ANALYZING THE RELATIONSHIPS BETWEEN HAZARD VULNERABILITY SCIENCE AND DISASTER MANAGEMENT POLICY AND PRACTICE: A CASE STUDY OF ATLANTIC HURRICANES

by

David Jean-Paul Alexander
A Dissertation
Submitted to the
Graduate Faculty
of
George Mason University
in Partial Fulfillment of
The Requirements for the Degree
of
Doctor of Philosophy
Earth Systems and Geoinformation Sciences

Committee:

______________________________	Dr. David W. Wong, Dissertation Director
______________________________	Dr. Paul Delamater, Committee Member
______________________________	Dr. Ruixin Yang, Committee Member
______________________________	Dr. Edmund Zolnik, Committee Member
______________________________	Dr. Anthony Stefanidis, Department Chair
______________________________	Dr. Donna M. Fox, Associate Dean, Office of Student Affairs & Special Programs, College of Science
______________________________	Dr. Peggy Agouris, Dean, College of Science
Date: _________________________	Summer Semester 2016 George Mason University Fairfax, VA

Analyzing the Relationships between Hazard Vulnerability Science and Disaster Management Policy and Practice: A Case Study of Atlantic Hurricanes

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at George Mason University

By

David Jean-Paul Alexander
Master of Science
Colorado Technical University, 2005
Master of Science
University of South Carolina, 1997
Bachelor of Arts
University of South Carolina – Aiken, 1993

Director: David W. Wong, Professor
Department of Geography and GeoInformation Science

Summer Semester 2016
George Mason University
Fairfax, VA

DEDICATION

As Thomas Edison once said: “The three great essentials to achieve anything worthwhile are, first, hard work; second, stick-to-itiveness; third, common sense.”

I dedicate this dissertation to my grandmother, Grace Posey Busbee and my lovely wife and children, Elena, Daniel, and Sophia Alexander. You have been an inspiration and constant throughout this process – reminding me that it is never ok to just settle but to remain vigilant in my grit and determination to achieve my dreams.

And to my children, you are never too old and it is never too late to learn something new. Life is a journey that offers experiences throughout for those who keep an open mind and eyes wide.

I could not have done this without you.

All my love and respect,

David Jean-Paul Alexander

ACKNOWLEDGEMENTS

We can never show enough appreciation and gratitude to those who foster our imagination and help to develop our critical thinking skills. I would like to express my gratitude to my dissertation advisor, David Wong, for his knowledge, time, effort, and relentless encouragement in driving me to complete this work and finish my degree.

I would also like to thank my colleagues at the Department of Homeland Security, especially Daniel Cotter, for allowing a flexible work schedule, and accommodating last minute requests for time off to meet critical deadlines. Their knowledge and insight into this subject were crucial to the development of my research objectives.

Finally, I would like to thank my family and friends for their support. While it took much longer than expected, I could not have done it without their reassurance and persistent motivation.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
CEM	Comprehensive Emergency Management
DPI	Disaster Preparedness Index
DRA	Disaster Relief Act of 1950
DRI	Disaster Risk Index
DR#	Disaster Declaration Number
EEI	Essential Element of Information
ESF	Emergency Support Function
FEMA	Federal Emergency Management Agency
FIPS	Federal Identification Processing System
GWR	Geographically weighted regression
HSIP	Homeland Security Infrastructure Data Product
HSPD	Homeland Security Presidential Directive
HVRA	Hazard Vulnerability Research Institute
IA	Individual Assistance
IRPTA	Intelligence Reform and Terrorism Prevention Act
LM	Lagrange Multiplier
LR	Likelihood Ratio
NAICS	North American Industry Classification Code
NEMIS	National Emergency Management Information System
NGA	National Geospatial Intelligence Agency
NICAR	National Institute for Computer-Assisted Reporting
NIMS	National Incident Management System
NRF	National Response Framework
NOAA	National Oceanic and Atmospheric Administration
OLS	Ordinary Least Squares regression
PA	Public Assistance
PKEMRA	Post Katrina Emergency Management Reform Act
SBA	Small Business Administration
SC	Schwarz Crteria
SoVI	Social Vulnerability Index
SLOSH	Sea, Lake, and Overland Surge from Hurricanes Model
TIGER	Topologically Integrated Geographic Encoding Referencing System
W	Joint Wald statistic

ABSTRACT

ANALYZING THE RELATIONSHIPS BETWEEN HAZARD VULNERABILITY SCIENCE AND DISASTER MANAGEMENT POLICY AND PRACTICE: A CASE STUDY OF ATLANTIC HURRICANES

David Jean-Paul Alexander

George Mason University, 2016

Dissertation Director: Dr. David W. Wong

Vulnerability indices have been used extensively in disaster management, and the social vulnerability index (SoVI) has been regarded as the most popular despite its appropriateness and performance not being validated conceptually and empirically.
A pedigree matrix and variable crosswalk were used to examine the conceptual relationships between hazard vulnerability science (three selected vulnerability indices, including SoVI) and disaster management (using disaster operations impact model data). The research indicates there are theoretical linkages between hazard vulnerability indicators and disaster management essential elements of information. The analysis also show that SoVI is conceptually the most appropriate among the three vulnerability index. Subsequently, I conducted an empirical study to assess the capability of SoVI to predict damages caused by natural disaster events. SoVI index scores were related to nine Atlantic hurricanes and their associated federal disaster costs and estimated damages at

the county level. Ordinary least squares regression, spatial econometrics, and geographically weighted regression are used to evaluate their empirical relationships. The study demonstrates that SoVI has little explanatory power in explaining federal disaster costs per capita and that the disaster impact model variables are more effective in explaining the variation in federal disaster costs per capital rather than the SoVI. The results also show that these relationships varied tremendously across the nine hurricane events. Although using logarithmic transformation to reduce skewness in variables improved model performance marginally, no model involving SoVI performs reasonably well. The research recommends using the disaster impact model outputs for constructing a more reliable predictive model to support disaster operations.

CHAPTER 1: INTRODUCTION

Disasters are not just one-off phenomena and represent the results of continuous social, economic, and environmental processes over time (Lavell 2008, p. 82). Vulnerability provides a conceptual link between disasters, built environment, and people. This research applies exploratory regression methods and spatial econometric models to examine the relationships between hazard vulnerability science, disaster impact modeling, and disaster management practice in the context of Atlantic Hurricanes in the United States from 1999-2004. It considers an operational framework that fuses those disciplines into an all-hazards, all-threats regime to provide a more practical mechanism for informing disaster management policy.

Figure 1 shows a map of the storm tracks for the nine (9) hurricanes and Table 1 lists the disaster declaration numbers. These observations represent the hurricanes that made landfall and received presidential disaster declarations during the study period that data was made available for this research. FEMA registers presidential disaster declarations with a unique identification number in the National Emergency Management Information System (NEMIS), more commonly referred to as a DR#, to track and monitor activities relating to these events.

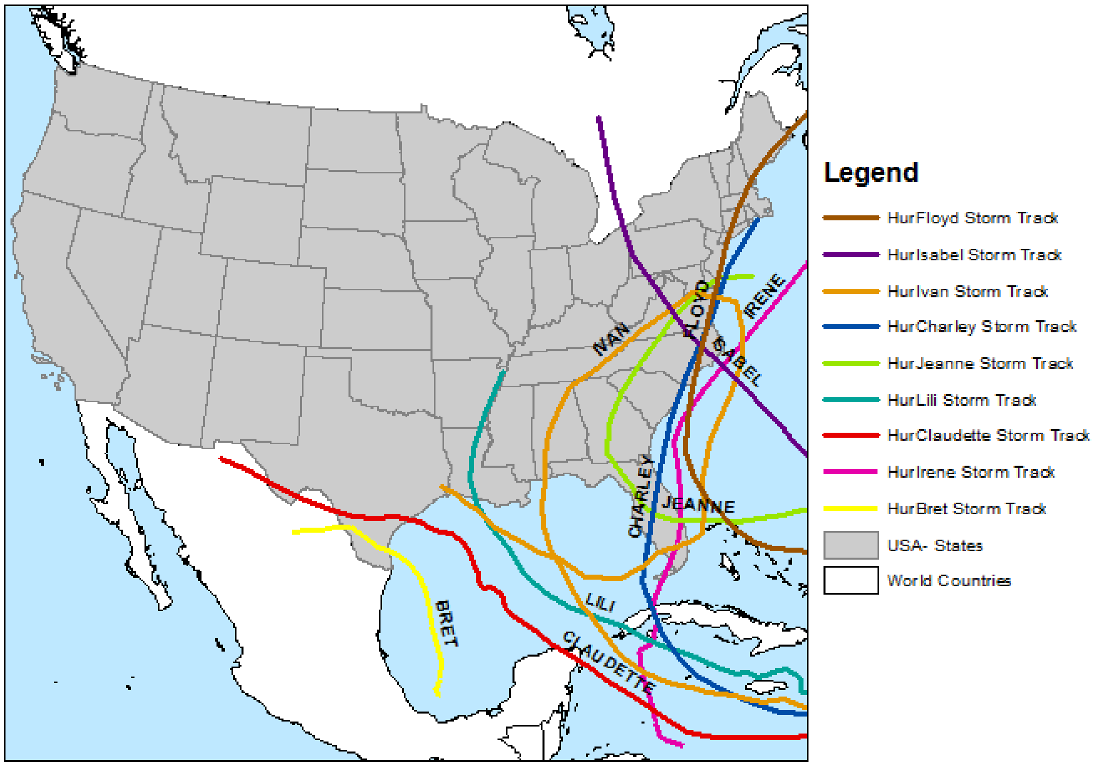


Figure 1: Map of Storm Tracks for Hurricanes included in Study

Table 1: List of Disaster Declarations for Hurricanes included in Study

DR#	State	Year	Hurricane
1287	Tx	1999	Bret
1292	NC	1999	Floyd
1293	Va	1999	Floyd
1294	Pa	1999	Floyd
1295	NJ	1999	Floyd
1296	NY	1999	Floyd
1297	De	1999	Floyd
1298	SC	1999	Floyd
1300	Fl	1999	Floyd
1302	Ct	1999	Floyd
1303	Md	1999	Floyd
1305	NH	1999	Floyd
1307	Vt	1999	Floyd
1308	Me	1999	Floyd
1306	Fl	1999	Irene
1437	La	2002	Lili
1479	Tx	2003	Claudette
1490	NC	2003	Isabel
1491	Va	2003	Isabel
1492	Md	2003	Isabel
1493	DC	2003	Isabel
1494	De	2003	Isabel
1496	WV	2003	Isabel
1539	Fl	2004	Charley
1543	SC	2004	Charley
1548	La	2004	Ivan
1549	Al	2004	Ivan
1550	Ms	2004	Ivan
1551	Fl	2004	Ivan
1553	NC	2004	Ivan
1554	Ga	2004	Ivan
1563	NJ	2003	Ivan
1565	NY	2004	Ivan
1557	Pa	2004	Ivan
1561	Fl	2004	Jeanne

STATEMENT OF THE PROBLEM

Hazard vulnerability is broadly defined as the potential for loss or capacity to suffer harm across social, economic and ecological dimensions (Kates 1985, Mitchell 1989, Gall 2007). While the occurrence of natural disasters cannot be prevented, losses from their impacts can be minimized through better understanding of natural disaster losses and informed policies that are risk-based, linking disaster operations, preparedness, and mitigation. The United States government responds to more than 50 declared disasters or emergencies per year totaling more than $3 billion annually in relief and recovery expenditures (Garrett and Sobel 2003). These facts are attributed in part to political motivations, as the Robert T. Stafford Disaster Relief and Emergency Assistance Act (Public Law 93-288) was amended in 1988 to provide the US president more discretion in declaring natural disasters (Garrett and Sobel 2002, Sobel et al. 2007). A more holistic interpretation is that a variety of factors from settlement patterns, land-use practices, and global climate change have placed society increasingly in harm's way. This perspective is underscored by the Gulf Coast hurricanes of Katrina and Wilma making landfall in 2005; in which, more than 1,500 people perished and initial direct losses covered by federal disaster assistance programs exceeded 25 billion dollars as these storms became the deadliest and costly hurricanes in United States history (FEMA 2013).

One way to counter the upward trend in disaster losses is through mitigation and preparedness strategies to reduce risk as people continue to settle in more hazard prone areas. The United Nations identified comprehensive mitigation and preparedness planning as critical opportunities to reduce future losses and costs associated with disasters at the World Summit for Sustainable Development in 1992 (UN/ISDR 2004). The causes of risk must be identified in order to assess the effectiveness of both corrective and prospective mitigation measures to properly inform response and recovery plans and appropriately influence disaster management policy (Cardona 2005). Neal (1997) indicated that the disaster management lifecycle has been traditionally viewed as an over-simplified heuristic device due to the lack of holistic understanding of the four phases of mitigation, preparedness, response, and recovery. Geis (2000) reiterates this view noting that "everything is interconnected in [disasters and emergency management] and a holistic, integrated approach is required" (p. 152). The complexity of emergency management, as realized through the disaster management lifecycle, depicted in Figure 2, below is often misinterpreted as a sequential process of cascading activities where preparedness precedes response, followed by recovery, ending with mitigation.

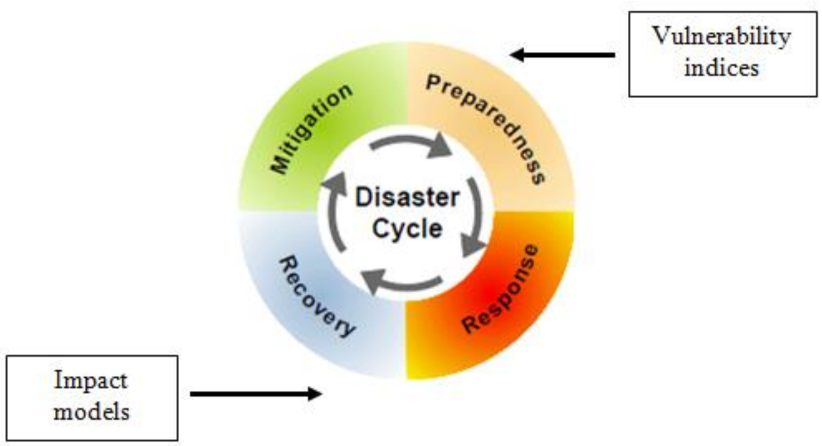


Figure 2: Disaster Lifecycle

The United States government passed the Disaster Mitigation Act in 2000 to reinforce the importance of pre-disaster mitigation planning to reduce disaster losses nationwide. The Disaster Mitigation Act of 2000 signaled a trend away from this elementary interpretation of the disaster management lifecycle toward a more integrated view where mitigation is recognized as an on-going process whose assessment indicators should inform policy and preparedness activities rather than a finite activity necessitated by disaster. This intellectual shift in the disaster management community, while significant, belies linkages between pre-event mitigation planning envisioned through hazard vulnerability indices and the conduct of disaster operations supported through event-specific impact modeling. Those same indicators used to quantify community vulnerability as part of on-going mitigation planning activities are seldom validated against ground-truth data from real-world events nor aligned to impact modeling efforts used by disaster response teams to support critical life-saving, damage assessment and recovery missions.

The difficulty in achieving effective disaster risk management has been partly the result of a lack of a comprehensive framework of disaster risk that facilitates multidisciplinary impact modeling and subsequent mitigation strategies (Cardona 2005). McEntire (2004) suggests that the concepts of hazard vulnerability "may help us to better describe and comprehend the true nature of disasters, since they deal with the goals of liability reduction and capability enhancement (i.e.: reducing risk and susceptibility and raising resistance and resilience)" (p.11). Alexander (2006) argues that "the key problem of vulnerability" serves "as a far greater determinant of disaster risk than hazards themselves" (p.2). Gall contends that hazard vulnerability, risk, and capacity assessments form the basis for effective mitigation and preparedness strategies (Gall 2007).

According to Cardona, these assessments are an unavoidable and necessary step in evaluating the performance of disaster management policy and risk reduction strategies (Cardona 2005b).). To avoid skewed vulnerability assessments and decision-making, hazard researchers need to take stock of existing indices (Gall 2007). Without calibrated measures of vulnerability and risk, applied to impact models utilized across the disaster management lifecycle, mitigation cannot be effective and losses will be difficult to reduce over time (Cutter 2003 and Gall 2007, p. 4) as evidenced by the magnitude of federal disaster losses in the United States over the preceding decade.

To date, substantial research has been conducted by social and physical scientists on disaster management with an emphasis toward hazard vulnerability and risk assessments to help focus efforts to strengthen communities and enhance their local resiliency. A multitude of hazard vulnerability and risk indices have been realized through this applied research. While this research has contributed to our understanding of vulnerability; it has done little to improve our ability to identify, measure, and reduce disaster risk (Birkmann 2007). These hazard indices often do not represent the true nature of a hazard or vulnerability as they are quantitative, subjective measures that act as proxies for natural hazard susceptibility (Cobb 2001, Cobb and Rixford 1998). Cardona states that "most existing indices and evaluation techniques do not adequately express risk and are not based on a holistic approach that invites intervention" (2005a p. i). In many cases, indices were defined based on the availability of data rather than the information that truly represents the hazard (King 2001). *Additionally, there is little research validating these indicators and no framework that integrates hazard* *vulnerability assessments with disaster operations and associated impact modeling activities*. In other words, research needs to establish linkages between the factors of vulnerability and the elements of disaster impact using empirical data from federal disaster assistance programs. Federal Operating procedures for Emergency Support Function #5 of the National Response Framework (NRF) compiles situational reports based on essential elements of information (EEIs) that cover population, infrastructure, and economic conditions. These EEIs are intended to serve as indicators for mobilizing federal assistance programs required to facilitate community recovery and rebuild. This dissertation attempts to address Cardona's concerns by examining hazard vulnerability based on disaster management policy and practice. It compares the social vulnerability index, a proxy measure of vulnerability, with ground-truth data that represents actual impacts from Atlantic hurricane disasters.

Schmidtlein et al. (2008) suggests that the inability to assess the validity of vulnerability indices is due to "the complexity of factors contributing to vulnerability, no variable has yet been identified against which to validate such indices" (p 3-4). Cutter et al. (2003) attempted to test the reliability and usefulness of the social vulnerability index (SoVI) to predict disaster impacts using the number of presidentially declared disasters at the county level. This examination yielded no statistically significant results. This lack of statistical correlation may be a reaffirmation of the theory about the political nature of disaster declarations. Downton and Pielke (2001) argue that disaster declarations are often treated as political rewards rather than as a result of disaster impacts. An alternate interpretation of the finding from Cutter et al. (2003) may suggest a dissonance between the concepts of vulnerability and the impacts of a disaster. Or the lack of correlation may indicate that there is no single variable that can be used to authenticate vulnerability indices, but validation must come from a multivariate approach. Questions like these indicate a need for further research in this area and the validation of hazard vulnerability indexes as useful instruments for formulating effective disaster management policies. Without applied research that demonstrates a direct link between vulnerability science and disaster impact, vulnerability indexing will continue to be considered an academic exercise (theoretical endeavor) rather than a practical tool for mitigating disaster risk.

Empirical based research on vulnerability indicators and indices will provide much needed insight into the validity of hazard vulnerability indicators to accurately assess the level of community susceptibility from Atlantic Hurricanes. It also h*elps bridge the research policy nexus described by Cutter et al 2008* (p. 598) and *improve our understanding of the components of vulnerability in the context of actual disasters based on empirical data*. This will help progress vulnerability science past the "leap of faith" conundrum expressed by Adger (2006, p. 275) *into a reliable metric based on proven indicators*.

Reliable hazard vulnerability indicators will go a long way toward understanding the predictors of hurricane disaster losses, thereby determining the factors most important in explaining the behavior of such losses. This knowledge will also help better enlighten decision-makers on the dimensions of hazard vulnerability to hurricanes and inform subsequent policies and mitigation strategies. Additionally, an operational framework for impact modeling that applies validated hazard vulnerability indicators and incorporates the geographic characteristics of hurricanes would be a crucial tool toward ensuring public safety and economic stability, given the heightened risk of future catastrophic hurricane disasters along the Atlantic-Gulf coast of the United States. Aligning indicators used by mitigation planners to determine hazard vulnerability, to those indicators used by disaster operators to derive impact models should result in better community preparedness and resiliency, improve disaster response and recovery efforts, and produce more informed policies. Such a model would help to expedite disaster recovery efforts, by ensuring appropriate resources are available to aid individuals and families and enable community rebuild. Theoretical contributions would likely serve as a grounding agent for many of the scholarly premises influencing disaster management research. McEntire (2004) suggests that disaster management theory grounded in reality is more likely to generate theories with practical implication; while theories based on faulty assumptions will produce conclusions that will inevitably be problematic. To put it more bluntly, "what gets measured, gets managed" and what the hazard research community attempts to measure and understand needs to be validated (Drucker 1954, Gall 2007, p. 11).

RESEARCH OBJECTIVES

The purpose of this dissertation is to examine the relationships between hazard vulnerability indicators, disaster impacts, and the essential elements of information (EEIs) that drive disaster operations with the objective of establishing an operational framework that integrates social vulnerability indicators with the modeling of community impacts to serve as a proxy for estimating the likelihood of and magnitude of direct federal assistance (i.e., quantified losses from a declared disaster) expected for Atlantic hurricane disaster declarations. It uses the following definitions of hazard and social vulnerability as a conceptual anchor. These definitions are both widely recognized by the hazard science community and consistent with U.S. disaster preparedness policy.

> Hazard vulnerability or "vulnerability to environmental hazards means the potential for loss. Since losses vary geographically, over time, and among different social groups, vulnerability also varies over time and space." (Cutter and Emrich 2006).
>
> "Social vulnerability to natural hazards is the potential for loss and the complex interaction among risk, mitigation, and the social fabric of a place" (Schmidlin et al. 2009) and "is defined as the susceptibility of social groups to the impacts of hazards, as well as their resiliency, or ability to adequately recover from them." (Cutter and Emrich, 2006; Sapam Ranabir Singh, Mohammad Reza Eghdami and Sarbjeet Singh, 2014).

This dissertation is informed by the following research questions:

a) Does vulnerability science have a nexus with disaster management?

b) Do hazard vulnerability indicators align with disaster operations variables?

c) Do social vulnerability indices accurately predict the exposure of a community to a natural hazard and therefore its *level of vulnerability or the level of damages and serve as a good predictor for disaster management purposes*?

d) Do hazard vulnerability indices account for the geography of the hazard across space or inadvertently treat the units of measure as discrete locations?

e) Do hazard vulnerability indices provide an effective planning tool for building disaster resiliency?

Demonstrating linkages between disaster impacts and vulnerability indices provides a validation point for the use of risk-based vulnerability assessments as a practical tool for creating local strategies and prioritizing the efforts necessary for building more resilient communities. It also provides a starting point for considering a vulnerability indexing method comprised of impact model simulations calibrated by empirical data from historical events rather than general socio-economic indicators or national estimates of loss. This approach is very similar to that employed by the National Hurricane Center (NHC), and validated by the meteorological community, to produce the Sea, Lake, and Overland Surges from Hurricanes (SLOSH) model. The SLOSH model is a numerical model that uses a proven set of characteristics (indicators) run through a set of statistical equations several thousand times to produce a composite measure of risk for an area based on estimated storm surge heights from historical, hypothetical, and predicted hurricanes (NHC website 2016).

DISSERTATION STRUCTURE

The remaining content of this dissertation is organized as follows. Chapter two provides a synthesis of hazard vulnerability science complemented by a review of disaster management policy and practice. It includes a discussion of existing weaknesses and gaps in the development, application, and validation of sound measures to support place vulnerability, hazard assessment, and impact modeling activities. Chapter two also outlines current challenges moving beyond hazard vulnerability and impact modeling theory into applied research and toward operationalizing it to support the various facets of the disaster management lifecycle.

Chapter three assesses the linkages between hazard vulnerability theory and disaster management policy and the selection of SoVI as the most applicable vulnerability index for evaluating whether hazard vulnerability indices can accurately predict exposure of a community to a hurricane disaster. It includes a comparative analysis of three hazard vulnerability indices (social vulnerability index, disaster risk index, and disaster preparedness index) and their underlying indicators to determine which variables are considered the most common elements of vulnerability. These vulnerability indices were chosen as representative of the three dimensions of hazard vulnerability: economic, social, and physical (UNDP / BCPR 2004). The social vulnerability index focuses on the social dimensions of vulnerability. The disaster risk index is more exposure based with an emphasis on ecological conditions. The disaster preparedness index emphasizes economic dimensions with additional elements for measuring emergency management factors to account for policy shifts toward prevention and mitigation strategies. Many of the preparedness factors in the disaster preparedness index are expressed as fiduciary terms such as funding for emergency operations, local funding for mitigation/planning, funding per capita, and public debt (Simpson 2006). Each index has its own merits and subsequent shortcomings. These characteristics will be fully discussed in this dissertation.

Chapter four discusses the statistical analysis approach for analyzing the predictive power of SoVI with the Federal disaster assistance data and the FEMA Disaster Operations Impact Models for the selected hurricanes. The chapter includes a discussion of the data sources and processing routines used to prepare the data for statistical analysis. Data used in this study differs from previous research such as Cutter et al. (2003) in that they include both frequency counts and financial totals for federal mitigation and disaster loan assistance programs for individuals and public, at the county unit for each presidentially declared hurricane disaster included in the research sample. Cutter (2003) only evaluated SoVI for correlation with the single variable of frequency of presidentially declared disasters at the county level. Chapter 4 also introduces the regression scenarios used for analyzing the relationships between hazard vulnerability science, disaster management policy, and disaster operations practice and for validating the accuracy of SoVI to serve as a good predictor of community vulnerability for disaster management purposes.

Chapter 5 attempts to quantify the findings from the comparative analysis completed in chapter 3 using a correlation analysis. It includes an exploratory regression to assist with variable selection for the OLS regression. Chapter 6 presents findings from the regression analysis based on the OLS models constructed to analyze the relationships between hazard vulnerability science and disaster management, using SoVI, and the FEMA disaster impact models. Chapter 7 addresses model bias in the OLS regression that includes skewness of data and missing variables. Chapter 8 seeks to resolve issues with spatial autocorrelation in the OLS regression by applying spatial econometrics and geographically weighted regression (GWR) to the same regression scenarios.

Chapter 9 provides a summary of findings and implications for future research, reasoning for a conceptual framework for operationalizing hazard vulnerability into disaster management practice by fusing impact modeling and vulnerability indexing, that integrates deterministic and probabilistic methods to incorporate results from historical, hypothetical, and predicted events to produce a more dependable, composite index for hazard vulnerability.

CHAPTER 2: LITERATURE REVIEW

DISASTER MANAGEMENT POLICY AND PRACTICE IN THE UNITED STATES: A BRIEF HISTORY

From a historical perspective, an increasing federalization of disaster policy and emergency management in the United States has been happening during the past sixty years. During this same period of federalization, disaster management practice has refocused from a reactive profession emphasizing preparedness (education and training) and response to a proactive emergency management approach emphasizing mitigation and protection measures (McEntire 2004, Sylves 2008). Disaster policy has shifted from its roots in civil defense where disasters are viewed as one-off local events best managed by local resources toward an all-hazards emergency management perspective that involves all levels of government with exceedingly more federal bearing (Sylves 2008). This one-off attitude means events are not assessed in context to other similar events to identify weaknesses or lessons learned that could affect operations for future like events or other events that may have similar characteristics because there was no effort to connect the dots or draw commonalities stressed in an all-hazards emergency management approach. Figure 3 illustrates these trends in disaster management and provides a timeline of key policy and legislation.

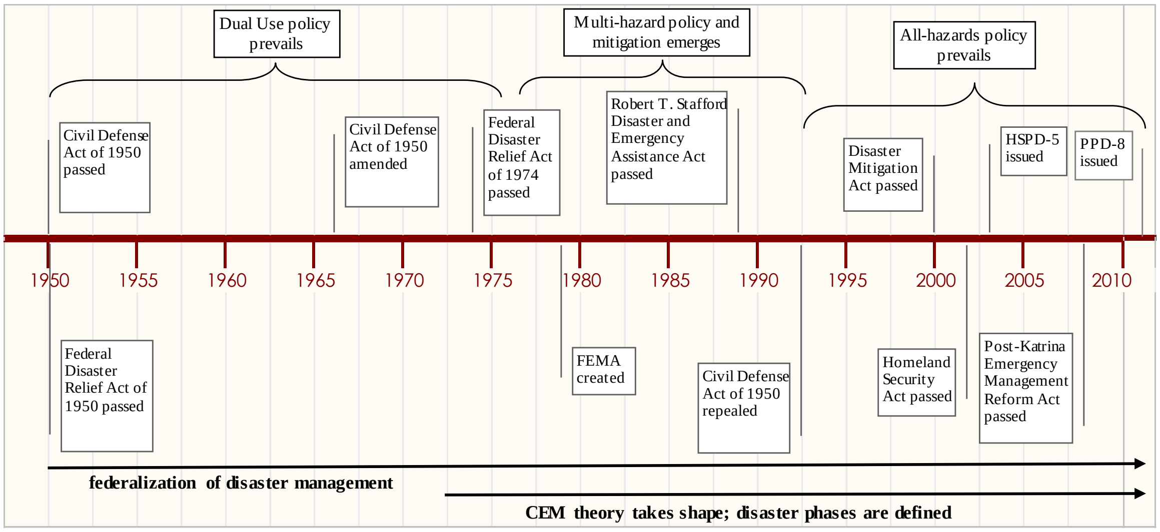


Figure 3: Timeline of Key Federal Disaster Policy and Legislation

The Federal Disaster Relief Act of 1950 (DRA) set forth a framework and process that underscores most of the major federal disaster legislation to this day (Sylves 2008). The 1950 DRA introduced the notion that state governors could request federal disaster assistance from the president. It also recognized the "dual use" philosophy of civil defense, where federal support to civil defense units provided overlapping benefits to emergency management. The 1950 DRA served as a companion measure for the Federal Civil Defense Administration (Sylves 2008). The Disaster Relief Act of 1966 furthered the "dual use" policy linking civil defense warning systems with natural disaster alerts; and that same year, Congress amended the 1950 Civil Defense Act to authorize funding on a "dual use basis to prepare for the threat of enemy attack and for natural disasters" (Sylves 2008, p. 50). These congressional attempts to unify disaster policy on the "dual use" premise did nothing to address the disjointed nature of federal disaster authorities that were spread across several agencies, antecedents of the organic and reactionary developments of the preceding acts.

Congress passed the Disaster Relief Act of 1974 to help remedy a series of presidential reorganizations of federal disaster functions across multiple agencies. This same law introduced three key concepts to federal disaster policy: 1) direct federal assistance to individuals and families affected by a disaster, 2) hazard mitigation as a precondition for federal disaster assistance, and 3) a multi-hazard approach to disasters (Sylves 2008). In many ways, the 1974 DRA signaled the start of a new trend in disaster management toward mitigation and the transition away from civil defense toward all-hazard emergency management.

Despite the 1974 DRA, federal disaster policy remained fragmented and dispersed across several agencies. In 1978, President James Carter sought to consolidate federal disaster management programs within his five principle executive agencies through the establishment of the Federal Emergency Management Agency (FEMA website 2012). FEMA was created by executive order on April 1, 1979 following Congressional approval of presidential reorganization plan 3 of 1978. Executive Order 12127 combined the Defense Civil Preparedness Agency, the Federal Insurance Administration, the National Fire Protection and Control Administration, the Federal Preparedness Agency within the General Services Administration, and the Federal Disaster Assistance Administration within the Department of Housing and Urban Development along with one hundred other federal disaster response programs reporting to twenty different congressional committees (Office of the President 1978, 1979). While the formation of

FEMA did not fully consolidate disaster policy under one agency; the Department of Agriculture retained primary responsibility for agricultural disasters. FEMA did incorporate hazard mitigation activities linked to preparedness and disaster assistance, introduce the notion of emergency support functions, and establish a single agency within the federal government dedicated to emergency management (Sylves 2008).

During the next two decades, Congress passed or repealed key pieces of federal disaster legislation and continued the trend of establishing mitigation as a cornerstone of federal disaster policy. It passed the Robert T. Stafford Disaster and Emergency Assistance Act in 1989, (Stafford Act) granting the president authority to declare disasters or emergencies. In 1993, Congress repealed the Civil Defense Act of 1950 transferring all civil defense emergency management functions under Title VI of the Stafford Act to be coordinated by FEMA. It passed the Disaster Mitigation Act in 2000 reinforcing the importance of pre-disaster mitigation planning to reduce disaster losses nationwide.

Following the terrorist acts of September 9, 2001, Congress passed the Homeland Security Act of 2002 (P.L. 107-296), placing FEMA within the newly formed Department of Homeland Security (DHS) and reaffirming an all-hazards, all threats approach to federal disaster management. This act was followed by executive issuance of Homeland Security Presidential Directive Five (HSPD-5) in 2003 that established the National Incident Management System (NIMS) and the National Response Framework (NRF). While citing an all-hazards and all-threats focus, the HSPD-5 policy lacked a risk-based perspective instead concentrating on threat scenario action plans and provisioning of disaster relief. That same year, the president issued Homeland Security Presidential Directive Eight (HSPD-8), intended to strengthen the policies to prevent, prepare for, respond to, and recover from terrorist attacks, major disasters, and other emergencies with an attention toward training, planning, equipment, and exercises for Federal incident management and asset preparedness.

The Homeland Security Acts and Presidential Directives passed between 2002-2011, coupled with enabling legislation passed by Congress in the preceding decades operationalized comprehensive emergency management (CEM) theory, incorporating all phases of disaster management within the encompassing federal policy and practice. The Intelligence Reform and Prevention of Terrorism Act of 2004 (P.L. 108-458 or IRPTA) required the implementation of NIMS and renewed emphasis on disaster preparedness to include comprehensive risk assessments for terrorism related attacks, but not for natural hazard or non-terrorism related events. The focus in IRPTA was on law enforcement and prevention and protection measures based on findings from the 911 Commission Report. In response to federal response failures to Hurricane Katrina in 2005, Congress passed the Post-Katrina Emergency Management Reform Act in 2007 (PKEMRA) reaffirming FEMA's placement as a distinct agency within DHS and placing certain functions transferred to the DHS preparedness directorate under the Homeland Security Act of 2002 back within FEMA (US GAO 2008).

In 2011, the National Preparedness System was established under the auspices of Presidential Policy Directive 8 (PPD-8). PPD-8 directed the development of a national preparedness goal implemented through a national preparedness system of integrated planning guidance, programs, and processes and defined national preparedness as a shared responsibility aimed at facilitating an integrated, all-of-Nation, capabilities-based approach to preparedness. The national preparedness system under PPD-8 encompasses the whole community from Government, businesses, communities, and citizens. It also incorporates a risk component that was lacking in its predecessor HSPD-8. Per Whitehouse policy memorandum 2011, "the national preparedness goal shall be informed by the risk of specific threats and vulnerabilities – taking into account regional variations - and include concrete, measurable, and prioritized objectives to mitigate that risk. The national preparedness goal shall define the core capabilities necessary to prepare for the specific types of incidents that pose the greatest risk to the security of the Nation, and shall emphasize actions aimed at achieving an integrated, layered, and all-of-Nation preparedness approach that optimizes the use of available resources."

The national preparedness system is intended to "allow the Nation to track the progress of our ability to build and improve the capabilities necessary to prevent, protect against, mitigate the effects of, respond to, and recover from those threats that pose the greatest risk to the security of the Nation" and capacity "for building and sustaining a cycle of preparedness activities over time" (Obama 2011). PPD-8 signifies a further transition in disaster management policy from one of response and recovery to one of disaster risk management and vulnerability assessment.

> “The national preparedness goal shall be informed by the risk of specific threats and vulnerabilities – taking into account regional variations - and include concrete, measurable, and prioritized objectives to mitigate that risk. The national preparedness goal shall define the core capabilities necessary to prepare for the specific types of incidents that pose the greatest risk to the security of the Nation, and shall emphasize actions aimed at achieving an integrated, layered, and all-of-Nation preparedness approach that optimizes the use of available resources. The national preparedness goal shall reflect the policy direction outlined in the National Security Strategy (May 2010), applicable Presidential Policy Directives, Homeland Security Presidential Directives, National Security Presidential Directives, and national strategies, as well as guidance from the Interagency Policy Committee process. The goal shall be reviewed regularly to evaluate consistency with these policies, evolving conditions, and the National Incident Management System (Obama 2011).”

DISASTER MANAGEMENT THEORY, PRINCIPLES, AND CONCEPTS

During the period of federalization of disaster policy and practice, disaster management began to emerge as a field of study, coalescing around a handful of core principles and holistic theory. Since 1950, the concept of CEM has become the traditional theory of disaster management (McEntire et al. 2001, McEntire 2004). CEM organizes disaster management into disaster phases: preparedness, response, recovery, and mitigation that represent the full lifecycle of disaster (Sylves 2008, McEntire et al. 2001, McEntire and Marshall 2003, McEntire 2004) as depicted in figure 2. While CEM may represent the bedrock of federal emergency management theory, the concept has underlying weaknesses (McEntire and Marshall 2003). Neal (1997) determined that the four phases recognized by CEM are useful, but CEM in general is an over-simplified heuristic device that does not recognize the complexity of disasters (McEntire 2004).

According to Britton, CEM fails to capture the wider political, economic, and cultural explanations of disaster (Britton 1999, McEntire and Marshall 2003, McEntire 2004).

To address the weaknesses in CEM, several paradigms have emerged in the academic literature. Some scholars have suggested a move toward the concepts of disaster resistant community (Geis 2000, Armstrong 2000). Others have emphasized a need to focus on resiliency (Britton and Clarke 2000, Burby et al. 2000, and Buckle et al. 2000). Boulle et al. (1992), Berk et al. (1993) and Mileti (1999) championed the concept of sustainability or sustainable hazards mitigation. Cutter (1996, 2001), Cutter et al. (2003), Blaikie et al. (1994), and Anderson (2000) recommended a focus on hazard vulnerability as a means to tie in all phases of disaster management.

Regardless of its weaknesses, CEM attempts to provide a holistic view of the disaster lifecycle and its concomitant functions. Geis (2001) notes that "everything is interconnected and a holistic, integrated approach [to disaster management] is required… (p. 152)." Mileti (1999) observes that "researchers have called for a broad view of the disaster problem… (p. 35)." McEntire (2004) furthered this notion stating that "comprehensive perspectives should become more valued in future disaster scholarship and that maintaining a reliance on the phases of disasters should be a priority in emergency management theory" (p. 35). While it is clear more research on the complexities of disaster is required to better understand the disaster problem as described by Mileti (1999), scholars need to direct more research toward understanding and measuring the relationship between mitigation, recovery, preparedness and response (McEntire et al 2001, McEntire and Marshall 2003, McEntire 2004).

The disaster management community historically has placed more emphasis on emergency response rather than disaster mitigation and recovery. This preference for response over preparedness has done little to address rising disaster losses (McEntire 2004). This is understandable given the limelight endeared by live video feeds of disaster victims, flooded homes, or streets filled with debris. Mitigation is not the sexiest of endeavors and more often than not goes unnoticed by the public until local protective measures fail during times of need.

Although disaster policy and operations remain largely event driven, a paradigm shift in emergency response practice has taken place over the past fifty years from simply responding to disasters and providing relief to victims toward emergency management as a discipline to better prepare for, respond to, mitigate for, and recover from disasters (McEntire et al 2001, McEntire and Marshall 2003, McEntire 2004, Sylves 2008). This philosophical shift has been strengthened by enabling legislation passed by Congress incorporating mitigation into routine federal disaster operations and as a requirement for federal assistance for local preparedness activities and post-disaster relief. This paradigm shift has also been reinforced by acknowledgement of several core principles that have invariably guided federal disaster policy and local emergency management practice during this period. These fundamental tenets of disaster management are:

- emergency management is a shared responsibility across all levels of government
- emergency response is primarily a local responsibility
- policy and practice should represent the full life cycle of disaster

- all-hazards approach to disaster management instead of maintaining unique and separate capacities

PPD-8 characterizes an evolution in national emergency management policy and application of CEM theory. By joining the traditional pillars of the disaster lifecycle with the law enforcement and interdiction elements of Homeland Security through prevention and protection, PPD-8 represents a logical progression toward all hazards, all threats emergency management. Encapsulated by five mission frameworks: Prevention, Protection, Response, Recovery, and Mitigation and their supporting initial operating plans; PPD-8 engenders a culture of preparedness, bridging comprehensive emergency management with disaster risk management, recognizing that" risk unmanaged leads to the occurrence of disaster" (Yodmani 2001). With its notions of risk, vulnerability, and regional variation, it is reasonable to assert that PPD-8 is largely based on a Hazards-of-Place construct of vulnerability assessment.

Other disaster management concepts also operate within the framework of CEM. Many of these concepts and operating models are encapsulated by the National Incident Management System (NIMS) that was established as federal emergency management doctrine under HSPD-5. NIMS covers the emergency management concepts of incident command system, unified command, multiagency coordination and addresses common terminology, training and qualifications, and information and technology to name a few. The NIMS is linked to PPD-8 and the coordinating structures of the underlying national preparedness system.

DISASTER OPERATIONS, IMPACT MODELING, AND ESSENTIAL ELEMENTS OF INFORMATION

The National Incident Management Systems (NIMS) serves as the foundation for disaster operations across all levels of government and community involved in emergency management. The NIMS unites the practice of emergency management and incident response throughout the country by focusing on five key areas or components (preparedness, communications and information management, resource management, command and management, and ongoing management and maintenance) and leveraging existing structures such as the incident command system to create a comprehensive and proactive system for those responding to incidents or planned events (FEMA NIMS Fact Sheet 2012). Disaster operational units apply the principles of NIMS, Incident Command System (ICS), and the various frameworks under PPD-8 to manage the conduct and maneuvers necessary to assist in the response, recovery, mitigation, and future planning and preparedness activities related to an incident. Many of the functions necessary to support disaster operations are executed by emergency support functions (ESFs) per the National Response Framework that aligns to NIMS (NRF Fact Sheet 2012). FEMA serves as the federal lead for ESF #5: Emergency Management. ESF#5 operates at all levels of disaster operations, serving as the emergency support team for DHS and the information and planning section for the disaster field office. ESF#5 facilitates the overall activities of the Federal Government in providing assistance to one or more affected States, coordinating with the local incident commander, as well as mission and decision support elements through collection, analysis, processing, and dissemination of information about a potential or actual disaster or emergency to all parties involved (ESF 5 – Information and Planning Annex 2003).

Standard operating procedures require that ESF#5 provide the initial assessment of the incident, work across the emergency support functions and mission support partners to compile timely and appropriate information on the incident, and disseminate necessary information to emergency managers and first responders. To achieve situational awareness, ESF#5 compiles situational reports based on essential elements of information (EEIs) from a variety of sources. These EEIs serve as the basis for understanding disaster conditions, forecasting potential impacts and consequences, provisioning key resources, tracking progress and ground crews, conducting current and future planning, and maintaining overall situational awareness of the incident. According to the ESF#5 - Information and Planning Annex, EEIs provide emergency managers early intelligence on the effect of a disaster on the population and infrastructure of an area and gage the resourcing requirements that might be required to support the incident response and recovery. For hurricane events, ESF#5 and disaster field units leverage hurricane storm track information supplied through the NOAA subtropical weather advisories published from the National Weather Service, storm surge information derived from the sea, lake, and overland surge (SLOSH) model outputs generated by the NOAA Coastal Services Center, and damage and impact assessments produced using the FEMA HAZUS-MH program (HLS GeoCONOPS v5.0 2013; FEMA Geospatial Standard Operating Procedures 2012).

> “This information [from the EEIs] facilitates accurate assessment of what response activities and materiel are required to save lives, relieve human suffering, and expedite response and recovery operations. During the early hours of a disaster and in the absence of “ground truth” information such as actual on-site surveys or imagery, GIS, computerized predictive modeling, and damage estimation software may be used to develop *initial* estimates of damage. As soon as possible, actual on-site ground surveys will be performed. Sources may include a Federal-State Preliminary Damage Assessment (PDA) and information from Federal, State, and local government agencies, among others, to establish “ground truth”… (ESF#5 – Information and Planning Annex 2003). See appendix A.

During the recovery and mitigation phases of disaster operations, public and individual assistance grant programs are initiated to support community rebuild and restoration and to provide citizens with housing and other needs. This direct federal assistance also includes grants issued through the hazard mitigation grants program to assist state and local governments with the development of hazard mitigation risk plans and with the implementation of long term mitigation measures to promote community resilience. The status of these projects and activities become EEIs within the situational reports produced by ESF#5.

In many ways, EEIs act as indicators for assessing the scope and severity of a disaster and the ensuing actions required to support disaster operations and serve as outcomes measures for assessing the impact of the disaster and tracking progress toward recovery. Since EEIs are intended to reflect ground-truth and the effects of a disaster on population and infrastructure, it begs a comparison with the indicators used to conduct hazard vulnerability assessments and derive the associated hazard vulnerability / risk indexes. This comparative analysis may reveal any potential relationships between the practice of disaster operations and disaster risk management and help to validate if vulnerability indicators are true surrogates of exposure, susceptibility, and risk.

HAZARD VULNERABILITY AND COMPREHENSIVE EMERGENCY MANAGEMENT

Hazard assessment and vulnerability research offers one of the more promising approaches to CEM within disaster management research, fusing the science of mitigation with the practice of emergency response. McEntire (2004) suggests that “vulnerability may [in fact] help us to understand the purpose of emergency management since it deals with the goals of liability reduction and capability enhancement (i.e., reducing risk and susceptibility and raising resistance and resilience (p. 11).”

As Cuny postulated in his work titled, “Disaster and Development”, the rise in disasters is related to a rise in the vulnerability of people induced by the development of the built environment and that the increase in vulnerability is not uniform and varies across regions (Cuny 1983). From this perspective, vulnerability is the only aspect emergency managers have control over in the disaster equation and may provide the best venue for accurately describing and understanding the true nature of disasters. Yodmani notes that within emergency management the “emphasis has shifted to using vulnerability analysis as a tool in disaster management” as part of a more comprehensive approach to disaster risk management that encompasses “three distinct but interrelated components: hazard assessment, vulnerability analysis, and enhancement of management capacity” and the ongoing development of disaster operations (Yodmani 2001, p. 2). Taking this one step further, hazard assessment and vulnerability thereby extends the practice of mitigation performed through risk indices into the realm of response operations often accomplished through the application of impact models. The fusion of impact modeling with vulnerability indexing may offer the best opportunity for studying the complexity of disasters and their associated response and recovery operations, and gaining a better understanding of disaster phenomena and how impact models relate to vulnerability assessments to complete the CEM feedback loop of the disaster lifecycle. This is especially true when considering the large number of variables involved in the two processes.

HAZARD VULNERABILITY RESEARCH TRENDS AND CONCEPTS

Hazard assessment and vulnerability research is a relatively new paradigm in the social sciences only materializing as an important theoretical topic in the 1980s (Bohle et al. 1994, Rygel et al. 2005). Alwang et al. conducted a multi-disciplinary review of vulnerability research and concluded that "practitioners from different disciplines use different meanings and concepts of vulnerability, which, in turn, have led to diverse methods of measuring vulnerability" (2001, p. 2). Cutter et al (2003, p.1) also concluded that "vulnerability has many different connotations depending on the research orientation and perspective" (Dow 1992, Cutter 1996, 2001, 2003). According to Cutter, vulnerability is broadly defined as the "potential for loss" (1996, p.529). Balikie et al. define vulnerability as "the characteristics of a person or group in terms of their capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard"

(Kumpulainen 2006, p. 67). Other researchers define vulnerability as the capacity to be wounded (Kates 1985, Dow 1992). The United Nations Development Project Bureau for Crisis Prevention and Recovery defines vulnerability as "a condition or process resulting from physical, social, economic, and environmental factors, which determines the likelihood and scale of damage from the impact of a given hazard" (UNDP 2004, p. 11). The European Union Spatial Program Observation Network (ESPON) Hazards Project defines "vulnerability as a set of conditions and processes resulting from physical, social, economic, and environmental factors that increase susceptibility of a community to the impact of hazards" (EPSON 2003, p. 12). Vulnerability encompasses the idea of response and coping, since it is determined by the potential for a community to react and withstand a disaster.

Rygel et al. (2005) have determined that two main perspectives or camps on vulnerability have formed within the academic literature based on the difference conceptualizations of vulnerability (Dow 1992, Cutter 1996, 2001, Wu et al. 2002, Adger et al. 2004). Cutter asserts that a third perspective exists based on "hazard of place" (Cutter 1996, 2003, Rygel 2005). The first perspective treats vulnerability as a pre-existing condition with an emphasis on potential exposure to hazards (Cutter 1996, Rygel et al. 2005). Cutter brands this perspective as an exposure-based model (Burton et al. 1993; Cutter 1996, 2001, 2003). Research from this perspective tends to assess the distribution of some hazardous conditions, the human occupancy of the hazard zone, and the degree of loss of life and property resulting from a particular event (Rygel et al. 2005). The second perspective on vulnerability advocates that not all individuals and groups exposed to a hazard are equally vulnerable and affected people display patterns of differential loss (Wu et al. 2002). This differential loss depends in part on the coping ability of those affected as well as exposure to the hazard (Anderson and Woodrow 1991, Dow 1992, Watts and Bohle 1993, Cutter 1996, Clark et al. 1998, Wu et al. 2002, Rygel et al. 2005). Coping ability in this context has been defined as a combination of resistance and resilience (Dow 1992, Cutter 1996, Clark et al. 1998, Wu et al. 2002). Resistance is expressed as the ability to absorb the damaging impacts of a hazard and continue functioning and resilience as the ability to recover from losses quickly (Rygel et al. 2005). Cutter refers to this perspective as vulnerability as a social condition, a measure of societal resistance or resilience to hazards (Blaikie et al, 1994, Hewitt 1997, Cutter 2001, 2003). The third perspective on vulnerability combines the elements of the first two perspectives and is referred to by Wu et al as the vulnerability of places framework (Wu et al. 2002, Rygel 2005). This perspective treats vulnerability as a biophysical risk and a social response within a specific geographic domain (Rygel 2005). Cutter expresses this perspective as the integration of potential exposures and societal resilience with a specific focus on particular places or regions (Kasperson et al. 1995; Cutter, Mitchell, and Scott 2000, Cutter 1996, 2001, 2003). This perspective attempts to address the "vulnerability paradox" described by Cutter to examine social and place inequalities – characteristics of community and the built environment. In this conceptualization, risk interacts with mitigation to produce hazard potential (Cutter 2003, p. 243). This construct is realized through the Hazards-of-Place model of vulnerability (Figure 4) as a means to understand the components of vulnerability (Cutter 1996, Cutter et al. 2000; Heinz Center 2002).

