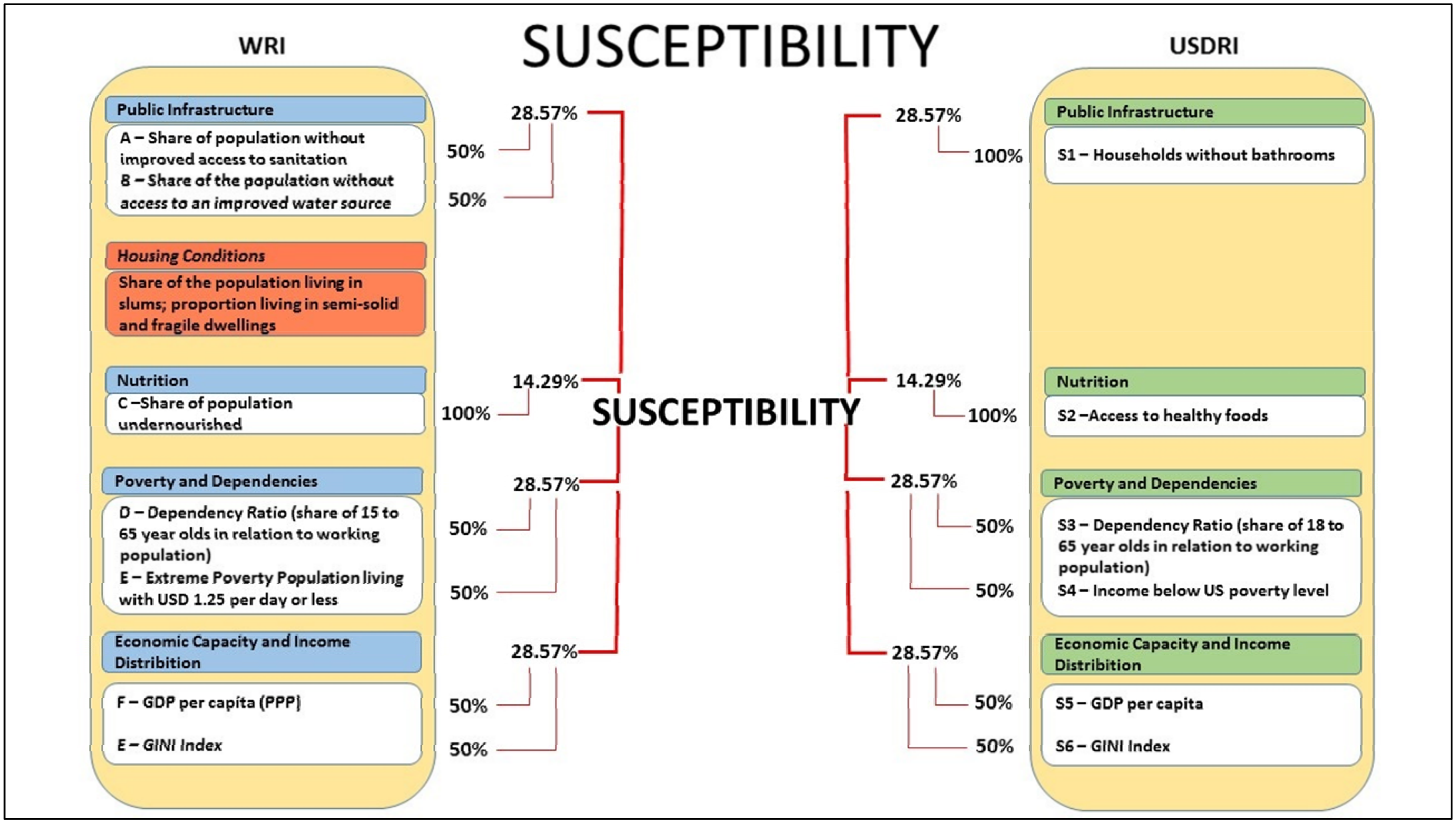

Figure 4.2: Makeup of the WRI (left) and USDRI susceptibility components

4.2). The USDRI variable weights mirror those of the WRI, except for households without bathrooms, which carries 100 percent of the public infrastructure category compared to 50 percent in the WRI.

For comparative purposes, all of the individual variables were rescaled. Indicators expressed as percentages were divided by 100. Non-scaled variables were normalized using a Min-Max rescaling technique, using the following equation:

$$X_{i,\,0\ to\ 1} = X_i - X_{min} / X_{max} - X_{min}$$

Rescaling results in variable values that are comparable. The normalization resulted in variables on a scale of 0 to 1, with the lowest variable value assigned a value of 0, the highest 1, and all others scaled in between. The end result for each component is a mix of unscaled (those that were already expressed as percentages) and scaled variables. This is an appropriate technique when some variables are already expressed as percentages (Tate 2013). For susceptibility, higher values equate to higher susceptibility. For the purposes of data presentation and comparison to the WRI, the final subcomponent score is multiplied by 100. Theoretically, scores for all three of the USDRI vulnerability subcomponents have a minimum possible value of 0 and maximum possible value of 100.

4.2.4 Analysis

In the WRI, the US (Figure 4.3) has a value of 16.67 for its susceptibility component. In the re-analysis, when state scores for susceptibility are weighted for population and scaled to the national level, the result is 21.8. The difference in these values is likely accounted for by the use of different data sources for each index. In addition, the degree of normalization used in each index is different, based on the different sample sizes (n = 51 for the USDRI, n = 173 for the WRI). For the smaller sample size of the USDRI, individual points for any data rescaled using the min-max technique could differ greatly from their actual value. South Carolina (Figure 4.4) has a susceptibility composite score of 23.26

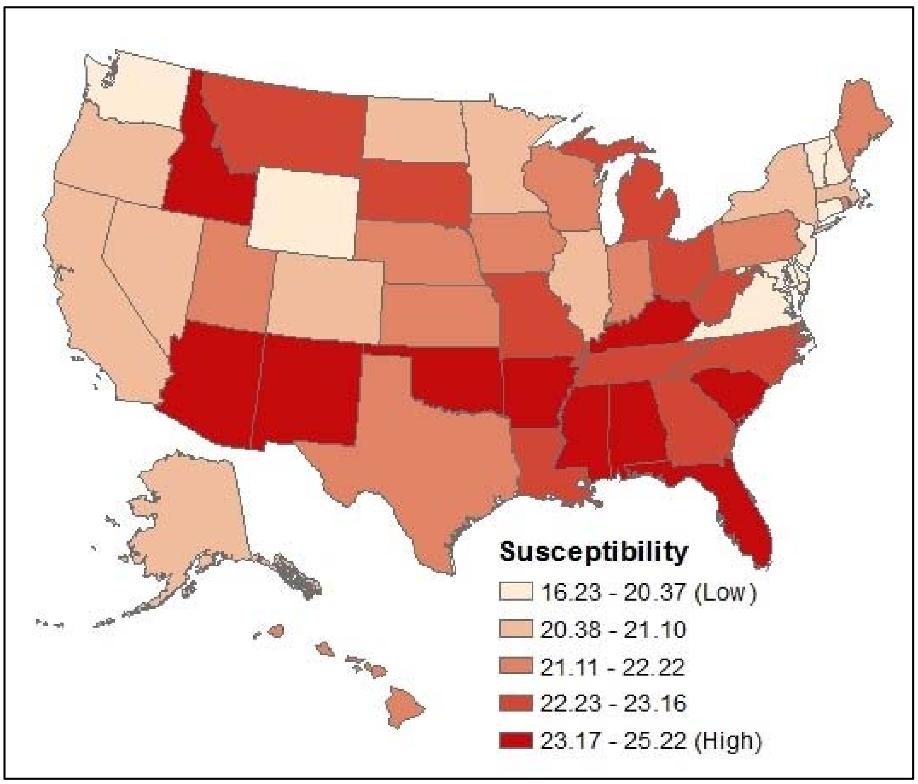

Figure 4.3: US state susceptibility. Data mapped using quantiles.

at the state level, which is 42nd among US states (Washington, D.C. included) – ranking it among the most susceptible.

On a state by state basis, mean susceptibility scores are 21.67 (standard deviation 1.61), ranging from 19.5 in Maryland (least susceptible) to 25.22 in Mississippi (most susceptible). The mean state susceptibility score is significantly different than the WRI mean susceptibility of 31.35 (sig. = .000). An area of high susceptibility scores occurs across southern areas of the US, while the Mid-Atlantic States and New England exhibit lower susceptibility scores.

South Carolina counties have a mean susceptibility of 21.44 (standard deviation 1.75). This is significantly different than WRI mean susceptibility (sig. = .000), but not USDRI susceptibility (sig. = 501). Susceptibility scores for SC counties range from 17.8 in Richland (least) to 24.68 in Allendale (most). There seems to be a distinct urban / rural pattern to lower and higher susceptibility, respectively. The three largest urban areas of the state – Charleston along the

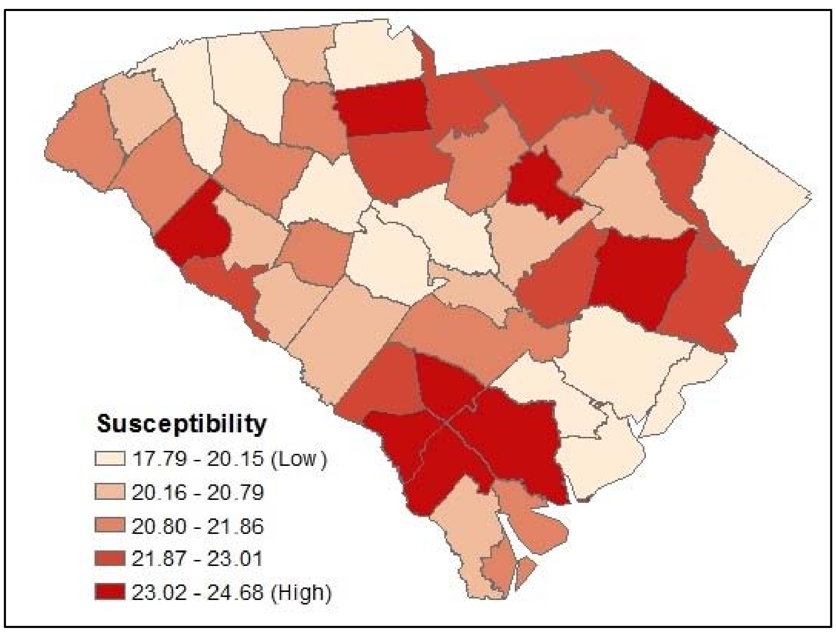

Figure 4.4: SC county susceptibility. Data mapped using quantiles.

coast, Columbia in the Midlands, and Greenville-Spartanburg in the upstate – are in areas that score in the lowest 20 percent of susceptibility.

A linear regression model was run, with susceptibility as the dependent variable and its components as explanatory variables (Table 4.2). Changes in variables that have an effect on susceptibility show as strong standardized beta coefficients (β). For US states, changes in GDP (standardized β = .458, sig = .000) and dependency ratio (standardized β = .372, sig = .000) had the strongest influence on susceptibility. At the SC county level, susceptibility was most

Table 4.2: Relationship between susceptibility and variables used to construct it

	US States		SC Counties	
Variable	Pearson's R	β	Pearson's R	β
Households without bathrooms	-.096	.107**	.439**	.065**
Access to healthy foods	.697**	.215**	-.121	.266**
Dependency ratio	.750**	.372**	.482**	.400**
Income below poverty level	.685**	.274**	.729**	.445**
GDP per capita	.847**	.458**	.670**	.580"
GINI index	.027**	.191**	.471**	.209**

(*significant at .05; **significant at .01)

influenced by changes in GDP (standardized β = .580, sig = .000), dependency ratio (standardized β = .400, sig = .00), as well as percent of those with income below the poverty level (standardized β = .445, sig = .000).

Spatial analysis of susceptibility using Moran's I shows that for the US (Moran's I = .31, z-score = 3.70, p-value = .000), statistically significant clustering exists while it does not for SC (Moran's I = .11, z-score = 1.47, p-value = .144). Further investigation using ALMI and Gi* highlight the spatial distribution of susceptibility. For the US, ALMI analysis identified a significant cluster of high susceptibility in the southern US, centered on Arkansas, Mississippi, and Alabama (Figure 4.5). ALMI also identified areas of lower susceptibility in the mid-Atlantic (Maryland) and the Northeast (Massachusetts). Gi* analysis also shows a cluster of high susceptibility in the southern US that includes nine states in the southern half of the US, seven of which have significant values (Figure

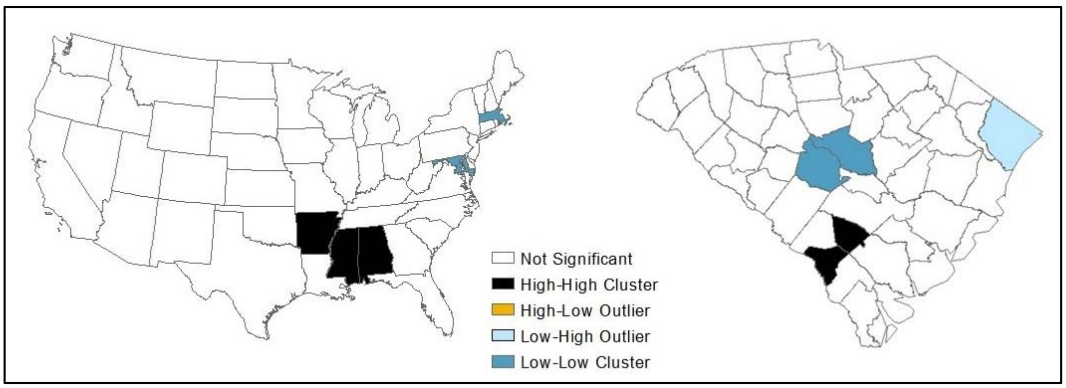

Figure 4.5: Spatial analysis of susceptibility using Anselin Local Moran's I.

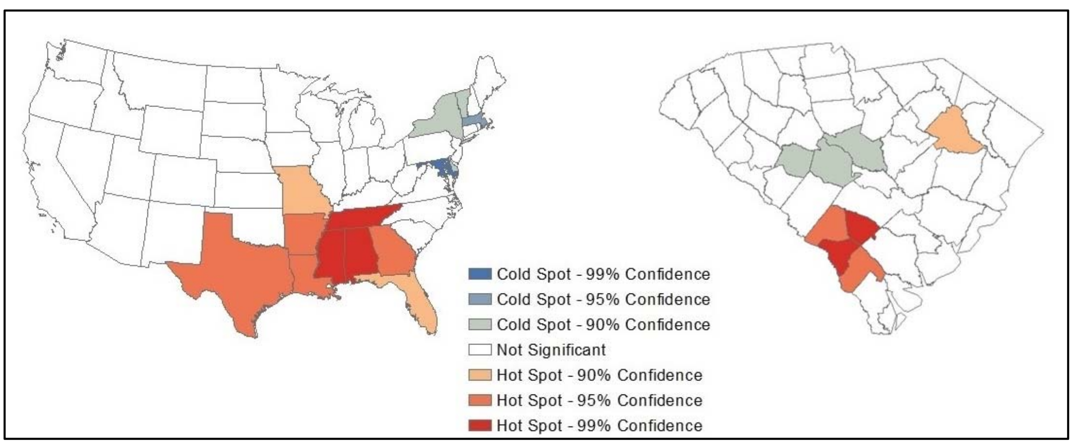

Figure 4.6: Spatial analysis of susceptibility using Getis-Ord Gi*.

4.6). Additionally, Gi* identifies an areas of low susceptibility in the mid-Atlantic and another in the Northeast.

For South Carolina, ALMI identified a statistically significant cluster of low susceptibility in the central part of the state centered on Richland and Lexington counties, as well as highlighting Horry County as having low susceptibility in an area of higher susceptibility. ALMI also shows a significant cluster of high susceptibility in the southwest part of the state, centered on Allendale and Bamberg counties. Gi* analysis identified the low susceptibility cluster in the center of the state as well as a high susceptibility cluster in the southwest part of the state that includes four counties.

4.3 The coping capacity subcomponent

The WRI coping capacity component is designed to assess the ability of nations (states or counties) to cope with the immediate effects of disasters. The WRI specifies five components that determine the ability to cope: government and authorities, disaster preparation and early warning, medical services, social networks, and poverty and dependencies (Figure 4.7). There is insufficient global data available at present on disaster preparation and early warning and social networks categories. As a result, they are not included in the initial version of the WRI. They can be included in later versions, as better data for these categories exists either globally or sub-nationally. For example, the number of Storm Ready communities in the US could serve as an indicator for disaster preparation and early warning, while participation in Citizen Corps programs or access to the internet could provide insight into social networks.

4.3.1 Data

Table 4.3: Indicators for USDRI Coping Capacity

Coping Capacity Indicator (N=4)	Source	Supporting Literature
	Government and Authorities	
Political Fragmentation	Hazards and Vulnerability Research Institute	Murphy (2007); Ansell et al. (2010); Lambsdorff (2008); Norris et al. (2008)
	Medical Services	
Primary care physicians per 10000	US Census American Community Survey (2008-2012)	IDEA (2005); Norris et al. (2008)
Hospital beds per 10000	US Census Statistical Abstract (state); US Census County and City Data Book (county)	McKee (2004); Auf de Heide and Scanlon (2007)
	Material / Economic Coverage	
Health Insurance Coverage	US Census American Community Survey (2008-2012)	IDEA (2005)

The indicators for the coping capacity subcomponent come from four different sources (Table 4.3). The previously discussed ACS provides data for primary care physicians and health insurance. The government and authorities metric is the number of governments and special districts per 10,000 people, with higher numbers representing more political fragmentation (Cutter et al. 2010). State level data on political fragmentation was obtained by using weighted averages of the county-level data. Finally, the data for the hospital beds indicator is drawn from two different sources published by the US Census Bureau. State hospital bed information comes from the 2012 US Statistical Abstract (https://www.census.gov/compendia/statab/). Data for county hospital beds comes from the City and County Data Book.

(http://www.census.gov/statab/www/ccdb.html).

4.3.2 Procedures

The coping capacity subcomponent followed the WRI. All of the variables were normalized on a scale from 0 to 1 and weighted according to WRI formula. For the government and authorities category the WRI had two variables weighted at 50 percent each, while the USDRI utilized only political fragmentation, weighted at 100 percent of the category. Once compiled, higher coping capacity scores indicate increased ability to cope. In order to fit into the overall vulnerability model, where higher scores equate to higher vulnerability, the inverse of the coping capacity scores were used (score subtracted from 100). Thus the score used in the final calculation describes lack of ability to cope, with higher scores meaning less ability.

4.3.2 Analysis

The US scores a 48.48 for lack of coping capacity in the WRI while in the reformulation the USDRI score is 47.79. South Carolina's coping capacity value is 39.18. This ranks the state 15th among US states, within the top third in terms of ability to cope with disasters.

The mean coping score for the states is 43.24, with a standard deviation of 8.56. This is significantly different than the WRI lack of coping mean of 69.79 (sig. = .000). Scores range from a low of 34.58 in Mississippi to a high of 78.61

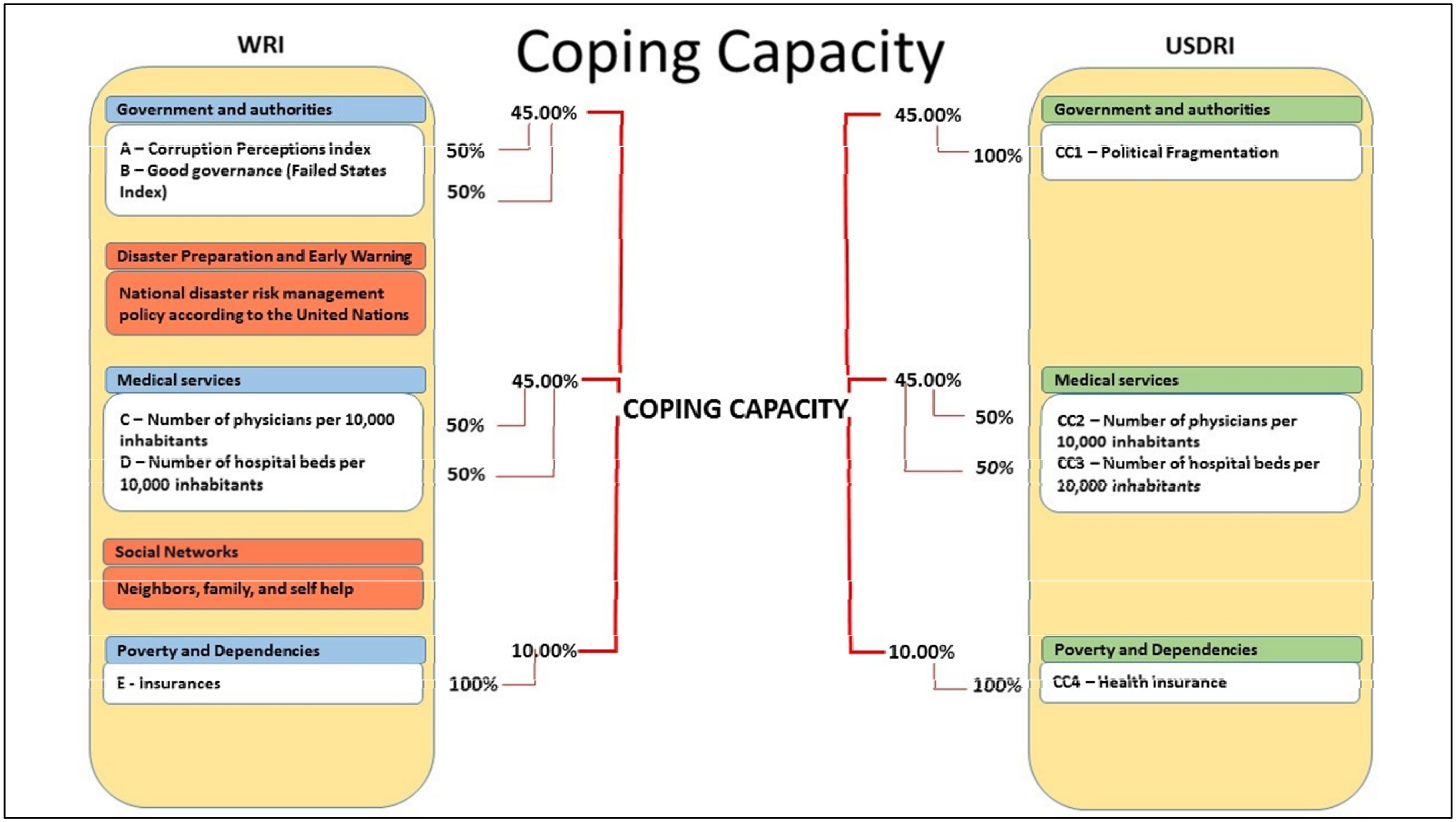

Figure 4.7: Makeup of the WRI (left) and USDRI coping capacity components

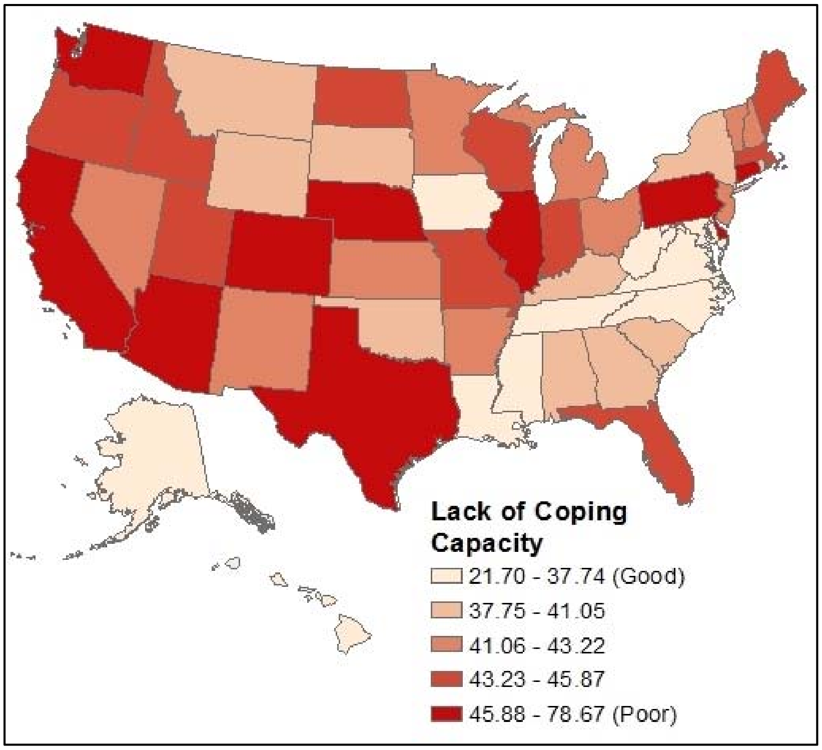

Figure 4.8: US state lack of coping capacity (Data mapped using quantiles)

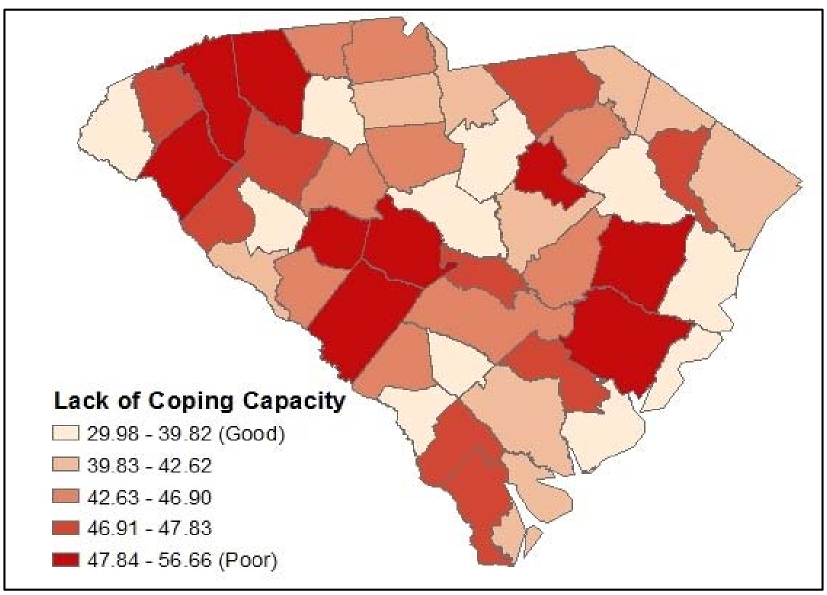

Figure 4.9: SC county lack of coping capacity (Data mapped using quantiles)

in Illinois. In general, low scores for the component, indicating better ability to cope, are found in the Southeast US, while many western states display less coping capacity (Figure 4.8). South Carolina's (Figure 4.9) county mean lack of coping capacity is 43.62, with a standard deviation of 5.75. This is significantly different than the WRI lack of coping mean (sig = .000), but not the USDRI lack of coping mean (sig = .501). Spartanburg County has the lowest capacity to cope, scoring 56.66, while Bamberg scores best among SC counties (29.98). There is no readily apparent pattern to high lack of coping scores in the state. The SC coastal counties appear do have generally lower scores, indicating better coping capacity. Examination of coping capacity at the SC county scale produces some counter-intuitive results, as some counties with apparent low ability to cope – such as Allendale – scoring well. This is likely a result of low populations and minimal governmental structures allowing the certain counties to score much better than anticipated. This phenomena repeats itself to varying degrees in the other vulnerability subcomponents, and could be the result of attempting to use variables vetted at the global scale for a sub-national index.

Multiple regression between coping capacity (Table 4.4) and its components shows that at the US state scale, changes in political fragmentation (standardized β = .934, sig = .000) have the most influence on coping capacity. At the SC county scale political fragmentation (standardized β = .693, sig = .000), hospital beds (standardized β = .742, sig = .000), and physicians (standardized β = .524, sig = .000) all influence on coping capacity.

Spatial data exploration of the coping capacity component using Moran's I shows no statistically significant results, indication that coping capacity displays a

Table 4.4: Relationship between coping capacity and variables used to construct it

Variable	US States		SC Counties	
	Pearson's R	β	Pearson's R	β
Political fragmentation	.946**	.934**	.277	.693**
Physicians per 10000	.116	.183**	.419**	.742**
Hospital beds per 10000	.388**	.228**	.797**	.524**
Health insurance	.125	.049**	-.039	.054**

(*significant at .05; **significant at .01)

random pattern at both the state (Moran's I = .07, z-score = 1.61, p-value = .271) and SC county level (Moran's I = .00, z-score = .24, p-value = .812). Further analysis using ALMI and Gi* did reveal some spatial patterns in coping capacity. For the states, ALMI showed both Illinois to be a statistically significant outlier, meaning the state had high lack of coping capacity when compared with its neighbors (Figure 4.10). On the other end of the spectrum, ALMI identified Virginia also as an outlier, with more coping capacity compared to neighboring states. Gi* analysis confirmed the low lack of coping scores in the mid-Atlantic (Figure 4.11), again identifying Virginia as having a statistically low score. Additionally, Gi* highlighted an area of high lack of coping in Southwest US.

In South Carolina, ALMI identified a significant cluster of poor coping capacity centered on Greenville County in the northwest part of the state, and also identified Greenwood and Union counties as having good coping capacity in an area with relatively poor capacity. Gi* also identified Greenville as the center of a low coping capacity cluster, while showing a cluster of better coping capacity centered on Colleton County in the southern part of the state.

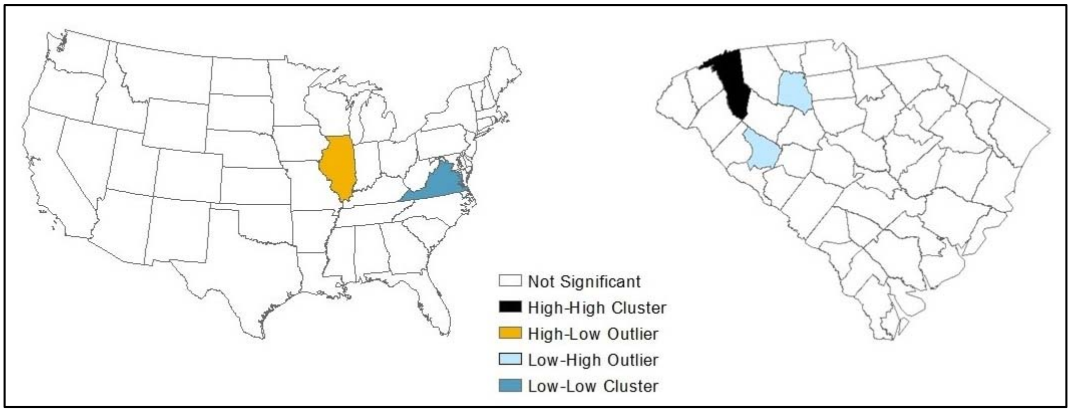

Figure 4.10: Spatial analysis of coping capacity using Anselin Local Moran's I.

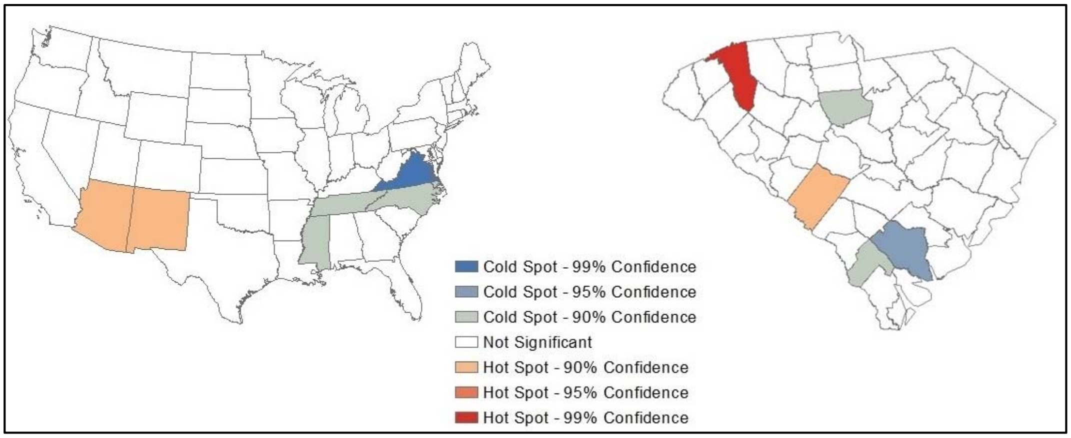

Figure 4.11: Spatial analysis of coping capacity using Getis-Ord Gi*.

4.4 The adaptive capacity subcomponent

The adaptive capacity component is designed to measure the ability to adapt to the negative consequences of future disasters. The WRI captures adaptive capacity using indicators in five categories: education and research, gender equity, environmental status / ecosystem protection, adaptation strategies, and investment (Figure 4.12). However, there are no consistent global indicators of adaptation strategies, so the set is excluded from the WRI computation.

4.4.1 Data

The adaptive capacity indicators utilized by the USDRI come from six different data sources (Table 4.5). The ACS provides the data for educational attainment as well as gender parity. Literacy rate data comes from the National Center for Educational Statistics, which conducted a 2003 survey of over 16,000 households in order to estimate basic prose skills (http://nces.ed.gov/naal/estimates/Overview.aspx). Under the category of environmental protection, the WRI utilizes the Environmental Performance Index database compiled by the Yale Center for Environmental Law and Policy. These data are not available at the subnational level; however, data are available for the three sub-elements. Drinking water safety data comes from the aforementioned Robert Wood Johnson Foundation County Health Rankings and Roadmaps. For the biodiversity and habitat protection indicator, the USDRI uses two datasets – percent protected areas and percent wetlands (National Landcover Dataset), by county and state and percent of harvest cropland (Census of Agriculture, 2007). Under the investment component, life expectancy is derived from data at the Institute for Health Metrics and Evaluation, a health research center. Data on health expenditure comes from two different sources. State level data comes from the Dartmouth Atlas of Healthcare as compiled by the Henry J. Kaiser foundation (http://kff.org/history-and-mission/). County health expenditure

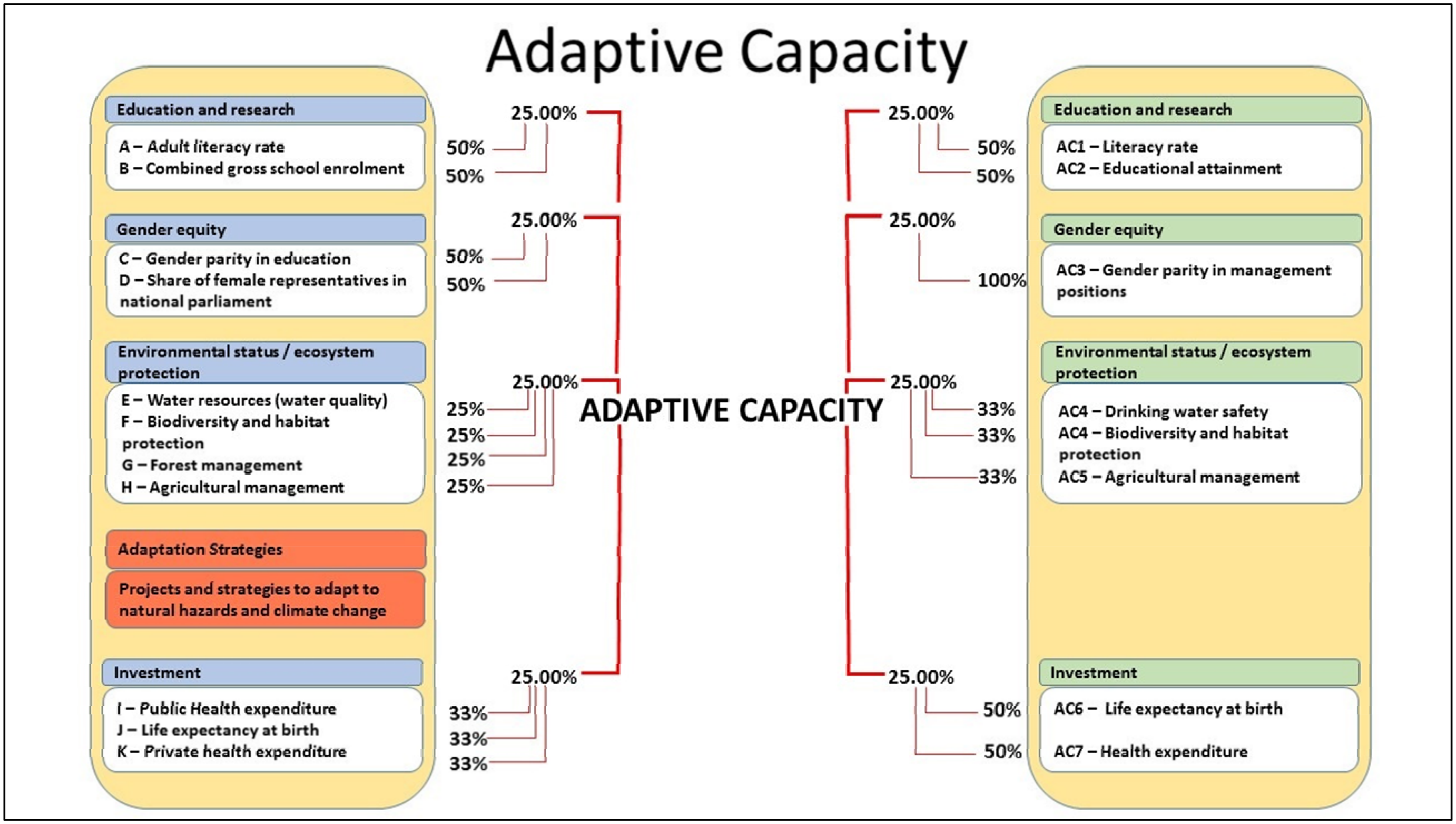

Figure 4.12: Makeup of the WRI (left) and USDRI adaptive capacity components

information comes from the Robert Wood Johnson Foundation County Health Rankings and Roadmaps.

Table 4.5: Indicators for USDRI Adaptive Capacity

Adaptive Capacity Indicator (N=8)	Source	Supporting Literature
	Education and Research	
Literacy Rate	National Center for Educational Statistics	Cutter et al. (2003); UNESCO (2006)
Educational Attainment (percent over age 25 with at least a high school diploma)	US Census American Community Survey (2008-2012)	Cummings et al. (2005); Cutter et al. (2003); Norris et al. (2008)
	Gender Equity	
Ratio of females to males in managament positions	US Census American Community Survey (2008-2012)	NRC (2006b)
	Environmental Status / Ecosystem Protection	
Drinking Water Safety	Robert Wood Johnson Foundation County Health Rankings and Roadmaps	Emerson et al. (2010)
Biodiversity and Habitat Protection (wetlands and protected areas)	Hazards and Vulnerability Research Institute; National Landcover Dataset 2006 (wetlands); Protected areas database of US 2012 (protected areas)	Brody et al. (2012); Beatley and Newman (2013)
Agricultural management (harvested area in cropland)	Hazards and Vulnerability Research Institute; USDA Census of Agriculture (2007)	UNDESA (2007); Barthel and Isendahl (2013)
	Investment	
Life expectancy at birth	Institute for Health Metrics 2010	WHO (2008); UNDP (2010c)
Healthcare expenditure	Countyhealthrankings.org (county data); Henry J. Kaiser Foundation (state data)	Cutter et al. (2003); Brooks et al. (2005)

4.4.2 Procedures

The USDRI adaptive capacity subcomponent was compiled using the same weights as the same WRI subcomponent, with indicator weights distributed equally in the categories and the four categories also weighted equally, with each contributing 25 percent to the overall component score. Normalization and scaling was accomplished in the same manner as in both the susceptibility and coping capacity components. As with coping capacity, the final scores were subtracted from 100 so that higher scores are worse, indicating a lack of ability to adapt.

Calculation of the adaptive capacity subcomponent of the USDRI yields a population weighted overall value of 39.84 for the US, higher than the WRI adaptive rating, which is 32.55. This could be a result of the fact that six of the eight USDRI adaptive capacity indicators, while similar, were different than their WRI counterparts. Another possible explanation for the large disparity in values is the normalization process. Within the USDRI, n = 51, while the WRI n = 173. The US indicators in the WRI likely scored well for adaptive capacity compared to the rest of the world, so the normalized scores for the US would be generally lower. In the USDRI the smaller sample size meant US states that might have scored well compared to other countries in the world would fare poorly as a result of the subnational normalization process. For example, Illinois' adaptive capacity score of 44.32 would rank it a modest 70th in the world, but places it in the bottom third of US states with a rank of 34. South Carolina's adaptive capacity score is 40.72, ranking it 28th among US states.

4.4.3 Analysis

The mean state score for lack of adaptive capacity is 39.11, with a standard deviation of 6.74. This is significantly different than the WRI lack of coping mean of 47.34 (sig. = .000). Scores range from 24.05 in Alaska (most adaptive) to 49.55 in Iowa (least adaptive). Areas of lower adaptability are found in the central part of the US, while both the east and west coasts show relatively more capacity to adapt (Figure 4.13). South Carolina's county mean lack of

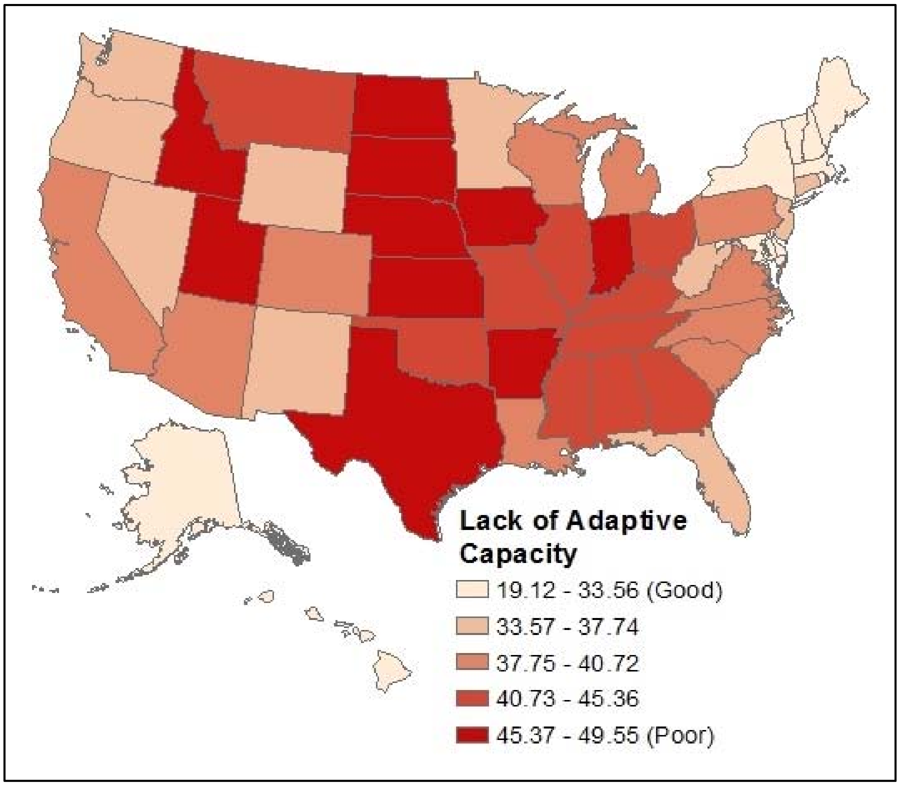

Figure 4.13: US state lack of adaptive capacity (Data mapped using quantiles)

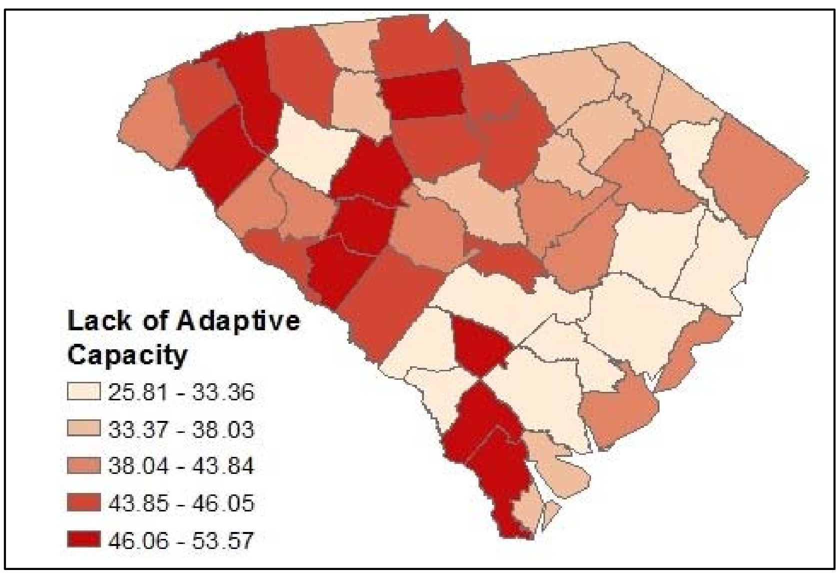

Figure 4.14: SC county lack of adaptive capacity (Data mapped using quantiles)

adaptive capacity is 40.12, with a standard deviation of 7.32. This is significantly different than the WRI mean (sig. = .000), but not the USDRI mean (sig. = .800).