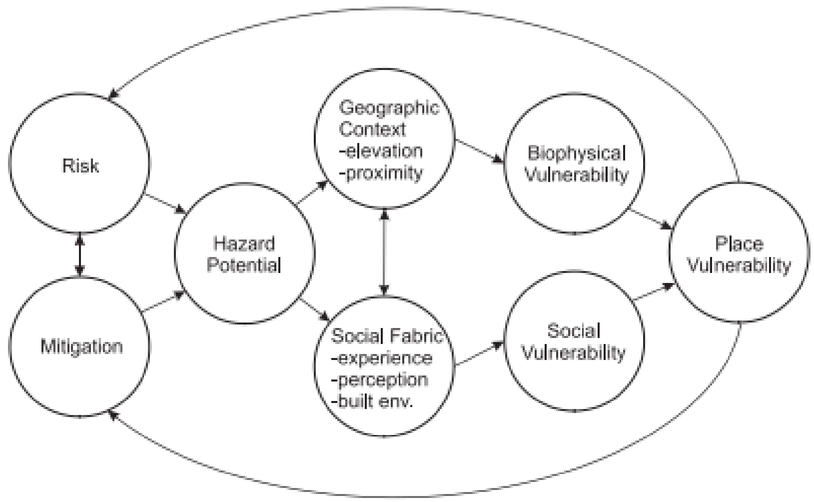


Figure 4: Hazards-of-Place Model (Cutter et al. 2003)

MEASURING VULNERABILITY IN HAZARDS RESEARCH

Vulnerability science is not nearly as advanced as risk estimation science (Hill and Cutter 2002, p. 25). Measuring vulnerability is usually achieved by constructing a vulnerability index based on several indicators that are reflective of a phenomenon (Pine 2009). Gall (2007) characterizes a vulnerability index as "an abstract theoretical construct in which two or more indicators of the construct are combined to form a single summary score" (p. 13). This construct requires a careful balance between simplifying the phenomenon and providing sufficient detail to detect characteristic differences (Deiner and Suh 1997). The complexity of the quantitative analysis used to derive the vulnerability index increases as the number of indicators selected increases in order to represent the phenomena. This yields a "complex measure [of vulnerability] that is almost impossible to verify, especially when the phenomena cannot be measured directly" (Gall 2007, p. 18).

The selection of vulnerability indicators is often subjective and descriptive having been chosen based on a particular theoretical framework or functional relationship (Deiner and Suh 1997). These indicators can be either direct variables of interest or proxy variables that serve as substitutes for the variables of interest (Gall 2007). Hill and Cutter (2002) find that current indices of vulnerability differ in indicator selection, statistical downscaling and incorporation of scale. Gall (2007) contends "there is no generally accepted set of indicators to assess social vulnerability nor is there empirical evidence for the connectivity or relative importance of those indicators" (p. 15-16). For example, indicators for the disaster risk index (DRI) are based on best-fit linear regressions or statistical relationships; while, indicators for the social vulnerability index (SoVI) are based on a combination of theoretical framework and functional relationships (Gall 2007, p. 17). The disaster preparedness index (DPI) also employs a combination approach to choosing its indicators.

Additionally, "vulnerability indices at all scales possess questionable reliability and explanatory power not only because of conceptual challenges but also because of the lack of empirical evidence, standards, and quality assessments in constructing these indices" (Gall 2007, p. 19). Deiner and Suh (1997) find that vulnerability science is plagued by significant amounts of subjective judgment in the research process. Andrews et al. (1994) argue that many indices rarely have adequate scientific foundations to support precise rankings. Cash and Moser (2000) infer that vulnerability assessments are often conducted at geographic scales that differ from the scale at which management occurs. Clark et al. (2000) propose choosing a vulnerability assessment scale that is congruent with the level at which social-environmental interactions are particularly intense or problematic for that hazard and at which management occurs. Eakin and Luers (2006, p. 381) suggests that "scale is not only a concern of the unit of analysis in research but also an issue of compatibility with decision making". According to Gall (2007), "implementation of theoretical knowledge in the form of vulnerability indices is currently subject to arbitrary choices by researchers" (p. 28). This lack of transparency, empirical basis, and uncertainty poses a challenge to the reliability, voracity, and utility of vulnerability indices to deliver robust vulnerability metrics (Gall 2007).

A brief discussion of the indices being examined by this research is provided in context to the aforementioned issues. The disaster risk index (DRI) is an outcome-oriented vulnerability index intended to "a) improve understanding of the relationship between development and disaster risk, b) enable the measurement and comparison of relative levels of physical exposure to hazard, vulnerability and risk, c) identify vulnerability indicators, and d) map international patterns of risk" (UNDP/BCPR 2004, p. 2). It is relevant to note that increased land-use and economic development are considered contributing factors to the increased susceptibility and vulnerability of the coastal United States to hurricane damage. According to Gall (2007), "the selection of the DRI indicators was guided by correlations with proxy measures and not by theoretical framework or expert opinion" (p. 54). DRI is based on the methodology: *Risk = Hazard **

*Population * Vulnerability*. The DRI is a backwards looking vulnerability index as it considers vulnerability from the context of past events rather than attempting to predict vulnerability through statistical modeling (Gall 2007). "All indicators are aggregated averages over a 21-year period from 1980-2000 (Gall 2007, p. 55). In the DRI, risk is expressed as hazard-mortality with population representing biophysical factors and vulnerability representing physical conditions. It is comprised of four hazard-specific vulnerability sub-indices as noted in Appendix C. Hazard-mortality serves as the dependent variable; while the independent variables include exposed population and twenty-six socioeconomic indicators. The DRI is derived from a stepwise linear regression used to determine the important indicators and produce the indicator weights (beta coefficients). The final DRI score is the sum of the weighted aggregation for each hazard type sub-indices. (See Appendix C). DRI indicators are not normalized and the unit of measurement is not unit-less like other vulnerability indices. It is expressed as the number of killed per 21-year average.

The disaster preparedness index (DPI) is based on the theoretical underpinnings of existing vulnerability science and applied research on vulnerability indicators. It leverages works from UNDP /BCPR (2004), Dwyer et al. (2004), Cutter et al. (2003), Simpson (2001), Tapsell et al. (2003), Cardona (2005a), and Davidson and Lambert (2001). According to Simpson (2006), the disaster preparedness index (DPI) is a composite result of the presumed relationship between community preparedness measures and the derivation of the vulnerability score as depicted in Appendix D. It is based on the equation: *Vulnerability = hazard * probability * frequency * Vulnerability* *measures (VM)*. Unlike the DRI, the selection of indicators for the disaster preparedness index was driven by expert opinion among identified experts in vulnerability science (Simpson 2006). The DPI considers 150 different indicators that are identified as functional measures of preparedness (FM) or vulnerability measures (VM). Functional measures are construed as community assets and include factors such as the physical, economic, sociocultural, and ecological dimensions of capital. Vulnerability measures are interpreted as community liabilities and include factors such as frequency and probability of the hazard as well as socio-economic factors like public debt, housing vacancy rate, and age of emergency operations plans (See Appendix D). DPI indicators are normalized and weighted based on statistical regression.

The social vulnerability index (SoVI) is based on the Hazards-of-place model posited by Cutter (1996a). However, it does not utilize expert opinion to determine the vulnerability indicators. It defines vulnerability through the interaction of biophysical and social conditions with the integrating mechanism as place. From the perspective of Hill and Cutter (2002, p. 15), "understanding the social vulnerability of places is just as essential as knowing about the biophysical exposure." This approach allows for more direct insertion of location as a factor of exposure and better understanding of the role of geography as a determinant of vulnerability. It allows us a means to discern between disaster-prone and disaster-resilient communities and what factors influence both outcomes (Hill and Cutter 2002).

In simple terms, "SoVI quantifies the social vulnerability of U.S. counties to environmental hazards and results in a comparative metric that facilitates the examination of the differences in social vulnerability among them…" (HVRI SoVI® webpage 2013)[1]. SoVI is constructed based on an initial analysis of 250 variables of social vulnerability identified through a broader review of vulnerability research. Cutter et al. (2003) tested these 250 variables for multicollinearity producing a subset of 42 normalized variables. Using principal component analysis, Cutter et al. (2003) reduced the 42 independent variables to 11 factors that represented 76.4% of the variance. The 11 factors, depicted in Table 2 below, consist of personal wealth, age, density of the built environment, single-sector economic dependence, housing stock and tenancy, race, ethnicity, occupation, and infrastructure dependence. Schmidtlein et al. (2008, p. 1110) suggests that the "SoVI algorithm does not appear to be substantially influenced by scalar changes, [and] it is sensitive to variations in construction." This highlights the need to validate SoVI using disaster outcome data to provide an empirical analysis of its ability to characterize community vulnerability.

1. Hazards Vulnerability Research Institute 2013. Social Vulnerability Index webpage. http://webra.cas.sc.edu/hvri/products/sovi.aspx. HVRI, University of South Carolina website. Accessed on multiple occasions in production of this research between January, 2012 to May, 2016.

Table 2: Dimensions of Social Vulnerability
US County Level 42-variable Component Summary

Factor	Name	Dominant Variable	Percent of Variation Explained	Cardinality
1	Personal Wealth	Per capita income	12.4	+
2	Age	Median age	11.9	-
3	Density of the Built Environment	No. Commercial establishments/sq. mile	11.2	+
4	Single-sector Economic Dependence	% employed in extractive industries	8.6	+
5	Housing Stock and Tenancy	% housing units that are mobile homes	7.0	-
6	Race – African American	% African American	6.9	+
7	Ethnicity – Hispanic	% Hispanic	4.2	+
8	Ethnicity – Native American	% Native American	4.1	+
9	Race – Asian	% Asian	3.9	+
10	Occupation	% Employed in service occupations	3.2	+
11	Infrastructure Dependence	% Employed in transportation, communication, and public utilities	2.9	+

(Source: Cutter et al. 2003, p. 252)

The objectives of this dissertation are to examine the relationships between hazard vulnerability science and disaster management policy and practice and to analyze the explanatory power of the social vulnerability index (SoVI) to accurately predict the federal costs and level of damages for a hurricane disaster using empirical data and model data for 9 Atlantic hurricanes. The first step involves conducting a comparative analysis of three hazard vulnerability indices (social vulnerability index, disaster risk index, and disaster preparedness index) and their underlying indicators to determine which variables are considered the most common elements of vulnerability. The second step involves performing a statistical analysis using exploratory OLS regression and spatial econometrics and geographically weighted regression. The statistical analysis encompasses five regression scenarios: scenarios 1-2 attempt to quantify the theoretical relationships between hazard vulnerability science and disaster management policy and practice; scenarios 3-4 attempt to analyze the explanatory power of hazard vulnerability science to accurately predict costs and damages; and scenario 5 attempts to quantify the relationships between disaster operations practice and disaster management policy.

CHAPTER 3: COMPARATIVE ANALYSIS OF HAZARD VULNERABILITY THEORY AND DISASTER MANAGEMENT POLICY

This research seeks to substantiate the following a) *hazard vulnerability theory and disaster management policy share common foundations* and b) the use of the *social vulnerability index (SoVI)* - to test the hypothesis that hazard vulnerability indices can be used to accurately predict the exposure of a community to a hurricane hazard or the level of damages in the community if a hurricane disaster of similar size and magnitude did occur. First, the study performs a qualitative analysis of hazard vulnerability indices using a pedigree matrix based on a qualitative taxonomy adopted from Gall (2007, p.33-34). This approach is widely used for critical analysis of indices and indicators (Gall 2007, Booysen 2002; Eyles and Furgal 2002, von Schirnding 2002) and allows for *an "apples to oranges" comparison of the scale and the composition of the social vulnerability, disaster risk, and disaster preparedness indices.* These vulnerability indices were chosen as representative of the leading concepts in hazard vulnerability science considering the three dimensions of hazard vulnerability: economic, social, and physical (UNDP / BCPR 2004). The social vulnerability index focuses on the social dimensions of vulnerability. The disaster risk index is more exposure based with an emphasis on ecological conditions. The disaster preparedness index emphasizes economic dimensions with additional elements for measuring emergency management factors to account for policy shifts toward prevention and mitigation strategies. Many of the preparedness factors in the disaster preparedness index are expressed as fiduciary terms such as funding for emergency operations, local funding for mitigation/planning, funding per capita, and public debt (Simpson 2006).

Hazard vulnerability indicators and disaster data are not free from bias regardless of the data source. Each hazard vulnerability index examined is based on certain theoretical aspects that emphasize different elements or components of vulnerability just as disaster management policy is influenced by currents of ideology. Cobb and Rixford (1998) contend that all indicator work has some political aspects that are value oriented and subjective in nature. Carly (1981) argues that all social indicators can and will be used to advocate particular political stances, and Cobb (2000, p. 20) claims that government data are subtly motivated by ideology. King (2001) suggests bias arises more from the misapplication of data based on availability rather than the applicability of the data to vulnerability. The goal is to compare and contrast the indices to understand the theoretical frameworks, structures, merits, and shortcomings of the vulnerability indices. The findings from this analysis answer the question regarding the most suitable vulnerability index for testing the hypothesis that hazard vulnerability indices can be used to accurately predict the exposure of a community to a hurricane hazard or the level of damages in the community if a hurricane disaster of similar size and magnitude did occur.

The first step in the qualitative assessment is to input the characteristics for each vulnerability index into a pedigree matrix using the scoring criteria and ratings listed in Table 3. Based on the pedigree matrix scoring system, an index is ranked from poor to excellent by averaging the results for each characteristic. Table 3 shows that SoVI received the highest qualitative score amongst the three indices. SoVI received an average score of good (3.1) on the pedigree matrix. It received a score of good or excellent on 7 of 9 dimensions. SoVI is based on well-established theory in hazard vulnerability science and uses a composite approach to selecting indicators that relies on expert opinion and statistical relationships. The data used to produce SoVI is public domain and regularly maintained. However, SoVI uses proxy indicators to determine vulnerability rather than direct measurements. This resulted in a medium score for technique. There has also been limited empirical validation of SoVI with independent measurements warranting a score of 2 for validity. Overall, SoVI scored 27 out of a possible 36 points or 75% on the pedigree matrix. This is 36 percentage points higher than the next closest candidate index. The other 2 indices each scored below 50% with average scores of 1.6 and 1.1. The DRI scored 14 points out of a possible 36 or 39%. It achieved low scores for conceptual framework, representativeness, reliability, and validity. Previous research suggests the DRI has issues with documentation, repeatability of results, very weak and low validation of results, and methodological limitations (Gall 2007, Openshaw and Alvanides 2005; Wrigley et al. 1997). Gall (2007) found that "bias related to hazard mortality ultimately diminishes the explanatory power of the DRI" (p. 107), and that the DRI is "contestable due to its implicit acceptance of ecological fallacy and/or modifiable areal unit problem since it neglects the socio-economic characteristics of its population at risk in demarcated zones" (p. 110). The DPI received the lowest score of the indices included in the pedigree matrix receiving 10 points out of a possible 36 or 28%. This is partly due to limited application of the DPI. Research was scarce on the actual implementation of the DPI based on the conceptual framework developed by Simpson 2006. It was also not clear if the data required to support the DPI were publicly available and maintained. The DPI received a score of 0 for sensitivity and reliability due to those factors. The theory behind the DPI was considered preliminary due to the limited availability of supporting research and many of the indicators used to comprise the DPI are based on survey or imputed data. These qualitative analysis findings indicate that SoVI is the most viable candidate index for testing the hypothesis.

Table 3: Results of Functional Analysis for Vulnerability Indices using Pedigree Matrix (Adapted from Gall 2007)

Score Matrix	Description		
4 - Excellent	Well established theory, readily available data, empirical measurements, method is best practice in community, validation by comparing to independent measurements same variable, easily reproduced		
3 - Good	Accepted theory, public domain data regular maintenance, historical data direct measurements, reliable method common in discipline, compared with independent measurements related variable, method require few transformations		
2 - Medium	Partial theory, public domain irregular maintenance, model derived data, accepted limited consensus, compared with measurements not independent, model specific data		
1 - Low	Preliminary theory, limited data access, educated guess measurements, preliminary methods, weak or indirect validation, modelled parameters		
0 - Poor	Speculation, proprietary data, specalutive measurements, method is unproven, no validation, not transferable		
	Hazard Vulnerability Index		
Criteria	**Disaster Risk Index**	**Disaster Preparedness Index**	**Social Vulnerability Index**
Conceptual Framework	1	1	4
Is the approach methods or data driven?	Both	Data driven	Methods
Purpose	3	3	4
Is the purpose of the index to inform policy-making, assess impact/damage, or capture trends?	Yes - Policy/Trends	Yes - Policy	Yes - Policy/Impact/Trends
Representativeness	1	1	3
How are indicators selected?	Statistical Relationship	Expert Opinion	Expert Opinion/Statistical Relationship
How many indicators are selected?	26 regressed to 10	150 regressed to 7	250 regressed to 29
Data	2	1	3
What are the data sources?	UN- Country mortality estimates	US census and survey data	US census socio-economic data
Are the data readily available?	Yes	No	Yes
What is the quality of the data?	Low	Unknown	Good
Technique	2	1	2
What are the indicators' levels of measurement (ordinal, ratio, interval)?	Ratio	Unitless	Unitless
Are indicators scaled/adjusted?	No	No	No
Are sub-indices used and if so how many?	Yes - 4	Yes - 7	Yes - 7
How are indicators combined statistically?	Best Fit Linear Regression	Best Fit Linear Regression	Principal Component
Are indicators/sub-indices weighted?	Yes	Yes	Yes
What is the index's level of measurement?	Country	County	County
Is the index scaled/adjusted?	Yes	Yes	Yes
Are spatial techniques used (mapping, spatial analysis, spatial statistics)?	Yes	No	Yes
Sensitivity	2	0	3
Are indicators sensitive of capturing variations	No	Unknown	Yes
Does the index capture longitudinal changes?	Yes	No	Yes
Feasibility	1	2	3
Do the authors provide sufficient information so that other users can replicate the approach?	No	Yes	Yes
Reliability	1	0	3
Does the index produce similar results after numerous repetitions?	No	Unknown	Yes
Validity	1	1	2
What elements of vulnerability are measured by the selected indicators?	physical/social vulnerability - hazard specific	physical/social/economic vulnerability	social/economic vulnerability
Does the index capture the phenomena in question?	Low - Weak and very indirect validation	Poor-no validation available	Medium - Compared with previous measurements not independent
Total	14	10	27
Average Score	**1.6**	**1.1**	**3.0**

Since it has been established that SoVI is the most viable hazard vulnerability index for testing if a hazard vulnerability index can accurately predict the impact or level of damages from a hurricane, the next step in the comparative analysis is to examine the relationship between hazard vulnerability theory and disaster management policy that employs the practice of impact modeling to generate the essential elements of information (EEIs) used to estimate the size and magnitude of a disaster. This is done by constructing a crosswalk matrix to cross referencing social vulnerability indicators (representing the science), essential elements of information (representing the disaster management policy), and disaster operations impact model variables (representing the disaster operations practice). FEMA produces the impact model variables using HAZUS-MH software and spatial algorithms that are consistent with ESF#5 operating procedures and the best practices described in the Homeland Security Geospatial Concept of Operations. The findings from this analysis answer the question whether *hazard vulnerability theory and disaster management policy and practice share common foundations.*

Figure 5 below indicates strong linkages exist between disaster management policy, practice, and hazard vulnerability science. SoVI includes variables that align with 3 of the 4 groupings of EEIs: disaster boundary areas, socio-economic/political, critical infrastructure information. The only EEI group omitted by SoVI is geophysical information. From the perspective of Hill and Cutter (2002, p. 15), "understanding the social vulnerability of places is just as essential as knowing about the biophysical exposure" as it allows for more direct insertion of location as a factor of exposure and better understanding of the role of geography as a determinant of vulnerability.

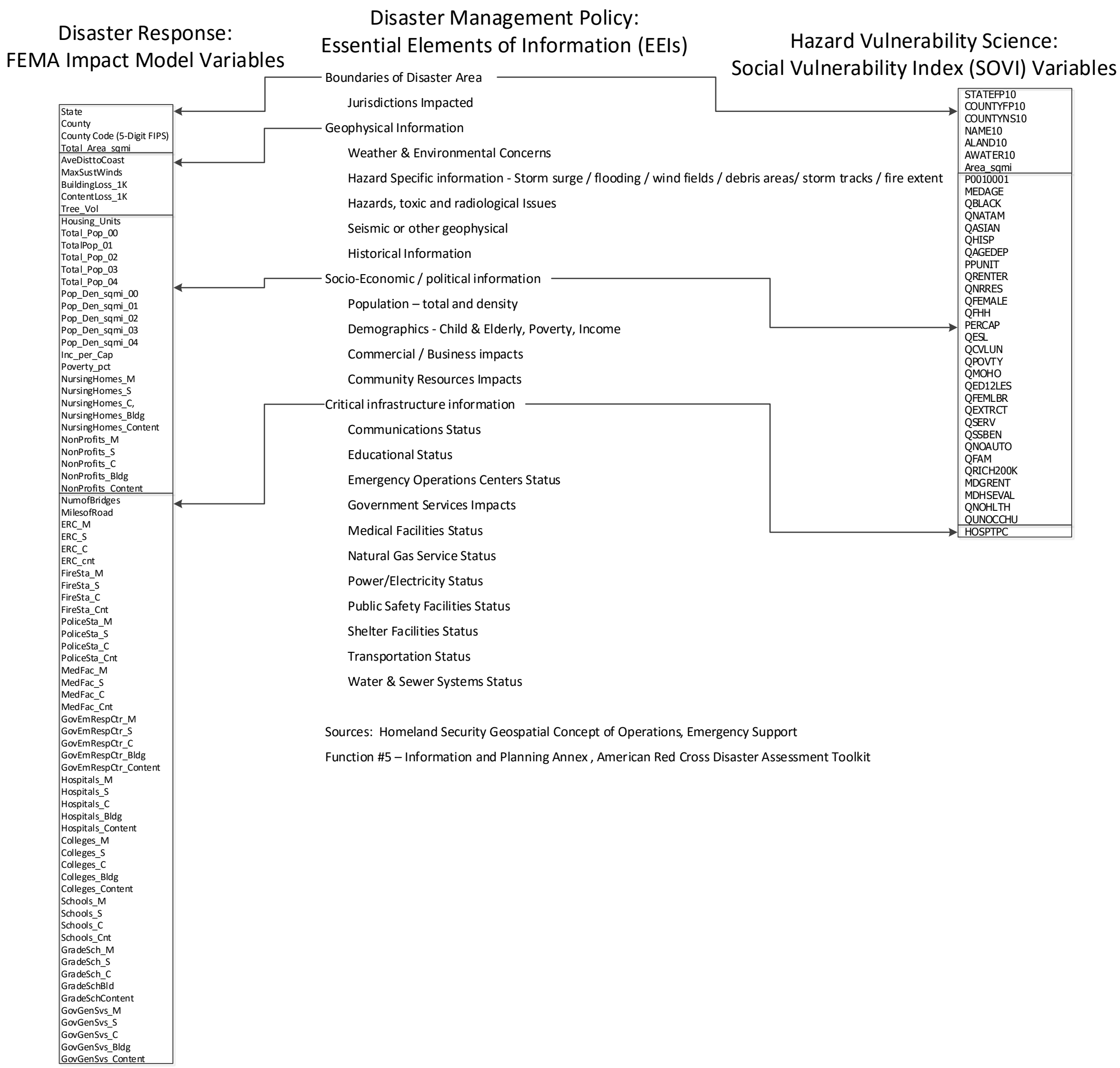


Figure 5: Crosswalk matrix of Variables for Disaster Management Policy (EEIs), Disaster Response Practice (Impact Model), and Vulnerability Science (SoVI).

Figure 5 also depicts linkages between SoVI and the disaster operations impact model variables. These linkages are consistent with the theoretical underpinnings of SoVI and suggest hazard vulnerability science and disaster management policy and practice share common foundations. As SoVI is based on the hazards-of-place model posited by Cutter et al. (1996a), it defines vulnerability through the interaction of biophysical and social conditions using place as the integrating mechanism. SoVI was initially comprised of 11 factors, depicted previously in Table 2, personal wealth, age, density of the built environment, single-sector economic dependence, housing stock and tenancy, race, ethnicity, occupation, and infrastructure dependence. SoVI was updated by the authors following the 2010 Decennial census and release of the American Community Survey to one based on 29-variables representing 7 factors that account for 72.5% of the variance as compared to earlier versions that utilized 11 factors that made up 74.6% of the variance. The 7 factors included in the current version of SoVI are: personal wealth, race and class, age, Hispanic ethnicity, nursing home residents, gender, and Native American ethnicity. These factors are essentially a more calibrated subset of the previous 11 factors. This dissertation uses the more current 7 factors versions of SoVI as those were the data provided by the HVRI for this dissertation.

Figure 5 above shows theoretical linkages between disaster management EEIs and disaster operations impact model variables. This is not surprising given that the disaster operations impact model was constructed to provide FEMA with initial estimates on the potential impact to life, property, and community disruption for a projected hurricane. It was developed to operationalize EEIs into an impact model based on HAZUS-MH and National Weather Service subtropical storm advisories. The impact model variables align with all 4 groupings of EEIs. EEIs provide FEMA a means “to assess quickly and accurately the effect of a disaster on the population and infrastructure of an area” and “facilitates accurate assessment of what response activities and materiel are required to save lives, relieve human suffering, and expedite response and recovery operations” (ESF #5 - Information and Planning Annex 2003, p. 11).

> ‘During the early hours of a disaster and in the absence of “ground truth” information such as actual on-site surveys or imagery, GIS, computerized predictive modeling, and damage estimation software may be used to develop initial estimates of damage.’ (ESF #5 - Information and Planning Annex 2003, p. 11)

The comparative analysis conducted for this dissertation utilized a two-tiered approach using a pedigree matrix and variable crosswalk matrix. The pedigree matrix was used to compare the various dimensions of vulnerability indices to determine that SoVI was the most applicable candidate index for testing the predictive power of hazard vulnerability indices. The crosswalk matrix was used to demonstrate that hazard vulnerability science and disaster management policy and practice have common foundations and share similar theoretical underpinnings. To examine the empirical relationship between hazard vulnerability science and disaster management policy and practice, depicted in Figure 5, this dissertation used exploratory OLS regression and correlation analysis.

CHAPTER 4: STATISTICAL REGRESSION ANALYSIS: DATA, METHODS, AND APPROACH

The findings from Chapter 3 of this research demonstrated common theoretical foundations between hazard vulnerability science and disaster management and practice. This was accomplished using a comparative analysis based on a pedigree assessment of hazard vulnerability indices and a crosswalk mapping of variables across these disciplines. The pedigree matrix results argue that SoVI has the best pedigree compared with two other leading composite vulnerability indices. It also argues that SoVI was constructed to serve as a reliable metric for disaster preparedness and mitigation planning.

According to Cutter et al (2003), SoVI provides the emergency management community and policy makers a useful tool to illustrate the geographic variation in social vulnerability, to identify areas where there is uneven capacities for preparedness and response, to target areas where resources might be used more effectively to reduce pre-existing vulnerability and promote risk mitigation measures, and as an indicator in determining the differential recovery from disasters (Cutter et al 2003, HVRI SoVI webpage 2013). Today, SoVI is actively being used in hazard mitigation planning and disaster response and recovery by states and federal agencies (Emrich and Cutter 2016). SoVI was used in support of Hurricane Sandy along the Mississippi coast and New Jersey

Shore and for the 2015 floods in South Carolina. Emrich and Cutter (2016) claim that SoVI "has high utility as a decision-support tool for emergency management" turning "historical disaster impact measures into actionable information for emergency managers, recovery planners, and decision makers because it empirically measures and visually depicts a population's (in)ability to adequately prepare for, respond to, and rebound from disaster events" (Emrich and Cutter 2016).

This chapter expands upon the findings from the comparative analysis conducted in chapter 3 and the work from Cutter et al. (2003) and Gall (2007) to quantify the theoretical foundations and to test the reliability and usefulness of SoVI to predict disaster impacts and form the basis for effective mitigation and preparedness strategies. It applies *exploratory regression using ordinary least squares combined with spatial econometrics and geographically weighted regression* to examine the relationship between the SoVI scores, federal disaster assistance outcome data, and impact model runs for nine (9) Atlantic hurricanes that occurred between the years 1999-2004. The hurricane disasters were selected based on the following criteria: a) geographic position along the Atlantic coastline, b) storm intensity between categories 1-5 on the Saffir-Simpson scale, and c) access to the micro-level disaster outcome data.

The statistical approach proposed in this research provides a means to determine: *a) if SoVI is a reliable metric for disaster management based on empirical data*, *b) quantify the relationship between the determinants of vulnerability and disaster policy and c) improve our understanding of the spatial dimensions of vulnerability*.

DATA SOURCES AND PROCESSING ROUTINES

Statistical analysis was conducted at the county level – unit of geography - using three types of data: social vulnerability index, disaster outcome, and FEMA impact model data. A complete list of data sources incorporated into this research is listed in table 4 below including those that served as inputs for the FEMA impact models.

Table 4: Data Sources

Type	Author	Source	Dataset	Year
Vulnerability data	Univ. of South Carolina	HVRI	SoVI - county level index using 29 variables	2009
Outcome data	FEMA	NEMIS	Disaster Assistance database	1999-2004
Outcome data	SBA	NICAR	SBA Disaster Loans data	1999-2004
Model Outputs	FEMA	HAZUS-MH	Impact Model data	2009
Model Outputs	NOAA	Hurrevac	NWS Hurricane Forecast Advisory data	1999-2004
Model Outputs	Census Bureau	Census 2000	TIGER 2000 data w/ SF3 demographic tables	2002
Model Outputs	NGA	HSIP	HSIP infrastructure data	2009

The disaster outcome data are based on a sample of disaster declarations for nine hurricanes spread along the Atlantic seaboard representing 1037 county level observations. An observation is a county that received a disaster declaration (604) or was captured in the impact model (1037 unique). Each observation includes a SoVI score that was computed using the complete SoVI dataset of counties and county equivalents. Table 5 below lists the total number of observations for each hurricane. The frequency counts for those counties declared that were included in the analysis are depicted in Figure 6 below. There were 214 counties declared under multiple hurricane events included in the analysis. The breakdown is as follows: 8 counties were declared under 5 hurricanes, 9 counties were declared under 4 hurricanes, 20 counties were declared under 3 hurricanes, and 177 counties were declared under 2 hurricanes. The remaining 390 counties were declared under a single hurricane event. Of the 214 counties declared under multiple hurricane events, the distribution by SoVI classification was as follows: 84 had a low SoVI score, 81 had a medium SoVI score, and 49 had a high SoVI score using the 3-classification scheme provided by the Univ. of South Carolina Hazards Vulnerability Research Institute.

Table 5: Number of Observations per Hurricane

	Number of Counties (Observations)		**Accuracy of Impact Model**	
Hurricane	Presidentially Declared	Projected by Impact Model	Pct. Declared indentified by Impact Model	Notes on Difference between Declared and Impact Model
Bret	13	20	100%	Overestimated by 7 counties or 35%
Charley	69	32	42%	Underestimated by 40 counties or 68%; identifed 3 counties not declared
Claudette	18	29	100%	Overestimated by 11 counties or 38%
Floyd	182	263	96%	Underestimated by 8 counties or 4%; identified 89 counties not declared
Irene	18	43	100%	Overestimated by 25 counties or 58%
Isabel	158	193	100%	Overestimated by 35 counties or 18%
Ivan	325	348	90%	Underestimated by 32 counties or 10%; identified 55 counties not declared
Jeanne	53	55	100%	Overestimated by 2 counties or 4%
Lili	44	54	100%	Overestimated by 10 counties or 19%
Totals	**880**	**1037**	**-**	
	604 unique - number of counties declared for a single hurricane			
	203 duplicates - number of counties declared under mutiple hurricanes			

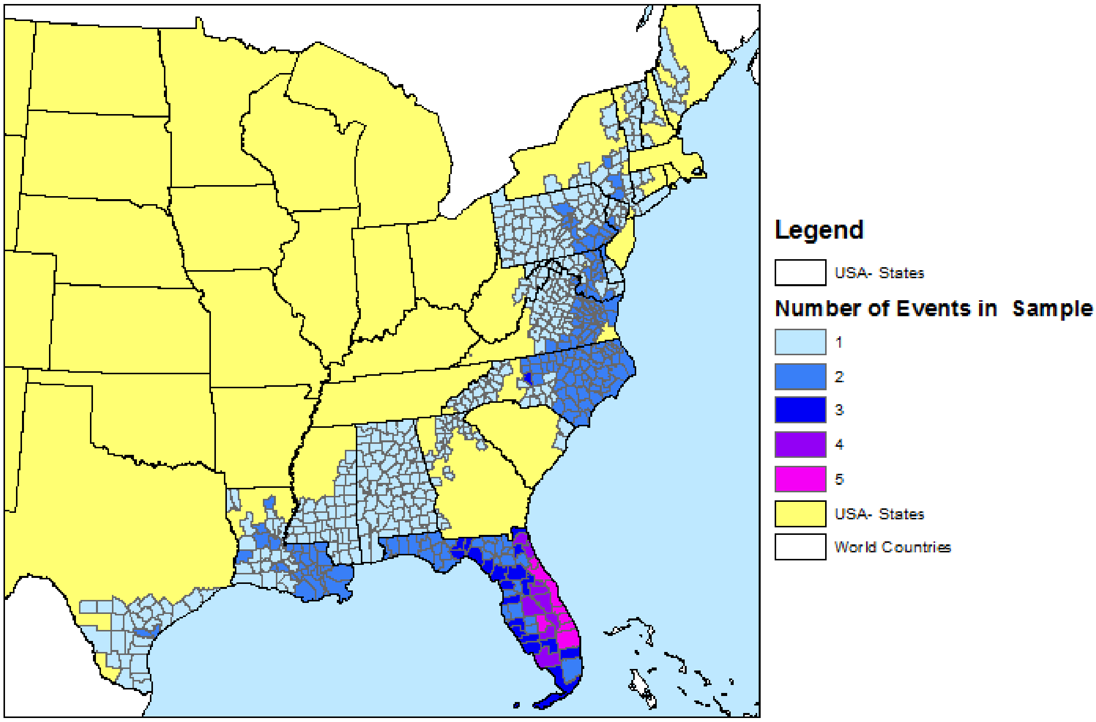


Figure 6: Map of Frequency Counts for Counties Declared under Multiple Hurricanes

The ***social vulnerability index data*** was supplied by the Hazard Vulnerability Research Institute at the University of South Carolina (HVRI). The HVRI also provides a complete county-level dataset of the social vulnerability index (SoVI) developed by Cutter et al. (2003). The version of the SoVI dataset represented in this analysis is based on a more current iteration of SoVI that relies on statistical analysis from 29 of the original 42 variables of economic, demographic, and housing characteristics that hazard vulnerability research suggests influence a county's ability to prepare for, respond to, and recover from a natural hazard (Cutter et al. 2003). This updated version of SoVI is based on 7 factors that account for 72.5% of the variance. Table 6 below provides the complete list of SoVI variables with component loadings for each of the 7 factors used to generate the county level SoVI index.

Table 6: SoVI variables and Component Loadings

Component	***Name***	***% Variance Explained***	***Dominant Variables***	***Component Loading***
1	Race (Black) and Class (Poverty)	16.599	QFHH	0.863
			QBLACK	0.752
			QPOVTY	0.715
			QNOAUTO	0.615
			QCVLUN	0.612
			QED12LES	0.547
			QFAM	0.547
2	Wealth	15.905	MEHSEVAL	0.891
			QRICH200K	0.854
			MDGRENT	0.85
			PERCAP	0.805
			QASIAN	0.681
3	Age (Old)	13.196	MEDAGE	0.889
			QAGEDEP	0.767
			QSSBEN	0.763
			QUNOCCHU	0.718
			PPUNIT	-0.596
			QRENTER	-0.669
4	Ethnicity (Hispanic)	9.479	QNOHLTH	0.744
			QHISP	0.725
			QEXTRCT	0.545
			QED12LES	0.532
			QFEMLBR	-0.621
5	Nursing Home Residents	7.471	QNRRES	0.666
			HOSPTPC	0.643
6	Ethnicity (Native American)	5.042	QNATAM	0.892
7	Employment in Service Industries	4.809	QSERV	0.739
			QFHH	-0.660
	Cumulative Variance Explained	**72.501**		

The SoVI dataset includes the following core data elements: County, State, individual variables, component loadings, 7-factors, SoVI Score, 5 and 3-level classifications, and National Percentile (where the county score ranks in comparison to the rest of the nation). (HVRI SoVI webpage 2012). See Appendix B for the complete list of variables included in the SoVI data schema. The composite index scores are mapped in Figure 7 using a 3-level classification scheme. It is worthwhile to note that a number of counties within coastal states have low SoVI scores coded in blue in map below. Figure 8 maps an extract of just those counties declared that were included in the analysis using the same classification scheme. Of the 604 counties declared that were included in the analysis, 177 or 19.4% had high SoVI scores, 266 or 44% had medium SoVI scores, and 221 or 36.6% had low SoVI scores.

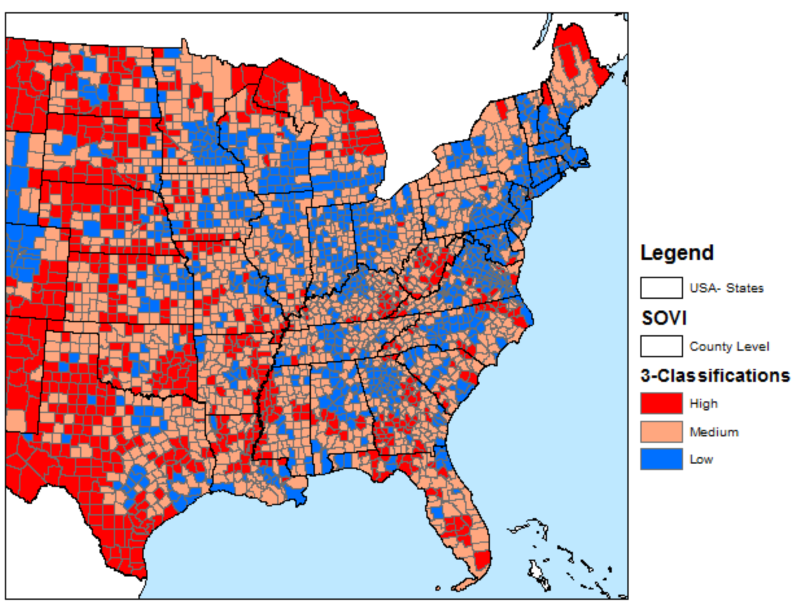


Figure 7: Map of SoVI Index Scores at County Level

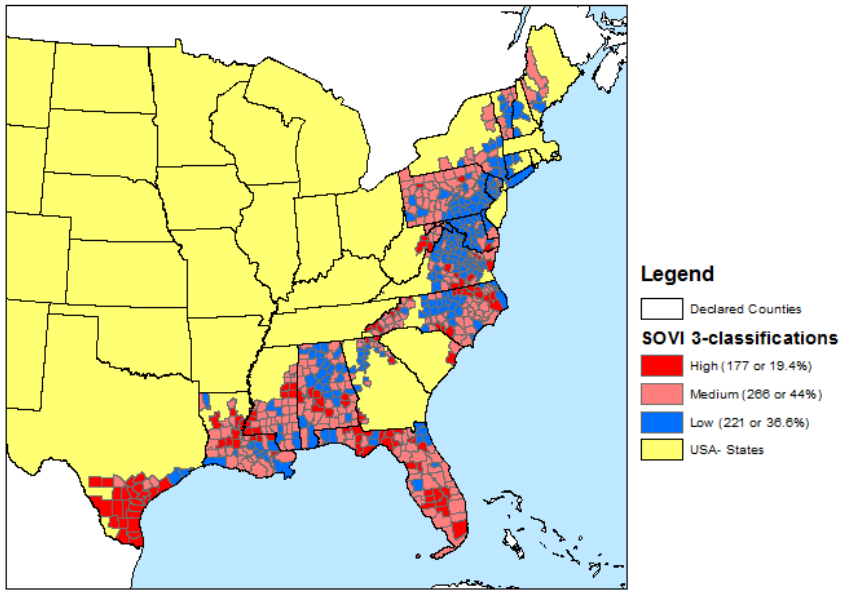


Figure 8: Map of SoVI Index Scores for Declared Counties included in Analysis

The ***federal disaster outcome data*** were supplied by FEMA based on an extract from the National Emergency Management System (NEMIS) and from the SBA through the National Institute for Computer-Assisted Reporting database. NEMIS is the system of record for managing disaster assistance issued under the provisions of the Robert T. Stafford Act. The FEMA Disaster assistance grant programs fall into three main categories: individual assistance, public assistance, and hazard mitigation assistance. Individual assistance (IA) grants provide financial assistance as a direct result of a major disaster for temporary housing, home repairs, replacement of a home, or permanent or semi-permanent housing construction and for other expenses or serious needs resulting from the disaster such as medical, funeral and burial, household items, cleaning, storage, heating, ventilation, and air condition, or other needs determined by FEMA (FEMA website 2012). The Public Assistance (PA) grants provide supplemental Federal disaster grant assistance to state, tribal, and local government including eligible Private Nonprofit organizations for debris removal, emergency protective measures, and the repair, replacement, or restoration of disaster-damaged, publicly owned facilities and the facilities of eligible Private Non-Profit organizations (FEMA website 2012). The Hazard mitigation (HM) grant program provides assistance for long-term hazard mitigation measures to be implemented during the initial community recovery to encourage protection of the damaged infrastructure from future events to end the cycle of repetitive damage and loss. The dataset compiled for this effort includes grant information aggregated at the county-level for disaster declarations issued for the selected hurricanes. It includes the following data elements: disaster number, disaster name, year, State, place name, place code, number of grants, and total amount in dollars. This dataset provides a tool for examining vulnerability indices using metrics based on direct federal assistance resulting from the impact of a natural hazard (i.e., hurricane).

SBA disaster loan program is managed by the Small Business Administration in coordination with FEMA. The U.S. Small Business Administration (SBA) provides disaster loans under the provisions of the Small Business Act, 15 U.S.C. 636(b), (c), and (f). The SBA offers these low interest disaster loans to homeowners, renters, businesses of all sizes and private, nonprofit organizations to repair or replace real estate, personal property, machinery and equipment, inventory and business assets that have been damaged or destroyed in a declared disaster (SBA website 2012). The National Institute for Computer-Assisted Reporting (NICAR) maintains a national level database of the

SBA disaster loan issued between 1980 and 2010. This dataset includes information on the borrower, disaster, location and amount of each loan issued by the SBA as well as the North American Industry Classification Codes (NAICS). There are a few limitations with the data. The SBA includes data on loans that were not fully dispersed. This is due to the fact that the SBA distributes loans as a series of payments not as a lump sum. SBA reports that occasionally borrowers decide not to accept the entire loan amount after getting an installment or two, this introduces some error in cost figures (IRE website 2013). The data also contains the mailing address of the borrower and not the location of the damaged property. This may skew financial calculations based on locations depending on the level of data aggregation. Regardless of these reporting issues, the SBA disaster loan dataset provides a useful tool for examining the effects of a particular disaster on small businesses and various sectors of the economy using the NAICS codes.

The disaster assistance data was aggregated to the county level using the 5-digit county FIPS code. To remove the duplicate records for hurricane events that encompassed multiple disaster declarations, the county records were unduplicated using a composite key based on event name and 5-digit county FIPS code. The amounts of federal assistance were then standardized per capita using Census 2000 population to control for county size and population variance. The SoVI scores were appended to the composite dataset for each county. The disaster outcome data was down selected to the 18 most meaningful variables. Data elements with little or no applicability to a statistical regression analysis were disregarded. Figure 9 below provides a visual representation of the data schema with the standardized variables highlighted in yellow: total amount of federal assistance per capita (TA_pcap), total amount of individual assistance per capita (IA_pcap), total amount of public assistance per capita (PA_pcap), total amount of hazard mitigation assistance per capita (HM_pcap), and total amount of SBA disaster loans assistance per capita (SBA_pcap). In total, there are nine federal disaster outcome datasets; one for each hurricane event included in the analysis. A complete list of variables for the disaster assistance data is enumerated in Appendix F.

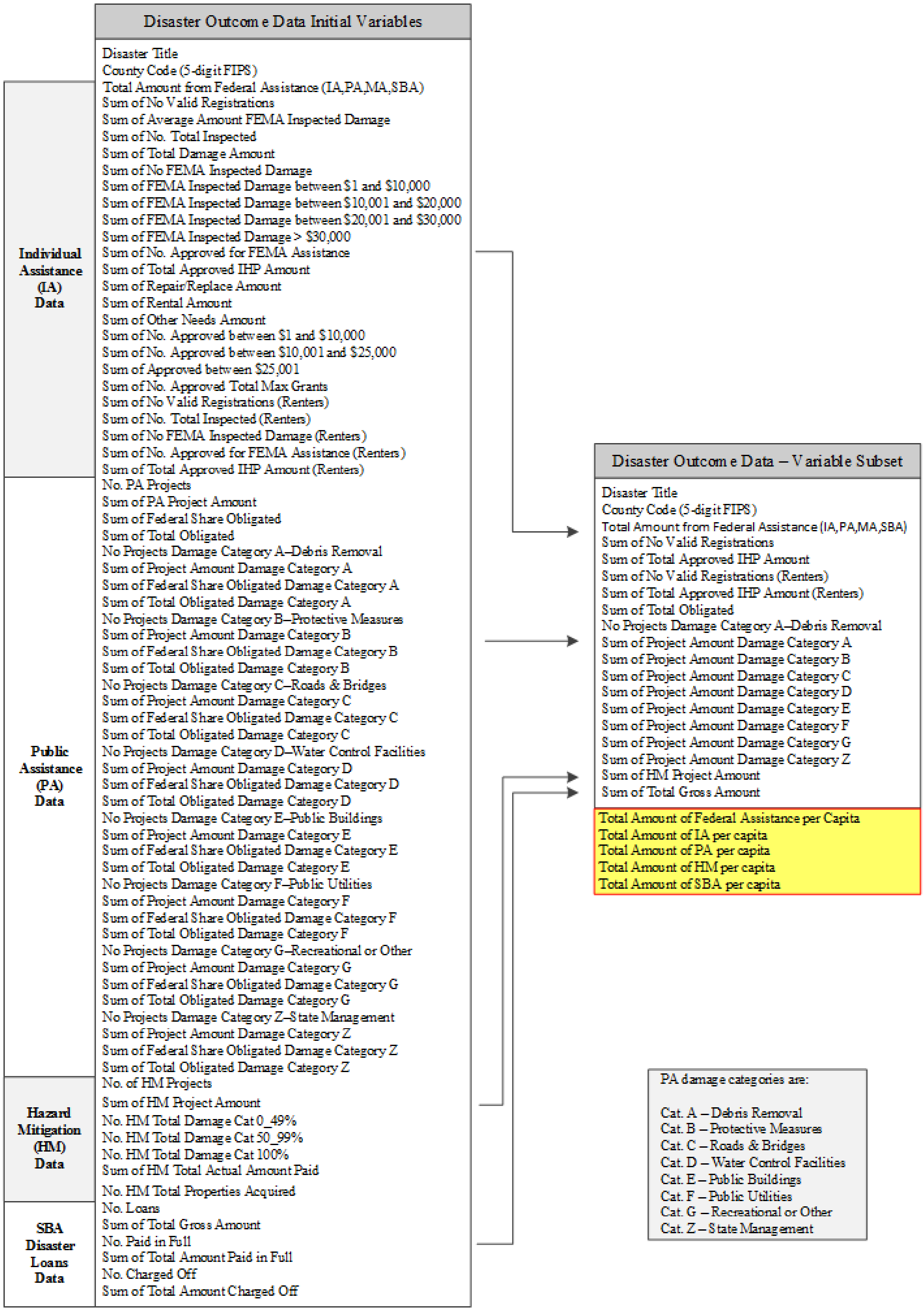


Figure 9: Schema for Disaster Assistance Outcome Datasets

The ***impact model data*** were also provided by FEMA and are based on their ESF#5 operating procedures. FEMA generates the impact models by loading the National Weather Service Advisories forecasts published through the Hurrevac software, Census 2000 socio-demographic data, and HSIP foundational data into the HAZUS-MH. The impact model data supplied represents the final run executed based on the last hurricane forecast advisory issued subsequent to hurricane landfall. HAZUS-MH provides the ability to generate empirical-based damage and impact assessments for hurricanes based on field tested fragility and loss estimation algorithms supported by the National Institute of Building Sciences (HAZUS-MH User Guide 2009). HAZUS-MH includes an extensive database of land-use, critical infrastructure, and population data. The National Oceanic and Atmospheric Administration (NOAA) publishes historical data in a GIS-ready format for sub-tropical storms based on the official National Hurricane Center(NHC) public warnings and forecast advisories. This dataset includes storm tracks, cones of uncertainty, and wind speed probabilities for each storm dating back to 1848 and is available for public download from the NOAA National Climatic Data Center.

The U.S. Census Bureau offers a comprehensive database of population and demographic data based on the Summary File 3 (SF3) and the Topologically Integrated Geographic Encoding Referencing system (TIGER) for all jurisdictions. The TIGER dataset provides for geographic representation of the SF3 data variables. The SF3 includes data from the “long form” of the census questionnaire that encompasses statistically adjusted variables for populations, race, gender, socio-economic, and other variables (US Census Bureau Fact Sheet 2000). This study utilizes the 2000 Decennial census data as a best representation of local population and demographics. The Decennial Census is a snapshot in time of the night-time population of the United States produced to assist with the reapportionment and redistricting of Congressional seats in the US House of Representatives. Use of the 2000 Decennial Census data also reduces the time differential between the hurricane disasters selected for study and the fixed-population and demographic data enumerated during the 2000 Census. This data was also used by Cutter et al. (2003) in the construction of the social vulnerability index (SoVI). These two factors will allow for more consistency in the analysis based on common data sources. The National Geospatial-Intelligence Agency (NGA) in partnership with the Departments of Homeland Security and Interior compiles the Homeland Security Infrastructure Protection (HSIP) Gold Data Product on an annual basis (since 2004) to provide a unified database of mission-critical geospatial information for use by Homeland Security and Homeland Defense (HLS/HD) partners to fill common operating data requirements in support of operational needs for preparedness, response, and recovery efforts to natural and man-made disasters. The HSIP Gold database encompasses more than 450 layers of critical information and key resources (CIKR) comprised of the best available Federal and commercial-proprietary data sets. HSIP Gold provides a comprehensive national level dataset of structural elements of the built environment including the LANSCAN Day/Night population dataset developed by Oak Ridge National Lab, the NAVTEQ national transportation dataset, and various facilities and public assets (NGA HSIP Fact Sheet 2012). Since SF3 data was discontinued by the US Census Bureau following the 2000 decennial census; hence, SoVI was updated in 2010 to uses the American

Community Survey data. FEMA will also need to update their operating procedures to include a replacement dataset for Census SF3 variables. Figure 10 below provides a visual representation of the data schema for the impact model data. The data elements that were duplicates or had little or no applicability to a statistical regression analysis were removed from the dataset. SoVI scores and total assistance per capita variables (TA_pcap) were appended to the composite dataset for each county.   In total, there are nine federal impact model datasets; one for each hurricane event included in the analysis. A complete list of variables for the impact model data is enumerated in Appendix E.