Bamberg County has the lowest ability to adapt, scoring 53.57, while Marion scores best with a 25.81. In general, lower adaptive capacities are found in the northwest part of the state, while better adaptive abilities are seen in counties along or near the coast (Figure 4.14).

Multiple regression (Table 4.6) shows that, at the state level, changes in gender parity and management (standardized β = .635, sig = .000) and health expenditure (standardized β = .369, sig = .000) have the most influence on adaptive capacity. For SC counties, the same was true, with changes in gender parity (standardized β = .887, sig = .000) and health care expenditure (standardized β = .412, sig = .000) having the most influence.

Table 4.6 Relationship between adaptive capacity and variables used to construct it

Variable	US States		SC Counties	
	Pearson's R	β	Pearson's R	β
Literacy rate	-.117	.081**	-.178	.085**
Educational attainment	.172	.061**	-.048	.089**
Gender parity in management	.875**	.635**	.890**	.887**
Drinking water safety	.306*	.055**	.075	.114**
Biodiversity and habitat protection	.340*	.132**	.397**	.102**
Agricultural management	.460**	.206**	-.024	.089**
Life expectancy	.247	.112**	-.144	.106**
Health expenditure	.702**	.369**	.484**	.412**

(*significant at .05; **significant at .01)

Examination of the adaptive capacity component at the county level for SC shows no significant clustering or dispersion (Moran's I = .08, z-score = 1.18, p-value = .240). For the US, Moran's I indicates some clustering of adaptive capacity scores (Moran's I =.40, z-score 4.55, p-value = .000). For the US, ALMI identifies a cluster of 3 states – South Dakota, Nebraska, and Iowa - with high lack of adaptive capacity in the Midwest US, while outlining two clusters of better adaptive capacity in the mid-Atlantic and Northeast (Figure 4.15). Gi* shows much the same pattern, identifying a large area of higher lack of adaptive

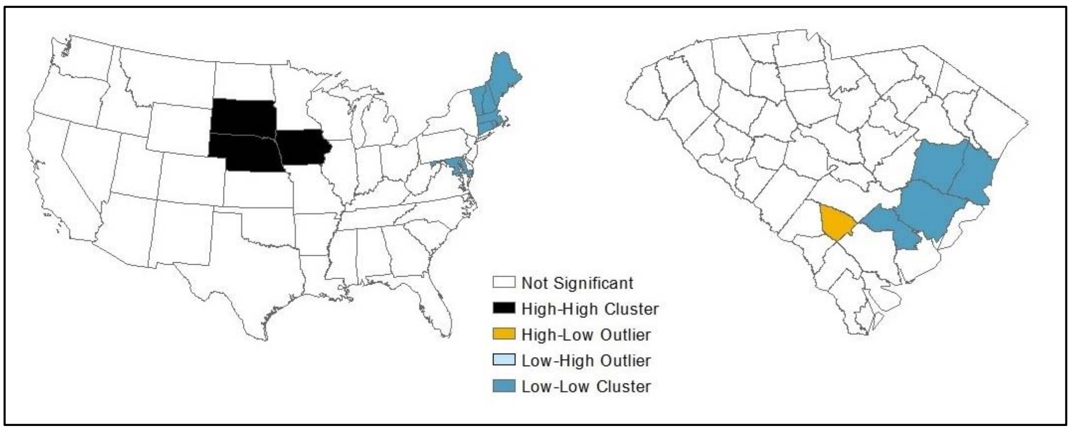

Figure 4.15: Spatial analysis of adaptive capacity using Anselin Local Moran's I.

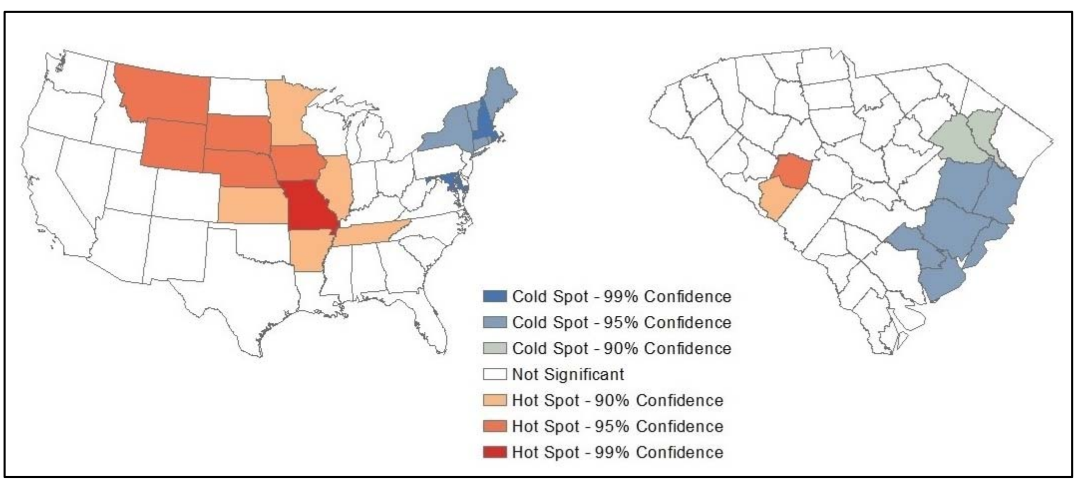

Figure 4.16: Spatial analysis of adaptive capacity using Getis-Ord Gi*.

capacity in the central US, which includes six states with significant values (Figure 4.16). Gi* also identified areas of better adaptive capacity in the mid-Atlantic and Northeast.

For South Carolina, ALMI identifies Bamberg County as a high-low outlier, showing high lack of adaptive capacity while its neighbors have low values for the component. ALMI also identifies an area of low (better) lack of adaptive capacity found in the southeastern part of the state includes four counties. Gi* identified much the same pattern, specifying Saluda County as a high lack of adaptive capacity hotspot and also outlining an area of better adaptive capacity that includes eight counties in the eastern part of the state.

4.5 Compiling the vulnerability component

Once the subcomponents were completed, the overall vulnerability component was compiled for both states and South Carolina counties. Each subcomponent (coping, adaptive capacity, susceptibility) was given a weight of .3333 and added together to determine the overall vulnerability score. Vulnerability scores range from 0 to 1, with values closer to 1 indicating vulnerability. The overall USDRI vulnerability score for the US, based on population-weighted state values, is 34.47, compared to the WRI calculated score of 32.57.

For states, the mean vulnerability score was 34.67, with a standard deviation of 4.23. State mean vulnerability is significantly different than the WRI mean of 49.50 (sig. = .000). Alaska has the lowest vulnerability at 26.82, while

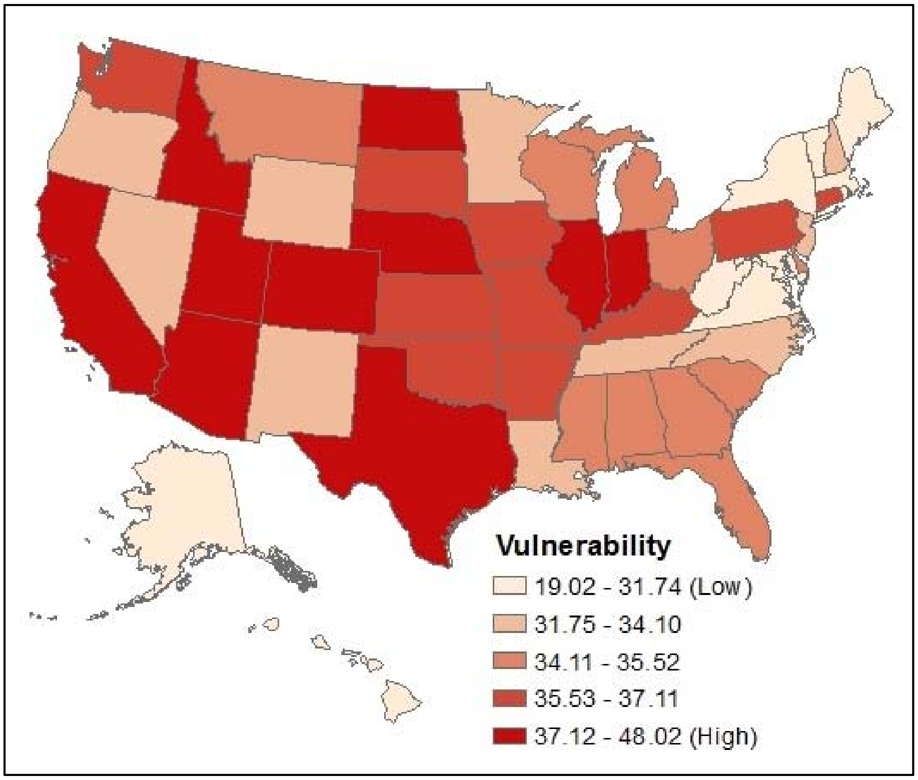

Figure 4.17: US state vulnerability (Data mapped using quantiles)

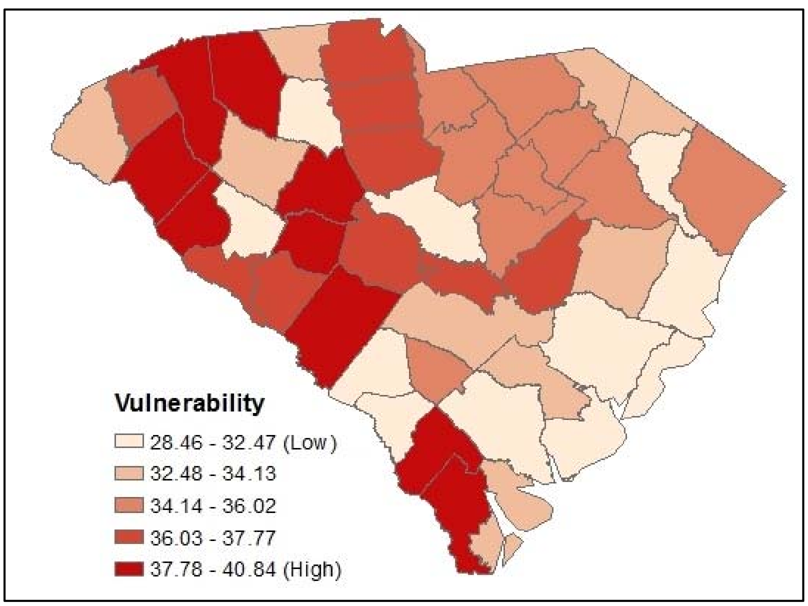

Figure 4.18: SC county vulnerability (Data mapped using quantiles)

Illinois has the highest (48.02). Visual examination of vulnerability shows that the highest component scores are in the Midwest and West US. Areas of low vulnerability are found along the eastern seaboard, especially in the Mid-Atlantic and New England (Figure 4.17).

Mean vulnerability for South Carolina counties is 35.06, with a standard deviation of 3.00. This is significantly different than the WRI mean (sig. = .000), but not the USDRI mean (sig. = .609). Higher vulnerability counties are found in the northwest part of the state, while many of the counties with lower vulnerability scores are found along the coast (Figure 4.18). The lowest county vulnerability component score in SC is Allendale County, which has a score of 29.63. Spartanburg County has the highest vulnerability in the state, with a component score of 40.84. South Carolina's overall vulnerability score of 34.4 ranks it 22nd among US states.

4.6 Alternate weighting of the vulnerability component

While the USDRI uses an expert-informed weighting scheme that mirrors the WRI, it is useful to consider alternate weighting schemes. Alternate schemes have the potential to provide greater insight into the vulnerability component and risk overall, as well as facilitate better understanding and ease of use of the index. Moreover, testing the robustness of results with alternate aggregation methods is one way, lacking the ability to achieve a perfect aggregation, of testing the sensitivity of the index (Saisana et al. 2005). The alternate weighting scheme utilized in this study was to equally weight all of the variables, which removes the subjective aspect of the WRI's expert-informed weighting scheme. On the downside, equal weighting of variables when subcomponents of an index have an unequal number of indicator variables – as is the case with both the WRI and USDRI – means that variables in subcomponents with more variables ultimately carry less weight.

The equally weighted subcomponent scores produced a slightly different vulnerability score at the state level, and a more marked difference at the county scale. In each case, the overall vulnerability score increased. For states, mean vulnerability increased from 34.67 using expert weights to 35.19 using equal weights (difference was statistically significant using a two sample t-test t = -2.62, p-value = 0.012). More importantly, equal weighting also shifted the pattern of vulnerability among states somewhat, with many states in the Southeast seeing an increase (Figure 4.19). Illinois had the largest decrease in vulnerability (-4.00) with equal weighting, while Alaska had the largest increase (+2.39). For South Carolina, mean county vulnerability increased to 36.24 under equal weighting, compared to a mean of 35.06 using expert weights, the difference in means also significant (t = -5.31, p-value = .000). All but eight of the state's 46 counties saw an increase in vulnerability using equal variable weights (Figure 4.20). Greenville County showed the best improvement (-2.22), while Marion had the largest increase (+4.44) in vulnerability. The overall results of equally weighting the variables are consistent with a 2005 study that found using different weighting schemes in vulnerability indexes caused slightly different vulnerability and subcomponent scores, but did not significantly change the observed pattern of vulnerability (Emrich, 2005).

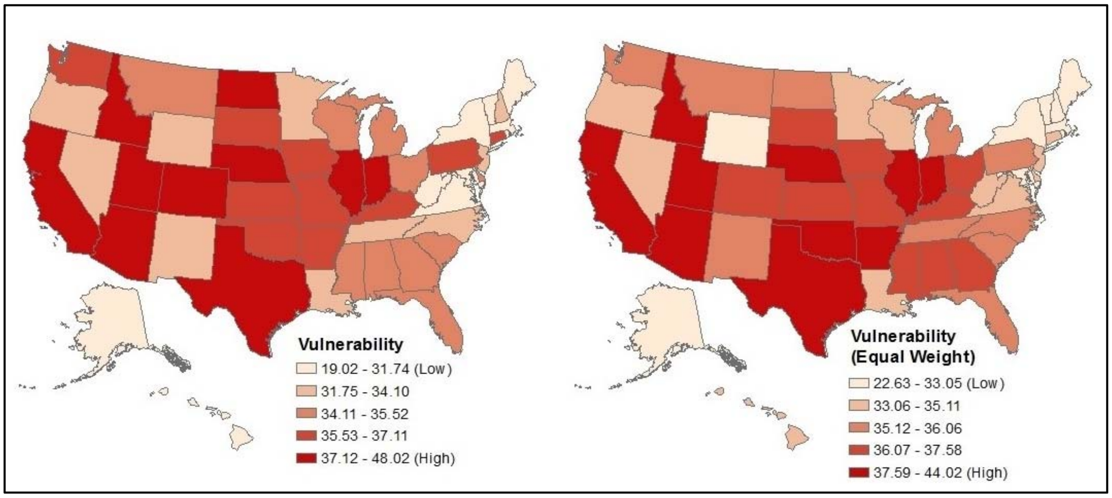

Figure 4.19: Comparison in the pattern of USDRI vulnerability expert weighted (left) and equal weighted (Data mapped using quantiles).

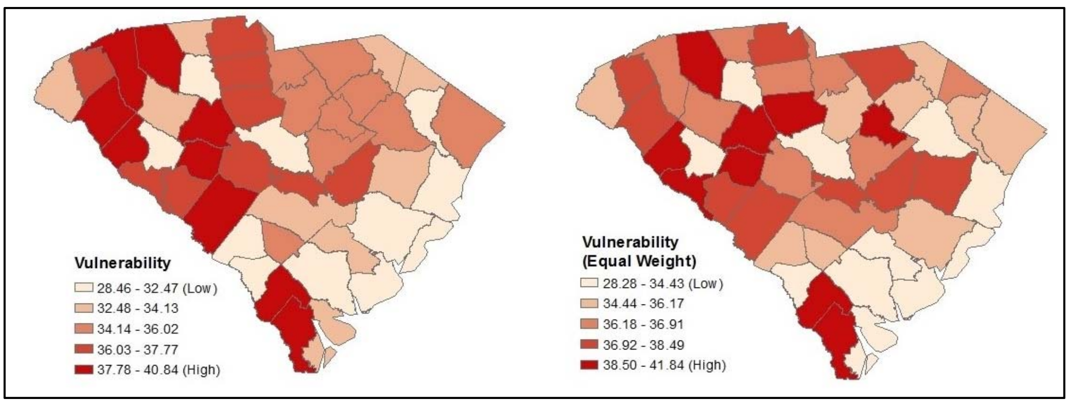

Figure 4.20: Comparison in the pattern of USDRI vulnerability for South Carolina counties expert weighted (left) and equal weighted (Data mapped using quantiles)

4.7 Exploratory data analysis of vulnerability

Table 4.7 shows correlations between vulnerability, both expert and equal weighted, and its subcomponents. Susceptibility shows the weakest correlation with vulnerability at the county level under both weighting methods, and at the state level when expert weighted. When equal weights are applied to the

Table 4.7: Correlation coefficients between vulnerability and its subcomponents

Subcomponent	United States		South Carolina	
	Vulnerability	Vulnerability (Equal Weight)	Vulnerability	Vulnerability (Equal Weight)
Susceptibility	.447**	.614**	-.067	.226
Coping Capacity	.792**	.409**	.606**	.753**
Adaptive Capacity	.771**	.817**	.782**	.627**

(*significant at .05; **significant at .01)

variables, susceptibility has a higher correlation with vulnerability. For the US, coping capacity shows the strongest linear relationship with vulnerability under the expert weighting scheme while adaptive capacity has the strongest relationship under an equal weighting scheme. The opposite is true at the SC county level.

A multiple regression model was created in order to determine the effect that the three subcomponents had on vulnerability. Vulnerability was used as the dependent variable, while its three subcomponents were input as the explanatory variables (Table 4.8). Analysis of the standardized beta coefficients shows how changes in the subcomponents impact overall vulnerability. At the US level,

Table 4.8: Standardized beta coefficients from regression of vulnerability (dependent) with its subcomponents (explanatory)

Subcomponent	United States		South Carolina	
	Vulnerability	Vulnerability (Equal Weight)	Vulnerability	Vulnerability (Equal Weight)
Susceptibility	.127**	.191**	.194**	.247**
Coping Capacity	.674**	.572**	.637**	.757**
Adaptive Capacity	.531**	.562**	.812**	.607**

(*significant at .05; **significant at .01)

changes in coping capacity have the most effect on vulnerability (β = .674, sig = .000). When equal weights are applied to the variables, changes in coping capacity (β = .572, sig. = .000) and adaptive capacity (β = .562, sig = .000) have almost the same effect on vulnerability. At the SC county level, changes in adaptive capacity (β = .812. sig = .000) have the most influence on vulnerability, while coping capacity (β = .757, sig = .000) has the most influence under equal weighting.

Using Moran's I to analyze the spatial nature of vulnerability produces different results at the state and county levels. At the state level, Moran's I indicates some degree of clustering and spatial autocorrelation for both the expert-weighted (Moran's I = .22, z-score = 2.87, p-value = .004) and equal weighted (Moran's I = .35, z-score = 4.36, p-value = .000) compilations of vulnerability. At the SC county scale, Moran's I notes no distinct autocorrelation or clustering of vulnerability with either weighting scheme.

ALMI analysis for vulnerability at the state level identified a significant cluster of high vulnerability in the Midwest centered on Illinois, while a cluster of low vulnerability is centered on Virginia / Maryland (Figure 4.21). Equal weighting of vulnerability variables showed much the same pattern, with the addition of a cluster of low vulnerability centered on Massachusetts, New Hampshire, and Vermont. Gi* analysis (Figure 4.22) showed a significant hotspot of high vulnerability in the Midwest that includes four states, and a cold spot of low vulnerability centered on Virginia and Maryland in the mid-Atlantic.

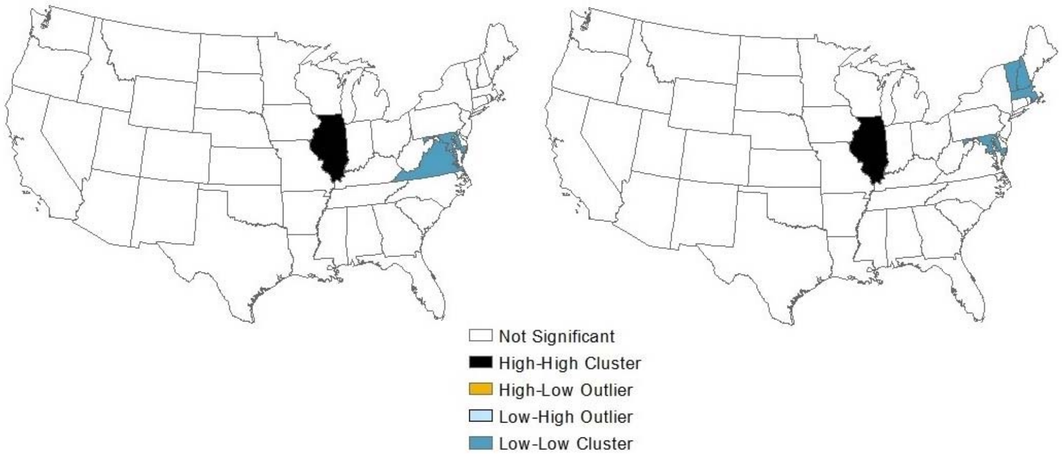

Figure 4.21: Spatial analysis of expert weighted (left) and equal weighted US vulnerability using ALMI

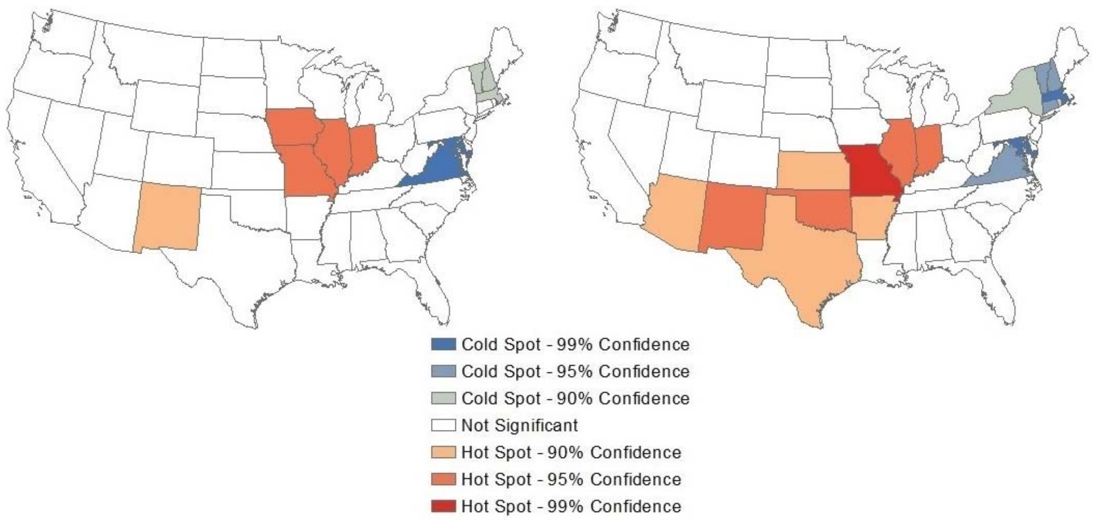

Figure 4.22: Spatial analysis of expert weighted (left) and equal weighted US vulnerability using Getis-Ord Gi*

When vulnerability indicators are equally weighted, the Midwest hotspot expands to nine states (five at the significant level) stretching from Indiana to Arizona. Equal weighting also shows an additional cold spot of vulnerability that includes five states in New England. These results suggest that, no matter the weighting scheme, the USDRI concept of vulnerability tends to cluster in space at the state level.

Spatial analysis of vulnerability for South Carolina indicates clusters of both high and low vulnerability (Figures 4.23 and 4.24). ALMI identifies the cluster of high vulnerability centered on Greenville using expert weights, and also shows Richland and Union counties as having significantly low vulnerability compared to their neighbors. ALMI also shows three coastal counties – Colleton, Charleston, and Georgetown – as a cluster of low vulnerability. When equal

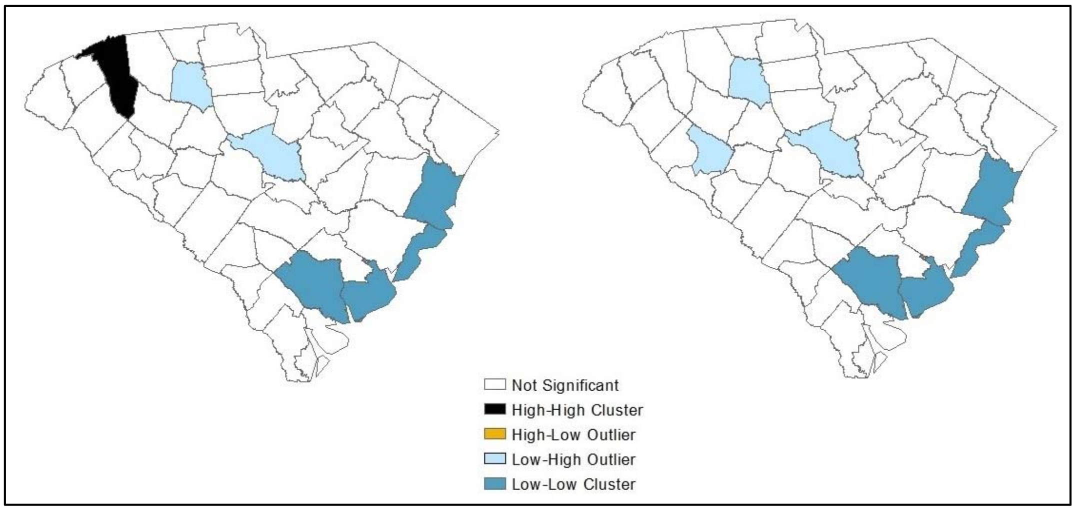

Figure 4.23: Spatial analysis of expert weighted (left) and equal weighted SC county vulnerability using ALMI

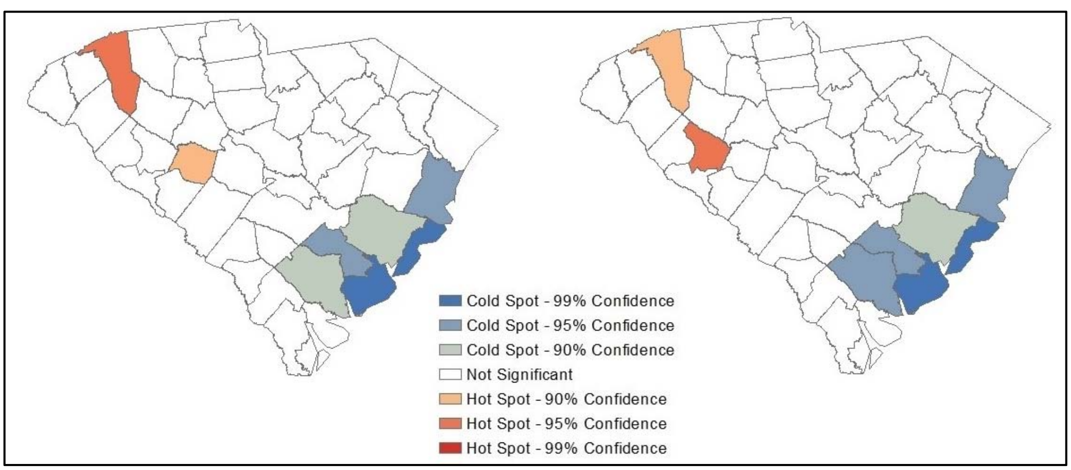

Figure 4.24: Spatial analysis of expert weighted (left) and equal weighted SC county vulnerability using Getis-Ord Gi*

weights are applied to the variables, ALMI shows much the same spatial pattern, although Greenville no longer shows as a cluster of high vulnerability, and Greenwood shows up as an additional high outlier. For expert weighted vulnerability, Gi* identifies a significant hotspot of high vulnerability centered on Greenville County, as well as a cold spot of low vulnerability involving five coastal counties.. Equal weighting the variables moves the high vulnerability hotspot to Saluda County, and shows the same area of low vulnerability along the coast.

4.8 Comparing the USDRI to the Social Vulnerability Index

Comparing the USDRI vulnerability component to an established vulnerability index is useful in assessing the picture of vulnerability the USDRI paints. One such index is the Social Vulnerability Index (SoVI). SoVI is an established composite index that measures social vulnerability to environmental hazards using 30 socioeconomic variables. These variables are compiled into dimensions using principal components analysis in order produce a vulnerability score at the geography of interest (Cutter 2003). As SoVI and the USDRI use different variables and are compiled differently the two are not directly comparable. However, spatial statistics allows comparisons of the patterns of vulnerability each index represents.

SoVI is compiled at the county level for the US; no SoVI scores exist at the state level. To facilitate comparison with the USDRI, SoVI county scores were weighted by population and aggregated into state-level scores. These state-level aggregations, as well as the county level SoVI data, were compared to their USDRI counterparts. Pearson's correlation coefficient showed no linear relationship between the measures of vulnerability at the state (R = -0.1, p-value = .485) or county (R = -0.10, p-value = .505) scales. Comparing the Moran's I values of the vulnerability scores provides little further insight. While the USDRI vulnerability component showed some moderate clustering and spatial autocorrelation at the state level, SoVI (Moran's I = -.04, z-score = .20, p-value = .843) does not. At the county level, where the USDRI vulnerability showed no spatial autocorrelation, SoVI shows at slight tendency to cluster, though not at a significant level (Moran's I = .15, z-score = 1.92, p-value = .055).

Further spatial analysis shows both similarities and differences in the pattern of vulnerability shown by the two methods. For the US states (Figure 4.25), ALMI showed a significant area of high vulnerability in the Midwest and areas of lower vulnerability in the Mid-Atlantic and Northeast. For SoVI, ALMI did

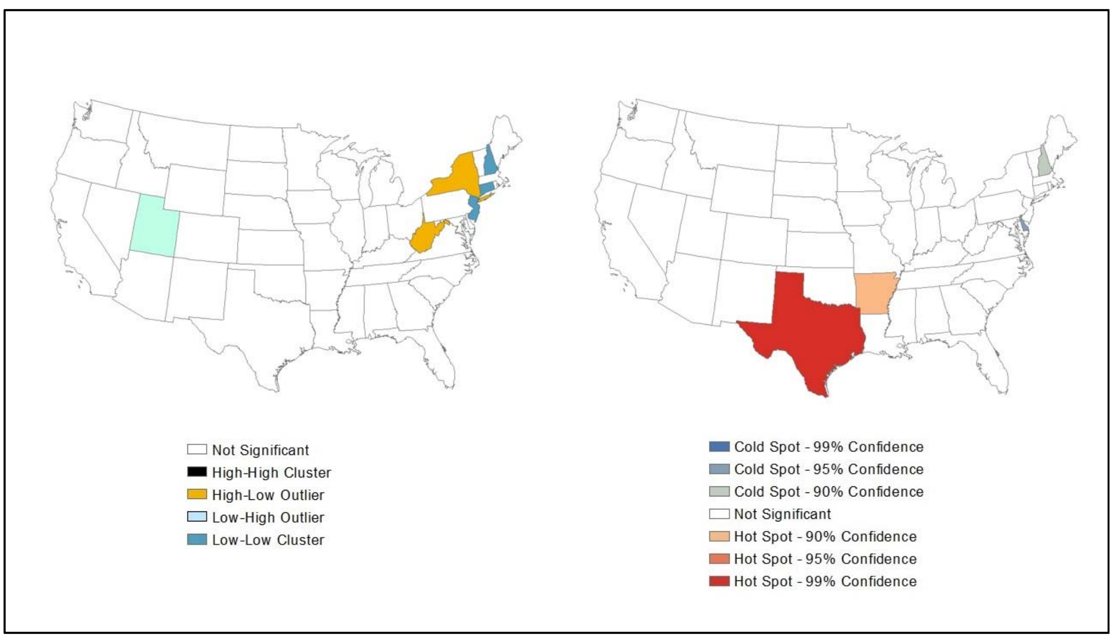

Figure 4.25: Spatial analysis of SoVI at the state level using ALMI (left) and Getis-Ord Gi*

not detect any cluster of significantly high vulnerability, but it did find Utah to be a low outlier surrounded by high values, implying higher vulnerability in some western states. New York and West Virginia show as high outliers for SoVI, meaning these states have significantly higher vulnerability than their neighbors. Like the USDRI, SoVI also shows significant clusters of lower vulnerability in the Northeast. Gi* analysis for SoVI shows a hotspot of high vulnerability that includes Texas and Arkansas, which were not identified as same in USDRI vulnerability. Gi* also indicates some lower vulnerability values in the Northeast, with Delaware showing as the center of an area of low vulnerability.

At the SC county level, both ALMI and Gi* identified Greenville County as the center of an area of high vulnerability in the USDRI, a conclusion that does not show up in analysis of SoVI. Using both methods of spatial analysis on SoVI showed vulnerability to be poor in the southern part of SC along the Savannah

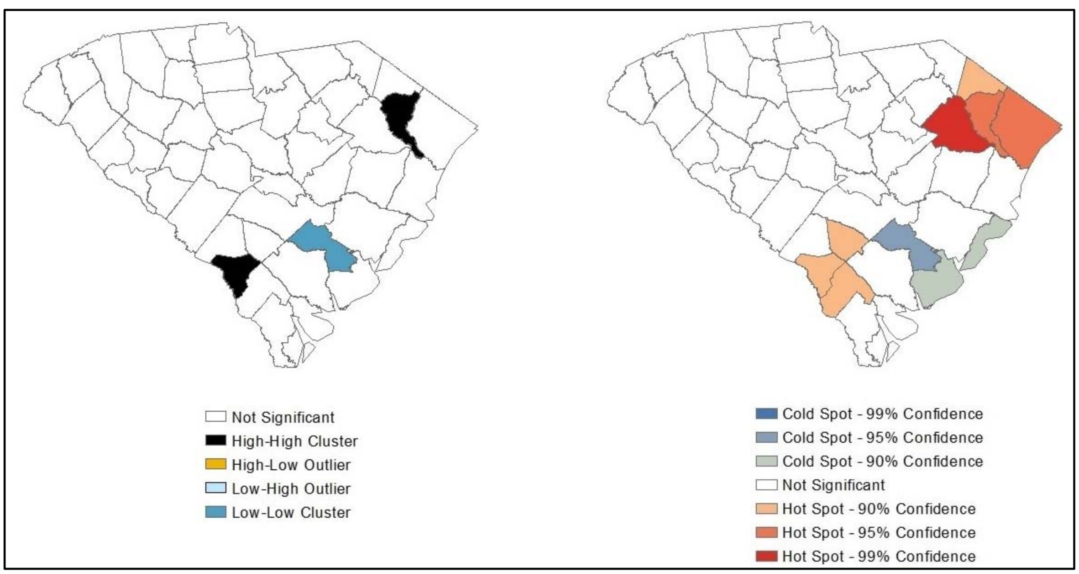

Figure 4.26: Spatial analysis of SoVI at the SC county level using ALMI (left) and Getis-Ord Gi*

River and in the eastern part of the state along the border with North Carolina (Figure 4.26). Similar to its results for USDRI vulnerability, Gi* identified an area of lower vulnerability on SC's coast, centered on Charleston County.

The variables found in the compilation of the SoVI express susceptibility, so it is also useful to compare the spatial patters of SoVI and the USDRI susceptibility component. In general, the USDRI susceptibility component appears more spatially similar to SoVI than the overall vulnerability component. For the US, ALMI identified clusters of low vulnerability in the Northeast US for both SoVI and susceptibility. Gi* identified clusters of high SoVI centered on Texas and Arkansas; for susceptibility it identified a nine state cluster of high susceptibility along the Gulf Coast which includes Texas and Arkansas.

At the SC county scale SoVI and USDRI susceptibility also display similarities. Both methods of spatial analysis identified clusters of low susceptibility in central SC, a conclusion supported by ALMI analysis of SoVI. In addition, both methods found high susceptibility / social vulnerability in southeast SC, centered on Barnwell and Allendale counties.

4.9 Summary and conclusions

This chapter has detailed the construction of the vulnerability component for the USDRI and its three sub-indices: susceptibility, coping capacity, and adaptive capacity. The USDRI vulnerability component consists of 18 variables, compared to the 22 variables found in the WRI, but close approximations of those found in the WRI were substituted. Other variables were close approximations of those found in the WRI.

The USDRI vulnerability component, examined using two different weighting schemes, shows areas of generally higher vulnerability in the Midwest and western US, with the East Coast states having lower vulnerability. Spatial analysis concurs with this assessment, finding clusters of high vulnerability in the Midwest and lower vulnerability in the mid-Atlantic and New England. For South Carolina, the USDRI generally found lower vulnerability scores in counties along the state's coast, and higher vulnerabilities in the northwest part of the state, an assessment supported by spatial analysis.

The vulnerability scores for states and counties were compared to scores from the Social Vulnerability Index, an established measure of socio-economic vulnerability. No correlation exists between the two at either scale of examination, but they do exhibit some similar spatial patterns at the state level, with spatial analysis for SoVI identifying higher vulnerability clusters in the central US, and lower vulnerability clusters along the US east coast. For South Carolina, spatial analysis different between the two measures of vulnerability; analysis of SoVI showed some clustering of vulnerability in the southeast part of the state, a conclusion not reached by analysis of USDRI vulnerability. Comparing SoVI to only the susceptibility component reveals that the two exhibit similar spatial patterns at both the state and county scale.

With the analysis of the exposure and vulnerability components of the USDRI complete, they can be compiled into the overall USDRI. The next chapter details the overall results of the USDRI model by exploring spatial patterns of risk and the relationships of USDRI determined risk with other metrics.

CHAPTER 5: ASSESSING RISK WITH THE UNITED STATES DISASTER RISK INDEX

5.1 Overview

Though the spatial and temporal aspects of hazards in the US are well documented, economic losses from hazards continue to increase. Per capita economic losses in the US increased from 1960 to 2010, even when population growth and wealth are taken into consideration (Gall et al. 2011). Although human losses (deaths and injuries) have declined in the same time period, the rise in economic loss highlights the need for better understanding of disaster risk in order to increase awareness and better mitigate against its effects.

This chapter presents the results of the USDRI as proof of concept for the downscaling of the WRI. By combining exposure and vulnerability into a single metric, the USDRI acknowledges that a comprehensive assessment of risk goes well beyond direct damage caused by the hazard being examined, extending to the social aspects of a population that leave it more vulnerable to physical or economic harm.

5.2 Compiling the USDRI

The previous chapters discussed in detail the construction of the exposure and vulnerability components of the USDRI. Once these are calculated, the assessment of risk using the USDRI is relatively straightforward. The scores for the exposure and vulnerability components are multiplied together, yielding an overall score for risk that ranges from 0 to 1. For display purposes, this score is multiplied by 100, with a possible range of overall risk from 0 (no risk) to 100 (extreme risk). Although 100 is the highest possible risk score, overall risk scores are typically under 40 as a result of the multiplication used in the final aggregation. If either exposure (possible) or vulnerability (unlikely) is zero, then the overall risk score is also zero, as absent either component, there is no risk.

5.2.1 Geographic distribution of risk at the state scale

Figure 5.1 shows the geographic distribution of USDRI risk for the United States. The Southeast US coastal states from Louisiana to North Carolina, with the exception of Mississippi, fall into the top 20 percent of riskiest states. This high risk area is influenced by exposure to tropical cyclones. Another area of high risk is along the West Coast, which is influenced by earthquake exposure, especially California. Areas of lower risk are found in the Great Lakes region as well as the Northeast. The influence of drought is also seen on the pattern of risk. For example, Mississippi has high cyclone exposure like the rest of the Southeast, but has one of the lower drought scores, which reduces its overall risk score compared to neighboring states. Conversely, Wyoming – a state with little

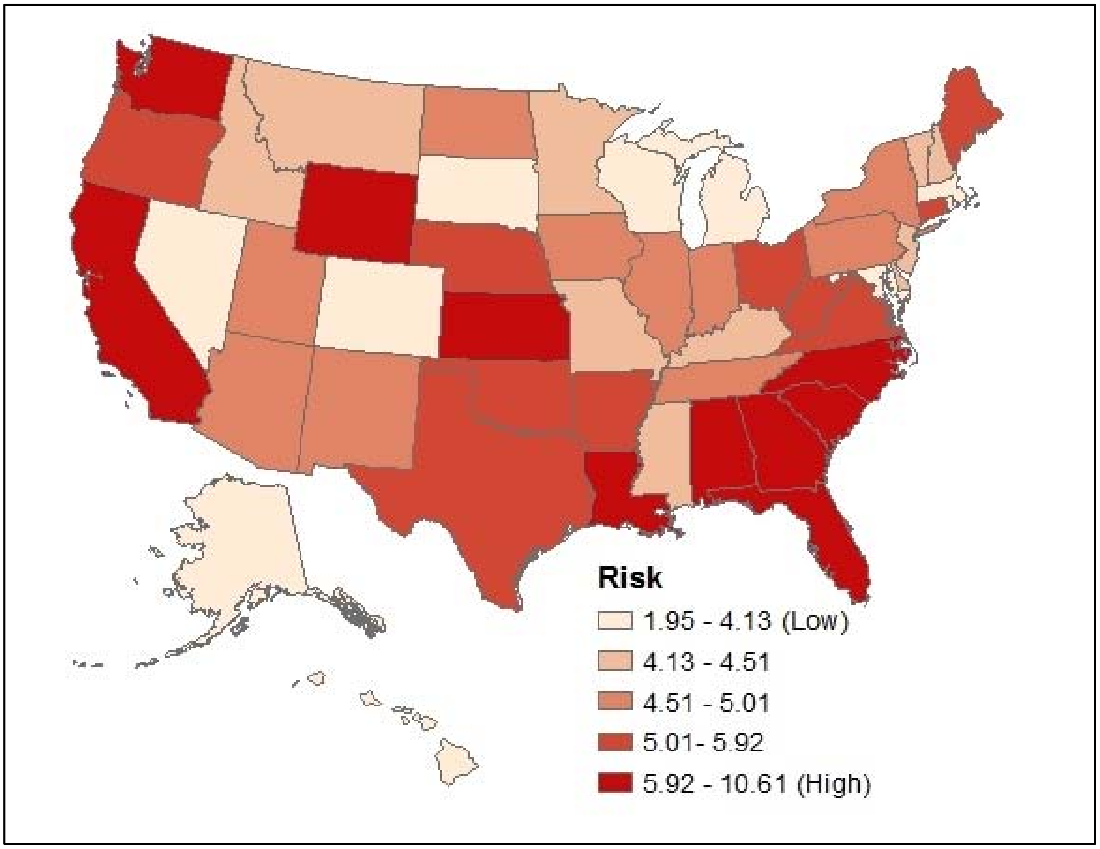

Figure 5.1: USDRI Risk (Data mapped using quantiles)

exposure to four of the five hazards in the model – has a very high risk score due to the high drought exposure found in the state. While Wyoming is certainly sensitive to drought, it is under essentially the same climate influences as its southern neighbor, Colorado. Colorado has a much lower risk evaluation as a result of a low drought exposure score, as well as a higher population base than Wyoming.