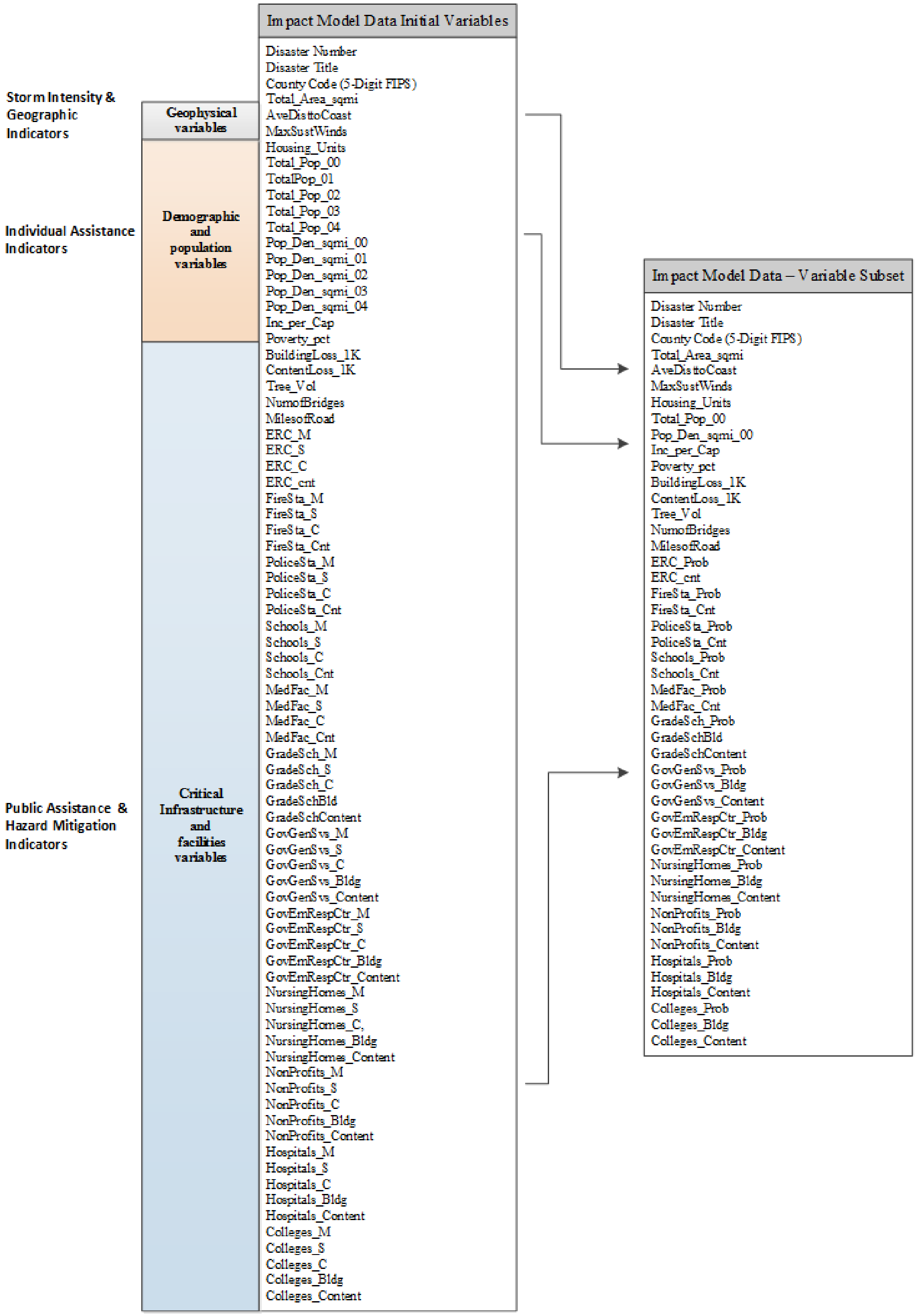


Figure 10: Schema for the Impact Model Datasets

The FEMA impact model accurately forecasted the declared counties for 8 of the 9 hurricane events used in the analysis (see table 5). The model only identified 42% of the declared counties for hurricane Charley. The model achieved 90% or higher accuracy for the remaining hurricanes of which it was 100% accurate for 6 of those hurricanes. While the FEMA impact model appears to be reliable in identifying counties that end up meeting requirements for presidential declaration (being declared), it has a tendency to over forecast the number of counties for consideration. Analyzing the causes of the model over forecasting are beyond the scope of this dissertation but should be examined in future research. Figure 11 below provides a comparison of the declared counties and the impact model counties included in the analysis. Counties shown in orange were over forecasted by the FEMA impact model.

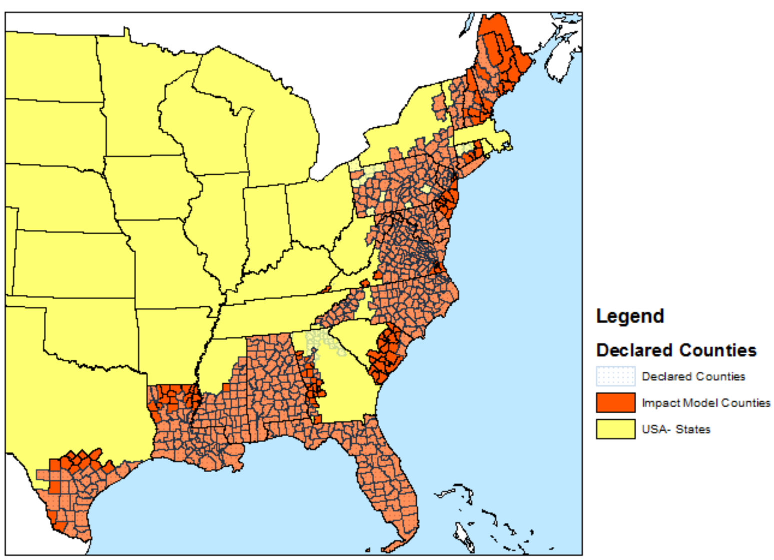


Figure 11: Map of Declared Counties and Impact Model Counties

Figures 12-20 provide detailed maps of the storm tracks, declared counties, impact model counties, and SoVI scores for each hurricane included in the analysis followed by a brief narrative explaining the accuracy of each model forecast and the related SoVI scores.

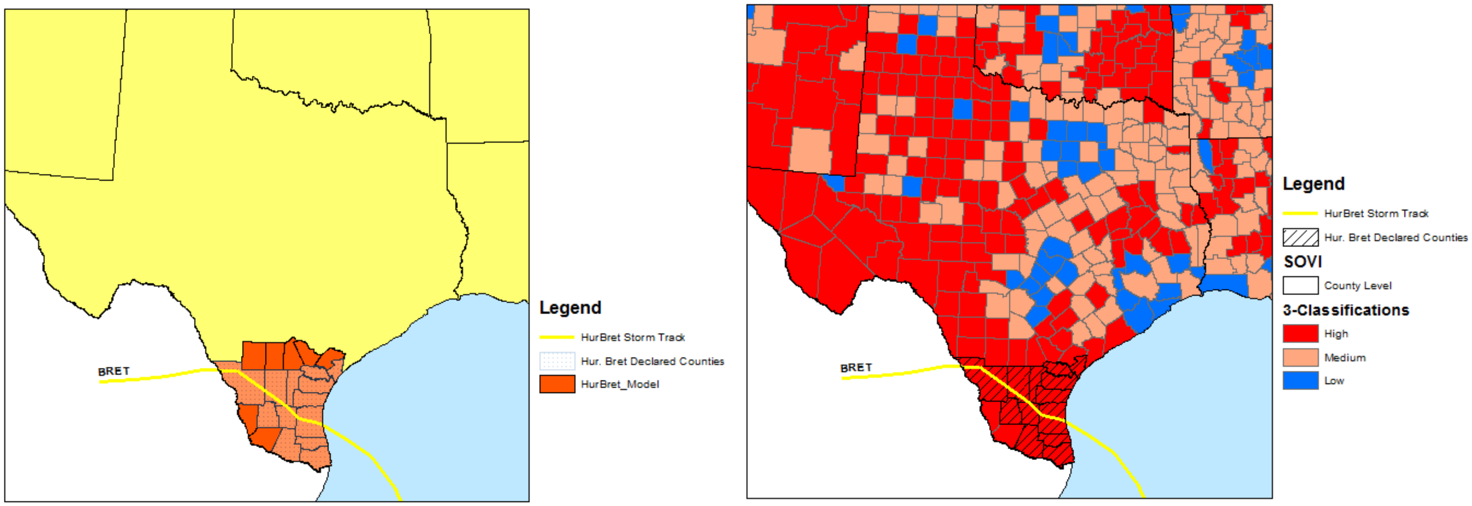


Figure 12: Map of Hurricane Bret Storm Track, Declared Counties, Impact Model Counties, and SoVI Scores

Hurricane Bret was the first hurricane of the 1999 Atlantic hurricane season and strengthened to a category 4 on the Saffir-Simpson scale prior to landfall (peaks winds of 145 mph). All the counties forecasted by the FEMA impact model and included in the disaster declaration are categorized as highly vulnerable in the SoVI index. The impact model over forecasted the number of counties for Hurricane Bret by 35%, but accurately predicted all 13 counties included in the disaster declaration. The impact model over forecast occurred in the northeastern and southwestern quadrants of the hurricane storm track.

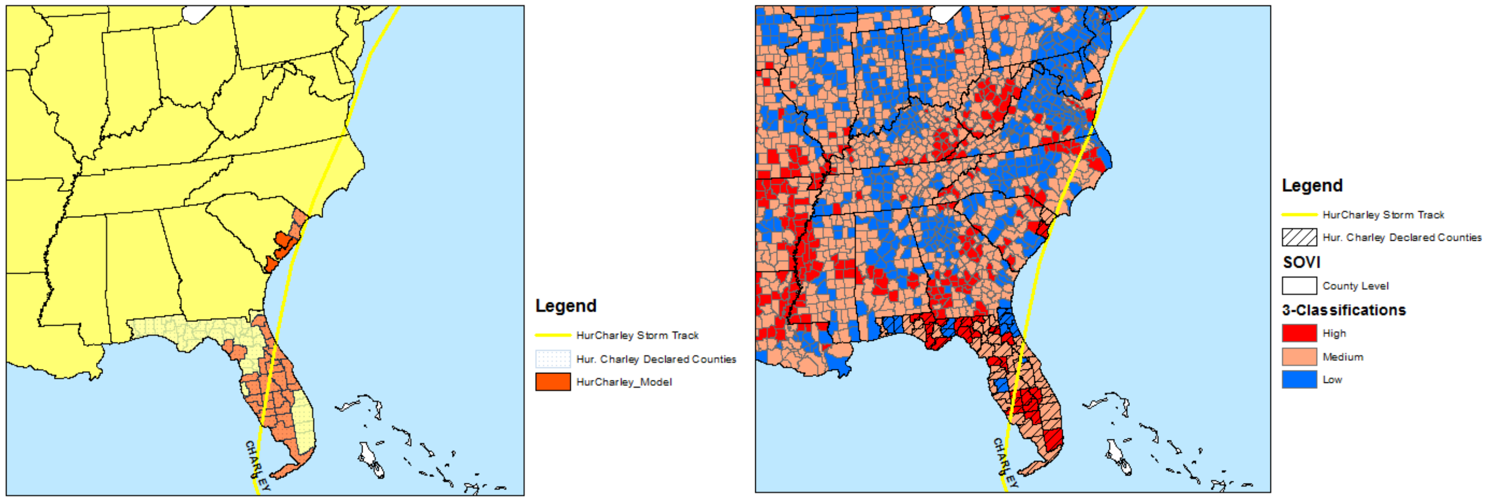


Figure 13: Map of Hurricane Charley Storm Track, Declared Counties, Impact Model Counties, and SoVI Scores

Hurricane Charley was the second hurricane of the 2004 Atlantic hurricane season making landfall as a category 4 on the Saffir-Simpson scale (peak winds of 150 mph). The FEMA impact model significantly under forecast the number of counties for Hurricane Charley by 68%, missing counties to the northwestern and southeastern quadrants of the hurricane storm track. The impact model also identified 3 counties that were not included in the declaration. For counties included in the Hurricane Charley impact model and disaster declaration, the SoVI index scores are a blend of low, medium, and high vulnerability.

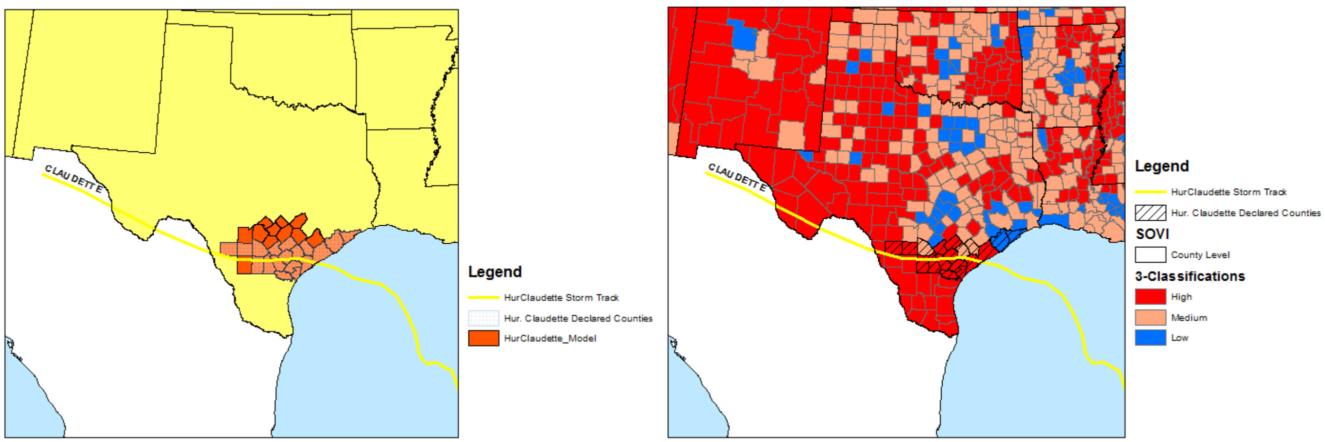


Figure 14: Map of Hurricane Claudette Storm Track, Declared Counties, Impact Model Counties, and SoVI Scores

Hurricane Claudette was the first hurricane of the 2003 Atlantic hurricane season making landfall as a strong category 1 on the Saffir-Simpson scale (peaks winds of 90 mph). The FEMA impact model over forecasted the number of counties for Hurricane Claudette by 38%, but accurately predicted all 18 counties included in the disaster declaration. The impact model over forecast occurred in the northeastern and northwestern quadrants of the hurricane storm track. The counties forecasted by the FEMA impact model and included in the disaster declaration were mostly categorized as highly vulnerable in the SoVI index as well as 2 counties with low and 3 counties with high SoVI scores.

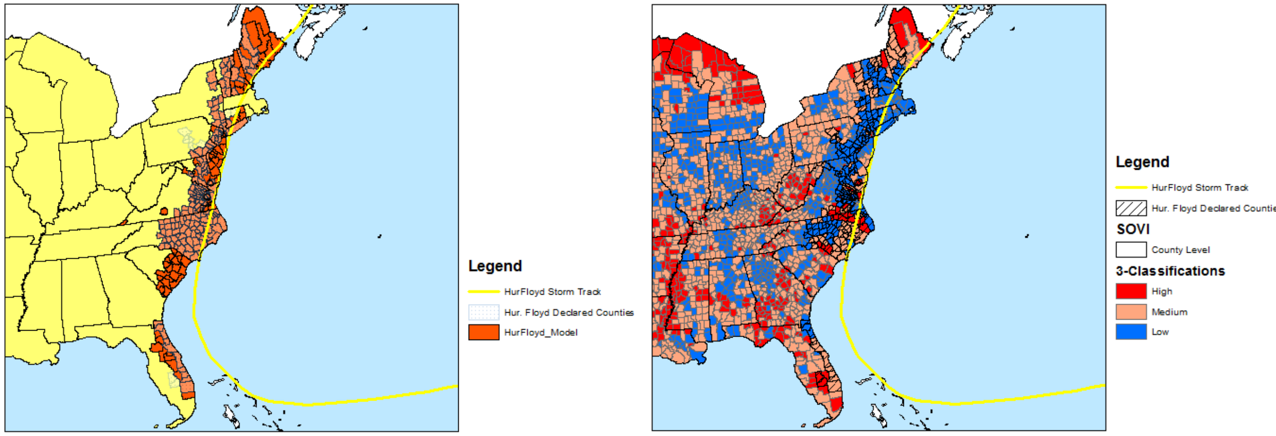


Figure 15: Map of Hurricane Floyd Storm Track, Declared Counties, Impact Model Counties, and SoVI Scores

Hurricane Floyd was the third hurricane of the 1999 Atlantic hurricane season making landfall as a strong category 4 on the Saffir-Simpson scale (peak winds of 155 mph). The FEMA impact model accurately forecast 96% of the counties declared for Hurricane Floyd; however, it significantly over forecast counties to the west of the hurricane storm track as Hurricane Floyd moved its way northward along the US coastline. The impact model missed 8 declared counties and forecast 89 more counties that were not included in the declaration. For counties included in the Hurricane Floyd impact model and disaster declaration, the SoVI index scores are a blend of low, medium, and high vulnerability.

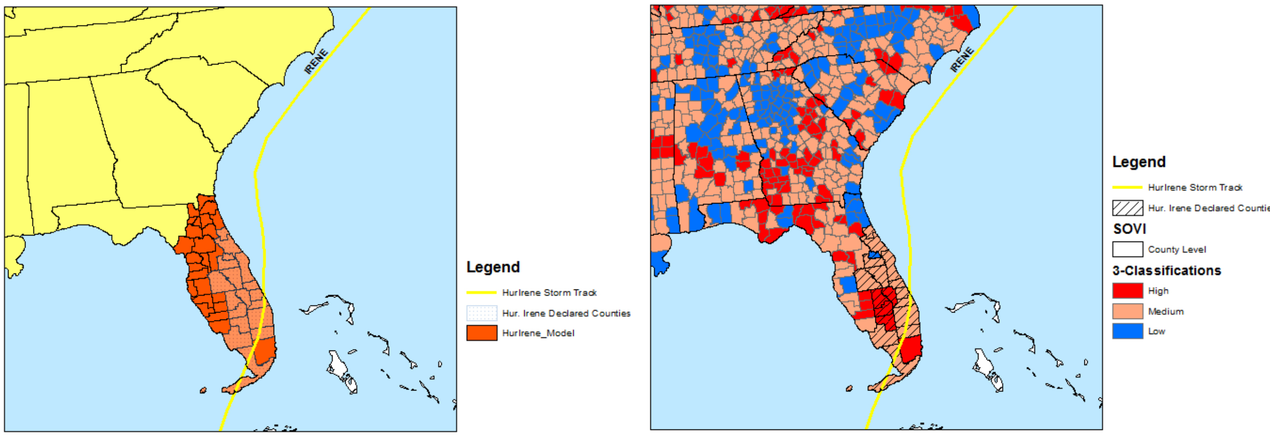


Figure 16: Map of Hurricane Irene Storm Track, Declared Counties, Impact Model Counties, and SoVI Scores

Hurricane Irene was the sixth hurricane of the 1999 Atlantic hurricane season making landfall in the US as a strong category 1 on the Saffir-Simpson scale (peaks winds of 110 mph). The FEMA impact model over forecasted the number of counties for Hurricane Irene by 58%, but accurately predicted all 18 counties included in the disaster declaration. The impact model over forecast occurred in the northwestern and southeastern quadrants of the hurricane storm track. For counties included in the Hurricane Irene impact model and disaster declaration, the SoVI index scores are a blend of low, medium, and high vulnerability.

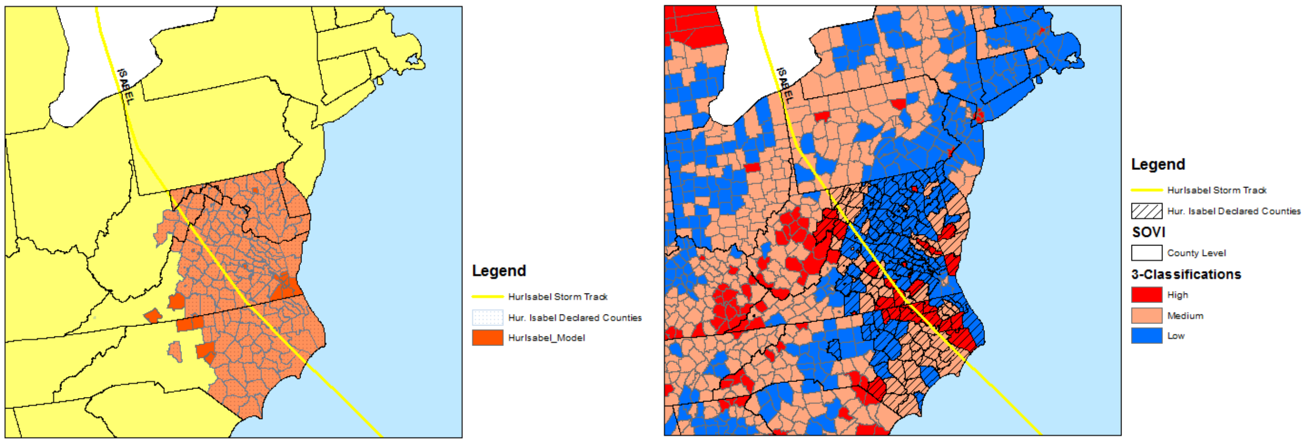
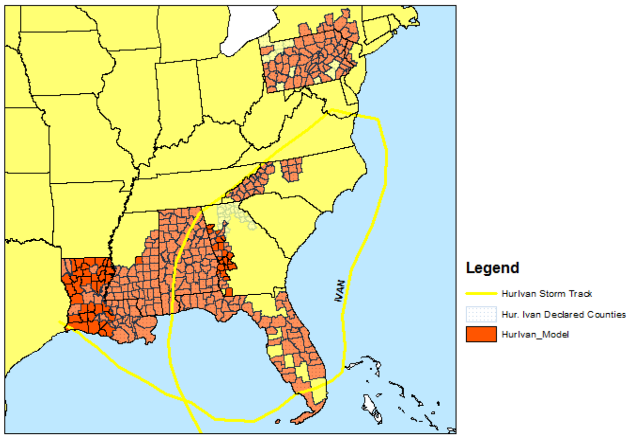


Figure 17: Map of Hurricane Isabel Storm Track, Declared Counties, Impact Model Counties, and SoVI Scores

Hurricane Isabel was the second hurricane of the 2003 Atlantic hurricane season making landfall as a strong category 1 on the Saffir-Simpson scale (peaks winds of 105 mph). The FEMA impact model over forecasted the number of counties for Hurricane Isabel by 18%, but accurately predicted all 158 counties included in the disaster declaration. The impact model over forecast occurred in the western and eastern quadrants of the hurricane storm track. For counties included in the Hurricane Isabel impact model and disaster declaration, the SoVI index scores are a blend of low, medium, and high vulnerability with a concentration of low vulnerability counties along the northeastern portion of the storm track.



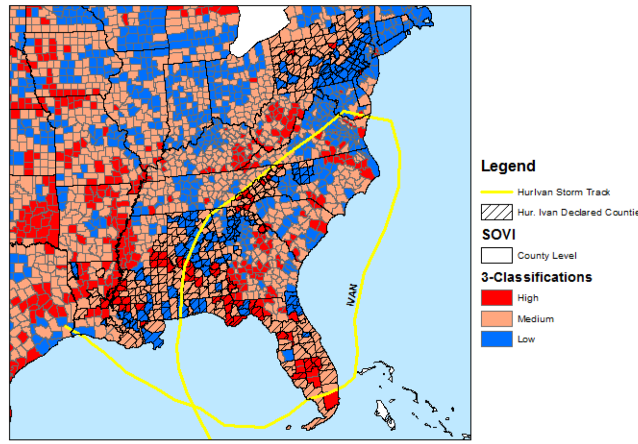


Figure 18: Map of Hurricane Ivan Storm Track, Declared Counties, Impact Model Counties, and SoVI Scores

Hurricane Ivan was the sixth hurricane of the 2004 Atlantic hurricane season making landfall in the US as a strong category 3 on the Saffir-Simpson scale (peaks winds of 125 mph). The FEMA impact model accurately forecast 90% of the counties declared for Hurricane Ivan; however, it significantly over forecast counties to the east as Hurricane Ivan moved northward into Alabama and to the west in Louisiana during a second landfall. The impact model missed 12 declared counties and forecast 55 more counties that were not included in the declaration. For counties included in the Hurricane Floyd impact model and disaster declaration, the SoVI index scores are a blend of low, medium, and high vulnerability.

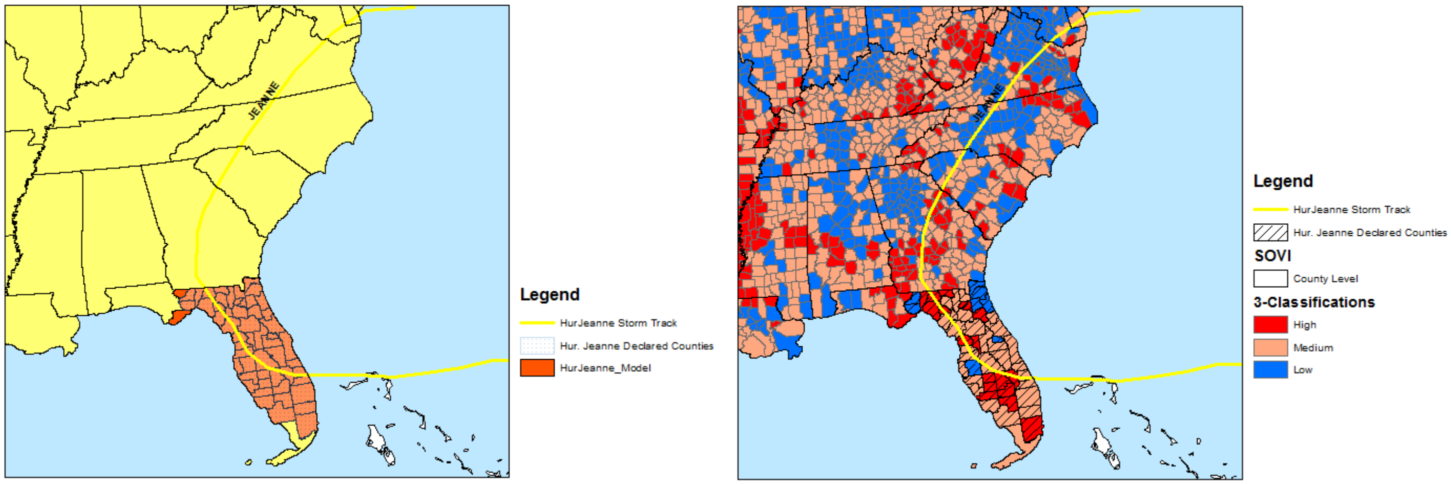


Figure 19: Map of Hurricane Jeanne Storm Track, Declared Counties, Impact Model Counties, and SoVI Scores

Hurricane Jeanne was the fifth hurricane of the 2004 Atlantic hurricane season making landfall in the US as a strong category 2 on the Saffir-Simpson scale (peaks winds of 120 mph). The FEMA impact model was highly accurately in the forecast for Hurricane Jeanne identifying 100% of the counties declared and over forecasting by just 2 counties in the western edge of the Florida pan handle. For counties included in the Hurricane Jeanne impact model and disaster declaration, the SoVI index scores are a blend of low, medium, and high vulnerability.

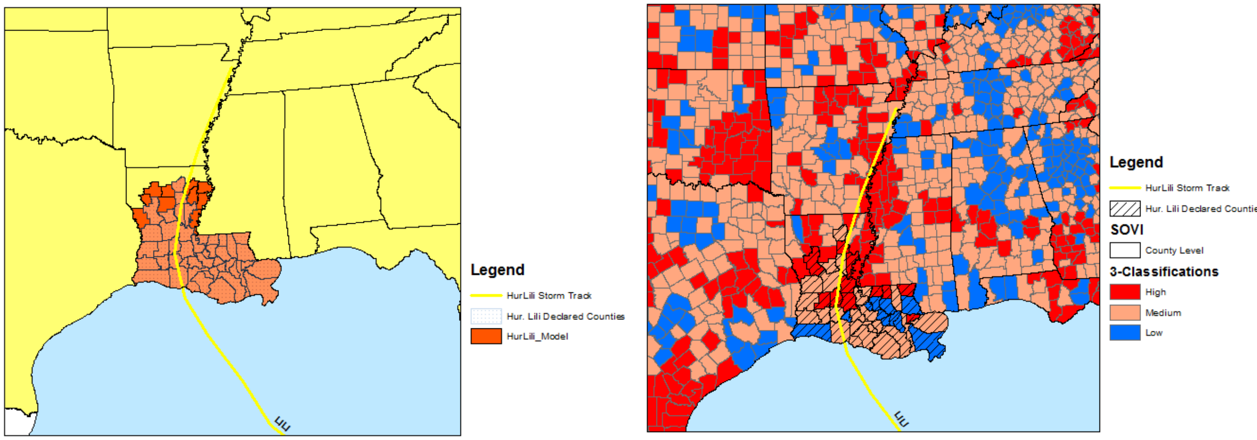


Figure 20: Map of Hurricane Lili Storm Track, Declared Counties, Impact Model Counties, and SoVI Scores

Hurricane Lili was the sixth hurricane of the 2002 Atlantic hurricane season making landfall in the US as a category 2 on the Saffir-Simpson scale (peaks winds of 75 mph). The FEMA impact model accurately forecast 100% of the counties declared for Hurricane Lili, identifying all 44 counties included in the disaster declaration. The impact model over forecasted the number of counties for Hurricane Lili by 19%. The impact model over forecast occurred in the northeastern and northwestern quadrants of the hurricane storm track. For counties included in the Hurricane Lili impact model and disaster declaration, the SoVI index scores are a blend of low, medium, and high vulnerability.

EXPLORATORY REGRESSION AND SPATIAL ECONOMETRICS APPROACH

Hazard vulnerability is perceived as a spatial varying phenomenon based on the hazards-of-place model. Vulnerability does not occur in isolation to each community. Statistical regression analysis has been used effectively to evaluate the relationship between human and environmental factors in climate vulnerability studies (Samson et al. 2011, p.2), forest management studies on modeling of forest growth factors (Shi et al. 2006, p. 996), and hazard vulnerability studies related to the spatial distribution of consent forms for individual requiring assistance during disaster in Japan (Arima et al. 2014, p.2), the analysis of vulnerability assessments (Emrich 2005, p.53), and in quantifying urban vulnerability to terrorist incidents (Piegorsch et al 2007, p.1417). Schmidtlein et al. 2008 infers that “there is no obvious avenue through which indices of social vulnerability may be validated” and hazard researchers “must strive at least to understand the limitations of [sic] their methodologies” (p. 1111).

While statistical regression analysis is often used to understand and explain complex phenomena like hazard vulnerability; it is not always easy to find a set of independent variables to explain or predict the phenomenon in question. Exploratory spatial regression is an iterative approach that applies ordinary least squares (OLS) regression and spatial autocorrelation (Moran’s I) to a set of candidate independent (explanatory) variables to identify if there is a viable model for answering the research question. The exploratory regression tool in ArcGIS was used to evaluate multiple models and combinations of candidate variables for the regression scenarios. This tool considers the following search criteria when evaluating potential models: minimum and maximum number of explanatory variables, minimum acceptable adjusted R-squared, maximum acceptable coefficient p-value, maximum variance inflation factor, minimum Jarque-Bera P-value, and minimum spatial autocorrelation (Moran's I) P-value. The Esri ArGIS software documentation defines a properly specified model as meeting the following criteria:

1) Coefficients are statistically significant for all independent variables.
2) Coefficients match the expected relationships between dependent and independent variables.
3) No multicollinearity exists.
4) Jarque-Bera is not statistically significant and residuals are normally distributed.
5) Spatial autocorrelation p-value is not statistically significant and residuals are randomly distributed, or exhibit no systematic patterns in the attribute space and geographical space.

Ordinary least squares (OLS) regression was used to determine the relationship between the variables, assess the goodness of fit, and derive the beta estimates to test for spatial dependence. The adjusted R-squared values were used to evaluate the performance of a model – how well it was able to explain the dependent variable. The P-values were used to identify the independent variables that are significant predictors. The variance inflation factors (VIF) were used to identify variable redundancy or multicollinearity. If there is a presence of multicollinearity, which is highly likely given that mulitcollinearity was discovered in the construction of SoVI, then exploratory regression analysis was used as a way to identify and eliminate variables causing multicollinearity. According to O'Brien (2007), the rule of thumb most commonly used as a sign of severe multicollinearity is 10. Menard (1995) suggests using a rule of 5 to indicate concern for serious multicollinearity. For this dissertation, Menard's rule of 5 was used as the parameter for the exploratory OLS regression.

The Jarque-Bera diagnostics, combined with a scatterplot review, were used to identify bias and outliers. Regression coefficients were analyzed to understand the strength and sign of the relationship between dependent and independent variables used in a model.

The Moran's I statistic was used to examine the regression residuals from model inputs to reveal any underlying spatial dimensions that may bias the data (Smith et al. 2007, Wong and Lee 2005) including spatial autocorrelation. Observations made at different locations may not be independent. For example, measurements made at nearby locations may be closer in value than measurements made at locations farther apart. This phenomenon is called spatial autocorrelation and was essentially defined by Tobler's First Law of Geography (Brent Hecht and Emily Moxley 2009, p. 1). Calculation of Moran's I involves the construction of a spatial weights matrix used to quantify the spatial relationships among the observations in the dataset. A statistically significant

Moran's I value would reaffirm Tobler's first law of geography in the context of hazard vulnerability as well as the relationship between spatial frequency, geophysical characteristics, and location to the hazard. Hazards-of-place theory considers hazard vulnerability to be unevenly distributed across space with place serving as the integrating mechanism. A statistically significant Moran's I would raise questions regarding the applicability of Cutter's Hazards-of-place theory to discreet phenomena and the spatial variation of hazard vulnerability. Is hazard vulnerability more a product of the existence of the hazard or of the presence of human and the built environment?

Standard regression models such as OLS can be inefficient as standard errors are often underestimated and spatial dimensions are often "treated as noise rather than informative patterns" (Samson et al. 2011, p. 2). There may be a mismatch between the spatial unit of observation and the spatial extent of the phenomena. This mismatch will result in spatial measurement errors and spatial autocorrelation between these errors and will bias the model (Anselin and Bera 1998). Since OLS regression is unable to discriminate spatial variation when geographical heteroscedasticity or local multicollinearity exists, a spatial econometrics approach is required. If the relationship varies as we move across the spatial data sample or the variance changes, alternative estimation procedures are needed to successfully model this variation and draw appropriate inferences (LeSage 1999, p. 2). Spatial econometrics models were constructed to deal with these types of spatial effects, specifically spatial autocorrelation and spatial heterogeneity. "Spatial autocorrelation (dependence) violates the Gauss-

Markov assumptions in regression modeling that explanatory variables are fixed in repeated sampling; and spatial heterogeneity violates the Gauss-Markov assumptions that a single linear relationship with constant variance exists across the sample data observations" (LeSage 1999, p. 2). The Lagrange Multiplier (LM) diagnostic was used to detect the presence and type of spatial dependence in the data and determine which spatial regression method to use: spatial error or spatial lag. The null hypothesis of the LM test is that there is no spatial dependence in the residuals. For this research, the spatial weights for the spatial regression models were based on queens-contiguity.

Additionally, geographically weighted regression (GWR), a local regression model that allows for the depiction of spatial heterogeneity in a regression context and the description of spatial non-stationarity through a spatial weighting function using the local estimate of model coefficients (Shi et al. 2006, p. 997), was also employed. Spatial non-stationarity refers to variations in relationships over space between some sets of variables because the "rates of change are not universal but determined by local culture or local knowledge, rather than a global utility assumed for each commodity" (Brunsdon 1996, p. 283). The spatial weights matrix serves as an expression of spatial dependence between observations (Fotheringham et al. 2002, p. 44).

Model results from OLS, spatial regression, and GWR were compared using goodness of fit measures: Akaike Information criterion (AIC), Schwarz criteria (SC), Likelihood ratio (LR), Lagrange Multiplier (LM), and the Joint Wald statistic (W) (Anselin 2005, p. 207). The LR, LM, and W tests address the same basic question, does leaving out explanatory variables reduce the fit of the model. When the model is linear, according to Johnston and DiNardo (1997 p. 150), these three test statistics have the following relationship W > LR > LM. To determine if the model is a better fit than OLS and if it is properly specified, these diagnostics were compared in the expected order per Anselin 2005 (p. 209): W > LR > LM. If the model is not compatible with the expected order, the model is likely mis-specified (missing a key explanatory variable) or under the influence of other factors not represented by the model.

SPATIAL REGRESSION SCENARIOS

Using the exploratory regression and spatial econometrics approach described in the preceding section, this research sought to evaluate if the theoretical relationships between SoVI and disaster management policy and practice are supported by the empirical evidence, using the selected 9 hurricanes. It also investigates the ability of SoVI and the FEMA impact models to accurately predict disaster impacts (expressed as costs per capita). It is intended to shed light on the voracity of SoVI to adequately measure and predict potential exposure and risk to a hurricane hazard. The statistical analysis was based on five regression scenarios listed in table 7 below. The dependent variables used in the analysis were the total federal assistance per capita and the SoVI score. Total federal assistance per capita was used as an expression of the overall impact of each event defined as the costs of federal programs for public assistance (PA), individual assistance (IA), mitigation (MA), and small business disaster assistance loans

(SBA). These data account for the majority of public (federal) hurricane disaster expenditures and represent the federal components of actual damage and cost of a disaster. Rygel et al. 2005 (p. 761) suggests that cost might be an important consideration when constructing vulnerability indices and for validating their utility to mitigation planning. SoVI was used as a dependent variable to better understand the relationship between social vulnerability, federal disaster outcomes, and impact model data elements.

The independent (explanatory) variables used in the statistical analysis are comprised of the federal disaster outcome data subset, the disaster impact model data subset, and the SoVI component factors. The disaster impact model data (demographic, socio-economic, infrastructure, and storm track data) represent the essential elements of information defined in disaster management policy (characteristics of impact and damage) discussed in the previous chapter. Essential elements of information are intended to serve as indicators for mobilizing federal assistance programs required to facilitate community recovery and rebuild. The SoVI data subset includes the component factors that make up the composite index score. The federal disaster outcome data subset includes costs and counts for each federal assistance program.

Regression scenario 1 seeks to quantify the theoretical relationships between hazard vulnerability science and disaster management policy and practice advanced in chapter 3. Regression scenarios 2 and 3 seek to quantify the predictive power of SoVI and its sub-factor components to predict disaster impact and costs. Regression scenario 4 seeks to offer a new approach to hazard vulnerability indexing based on disaster impact modeling. It examines the relationship between disaster costs and impact results to demonstrate a statistical basis for this approach. Regression scenario 5 seeks to improve upon SOVI by incorporating variables representing the geophysical properties of the hazard (average distance to coast and max sustained winds). SoVI did not have linkages to this group of disaster management EEIs as depicted in Figure 5.

To determine if spatial econometrics is able to produce a better fit model, the results of OLS, spatial regression, and GWR are compared using the AIC, Schwarz criterion, R-squared values, and model coefficients.

Table 7: Regression Scenarios used in the Statistical Analysis

	Dependent Variable	Independent (Explanatory) Variables	Objective
Regression Scenario 1	SoVI score	Disaster Impact Model Data Subset	How do disaster impact model data elements relate to SoVI? Which disaster impact model data elements have the strongest relationships to SoVI?
Regression Scenario 2	Total Federal Assistance per Capita (TA_pcap)	SoVI Score	Can SoVI accurately predict disaster impacts as expressed by total federal assistance per capita?
Regression Scenario 3	Total Federal Assistance per Capita (TA_pcap)	SoVI Factors	How do SoVI Component factors relate to disaster impacts as expressed by total federal assistance per capita?
Regression Scenario 4	Total Federal Assistance per Capita (TA_pcap)	Disaster Impact Model Data Subset	Can the disaster impact model data accurately predict disaster impacts as expressed by total federal assistance per capita?
Regression Scenario 5	Total Federal Assistance per Capita (TA_pcap)	SOVI + AveDistC + MaxSustWin	Can the performance of SoVI be improved by adding missing variables for the hazard?

*Each regression scenario was run for every hurricane included in the analysis. A total of 45 regressions 5 scenarios times 9 hurricanes.

CHAPTER 5: RESULTS OF CORRELATION ANALYSIS AND EXPLORATORY REGRESSION

Findings from chapter 3 demonstrated the conceptual alignment of SoVI with the disaster management policy EEI groupings for disaster boundary areas, socio-economic, and critical infrastructure information but not with the grouping for geophysical information. It also demonstrated alignment of SoVI and FEMA impact model data variables. These conceptual relationships were demonstrated in the crosswalk matrix depicted in Chapter 3, Figure 5. Based on these conclusions and hazard vulnerability theory, one expects to find strong statistical correlations between SoVI scores and key disaster impact variables.

This chapter attempts to quantify these conceptual linkages using a combination of correlation analysis and exploratory OLS regression with SoVI as the dependent variable and disaster impact model data elements as the independent (explanatory) variables. These are the same variable sets used in the crosswalk matrix depicted in Chapter 3, Figure 5. Correlation analysis provides a means for determining the degree of linear association between the variables. Exploratory regression analysis provides a means to assess the statistical relationships between the variables, to eliminate redundant variables, and find a potential set of variables able to explain the dependent variable. Statistically significant results would substantiate the conclusions from chapter 3.

CORRELATION ANALYSIS

By way of comparison with Cutter et al. 2003a, the Pearson Product-Moment Correlation Coefficient was calculated for the 604 declared counties using two sets of values: actual SoVI index score and the frequency count of hurricane events. The Pearson coefficient was 0.028714. Just as Cutter et al. 2003a found, there was no statistical correlation between the frequency counts and SoVI index score for the declared counties included in the analysis. However, this correlation analysis does not consider us of soVI in a disaster operation context. It is a gross assessment of the correlation between the number of hurricane events and the SoVI score for a county over the sample period.

To examine the utility of SoVI in disaster operations as claimed by Cutter and Emrich 2016, Pearson correlation coefficients were generated for each set of variables for the 9 hurricanes. The complete correlation matrixes are provided in the appendix. Table 8 below provides a consolidated view that shows the correlation of SoVI with the independent variables for each of the 9 hurricanes. This table indicates that there are strong statistical correlations between SoVI and the variables linked to the socio-economic information grouping. Each variable was statistically significant at the 95% confidence level for 5 or more hurricanes. PCTPOV (percent poverty) was significant for all 9 hurricanes. SoVI had few statistically significant correlations with the variables linked to the geophysical information grouping. One exception was AVEDISTC (average distance to coast) that was significant for 5 hurricanes. Additionally, SoVI was not significantly correlated with most of the variables linked to critical infrastructure information. A few exceptions include NUMBRIDGE (number of bridges), ROADMI (miles of road), FIRESTA_CNT (number of fire stations), and SCH_CNT (number of schools). These findings are consistent with the conclusions from chapter 3. This table also shows conflicting information for some variables (ie; both positive and negative correlations for the same variables across different storms); as result, the correlation matrixes were not helpful in variable selection. Exploratory OLS regression was used as a more manageable method given the difficulty in synthesizing the information from the correlation matrixes.

Table 8: Pearson Correlation Coefficients for SoVI and FEMA Impact Model Data

		Hurricane								
		Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
Disaster Mgmt. Policy EEI Groupings	Variables	SOVI	SOVI	SOVI	SOVI	SOVI	SOVI	SOVI	SOVI	SOVI
Boundary Information	AREASQMI	-0.069	0.095	0.090	0.101	0.129	0.081	0.015	0.019	-0.023
Socio-Economic Information	HUNITS	-0.428	**-0.567**	**-0.765**	**-0.288**	**-0.476**	**-0.284**	**-0.177**	-0.258	-0.083
	POP2000	-0.413	**-0.577**	**-0.768**	**-0.326**	**-0.500**	**-0.318**	**-0.209**	-0.249	-0.107
	POPDEN00	-0.474	**-0.668**	**-0.590**	-0.041	**-0.721**	-0.126	**-0.131**	**-0.306**	-0.060
	PERCAPINC	-0.481	**-0.455**	**-0.660**	**-0.702**	**-0.493**	**-0.750**	**-0.538**	**-0.505**	**-0.672**
	PCTPOV	**0.554**	**0.656**	**0.823**	**0.815**	**0.733**	**0.826**	**0.615**	**0.536**	**0.841**
Geophysical Information	AVEDISTC	0.233	0.316	**0.564**	**0.211**	0.432	**0.185**	0.073	**0.305**	**0.502**
	TREEVOL	0.236	-0.073	-0.306	0.093	-0.330	0.018	-0.054	-0.164	0.081
	MAXSUSWIN	-0.136	0.084	0.168	-0.014	-0.115	-0.036	**0.154**	0.014	0.215
	BLDGLOSS1K	0.332	0.067	-0.313	0.031	-0.250	-0.063	-0.041	-0.073	0.003
	CNTLOSS1K	0.172	0.059	-0.313	0.035	-0.252	-0.018	-0.040	-0.078	0.000
Critical Infrastructure Information	NUMBRIDGE	-0.513	**-0.430**	**-0.692**	**-0.220**	-0.431	**-0.203**	**-0.293**	**-0.333**	0.069
	ROADMI	-0.440	**-0.464**	**-0.763**	**-0.228**	-0.440	**-0.329**	**-0.221**	**-0.287**	0.118
	ERC_CNT	-0.147	-0.268	-0.101	**-0.230**	-0.343	-0.075	**-0.259**	**-0.274**	0.204
	FIRESTA_CT	-0.419	-0.282	**-0.601**	**-0.303**	**-0.493**	**-0.184**	**-0.356**	**-0.313**	**-0.298**
	POLSTA_CT	-0.254	-0.354	**-0.470**	**-0.275**	-0.412	-0.062	**-0.263**	-0.250	0.113
	SCH_CT	-0.477	**-0.584**	**-0.503**	**-0.247**	**-0.550**	**-0.239**	**-0.192**	**-0.429**	-0.069
	MEDFAC_CT	-0.495	**-0.443**	-0.441	**-0.244**	-0.358	-0.090	**-0.131**	**-0.300**	0.025
	ERC_prob	0.429	-0.238	0.087	0.027	-0.213	0.013	-0.025	0.021	0.247
	Fire_prob	0.102	0.337	-0.164	**0.142**	-0.175	**0.160**	-0.021	0.247	0.216
	Pol_prob	0.217	0.318	-0.155	0.134	-0.220	**0.160**	-0.020	**0.278**	0.193
	Sch_prob	0.332	0.228	-0.203	**0.149**	-0.240	0.151	-0.028	0.213	0.156
	Med_prob	-0.174	**0.386**	-0.176	0.072	-0.201	0.139	-0.017	**0.313**	0.233
	Gra_prob	0.329	0.313	-0.226	**0.142**	-0.236	**0.162**	-0.024	0.228	0.155
	Gov_prob	0.325	0.311	-0.227	**0.143**	-0.236	**0.162**	-0.024	0.229	0.154
	GovE_prob	0.325	0.311	-0.226	**0.143**	-0.236	**0.162**	-0.024	0.229	0.154
	NH_prob	0.226	0.315	-0.213	**0.140**	-0.236	**0.162**	-0.022	0.225	0.128
	Nonp_prob	0.307	0.318	-0.226	0.136	-0.236	**0.160**	-0.025	0.221	0.150
	Hosp_prob	0.358	0.302	-0.227	**0.150**	-0.236	**0.166**	-0.023	0.235	0.161
	Coll_prob	0.325	0.310	-0.226	**0.144**	-0.237	**0.162**	-0.024	0.230	0.154
	Values in bold are different from 0 with a significance level alpha=0.05									

EXPLORATORY OLS REGRESSION

The ARCGIS exploratory regression tool was used to build OLS models using all possible combinations of explanatory variables included in the FEMA impact model datasets (30 potential variables). The regression scenario is illustrated in Figure 21 below.

Dependent Variable	**Exploratory Regression Candidate Indepdendent (Explanatory) Variables**	**Independent Variables for OLS\GWR Model Runs**
SoVI score	HUNITS: Number of Housing Units in affected county tracks	
	POP2000: Total Population in affected county tracts	
	AREASQMI: Area of county	
	POPDEN00: Population 2000 Density	
	PERCAPINC: Per capita Income	
	PCTPOV: Percent Poverty	
	AVEDISTC: Average Distance to Coast	
	TREEVOL: Estimation of tree volume in tons	
	MAXSUSWIN: Sustained wind speed at the time of landfall	
	BLDGLOSS1K: Building loss as cost to re-build estimated number of structures damaged	
	CNTLOSS1K: Content/Interior damage estimated from number of structures damaged	**POPDEN00:**
	NUMBRIDGE: Number of Bridges in affected area	**PCTPOV:**
	ROADMI: Number of Roads miles in affected area	**AVEDISTC:**
	ERC_CNT: Count of affected Emergency Response Centers	**MAXSUSWIN:**
	FIRESTA_CT Count of affected Fire Stations	**BLDGLOSS1K**
	POLSTA_CT: Count of affected Police Stations	**NUMBRIDGE:**
	SCH_CT: Count of affected Schools	
	MEDFAC_CT: Count of affected Medical Facilities	
	ERC_PROB: Damage Probability to Emergency Response Centers	
	FIRE_PROB: Damage Probability to Fire Stations	
	POL_PROB: Damage Probability to Police Stations	
	SCH_PROB: Damage Probability to Schools	
	MED_PROB: Damage Probability to Medical Facilities	
	GRA_PROB: Damage Probability to Grade Schools	
	GOV_PROB: Damage Probability to Government Services	
	GOVE_PROB: Damage Probability to Government Emergency Services	
	NH_PROB: : Damage Probability to Nursing Homes	
	NONP_PROPB: : Damage Probability to Not for Profits	
	HOSP_PROB: : Damage Probability to Hospitals	

Figure 21: Exploratory Regression - Model Variables

The parameter settings for the exploratory OLS regression are depicted in Figure 22, and these settings were consistent for all 9 hurricanes. The objective was to identify a consistent set of variables that would be effective for all 9 hurricanes. The output reports, produced by ArcGIS for the exploratory OLS regression, include 6 sections: passing models (by number of independent variables), summary of global model diagnostics, summary of variable significance, summary of multicollinearity, summary for residual normality, and summary for spatial autocorrelation. At this stage, it is reasonable to focus on 3 key outputs from the exploratory OLS regression: passing models, summary of global model diagnostics, and summary of multicollinearity.

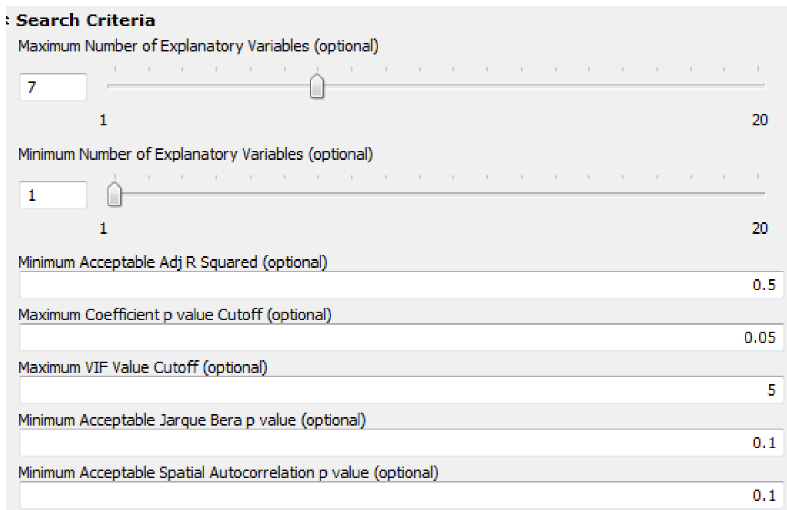


Figure 22: Exploratory OLS Parameter Settings

Bret, Claudette, Irene, and Lili each had passing models, while the remaining 5 hurricanes had no passing models. Analyzing the passing models was unable to identify a consistent set of variables that could be used across all 9 hurricanes. For example, both Bret and Claudette had passing models with 4 variables; however, the combination of variables was different for the 2 hurricanes as shown in Figure 23 below.

Hurricane Bret

Passing Models

AdjR2	AICc	JB	K(BP)	VIF	SA	Model			
0.880487	51.282098	0.601377	0.241331	2.511938	0.569830	+PCTPOV***	-ROADMI***	+ERC_CNT***	+HOSP_PROB***
0.880307	51.301655	0.666149	0.216128	2.507424	0.565024	+PCTPOV***	-ROADMI***	+ERC_CNT***	+GOV_PROB***
0.880305	51.301899	0.665068	0.216552	2.507487	0.565148	+PCTPOV***	-ROADMI***	+ERC CNT***	+COLL PROB***

Hurricane Claudette

Passing Models

AdjR2	AICc	JB	K(BP)	VIF	SA	Model			
0.882260	62.385525	0.363830	0.737212	1.433980	0.478092	-HUNITS***	-AREASQMI**	+PCTPOV***	+ERC_CNT**
0.869891	64.183565	0.563682	0.095204	1.645996	0.536662	-POPDEN00***	+PCTPOV***	-ROADMI***	-NONP_PROB**
0.869868	64.186816	0.566379	0.092965	1.646210	0.538531	-POPDEN00***	+PCTPOV***	-ROADMI***	-GOV_PROB**

Figure 23: Sample of Passing Models for Bret and Claudette

Analysis of the OLS model diagnostics summary depicted in table 9 also indicated there are severe issues of multicollinearity between many of the variables across all the hurricane model runs based on the percentage of model combinations passing with VIF scores of less than 5.0. This indicates there are a number of redundant variables measuring the same aspect of the dependent variable. The Jarque-Bera statistic was insignificant in 8 of the 9 hurricanes at percentages of 61.03 or higher, suggesting the residuals are normally distributed with linear relationships. And hurricanes Bret, Claudette, Irene, and Lili had essentially no issues with spatial autocorrelation with over 71% of model combinations passing the Moran's I test. However, these diagnostics have little meaning until the multicollinearity issues are resolved and a good set of independent variables have been identified.

Table 9: Exploratory Regression Model Diagnostics

	Percentage of Passing Models								
Diagnostic	**Bret**	**Charley**	**Claudette**	**Floyd**	**Irene**	**Isabel**	**Ivan**	**Jeanne**	**Lili**
Min Jarque-Bera p-value > 0.10	93.33	68.66	96.27	61.03	91.94	65.22	0.00	99.25	99.66
Min Spatial Autocorrelation p-value > 0.10	98.68	25.00	98.75	0.00	97.87	0.00	0.00	25.00	71.43
Max VIF Value < 5.0	5.75	22.06	11.41	21.35	2.01	43.48	11.62	43.03	9.80

1) No multicollinearity exists (VIF less than 5).
2) Jarque-Bera is not statistically significant and residuals are normally distributed.
3) Spatial autocorrelation p-value is not statistically significant and residuals are randomly distributed, or exhibit no systematic patterns in the attribute space and geographical space.

The next step of the exploratory OLS regression analysis was to examine the summaries of multicollinearity to eliminate redundant variables based on the VIF score, number of violations, and covariates for each hurricane run. The results of this examination were that six variables were selected for inclusion in the OLS regression model to eliminate issues of multicollinearity. Population density (POPDen00) was chosen as an indicator of individual assistance; even though, it had mixed significance across the 9 hurricanes. Percent poverty (PctPOV) was highly significant for all the hurricanes and was selected as an indicator of disadvantaged at risk population. Average distance to coast (AVEDISTC) and maximum sustained wind speed (MAXSUSWIN) were chosen to represent the geophysical properties of hurricanes. The variables for probability of damage for the different facility types (police, fire, medical, etc.) had collinearity with total building loss (BldLoss1k) for all facilities, so that variable was chosen to represent those elements of public assistance from the impact model data. The facility probabilities and facility counts were also highly collinear amongst one another, so it made sense to remove these variables from the final selection. Number of bridges

(NUMBRIDGE) was collinear with road mileage affected and was chosen to represent public infrastructure damaged. HUNITS and POP2000 were routinely correlated with each other as well as with the variables for facility probabilities and facilities counts, so they were also eliminated from the selection. 5 of these 6 selected variables had significant correlations with SOVI based on the correlation analysis depicted in Table 8.

REGRESSION SCENARIO 1 – ANALYSIS OF VARIABLE SELECTION USING OLS REGRESSION

The final step is to run classic OLS regression for each of the 9 hurricanes to demonstrate the effectiveness of those six variables and if this model will produce more consistent results. This will help quantify the conceptual relationships from chapter 3 and provide the benchmark variables for regression scenario 4. Model diagnostics for the OLS model are shown in table 10 below. The adjusted R-squared values indicate the model was able to explain 57% or above of the variance in SoVI for 6 of 9 hurricanes and approximately 40% for 2 of the remaining 3 hurricanes. Adjusted R-squared values were lowest for hurricane Jeanne at 28.9%. The other model diagnostics and results were examined to determine the reliability of the adjusted R-squared values. The probabilities for the Koenker (BP) statistics were insignificant for all the hurricanes, suggesting the data is generally stationary with little regional variation. Since the Koenker (BP) statistics were insignificant, we consult the probabilities from table 11 to determine if the model coefficients were statistically significant. Results varied across hurricane run.

Model coefficients for PCTPOV were significant for 7 of 9 hurricanes, while the model coefficients for the remaining variables were significant in 2 or less hurricanes. The Jarque-Bera probabilities were also insignificant indicating the residuals are normally distributed and confirmed by the histograms depicted in figure 25. The scatterplots from figure 24 suggests the relationships are linear. POPDEN00, BLDGLOSS1K, and NUMBRIDGE have a surprisingly negative relationship to SoVI. When vulnerability is high, building loss and number of bridges are low. AVEDISTC has an anomalous, positive relationship to SoVI. When SoVI is high, average distance to the coast is high. MAXSUSWIN has a mixed relationship with SoVI. PCTPOV has the expected positive relationship with SoVI. When SoVI is high, percent poverty is high. Over and under predictions for the residuals displayed in figure 26 exhibit a random pattern, indicating the models are properly specified. However, a more critical review of the scatterplots from figure 24 and the variable coefficients listed in Table 11 suggests that the OLS models may be suffering from skewness in the data. This skewness issue will be examined further in the remaining regression analysis.

The results from the chapter 5 analysis identified 6 variables for inclusion in an OLS regression model. These 6 variables addressed the following issues critical to performing a meaningful OLS regression: a) eliminate multicollinerity, b) significant correlation with SoVI, c) theoretical basis in disaster management and hazard vulnerability, and d) best able to explain the most variance across the 9 hurricanes.

Table 10: Regression Scenario 1 - OLS Model Diagnostics

Hurricane	Multiple R-Squared [d]	Adjusted R-Squared [d]	Joint F-Statistic [e]	Joint F-Statistic Probability	Joint Wald Statistic [e]	Joint Wald Probability	Koenker (BP) Statistic [f]	Koenker (BP) Probability	Jarque-Bera Statistic [g]	Jarque-Bera Probability	Akaike's Information Criterion (AICc) [d]
Bret	0.71911	0.438221	2.560117	0.138735	75.89167	0.000000*	5.281359	0.508266	0.170562	0.918254	93.662086
Charley	0.665421	0.574172	7.292369	0.000221*	219.211	0.000000*	4.866328	0.561069	0.404	0.817095	115.593
Claudette	0.847958	0.765026	10.22475	0.000587*	438.2385	0.000000*	5.073021	0.534482	0.085261	0.958265	84.180085
Floyd	0.669643	0.65953	66.21622	0.000000*	441.5511	0.000000*	6.211095	0.399964	17.98053	0.000125*	745.28418
Irene	0.846996	0.763539	10.14893	0.000606*	225.6268	0.000000*	11.794519	0.066713	0.228974	0.891823	73.684669
Isabel	0.713583	0.702202	62.70047	0.000000*	257.6172	0.000000*	7.0328	0.317824	42.301629	0.000000*	591.92581
Ivan	0.417186	0.404917	34.00117	0.000000*	182.3723	0.000000*	17.400173	0.007920*	16.278567	0.000292*	1118.2135
Jeanne	0.371697	0.289744	4.535514	0.001087*	51.85256	0.000000*	6.215869	0.399448	0.554575	0.757837	221.33428
Lili	0.750893	0.710497	18.58843	0.000000*	159.2947	0.000000*	7.253086	0.298075	0.046342	0.977096	145.74506

*** Significant level at p = 0.05.**

Table 11: Regression Scenario 1 - OLS Model Results

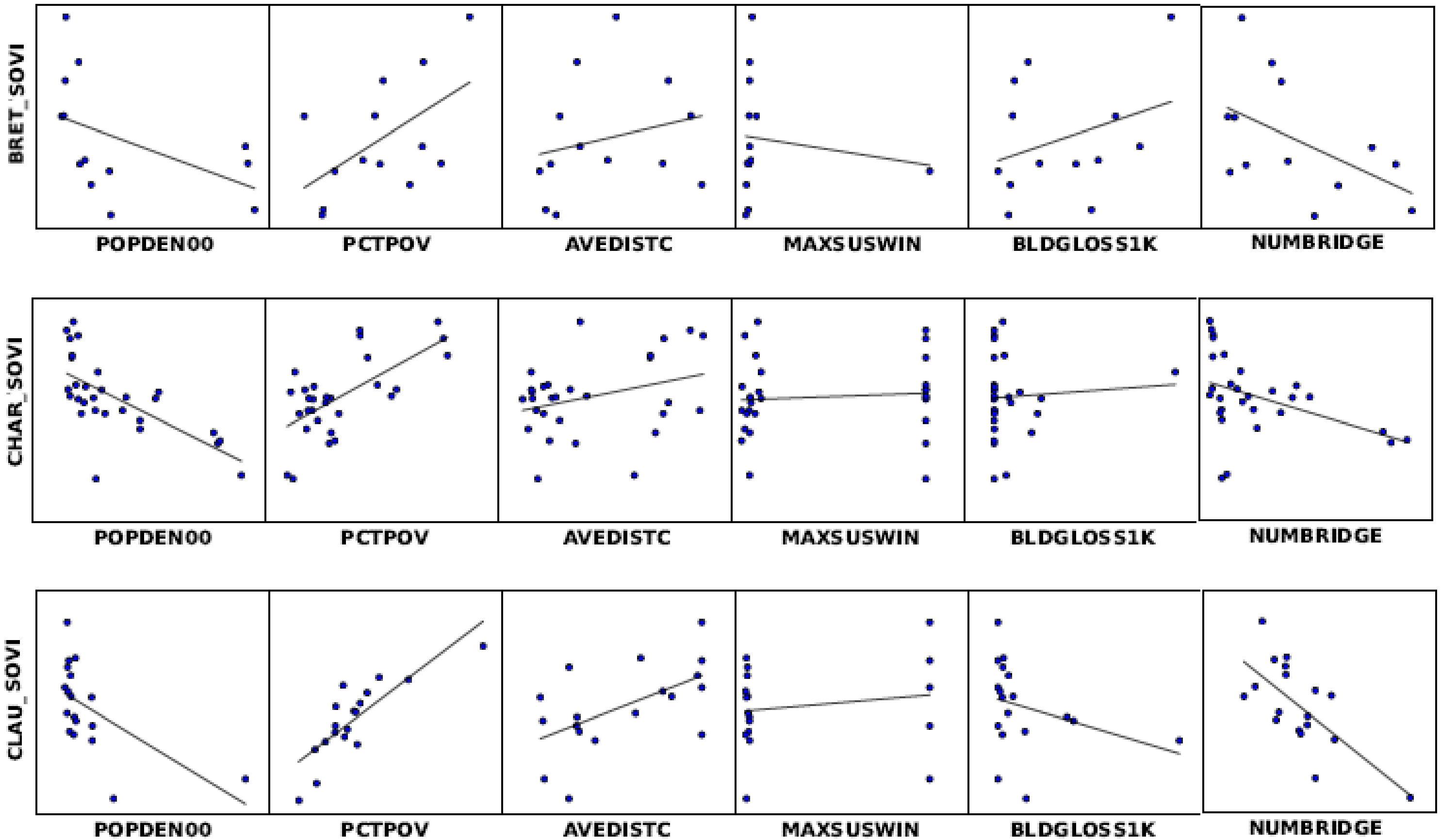
	Model Coefficients								
Independent Variable	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
POPDEN00:	0.000011	-0.003504	-0.004537	0.000000	-0.004143	-0.000157	0.000001	-0.000189	0.000646
PCTPOV:	16.392748	19.820064	22.625353	36.323401	19.737047	40.323905	19.475065	23.284709	29.314799
AVEDISTC:	0.002657	0.006304	0.002821	0.003439	0.013934	0.004957	-0.002141	-0.002638	0.012664
MAXSUSWIN:	-0.001118	-0.000506	-0.000776	-0.000059	0.001437	0.000865	-0.000662	-0.001253	0.000701
BLDGLOSS1K	0.000053	0.000000	-0.000019	0.000000	0.000000	-0.000001	0.000000	0.000000	0.000000
NUMBRIDGE:	-0.012072	0.000515	-0.008507	-0.001112	-0.000474	-0.005159	-0.002785	-0.003003	-0.000567

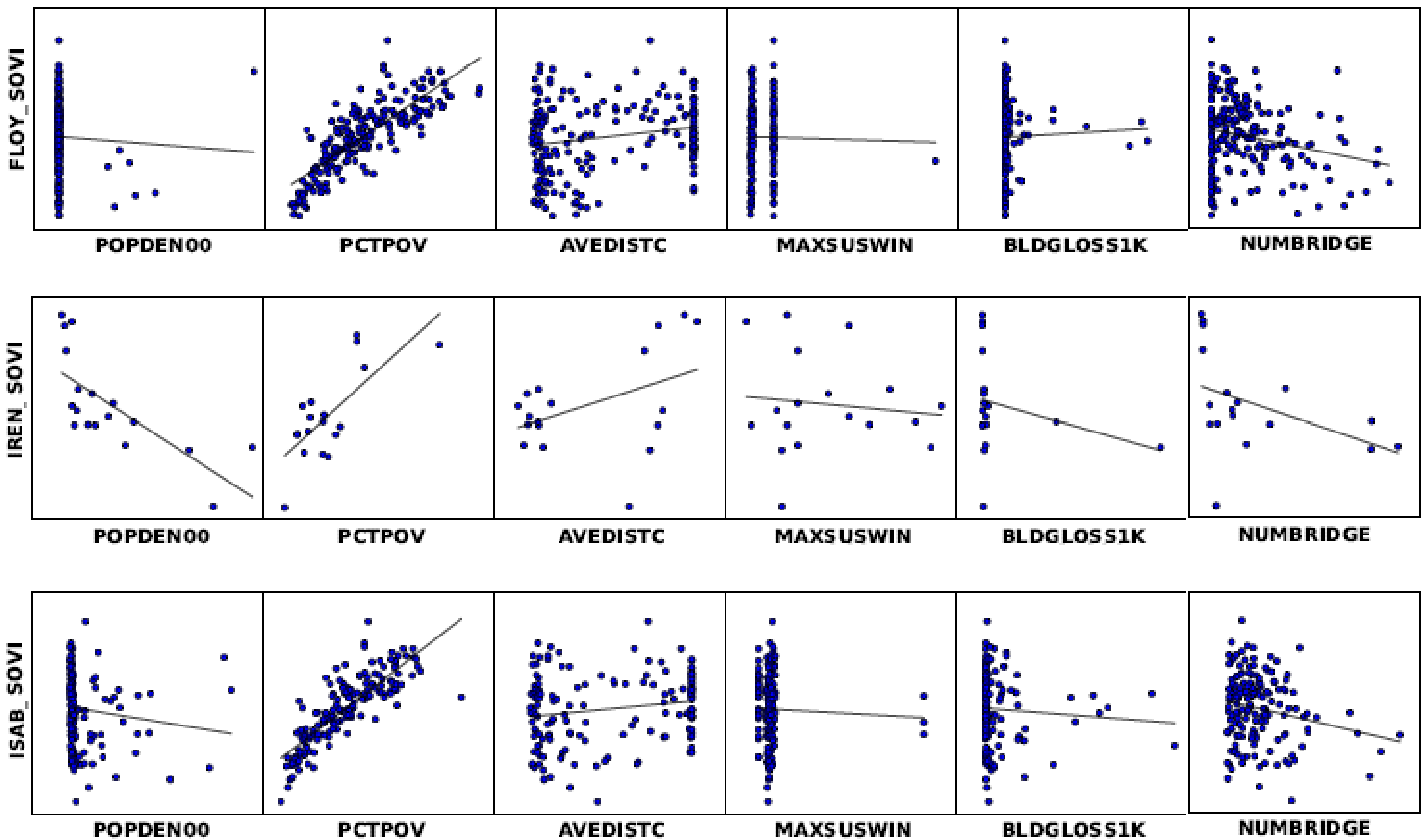
	Model Probabilities								
Independent Variable	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
POPDEN00:	0.999189	0.014726*	0.196946	0.582723	0.002290*	0.100613	0.195095	0.759844	0.389742
PCTPOV:	0.111868	0.006485*	0.011634*	0.000000*	0.055473	0.000000*	0.000000*	0.000374*	0.000000*
AVEDISTC:	0.907508	0.577584	0.821141	0.238736	0.383405	0.177807	0.485257	0.803634	0.041355*
MAXSUSWIN:	0.726819	0.442082	0.475906	0.699722	0.969398	0.374549	0.041300*	0.106435	0.342077
BLDGLOSS1K	0.497314	0.169864	0.693271	0.509607	0.109052	0.557552	0.59712	0.406443	0.86143
NUMBRIDGE:	0.374873	0.821413	0.073354	0.135559	0.818712	0.002979*	0.000380*	0.145602	0.715491

	Model Robust Probabilities								
Independent Variable	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
POPDEN00:	0.998926	0.000119*	0.027702*	0.420366	0.000092*	0.113326	0.209458	0.684542	0.254987
PCTPOV:	0.113082	0.003724*	0.000030*	0.000000*	0.011637*	0.000000*	0.000000*	0.000378*	0.000000*
AVEDISTC:	0.920517	0.570285	0.810349	0.18692	0.258171	0.177941	0.537879	0.778056	0.026447*
MAXSUSWIN:	0.684772	0.373162	0.247845	0.61361	0.949765	0.178313	0.025012*	0.086945	0.334765
BLDGLOSS1K	0.471809	0.000337*	0.525283	0.412378	0.010589*	0.332087	0.352089	0.056875	0.629357
NUMBRIDGE:	0.297528	0.659353	0.006394*	0.095866	0.694323	0.003385*	0.000087*	0.008832*	0.636639

	Model Variance Inflation Factors (VIF)								
Independent Variable	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
POPDEN00:	8.914447	2.546206	2.187917	1.26932	2.807564	1.133472	1.385762	1.683228	1.507882
PCTPOV:	1.730067	1.590533	2.705854	1.14749	2.225361	1.059329	1.256976	1.560114	1.227641
AVEDISTC:	2.246167	1.284819	2.06197	1.244665	3.437236	1.462683	1.183625	1.547705	1.564522
MAXSUSWIN:	2.373553	1.281939	2.018525	1.067006	3.29992	1.116614	1.214682	1.202655	1.05646
BLDGLOSS1K	1.951325	1.155562	1.296542	1.061165	3.44602	1.196571	1.078852	1.299882	1.086706
NUMBRIDGE:	9.507743	2.130976	1.667509	1.367457	2.652962	1.167186	1.434354	1.873098	1.413117

*** Significant level at p = 0.05.**


BRET_SOVI
CHAR_SOVI
CLAU_SOVI
POPDEN00
PCTPOV
AVEDISTC
MAXSUSWIN
BLDGLOSS1K
NUMBRIDGE


FLOY_SOVI
IREN_SOVI
ISAB_SOVI
POPDEN00
PCTPOV
AVEDISTC
MAXSUSWIN
BLDGLOSS1K
NUMBRIDGE

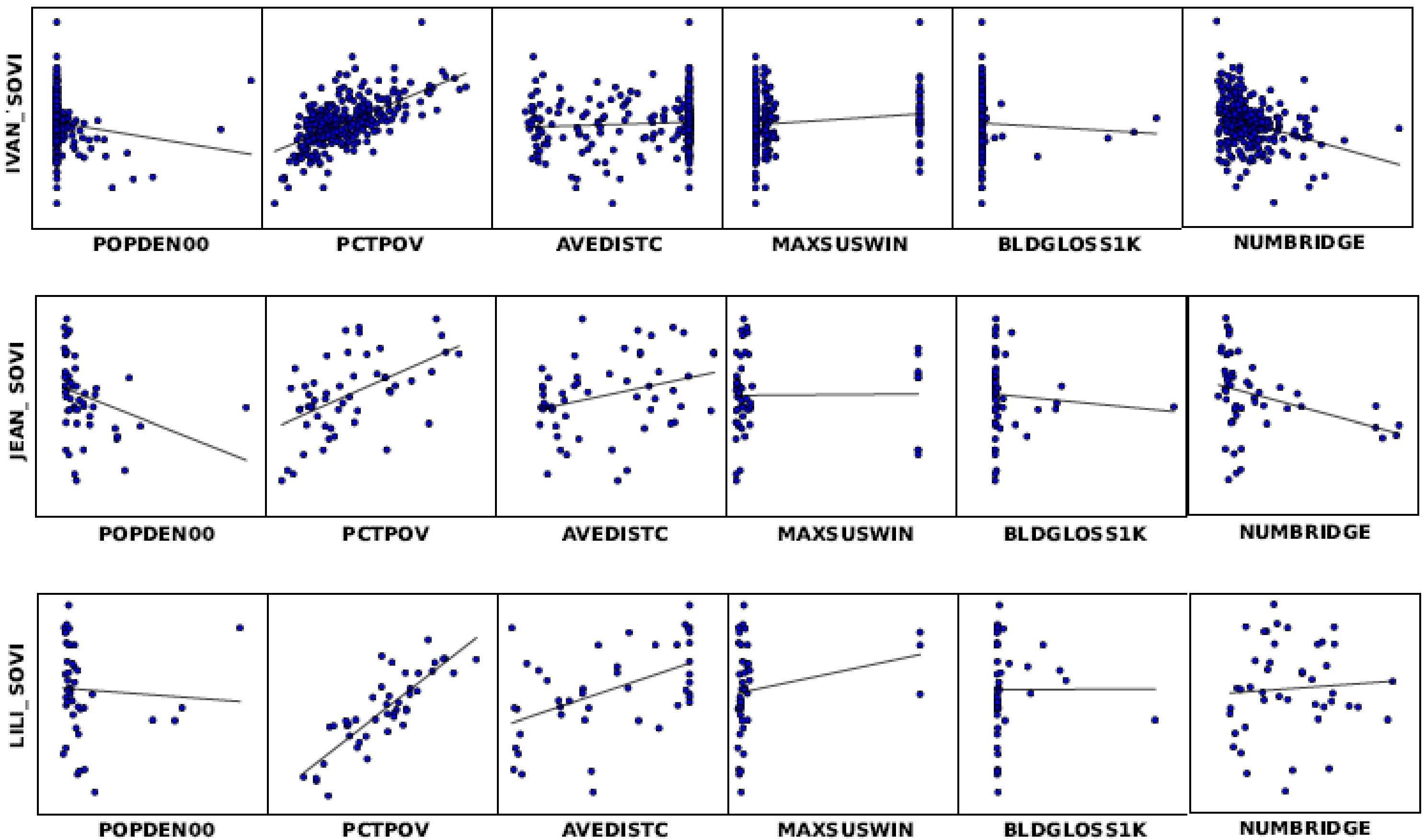
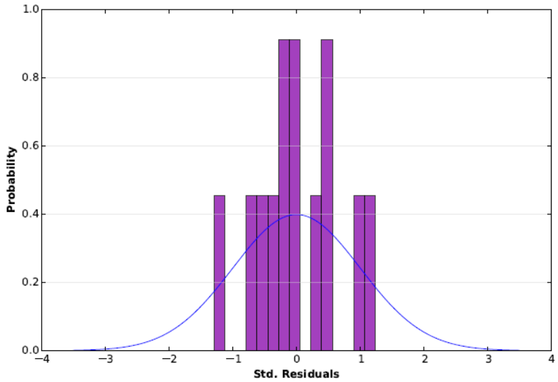
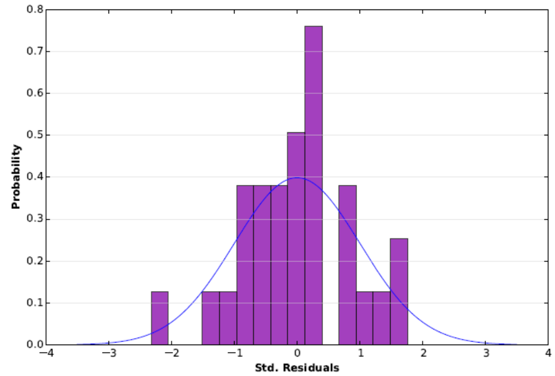


Figure 24: Scatterplots of Variable Relationships for Regression Scenario 1

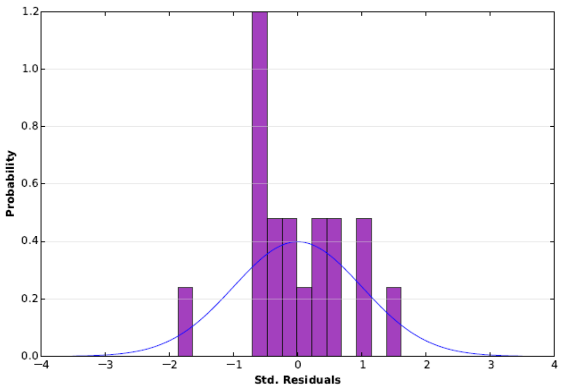
Hurricane Bret



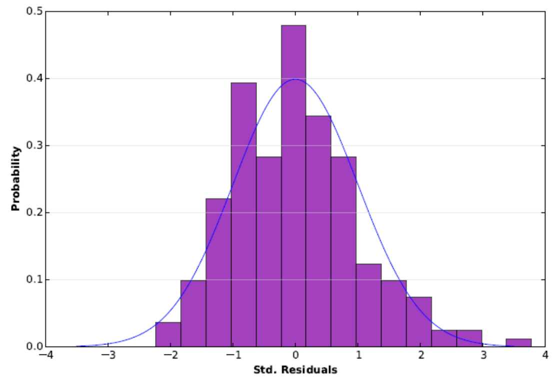
Hurricane Charley



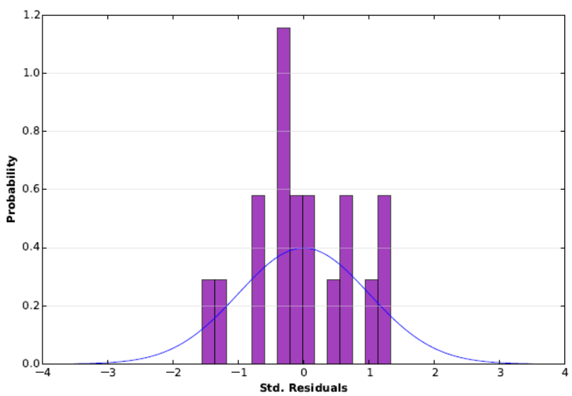
Hurricane Claudette



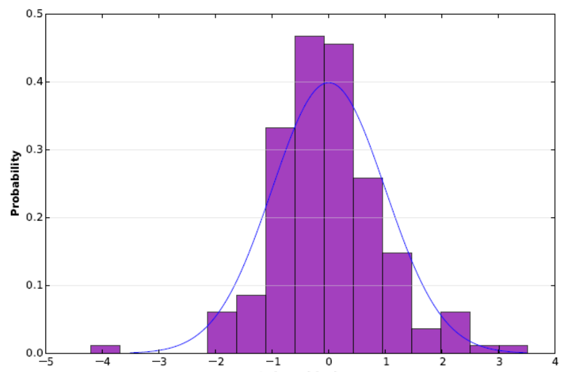
Hurricane Floyd



Hurricane Irene



Hurricane Isabel



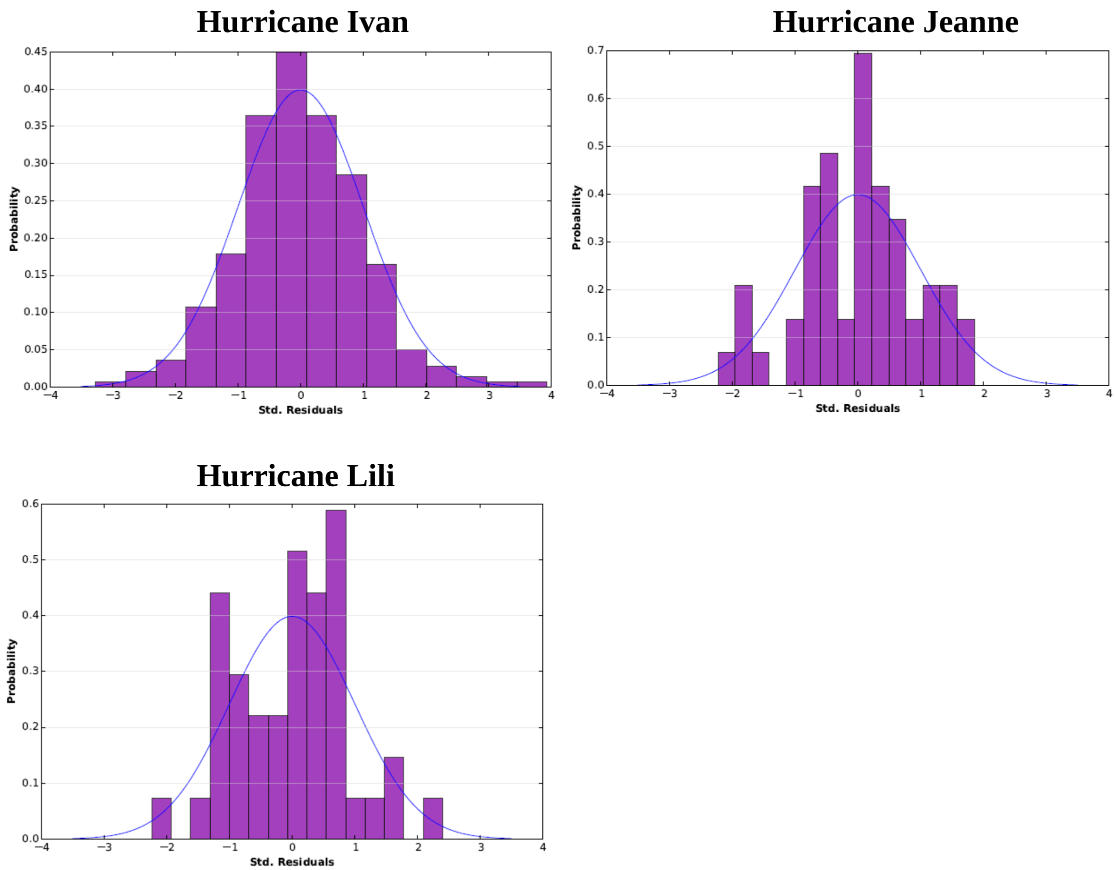
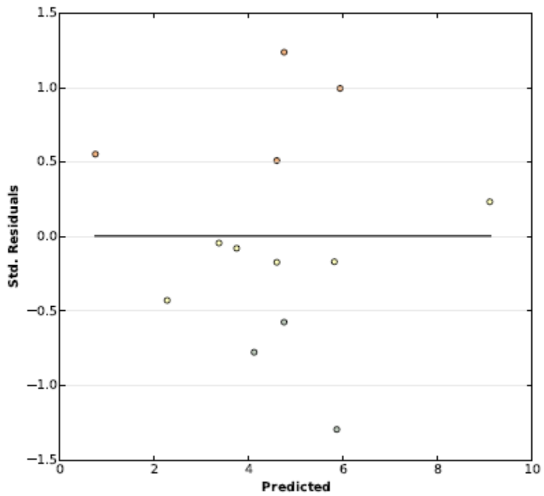
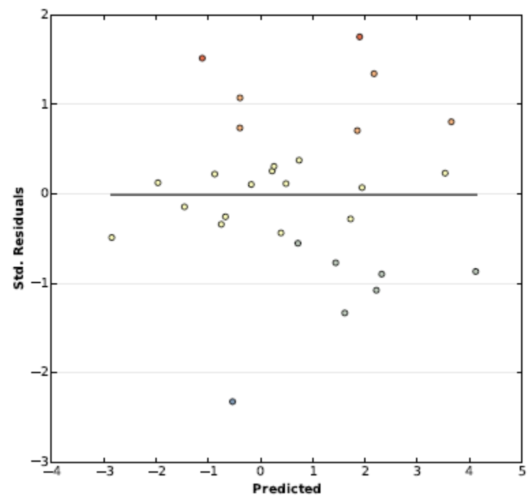


Figure 25: Histograms of Residuals for Regression Scenario 1

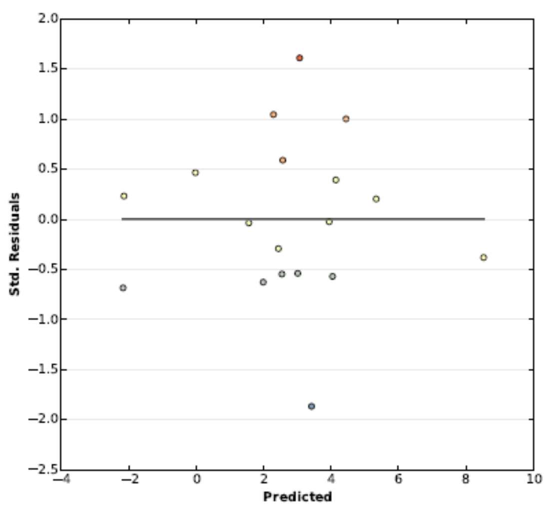
Hurricane Bret



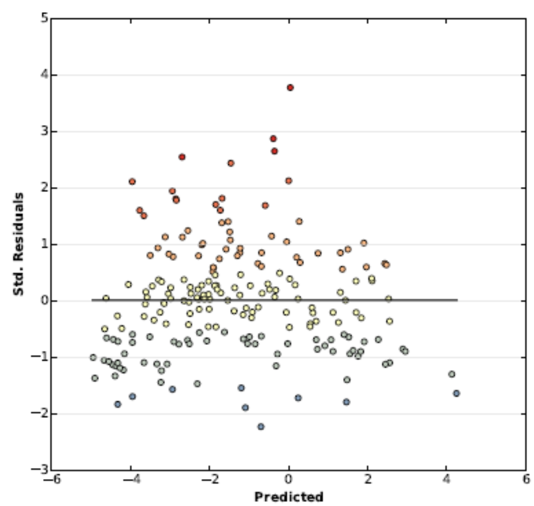
Hurricane Charley

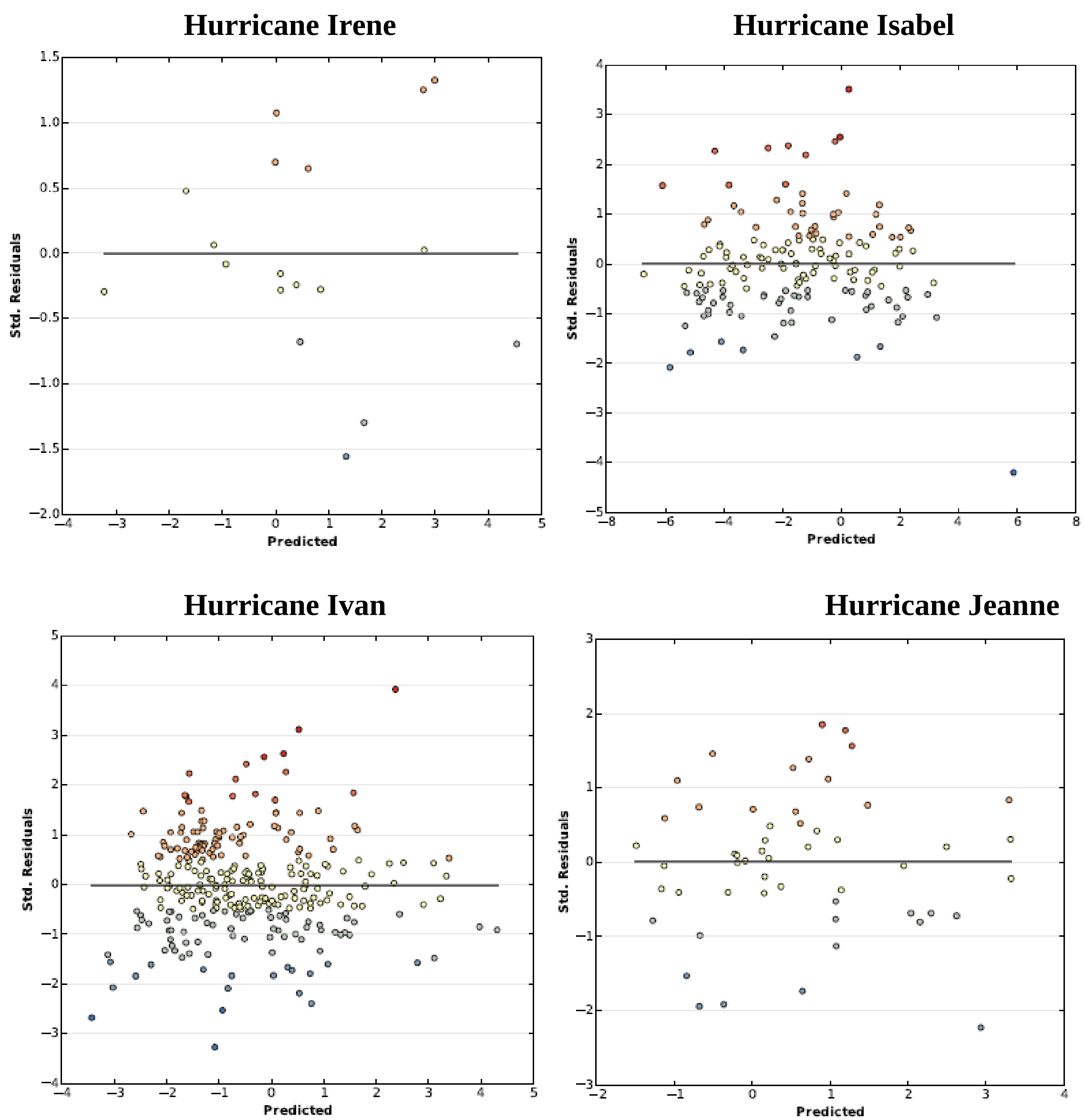


Hurricane Claudette



Hurricane Floyd





Hurricane Irene
Hurricane Isabel
Hurricane Ivan
Hurricane Jeanne
Std. Residuals
Predicted

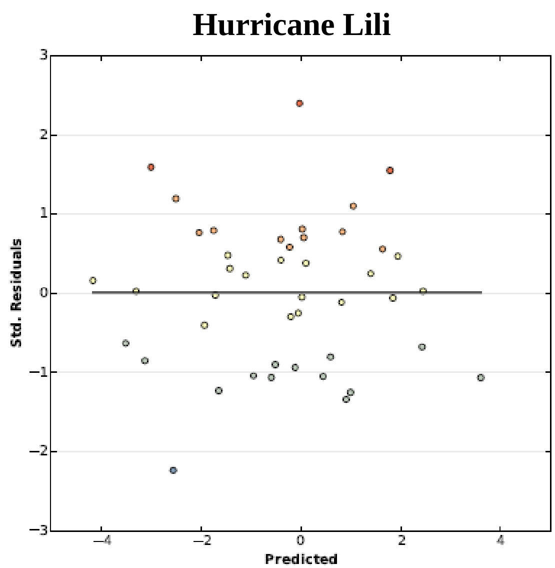


Figure 26: Scatterplots of Over/Under Predictions for Regression Scenario 1

CHAPTER 6: RESULTS OF INITIAL OLS REGRESSION

This chapter attempts to analyze the relationships between hazard vulnerability science and disaster management, using SoVI, and the FEMA disaster impact models. The OLS models are constructed using the six independent variables identified in chapter 5, to accurately predict the level of damages in the community -- expressed as total cost of federal assistance. It involved running 3 scenarios using OLS regression where total amount of federal assistance per capita (TA_pcap) serves as the dependent variable.

Table 12: Scenarios used for the Initial OLS Regressions

	Dependent Variable	Independent (Explanatory) Variables	Objective
Regression Scenario 1	SoVI score	Disaster Impact Model Data Subset	How do disaster impact model data elements relate to SoVI? Which disaster impact model data elements have the strongest relationships to SoVI?
Regression Scenario 2	Total Federal Assistance per Capita (TA_pcap)	SoVI Score	Can SoVI accurately predict disaster impacts as expressed by total federal assistance per capita?
Regression Scenario 3	Total Federal Assistance per Capita (TA_pcap)	SoVI Factors	How do SoVI Component factors relate to disaster impacts as expressed by total federal assistance per capita?
Regression Scenario 4	Total Federal Assistance per Capita (TA_pcap)	Disaster Impact Model Data Subset	Can the disaster impact model data accurately predict disaster impacts as expressed by total federal assistance per capita?
Regression Scenario 5	Total Federal Assistance per Capita (TA_pcap)	SOVI + AveDistC + MaxSustWin	Can the performance of SoVI be improved by adding missing variables for the hazard?

*Each regression scenario was run for every hurricane included in the analysis. A total of 45 regressions 5 scenarios times 9 hurricanes.

REGRESSION SCENARIO 2 - OLS REGRESSION USING SOVI AS THE INDEPENDENT VARIABLE

This model was run using the SoVI score as the independent (explanatory) variable. OLS models were run for all 9 hurricanes included in the research sample. Based on this scenario, one expects to find a positive relationship between the dependent and independent variables, where a county with a larger amount of federal assistance would have a high SoVI score compared to a county with a lower SoVI score for each hurricane event. Table 13 shows the diagnostics for the OLS regression model runs for each hurricane. Table 14 shows the results for those same OLS model runs.

Model diagnostics for the OLS regression model runs indicates poor model performance for 8 of 9 hurricanes. The AIC scores varied widely across hurricanes from 142.386169 to 4582.9921 suggesting the model is miss-specified or not a good match. The adjusted R-squared values show the model was able to explain less than 5% of the variance for 8 of 9 hurricanes. The only model run to demonstrate significant explanatory power was hurricane Bret, where SoVI was able to explain 38% of the variance. To determine the reliability of the adjusted R-squared values, the other model diagnostics and results were examined.

Table 13: Regression Scenarios 2 - OLS Model Diagnostics

Hurricane	Multiple R-Squared [d]	Adjusted R-Squared [d]	Joint F-Statistic [e]	Joint F-Statistic Probability	Joint Wald Statistic [e]	Joint Wald Probability	Koenker (BP) Statistic [f]	Koenker (BP) Probability	Jarque-Bera Statistic [g]	Jarque-Bera Probability	Akaike's Information Criterion (AICc) [d]
Bret	0.439957	0.389044	8.641339	0.013457*	6.035907	0.014018*	6.762961	0.009307*	0.907866	0.635125	142.38617
Charley	0.056786	0.042708	4.033743	0.048632*	2.157323	0.141892	5.085072	0.024133*	954.17522	0.000000*	1045.2858
Claudette	0.024964	-0.035976	0.409651	0.531206	0.751308	0.386062	1.201044	0.273113	13.382542	0.001242*	214.71787
Floyd	0.046563	0.041266	8.790569	0.003438*	11.65113	0.000642*	4.598464	0.032001*	2481.7665	0.000000*	2583.7908
Irene	0.000749	-0.061704	0.011989	0.914173	0.041988	0.837642	0.011583	0.914293	44.890553	0.000000*	167.84771
Isabel	0.018167	0.011873	2.886423	0.091322	2.148428	0.142716	2.67614	0.101862	5171.9218	0.000000*	2160.234
Ivan	0.000984	-0.002109	0.318171	0.5731	0.614361	0.43315	0.191101	0.662002	133056.45	0.000000*	4582.9921
Jeanne	0.060907	0.042493	3.307715	0.074829	4.732622	0.029596*	0.83708	0.360233	149.92669	0.000000*	718.72639
Lili	0.000376	-0.023424	0.015819	0.900512	0.081528	0.775237	0.024833	0.874783	619.12948	0.000000*	489.7047

*** Significant level at p = 0.05.**

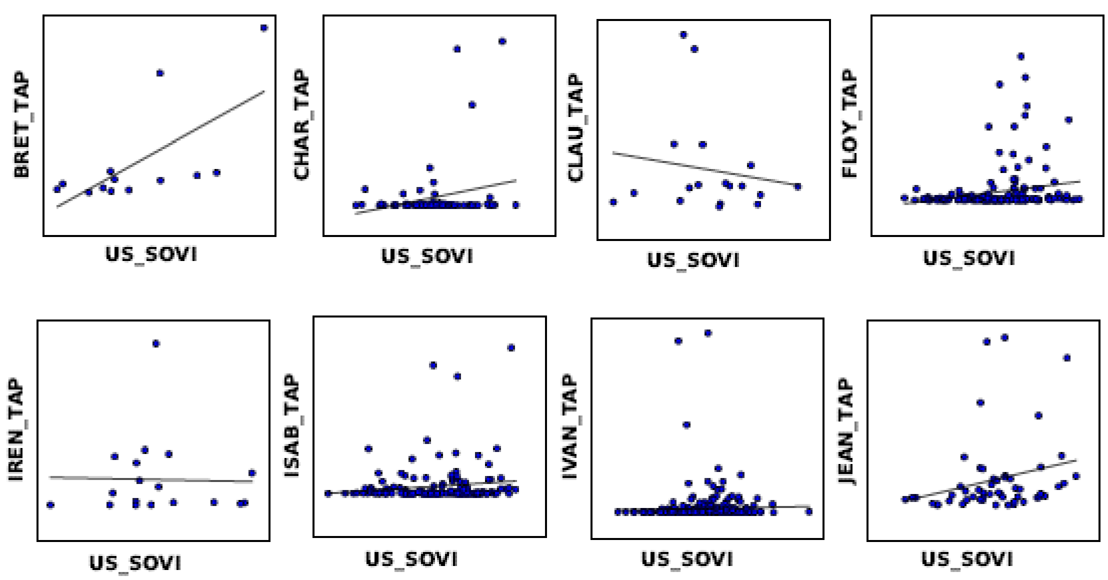
Table 14: Regression Scenarios 2 - OLS Model Results

	Dependent variable: Total federal assistance per capita (TA_pcap)								
Hurricane	**Number of Observations**	**Independent Variable**	**Coefficient**	**StdError**	**t-Statistic**	**Probability**	**Robust StdError**	**Robust_t**	**Robust Probability**
Bret	13	SOVI	16.201585	5.511464	2.939615	0.013461*	6.594566	2.456808	0.031853*
Charley	69	SOVI	53.90682	26.84044	2.008418	0.048632*	36.701693	1.468783	0.146576
Claudette	18	SOVI	-4.60126	7.189025	-0.64004	0.531206	5.308451	-0.86678	0.398874
Floyd	182	SOVI	24.939132	8.411488	2.964889	0.003443*	7.306296	3.413376	0.000803*
Irene	18	SOVI	-0.287484	2.625574	-0.109494	0.914169	1.40297	-0.20491	0.840225
Isabel	158	SOVI	10.783885	6.34739	1.698948	0.09133	7.357239	1.465752	0.144739
Ivan	325	SOVI	4.081723	7.236239	0.564067	0.573106	5.207528	0.783812	0.433715
Jeanne	53	SOVI	24.849205	13.66307	1.818713	0.074831	11.422512	2.175459	0.034255*
Lili	44	SOVI	-0.562794	4.474675	-0.125773	0.900513	1.971038	-0.28553	0.776642

*** Significant level at p = 0.05.**

The Jarque-Bera statistics were significant for all hurricanes indicating model bias; the residuals are not normally distributed. This interpretation was confirmed by the histograms depicted in figure 28 that reveal significant influence from outliers. The scatterplots of the over and under predictions of residuals portrayed in figure 29 were not randomly distributed, heteroskedastic, and likely non-linear. These scatterplots also indicate structural problems with a systematic scale issue for 4 hurricanes. The Koenker

(BP) statistic was significant for 3 hurricanes (Bret, Charley and Floyd) and insignificant for the remaining 6 hurricanes. This suggests the data for hurricanes Bret, Charley, and Floyd are non-stationary, and the robust probabilities were consulted to determine coefficient significance. The coefficients for hurricanes Bret and Floyd were significant based on the robust probabilities. For the remaining 6 hurricanes, the probabilities were consulted. The coefficients were insignificant based on the probabilities. The scatterplots from figure 27 show linear relationships for 6 hurricanes and narrowly linear relationships for the remaining 3 hurricanes (Irene, Ivan, and Lili). The relationship between dependent and independent variable was positive as expected for 6 of 9 hurricanes. The relationship was negative for hurricanes Claudette, Irene, and Lili. This is anomalous as one expects when damages are high that vulnerability is high.