According to the WRI, the US risk score is 3.99. In the reformulation, the USDRI produces a value of 5.99. This is likely due to the larger sample size of the WRI as well as its use of different variables. The mean risk score for states is 5.14, with a standard deviation of 1.68. This is significantly different than the

WRI mean risk score of 7.40 (sig. = .002). The lowest risk state is Alaska at 1.95, while California has the highest score (10.61). Alaska's risk score would place it 166th of the 173 countries included in the WRI, in the lowest 10 percent of countries based on disaster risk, between Bahrain and the United Arab Emirates. California's score places it in the top 20% of most risk WRI countries, ranking it 33rd between Cape Verde and Indonesia. Table 5.1 details the 10 lowest and highest USDRI risk scores for US states.

Table 5.1: USDRI highest and lowest risk states

Most Risk		Least Risk	
State	Risk Score	State	Risk Score
1. California	10.61	41. South Dakota	4.13
2. Wyoming	10.11	42. Michigan	4.12
3. Louisiana	9.20	43. Massachusetts	4.00
4. Florida	7.93	44. Wisconsin	3.95
5. Alabama	7.88	45. Nevada	3.89
6. Georgia	7.37	46. Colorado	3.86
7. North Carolina	6.76	47. Rhode Island	3.71
8. Washington	6.46	48. Maryland	3.64
9. Kansas	6.25	49. Hawaii	3.61
10. South Carolina	5.93	50. Alaska	1.95

With the large influence of drought exposure on the USDRI model, it is worthwhile to examine the model without drought included in order to fully assess its usefulness in assessing physical risk to hazards in the US. Figure 5.2 details risk without drought included in the exposure component. Areas of high risk are still evident in the Southeast and on the West Coast. However, the Midwest and Southwest display much lower risk, while the Northeast displays increased risk as a result of the much lower risk in other areas. Without drought, the mean state risk is .87, with a standard deviation of 1.19. Population weighted risk

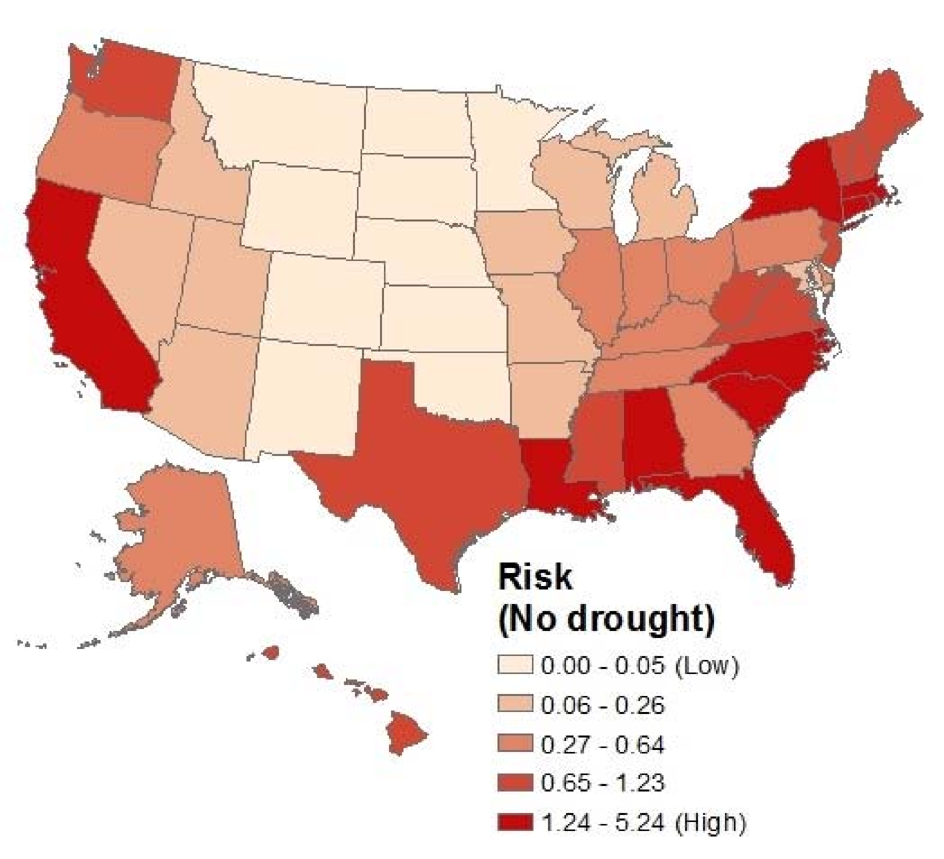

Figure 5.2: USDRI Risk without drought in the exposure component (Data mapped using quantiles)

Table 5.2: USDRI (no drought) highest and lowest risk states

Most Risk		Least Risk	
State	Risk Score	State	Risk Score
1. Louisiana	5.24	41. North Dakota	<.01
2. California	4.94	42. Nebraska	<.01
3. Florida	3.34	Oklahoma	<.01
4. Connecticut	2.36	Minnesota	<.01
5. Massachusetts	2.03	South Dakota	<.01
6. Rhode Island	1.81	Wyoming	<.01
7. Alabama	1.64	Montana	<.01
8. South Carolina	1.50	Kansas	<.01
9. New York	1.41	Colorado	<.01
10. North Carolina	1.24	New Mexico	<.01

decreases to 1.44 from 5.99. The least risky state is New Mexico, at less than .01 percent, while Louisiana is the highest risk state, at 5.24 percent. Table 5.2

shows the most and least risky states without drought in the model.

5.2.1 Geographic distribution of risk at the SC county scale

South Carolina has an overall USDRI risk score of 5.93. Figure 5.3 shows USDRI risk calculated for South Carolina counties. Areas of higher risk are generally seen in counties along the coast as well as in a group of five counties in the northwest part of the state, while lower risk exists in the central part of the state north to the state's border with North Carolina. Mean risk for the state is 6.35, with a standard deviation of 3.00. This is not significantly different from the WRI risk mean (sig. = .180), but is different than the USDRI risk mean (sig. = .015). The highest risk county is Jasper at 21.44 (Table 5.4), while the lowest risk is McCormick, at 1.71. Jasper County's exposure, due mainly to drought, greatly influences its risk score, as detailed in the previous chapter. McCormick County's risk score would place it 168th of 173 countries in the WRI, between Iceland and Kiribati. Jasper's poor risk score would actually rank it 4th highest in the world, between the Philippines and Bangladesh. It is hard to fathom that Jasper's disaster risk is actually this high; this score is likely a result of the heavy influence of drought on the county score. Table 5.3 details the top and bottom ten SC counties in terms of risk. As with state level USDRI risk, omitting drought from the model generates a much different county pattern of risk (Figure 5.4), with higher risk areas found along the coast, and less risky in the west and northwest areas of the state. This pattern is explained in Table 3.2, as without drought, tropical cyclone and sea-level rise dominate exposure for the state.

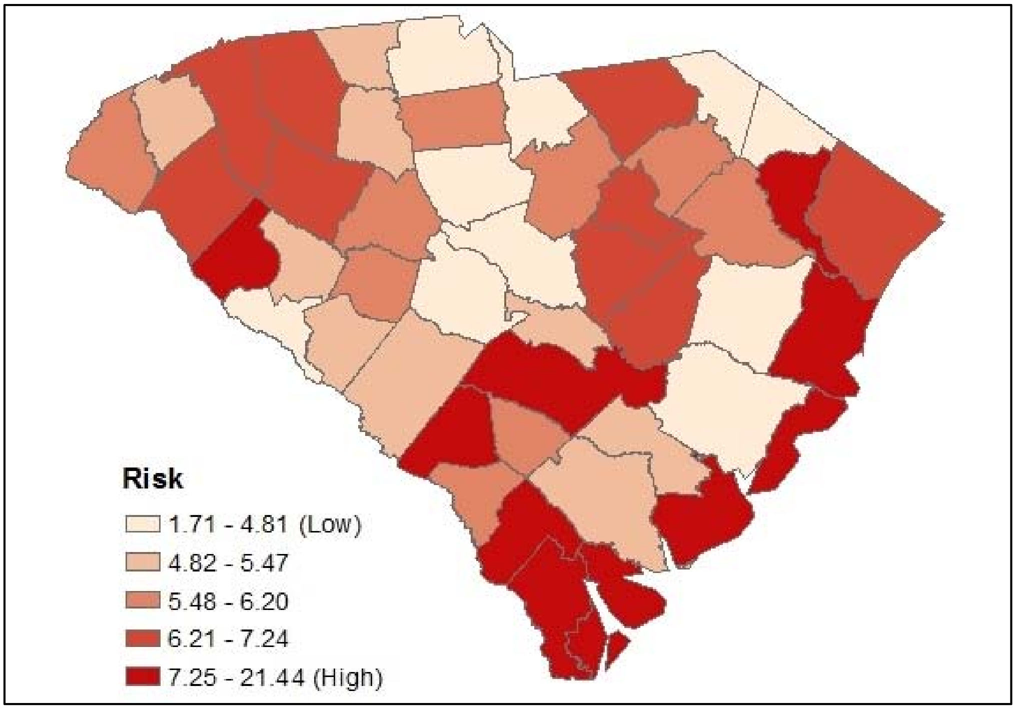

Figure 5.3: USDRI Risk for South Carolina counties (Data mapped using quantiles)

Table 5.3: USDRI highest and lowest risk South Carolina counties

Most Risk		Least Risk	
County	Risk Score	County	Risk Score
1. Jasper	21.44	37. Williamsburg	4.81
2. Marion	13.84	38. York	4.57
3. Georgetown	11.03	39. Lancaster	4.50
4. Charleston	8.55	40. Fairfield	4.20
5. Beaufort	8.47	41. Dillon	4.19
6. Hampton	7.84	42. Lexington	4.17
7. Abbeville	7.47	43. Berkeley	3.81
8. Barnwell	7.33	44. Marlboro	3.78
9. Orangeburg	7.32	45. Richland	3.40
10. Spartanburg	7.24	46. McCormick	1.71

Overall mean risk without drought is 1.29, with a standard deviation of 1.69. With this version of risk, Georgetown County has the highest risk in the state at 7.27 (Table 5.4). Edgefield has the lowest, at < .01.

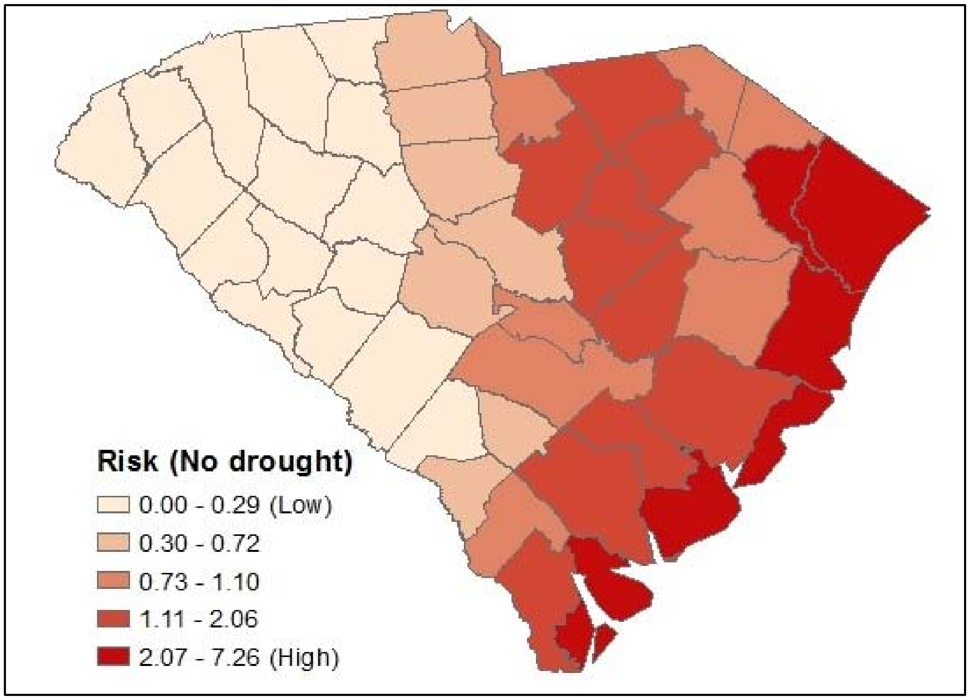

Figure 5.4: USDRI Risk for SC counties without drought in the exposure component (Data mapped using quantiles)

Table 5.4: USDRI (no drought) highest and lowest risk South Carolina counties

Most Risk		Least Risk	
County	Risk Score	County	Risk Score
1. Georgetown	7.26	37. Saluda	0.07
2. Charleston	5.46	38. Oconee	0.05
3. Horry	4.94	39. Laurens	0.03
4. Marion	4.54	40. Aiken	0.03
5. Beaufort	3.97	41. Anderson	0.01
6. Jasper	2.06	42. Greenwood	0.01
7. Dorchester	1.91	43. Greenville	< .01
8. Clarendon	1.68	44. Abbeville	< .01
9. Lee	1.68	45. Pickens	< .01
10. Sumter	1.54	46. Edgefield	< .01

5.3 Visualizing risk by individual hazard

One of the strong points of the USDRI model is that the components are modular and can be assessed individually. A state or county may have a poor overall vulnerability score; closer examination of the vulnerability sub-components can suggest strategies to reduce vulnerability. The same is true for the exposure portion of the equation. The WRI accommodates any hazard for which a geo-referenced exposure surface can be calculated. This gives the model great utility, as it allows for current or hypothetical (e.g. changes in hazard exposure as a result of climate change) information in the exposure component.

The USDRI in its current form utilizes five hazards, but it is a relatively simple process to calculate risk for any subset the hazards by modifying the exposure component to include the hazard(s) of interest. Figure 5.5 shows the distribution of risk – calculated using the full vulnerability component but only the exposure for each individual hazard - for each of the hazards included in the USDRI. This flexibility lets practitioners focus their efforts on the hazards that impact their area of interest the most, or those that the area of interest is least prepared to handle.

5.4 Exploratory data analysis of risk

Correlations between risk and the components and subcomponents of the USDRI show an interesting trend (Table 5.5) in that risk is highly correlated with exposure, but only weakly so with vulnerability. All of the subcomponents of vulnerability show a similar weaker correlation with risk. At the county level (Table 5.6), exposure is even more closely correlated with risk, while vulnerability

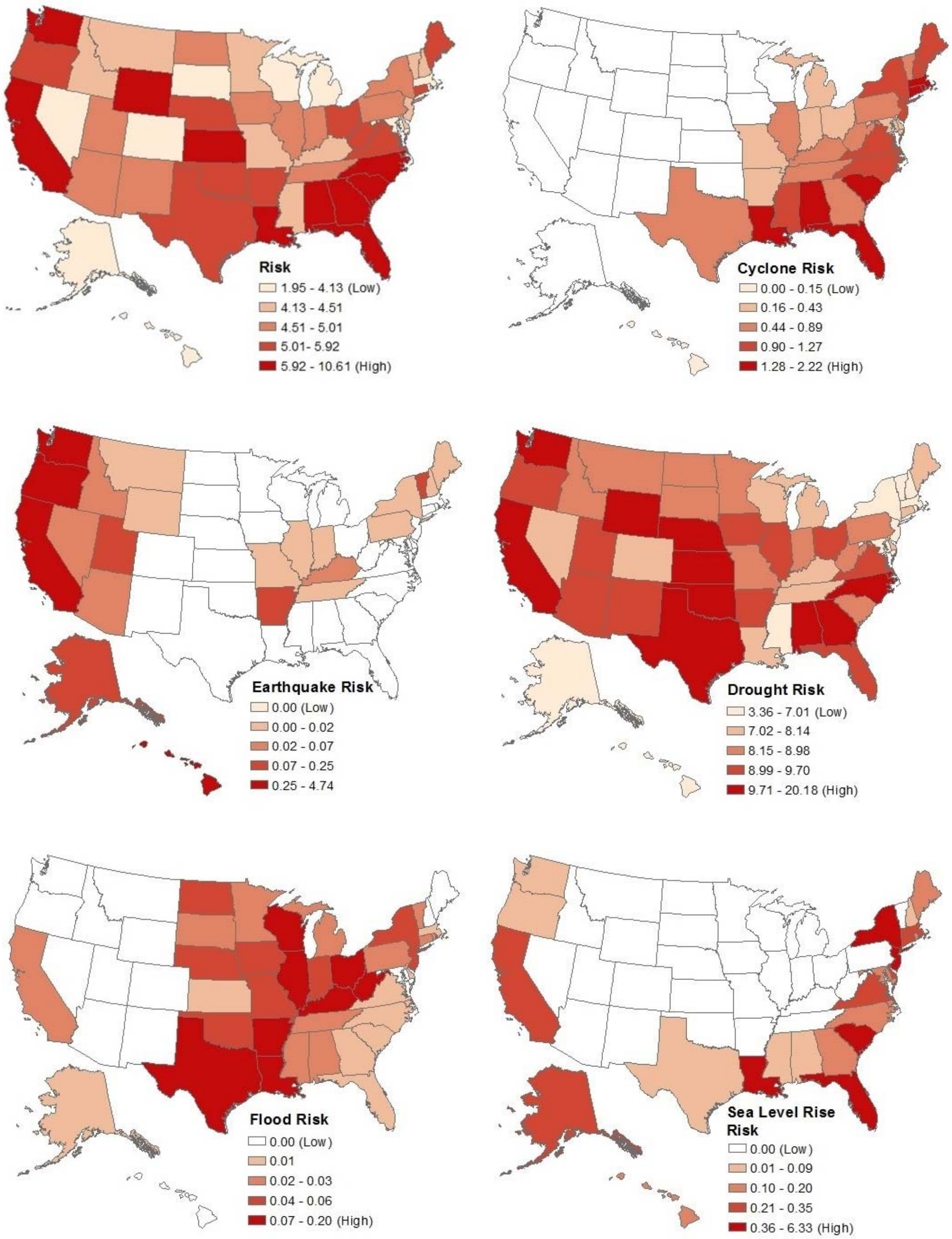

Figure 5.5: USDRI Risk for (clockwise from top left) 1) All USDRI hazards; 2) cyclones; 3) drought; 4) sea level rise; 5) floods; and 6) earthquakes (Data mapped using quantiles)

Table 5.5: Correlation matrix for state risk and the components of the US state USDRI

	Risk	*Exposure*	*Vulnerability*	*Susceptibility*	*Coping*	*Adaptive*
Risk	1					
Exposure	.948**	1				
Vulnerability	.304*	.002	1			
Susceptibility	.232	.108	.447**	1		
Coping	.209	-.042	.792**	.007	1	
Adaptive	.252	.029	.771**	.585**	.233	1

(*significant at .05; **significant at .01)

and its subcomponents have no appreciable correlation with risk. At both the county and state level, when drought is removed from the model, risk is even more highly correlated ($R > .99$) with exposure.

Table 5.6: Correlation matrix for county risk and the components of the SC county USDRI

	Risk	*Exposure*	*Vulnerability*	*Susceptibility*	*Coping*	*Adaptive*
Risk	1					
Exposure	.978**	1				
Vulnerability	.076	-.114	1			
Susceptibility	.038	.059	-.067	1		
Coping	.124	0.01	.606**	-.114	1	
Adaptive	-0.01	-.162	.782**	-.227	.012	1

(*significant at .05; **significant at .01)

Table 5.7 details the correlation coefficients among the WRI and its subcomponents. Of note is the strong correlation between the WRI and the exposure component, as well as weaker correlations between risk and the vulnerability subcomponents. This mirrors the overall pattern in correlations noted at both scales of the USDRI. Additionally, the WRI subcomponents of vulnerability are more closely correlated with the vulnerability component than their USDRI counterparts. Thus, the general trend as the WRI model is downscaled is for the correlation between risk and exposure to increase, while the correlation between risk and vulnerability decreases. This suggests the need

Table 5.7: Correlation matrix for country risk and the components of the WRI

	Risk	*Exposure*	*Vulnerability*	*Susceptibility*	*Coping*	*Adaptive*
Risk	1					
Exposure	.920**	1				
Vulnerability	.428**	.090	1			
Susceptibility	.037**	0.057	.942**	1		
Coping	.468**	.152*	.946**	.806**	1	
Adaptive	.362**	.032	.947**	.843**	.878**	1

(*significant at .05; **significant at .01)

to put variables in local context in order to better portray vulnerability as well as the need for further refinement of the model in terms of how it combines exposure and vulnerability.

Spatial analysis of USDRI risk underscores how heavily it is influenced by the exposure component. Analysis of USDRI risk with Moran's I shows no spatial autocorrelation with (Moran's I = .04, z-score .70, p-value .483) drought included in exposure. Without drought, overall risk does show some autocorrelation (Moran's I = .17, z-score = 2.26, p-value = .024), albeit weak. ALMI and Gi* both highlight the large spatial differences drought brings to the exposure component. With drought, both ALMI (Figure 5.6) and Gi* (Figure 5.7) show an area of high risk in the Southeast US, with both Florida and Georgia showing as significant. When drought is removed, the two diverge somewhat on where significant areas of high risk exist in the US. The only significant finding using ALMI to examine risk is that California is a high outlier, meaning it has high risk compared to states that border it. Gi* identifies a significant area of low risk that includes seven states from Missouri to Utah, while indicating higher risk (though not significant) in New England and along the Gulf Coast.

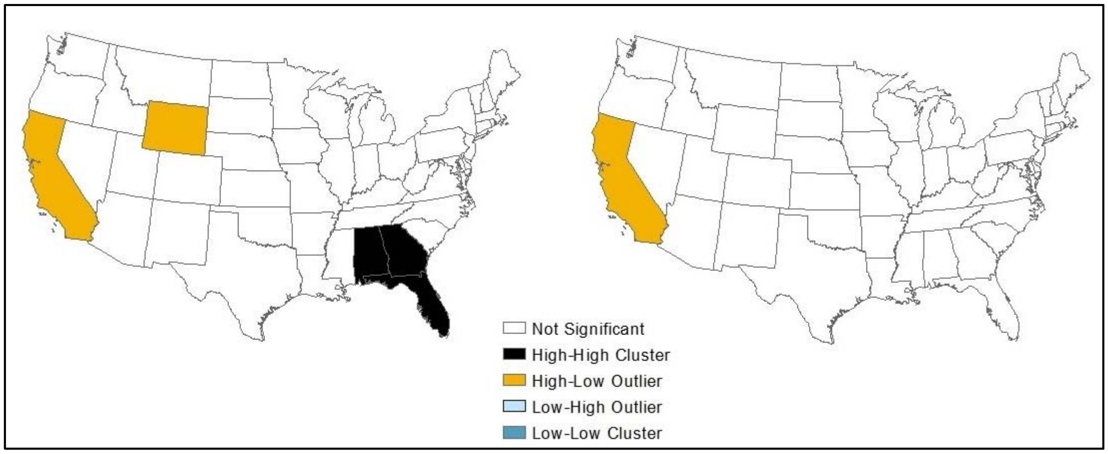

Figure 5.6: Spatial analysis of risk at the state level using ALMI for risk (left) and risk without drought

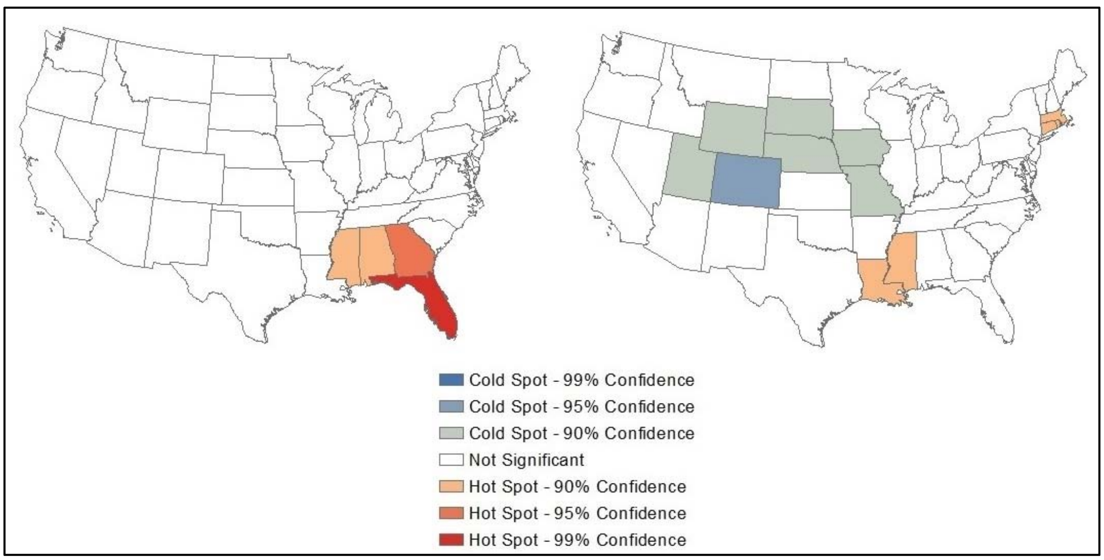

Figure 5.7: Spatial analysis of risk at the state level using Getis-Ord Gi*for risk (left) and risk without drought

When the ALMI and Gi* maps are compared to the same maps for exposure, it is clear that the spatial arrangement of risk and exposure are similar. ALMI shows high risk and exposure in the Southeast, and identifies Wyoming as a high outlier for each metric. Without drought in the index, ALMI shows California as a high outlier for both exposure and risk (see Figure 3.9 for comparison to Figure 5.6). Gi* also shows very similar spatial patterns between risk and exposure.

Not surprisingly, the spatial patterns of risk at the SC county level also closely mirror the spatial patterns that exposure exhibits. With drought in the exposure component, Moran's I analysis shows no significant spatial autocorrelation (Moran's I = .11, z-score = 1.75, p-value = .080). However, without drought Moran's indicates significant clustering (Moran's I = .45, z-score = 5.67, p-value = .000). ALMI analysis for risk identifies a high risk cluster containing two counties (Jasper and Beaufort) in the southern part of SC, as well as identifying Georgetown County as the center of a high risk cluster in the eastern part of SC (Figure 5.8). Without drought in the index, ALMI shows a cluster of four high risk counties along the SC coast. In both cases, this is exactly the same spatial clustering noted by ALMI for exposure (see Figure 3.11). Gi* identifies the same significant cluster of high risk / exposure in the southern part of the state, adding Hampton as part of the cluster (Figure 5.9). Like ALMI, Gi* also indicates a cluster of high risk in the eastern part of the state, though not at a significant level. Without drought, the Gi* profile for both exposure and risk is nearly identical, with a large area of high exposure / risk along the SC coast and an area of significantly low exposure / risk in the northwest part of the state (see Figure 3.12 for comparison with Figure 5.6). The spatial pattern of risk in SC is in contrast to that of vulnerability, which notes the opposite pattern – high vulnerability in the northeast part of the state and low vulnerability along the

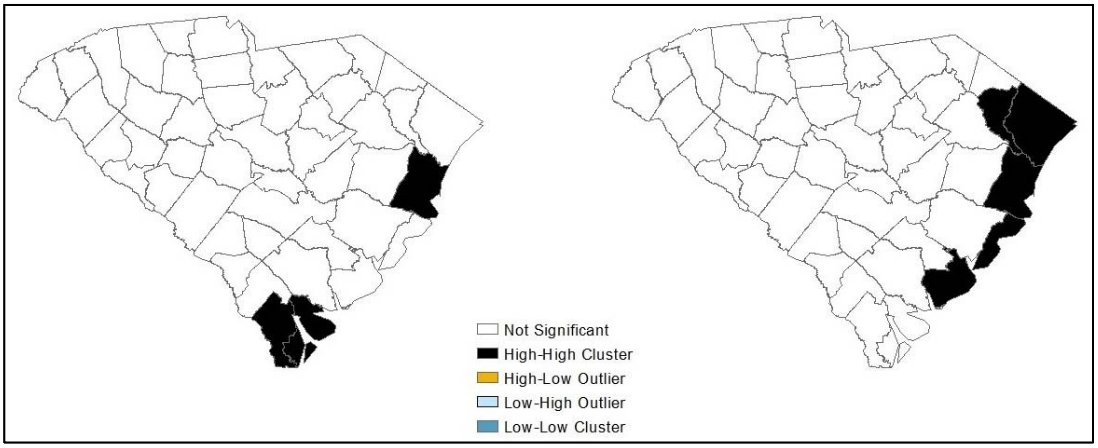

Figure 5.8: Spatial analysis of risk at the county level using ALMI for risk (left) and risk without drought

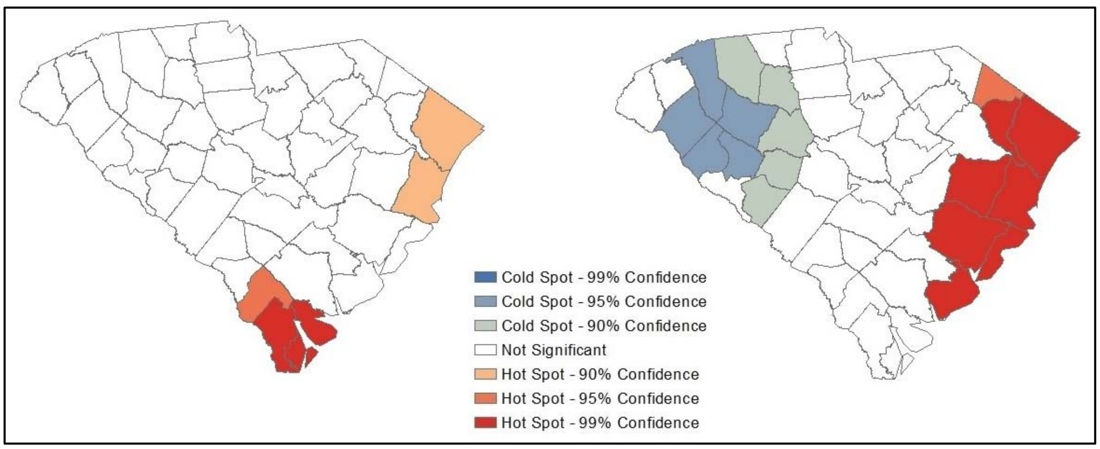

Figure 5.9: Spatial analysis of risk at the county level using Getis-Ord Gi* for risk (left) and risk without drought

coast (see Figure 3.28). As with the state level, the spatial pattern of risk at the county level is heavily influenced by exposure and less so by vulnerability.

5.5 Evaluating disaster risk against known losses

One method to assess the efficacy of the WRI/USDRI is to evaluate how well disaster risk relates to known human (see Gall et al. 2007) and economic (Schmidtlein et al. 2010) losses. There are a variety of web-based sources of hazard loss data. These include the Emergency Events Database (EM-DAT), the Natural Hazards Assessment Network (NATHAN), the National Climatic Data Center's Storm Events Database, and the Hazards and Vulnerability Research Institute's (University of South Carolina) Spatial Hazard Events and Losses Database for the United States (SHELDUS). Of these sources, both Storm Events and SHELDUS contain data at the US county level (Gall et al. 2009). SHELDUS is more appropriate for use in this study, as it contains losses for earthquakes, while Storm Events does not.

5.5.1 USDRI and state / county losses

The latest version of SHELDUS contains over 810,000 records of hazard loss from 1960 – 2012. The database includes every hazard loss recorded in that timeframe, with the exception of the years 1993-1995, in which only hazards that caused at least one fatality or resulted in at least $50,000 in damage are recorded. SHELDUS does have some drawbacks that could hinder its effectiveness as a metric for evaluating the USDRI. First, loss data in SHELDUS that spans multiple counties is spread over those counties, which means that overall losses reflected at the county and even state level could be different than actual losses experienced. (HVRI, 2014). Another drawback of SHELDUS data is that single hazards can span multiple hazard categories, which makes categorizing losses difficult. Finally, SHELDUS loss data are estimates, which can impact the accuracy of the database (Borden and Cutter 2008). Despite these shortcomings, SHELDUS is the most comprehensive source of hazard loss data available for the US at the county level and the most appropriate for evaluating the USDRI.

The relationship between USDRI risk (including its components and subcomponents) and hazard loss data was explored using correlation and ordinary least squares regression. Losses included those incurred in all hazards found in the SHELDUS database, as well as a separate analysis that included on losses incurred only in the hazard events found in the USDRI exposure component. Tables 5.7 and 5.8 detail the correlations among the USDRI and SHELDUS loss data at the state and county level. Of note, the USDRI contains one exposure variable – sea level rise – that is not accounted for in any loss database as it is not currently a loss-causing hazard. Deleting sea level rise from the exposure component does not result in a statistically significant change in mean exposure.

At the state level, there are mainly moderate correlations between USDRI risk and both human and economic losses, with the strongest being between risk and overall loss (Pearson's R = .507, significant at the .01 level). Adjusting the monetary losses to include only DRI hazards actually decreases this correlation (Pearson's R = .440, significant at the .01 level). The opposite is true in terms of human losses, where limiting the fatalities and injuries increases the correlation with risk. This pattern repeats itself when exposure is compared to losses. Overall, USDRI risk has stronger relationships with monetary losses. Removing drought from the exposure component improves the relationship between both USDRI risk and exposure and all of the loss metrics. Interestingly, the

Table 5.8: Correlation matrix for state risk, exposure, vulnerability, and SHELDUS loss data

	Risk	Risk (No Drought)	Exposure	Exp. (No drought)	Vulnerabil-ity	State SoVI	Loss	Loss (DRI Hazards)	Loss (DRI Haz., no drought)	Human losses	Human losses (DRI hazards)
Risk	1										
Risk (No Drought)	.599**	1									
Exposure	.944**	.617**	1								
Exp. (No drought)	.557**	.993**	.602**	1							
Vulnerability	.320*	-.023	.004	-.086	1						
State SoVI	-.014	.003	.011	.005	-.095	1					
Loss	.507**	.637**	.418**	.597**	.251	.244	1				
Loss (DRI Hazards)	.440**	.553**	.366**	.517**	.207	.262	.959**	1			
Loss (DRI Haz., no drought)	.460**	.586**	.397**	.550**	.233	.257	.941**	.988**	1		
Human losses	.306*	.412**	.225	.394**	.238	.221	.735**	.589**	.546**	1	
Human losses (DRI hazards)	.440**	.630**	.429**	.637**	.119	.177	.698**	.531**	.509**	.814**	1

(*significant at .05; **significant at .01)

Table 5.9: Correlation matrix for SC county risk, exposure, vulnerability, and SHELDUS loss data

	Risk	Risk (No Drought)	Exposure	Exp. (No drought)	Vulnerability	State SoVI	Loss	Loss (DRI Hazards)	Loss (DRI Haz., no drought)	Human losses	Human losses (DRI hazards)
Risk	1										
Risk (No Drought)	.465**	1									
Exposure	.976**	.570**	1								
Exp. (No drought)	.447**	.997**	.560**	1							
Vulnerability	.095	-.349*	-.102	-.381**	1						
State SoVI	.271	.120	.303*	.109	-.095	1					
Loss	.070	.695**	.153	.710**	-.322*	-.255	1				
Loss (DRI Hazards)	.038	.668**	.109	.669**	-.294*	-.241	.952**	1			
Loss (DRI Haz., no drought)	.038	.668**	.109	.669**	-.294	-.241	.952**	1	1		
Human losses	-.126	.128	-.126	.119	-.041	-.260	.314*	.328*	.328*	1	
Human losses (DRI hazards)	-.023	.036	-.024	0.029	-.014	-.072	.217	.294*	.294*	.689**	1

(*significant at .05; **significant at .01)

relationship between risk and human losses has a large increase (correlation = .630, significant at the .01 level) without drought in the model.

At the SC county level, risk and losses show no relationship. Removing drought from the model greatly improves the relationship between risk and monetary loss. However, the relationship between risk and human loss remains poor. This is likely the result of the disproportionate influence of large hazards at smaller scales. At this scale, human losses are rare, and the presence of extreme events where a small number of events accounts for many losses likely skews the results.

When vulnerability is compared to losses, mainly weak correlations exist. The vulnerability component shows no relationship with loss at the state level, and only a weak relationship with monetary loss at the county level. By comparison, the Social Vulnerability Index, shows a weak relationship with loss at the state level, and a weak negative relationship with loss at the SC county level. Of note, the identical correlation between losses from hazards included in the index with and without drought at the county level (Table 5.8) is a result of the fact that the drought surface for SC counties was uniform, meaning that its removal from the loss data subtracted an equal amount of loss from each county.

5.5.2 WRI and global losses

It is also possible to compare components of the WRI to global losses in order to see how the relationship between the USDRI and losses compares to the same relationship at the global scale. Loss data at the global scale was obtained from the EM-DAT database (http://www.emdat.be/database), which contains data on global disasters from 1900 to the present. The scope of EM-DAT data is different than that of SHELDUS data. While SHELDUS contains almost all loss-causing events in the US, EM-DAT is geared toward mortality, and contains only events that caused 10 or more fatalities or 100 or more injuries. Data for losses from 1960 – 2012 (the same timeframe used to examine losses from SHELDUS against the WRI) was extracted from EM-DAT. Only those losses in the exposure component of the WRI were included. As with SHELDUS data, EM-DAT does not include potential hazards, so there is no loss data for sea level rise. As the WRI does not assess risk for every country, the EM-DAT global data was downsized to include only those countries that the WRI examined. Of the 173 countries included in the WRI, 13 did not have any losses for WRI hazards in the EM-DAT database.

Table 5.10 shows the correlations between WRI components and EM-DAT losses. Published WRI exposure data does not include exposure without drought, so that correlation is not included. The results of the correlation analysis are similar to that of the USDRI. The overall WRI risk score shows no correlation with losses, and the exposure component of the WRI shows only a weak correlation with monetary losses. The vulnerability component of the WRI shows no correlation with monetary loss, and a weak correlation with injuries and fatalities. These results suggest that the lack of correlation found in the downscaled USDRI (when drought is included) is commensurate with the relationship of WRI risk to losses.

Table 5.10: Correlation matrix for WRI components and EM-DAT loss data

	Risk	Exposure	Vulnerability	Monetary Loss	Human Loss
Risk	1				
Exposure	.920**	1			
Vulnerability	.428**	.090	1		
Monetary Loss	.043	.187*	.037	1	
Human Loss	.023	-.004	.150*	.453**	1

(*significant at .05; **significant at .01)

5.5.3 Predicting Losses

Ordinary least squares regression was utilized to further examine the statistical relationship between risk and loss. The results for regression of USDRI risk with SHELDUS loss data – which include the same loss categories from the correlation analysis - are presented in table 5.11. The results suggest that, at the state level, risk as defined by the USDRI does not predict much of the variability in loss. The best relationship risk has with a dependent loss variable is total hazard losses (R^2 of .2568). Surprisingly, risk explains less of the variability in losses specific to the hazards in the USDRI exposure component. When drought is removed from the USDRI calculation, the amount of variance in the loss data that risk accounts for increases, in all cases. Without drought, risk accounts for just over 40 percent of the variability in overall losses (R^2 = .4058) and just under 40 percent of the variability in hazards specific to the USDRI model (R^2 = .3966).

Table 5.11: Regression results for USDRI (state level) components against losses

Independent Variable	Dependent Variable - US State Losses		
	R Squared	F	*p*
Risk	0.2568	16.93	0.0002
Risk (No Drought)	0.4058	33.47	0
Exposure	0.1748	10.38	0.0023
Exposure (No Drought)	0.3568	27.18	0
Vulnerability	0.0628	3.282	0.0762

Independent Variable	Dependent Variable - US State Losses (DRI Hazards)		
	R Squared	F	*p*
Risk	0.194	11.79	0.0012
Risk (No Drought)	0.3062	21.63	0
Exposure	0.1337	7.56	0.0083
Exposure (No Drought)	0.2673	17.88	0.0001
Vulnerability	0.0429	2.197	0.1447

Independent Variable	Dependent Variable - US State Loss (DRI Hazards - No Drought)		
	R Squared	F	*p*
Risk	0.2117	13.16	0.0007
Risk (No Drought)	0.3436	25.65	0
Exposure	0.1578	9.814	0.0039
Exposure (No Drought)	0.303	21.3	0
Vulnerability	0.0289	1.46	0.2328

Independent Variable	Dependent Variable - US State Fatalities and Injuries		
	R Squared	F	*p*
Risk	0.0936	5.059	0.029
Risk (No Drought)	0.1698	10.02	0.0027
Exposure	0.0508	2.622	0.1118
Exposure (No Drought)	0.1556	9.029	0.0042
Vulnerability	0.0565	2.936	0.0924

Independent Variable	Dependent Variable - US State Fatalities and Injuries (DRI Hazards)		
	R Squared	F	*p*
Risk	0.194	11.8	0.0012
Risk (No Drought)	0.3966	32.21	0
Exposure	0.184	11.05	0.0017
Exposure (No Drought)	0.4059	33.48	0
Vulnerability	0.0142	0.7073	0.4044

Regression analysis brings out some other interesting trends in the USDRI. For one, in all of the relationships examined, the amount of variability in loss explained by the exposure component is nearly equal to and mirrors changes in the variability explained by risk. This underscores the previous finding that risk is heavily influenced by exposure in the USDRI calculation. Another interesting aspect of the data is that the vulnerability component of the USDRI explains virtually none of the variance in any of the loss data. The best R^2 for the vulnerability component is .0628, against overall losses. This compares to the aggregated state Social Vulnerability Index (not included in Table 5.11), which at its best has an R^2 of .0688 against the loss metrics used in this study.