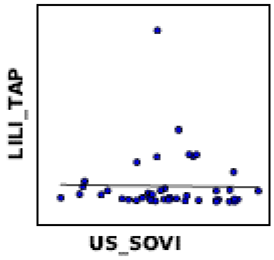
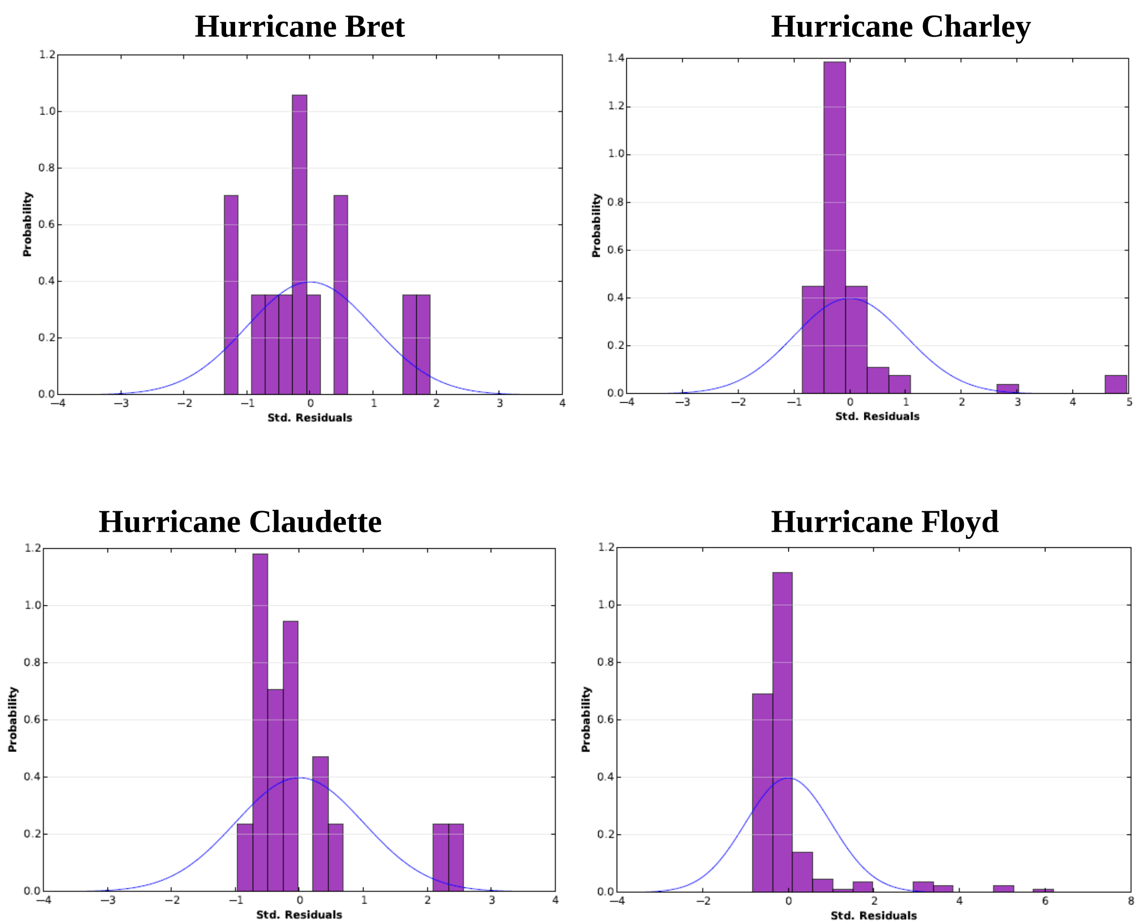


Figure 27: Scatterplots of Variable Relationships for Regression Scenario 2



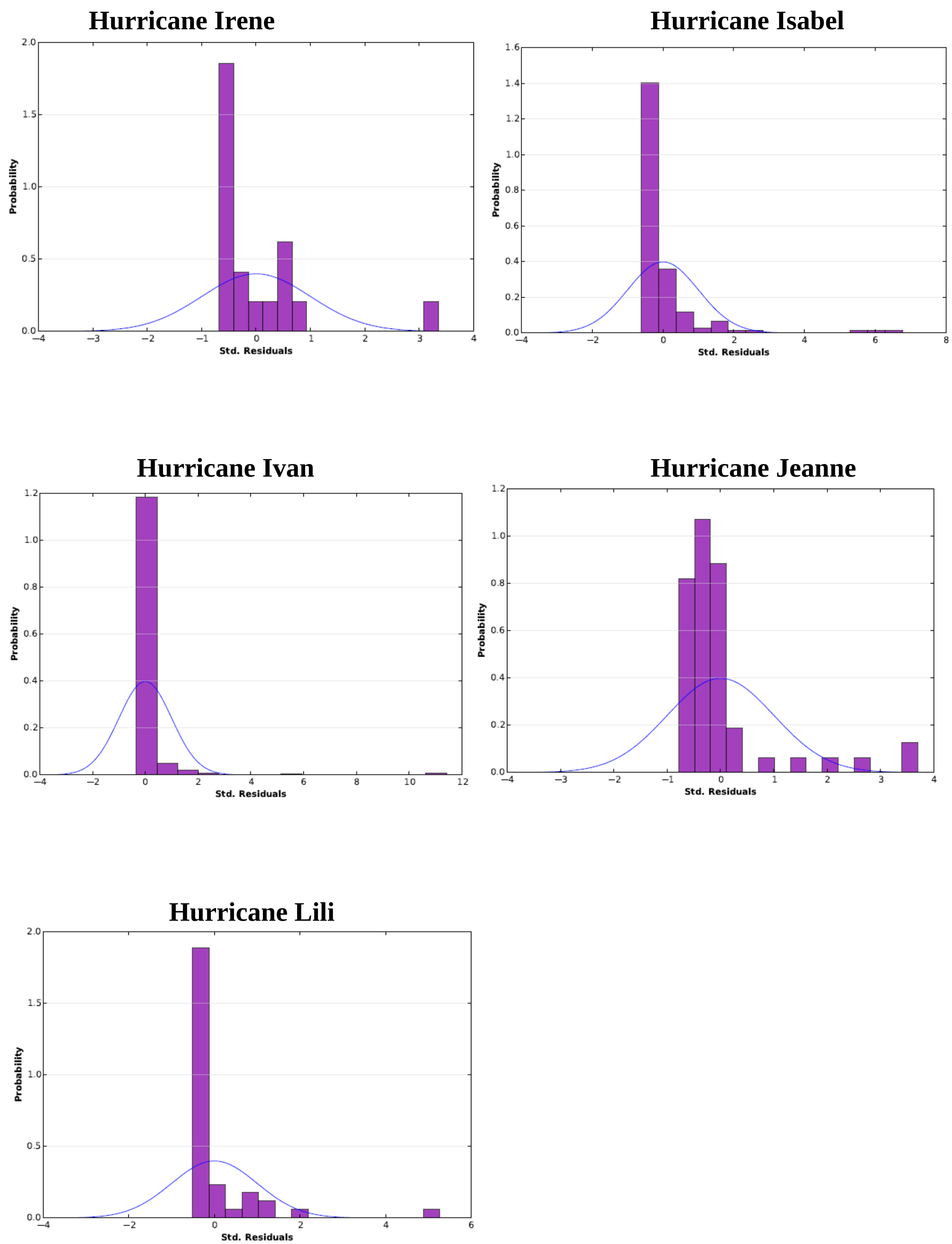
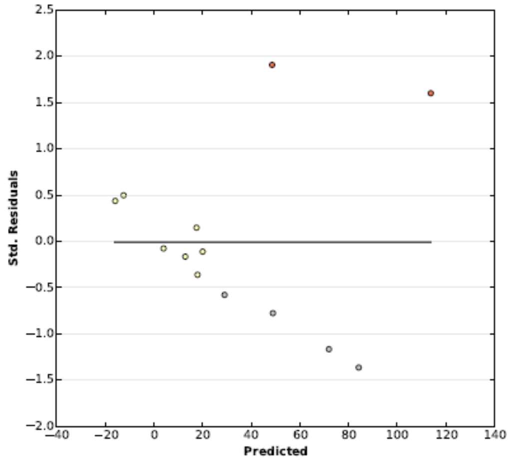
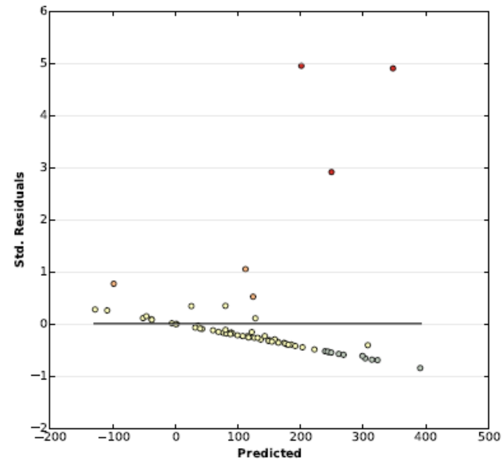


Figure 28: Histograms of Residuals for Regression Scenario 2

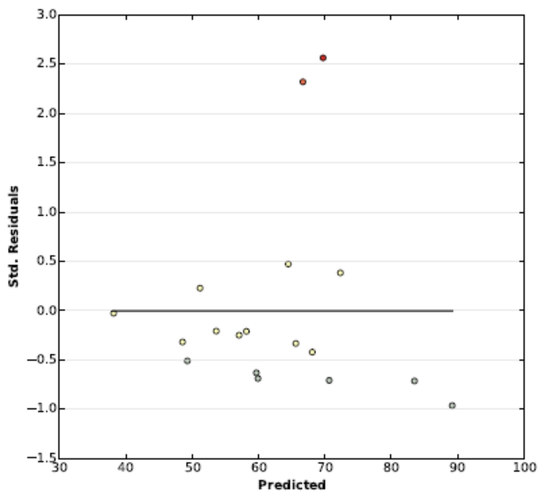
Hurricane Bret



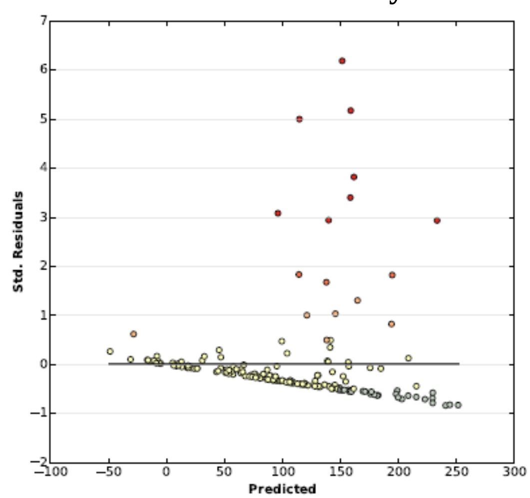
Hurricane Charley



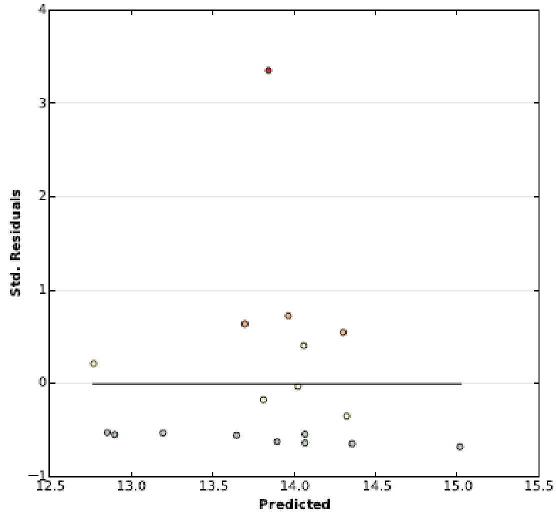
Hurricane Claudette



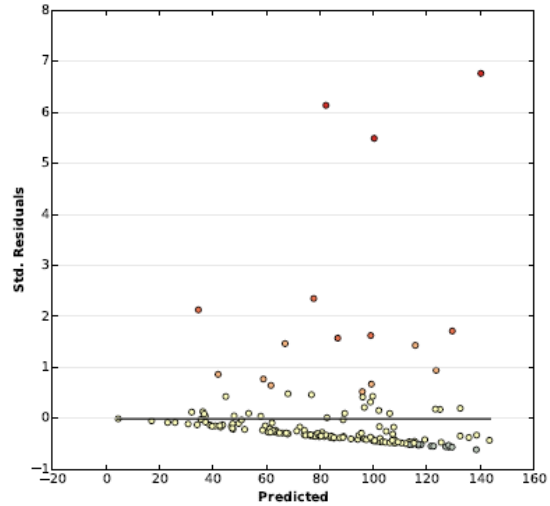
Hurricane Floyd



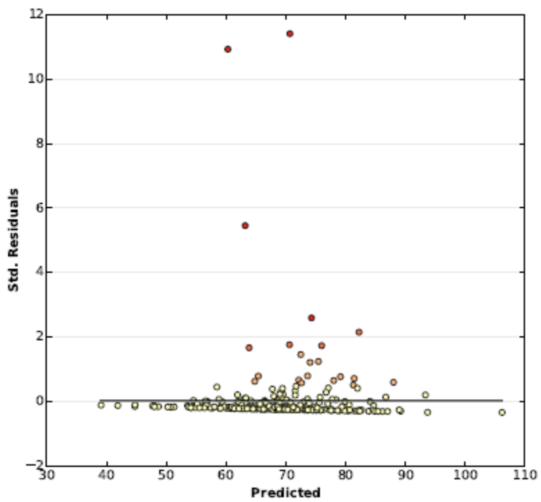
Hurricane Irene



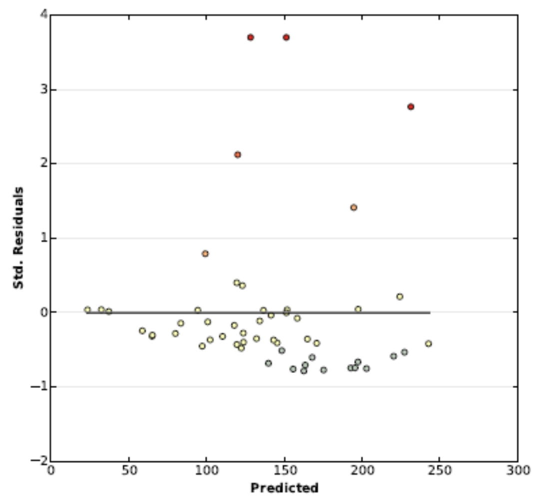
Hurricane Isabel



Hurricane Ivan



Hurricane Jeanne



Hurricane Lili

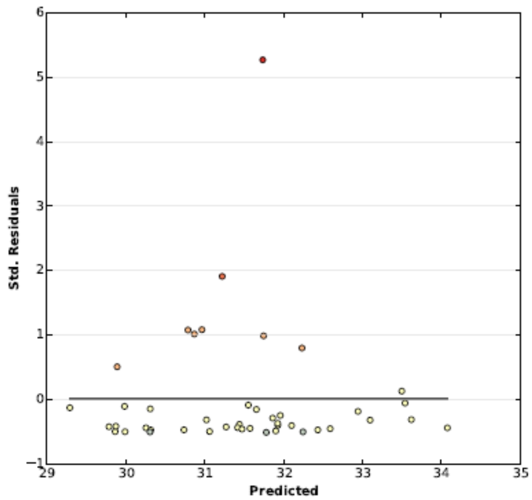


Figure 29: Scatterplots of Over/Under Predictions for Regression Scenario 2

Moran's statistics were run to determine if spatial autocorrelation issues were influencing model performance. These statistics are listed in Table 15 below. The Moran's I results indicate the presence of spatial autocorrelation in the OLS model runs for 7 of the 9 hurricanes. This map shows residual clustering that is closely associated with the hurricane storm tracks and points of landfall as depicted in figure 40 below. While the histograms from figure 37 also showed significant outliers and removing these outliers might boost model performance; it might introduce new bias by eliminating significant geographic components from the analysis. By their nature, hurricane events are spatially biased by their storm tracks and geophysical properties.

Table 15: Regression Scenarios 2 – Spatial Autocorrelation (Moran's I) Statistics

Hurricane	Index	Expected	Variance	P-value	Z-score	Pattern
Bret	0.006792	-0.08333	0.031607	0.6122	0.506935	Random
Charley	0.322099	-0.01471	0.002821	0.000000	6.341552	Clustered
Claudette	0.272718	-0.05882	0.024413	0.03384	2.12192	Clustered
Floyd	0.371938	-0.00553	0.000685	0.000000	14.420553	Clustered
Irene	0.044825	-0.05882	0.006309	0.19192	1.304923	Random
Isabel	0.117097	-0.00637	0.000128	0.000000	10.914423	Clustered
Ivan	0.309543	-0.00309	0.000285	0.000000	18.53457	Clustered
Jeanne	0.550929	-0.01923	0.008508	0.000000	6.181359	Clustered
Lili	0.226272	-0.02326	-0.023256	0.00095	3.303801	Clustered

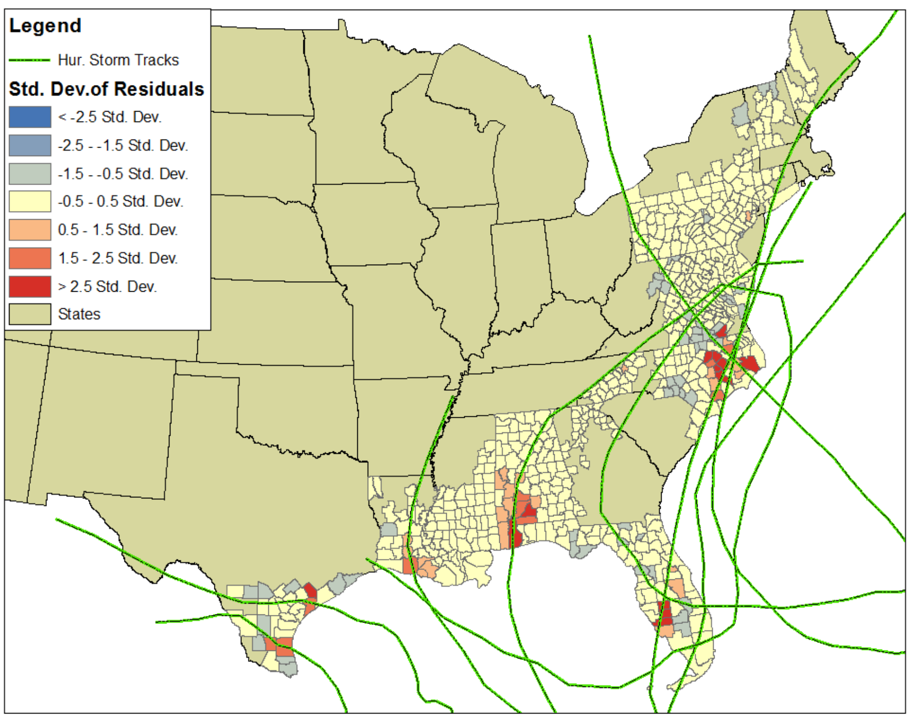


Figure 30: Map of OLS Residuals and Hurricane Storm Tracks - Regression Scenario 2

Collectively, the results from OLS regression for scenario 3 suggest model bias is a result of model mismatch or model mis-specification rather than data outliers. The results also suggest there is a problem with skewness in the data based on the scatterplots and spatial autocorrelation from the Moran's I statistics.

REGRESSION SCENARIO 3 –OLS REGRESSION USING SOVI FACTORS AS INDEPENDENT VARIABLES

Since the results from regression scenario 2, that tested the explanatory power of the SoVI composite index, were dubious, it begs the question whether particular sub-factors of SoVI are statistically more significant than others? If certain SoVI sub-factors are significant, how does their significance in explaining disaster impacts compare to their significance in explaining social vulnerability? For example, wealth (factor 2) is able to explain 15.9% of the variance in SoVI and has a negative relationship. Employment in services industries (factor 7) has a variance of 4.8% and has a positive relationship with SoVI. Do these same relationships hold true in explaining disaster impacts using total federal assistance per capita?

This model was run using the individual SoVI factors as the independent (explanatory) variables as depicted in figure 31 and total federal assistance per capita as the dependent variable. Table 16 shows the diagnostics for the OLS regression model runs for each hurricane. Table 17 shows the results for those same OLS model runs.

Dependent Variable	Independent (Explanatory) Variables
Total Federal Assistance Per Capita (TA_pcap)	Factor 1: Race (Black and Class (Poverty)
	Factor 2: Wealth
	Factor 3: Age (Old)
	Factor 4: Ethnicity (Hispanic)
	Factor 5: Nursing Home Residents
	Factor 6: Ethnicity (Native American)
	Factor 7: Employed in Service Industries

Figure 31: Regression Scenario 3 - Model Variables

Model diagnostics for the OLS regression model runs indicates poor model performance for 8 of 9 hurricanes. The AIC scores varied widely across hurricanes from 182.9896 to 4588.9938 suggesting the model is miss-specified or not a good match. The adjusted R-squared values show the model was able to explain less than 36.2% of the variance for 8 of 9 hurricanes. The only model run to demonstrate significant explanatory power was hurricane Bret, where SoVI factors were able to explain 54.7% of the variance. To determine the reliability of the adjusted R-squared values, the other model diagnostics and results were examined.

Table 16: Regression Scenarios 3 - OLS Model Diagnostics

Hurricane	Multiple R-Squared [d]	Adjusted R-Squared [d]	Joint F-Statistic [e]	Joint F-Statistic Probability	Joint Wald Statistic [e]	Joint Wald Probability	Koenker (BP) Statistic [f]	Koenker (BP) Probability	Jarque-Bera Statistic [g]	Jarque-Bera Probability	Akaike's Information Criterion (AICc) [d]
Bret	0.811337	0.547209	3.071759	0.117449	30.07348	0.000092*	6.940101	0.435143	0.761536	0.635125	197.57481
Charley	0.243238	0.156397	2.800948	0.013533*	9.472276	0.220502	9.677897	0.207573	914.72088	0.000000*	1044.7706
Claudette	0.247376	-0.279461	0.469549	0.836032	6.437539	0.489686	3.355406	0.850295	8.797751	0.012291*	242.84324
Floyd	0.150531	0.116357	4.40484	0.000158*	18.1237	0.011424*	16.429522	0.021469*	1992.8547	0.000000*	2575.6883
Irene	0.62505	0.362584	2.381456	0.103372	21.50377	0.003092*	8.672846	0.277005	0.33208	0.847012	182.9896
Isabel	0.123081	0.082158	3.00764	0.005517*	21.0764	0.003659*	19.2176	0.007532*	3748.8675	0.000000*	2155.4392
Ivan	0.020751	-0.000873	0.959624	0.460836	15.06514	0.035173*	3.61412	0.822994	133706.87	0.000000*	4588.9938
Jeanne	0.158187	0.027238	1.208008	0.31815	12.33647	0.090023	6.222075	0.514071	127.59663	0.000000*	728.62673
Lili	0.443381	0.335149	4.096591	0.002119*	11.12821	0.133123	10.20097	0.177468	189.67466	0.000000*	480.63696

The Jarque-Bera statistics were significant for 7 of 9 hurricanes indicating model bias; the residuals are not normally distributed. This interpretation was confirmed by the histograms depicted in figure 33 that reveal significant influence from outliers. The scatterplots of the over and under predictions of residuals portrayed in figure 46 were not randomly distributed, heteroskedastic, and likely non-linear. These scatterplots also indicate structural problems with a systematic scale issue for 4 hurricanes. The Koenker (BP) statistic was significant for 3 hurricanes (Bret, Charley and Floyd) and insignificant for the remaining 6 hurricanes. This suggests the data for hurricanes Bret, Charley, and Floyd are non-stationary, and the robust probabilities were consulted to determine coefficient significance. The coefficients for hurricanes Bret and Floyd were significant based on the robust probabilities. For the remaining 6 hurricanes, the probabilities were consulted. The coefficients were insignificant based on the probabilities. The scatterplots from figure 32 show linear relationships for 6 hurricanes and narrowly linear relationships for the remaining 3 hurricanes (Irene, Ivan, and Lili). The relationship between dependent and independent variable was positive as expected for 6 of 9 hurricanes. The relationship was negative for hurricanes Claudette, Irene, and Lili. This is anomalous as one expects when damages are high that vulnerability is high.

The relationships for the model coefficients also varied across hurricanes and factors. In many cases, the type of relationship (positive or negative) contradicts the cardinality of that factor to SoVI. For example, factor 2 (wealth) has a negative cardinality to SoVI but has a positive relationship to the dependent variable for 4 hurricanes and a negative relationship for the other 5 hurricanes. The scatterplots in figure 32 illustrate the varying type of relationship between the factors across the 9 hurricanes. Figure 32 also shows that the relationship between the SOVI factors and the dependent variable are linear. The Jarque-Bera statistic was significant for 8 of 9 hurricanes. This indicates the residuals are not normally distributed. Histograms of the model residuals shown in figure 33 illustrate this model bias. Scatterplots of the over and under predictions of residuals portrayed in figure 35 suggest a systematic scale issue likely a product of many the values in the data being close to zero. Patterns are not strongly random indicating the model is mis-specified.

Table 17: Regression Scenarios 3 - OLS Model Results

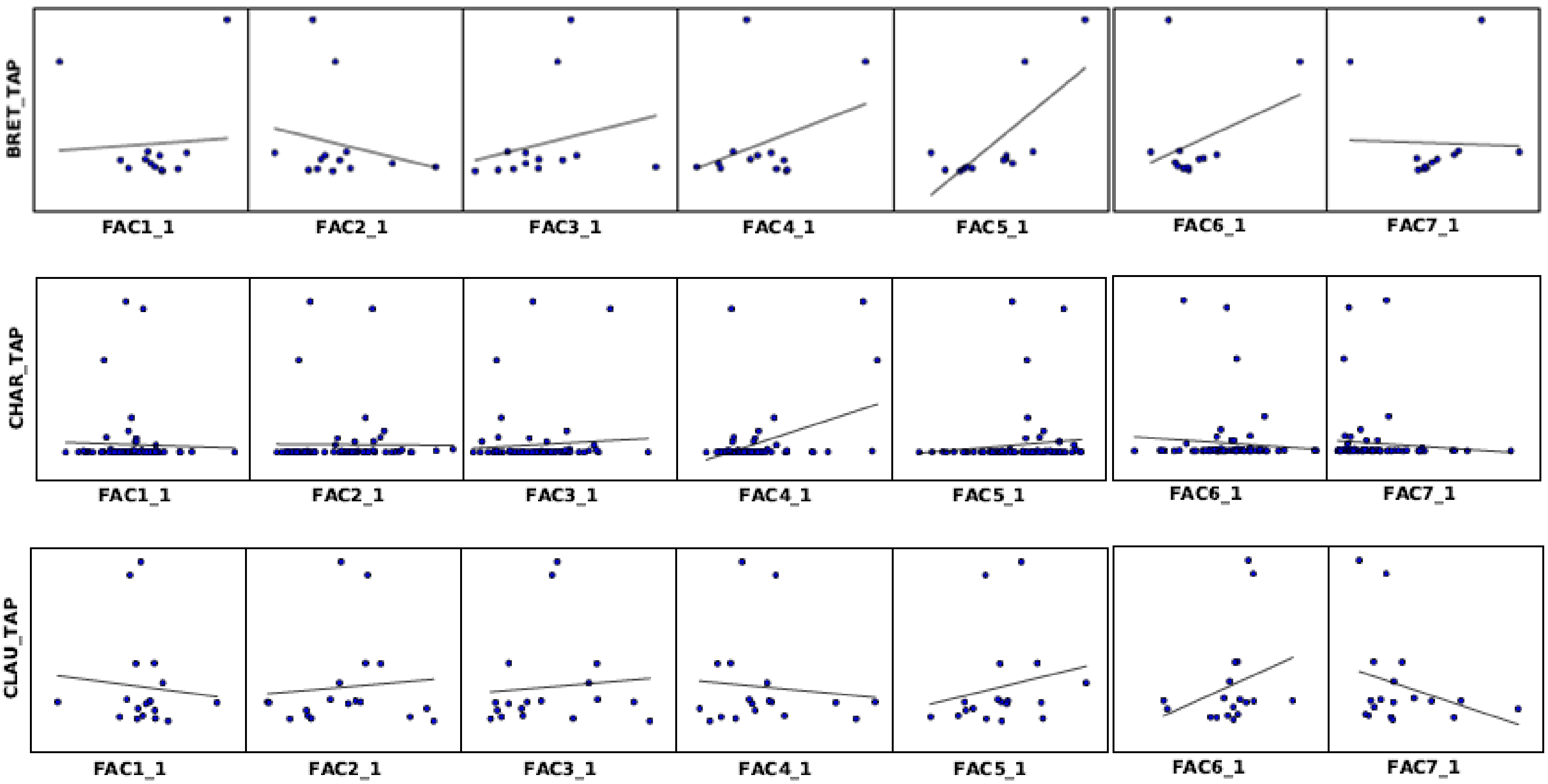
Independent Variable	Model Coefficients								
	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
FAC1_1	18.421029	-158.756758	-33.212513	84.829814	-16.782261	19.637034	26.443192	-0.774155	2.317433
FAC2_1	-8.849103	-113.01237	-90.929078	-16.438214	3.222512	17.481491	18.139109	42.301036	-5.829686
FAC3_1	16.325053	58.865787	-7.606049	-18.350379	8.169451	65.379476	4.63209	23.237875	-36.010008
FAC4_1	24.027707	186.957731	-68.980873	8.479094	-1.912594	-2.367885	-30.906939	42.577833	36.713073
FAC5_1	70.287114	246.184739	21.370388	-40.230295	4.047105	-56.24415	-56.303033	-41.763175	4.848822
FAC6_1	-20.197777	133.316275	203.452726	-114.565682	24.089884	-19.565104	4.793672	-135.285238	106.953853
FAC7_1	-3.155066	-12.590206	12.602757	-15.901496	13.590143	47.472229	13.024275	-8.751855	6.704872

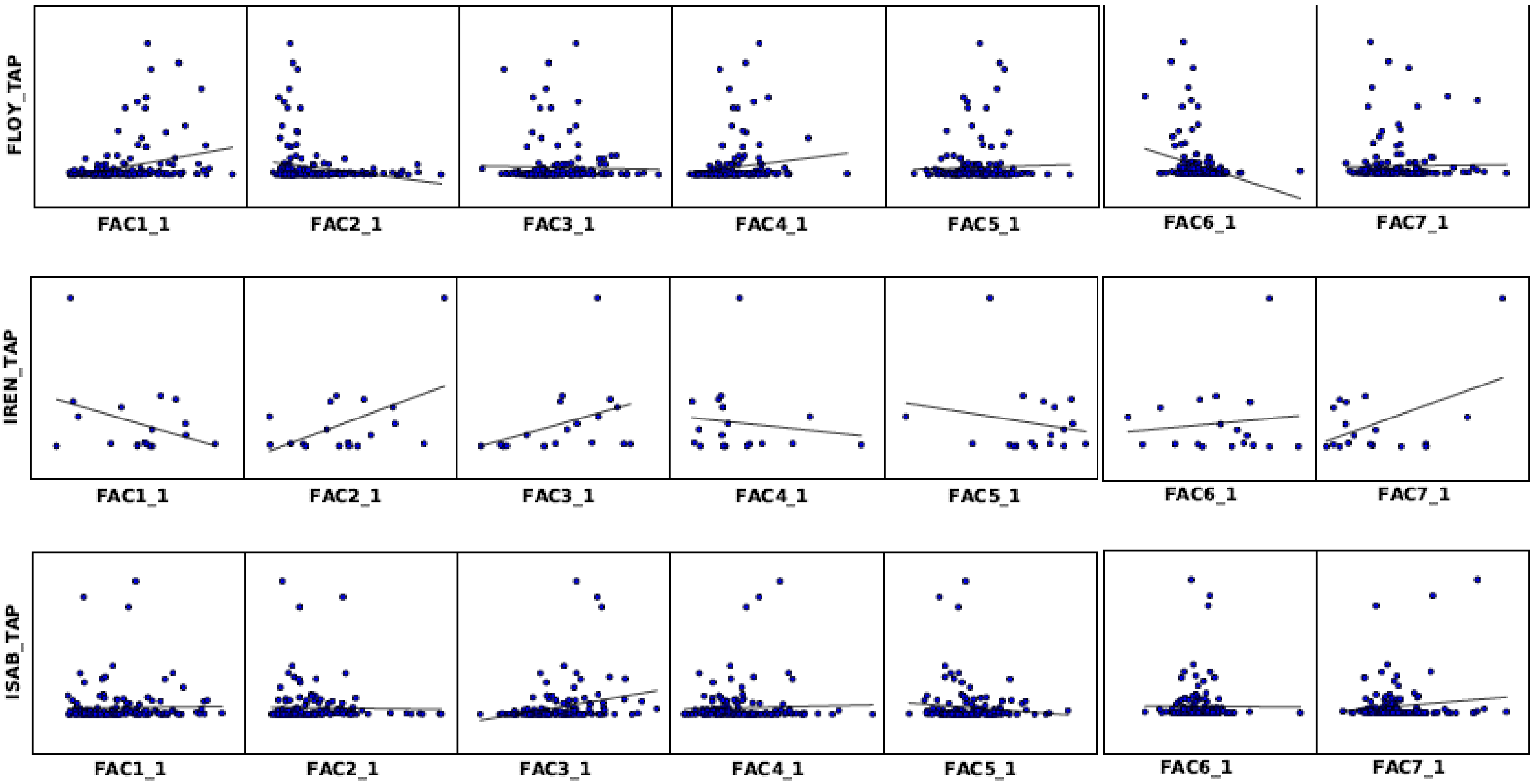
Independent Variable	Model Probabilities								
	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
FAC1_1	0.560587	0.17482	0.429633	0.004087*	0.457609	0.389727	0.111288	0.992405	0.863951
FAC2_1	0.890871	0.139641	0.317663	0.417856	0.590584	0.239713	0.329272	0.368435	0.676212
FAC3_1	0.338375	0.217729	0.773453	0.407736	0.152324	0.000447*	0.796692	0.410784	0.036157*
FAC4_1	0.220224	0.000390*	0.229369	0.81678	0.689714	0.945377	0.312372	0.107069	0.036267*
FAC5_1	0.044116*	0.048495*	0.741021	0.281386	0.804427	0.057848	0.043703*	0.585471	0.743507
FAC6_1	0.838368	0.515042	0.274754	0.024827*	0.479905	0.630734	0.908437	0.392983	0.001246*
FAC7_1	0.887142	0.804985	0.657391	0.545933	0.145208	0.028707*	0.406433	0.802291	0.48078

Independent Variable	Model Robust Probabilities								
	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
FAC1_1	0.642006	0.047083*	0.085274	0.002974*	0.235542	0.164844	0.023599*	0.986988	0.838012
FAC2_1	0.855597	0.079476	0.150334	0.262055	0.463509	0.195473	0.228806	0.341485	0.593075
FAC3_1	0.250159	0.394136	0.45734	0.354168	0.014836*	0.001383*	0.704236	0.226939	0.087434
FAC4_1	0.301822	0.050657	0.068954	0.760377	0.654468	0.936597	0.026165*	0.044978*	0.057852
FAC5_1	0.05731	0.045914*	0.456348	0.104851	0.66509	0.036391*	0.015449*	0.502508	0.699344
FAC6_1	0.879104	0.360848	0.091158	0.009380*	0.290162	0.351914	0.769574	0.130125	0.029151*
FAC7_1	0.875916	0.622743	0.354379	0.641626	0.042378*	0.284255	0.340927	0.635379	0.407097

Independent Variable	Model Variance Inflation Factors (VIF)								
	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
FAC1_1	5.667387	1.673733	2.42134	1.752976	2.328867	1.72358	1.227935	2.032116	2.250987
FAC2_1	6.420104	2.65557	5.081819	1.818677	2.575472	1.438096	1.187365	3.207995	1.275695
FAC3_1	3.040694	1.330645	1.808037	1.059212	2.744101	1.082927	1.133501	1.864101	1.458473
FAC4_1	5.898662	1.127654	6.42164	1.48697	1.945152	1.156039	1.639683	1.223708	1.357111
FAC5_1	1.909903	3.425664	2.201719	1.557819	5.511911	1.604956	1.526155	4.500051	2.072715
FAC6_1	17.983911	1.449433	7.722353	1.449322	2.957143	1.337944	1.343235	2.301826	1.966009
FAC7_1	7.636859	1.513991	4.719912	1.240182	2.90036	1.232205	1.071997	2.125124	1.906039

*** Significant level at p = 0.05.**


BRET_TAP
CHAR_TAP
CLAU_TAP
FAC1_1
FAC2_1
FAC3_1
FAC4_1
FAC5_1
FAC6_1
FAC7_1


FLOY_TAP
IREN_TAP
ISAB_TAP
FAC1_1
FAC2_1
FAC3_1
FAC4_1
FAC5_1
FAC6_1
FAC7_1

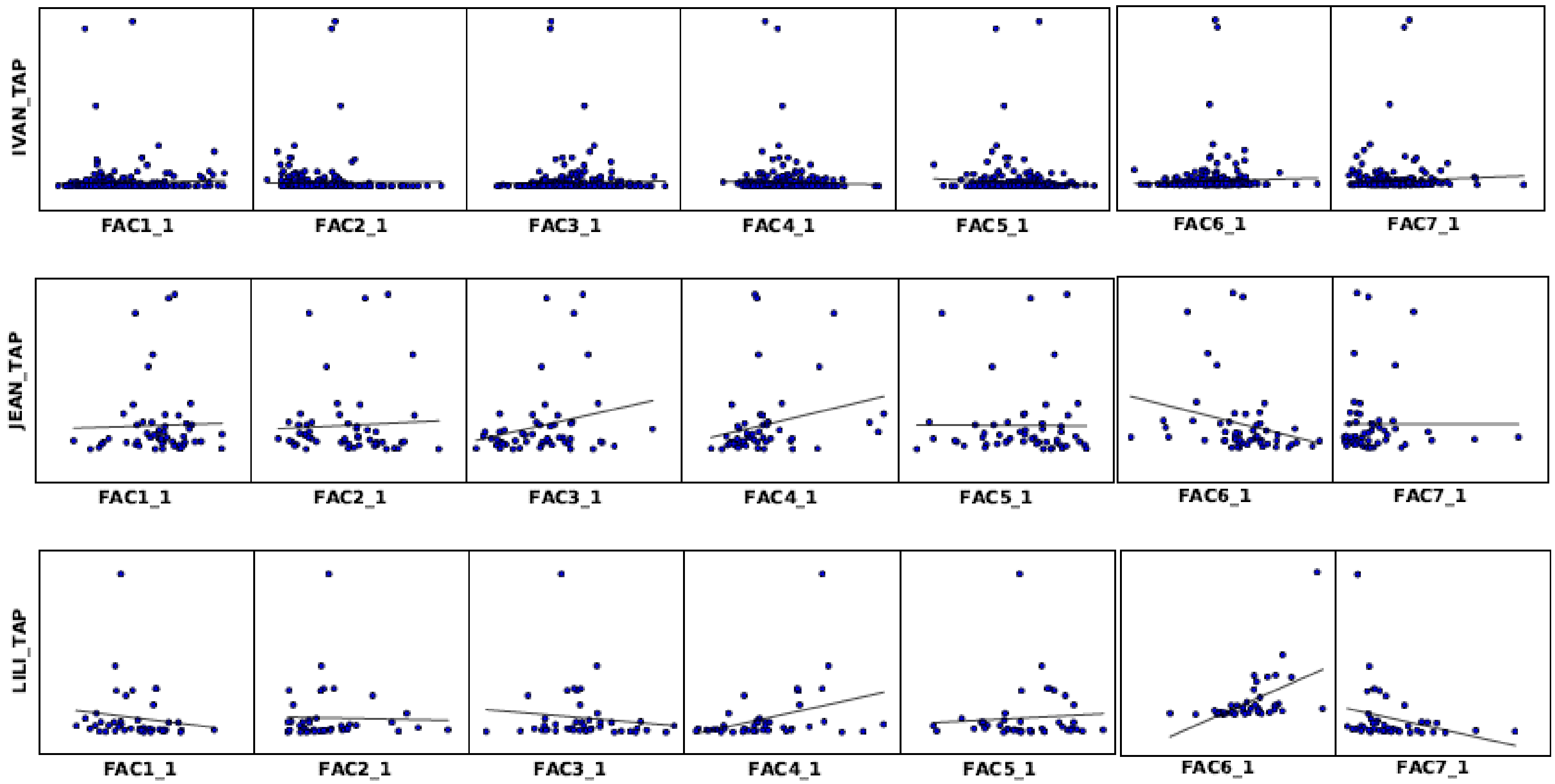
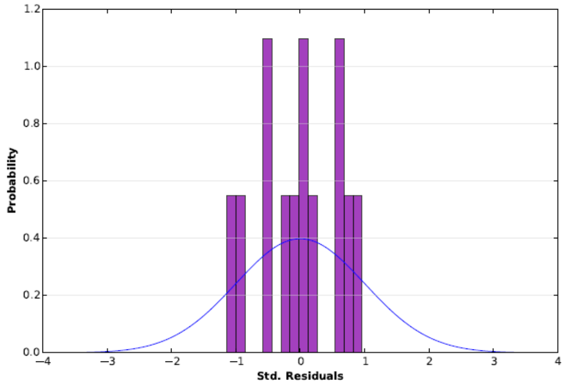
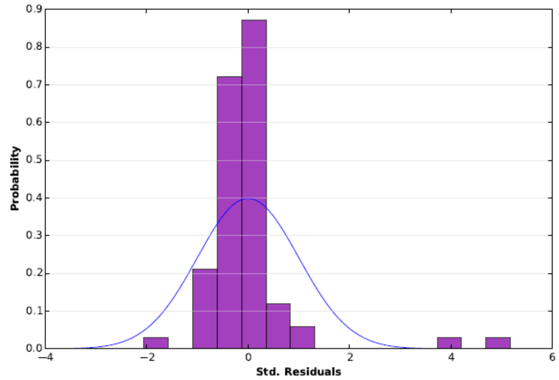


Figure 32: Scatterplots of Variable Relationships for Regression Scenario 3

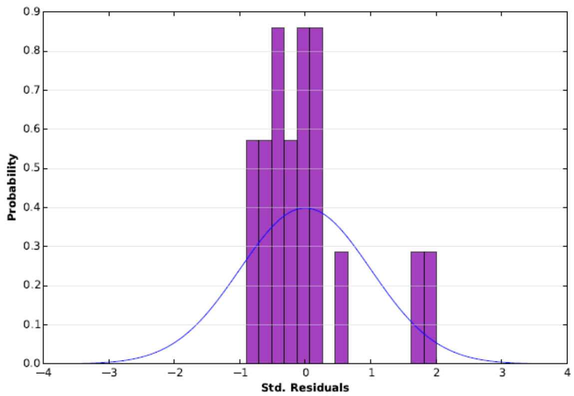
Hurricane Bret



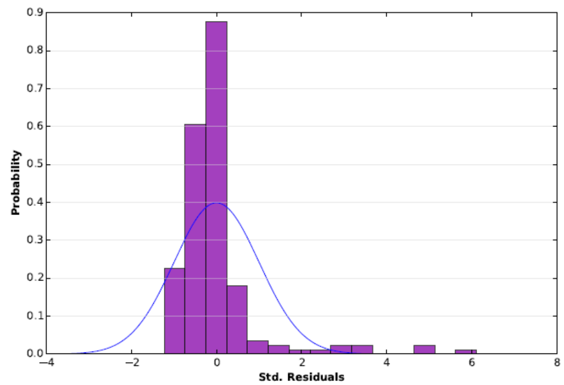
Hurricane Charley



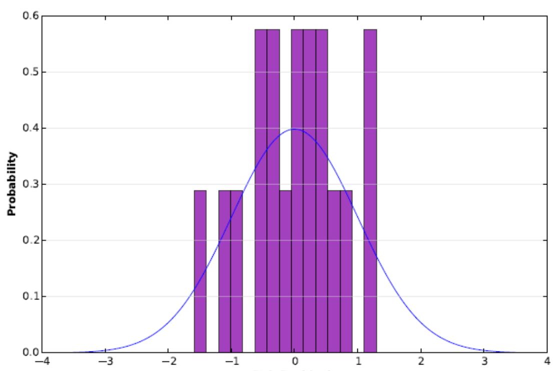
Hurricane Claudette



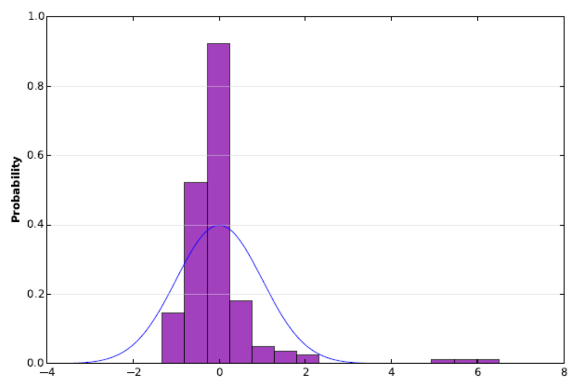
Hurricane Floyd



Hurricane Irene



Hurricane Isabel



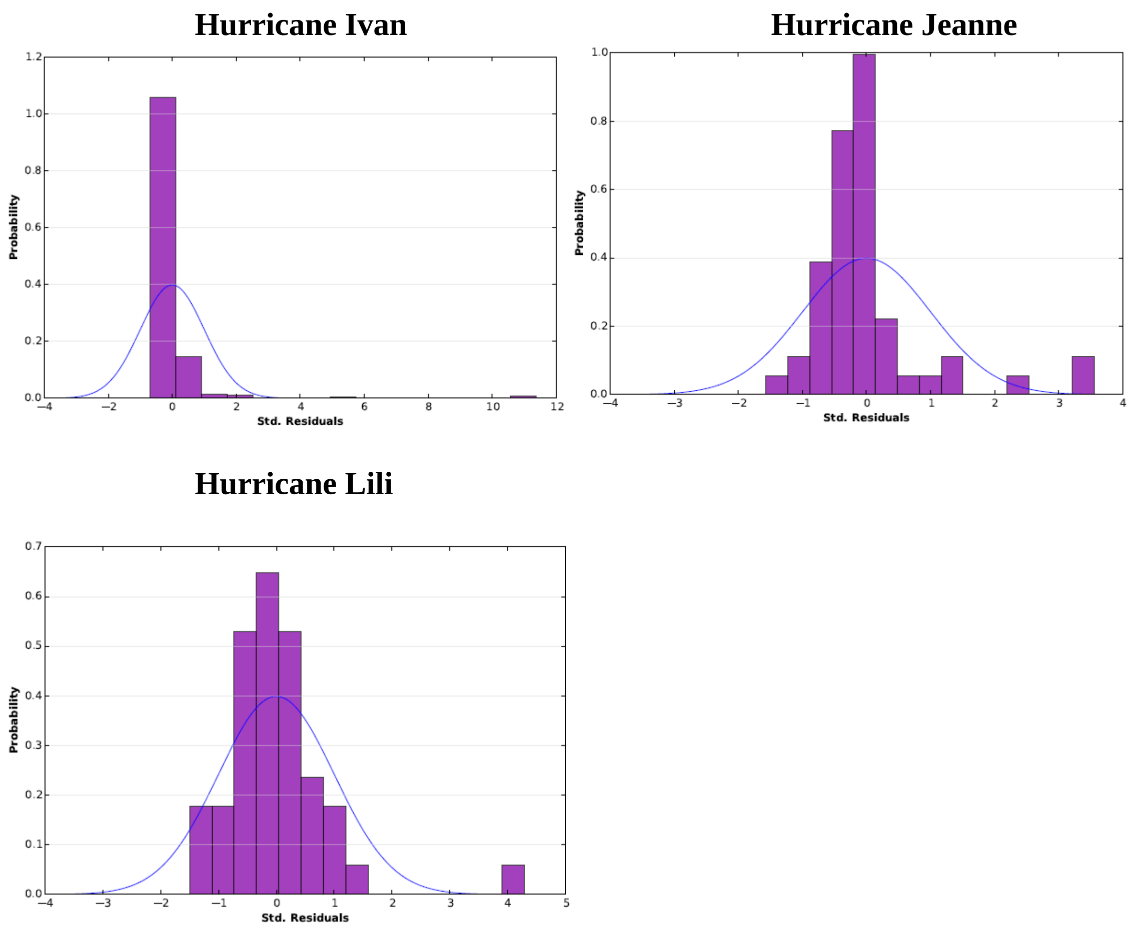
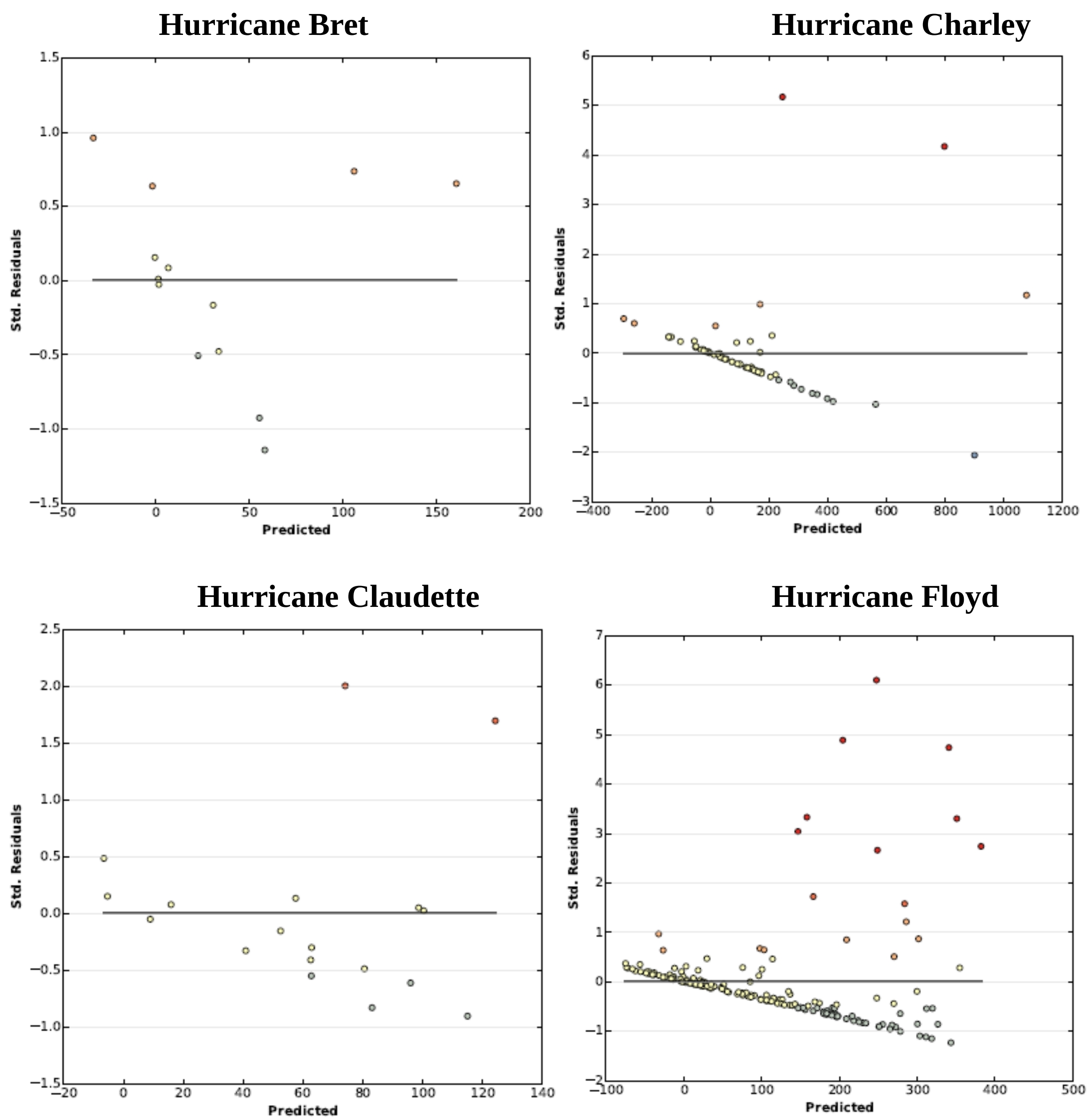
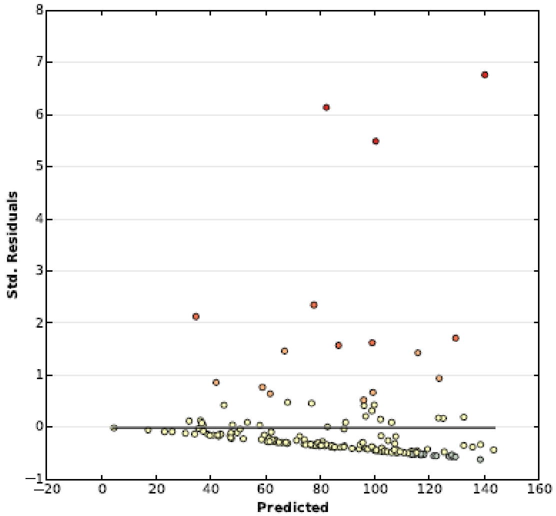


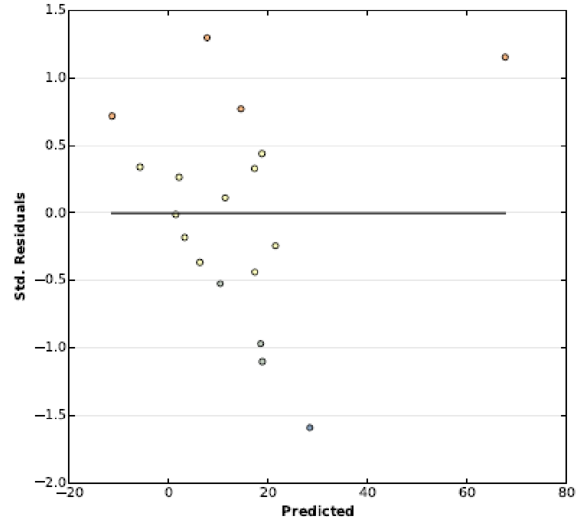
Figure 33: Histograms of Residuals for Regression Scenario 3


Hurricane Bret
Std. Residuals
Predicted
Hurricane Charley
Std. Residuals
Predicted
Hurricane Claudette
Std. Residuals
Predicted
Hurricane Floyd
Std. Residuals
Predicted

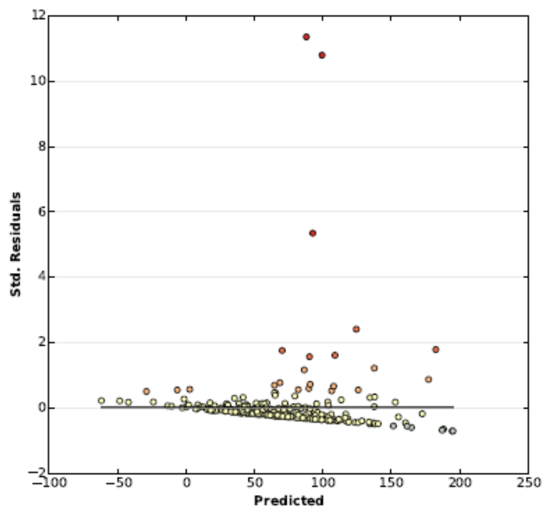
Hurricane Irene



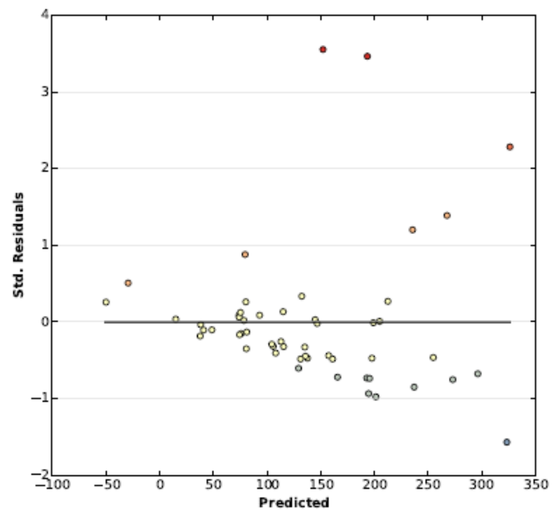
Hurricane Isabel



Hurricane Ivan



Hurricane Jeann



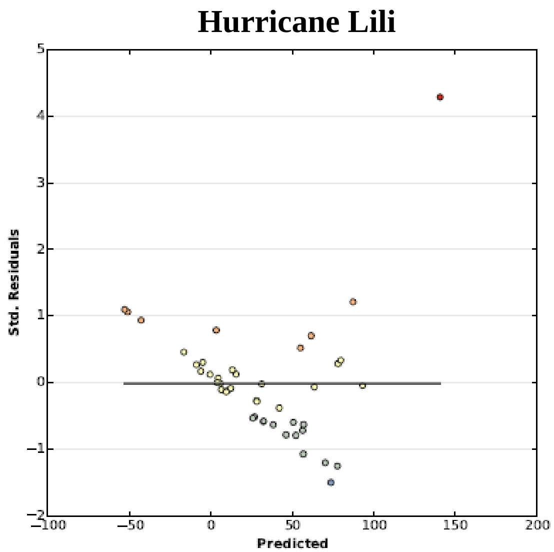


Figure 34: Scatterplots of Over/Under Predictions for Regression Scenario 3

Moran’s I statistics were run to examine the effects of spatial autocorrelation. Table 18 shows that 6 of 9 hurricanes had spatial autocorrelation. These results are contrary to the Koenker statistic that was insignificant for 7 of 9 hurricanes. A composite map of the OLS residuals displayed in figure 46 shows clustering is associated with the hurricane storm tracks and points of landfall. These findings are consistent with findings for regression scenarios 2-3.