At the SC county level, many of the same trends are noted in the regression analysis of USDRI components against losses (Table 5.12). Overall risk shows almost no ability to account for variance in any of the loss metrics, with all R^2 values close to zero. With drought removed from the exposure component, the amount of variance risk explains in economic losses jumps considerably; risk accounts for just over 48 percent of the variance in total losses (R^2 .4826). As with the state level analysis, the ability of the exposure component to explain variance in loss mirrors risk, and actually is slightly stronger, with an R^2 of .5034 against overall losses. Vulnerability performs no better explaining variance in loss; its best R^2 is .0863. When county level Social Vulnerability (not included in Table 5.12) is regressed against losses, the most

Table 5.12: Regression results for USDRI (county level) components against losses

Independent Variable	Dependent Variable - SC County Losses		
	R Squared	F	*p*
Risk	0.0049	0.2168	0.6438
Risk (No Drought)	0.4826	41.04	0
Exposure	0.0234	1.055	0.31
Exposure (No Drought)	0.5034	44.61	0
Vulnerability	0.104	5.106	0.0288
Independent Variable	Dependent Variable - SC County Losses (DRI Hazards)		
	R Squared	F	*p*
Risk	0.0015	0.0637	0.8019
Risk (No Drought)	0.4457	35.38	0
Exposure	0.0118	0.527	0.4717
Exposure (No Drought)	0.4482	35.73	0
Vulnerability	0.0863	4.156	0.0475
Independent Variable	Dependent Variable - SC County Losses (DRI Hazards - No Drought)		
	R Squared	F	*p*
Risk	0.0014	0.0635	0.8023
Risk (No Drought)	0.4456	35.37	0
Exposure	0.0118	0.5263	0.4717
Exposure (No Drought)	0.4481	35.72	0
Vulnerability	0.0863	4.156	0.0475
Independent Variable	Dependent Variable - SC County Fatalities and Injuries		
	R Squared	F	*p*
Risk	0.0159	0.7115	0.4035
Risk (No Drought)	0.0164	0.7327	0.3966
Exposure	0.0159	0.7089	0.4044
Exposure (No Drought)	0.0142	0.6352	0.4797
Vulnerability	0.0017	0.0737	0.7873
Independent Variable	Dependent Variable - SC County Fatalities and Injuries (DRI Hazards)		
	R Squared	F	*p*
Risk	0.0005	0.0229	0.8805
Risk (No Drought)	0.0013	0.0577	0.8112
Exposure	0.0006	0.0248	0.8756
Exposure (No Drought)	0.0008	0.0364	0.8495
Vulnerability	0.0002	0.009	0.9249

variance it explains is in county fatalities and injuries, with an R^2 of .0678 against the same.

Comparing the WRI to EM-DAT loss data through regression shows some of the same trends found in the downscaled USDRI (Table 5.13). WRI risk shows no ability to explain variability in EM-DAT economic or human loss data from 1960-2012 at the country level. When examined separately, the exposure and vulnerability components of the WRI also explain no variability in county level loss. In general, the ability of the WRI methodology to explain human and economic losses is poor, as only at the state level of examination does the model

Table 5.13: Regression results for WRI (country level) components against losses

	Dependent Variable - Country Losses		
Independent Variable	R Squared	F	*p*
WRI Risk	0.0019	0.3192	0.5728
WRI Exposure	0.0349	6.176	0.0139
WRI Vulnerability	0.0013	0.2299	0.6322
	Dependent Variable - Country Fatalities and Injuries		
Independent Variable	R Squared	F	*p*
WRI Risk	0.0005	0.0917	0.7624
WRI Exposure	0	0.0029	0.9571
WRI Vulnerability	0.0227	3.962	0.0481

display any relationship to losses. While losses are not the only way to assess the usefulness of a risk index, they are certainly a very visible one.

5.6 Reliability analysis

In order to test whether the variables used in the calculation of the USDRI are measuring the same underlying construct, the Cronbach Coefficient Alpha

(∝) was used to measure the internal consistency of the model. The most common use of ∝ is to measure reliability based on the correlation between sub-indicators. Values for ∝ range from 0 to 1, with values closer to 1 representing better correlation, indicating that the sub-indicators measure the item of interest (in this case, risk) well (Cronbach, 1951; Nardo et al. 2005). Acceptable values of ∝ range from .6 to .9, but values over .7 are more commonly recognized. Running the test on the 24 variables in the USDRI (19 vulnerability and 5 exposure variables - 1 for each hazard) resulted in an ∝ of .64 at both the state and county scale, meaning that the USDRI represents the input provided by the variables. The marginal ∝ at both scales could be due to sample size, which generally should be above n=100 for an unbiased estimate (Yurdugul, 2008). Increasing sample size at the state level is problematic, but can be accomplished at the county level by adding more states to the study area. Dropping variables that show little or no correlation to the overall index can also increase the reliability of the USDRI in future iterations. Candidates for variables to exclude at the state level are the Gini Index (correlation to overall index of .02), literacy rate (.084), and political fragmentation (.180). At the county level, low correlation variables that might be excluded to improve reliability include hospital beds / 10,000 (.056), drinking water safety (.08), and dependency ratio (.118). That different variables are poorly correlated with the overall index at different scales underscores importance of context-specific evaluation of vulnerability at different scales and in different places.

5.7 Summary and conclusions

This chapter detailed and assessed the USDRI concept of risk, which is comprised of the exposure and vulnerability components that were detailed in the previous two chapters. In this proof of concept, modeled after the World Risk Index, there is a distinct spatial expression of exposure, vulnerability and the risk surface that results from combining the two. In the US, there are distinct areas of higher risk to the natural hazards included in the index found in the Southeast US and along the West Coast. At the county level in South Carolina, risk is mainly concentrated in the coastal areas.

Closer examination of the risk determined by the USDRI shows that it is heavily influenced by its exposure component, while the contribution of the vulnerability component seems more ambiguous. This is also the case with the WRI at the global scale. As a test of the ability to downscale the WRI to assess risk, the USDRI succeeds, but it is clear that there is room for improvement of the model at the subnational scale. In addition, when risk is examined against hazard losses, it is apparent that including drought in the index greatly lowers the relationship between risk and loss. Without drought in the model, USDRI risk does a much better job of explaining the variability in human and economic losses.

CHAPTER 6: CONCLUSION – THE WAY AHEAD FOR THE USDRI

6.1 Overview

This dissertation explored the utility of downscaling a global scale risk index to the subnational scale in the United States. To establish the analysis within risk and vulnerability research, a contemporary, global scale risk index – the World Risk Index - was utilized as a basis for the downscaling effort. A subnational index for the US at both the state and county scale was created using the same methodology as the global scale index. This subnational index was then examined using spatial statistics to determine patters of exposure, vulnerability, and risk. In addition, regression was used to examine the main components of the index, as well as to determine the relationship between the index and both monetary and human losses.

Three main questions guided this research. First, can the WRI be customized to the subnational scale in the United States? Which indicators are appropriate for use at the state and county level in the US? Next, does the disaggregation of disaster risk to state and county scales provide more detailed understanding of the spatial distribution of risks and the components of risk? Or, given the availability, quality, and resolution of data do the drivers of disaster risk at the subnational level merely mirror the extant pattern at the national scale?

Finally, how does the risk assessment produced by a top-down approach compare to other US risk assessments? What unique value or insights can be gained from using a top down approach?

The purpose of this chapter is to summarize the key findings of this research and answer the questions posed by the research. The contribution of this research, a critique of it, as well as directions for future research are also presented.

6.2 Summary of research findings

The main purpose of this dissertation was to replicate a global-level composite risk index for US at the state and county level. This research was concerned mainly with establishing a proof of concept for the subnational index based on current understandings of risk and its components and created by downscaling an established index at the global level, the World Risk Index. Using an established methodology allowed for an assessment of the veracity of global level variables and overall risk assessment at a finer sub-national resolution, which could in turn serve as an example for other sub-national replications. Such downscaling can increase information about risk and its drivers, generate discussion about risk, and perhaps provide insight into solutions that reduce risk.

The modularity of the WRI is one of its strongest points. The index produces not only an overall risk score, but also scores for exposure, susceptibility, coping capacity, and adaptive capacity. The disaggregation of components allows for actions targeted against a particular hazard or vulnerability component as well as actions that can influence multiple components. It could also allow resources to be prioritized into order to improve a society's weakest areas. The modularity of the WRI is also forward-looking, as it can provide for risk assessments for future and evolving hazards, such as those associated with global climate change.

6.2.1 Research Question 1

The creation of the USDRI in this dissertation demonstrates that the World Risk Index methodology can be captured at smaller scales, where both understanding of risk and actions to reduce it are of critical importance. Exposure data, as well as raw data for the vulnerability subcomponents, are shown available from public sources. The physical calculation of the index requires relatively few resources; the needed resources include a computer capable of running and rendering maps with a geographic information system, GIS software such as ESRI's ARCInfo, statistics software, spreadsheet software for storing and manipulating data. This work presents a relatively straightforward –though involved - methodology for capturing risk at different scales at the subnational national level.

Some of the global indicators used in the WRI were appropriate for use at subnational scales. Variables such as literacy rate and healthcare expenditure that were used in the global level index have explanatory power at the subnational level and are appropriate for inclusion in the USDRI. Some global variables were omitted entirely in the calculation of the USDRI, as no close proxies existed at the subnational level. For example, the WRI uses the number of female representatives in national parliament as a measure of gender equity. While calculable at the global level for nations, it is problematic to do so at the US state and county level as no current database has compiled this information.

Substitutions were required for others variables, as some that apply on a global scale made less sense at the subnational scale. For instance, the measure of poverty – a proven vulnerability indicator – used at the global level was percent of the population living on less than $1.25 US/day, which is the international poverty level. For a developed nation such as the US, the number of people living below the international poverty level is negligible. Data do not exist to quantify this measure for the US in any case. A more appropriate substitute for this variable was the percent living below the US poverty level, which for 2010 was $11,139/individual, or $30.52/day (IRP, 2010). Other variables where data were available at both the global and subnational level had little explanatory power for states and counties. An example of this is gender parity in education, which was used as an adaptive capacity variable in the WRI. Although important at the global level, in the US gender parity in education is more related to demographics than inequalities; all but two states had more females enrolled than males. A more meaningful measure of gender parity at the state and county level is in the workforce so this was the substitution.

The discussion of each subcomponent in Chapters Three and Four detailed the disposition of each global variable in the USDRI. The exposure

Table 6.1: Disposition of WRI vulnerability variables in the USDRI

	Suceptibility	
Unchanged	**Proxy Used**	**Dropped**
Dependency Ratio	Share of population without access to improved sanitation	Share of population without access to an improved water source
GDP per capita	Share of population undernourished	
GINI Index	Extreme poverty population	
	Coping Capacity	
Unchanged	**Proxy Used**	**Dropped**
Physicians per 10,000 inhabitants	Corruption Perceptions Index	Good governance
Hospital bed per 10,000 inhabitants	Insurances	
	Adaptive Capacity	
Unchanged	**Proxy Used**	**Dropped**
Literacy rate	Combined gross school enrollment	Share of female representatives in national parliament
Biodiversity and habitat protection	Gender parity in education	Forest management
Agricultural management	Water quality	
Public health expenditure	Private health expenditure	
Life expectancy		

component of the USDRI utilized the same methodology and data as its WRI counterpart with the exception of sea level rise data, for which more recent information is available for the US. Of the 23 variables in the vulnerability component of the WRI, ten were used in essentially the same form in the USDRI, nine required use of a close proxy, and four were dropped altogether (Table 6.1). The inability to directly replicate the WRI vulnerability variables speaks to the issue of data availability at different scales. Some data may only reside at the global scale, while at the local levels more detailed (in content and in georeferencing) data is often available. While changing variables at different scales based on availability can compromise top-down consistency between scales, it also opens the door to the idea of contextualization of the WRI at subnational scales. Whenever possible, future use of the WRI should use vulnerability indicators that best describe vulnerability in the area of study.

6.2.2 Research Question 2

The results of this analysis show that disaggregating disaster risk provides valuable insight into the drivers of that risk. Assessing risk at smaller scales showed variations in risk and its components between scales (Table 6.2). At the US level, the overall mean risk score for the country was 5.14, with a range from

Table 6.2: Differences in WRI and USDRI Disaster Risk Scores for the US

	WRI Mean	USDRI State Mean	WRI / USDRI State Diff
Overall Risk	7.40	5.14	2.26**
Exposure	14.73	14.84	-.11
Vulnerability	49.5	34.67	14.83**
Susceptibility	31.35	21.67	'9.68**
Coping Capacity	69.79	43.24	26.55**
Adaptive Capacity	47.34	39.11	'8.23**

(*significant at .05; **significant at .01)

1.95 to 10.61. These figures alone show the value in assessing risk to hazard at smaller scales, as doing so brings out patterns and differences that are masked by a single score at a larger geographic scale. Table 6.2 shows the differences in the WRI and USDRI calculated mean scores for risk, exposure, and vulnerability and its components. USDRI state scores were significantly different from their WRI counterparts for vulnerability and all of its components. These differences likely result from the aforementioned use of some proxy variables in the USDRI. In addition, aggregation bias provides a possible explanation for the differences. Specifically, the modifiable areal unit problem occurs when similar analysis produces different results based on the scale of analysis. Interestingly, for risk the USDRI mean state score was significantly different than the WRI mean risk score for the US. The exposure mean is almost equal to the WRI exposure mean. However, the US state vulnerability mean is significantly lower, which makes the US state risk mean also significantly lower than WRI risk.

In addition, the compilation method of the USDRI also allows for assessment and better understanding of each individual component of risk, and how these components contribute to risk, at smaller scales (see Appendices 1-4). The main driver of risk within the WRI is exposure; this is consistent at all levels examined. This aspect of the WRI/USDRI methodology seems to be inherent in the mathematical calculation of the model given the high range of exposure values and the relatively lower range of vulnerability values found in the state and county samples used in index calculation. In any case, this merits careful examination in future compilations using the WRI methodology.

Spatial analysis also provides for a better understanding of risk, displaying patterns and clusters of risk that are not readily apparent or discernable at larger scales. In general, visual examination of the USDRI risk results shows high areas of risk in the Southeast US and along the West Coast, while areas in the center of the country have a greater diversity of risk scores. Significant differences in the geographic patterns of risk emerge when drought is excluded from the exposure component, as the risk that was present in the Midwest virtually disappears. For South Carolina, visual examination of risk shows a much less clear spatial arrangement, though without drought, disaster risk appears concentrated in coastal areas.

Although analysis for spatial autocorrelation showed little at the US level, significant clustering was indicated at the SC county level when drought was removed from the exposure component. ALMI and Getis-Ord Gi* analysis identified significant clusters of risk at both the state and county level. For the US, high risk clusters were in the Southeast (with drought) and along the Gulf Coast and in New England (without). In South Carolina, some clustering of high risk is noted with drought, but a clear pattern of high risk in coastal areas and lower risk in the northwest part of the state emerges when drought is removed. In general, the spatial arrangement and clustering of risk closely resembles that of exposure, indicating, at least in this iteration of the model, once again that exposure is a main driver of risk. In short, from a geographic perspective, when disaggregating risk, exposure, and vulnerability from the global to subnational levels, scale matters. This conclusion is reinforced by correlation and regression analysis of the relationships between risk and the components, and again requires further analysis in future builds of the USDRI.

6.2.3 Research Question 3

The top-down, deductive approach used in the construction of the WRI and the downscaled USDRI has many benefits. The approach is easy to understand and replicate, as is based on recognized definitions and conceptions of risk and its components. The method is also easy to adjust. For instance, within the dissertation, the expert weighing used for the WRI was critically examined by substituting an equal weighting scheme. When equally weighted, vulnerability scores increased at both the state and county levels, with statistically significant differences in vulnerability and its components at each level. However, consistent with other studies, the overall spatial pattern of vulnerability remained the same irrespective of the weighting scheme.

This research question also sought to compare how risk as defined by the USDRI compared to other measures of subnational US risk. This proved somewhat difficult to accomplish, as this dissertation exists precisely because these other measures of risk do not at the US level. However, some methods of comparative analysis were feasible. For one, the vulnerability component of the USDRI was compared to the Social Vulnerability Index (SoVI), an existing vulnerability index that, in the WRI conceptualization, only measures susceptibility. Although there is no “right answer” for vulnerability since it is a precondition that is difficult to assess after the fact, comparison of USDRI and

SoVI vulnerability showed both similarities and differences. At the state level, there were some similarities in the broad pattern of vulnerability between the USDRI and SoVI, Specifically, Gi* analysis identified a small cluster of higher vulnerability in the south central US based on SoVI, and a larger cluster of vulnerability in the same area based on the USDRI. At the SC county level, both methods showed clusters of low vulnerability along the coast, but disagreed on where vulnerability was concentrated elsewhere in the state. Comparisons between SoVI and only the susceptibility component revealed many spatial similarities between the two at both scales of analysis.

Another method of assessing the merits of the USDRI's top-down approach was to compare USDRI risk to known losses. This was done at both the state and county levels. For US states, there was little correlation between USDRI risk and economic or human losses, however, when drought was removed from exposure, moderate correlations emerged between risk and all types of losses used in the analysis. This pattern repeated itself when regression was used to determine if risk explained the variability in losses. At the county level, the trend in risk vs. losses was much the same for economic losses. However, risk at the county level showed little correlation with human loss; nor could it explain variability in deaths or injuries from hazard even when the exposure component was adjusted. This is likely a result of the influence of extreme loss-causing events at smaller scales of analysis, or could be a product of poor loss data. Finally, the original WRI was also compared to losses in the same manner. USDRI risk at both the state and country level showed closer correlation with and better ability to explain variance in loss than the WRI. As a whole these results suggest that while the top-down methodology used to create the USDRI is understandable and appropriate, the inputs into the WRI should be carefully considered and put into context. In other words, the results show that place matters. Interpretation of the USDRI results should be conducted with full knowledge and understanding of the underlying variables used in the model, the weighting and aggregation process, and the context of the area for which they are computed.

6.3 Contributions and critiques

This dissertation detailed the construction of the United States Disaster Risk Index, a proof of concept composite index designed to assess and promote the further understanding of risk at subnational levels. As such, this work produces the first contemporary risk index for the United States at multiple scales. It incorporates a number of concepts, such as its modularity for all components, as well as its inclusion of both natural and societal factors in the risk equation, elements that are not currently used at the US state scale.

The main contribution of this research is the creation of an easily understood and utilized tool that has immediate utility in examining disaster risk, especially its spatial arrangement, and the variety of factors that contribute to it. The USDRI can serve as a both a nexus of insight and study on the subject of disaster risk at the sub-national level, as well as a targeted disaster risk management tool appropriate for informing policy and planning. The ability to change or give the USDRI variables different weights allows for contextualization of the index for any hazard and / or socioeconomic situation.

From a geographic perspective, the USDRI details human environment interaction in its overall definition, and also considers and allows for the spatial arrangement of risk and its components at multiple scales. This contributes to furthering and exploring the methodology of other work on the composite indexing of risk, notably Birkmann (2007). The utilization of both exposure and vulnerability components in the risk equation allows for further study into the interplay between the two. The spatial analysis of risk, exposure, and vulnerability presented in this work provides a basis conceptualizing the arrangement of each, which highlights geographic areas or aspects of risk that merit closer examination. The ability of the USDRI to show risk and its components at different scales allows for a more complete understanding of risk by showing how it varies at more local scales. This is consistent with Barnett et al. (2008), which concluded that vulnerability is context specific and that examinations of it at larger scales lose relevance and meaning (Barnett et al. 2008).

The USDRI can also assist the US in implementing the 2005 Hyogo Framework for Action (UNISDR, 2012). In its most recent progress report on the Hyogo Framework, the National Science and Technology Council – Disaster Reduction Subcommittee recognized as a limitation the lack of a national multi-hazard risk assessment to inform planning and development decisions (NSTC, 2010). With further validation and refinement, the USDRI can fulfill the Hyogo requirement for the US to have a multi-hazard risk index that is comparable to the national level scores created by the WRI.

This research exposed potential methodological shortcomings in the construction of the WRI and the deconstruction of it to the sub-national scale (USDRI). The most prominent of these was makeup of the exposure component. In its current form, the exposure component contained hazards with a variety of onset speeds and durations. Measuring exposure for different time periods, although driven by methodology and data availability, can be problematic. Shorter time periods do not seem to capture the true nature of the US hazard experience, as was seen with the lack of flood exposure with only an eight year period of data as well as the shortcomings noted with earthquake exposure, specifically the failure of the index to recognize the earthquake risk to the southeast US.

The most prominent of the hazards included in the exposure component was drought, which exerted a seemingly inordinate amount of influence on the human-focused nature of exposure as well as the overall risk scores and spatial distribution of risk. The multi-hazard approach of the USDRI is a strong point, but the hazards included in future iterations of the index should be chosen with care to ensure they do an adequate job informing the model as to the type of risk that affects places.

In its current form, the index utilized a physical exposure component. This implies that the risk score produced by the index indicates risk to life or health. Thus the inclusion of both drought and sea level rise in the index are dubious at best. According to SHELDUS data, there were no fatalities or injuries due to drought in the US for the period 1960-2012 (HVRI, 2014). Further, sea level rise is a possible hazard and will not likely result in many direct human losses. Perhaps predictably, the USDRI assessed risk had little ability to explain human losses to hazard in the US unless drought was removed from the exposure component. This highlights the need to contextualize inputs to the index based on the study area. In a more developed country like the US, hazards such as drought and sea level rise may be more appropriate for use in determining economic risk versus risk to humans.

There are hazards not included in the USDRI that do relate to human risk and should be included in the exposure component. The most prominent, from a US perspective, are severe weather and tornadoes. In 2012, these two hazards combined for 44 percent of US human losses; for the period 1960-2011 they accounted for 44 percent. (HVRI, 2014). This, once again, highlights the need to tailor the exposure component to the hazard profile of the study area.

The weighting scheme of the vulnerability component is also a likely shortcoming and potential source of error in the WRI/USDRI. The USDRI replicated the weights the WRI assigned to each variable and subcomponent. Although the weighting scheme used in the WRI was expert judgments, such weighting schemes often suffer from subjectivity. In addition, the weights were intended for use on a global scale, not a national or subnational scale. Different dynamics at more local scales could render the weights or even the variables themselves less useful and in need of replacement at these scales. Even so, equal weighting is not entirely appropriate for the USDRI as it is currently constructed. When subcomponents do not have an equal number of variables, weighting variables equally leads to some variables and components having much more influence on the model than others. The USDRI should be modified so all components have an equal number of variables, allowing for the establishment of a baseline of vulnerability and risk, or expert opinion about vulnerability at other than global scales should inform indicator selection for the index. Alternately, the mean of the variables in each vulnerability subcomponent could be used as the component score, which reduces the effect of having a different number of variables in each subcomponent, albeit at the expense of making the model more generalized.

Statistical examination showed the risk assessed by the USDRI is closely related to the exposure component at both the state and county level. The relationship between vulnerability and risk was much weaker. This does not necessarily indicate the results of the USDRI are "wrong", but it does require further investigation. The current USDRI suggests risk reduction strategies that focus on reducing exposure. A contextual re-evaluation of the hazards included in the exposure component as well as the vulnerability indicators and their weighting may paint a different picture of risk drivers.

6.4 Future Research

This dissertation has created many avenues for future research. First, indices like the USDRI can capitalize on locally available data to include variables that cannot currently be included in global indices. The WRI recognized many variables - such as housing conditions, disaster preparation and early warning, social networks, and adaptation strategies - that are appropriate for use in its conception of vulnerability. However, it could not include them because data were lacking or did not exist. Incorporating these variables could improve model's representation of vulnerability and, by extension, risk.

Future downscales of the WRI should carefully consider the hazards included in the exposure component. Although the multi-hazard exposure component makes the WRI comprehensive, it opens the door to over-representing certain hazards. This work has shown that including drought at the subnational level is questionable because of its undue influence. In addition, the WRI includes sea-level rise, meaning it mixes not only fast and slow onset hazards, but also current and potential hazards. Future attempts to represent exposure for the US in an index could reconfigure the component to omit these hazards, as well as consider the inclusion of other hazards that impact the US, such as tornadoes and wildfires. Along the same lines, the time frame of the hazard data included in future work should be expanded as much as possible to best represent the hazards that impact the study area. In general, better exposure data will help improve the risk profiles produced by the index.

Another consideration for future work on downscaling the WRI is experimenting with different variable weights as well as the overall aggregation method for the index. Although the proxy variables used in the WRI are grounded in vulnerability literature, expert weighting of the current variables or of others used in future versions of the model may improve its performance. Changing the aggregation method could help improve the model's performance in predicting loss, or help strike a balance between the influence of the exposure and vulnerability components. In addition, the global variables used in the index produced some counter-intuitive results as the subnational scale, underscoring the need for the utilization of variables appropriate for the chosen study area in future work.

The WRI as currently configured measures risk of physical exposure to hazards. However, it can be configured to represent other types of risk, such as risk of economic damage. In fact, the PREVIEW dataset utilized in this study also has economic exposure surfaces. Computing economic exposure for the US at the state and county scales and using the same as exposure input for the WRI model would lead to a comprehensive assessment of economic risk. This, in turn, could provide more insight into overall US hazard risk as well as complement this study's assessment of physical risk. Moreover, including long duration areal hazards like drought in an economic risk index for the US is appropriate, as drought is a large contributor to US economic losses from hazards. Additionally, in keeping faith with the original overall intent of this research, the exposure and vulnerability components of the model can be configured to assess environmental security at the subnational level from a hazards perspective.

A potential use of the WRI is in assessing risk to future hazards. The inclusion of sea-level rise in the current model provides the groundwork for the potential utilization of the index to assess risk from global climate change. This can be accomplished by adjusting current levels of exposure to climate sensitive hazards to levels hypothesized in future climate scenarios, or by creating exposure surfaces for hazards that may emerge in the future, as was done with sea level rise in this study.

Future subnational versions of the WRI can be used to assess changes in risk and vulnerability over time. If the model is constructed on a fixed time period with the most recent data, subsequent iterations will show changes in the subcomponents. Change detection can be used to monitor risk and vulnerability, or to assess the effectiveness of policies or programs designed to reduce the same.

Finally, one of the intended uses of a comprehensive index for assessing risk at the subnational scale is to assess state security, with a focus on environmental security. Using the downscaled WRI in such a manner could have a wide variety of tactical and strategic applications, such as monitoring state stability, increased local knowledge for governmental and non-governmental organizations that may operate in a given area, assessments of sensitivity to current and future environmental hazards, and increased knowledge of risk and its drivers at other than global scales.

6.5 Postscript

This research has explored the utility of downscaling a global risk index to two different scales at the subnational level. The development of the USDRI, examination of its results, critical examination of the insights it provides, and the further utilization of it can serve as a critical input to hazard risk management. Specifically, the USDRI serves as a starting point to better understand risk, its spatial distribution, and its physical and socio-economic drivers. Ideally, the USDRI as presented in this research and future use of it will bring its concept of risk into practice to inform policy and planning of risk reduction efforts at the scales where such action is appropriate and feasible. Finally, the lessons learned in this study can be applied to studies that downscale the WRI for other nations. In keeping with the ultimate intent of this work, the results and insights presented here can be used as a stepping stone to foster a better understanding of environmental risks that could threaten stability or state cohesion at a time when human vulnerability is gaining recognition as an important aspect of environmental security.

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APPENDIX A: SELECTED TABLES

Table A.1: US state scores for USDRI, components, and subcomponents

Rank	State	Risk	Risk (No drought)	Exposure	Exposure (No drought)	Vulnerability	Susecptibility	Lack of Coping Capacity	Lack of Adaptive Capacity
51	California	10.61	4.94	25.99	12.11	40.81	21.10	62.51	38.83
50	Wyoming	10.11	0.02	30.70	0.05	32.92	19.99	41.05	37.74
49	Louisiana	9.20	5.24	28.10	16.00	32.76	23.07	34.79	40.43
48	Florida	7.93	3.34	22.59	9.50	35.13	23.32	45.87	36.21
47	Alabama	7.88	1.64	22.35	4.65	35.26	23.55	38.90	43.34
46	Georgia	7.37	0.45	20.90	1.27	35.29	22.59	38.97	44.31
45	North Carolina	6.76	1.24	20.19	3.70	33.49	22.30	37.74	40.45
44	Washington	6.46	0.92	18.14	2.58	35.60	20.29	51.13	35.38
43	Kansas	6.25	0.01	16.98	0.02	36.79	22.18	41.43	46.77
42	South Carolina	5.93	1.50	17.25	4.37	34.38	23.26	39.18	40.72
41	Connecticut	5.92	2.36	16.61	6.61	35.65	20.33	52.19	34.42
40	Virginia	5.79	1.05	18.27	3.31	31.70	19.99	36.12	39.00
39	Texas	5.65	0.78	13.33	1.84	42.36	22.22	58.86	46.02
38	Oregon	5.38	0.53	15.98	1.56	33.64	21.05	45.12	34.77
37	Nebraska	5.35	0.04	13.47	0.10	39.71	21.50	49.96	47.68
36	Oklahoma	5.31	0.04	14.68	0.11	36.18	23.31	39.88	45.36
35	Ohio	5.20	0.40	14.65	1.13	35.52	22.34	41.83	42.39
34	Maine	5.20	1.21	17.02	3.97	30.57	21.50	43.43	26.78
33	Arkansas	5.05	0.26	13.60	0.70	37.11	24.10	41.51	45.72
32	West Virginia	5.04	0.80	15.88	2.51	31.74	23.16	34.78	37.29
31	Illinois	5.01	0.45	10.42	0.94	48.02	21.08	78.67	44.32
30	Utah	4.88	0.10	12.54	0.26	38.89	22.04	45.71	48.92
29	Iowa	4.81	0.06	13.30	0.17	36.16	21.53	37.42	49.55
28	Arizona	4.78	0.06	12.55	0.16	38.11	23.58	51.17	39.60
27	Indiana	4.78	0.30	12.75	0.81	37.51	21.88	44.49	46.18
26	Pennsylvania	4.68	0.60	12.61	1.61	37.08	21.53	49.93	39.80
25	New Mexico	4.59	0.00	13.51	0.00	34.01	24.85	41.32	35.86
24	New York	4.58	1.41	14.54	4.48	31.47	20.73	40.12	33.56
23	Tennessee	4.54	0.47	13.30	1.37	34.10	22.89	35.04	44.39
22	North Dakota	4.53	0.04	12.08	0.11	37.51	20.58	43.92	48.04
21	Mississippi	4.51	1.14	13.17	3.34	34.26	25.22	34.58	42.99
20	New Jersey	4.50	1.16	13.47	3.48	33.43	20.37	42.29	37.64
19	Idaho	4.49	0.07	11.71	0.19	38.35	23.24	45.77	46.04
18	Delaware	4.49	0.44	12.96	1.27	34.63	20.02	51.92	31.95
17	Minnesota	4.48	0.03	13.46	0.08	33.29	20.65	41.89	37.35
16	Vermont	4.39	0.89	14.14	2.86	31.08	20.21	41.28	31.75
15	Missouri	4.36	0.21	12.02	0.59	36.26	22.36	45.02	41.39
14	Montana	4.19	0.01	11.87	0.04	35.32	22.75	39.33	43.89
13	New Hampshire	4.17	1.23	13.04	3.84	32.01	19.52	43.22	33.30
12	Kentucky	4.16	0.64	11.68	1.81	35.64	23.73	38.52	44.67
11	South Dakota	4.13	0.02	11.14	0.07	37.10	22.72	39.78	48.83
10	Michigan	4.12	0.23	11.87	0.65	34.72	22.55	42.75	38.86
9	Massachusetts	4.00	2.03	12.85	6.51	31.12	20.45	45.15	27.77
8	Wisconsin	3.95	0.08	11.41	0.24	34.64	21.15	43.89	38.89
7	Nevada	3.89	0.08	11.66	0.23	33.40	21.08	41.66	37.46
6	Colorado	3.86	0.00	9.85	0.00	39.21	20.46	56.82	40.36
5	Rhode Island	3.71	1.81	12.07	5.88	30.76	21.15	40.04	31.09
4	Maryland	3.64	0.19	12.75	0.67	28.57	19.50	34.88	31.35
3	Hawaii	3.61	0.87	12.35	2.98	29.25	20.53	35.01	32.23
2	D.C.	2.23	0.05	11.73	0.24	19.02	16.23	21.70	19.12
1	Alaska	1.95	0.27	7.29	1.02	26.82	19.67	36.76	24.05

Table A.2: SC county scores for USDRI, components, and subcomponents

Rank	County	Risk	Risk (No drought)	Exposure	Exposure (No drought)	Vulnerability	Susecptibility	Lack of Coping Capacity	Lack of Adaptive Capacity
46	Jasper	21.44	2.06	55.24	5.30	38.81	20.50	47.10	48.85
45	Marion	13.84	4.54	43.36	14.21	31.93	23.01	46.99	25.81
44	Georgetown	11.03	7.26	34.49	22.72	31.98	22.85	39.74	33.36
43	Charleston	8.55	5.46	28.57	18.25	29.93	17.82	31.03	40.96
42	Beaufort	8.47	3.97	25.53	11.97	33.16	21.38	40.08	38.03
41	Hampton	7.84	0.95	19.84	2.39	39.52	23.48	47.41	47.70
40	Abbeville	7.47	0.00	19.75	0.00	37.81	23.84	47.38	42.22
39	Barnwell	7.33	0.29	22.85	0.92	32.08	22.91	46.43	26.90
38	Orangeburg	7.32	1.10	21.61	3.24	33.89	21.84	46.84	33.00
37	Spartanburg	7.24	0.10	17.74	0.24	40.84	20.15	56.66	45.71
36	Laurens	6.86	0.03	20.58	0.09	33.35	21.27	47.20	31.59
35	Greenville	6.82	0.00	17.42	0.01	39.13	19.00	50.46	47.94
34	Horry	6.79	4.94	19.30	14.02	35.20	19.48	42.62	43.52
33	Clarendon	6.73	1.68	18.30	4.56	36.80	22.70	43.86	43.84
32	Chesterfield	6.65	1.51	18.89	4.29	35.21	22.02	47.44	36.19
31	Lee	6.61	1.68	18.68	4.73	35.41	23.38	48.09	34.76
30	Anderson	6.59	0.01	16.97	0.03	38.83	21.29	48.21	47.01
29	Sumter	6.22	1.54	17.54	4.34	35.45	20.79	42.14	43.43
28	Kershaw	6.20	1.39	17.50	3.93	35.42	21.05	39.17	46.05
27	Oconee	6.12	0.05	18.05	0.16	33.93	21.84	39.82	40.14
26	Saluda	6.05	0.07	15.28	0.17	39.60	21.54	49.01	48.28
25	Darlington	6.02	1.47	17.60	4.29	34.23	21.38	46.02	35.31
24	Newberry	5.94	0.15	15.23	0.40	39.02	19.60	44.50	52.95
23	Chester	5.75	0.72	15.60	1.95	36.85	23.22	39.99	47.35
22	Florence	5.65	0.98	16.54	2.86	34.16	20.25	38.46	43.79
21	Allendale	5.60	0.48	18.91	1.63	29.64	24.68	34.82	29.42
20	Bamberg	5.50	0.64	15.33	1.78	35.86	24.04	29.98	53.57
19	Union	5.47	0.15	17.93	0.48	30.52	21.86	35.37	34.34
18	Colleton	5.25	1.34	17.26	4.41	30.39	23.70	40.49	26.99
17	Aiken	5.21	0.03	13.68	0.07	38.09	20.57	49.77	43.96
16	Calhoun	5.11	0.98	13.62	2.62	37.53	20.76	47.83	44.02
15	Pickens	5.09	0.00	13.64	0.00	37.33	20.52	47.34	44.14
14	Edgefield	5.06	0.00	13.59	0.00	37.27	20.48	43.93	47.41
13	Greenwood	5.06	0.01	16.03	0.03	31.54	20.65	31.31	42.69
12	Cherokee	5.00	0.21	14.77	0.63	33.88	20.75	43.91	36.98
11	Dorchester	5.00	1.91	15.10	5.78	33.08	19.67	47.45	32.13
10	Williamsburg	4.81	1.07	14.54	3.23	33.08	23.67	48.41	27.17
9	York	4.57	0.68	12.27	1.82	37.28	19.10	46.90	45.84
8	Lancaster	4.50	0.92	12.49	2.56	36.02	22.35	41.05	44.68
7	Fairfield	4.20	0.72	11.12	1.90	37.77	22.95	45.03	45.34
6	Dillon	4.19	1.09	12.27	3.19	34.13	23.74	40.97	37.68
5	Lexington	4.17	0.57	11.43	1.57	36.44	18.05	50.75	40.53
4	Berkeley	3.81	1.47	11.73	4.53	32.47	19.23	49.57	28.63
3	Marlboro	3.78	0.85	11.53	2.60	32.77	22.54	39.88	35.89
2	Richland	3.40	0.66	11.95	2.33	28.46	17.79	33.46	34.14
1	McCormick	1.71	0.07	4.67	0.20	36.62	22.76	41.75	45.38

Table A.3: US state exposure in percent of population exposed annually (sea level rise expressed in percent exposed to 1 meter rise in sea level)

Rank	State	Exposure	Earthquake	Cyclone	Flood	Drought	Sea Level Rise
51	Wyoming	30.70	0.05	0.00	0.00	30.65	0.00
50	Louisiana	28.10	0.00	5.89	0.46	12.09	9.66
49	California	25.99	11.61	0.00	0.07	13.88	0.43
48	Florida	22.59	0.00	5.30	0.03	13.09	4.17
47	Alabama	22.35	0.00	4.55	0.06	17.70	0.03
46	Georgia	20.90	0.00	1.10	0.02	19.63	0.14
45	North Carolina	20.19	0.00	3.37	0.03	16.49	0.30
44	Virginia	18.27	0.01	2.80	0.04	14.96	0.46
43	Washington	18.14	2.45	0.00	0.00	15.56	0.13
42	South Carolina	17.25	0.00	3.70	0.03	12.88	0.64
41	Maine	17.02	0.08	3.61	0.00	13.05	0.28
40	Kansas	16.98	0.00	0.00	0.02	16.97	0.00
39	Connecticut	16.61	0.00	6.24	0.05	10.00	0.32
38	Oregon	15.98	1.44	0.00	0.00	14.42	0.12
37	West Virginia	15.88	0.00	2.24	0.27	13.36	0.00
36	Oklahoma	14.68	0.00	0.00	0.10	14.58	0.00
35	Ohio	14.65	0.01	0.85	0.27	13.52	0.00
34	New York	14.54	0.03	3.50	0.18	10.06	0.77
33	Vermont	14.14	0.82	1.98	0.06	11.27	0.00
32	Arkansas	13.60	0.23	0.22	0.25	12.90	0.00
31	New Mexico	13.51	0.00	0.00	0.00	13.50	0.00
30	New Jersey	13.47	0.00	2.42	0.19	9.99	0.87
29	Nebraska	13.47	0.00	0.00	0.10	13.37	0.00
28	Minnesota	13.46	0.00	0.00	0.08	13.37	0.00
27	Texas	13.33	0.00	1.62	0.19	11.49	0.04
26	Tennessee	13.30	0.07	1.25	0.05	11.94	0.00
25	Iowa	13.30	0.00	0.00	0.17	13.13	0.00
24	Mississippi	13.17	0.00	3.18	0.07	9.84	0.07
23	New Hampshire	13.04	0.06	3.68	0.00	9.20	0.10
22	D.C.	12.96	0.00	0.86	0.03	11.69	0.38
21	Massachusetts	12.85	0.00	6.09	0.03	6.34	0.39
20	Maryland	12.75	0.00	0.43	0.01	12.08	0.23
19	Indiana	12.75	0.02	0.66	0.13	11.94	0.00
18	Pennsylvania	12.61	0.06	1.48	0.07	11.00	0.00
17	Arizona	12.55	0.16	0.00	0.00	12.39	0.00
16	Utah	12.54	0.25	0.00	0.00	12.28	0.00
15	Hawaii	12.35	2.66	0.10	0.00	9.37	0.23
14	North Dakota	12.08	0.00	0.00	0.11	11.97	0.00
13	Rhode Island	12.07	0.00	5.59	0.11	6.19	0.18
12	Missouri	12.02	0.03	0.40	0.16	11.43	0.00
11	Montana	11.87	0.04	0.00	0.00	11.84	0.00
10	Michigan	11.87	0.00	0.58	0.07	11.22	0.00
9	Delaware	11.73	0.00	0.24	0.00	11.49	0.00
8	Idaho	11.71	0.18	0.00	0.00	11.52	0.00
7	Kentucky	11.68	0.11	1.15	0.55	9.87	0.00
6	Nevada	11.66	0.22	0.00	0.00	11.43	0.00
5	Wisconsin	11.41	0.00	0.00	0.24	11.18	0.00
4	South Dakota	11.14	0.00	0.00	0.06	11.08	0.00
3	Illinois	10.42	0.02	0.67	0.25	9.48	0.00
2	Colorado	9.85	0.00	0.00	0.00	9.84	0.00
1	Alaska	7.29	0.38	0.00	0.05	6.27	0.58

Table A.4: SC county exposure in percent of population exposed annually (sea level rise expressed in percent exposed to 1 meter rise in sea level)

Rank	County	Exposure	Earthquake	Cyclone	Flood	Drought	Sea Level Rise
46	Jasper	55.24	0.00	4.38	0.01	50.00	0.92
45	Marion	43.36	0.00	14.21	0.00	29.15	0.00
44	Georgetown	34.49	0.00	20.60	0.05	12.15	2.06
43	Charleston	28.57	0.00	11.74	0.09	11.23	6.43
42	Beaufort	25.53	0.00	9.80	0.17	13.75	2.00
41	Barnwell	22.85	0.00	0.92	0.00	21.93	0.00
40	Orangeburg	21.61	0.00	3.23	0.01	18.37	0.00
39	Laurens	20.58	0.00	0.07	0.02	20.49	0.00
38	Hampton	19.84	0.00	2.34	0.00	17.45	0.05
37	Abbeville	19.75	0.00	0.00	0.00	19.75	0.00
36	Horry	19.30	0.00	13.57	0.03	5.32	0.43
35	Allendale	18.91	0.00	1.63	0.00	17.29	0.00
34	Chesterfield	18.89	0.00	4.29	0.01	14.60	0.00
33	Lee	18.68	0.00	4.73	0.00	13.95	0.00
32	Clarendon	18.30	0.00	4.51	0.05	13.74	0.00
31	Oconee	18.05	0.00	0.00	0.15	17.89	0.00
30	Union	17.93	0.00	0.48	0.00	17.45	0.00
29	Spartanburg	17.74	0.00	0.24	0.00	17.49	0.00
28	Darlington	17.60	0.00	4.28	0.01	13.31	0.00
27	Sumter	17.54	0.00	4.34	0.00	13.20	0.00
26	Kershaw	17.50	0.00	3.92	0.01	13.57	0.00
25	Greenville	17.42	0.00	0.01	0.00	17.41	0.00
24	Colleton	17.26	0.00	3.58	0.00	13.29	0.82
23	Anderson	16.97	0.00	0.00	0.03	16.94	0.00
22	Florence	16.54	0.00	2.86	0.00	13.68	0.00
21	Greenwood	16.03	0.00	0.00	0.03	16.00	0.00
20	Chester	15.60	0.00	1.94	0.01	13.65	0.00
19	Bamberg	15.33	0.00	1.78	0.00	13.55	0.00
18	Saluda	15.28	0.00	0.10	0.07	15.12	0.00
17	Newberry	15.23	0.00	0.37	0.02	14.83	0.00
16	Dorchester	15.10	0.00	5.67	0.00	9.32	0.11
15	Cherokee	14.77	0.00	0.63	0.01	14.14	0.00
14	Williamsburg	14.54	0.00	3.23	0.00	11.31	0.01
13	Aiken	13.68	0.00	0.07	0.01	13.61	0.00
12	Pickens	13.64	0.00	0.00	0.00	13.64	0.00
11	Calhoun	13.62	0.00	2.62	0.00	11.00	0.00
10	Edgefield	13.59	0.00	0.00	0.00	13.59	0.00
9	Lancaster	12.49	0.00	2.56	0.00	9.93	0.00
8	Dillon	12.27	0.00	3.17	0.02	9.09	0.00
7	York	12.27	0.00	1.81	0.01	10.45	0.00
6	Richland	11.95	0.00	2.32	0.01	9.62	0.00
5	Berkeley	11.73	0.00	3.78	0.03	7.47	0.72
4	Marlboro	11.53	0.00	2.53	0.07	8.93	0.00
3	Lexington	11.43	0.00	1.53	0.04	9.86	0.00
2	Fairfield	11.12	0.00	1.87	0.03	9.22	0.00
1	McCormick	4.67	0.20	0.00	0.00	4.47	0.00