Table 18: Regression Scenarios 3 – Spatial Autocorrelation (Moran's I) Statistics

Hurricane	Index	Expected	Variance	P-value	Z-score	Pattern
Bret	0.000275	-0.083333	0.033732	0.648945	0.455228	Random
Charley	0.138791	-0.014706	0.002819	2.890929	0.003841	Clustered
Claudette	0.206822	-0.058824	0.025406	1.666608	1.666608	Clustered
Floyd	0.303788	-0.005525	0.000692	11.75847	0.000000	Clustered
Irene	-0.03173	-0.058824	0.010339	0.266423	0.789913	Random
Isabel	0.109644	-0.006369	0.000131	10.11899	0.000000	Clustered
Ivan	0.304275	-0.003086	0.000284	18.23266	0.000000	Clustered
Jeanne	0.476162	-0.019231	0.008567	5.352211	0.000000	Clustered
Lili	0.060925	-0.023256	0.007428	0.976738	0.328699	Random

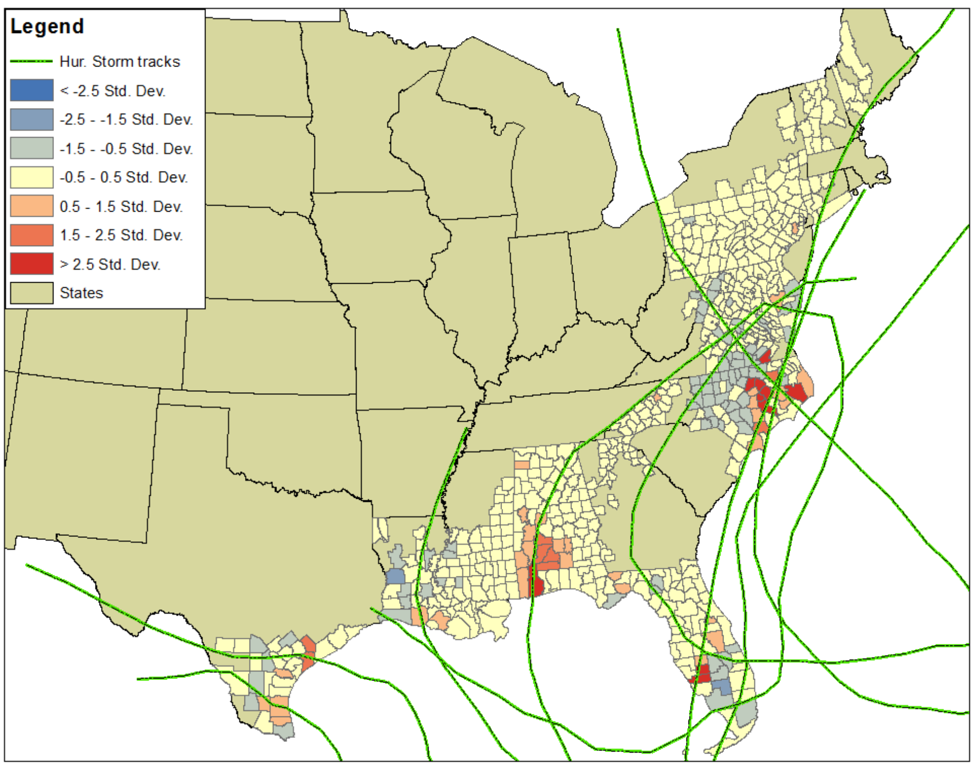


Figure 35: Map of OLS Residuals and Hurricane Storm Tracks – Regression Scenario 3

The results from OLS regression for scenario 3 also suggest model bias is a result of model mismatch or model mis-specification rather than data outliers. These results also suggest there is a problem with skewness in the data based on the scatterplots and spatial autocorrelation from the Global Moran's I statistics.

REGRESSION SCENARIO 4 –OLS REGRESSION USING THE SIX INDEPDENDENT VARIABLES

This model was run using the 6 independent (explanatory) variables from the FEMA impact models as depicted in figure 36. OLS models were run for all 9 hurricanes included in the research sample. This scenario examines the relationship between actual damages and impact model data to determine, if there is a statistical basis for indexing hazard vulnerability using a combination of these data rather than proxy measures of susceptibility used to compile SoVI. To validate the efficacy of this approach, it attempts to quantify the relationships between disaster operations practice and disaster management policy using disaster costs and disaster impact model data. A key question considered by regression scenario 4 is: if impact model variables have significant explanatory power for total amount of federal assistance per capita as an expression of actual damages, then could SoVI be refactored from these same variables to be a more effective measure of vulnerability? This approach would directly link hazard vulnerability across disaster operations policy and practice and provide a basis for establishing common variables across disaster management that could be used to improve the reliability of hazard vulnerability indexes. This OLS model was able to explain over 57% of the variance in SoVI for 6 of 9 hurricanes when applied in regression scenario 1. The question is will these 6 variables be able to produce similar results using the total amount of federal assistance per capita as the dependent variable?

Dependent Variable	Exploratory Regression Candidate Indepdendent (Explanatory) Variables	Independent Variables for OLS\GWR Model Runs
Total Federal Assistance Per Capita (TA_pcap)	HUNITS: Number of Housing Units in affected county tracks	
	POP2000: Total Population in affected county tracts	
	AREASQMI: Area of county	
	POPDEN00: Population 2000 Density	
	PERCAPINC: Per capita Income	
	PCTPOV: Percent Poverty	
	AVEDISTC: Average Distance to Coast	
	TREEVOL: Estimation of tree volume in tons	
	MAXSUSWIN: Sustained wind speed at the time of landfall	
	BLDGLOSS1K: Building loss as cost to re-build estimated number of structures damaged	
	CNTLOSS1K: Content/Interior damage estimated from number of structures damaged	**POPDEN00:**
	NUMBRIDGE: Number of Bridges in affected area	**PCTPOV:**
	ROADMI: Number of Roads miles in affected area	**AVEDISTC:**
	ERC_CNT: Count of affected Emergency Response Centers	**MAXSUSWIN:**
	FIRESTA_CT Count of affected Fire Stations	**BLDGLOSS1K**
	POLSTA_CT: Count of affected Police Stations	**NUMBRIDGE:**
	SCH_CT: Count of affected Schools	
	MEDFAC_CT: Count of affected Medical Facilities	
	ERC_PROB: Damage Probability to Emergency Response Centers	
	FIRE_PROB: Damage Probability to Fire Stations	
	POL_PROB: Damage Probability to Police Stations	
	SCH_PROB: Damage Probability to Schools	
	MED_PROB: Damage Probability to Medical Facilities	
	GRA_PROB: Damage Probability to Grade Schools	
	GOV_PROB: Damage Probability to Government Services	
	GOVE_PROB: Damage Probability to Government Emergency Services	
	NH_PROB: : Damage Probability to Nursing Homes	
	NONP_PROPB: : Damage Probability to Not for Profits	
	HOSP_PROB: : Damage Probability to Hospitals	

Figure 36: Regression Scenario 4 - Model Variables

Model diagnostics for regression scenario 4 are shown in table 19 below. These diagnostics indicate the model had low explanatory power for 8 of 9 hurricanes based on the adjusted R-squared values. The model was able to explain 63.45% of the variance for hurricane Charley. It was able to explain less than 10% of the variance for 3 of 9 hurricanes. These results are much lower than those from regression scenario 1, suggesting there are weak linkages between these variables and disaster management policy. The other model diagnostics were examined to determine the reliability of the adjusted R-squared values. The probabilities for the Koenker (BP) statistics were insignificant for 7 of 9 hurricanes indicating the data are stationary. For these 7 hurricanes, the probabilities were consulted from table 20 to determine if the model coefficients were statistically significant. For the other 2 hurricanes, the robust probabilities were consulted to determine if the model coefficients were significant. Results varied across hurricane run. Model coefficients for POPDEN00 and AVEDISTC were significant for only 1 hurricane. PCTPOV and NUMBRIDGE had significant model coefficients for 2 hurricanes. BLDGLOSS1K had significant model coefficients for 3 hurricanes; while MAXSUSWIN had significant model coefficients for 4 hurricanes. The variables representing hurricane intensity and damage to critical facilities were significant in the most hurricanes. The Jarque-Bera probabilities were significant for 6 of 9 hurricanes. This indicates there are problems with model bias, as the residuals are not normally distributed. This is confirmed by the histograms depicted in figure 38.

Scatterplots from figure 37 shows that the relationships between the dependent and independent variables are linear. The types of relationships were mixed for some of the variables and contradict current hazard vulnerability science. For example, figure 37 shows that POPDEN00 has a negative linear relationship; when the dependent variable is high, POPDEN00 is low. PCTPOV, AVEDISTC, and MAXSUSWIN also exhibited negative linear relationships for several of the hurricanes. BLDGLOSS1K had a positive linear relationship for 8 of 9 hurricanes, and NUMBRIDGE had a negative linear relationship for 8 of 9 hurricanes. The type of relationship for BLDGLOSS1K is expected but not for NUMBRIDGE. These results suggest the model is mis-specified. The scatterplots of the over and under predictions of residuals shown in figure 39 substantiate this determination. The scatterplots from figure 39 indicate a systematic scale issue and show that residuals are not randomly distributed. This indicates the model indeed is not properly specified or that an external influence had not been accounted for in the model design. It might also mean variable relationships are non-linear.

Table 19: Regression Scenarios 4 - OLS Model Diagnostics

Hurricane	Multiple R-Squared [d]	Adjusted R-Squared [d]	Joint F-Statistic [e]	Joint F-Statistic Probability	Joint Wald Statistic [e]	Joint Wald Probability	Koenker (BP) Statistic [f]	Koenker (BP) Probability	Jarque-Bera Statistic [g]	Jarque-Bera Probability	Akaike's Information Criterion (AICc) [d]
Bret	0.718711	0.437421	2.555058	0.139224	13.51992	0.035484*	6.882315	0.331868	0.665478	0.716957	176.76731
Charley	0.712898	0.634597	9.104626	0.000046*	214.6438	0.000000*	12.250175	0.056615	8.397654	0.015013*	447.29988
Claudette	0.381908	0.044767	1.132783	0.404808	11.54688	0.072875	6.275699	0.393025	5.912837	0.052005	230.79853
Floyd	0.097917	0.070302	3.545812	0.002349*	19.6831	0.003153*	9.282536	0.158301	3331.5419	0.000000*	2861.263
Irene	0.562145	0.323316	2.353749	0.103727	15.09174	0.019555*	11.519109	0.073598	0.252104	0.881569	177.28128
Isabel	0.18542	0.153052	5.72859	0.000022*	22.64386	0.000925*	10.603784	0.101421	7165.6886	0.000000*	2132.712
Ivan	0.371064	0.357823	28.02438	0.000000*	34.47197	0.000005*	20.965804	0.001861*	133715.78	0.000000*	4023.0754
Jeanne	0.326322	0.238451	3.713649	0.004295*	25.96647	0.000226*	15.529667	0.016514*	92.837968	0.000000*	713.90471
Lili	0.224036	0.098205	1.780442	0.130105	60.86973	0.000000*	2.103655	0.909923	1063.348	0.000000*	492.07497

*** Significant level at p = 0.05.**

Table 20: Regression Scenarios 4 - OLS Model Results

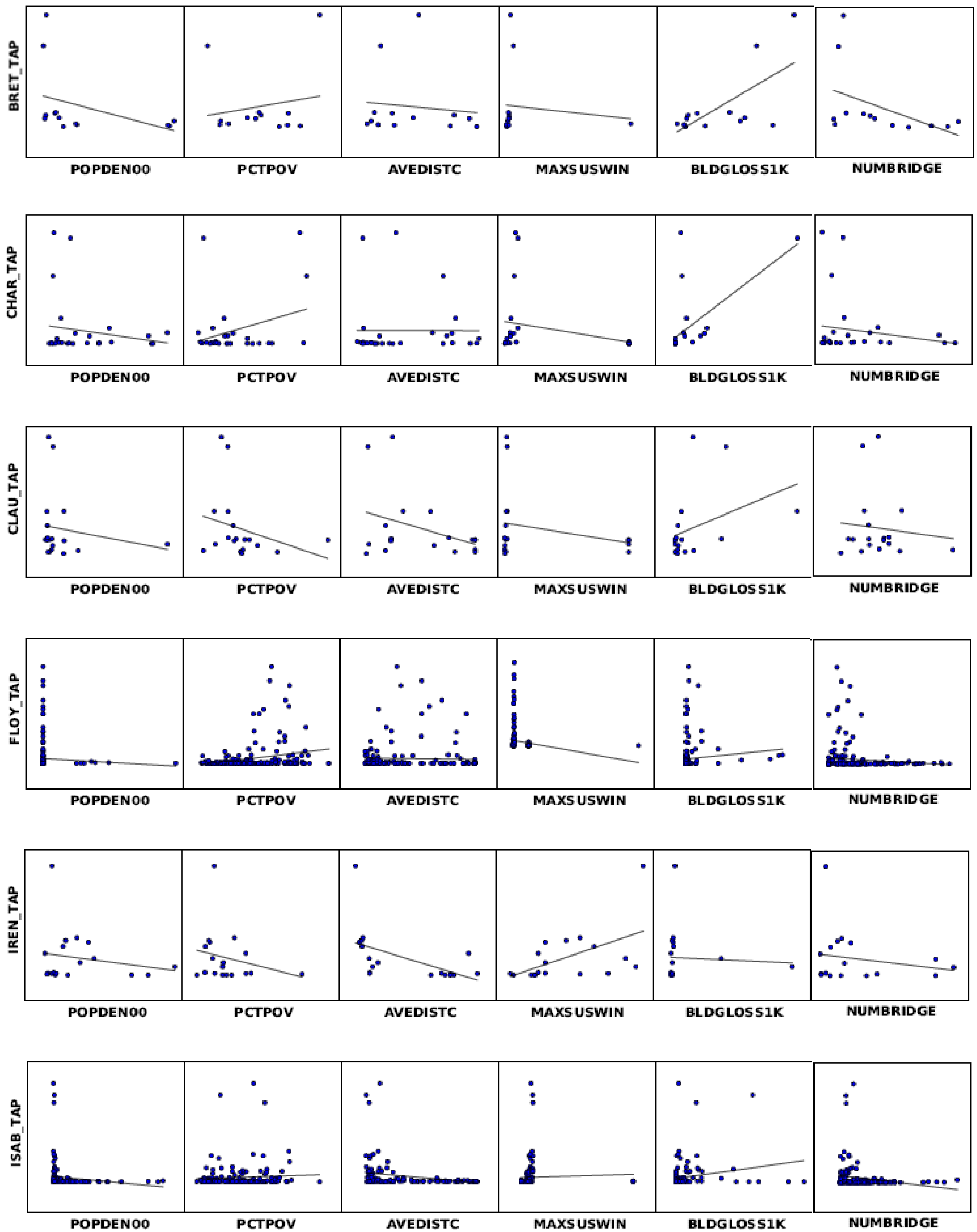
	Model Coefficients								
Independent Variable	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
POPDEN00:	-0.169416	0.199805	-0.18772	-0.000094	0.002421	-0.039102	0.000059	-0.013242	-0.067539
PCTPOV:	12.644482	8412.269943	-328.12532	1273.464874	-114.83103	404.920367	349.035795	423.306072	162.177375
AVEDISTC:	0.14885	-5.935837	-0.730191	-0.388654	-0.020655	-1.805775	-0.437821	-0.505849	-0.706828
MAXSUSWIN:	0.024781	-0.503677	0.011483	-0.059964	1.407761	-0.064575	-0.074523	-0.141433	-0.008643
BLDGLOSS1K	0.004691	0.000182	0.002779	0.000076	-0.000003	0.000346	0.000311	0.000031	0.000022
NUMBRIDGE:	-0.046161	-0.956201	-0.25616	-0.049658	-0.042378	-0.212317	-0.195738	-0.413325	0.075673

	Model Probabilities								
Independent Variable	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
POPDEN00:	0.532206	0.625208	0.353913	0.542141	0.899076	0.002092*	0.597207	0.837232	0.083562
PCTPOV:	0.955273	0.000378*	0.471171	0.000758*	0.497878	0.173025	0.125641	0.506317	0.377184
AVEDISTC:	0.789959	0.094514	0.329334	0.467336	0.941003	0.000249*	0.32402	0.647671	0.026913*
MAXSUSWIN:	0.751165	0.017870*	0.855899	0.033715*	0.053381	0.612935	0.111775	0.081185	0.817984
BLDGLOSS1K	0.038455*	0.000034*	0.334913	0.455397	0.470032	0.059763	0.000000*	0.000218*	0.080372
NUMBRIDGE:	0.886025	0.177379	0.331888	0.715497	0.26277	0.344648	0.08081	0.05673	0.344421

	Model Robust Probabilities								
Independent Variable	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
POPDEN00:	0.466301	0.38159	0.122727	0.102117	0.865208	0.001519*	0.302015	0.40923	0.014286*
PCTPOV:	0.952869	0.014504*	0.241107	0.000669*	0.380394	0.156213	0.144727	0.195671	0.075426
AVEDISTC:	0.660213	0.090997	0.193359	0.266395	0.921908	0.000187*	0.517367	0.587015	0.022499*
MAXSUSWIN:	0.618265	0.026027*	0.723466	0.06897	0.117232	0.137813	0.000163*	0.000064*	0.672183
BLDGLOSS1K	0.054716	0.000000*	0.125452	0.136099	0.333246	0.364391	0.012191*	0.064324	0.000952*
NUMBRIDGE:	0.839677	0.055046	0.129626	0.425124	0.202482	0.089912	0.028920*	0.013891*	0.179462

	Model Variance Inflation Factors (VIF)								
Independent Variable	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
POPDEN00:	8.914447	2.546206	2.187917	1.26932	2.807564	1.133472	1.385762	1.683228	1.507882
PCTPOV:	1.730067	1.590533	2.705854	1.14749	2.225361	1.059329	1.256976	1.560114	1.227641
AVEDISTC:	2.246167	1.284819	2.06197	1.244665	3.437236	1.462683	1.183625	1.547705	1.564522
MAXSUSWIN:	2.373553	1.281939	2.018525	1.067006	3.29992	1.116614	1.214682	1.202655	1.05646
BLDGLOSS1K	1.951325	1.155562	1.296542	1.061165	3.44602	1.196571	1.078852	1.299882	1.086706
NUMBRIDGE:	9.507743	2.130976	1.667509	1.367457	2.652962	1.167186	1.434354	1.873098	1.413117

*** Significant level at p = 0.05.**


BRET_TAP
CHAR_TAP
CLAU_TAP
FLOY_TAP
IREN_TAP
ISAB_TAP
POPDEN00
PCTPOV
AVEDISTC
MAXSUSWIN
BLDGLOSS1K
NUMBRIDGE

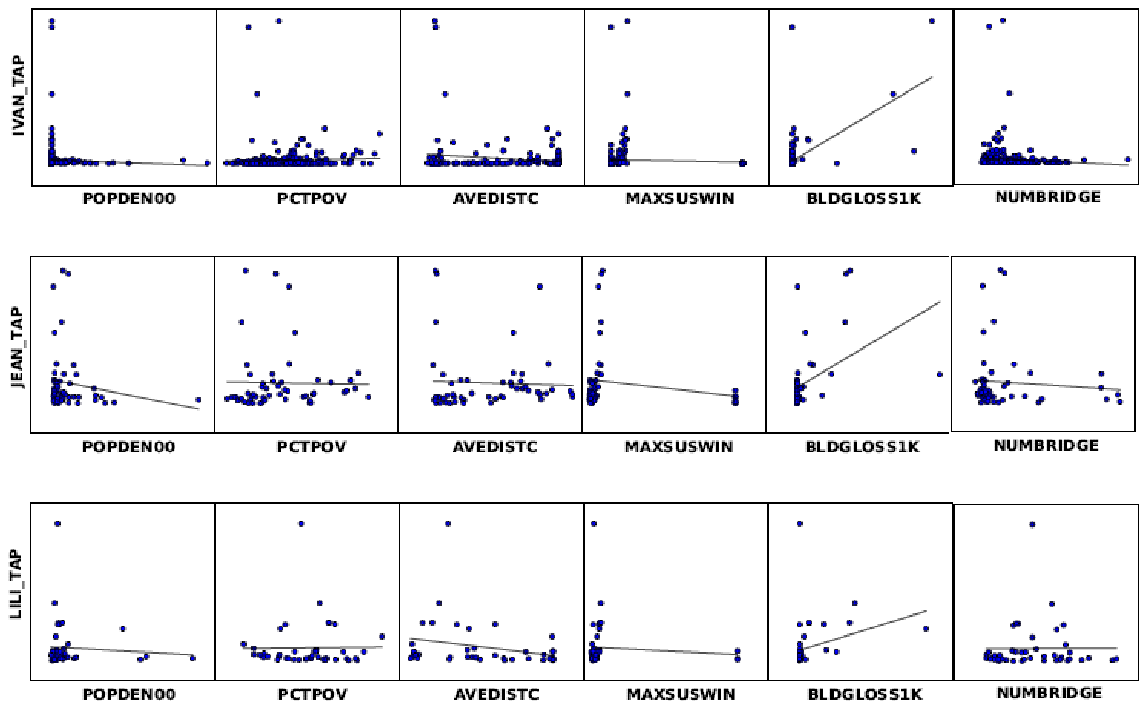
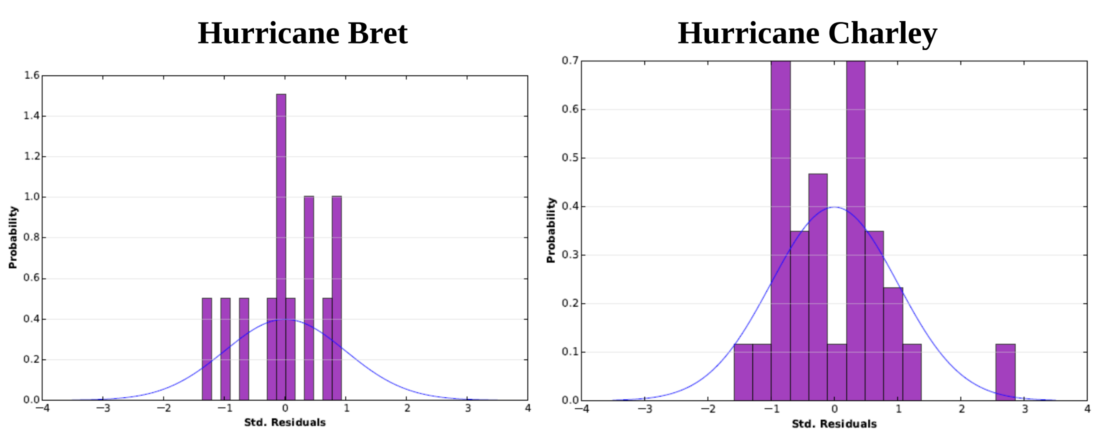
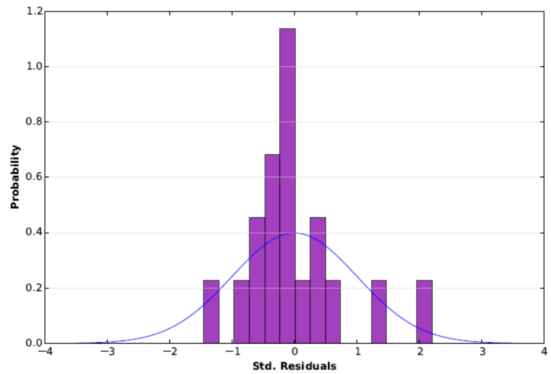


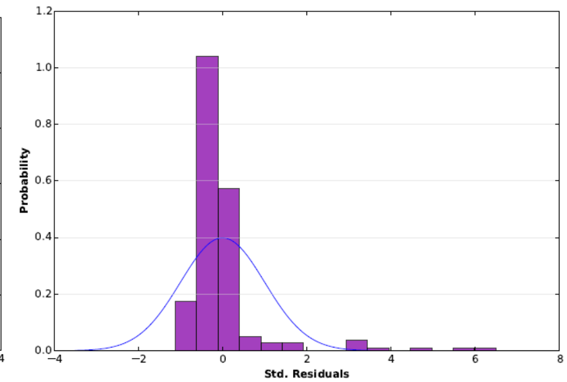
Figure 37: Scatterplots of Variable Relationships for Regression Scenario 4



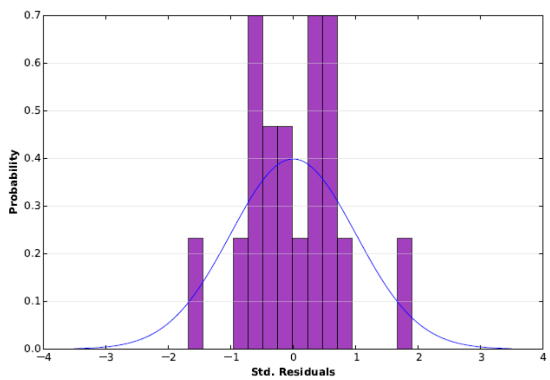
Hurricane Claudette



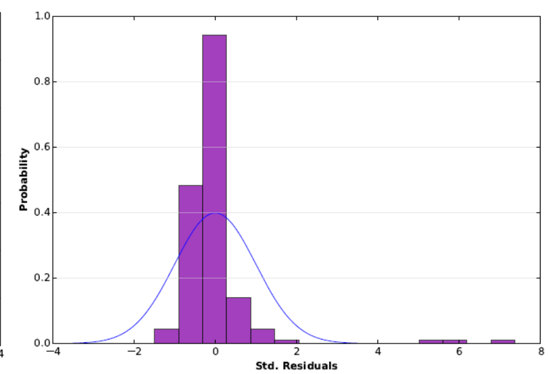
Hurricane Floyd



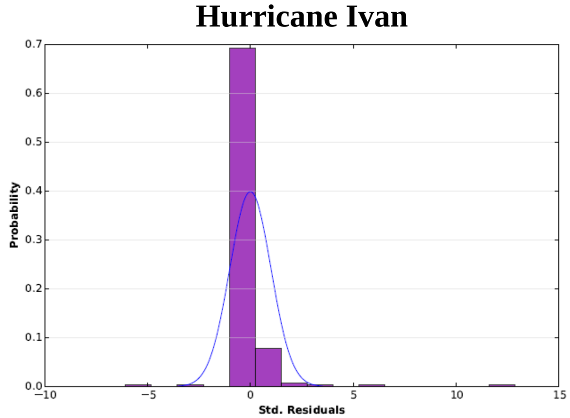
Hurricane Irene



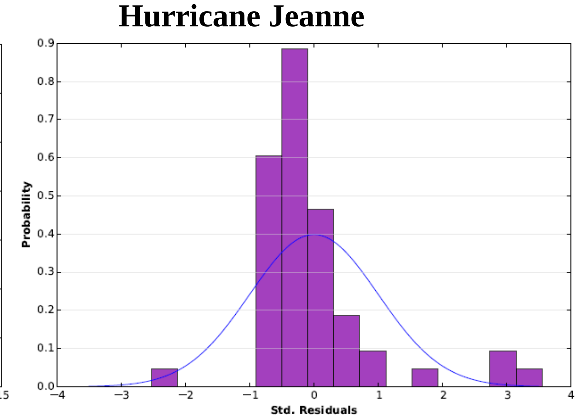
Hurricane Isabel



Hurricane Ivan



Hurricane Jeanne



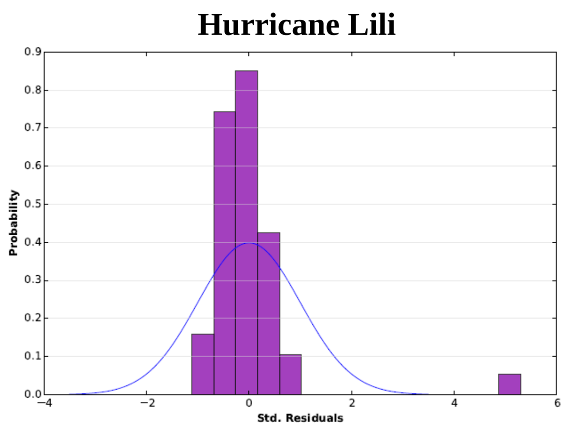
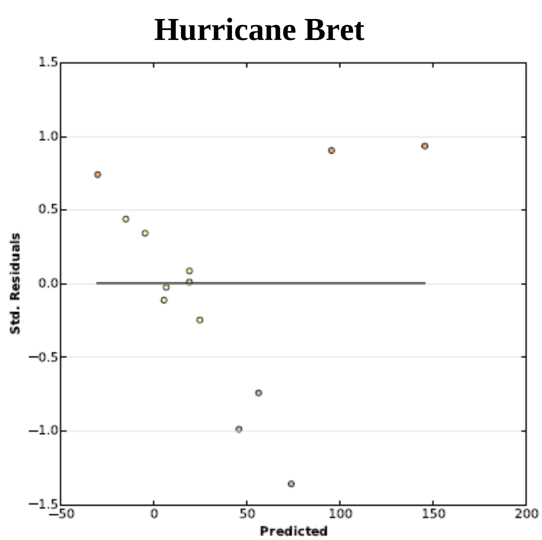
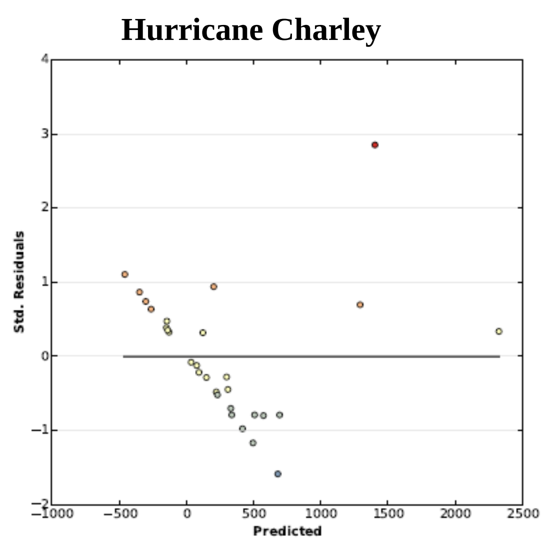
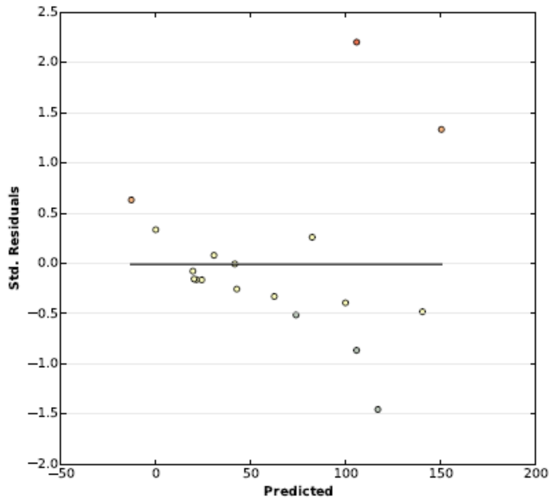


Figure 38: Histograms of Residuals for Regression Scenario 4

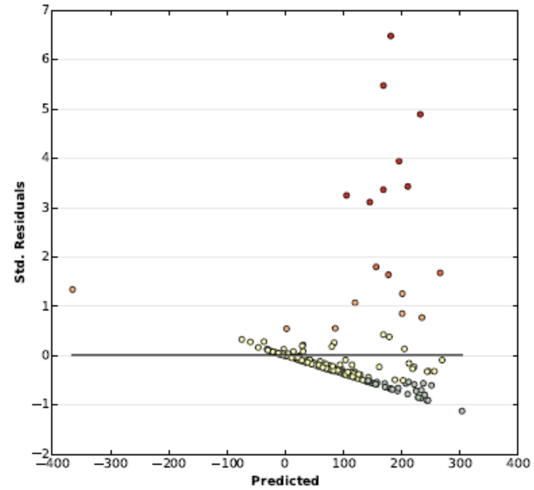




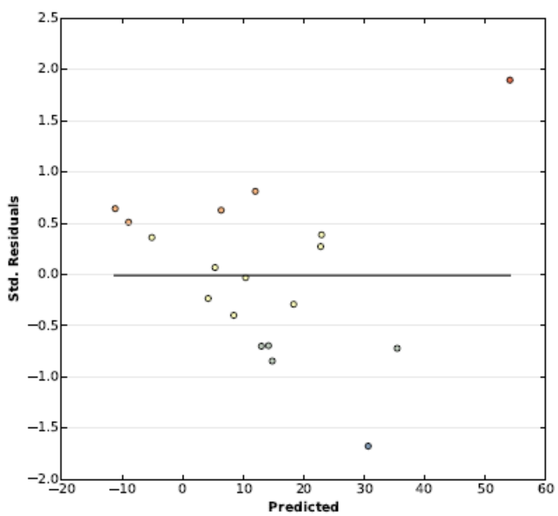
Hurricane Claudette



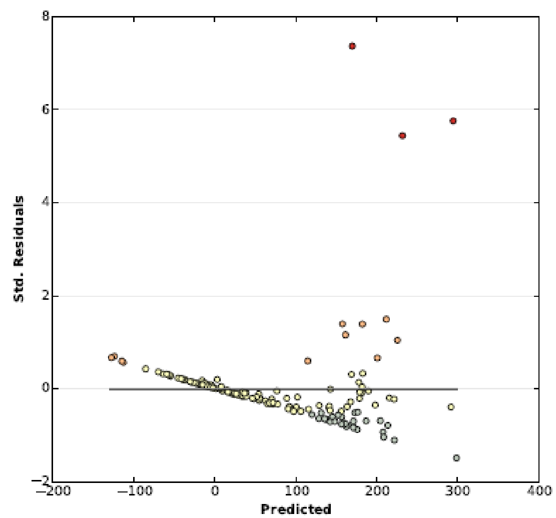
Hurricane Floyd



Hurricane Irene



Hurricane Isabel



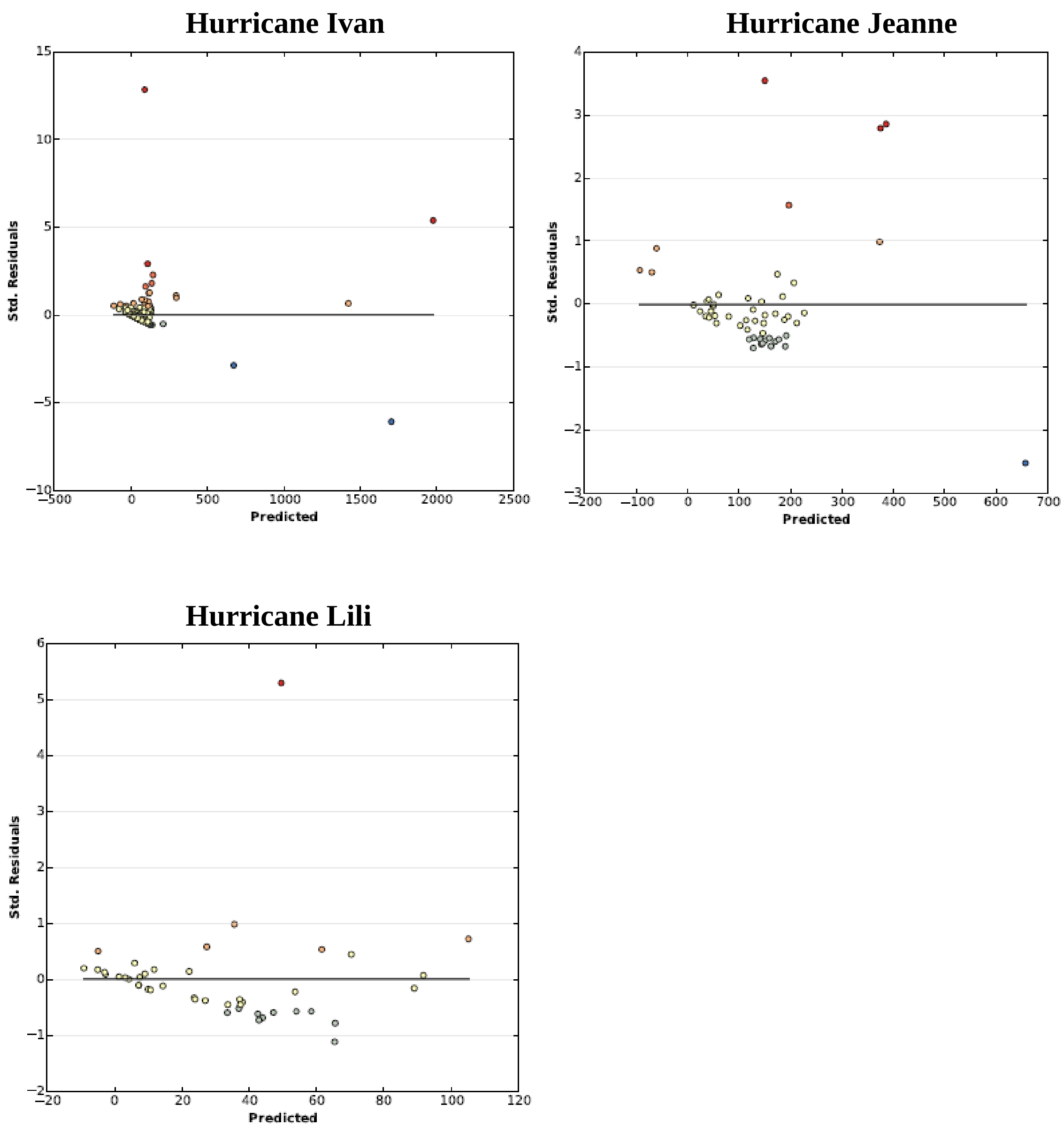


Figure 39: Scatterplots of Over/Under Predictions for Regression Scenario 4

Moran's I statistics were computed using the residuals from the OLS model to examine the effects of spatial autocorrelation. Table 21 shows that 5 of 9 hurricanes had spatial autocorrelation. These results are contrary to the Koenker statistics for hurricanes

Floyd, Isabel, and Lili. A composite map of the OLS residuals displayed in figure 40 shows clustering is associated with the hurricane storm tracks and points of landfall, findings consistent with regression scenarios 2-3.

Table 21: Regression Scenario 4 – Spatial Autocorrelation (Moran's I) Statistics

Hurricane	Index	Expected	Variance	P-value	Z-score	Pattern
Bret	-0.18406	-0.08333	0.03302	0.57933	-0.55436	Random
Charley	-0.08521	-0.03571	0.00645	0.53754	-0.61653	Random
Claudette	-0.09083	-0.05882	0.02521	0.84028	-0.20154	Random
Floyd	0.26961	-0.00495	0.00051	0.00000	12.17089	Clustered
Irene	-0.08752	-0.05882	0.00980	0.77188	-0.28992	Random
Isabel	0.09554	-0.00637	0.00058	0.00002	4.24298	Clustered
Ivan	0.16302	-0.00344	0.00030	0.00000	9.54322	Clustered
Jeanne	0.35236	-0.01923	0.00870	0.00007	3.98417	Clustered
Lili	0.10991	-0.02326	0.00440	0.04476	2.00686	Clustered

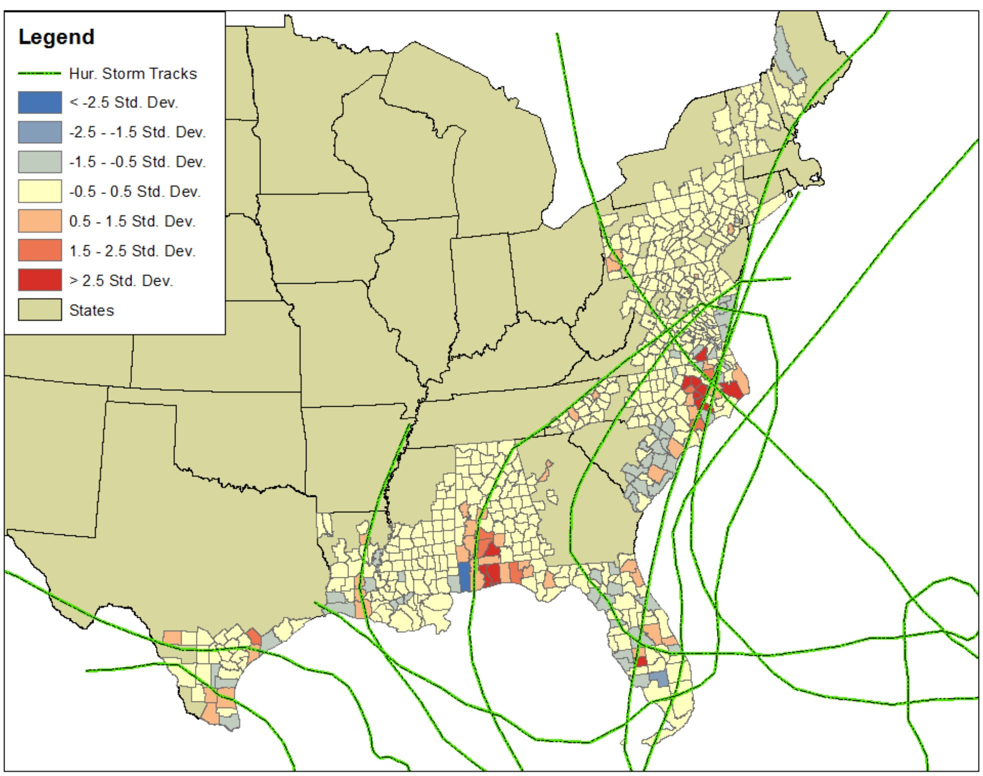


Figure 40: Map of OLS Residuals & Hurricane Storm Tracks Regression Scenario 4

The OLS regressions for this chapter suffered from three fundamental issues that introduced bias into the OLS models: skewness in the data, model misspecification, and spatial autocorrelation. The next two chapters are devoted to resolving these issues to produce more meaningful results.

CHAPTER 7: ADDRESSING MODEL BIAS IN THE OLS REGRESSION

LOG TRANSFORMATIONS OF MODEL VARIABLES

This chapter seeks to resolve the skewness issue affecting the OLS regression models by applying log transformations to the model variables. Logarithmic transformations will have the effect of compressing the high values of the transformed variables, and expanding the low end values; thereby, linearizing the relationship between the variables. To determine the effectiveness of the log transformations, the descriptive statistics were consulted including the mean, median, skewness, and kurtosis parameters. The **Skewness** measure indicates the level of non-symmetry; if the distribution of the data is symmetric then skewness will be close to 0. **Kurtosis** is a measure of the peakedness of the data; for normally distributed data the kurtosis is 0. The Jarque-Bera statistics were used as the goodness-of-fit test to determine whether the transformed data have skewness and kurtosis matching a normal distribution. The Akaike's Information Criteria (AICc) was used to assess the quality of the OLS model. AICc is a measure of the relative quality of the statistical models for a given set of data and provides a relative estimate of the information lost when a given model is used to represent the dependent variable. Low AICc scores indicate little data is lost.

Log transformations were performed on the following 6 variables: TA_PCAP (total federal assistance per capita), POPDENN00 (population density 2000), AVEDISTC (average distance to coast), MAXSUSWIN (maximum sustained wind speeds), BLDGLOSS1K (building loss in thousands of dollars), and NUMBRIDGE (number of bridges). Histograms of these log transformations as well as the descriptive statistics are provided in the appendix.

The OLS models for regression scenarios 2-4 were re-run using the log variables. Table 22-24 shows a comparison of the Jarque-Bera statistics and Akaike's Information Criteria (AICc) scores for regression scenarios 2-4 as well as the adjusted R-squares for each OLS model run. The model diagnostics for each regression scenario were updated and interpreted as follows. Log transformation had positive effects on the OLS regression models. First, the log transformations were able to resolve a majority of the skewness issues experienced with the initial OLS models. For regression scenario 2, depicted in Table 22, 8 of 9 hurricanes had issues with skewness in the data based on the Jarque-Bera test of normality prior to the log transformation. After the log transformations, 8 of 9 hurricanes had insignificant Jarque-Bera statistics indicating the data was normally distributed for all but hurricane Jeanne. The AICc scores also showed significant improvement indicating the OLS models using the log transformations are better specified.

Table 22: Regression Scenario 2 – Model Diagnostics using Log Transforms

Hurricane	Multiple R-Squared	Adjusted R-Squared	Jarque-Bera Statistic	Jarque-Bera Probability	Jarque-Bera Probability after Log transform	Akaike's Information Criterion (AICc)	AICc after Log transform
Bret	0.460711	0.411685	0.303774	0.635125	0.859085	142.386169	49.096068
Charley	0.006365	-0.008465	5.314557	0.000000*	0.070139	1045.28583	319.91205
Claudette	0.005001	-0.057186	0.306689	0.001242*	0.857834	214.717872	62.08617
Floyd	0.049851	0.044573	3.495747	0.000000*	0.174144	2583.79078	812.84168
Irene	0.034394	-0.025957	1.19597	0.000000*	0.549919	167.847711	87.945829
Isabel	0.000833	-0.005572	3.431808	0.000000*	0.179801	2160.23395	679.8851
Ivan	0.004155	0.001072	0.921261	0.000000*	0.630886	4582.99211	1434.6158
Jeanne	0.10119	0.083566	17.733077	0.000000*	0.000141*	718.726391	204.08667
Lili	0.03614	0.013191	0.064575	0.000000*	0.968228	489.7047	171.028079

*** Significant level at p = 0.05.**

For regression scenario 3, depicted in Table 23, 7 of 9 hurricanes had issues with skewness in the data based on the Jarque-Bera test of normality prior to the log transformation. After the log transformations, all 9 hurricanes had insignificant Jarque-Bera statistics after the log transformations, indicating the data was normally distributed. The AICc scores also showed significant improvement indicating the OLS models using the log transformations are better specified.

Table 23: Regression Scenario 3 – Model Diagnostics using Log Transforms

Hurricane	Multiple R-Squared	Adjusted R-Squared	Jarque-Bera Probability	Jarque-Bera Probability after Log transform	Akaike's Information Criterion (AICc)	AICc after Log transform
Bret	0.878039	0.707294	0.635125	0.599275	197.574814	99.104237
Charley	0.308227	0.228843	0.000000*	0.407183	1044.770559	309.6079
Claudette	0.410446	-0.002242	0.012291*	0.89722	242.843238	85.451124
Floyd	0.153525	0.119472	0.000000*	0.525137	2575.688267	804.72538
Irene	0.442073	0.051525	0.847012	0.564294	182.989604	110.85803
Isabel	0.203745	0.166586	0.000000*	0.713352	2155.439167	657.07912
Ivan	0.050723	0.029761	0.000000*	0.504556	4588.99382	1431.5481
Jeanne	0.210822	0.088061	0.000000*	0.07555	728.626731	212.88866
Lili	0.561286	0.475981	0.000000*	0.125499	480.636957	153.08985

*** Significant level at p = 0.05.**

For regression scenario 4, depicted in Table 24, 6 of 9 hurricanes had issues with skewness in the data based on the Jarque-Bera test of normality prior to the log transformation. After the log transformations, 6 of 9 hurricanes had insignificant Jarque-Bera statistics after the log transformations, indicating the data was normally distributed. The AICc scores also showed significant improvement indicating the OLS models using the log transformations are better specified. Even the 3 hurricanes with significant Jarque-Bera statistics (Ivan, Jeanne, and Lili) showed significant improvement in their AICc scores after the log transformation also indicating improvement in the model fit.

Table 24: Regression Scenario 4 – Model Diagnostics using Log Transforms

Hurricane	Multiple R-Squared	Adjusted R-Squared	Jarque-Bera Statistic	Jarque-Bera Probability	Jarque-Bera Probability after Log transform	Akaike's Information Criterion (AICc)	AICc after Log transform
Bret	0.833526	0.667051	0.814979	0.716957	0.665318	176.76731	77.14907
Charley	0.812877	0.761843	0.334743	0.015013*	0.845885	447.29988	99.02725
Claudette	0.51137	0.244844	3.485527	0.052005	0.175036	230.79853	226.568
Floyd	0.352909	0.3331	0.591506	0.000000*	0.743971	2861.263	839.3799
Irene	0.785095	0.667874	0.096468	0.881569	0.952911	177.28128	85.18548
Isabel	0.639705	0.625388	8.058707	0.000000*	0.017786*	2132.712	533.5655
Ivan	0.367562	0.354247	15.779169	0.000000*	0.000375*	4023.0754	1162.85
Jeanne	0.635223	0.587643	14.442282	0.000000*	0.000731*	713.90471	169.0749
Lili	0.430938	0.338657	3.924639	0.000000*	0.140532	492.07497	161.3563

*** Significant level at p = 0.05.**

Generally, the log transformations had little effect on the adjusted R-squared values for the updated regression models. SoVI still performs poorly in explaining the dependent variable, total federal assistance per capita (regression scenarios 2-3) using OLS regression. The FEMA impact model data (regression scenario 4) performs markedly better in explaining the dependent variable. Those OLS models were able to explain over 50% of the variance for 6 of 9 hurricanes and between 35-43% of the variance for the remaining 3 hurricanes. SoVI, on the other hand, was only able to explain a substantial amount of the variance for hurricane Bret, and the SoVI factors (regression scenario 3) didn't perform much better explaining considerable variance for only 2 hurricanes (Bret and Lili).

ADDING MISSING INDEPENDENT VARIABLES

The OLS regressions for scenarios 2-3 indicated model-misspecification due to key explanatory variables missing. The results from the comparative analysis in chapter 3 also indicated SoVI was missing variables for the geophysical properties of the hazard. To address this issue, variables for AVEDISTC and MAXSUSTWIN were combined with SoVI for regression scenario 5. Figure 41 provides an illustration of the regression model.

Dependent Variable	Independent (Explanatory) Variables
Total Federal Assistance Per Capita (TA_pcap)	SOVI score
	AVEDISTC:
	MAXSUSWIN:

Figure 41: Regression Scenario 5 - Model Variables

OLS models were run for all 9 hurricanes included in the research sample. Table 25 shows the diagnostics for the OLS regression model runs for each hurricane. Table 26 shows the results for those same OLS model runs. The model diagnostics for the OLS regression model runs indicate some measure of improvement with the additional geophysical variables; however, the model still performed poorly for 5 of 9 hurricanes. The AIC scores still varied widely across hurricanes from 50.971792 to 1429.1043 suggesting the independent variables are not reliable predictors of the phenomena. The adjusted R-squared values show the model was able to explain less than 13% of the variance for 5 of 9 hurricanes. Four model runs were able to demonstrate significant explanatory power (hurricanes Bret, Charley, Irene, and Isabel), SoVI was able to explain more than 39.8% of the variance. To determine the reliability of the adjusted R-squared values, the other model diagnostics and results were examined.

Scatterplots of the variables relationships in figure 42 suggest that while the log transformations improved the models, these transformations had limited effect in linearizing the variables. The Jarque-Bera statistic was significant for only hurricane Jeanne indicating the residuals are normally distributed. This interpretation was confirmed by the histograms depicted in figure 43. The scatterplots of the over and under predictions of residuals portrayed in figure 44 also show randomly distributed patterns indicating good model specification.

The Koenker (BP) statistic was significant for 4 hurricanes (Charley, Isabel, Ivan and Jeanne) and insignificant for the remaining 5 hurricanes. This suggests the data for hurricanes Charley, Isabel, Ivan and Jeanne are non-stationary, and the robust probabilities were consulted to determine coefficient significance. The all coefficients for hurricane Isabel were significant based on the robust probabilities. Significant coefficients varied for the remaining 8 hurricanes. Hurricanes Claudeette and Ivan had no significant coefficients. The variables relationships depicted in the scatterplots from figure 42 are dubious as results are inconsistent across the 9 hurricanes.

Table 25: Regression Scenarios 5 - OLS Model Diagnostics

Hurricane	Multiple R-Squared	Adjusted R-Squared	Joint F-Statistic	Joint F-Statistic Probability	Joint Wald Statistic	Joint Wald Probability	Koenker (BP) Statistic	Koenker (BP) Probability	Jarque-Bera Statistic	Jarque-Bera Probability	Akaike's Information Criterion (AICc)
Bret	0.709201	0.612268	7.316393	0.008705*	38.20263	0.000000*	0.850643	0.837319	0.243416	0.885407	50.971792
Charley	0.424543	0.397984	15.98459	0.000000*	44.32056	0.000000*	10.932933	0.012094*	1.924249	0.38208	286.806974
Claudette	0.022418	-0.187064	0.022418	0.9546	0.613896	0.893244	7.301925	0.062872	0.172165	0.917518	69.05402
Floyd	0.064219	0.048447	4.071808	0.007924*	13.29606	0.004038*	6.708372	0.081797	3.769291	0.151883	814.274652
Irene	0.760445	0.709112	14.8139	0.000126*	57.55005	0.000000*	1.591069	0.661417	0.542779	0.76232	70.140026
Isabel	0.449037	0.438304	41.83687	0.000000*	138.6425	0.000000*	16.698923	0.000815*	2.260761	0.32291	590.073759
Ivan	0.033215	0.024179	3.676071	0.012509*	10.20795	0.016879*	10.937571	0.012068*	1.004799	0.605077	1429.1043
Jeanne	0.183987	0.134027	3.682687	0.018046*	17.96033	0.000448*	8.248262	0.041150*	27.490687	0.000001*	203.751457
Lili	0.140414	0.075945	2.178013	0.105634	9.117218	0.027772*	3.541809	0.31538	0.003536	0.998234	170.969214

*** Significant level at p = 0.05.**

Table 26: Regression Scenarios 5 - OLS Model Results

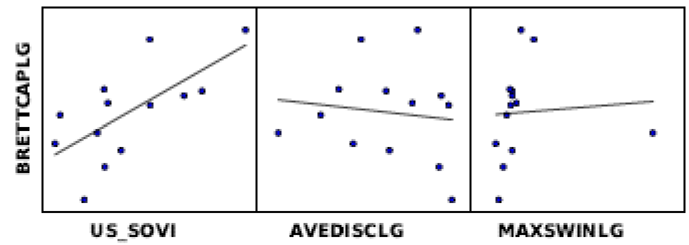
	Model Coefficients								
Independent Variable	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
SoVI:	0.649582	0.05465	-0.009117	0.215138	0.512772	0.089231	0.042695	0.248105	-0.052928
AVEDISTC:	-0.98998	0.669204	-0.062638	-0.104114	-1.379715	-0.764183	0.147966	0.156971	-0.660379
MAXSUSWIN:	-0.711665	0.182995	-0.10497	-0.069511	1.117839	0.464471	0.096403	-0.441259	0.324228

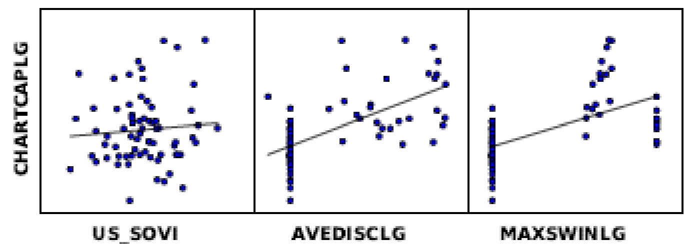
	Model Probabilities								
Independent Variable	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
SoVI:	0.001258*	0.616812	0.943055	0.001227*	0.006416*	0.045860*	0.454584	0.025318*	0.690334
AVEDISTC:	0.023076*	0.008263*	0.836887	0.39347	0.000488*	0.000000*	0.072052	0.46175	0.040133*
MAXSUSWIN:	0.19251	0.191044	0.661533	0.28771	0.666189	0.000000*	0.05235	0.042243*	0.361363

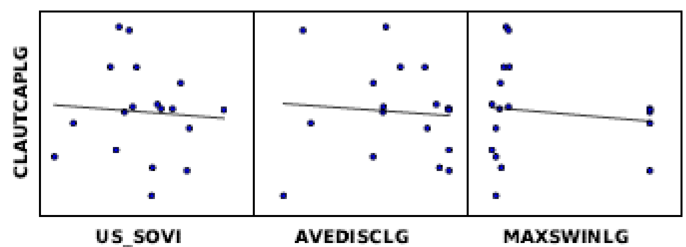
	Model Robust Probabilities								
Independent Variable	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
SoVI:	0.000394*	0.618939	0.940717	0.000775*	0.001408*	0.032582*	0.39541	0.001005*	0.643623
AVEDISTC:	0.004516*	0.026502*	0.880856	0.378696	0.000048*	0.000000*	0.07875	0.539719	0.014828*
MAXSUSWIN:	0.021746*	0.276939	0.460464	0.229339	0.604263	0.000000*	0.073799	0.016273*	0.358716

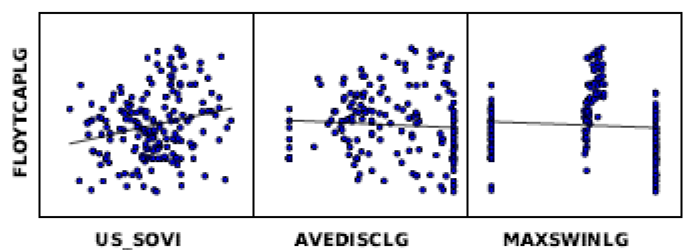
	Model Variance Inflation Factors (VIF)								
Independent Variable	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
SoVI:	1.287732	1.010332	1.304326	1.022274	1.112316	1.023593	1.024313	1.080767	1.296839
AVEDISTC:	2.020382	3.140456	1.283182	1.12556	2.001102	1.058808	1.081743	1.076117	1.292116
MAXSUSWIN:	1.715992	3.127213	1.027488	1.134944	1.849485	1.036331	1.104537	1.00484	1.102006

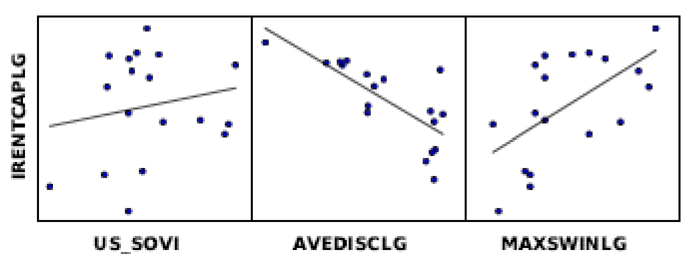
*** Significant level at p = 0.05.**


BRETTCAPLG
US_SOVI
AVEDISCLG
MAXSWINLG


CHARTCAPLG
US_SOVI
AVEDISCLG
MAXSWINLG


CLAUTCAPLG
US_SOVI
AVEDISCLG
MAXSWINLG


FLOYTCAPLG
US_SOVI
AVEDISCLG
MAXSWINLG


IRENTCAPLG
US_SOVI
AVEDISCLG
MAXSWINLG

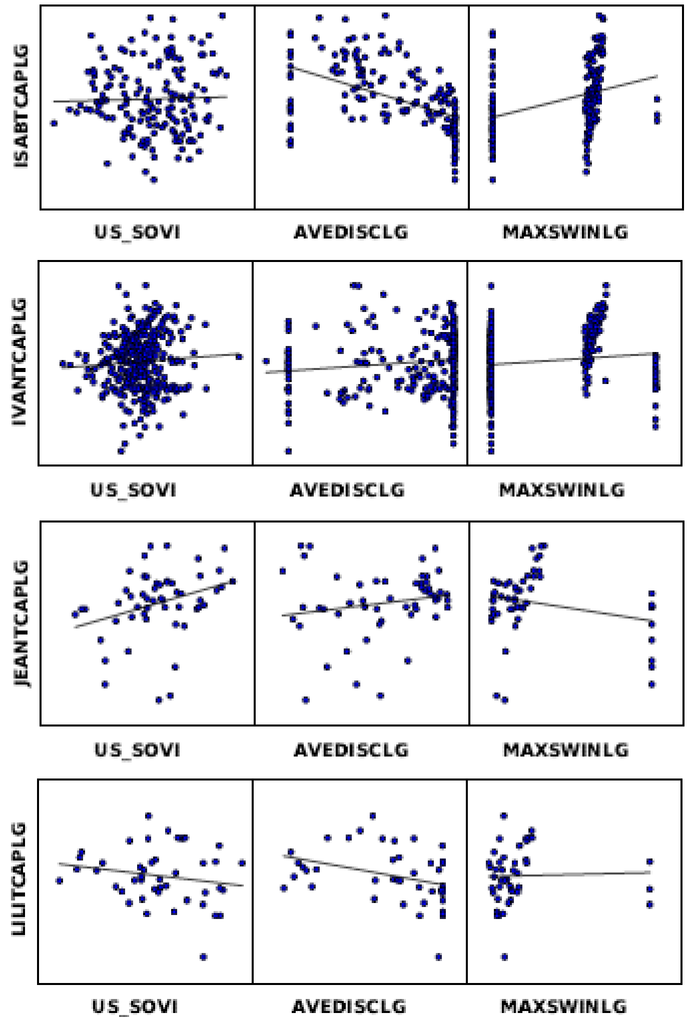
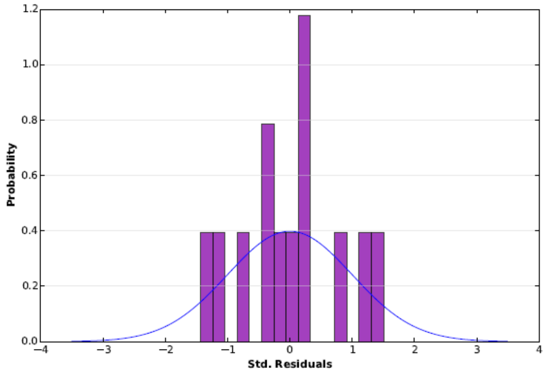
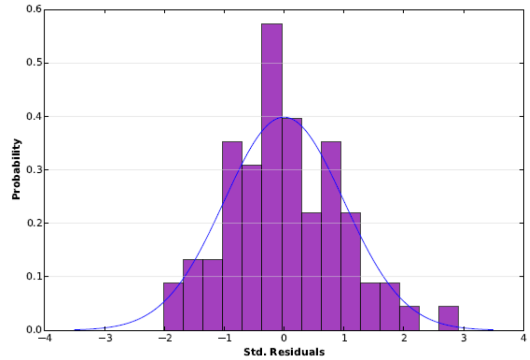


Figure 42: Scatterplots of Variable Relationships for Regression Scenario 5

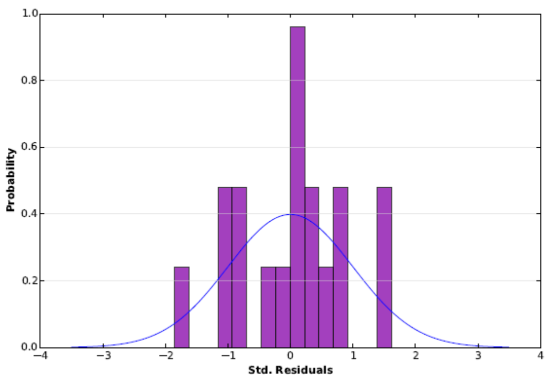
Hurricane Bret



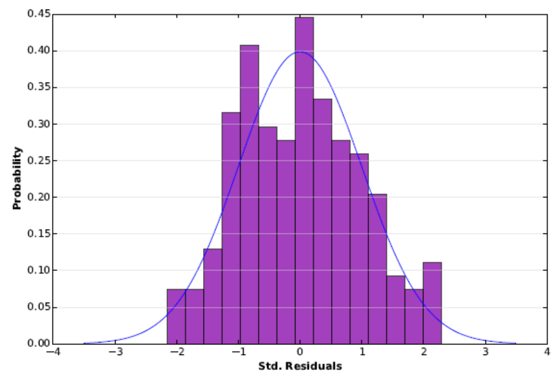
Hurricane Charley



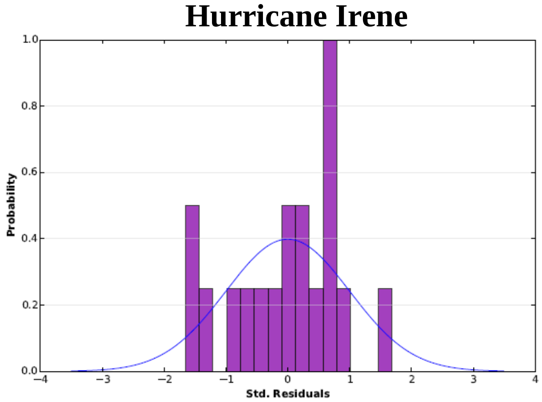
Hurricane Claudette



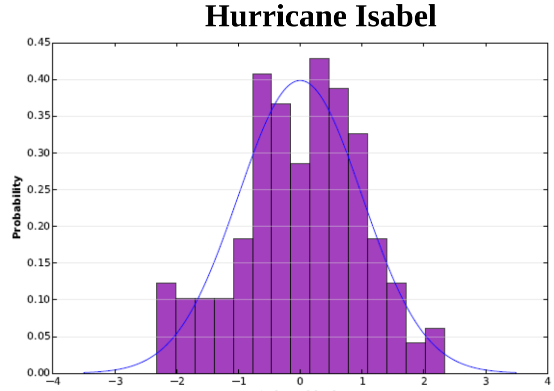
Hurricane Floyd



Hurricane Irene



Hurricane Isabel



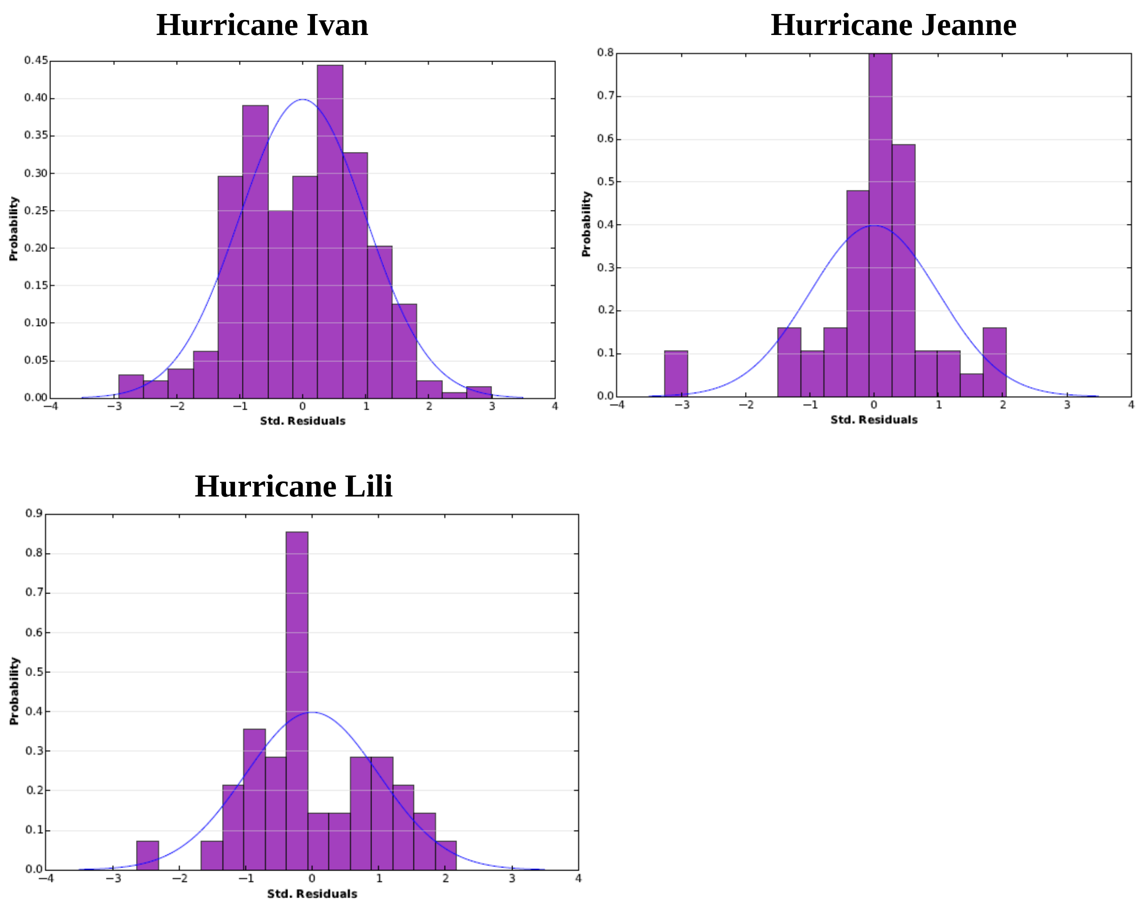
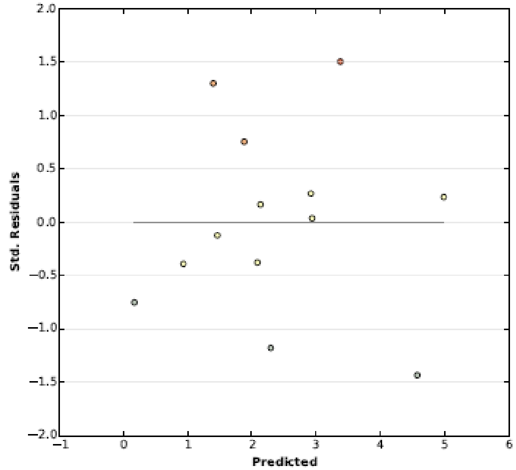
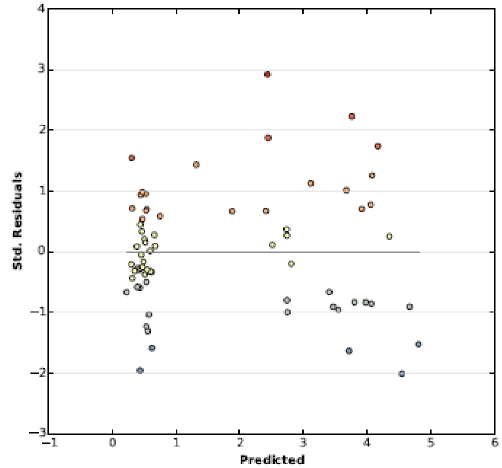


Figure 43: Histograms of Residuals for Regression Scenario 5

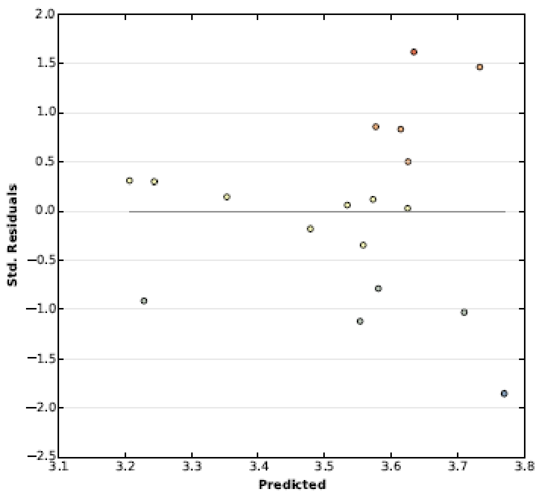
Hurricane Bret



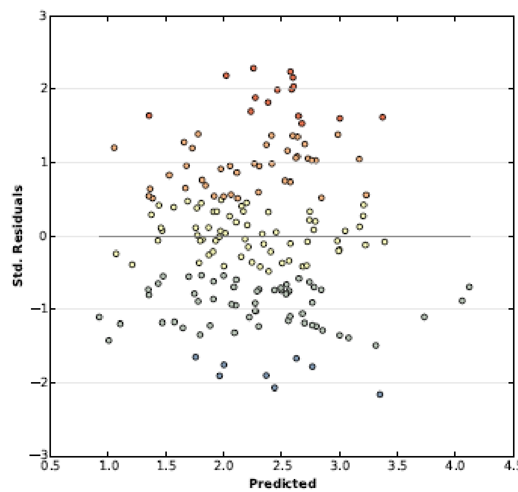
Hurricane Charley



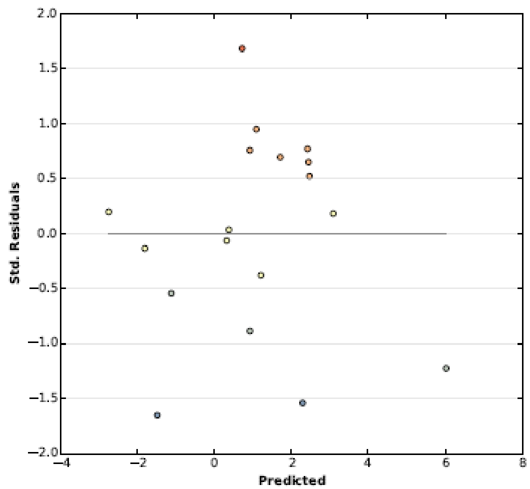
Hurricane Claudette



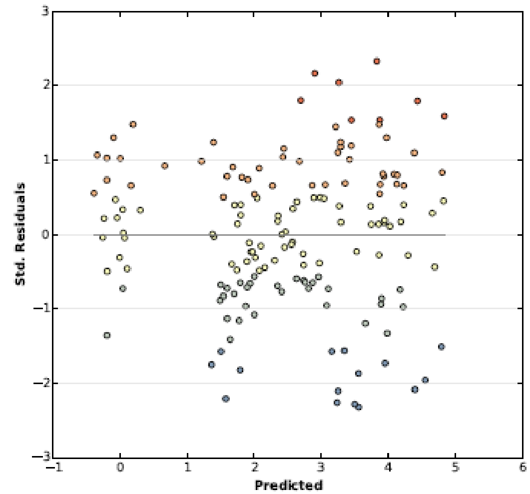
Hurricane Floyd



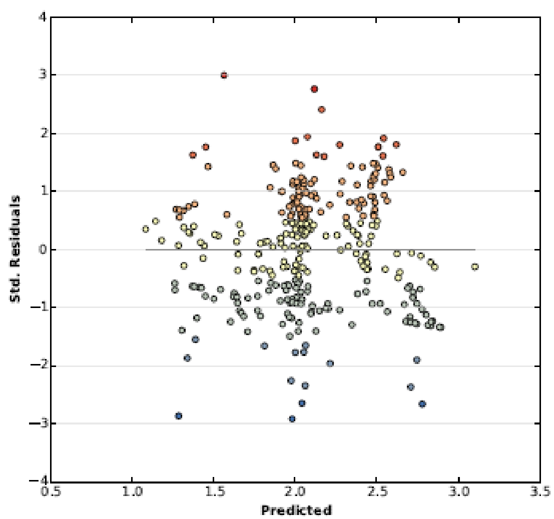
Hurricane Irene



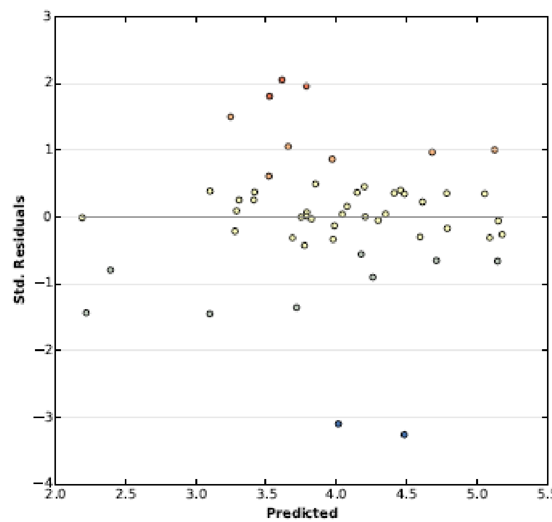
Hurricane Isabel



Hurricane Ivan



Hurricane Jeanne



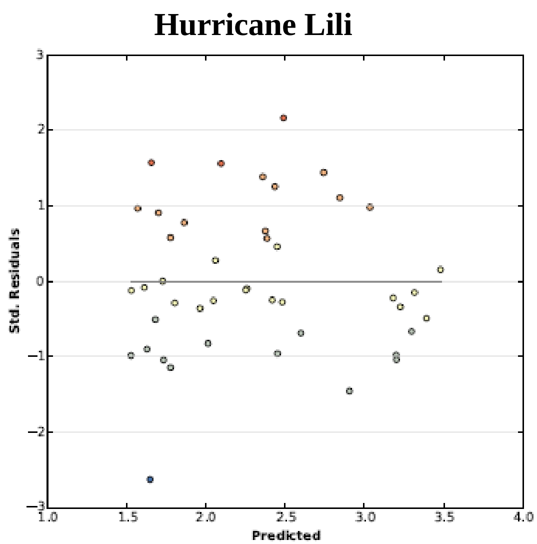


Figure 44: Scatterplots of Over/Under Predictions for Regression Scenario 5

Moran's statistics were run to determine if spatial autocorrelation issues were influencing model performance for regression scenario 5. These statistics are listed in Table 27 below. The Moran's I results indicate the presence of spatial autocorrelation in the OLS model runs for 6 of the 9 hurricanes.

Table 27: Regression Scenarios 5 – Spatial Autocorrelation (Moran's I) Statistics

Hurricane	Index	Expected	Variance	P-value	Z-score	Pattern
Bret	0.166484	-0.08333	0.032842	0.168047	1.378505	Random
Charley	0.269884	-0.014706	0.003725	0.000003	4.662683	Clustered
Claudette	0.037203	-0.058824	0.029242	0.574424	0.561548	Random
Floyd	0.506618	-0.005525	0.000754	0.00000	18.650511	Clustered
Irene	0.033397	-0.058824	0.01044	0.366754	0.902571	Random
Isabel	0.111404	-0.006369	0.000151	0.00000	9.577545	Clustered
Ivan	0.514572	-0.003086	0.000406	0.00000	25.675267	Clustered
Jeanne	0.274333	-0.019231	0.00918	0.002184	3.06395	Clustered
Lili	0.377364	-0.023256	0.009482	0.000039	4.114154	Clustered

CHAPTER 8: RESOLVING SPATIAL AUTOCORRELATION

Model bias from data skewness and missing variables were resolved using regression scenarios 4 and 5. Regression scenario 5 produced the best results in the OLS regression analysis. It used 6 independent variables from the FEMA impact models of which 5 variables had log transformations performed. Regression scenario 6 produced the best results using SoVI as the independent variable plus log transformations for 2 geophysical variables. This chapter seeks to resolve the third issue encountered in the OLS regression that of spatial autocorrelation by applying spatial econometrics and geographically weighted regression (GWR) to these same regression scenarios. This approach is supported by the global Moran's I statistics that indicate significant clustering in a majority of the 9 hurricanes models examined. This allows for an "apples to apples" comparison to determine if a modified SoVI model can produce better results or a model based on FEMA impact model data can produce the best results.

For regression scenarios 4-5, spatial regression was run using queens-contiguity spatial weights for each of the 9 hurricanes to determine the significance of the spatial dependency identify in the global Moran's I results. The Lagrange Multiplier (LM) diagnostics were interpreted to decide if spatial regression is necessary and whether to use spatial lag or error terms to account for the spatial effects. The LM diagnostics for each regression scenario are presented in tables 53-54 below.

For regression scenario 4, the LM diagnostics indicated that spatial dependency was significant for hurricanes Floyd, Isabel, Ivan, and Jeanne. Spatial regression should be run using both spatial lag for hurricanes Isabel and Ivan. Spatial error should be used for hurricanes Floyd and Jeanne.

Table 28: Regression Scenarios 4 – Lagrange Multiplier Diagnostics

	Hurricane								
Diagnostic	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
Moran's I	0.1076	1.6911	-0.1242	10.7643	0.6397	5.7964	13.5463	5.7136	2.6778
Moran's I Probability	0.9143	0.09082	0.90113	0.00000	0.52237	0.00000	0.00000	0.00000	0.00741
Lagrange Multiplier (lag)	0.22160	0.0005	0.11570	95.0065	0.11580	33.6402	203.5972	13.7565	2.07440
Lagrange Multiplier (lag) Probability	0.63780	0.98156	0.73376	0.00000	0.73369	0.00000	0.00000	0.00021	0.14979
Robust LM (lag)	0.01000	1.4109	1.87750	1.2228	0.73140	8.1768	38.737	0.0772	0.09750
Robust LM (lag) Probability	0.92033	0.2349	0.17062	0.26881	0.39244	0.00424	0.00000	0.78111	0.75489
Lagrange Multiplier (error)	0.3222	1.3249	0.82820	97.645	0.02590	25.4876	164.8695	19.5393	2.06260
Lagrange Multiplier (error) Probability	0.5703	0.24971	0.36278	0.00000	0.87224	0.00000	0.00000	0.01549	0.15095
Robust LM (error)	0.1105	2.7353	2.59010	3.8613	0.64150	0.0242	0.0093	5.86	0.08570
Robust LM (error) Probability	0.73952	0.09815	0.10754	0.04941	0.42318	0.87647	0.92304	0.01549	0.76969

For regression scenario 5, the LM diagnostics indicated that spatial dependency was significant for hurricanes Charley, Floyd, and Isabel. Spatial regression should be run using spatial lag.

Table 29: Regression Scenarios 5 – Lagrange Multiplier Diagnostics

	Hurricane								
Diagnostic	Bret	Charley	Claudette	Floyd	Irene	Isabel	Ivan	Jeanne	Lili
Moran's I	1.3528	3.4434	1.0197	11.7744	2.0170	7.1032	17.6306	6.5758	4.0338
Moran's I Probability	0.17613	0.00057	0.30787	0.00000	0.04370	0.00000	0.00000	0.00000	0.00005
Lagrange Multiplier (lag)	1.15160	17.774	0.06070	130.4274	0.02950	85.8121	295.9508	28.0861	8.26740
Lagrange Multiplier (lag) Probability	0.28322	0.00002	0.80538	0.00000	0.86371	0.00000	0.00000	0.00000	0.00404
Robust LM (lag)	1.45180	10.499	2.68090	4.9956	3.29520	45.6922	2.6786	0.0086	0.46410
Robust LM (lag) Probability	0.22824	0.00119	0.10156	0.02541	0.06948	0.00000	0.10170	0.92619	0.49572
Lagrange Multiplier (error)	0.1609	8.5752	0.00850	125.4459	0.64550	42.8047	294.2014	30.4693	9.57090
Lagrange Multiplier (error) Probability	0.68829	0.00341	0.92650	0.00000	0.42172	0.00000	0.00000	0.00000	0.00198
Robust LM (error)	0.4612	1.3002	2.62870	0.0141	3.91130	2.6849	0.9293	2.3917	1.76770
Robust LM (error) Probability	0.49708	0.25417	0.10495	0.90540	0.04796	0.10131	0.33505	0.12198	0.18367

Tables 55-56 compare the results from the OLS and spatial regression diagnostics for regression scenario 4 and 5, respectively. The model results were interpreted by 1) comparing the AIC and Schwarz criterion to determine if the spatial regression is a better fit versus the OLS and 2) using the order of precedence per Anselin (2005, p. 209) to determine if the model is properly specified which is W > LR > LM.

For regression scenario 4, the AIC and Schwarz criterion (SC) were lower in the regression models versus the OLS models. For the order of precedence test, the results were mixed. Hurricanes Ivan and Jeanne satisfied this test indicating the spatial regression is an improvement and the model is properly specified. Hurricanes Floyd and Isabel failed this test. LR diagnostics were less than the LM diagnostics for these two hurricanes. This suggests the models are missing a key explanatory variable or external influence.

Table 30: Regression Scenarios 4 – Spatial Regression Diagnostics

Spatial Weights: Queens Contiguity								
	Hurricane							
Diagnostic	Floyd OLS	Floyd Spatial Error	Isabel OLS	Isabel Spatial Lag	Ivan OLS	Ivan Spatial Lag	Jeanne OLS	Jeanne Spatial Error
Multiple R-Squared	0.352909	0.65484	0.639705	0.714097	0.36756	0.737381	0.635223	0.786302
Adjusted R-Squared	0.3331	-	0.625388	-	0.354247	-	0.587643	-
Joint F-Statistic	17.8157	-	44.6835	-	27.6062	-	13.3507	-
Joint F-Statistic Probability	0.00000	-	0.000000	-	0.000000	-	0.00000	-
Joint Wald Statistic	-	205.4592558	-	31.87090247	-	391.4470164	-	40.34307662
Koenker (BP) Statistic	24.2989	2.5723	19.3256	11.6106	18.2213	1029.0638	9.3593	8.6813
Koenker (BP) Probability	0.00046	0.86029	0.00365	0.07124	0.0057	0.00000	0.15436	0.19231
Jarque-Bera Statistic	0.5915	-	8.0587	-	15.7792	-	14.4423	-
Jarque-Bera Probability	0.74397	-	0.01779	-	0.00037	-	0.00073	-
Akaike's Information Criterion (AICc)	836.638	742.814	530.599	503.668	1160.34	957.202	163.802	143.234
Swartz Criterion	859.83	766.007	552.037	528.169	1186.08	986.616	177.594	157.026
Likelihood Ratio	-	93.8236	-	28.9306	-	205.1391	-	20.5678

For regression scenario 5, the AIC and Schwarz criterion (SC) were lower in the regression models versus the OLS models for hurricanes Floyd and Isabel but not the case for hurricane Charley. For the order of precedence test, the results were also mixed. Hurricanes Charley and Isabel satisfied this test indicating the spatial regression is an improvement and the model is properly specified. Hurricanes Floyd failed this test; the LR diagnostic was less than the LM diagnostic. This suggests the model is missing a key explanatory variables or external influence.

Table 31: Regression Scenarios 5 – Spatial Regression Diagnostics

Spatial Weights: Queens Contiguity						
	Hurricane					
Diagnostic	CharleyOLS	Charley Spatial Lag	Floyd OLS	Floyd Spatial Lag	Isabel OLS	Isabel Spatial Lag
Multiple R-Squared	0.424543	0.431873	0.064219	0.620315	0.44904	0.718823
Adjusted R-Squared	0.397984	-	0.048447	-	0.438304	-
Joint F-Statistic	15.9846	-	4.07181	-	41.8369	-
Joint F-Statistic Probability	0.00000	-	0.007924	-	0.000000	-
Joint Wald Statistic	-	132.8728817	-	269.1607735	-	143.0341849
Koenker (BP) Statistic	8.0206	78.0027	4.1814	3.8411	13.8284	3.5381
Koenker (BP) Probability	0.04559	0.00000	0.24253	0.27915	0.00315	0.31586
Jarque-Bera Statistic	1.9242	-	3.7693	-	2.2608	-
Jarque-Bera Probability	0.38208	-	0.15188	-	0.32291	-
Akaike's Information Criterion (AICc)	283.855	2793.02	811.934	687.152	587.679	503.581
Swartz Criterion	292.791	2819.52	824.75	703.173	599.929	518.894
Likelihood Ratio	-	67.5026	-	126.7813	-	86.0981

Given that the spatial regression results were inconclusive, the GWR models were used to explore the spatial dependency and assess model fitness for the regression scenarios. For regression scenario 4, GWR executed for 4 of 9 hurricanes; the remaining hurricane models failed to execute due to a severe model design error in ArcGIS. This type of error is usually due to global or local multicollinearity or non-linear relationships.

Table 32 shows the Residual squares ranged from 61.15 to 799.79. Comparing the AIC results between OLS and GWR models suggests there is modest benefit in moving from a global regression model to a local regression model. Not a reliable indicator, but the local R-squared values were slightly better for the GWR model indicating the local model has better explanatory power. GWR calculates the R-squared values by normalizing the numerator and denominator by their degrees of freedom; thereby, losing the interpretation of the value as a proportion of the variance explained, because the effective number of degrees of freedom in GWR is a function of the bandwidth rather than the number of variables like in OLs. As a result, the GWR R-squared is not considered a reliable indicator.

Additionally, examining the condition number, a diagnostic for local collinearity, for each GWR model indicates there are no real issues with local collinearity. This conclusion was confirmed by the coefficient standard error values for each model which were also very low. GWR model results still exhibit spatial autocorrelation as shown in table 33 below. Maps of the GWR residuals depicted in figure 45 shows clustering of residuals consistent with the local Moran's I. This clustering also appears to be closely associated with the hurricane storm tracks and points of landfall. Overall analysis of the GWR results indicates that using a GWR approach yields a slight improvement over the OLS global model.

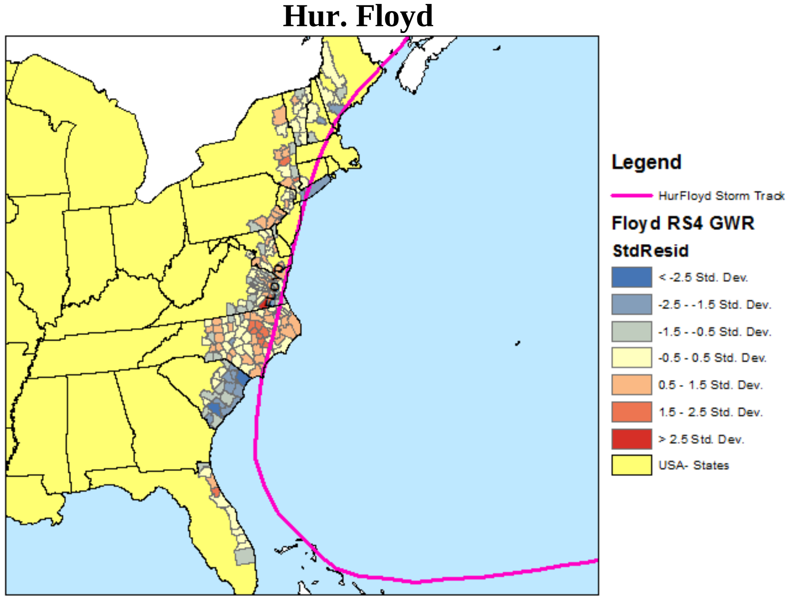
Table 32: Regression Scenario 4 - GWR Model Results

	GWR - Local Regression							OLS - Global Regression		
Hurricane	Bandwidth	Residual Squares	Effective Number	Sigma	AICc	R2	R2Adjusted	AIC	R2	R2Adjusted
Floyd	582,843.39	528.74	15.212884	1.67798	799.40	0.499681	0.461814	839.37989	0.35291	0.3331
Isabel	215,757.20	181.42	20.076767	1.46893	507.43	0.731352	0.694194	533.56548	0.63971	0.625388
Ivan	1,338,256.39	799.79	10.084589	1.684334	1143.17	0.416394	0.397587	1162.8503	0.36756	0.354247
Lili	601,684.65	61.15	7.830796	1.300209	160.80882	0.454943	0.352006	161.35629	0.43094	0.338657

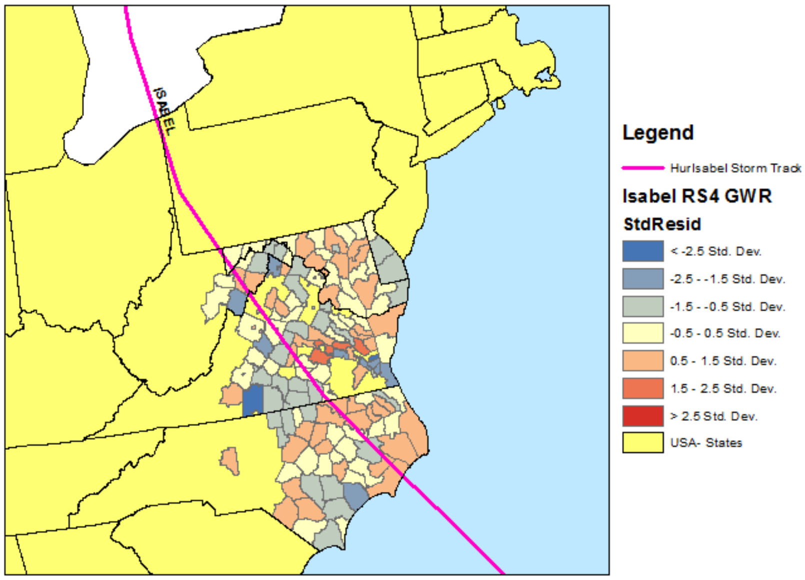
Table 33: Regression Scenario 4 - GWR Moran's I Results

Hurricane	Index	Expected	Variance	P-value	Z-score	Pattern
Floyd	0.183123	-0.00495	0.000505	0.000000	8.367848	Clustered
Isabel	0.007733	-0.006369	0.000555	0.549432	0.598612	Random
Ivan	0.163014	-0.003436	0.000304	0.000000	9.542683	Clustered
Lili	0.109926	-0.023256	0.004402	0.044705	2.007417	Clustered

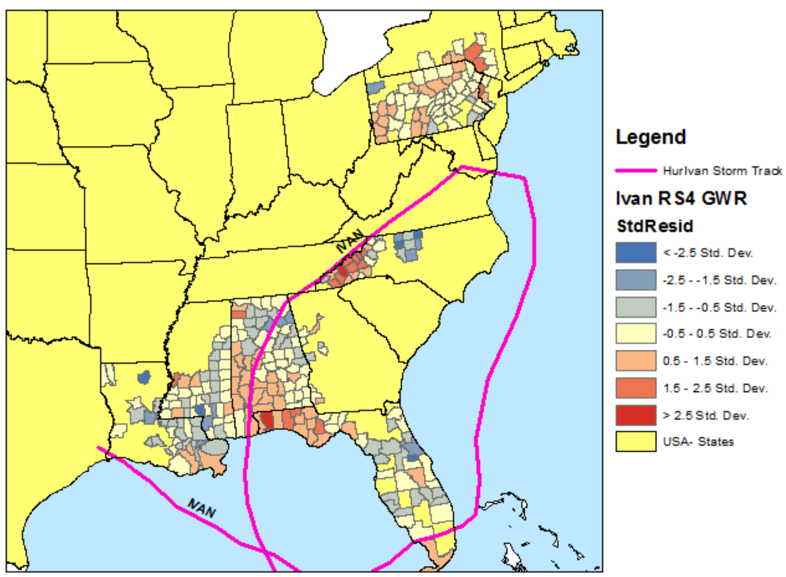
Hur. Floyd



Hur. Isabel



Hur. Ivan



Hur. Lili

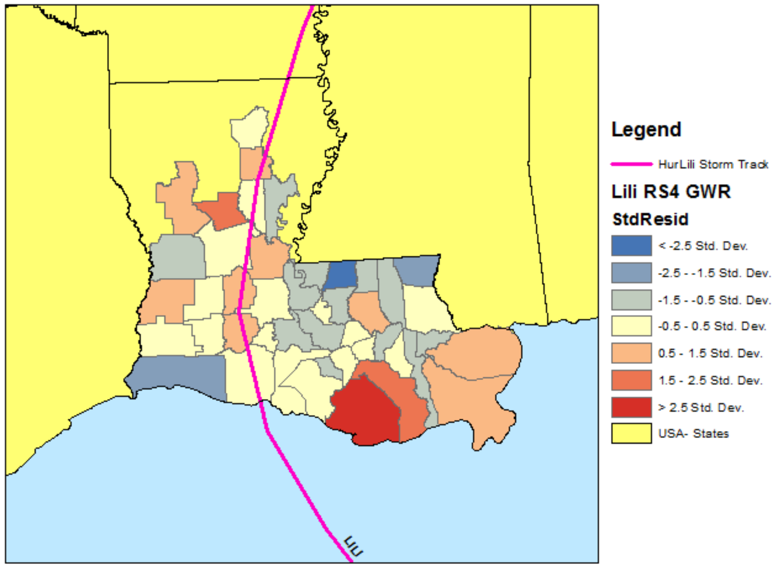


Figure 45: Regression Scenario 4 - GWR Residual Maps

For regression scenario 5, GWR executed for 7 of 9 hurricanes; the remaining hurricane models failed to execute due to a severe model design error in ArcGIS. This type of error is usually due to global or local multicollinearity or non-linear relationships. The Residual squares ranged from 61.15 to 879.21. Comparing the AIC results between OLS and GWR models shown in table 34 suggests there is a benefit in moving from a global regression model to a local regression model. Not a reliable indicator, but the local R-squared values were better for the GWR model indicating the local model has better explanatory power. Based on a review of the condition number, a diagnostic for local collinearity, for each GWR model indicates there are no issues with local collinearity. This conclusion was confirmed by the coefficient standard error values for each model which were also very low. Table 35 below and maps of the GWR residuals depicted in figure 46 shows clustering of residuals consistent with the local Moran's I. This clustering also appears to be closely associated with the hurricane storm tracks and points of landfall. Overall analysis of the GWR results indicates that using a GWR approach yields a modest improvement over the OLS global model for regression scenario 5.

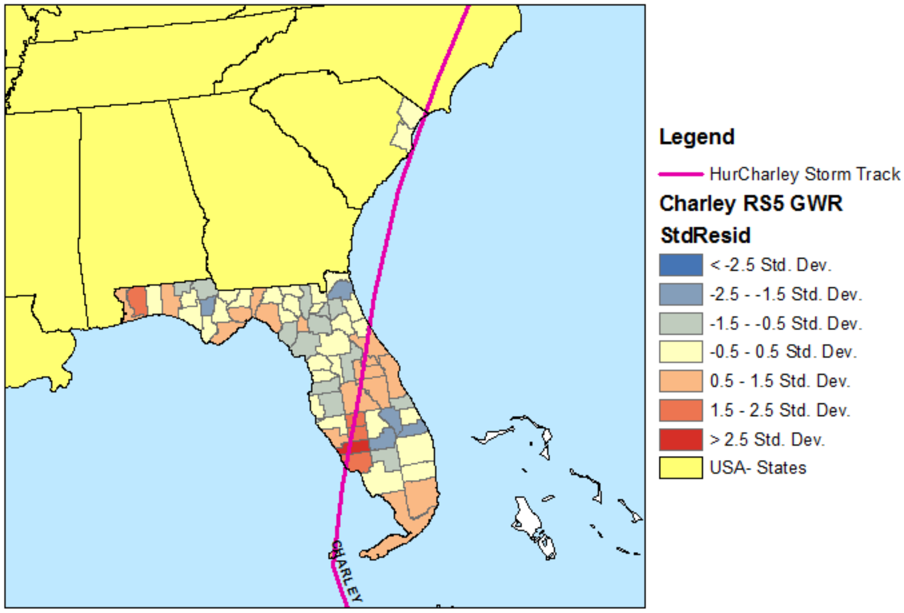
Table 34: Regression Scenario 5 - GWR Model Results

	GWR - Local Regression							OLS - Global Regression		
Hurricane	Bandwidth	Residual Squares	Effective Number	Sigma	AICc	R2	R2Adjusted	AIC	R2	R2Adjusted
Charley	471,028.98	198.692760	7.078416	1.791307	284.324128	0.480534	0.429542	286.80697	0.42454	0.397984
Claudette	4,615,665.04	21.227748	4.008216	1.231730	69.068143	0.226000	-0.187540	69.05402	0.02242	-0.187064
Floyd	161,097.20	315.58	35.208039	1.466231	686.46	0.665566	0.58763	814.27465	0.06422	0.048447
Isabel	240,305.65	273.50	11.287251	1.365357	555.61	0.584533	0.555401	590.07376	0.44904	0.438304
Ivan	374,776.87	879.21	20.107499	1.698133	1281.11	0.432551	0.396989	1429.1043	0.03322	0.024179
Jeanne	188,306.96	65.06	11.622222	1.253896	187.396716	0.547101	0.430836	203.75146	0.18399	0.134027
Lili	601,684.65	61.15	7.830796	1.300209	160.80882	0.454943	0.352006	170.96921	0.14041	0.075945

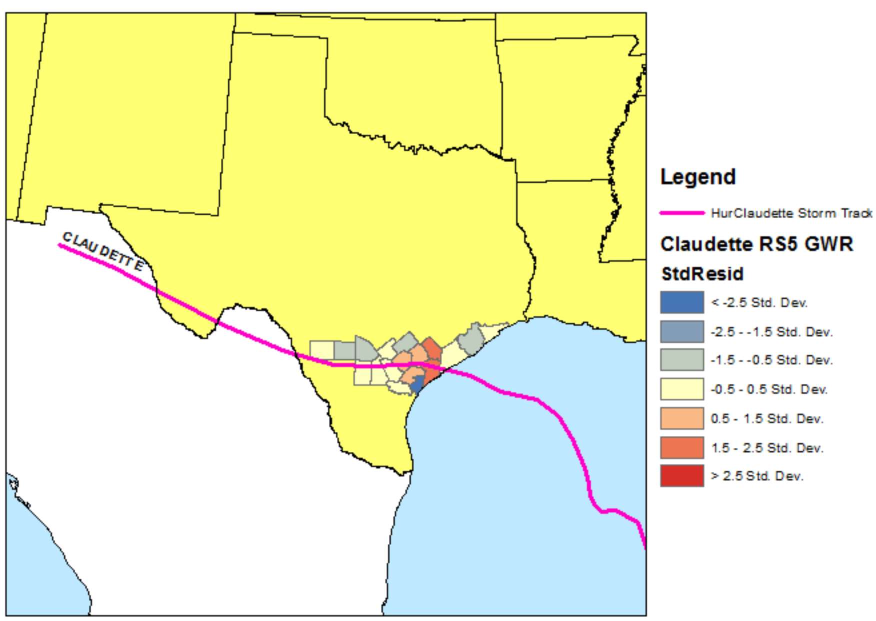
Table 35: Regression Scenario 5 - GWR Moran's I Results

Hurricane	Index	Expected	Variance	P-value	Z-score	Pattern
Floyd	0.183123	-0.00495	0.000505	0.000000	8.367848	Clustered
Isabel	0.007733	-0.006369	0.000555	0.549432	0.598612	Random
Ivan	0.163014	-0.003436	0.000304	0.000000	9.542683	Clustered
Lili	0.109926	-0.023256	0.004402	0.044705	2.007417	Clustered

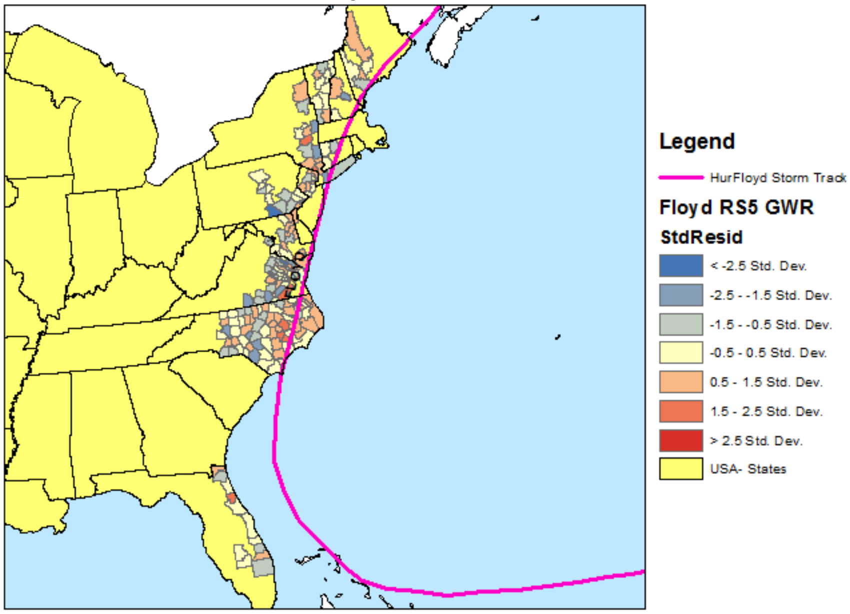
Hur. Charley



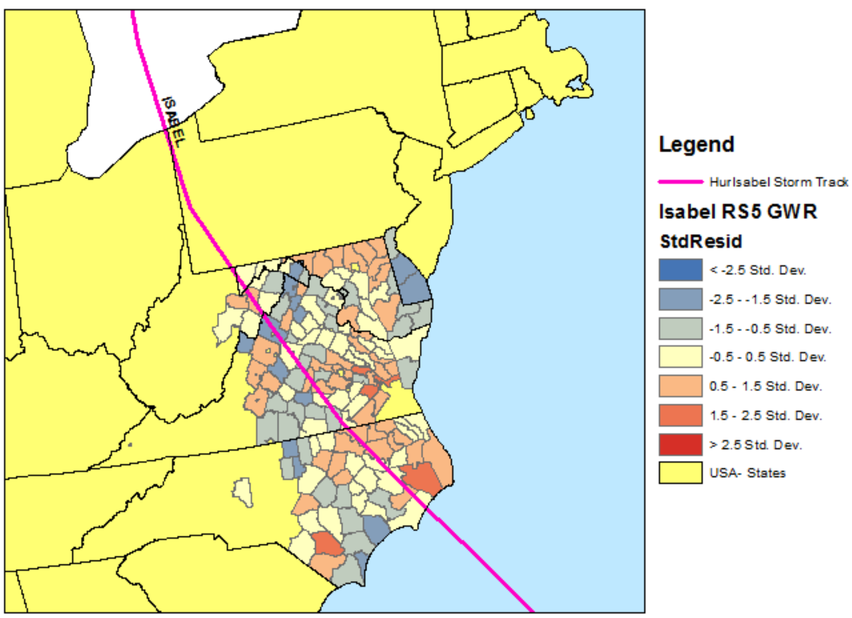
Hur. Claudette



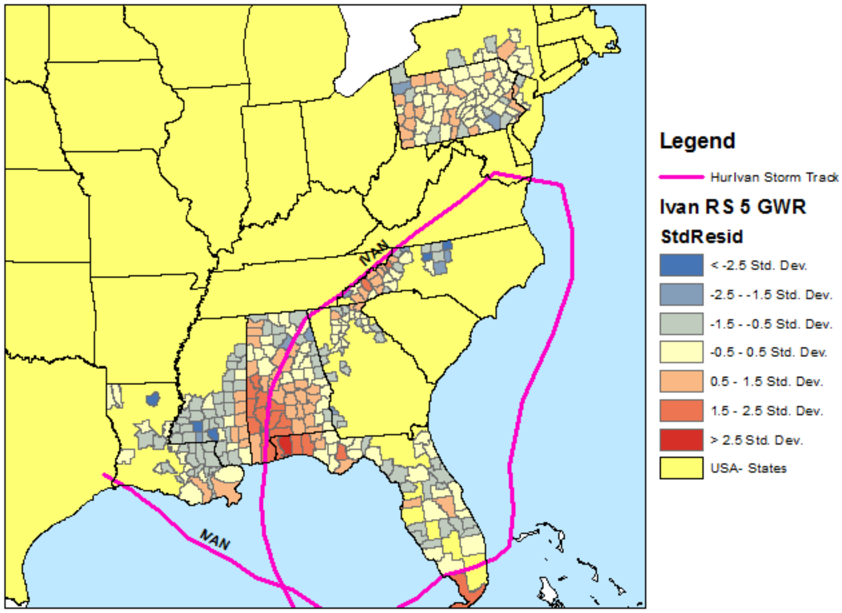
Hur. Floyd



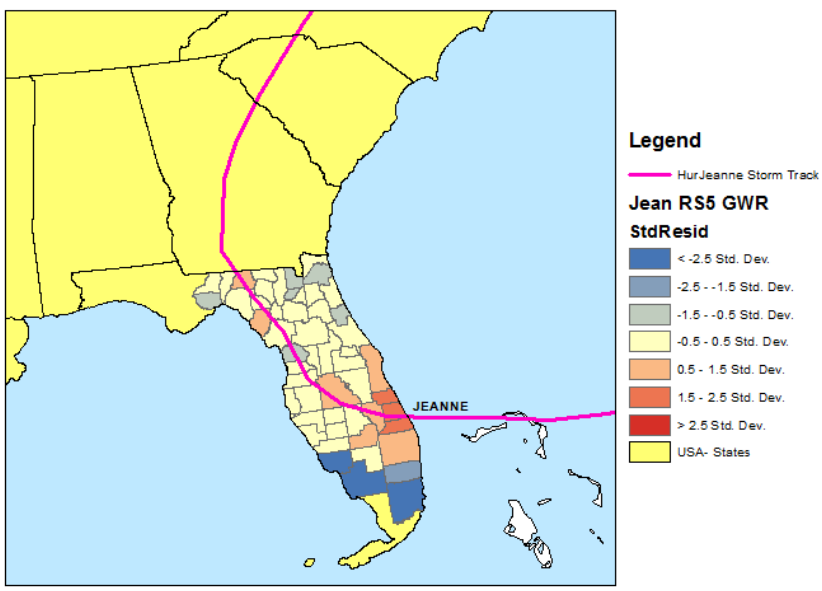
Hur. Isabel



Hur. Ivan



Hur. Jeanne



Hur. Lili

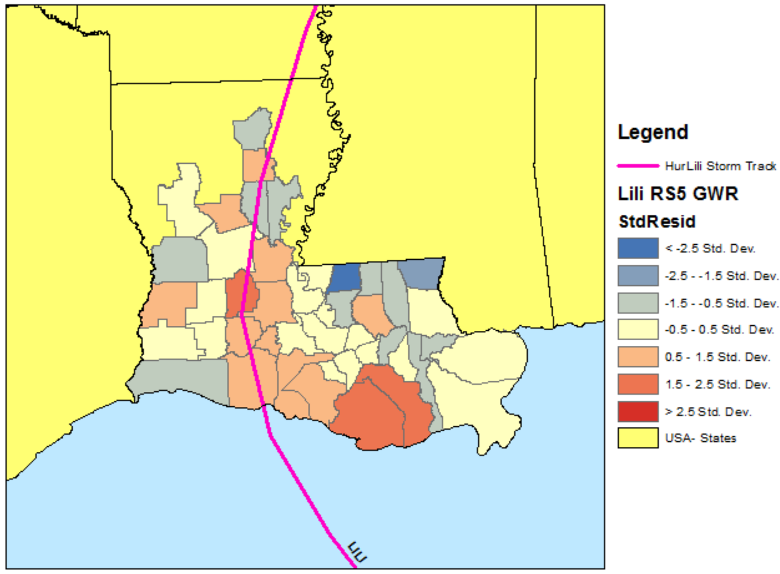


Figure 46: Regression Scenario 5 - GWR Residual Maps

CHAPTER 9: SUMMARY AND CONCLUSIONS

This dissertation explored the relationships between hazard vulnerability science, disaster management policy, and disaster operations practice using a case study of 9 Atlantic hurricanes occurring between 1999 and 2004. Qualitative analysis was conducted to establish common linkages and theoretical underpinnings between hazard vulnerability indices and disaster management policy and practice. Exploratory regression and spatial econometric methods were utilized to quantify relationships across these disciplines. Five main questions guided this research:

1. Does vulnerability science have a nexus with disaster management?
2. Do hazard vulnerability indicators align with disaster operations variables?
3. Do hazard vulnerability indices accurately predict the exposure of a community to a natural hazard and therefore its *level of vulnerability or the level of damages and serve as a good predictor for disaster management purposes*?
4. Do hazard vulnerability indices account for the geography of the hazard across space or inadvertently treat the units of measure as discrete locations?
5. Do hazard vulnerability indices provide an effective planning tool for building disaster resiliency?

This chapter summarizes this research and discusses key findings. The contribution and implications of this research, a critique of it, and opportunities for future research are presented.

SUMMARY OF RESEARCH FINDINGS

This dissertation was concerned with establishing the conceptual linkages between hazard vulnerability science and disaster management policy and practice. This research was able to establish common conceptual foundations and theoretical underpinnings across these three disciplines, using a pedigree matrix and variable cross walk (Chapter 3). The pedigree matrix was used to compare and contrast three hazard vulnerability indices (social vulnerability index, disaster risk index, and disaster preparedness index) and to select the best one suited to test - if a hazard vulnerability index can accurately predict the exposure of a community to a natural hazard and therefore its level of vulnerability or the level of damages and serve as a good predictor for disaster management purposes. The comparative analysis was based on a qualitative taxonomy adopted from Gall (2007, p.33-34) that allowed for an "apples to oranges" comparison of the scale and the composition of the indices. Results from the pedigree analysis determined that SoVI was the best suited index for testing the predictive power of hazard vulnerability indices.

The results from the comparative analysis also showed that there is general alignment between the indicators used by hazard vulnerability science (SoVI), the essential elements of information (EEIs) used by disaster management policy, and the disaster impact model variables used by disaster response. EEIs were grouped into four main categories: disaster area, geophysical information, socio-economic information, and critical infrastructure information. EEIs for geophysical information were not aligned with any hazard vulnerability indicators, but hazard vulnerability indicators were aligned to the EEI groupings for disaster area, socio-economic, and critical infrastructure.

A correlation analysis of SoVI with the FEMA impact model variables that are linked to disaster management policy substantiated the findings from the comparative analysis. SoVI had strong statistical correlations with the socio-economic grouping of EEIs and weak correlations with the critical infrastructure grouping. Additionally, the correlation analysis showed that SoVI had few statistically significant correlations with the geophysical information. There was conflicting information for several variables across different storms, so the utility of the correlation matrices was limited. Exploratory regression was used as a more manageable method to quantify the statistical relationships between hazard vulnerability science and disaster management policy and practice. It also provided a means to eliminate redundant variables and choose a good set of independent variables. From the exploratory regression, six variables were chosen and analyzed for effectiveness using OLS regression. The six variables were SoVI: POPDEN, PCTPOV, AVEDISTC, MAXSUSTWIN, BLDGLOSS1K, and NUMBRIDGES. These variables map to the four EEI groupings and allowed for an apple to apples comparison in the subsequent OLS regressions.

Findings from the comparative and correlation analyses were consistent. Since hazard vulnerability indices are usually general measures of susceptibility, they tend to be weak in indicating the geophysical characteristics of the hazards they intend to measure. The hazard vulnerability indices also placed more emphasis on population characteristics and less emphasis on critical infrastructure information. This is contrary to the central tenants of hazard vulnerability science: vulnerability provides a conceptual link between disasters, built environment, and people. Often, people are less at direct risk and critical infrastructure is more at risk. People can be evacuated, but not critical infrastructure. In other words, hazard vulnerability and disaster impacts are felt as more a function of the built environment and not as a population. Therefore, it is reasonable to suggest that hazard vulnerability science should include more infrastructure related indicators rather than population related indicators.

A main purpose of this dissertation was to empirically validate SoVI as a reliable measure of vulnerability and its capacity to predict the costs and level of damages for a disaster using Atlantic hurricanes as the case study. Results from the empirical analysis were dubious, varying widely across the 9 hurricanes included in the research sample. SoVI had little predictive power in explaining disaster costs and damages based on OLS regression and spatial econometrics performed for regression scenarios 2-5. The initial OLS models suffered from skewness in the data and missing variables. To resolve these issues, log transformations were performed on the variables and geophysical variables (AVEDISTC and MAXSUSTWIN) were combined with SoVI to improve model performance. Global Moran's I statistics for the OLS regression indicated the presence of spatial autocorrelation in a majority of the hurricane regression runs. Maps of the residuals showed that spatial clustering was associated with the hurricane storm tracks and points of landfall. Spatial econometric and GWR models were used as a means to resolve the effects of spatial autocorrelation. However, spatial regression models were unable to capture the spatial autocorrelation effectively and provided only marginal improvement over the OLS models.

Regression scenario 4 demonstrated that the disaster operations impact model data had more predictive power in explaining disaster costs and damages than SoVI. While the disaster impact model is constructed from variables that cross map with variables associated with disaster management policy and practice, statistical relationships between the disaster impact model variables and actual disaster costs and damages were not as strong as expected. When using the 6 disaster impact model variables with statistically significant correlations with SoVI and log transformations to address skewness, regression scenario 4 produced solid results in predicting total amount of federal assistance per capita. Adjusted R-squared values exceeded 58.7% for 5 of the 9 hurricane regressions, and ranged from 24-35% for the remaining 4 models.

Regression scenario 5 did not fare as well despite the log transformation and additional geophysical variables. SoVI still performed poorly compared to the disaster impact model data in explaining the disaster costs and damages. Regression scenario 5 failed to validate that combining SoVI with missing variables for the specific hazard could serve as a basis for constructing a more dependable, composite index for hazard vulnerability. While the performance of SoVI did improve with the addition of the missing variables, it still did not perform as well as the disaster impact model constructed by FEMA. These findings indicate there is disconnectedness between hazard vulnerability indices and disaster management policy.

This research found that there were stronger statistical relationships between SoVI and the disaster operations impact model based on results from the exploratory regression, but weaker relationships between SoVI and disaster outcomes using the federal disaster assistance data. SoVI had little ability to explain disaster impact expressed as total federal assistance per capita. These findings indicate disconnectedness between hazard vulnerability science and disaster management policy. It appears that how we link vulnerability to disaster response and recovery operations is not the same as how we link those two domains to disaster policy. These findings in part substantiate the hazards-of-place theory that vulnerability is a function of the interactions between hazard, place, and society, but refute the claim by Emrich and Cutter (2016) that SoVI "has high utility as a decision-support tool for emergency management" turning "historical disaster impact measures into actionable information for emergency managers, recovery planners, and decision makers because it empirically measures and visually depicts a population's (in)ability to adequately prepare for, respond to, and rebound from disaster events" (Emrich and Cutter 2016, p.???). This research also question the claim by Cutter et al. (2003) that SoVI provides the emergency management community and policy makers a useful tool to illustrate the geographic variation in social vulnerability, to identify areas where there is uneven capacity for preparedness and response, to target areas where resources might be used more effectively to reduce pre-existing vulnerability and promote risk mitigation measures, and as an indicator in determining the differential recovery from disasters (Cutter et al 2003, HVRI SoVI webpage 2013). This research was unable to demonstrate the effectiveness of SoVI in explaining disaster impacts expressed as total federal cost per capita.

Furthermore, SoVI is constructed from proxy measures for social vulnerability. While SoVI was initially developed to include indicators for the built environment, it does not adequately account for critical infrastructure and other key characteristics of the built environment. More significantly, SoVI does not account for any of the geophysical properties of the various natural hazards (i.e.; wind speed, rainfall amounts, etc.). Developing a composite measure of vulnerability must factor in the diversity of place, variation of the hazard, and complexity of the built environment or become too homogenized. These results show that SoVI is an inconsistent measure of vulnerability and that it is not able to reliably capture the complexity of regional and event specific variation necessary to accurately predict the level of damages or costs for a hurricane disaster.

CONTRIBUTIONS AND IMPLICATIONS

This dissertation examined the relationship between hazard vulnerability science, disaster management policy, and disaster operations practice. It provided a quantitative analysis of the reliability and utility of SoVI to accurately predict exposure of a community to a disaster, therefore its level of vulnerability or the level of damages, and serve as a good predictor for disaster management purposes using empirical data for 9 Atlantic hurricanes. It also provided the first cross mapping between the indicators used by hazard vulnerability science (SoVI), the essential elements of information (EEIs) used by disaster management policy, and the disaster impact model variables used by disaster response.

One of the main contributions of this research is that it improves our understanding of the research policy nexus described by Cutter et al 2008 (p. 598). Since 1964, the US has continuously pursued a research policy nexus to better understand hazards, community vulnerability, and societal tolerance of risk and broad dissemination of this knowledge to inform policy and improve decision making (Cutter et al. 2008, p. 598). We have yet to design "robust and credible measures of vulnerability" that are accepted by the research and practitioner communities (Adger 2006, p. 268, Gall 2007, p. 12). We have yet to develop a proven vulnerability index that incorporates the components of disaster response and recovery with mitigation and resiliency and that is more directly integrated with disaster management policy. This research demonstrated that developing a composite measure of vulnerability must include diversity of place, variation of the hazard, and complexity of the built environment.

These contributions have implications for national disaster management policy by increasing our understanding of how vulnerability indices correlate with actual exposure and level of damage, and for developing a measure of community resiliency that is based on a set of proven indicators that takes into account 1) potential exposure, 2) likely impact to people, infrastructure, and environment, 3) capacity to cope, and 4) ability to recover. This enhanced understanding may lead to more sustainable practices, more effective policies, and actionable guidance and provide a means for comparing our disaster preparedness, practice, and resiliency across space and over time. It may also help pivot the nation away from a disaster response focus toward one of preparedness, with an emphasis on building resiliency.

FUTURE RESEARCH

> "Measuring vulnerability – i.e. selecting vulnerability indicators and determining their interactions – is [still] less empirical and more a leap of faith" (Adger 2006, p. 275).

This dissertation has created many avenues for future research. First, hazard vulnerability science should seek an alternative approach to the equation; *Disaster = Hazard * Vulnerability*, by examining the "risk that people and communities are exposed to with their social, economic, and cultural abilities to cope with the damages that occurred" (Hilborst and Bankoff 2008, p. 2). Vulnerability should not be considered a property of disaster or hazard, but an outcome. Hazards are natural, disasters are not. Disasters are not just one-off phenomena; they represent the results of continuous social, economic, and environmental processes over time. According to Lavell (2008, p.82), "as long as disaster is seen as externally imposed, little advance will be achieved in" building resiliency and reducing vulnerability. Subsequently, vulnerability provides a conceptual link toward improving the understanding between disasters, built environment, and people. According to Hilhorst and Bankoff, "vulnerability is the key to understanding risk" (2008, p. 1) and "the ways in which human systems place people at risk in relation to each other and their environment" (Cannon 1994, p. 14). Petak and Atkisson (1982) maintains that much of the scientific work on modeling, estimating, and forecasting disaster impacts are examples of risk assessments applied to natural hazards. Hill and Cutter (2002) contend that vulnerability assessments should include risk and exposure and are more difficult to undertake than simple risk analyses because they require more data, have more complex interactions, and involve more advanced and composite techniques of statistical analysis.

Cutter (2002) argues that vulnerability science has not adequately developed an approach to the "integration of natural sciences, engineering sciences, and social sciences to produce credible vulnerability assessments at the local level" (p. 159). This suggests more investigation in necessary toward understanding what characteristics or decisions are occurring or present that could be modified or changed to reduce long term risk and how these potential indicators relate to the actual costs/damages.

Another consideration for future work would be to develop a hazard vulnerability index that integrates deterministic and probabilistic methods to incorporate results from historical, hypothetical, and predicted events to produce a more dependable, composite index for hazard vulnerability. This hazard vulnerability index would be based on impact model simulations, calibrated by empirical data from historical events, rather than general socio-economic indicators or national estimates of loss. This approach is very similar to the one employed by the National Hurricane Center (NHC), and validated by the meteorological community, to produce the Sea, Lake, and Overland Surges from Hurricanes (SLOSH) model. The SLOSH model is a numerical model that uses a proven set of characteristics (indicators) run through a set of statistical equations several thousand times to produce a composite measure of risk for an area based on estimated storm surge heights from historical, hypothetical, and predicted hurricanes (NWS website 2016). This type of approach would provide a more useful, understood, and acceptable metric of risk.

Future research should also consider experimenting with integrating hazard vulnerability into an operational framework constructed from the premise that vulnerability assessments will be assembled in part with the inputs from pre-impact models and forecasts and these same models and forecasts would be used in near real-time as part of the response and recovery. The fusion of vulnerability assessments and impact model/forecasting would incorporate the likelihood of the hazard occurring, the potential level of impact to the population and the potential damage to the infrastructure, environment, and economy. A conceptual diagram of this framework is depicted in Figure 47. The framework envisions that both sets of results would be continuously calibrated with actual outcome data creating a regime similar to other first responder approaches that encompasses training, exercising, executing, evaluating and correcting. This would provide a basis for improving and refining the accuracy and performance of all components of the framework (vulnerability assessment, mitigation planning, pre-event forecast modeling for resource management, post disaster impact and recovery) with the potential result of producing more common disaster operations practice. These common practices could serve as the bases for determining capability maturity and assessing community readiness and resiliency.

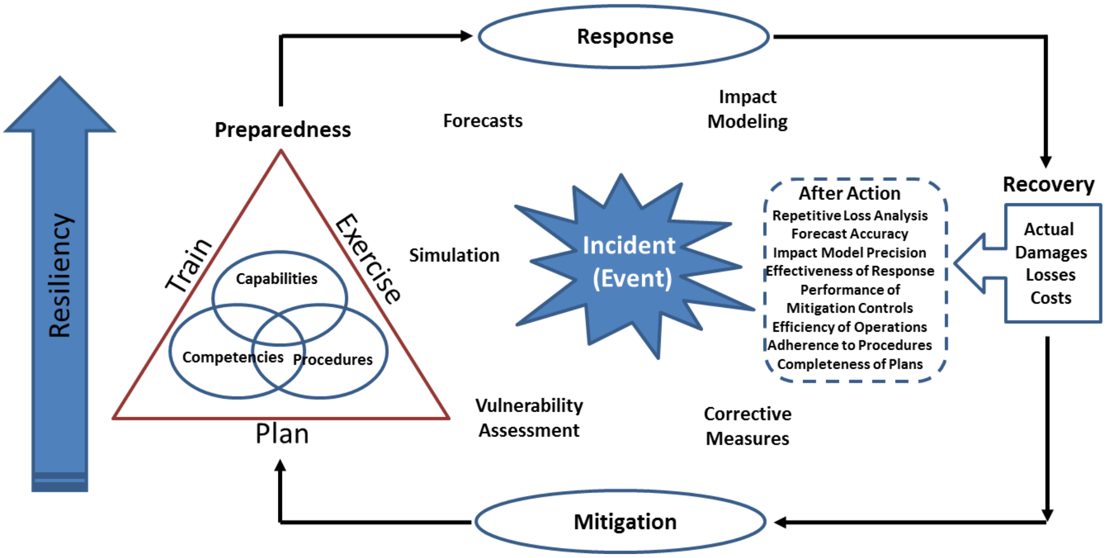


Figure 47: Conceptual Diagraph of Disaster Operations Framework

APPENDIX A: List of Essential Elements of Information (EEIs)

- Boundaries of the disaster area
- Social, economic, and political impacts
- Jurisdictional boundaries
- Status of transportation systems and critical transportation facilities
- Status of communications systems
- Access points to the disaster area
- Status of operating facilities
- Hazard-specific information
- Weather data affecting operations
- Seismic or other geophysical information
- Status of critical facilities and distribution systems
- Status of remote sensing and reconnaissance activities
- Status of key personnel
- Status of ESF activation
- Status of disaster or emergency declaration
- Major issues and activities of ESFs
- Resource shortfalls and status of critical resources
- Overall priorities for response
- Status of upcoming activities
- Donations
- Historical and demographic information
- Status of energy systems
- Estimates of potential impacts based on predictive modeling (as applicable)
- Status (statistics) on recovery programs (human services, infrastructure, SBA)
- Status and analysis of initial assessments (needs/damage assessments, PDAs)
- Status of efforts under other Federal emergency operations plans

(Source: Section VII B. of ESF#5 – Information and Planning Annex 2003)

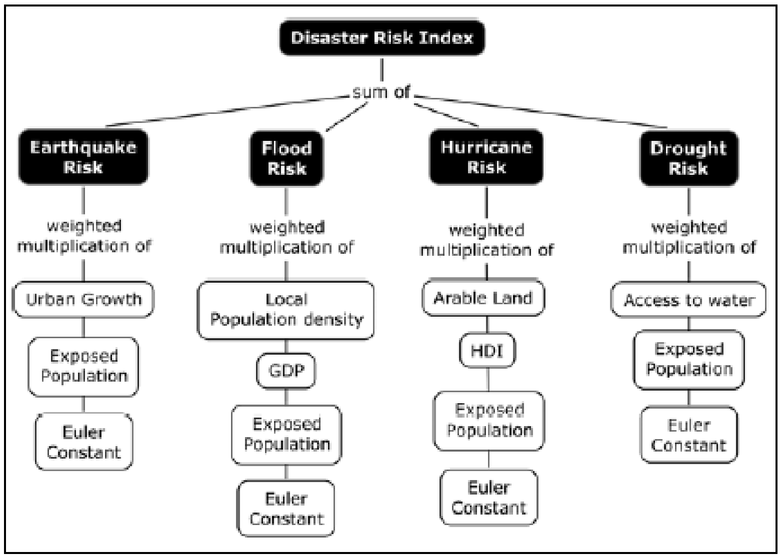
APPENDIX B: List of Variables from the Social Vulnerability Index 2006-2010

VARIABLE	DESCRIPTION
QASIAN	Percent Asian
QBLACK	Percent Black
QHISP	Percent Hispanic
QNATAM	Percent Native American
QAGEDEP†	Percent of Population Under 5 Years or 65 and Over
QFAM†	Percent of Children Living in Married Couple Families
MEDAGE	Median Age
QSSBEN	Percent of Households Receiving Social Security
QPOVTY	Percent Poverty
QRICH200K	Percent of Households Earning Greater Than $200,000 Annually
PERCAP	Per Capita Income
QESL†	Percent Speaking English as a Second Language with Limited English Proficiency
QFEMALE	Percent Female
QFHH	Percent Female Headed Households
QNRRES	Percent of Population Living in Nursing and Skilled-Nursing Facilities
HOSPTPC	Hospitals Per Capita (County Level ONLY)
QNOHLTH†	Percent of Population Without Health Insurance (County Level ONLY)
QED12LES	Percent with Less Than 12th Grade Education
QCVLUN	Percent Civilian Unemployment
PPUNIT	People Per Unit
QRENTER	Percent Renters
MDHSEVAL†	Median House Value
MDGRENT†	Median Gross Rent
QMOHO	Percent Mobile Homes
QEXTRCT	Percent Employment in Extractive Industries
QSERV	Percent Employment in Service Industry
QFEMLBR	Percent Female Participation in Labor Force
QNOAUTO†	Percent of Housing Units with No Car
QUNOCCHU	Percent Unoccupied Housing Units

*Note: QSPNEEDS (Percent of Population with a Disability) was included in SoVI® 2005-09 but excluded from SoVI® 2006-10 because estimates were not available for all counties.

(Source: SoVI Webpage -- Hazards and Vulnerability Research Institute – University of South Carolina 2013)

APPENDIX C: List of Variables from the Disaster Risk Index



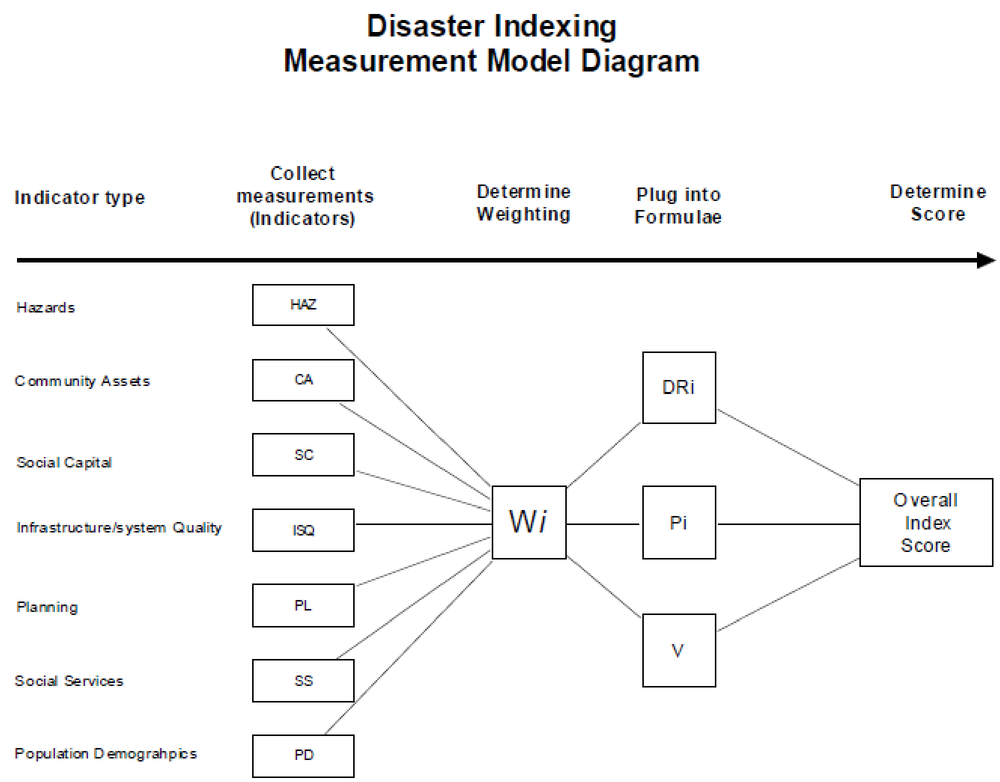
Note: The Euler Constant is the mathematical constant *e*, which is the base of the natural logarithm.

DRI Variables:

Variable	Indicator Type
Urban Growth	EQ
Exposed Population - Earthquake	EQ
Local Population Density	FR
GDP	FR
Exposed Population – Flood	FR
Arable Land	HR
HDI (ave. of (weighted ave of Adult Literacy rate (2) X Gross Enrollment (1) X GDP)	HR
Exposed Population – Hurricane	HR
Access to water	DR
Exposed Population – Drought	DR

(Source: Gall 2007, p. 55 – Structure of the Disaster Risk Index)

APPENDIX D: List of Variables from the Disaster Preparedness Index



DPI Variables:

Variable	Indicator Type
Hazard -MMI with a 50 year return period	HAZ
Hazard -MMI with a 500 year return period	HAZ
Hazard - % of urbanized area with soft soil	HAZ
Hazard - % of urbanized area with high liquefaction susceptibility	HAZ
Hazard - % of buildings that are wood	ISQ
Hazard -Population density (people per sq km)	PD
Hazard - Tsunami potential indicator	PL
Exposure-Population	PD

Exposure-Per Capita GDP	CA
Exposure-Number of Housing Units	ISQ
Exposure-Urbanized land Area	ISQ
Vulnerability -Seismic code indicator	PL
Vulnerability -City wealth indicator	CA
Vulnerability -City age indicator	ISQ
Vulnerability -% of population aged 0-4 and 65+	PD
Emergency Response-Avg growth in GDP over 10 years	CA
Emergency Response-housing vacancy rate	PD/ISQ
Emergency Response-hospitals per 100,000 residents	SS
Emergency Response-physicians per 100,000 residents	SS
Exposure-average daily number of tourists	PD
Exposure-median home value	CA
Exposure-income generated from agriculture	CA
Exposure-number of business units	CA/ISQ
Exposure-value of power lines	ISQ
Vulnerability-%pop aged 16–64 that has a mobility limitation	PD
Vulnerability-Public education indicator (awareness about hurricanes)	SC
Vulnerability- Avg BCEGS grade	PL
Vulnerability- % of homes that are mobile	ISQ
Vulnerability- businesses with less than 20 employees	PD/ISQ
Vulnerability- % of county land detached from mainland	CA
Emergency Response-number of shelters available	SS
Emergency Response-number of hospital beds per 100,000	SS
Emergency Response-City layout (roads in grid -0, otherwise -1)	ISQ
House Insurance	EA
Income	CA
Tenure Type	CA
Age	PD
Debt	EA
Employment	PD/SC
Car Ownership	CA
English Skills	PD/SC
Household Type	PD/CA
Health Insurance	EA
Residence Type	CA
Disability	PD
Gender	PD
Exposure-Population growth rate-average annual rate	PD
Exposure-Urban growth- avg annual rate %	ISQ
Exposure-people per 5km sq	PD
Exposure-Poverty people living below poverty level	PD
Exposure-Capital Stock in millions of $ per sq km	EA
Exposure-Imports and Exports of Goods and Service as % of GDP	CA/EA

Exposure-Gross domestic fixed investment	CA
Socioeconomic-dependents as % of working age population	PD
Socioeconomic-unemployment rate	PD
Socioeconomic-debt service burden	EA
Socioeconomic-soil degradation	CA
Resilience-Infrastructure and Housing Insurance as % of GDP	CA/EA
Risk Identification-systematic inventory of disaster losses	PL
Risk Identification-hazard monitoring and forecasting	PL
Risk Identification-vulnerability and risk assessment	PL
Risk Identification-public information and community participation	SC
Risk Identification-risk management training and education	PL
Disaster Management-Organization of EM operations	PL
Disaster Management-emergency response planning and implementation of warning system	PL
Disaster Management-supply of tools, equipment, and infrastructure	CA/ISQ
Disaster Management-Simulation-test and updating of response capability	PL
Disaster Management -community preparedness and training	SC
Disaster Management -rehabilitation and reconstruction planning	PL
Government/Financial - multisector coordination	SC/SS
Government/Financial - existence of social safety nets	SC/CA
Government/Financial -budget allocation and mobilization	CA/PL
Government/Financial - Insurance Coverage and loss transfer strategies for public assets	EA/CA
Government/Financial - housing and private sector insurance and reinsurance coverage	EA
Per Capita Income	CA
Median Age	PD
# of commercial establishments/mile sq	ISQ
single-sector economic --> % employed in extractive industries	PD
Housing stock and tenancy--> % of homes that are mobile	ISQ
% African American	PD
% Hispanic	PD
% Native American	PD
% Asian	PD
% employed in service occupations	PD
% employed in transportation communication and public utilities	PD
Hazard-Change in vibration intensity	HAZ
Hazard-Liquefaction (softening of subsoil)	HAZ
Hazard-Tsunami	HAZ
Hazard-Fire Following earthquake	HAZ
Vulnerability -Preparedness (very good,good, average, below avg)	PL
Vulnerability-Quality of Construction (very good, good, avg, below avg)	ISQ
Vulnerability- Building Density	ISQ
Vulnerability- Population Density	PD

Exposure-Average value of household for residential buildings	CA
Exposure-GDP for commercial/industrial buildings	CA
Number of earthquakes over last 50 years/10,0000 sq km >6.0 Richter	HAZ
Number of tsunamis with run up 2m over last 50 years /10,000 sq km coast area	HAZ
Number of nuclear facilities	ISQ
Number of shipping ports	ISQ
Average number of tourists	PD
FIRE response time	SS
# of fire stations per 1000	SS
Number of personnel per 1000 pop	SS
funding per 1000 pop	SS/PL
vehicles per 1000 pop	SS
EMS Response time	SS
# of available hospital/clinic beds per 1000	SS
# of medical personnel per 1000	SS
POLICE avg response time	SS
# of personnel per 1000 pop	SS
funding per person	SS/PL
Pre-existing emergency ordinances	PL
Existing Special Area Zoning	PL
Hazard maps	PL
local funding for mitigation/planning	PL
pre-existing recovery plan	PL
existence of Emergency EMO yes/no	PL/SS
staffing of EMO per 1000	PL/SS
existence of emergency plan yes/no	PL
EOC activation plan	PL
Age of EOC plan	PL
training or simulation using plan yes/no	SC
funding per capita	PL
est. emergency ops center yes/no	PL/SS
availability mass care sites yes/no	SS
drills and exercises yes/no	SC
existence of level of activity (LEPC) yes/no	SS
existence of community based org. yes/no	SS
disaster response designated yes/no	SS
general social service yes/no	SS
National Org Yes/No	SS
volunteer org (yes/no)	SS
daily newspapers yes/no	SC
# of local radio stations	SC
earthquake MM scale mult -10	HAZ
chemical facilities	HAZ
railway facilities	HAZ

nuclear plant	HAZ
existence of evacuation plan	PL
warning system	PL
Total city budget per person	CA
cash reserves in general fund	CA
cash reserves as % of annual budget	CA
% of budget to debt service	CA
city's bond rating	CA
Unemployment	PD
overcrowding - households with more than one person per room	PD
long term sick	PD
single parents	PD
elderly over 75+	PD
Preexisting health problems	PD

(Source: Simpson 2006, p. 14-18 – Disaster Preparedness Index Working Paper)

APPENDIX E: List of Variables from the Disaster Operations Model

Source: FEMA, Mapping and Analysis Center 2012

<u>Geography/Demographics</u>

County_State_County_FIPS:
County and State name with corresponding State and County FIPS code
Calculation: Concatenation
Source: U.S. 2000 Census (SF1) Summary File

Housing units:
Summation of Housing Units (a house, an apartment, a mobile home or trailer, a group of rooms, or a single room occupied as a separate living quarters, or if vacant, intended for occupancy as separate living quarters) in the affected tracts
Calculation: None
Source: U.S. 2000 Census (SF1) Summary File

Total Population (2000):
2000 Population in affected census tracts
Calculation: None
Source: U.S. 2000 Census (SF1) Summary File

Total Population (Hurricane Year):
Population in affected census tracts
Calculation: Estimation of 2001, 2002, 2003, and 2004
Source: U.S. 2000 Census (SF1) Summary File

Total Area (sq mi):
Total area in square miles of each affected census county
Calculation: None
Source: U.S. 2000 Census (SF1) Summary File

Population Density (/sqmi) (2000):
Number of people per square mile
Calculation:Population of 2000 divided by the Total Area
Source: U.S. 2000 Census (SF1) Summary File

Income per Capita ($):
The mean income computed for every man, woman, and child in a county
Calculation: None
Source: U.S. Census (SF3) Summary File

Poverty Percent:
Percent of Sample Population below Poverty
Calculation: Count of Population below poverty/Sample Population Count
Source: U.S. Census (SF3) Summary File

Average distance to coast:
Mean distance to coast from the centroid of the census county
Any distance greater than 100 miles will be reported as 100 miles
Calculation: Mean total when rolled up from the Tract Level
Source: HAZUS

Tree Volume:
Estimation of tree volume that is likely to be collected and discarded at public expense
Calculation: Summed when rolled up from the Tract level
Source: HAZUS

Max Sustained Winds:
HAZUS does not report if less than 50 mph. Null values are replaced with 999.
Sustained wind speed at the time of landfall (one minute average over water)
Calculation: Maximum when rolled up from the Tract Level
Source: HAZUS

Building Loss ($1K):
Building loss is calculated using the cost to re-build the structure.
Initially building loss is calculated categorically by material type. The category totals are then manually summed to get a total of all building loss by county.
Calculation: Sum of Building Loss (Wood + Steel + Manufactured Homes + Masonry + Concrete)
Source: National Institute of Building Sciences (NIBS), HAZUS

Content Loss ($1K):
Content/Interior damage is estimated using an implicit model. The economic damage to the interior of the building is a function of the damage to the roof cover, roof sheathing, roof structure and the windows and doors.
Calculation: Sum of Building Loss (Wood + Steel + Manufactured Homes + Masonry + Concrete)
Source: National Institute of Building Sciences (NIBS), HAZUS

Number of Bridges:
Number of Bridges in the affected counties
Calculation: Summed when rolled up from the Tract level
Source: National Institute of Building Sciences (NIBS), HAZUS

Miles of Road:
Miles of Nonfederal roadways in the affected counties
- (exclude Fed. Highways, Nat'l Park, Indian Land, Mining)

Calculation: Summed when rolled up from the Tract level
Source: NAVTEQ

<u>Economic Facilities (EF)</u>

Emergency Response Centers:
Moderate (M) - Moderate Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Severe (S) - Severe Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Complete (C) - Complete Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Count - Count of effected Emergency Response Centers
Calculation: Summed when rolled up from the Tract level
Source: HAZUS

Fire Stations:
Moderate (M) - Moderate Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Severe (S) - Severe Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Complete (C) - Complete Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Count - Count of effected Fire Stations
Calculation: Summed when rolled up from the Tract level
Source: HAZUS

Police Stations:
Moderate (M) - Moderate Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Severe (S) - Severe Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Complete (C) - Complete Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Count - Count of effected Police Stations

Calculation: Summed when rolled up from the Tract level
Source: HAZUS

Schools: All schools - Private and public, High, middle, elementary.
Moderate (M) - Moderate Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Severe (S) - Severe Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Complete (C) - Complete Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Count - Count of effected Schools
Calculation: Summed when rolled up from the Tract level
Source: HAZUS

Medical Facilities: Medical Offices and Clinics
Moderate (M) - Moderate Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Severe (S) - Severe Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Complete (C) - Complete Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Count - Count of effected Medical Facilities
Calculation: Summed when rolled up from the Tract level
Source: HAZUS

Economic Loss (EL)
Grade Schools: Grade Schools and Libraries
Moderate (M) - Moderate Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Severe (S) - Severe Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Complete (C) - Complete Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Building - Total cost of Grade School building(s)
Calculation: Summed when rolled up from the Tract level
Content - Total cost of the contents in the Grade School building(s)
Calculation: Summed when rolled up from the Tract level
Source: HAZUS

Hospitals: Hospitals
Moderate (M) - Moderate Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Severe (S) - Severe Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level

Complete (C) - Complete Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Building - Total cost of hospital building(s)
Calculation: Summed when rolled up from the Tract level
Content - Total cost of the contents in the hospital building(s)
Calculation: Summed when rolled up from the Tract level
Source: HAZUS

Nonprofits: Church / Membership Organizations
Moderate (M) - Moderate Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Severe (S) - Severe Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Complete (C) - Complete Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Building - Total cost of Nonprofit building(s)
Calculation: Summed when rolled up from the Tract level
Content - Total cost of the contents in the Nonprofit building(s)
Calculation: Summed when rolled up from the Tract level
Source: HAZUS

Nursing Homes: Nursing Homes and Eldercare Facilities
Moderate (M) - Moderate Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Severe (S) - Severe Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Complete (C) - Complete Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Building - Total cost of Nursing Home building(s)
Calculation: Summed when rolled up from the Tract level
Content - Total cost of the contents in the Nursing Home building(s)
Calculation: Summed when rolled up from the Tract level
Source: HAZUS

Government Emergency Response Centers:
Moderate (M) - Moderate Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Severe (S) - Severe Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Complete (C) - Complete Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Building - Total cost of Government Emergency Response Center building(s)
Calculation: Summed when rolled up from the Tract level

Content - Total cost of the contents in the Government Emergency Response Center building(s)
Calculation: Summed when rolled up from the Tract level
Source: HAZUS

Government General Services:
Moderate (M) - Moderate Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Severe (S) - Severe Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Complete (C) - Complete Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Building - Total cost of Government General Services building(s)
Calculation: Summed when rolled up from the Tract level
Content - Total cost of the contents in the Government General Services building(s)
Calculation: Summed when rolled up from the Tract level
Source: HAZUS

Colleges: All 2-yr, 4-yr Colleges and Universities
Moderate (M) - Moderate Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Severe (S) - Severe Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Complete (C) - Complete Damage Probability (0.0 - 1.0)
Calculation: Mean total when rolled up from the Tract Level
Building - Total cost of college building(s)
Calculation: Summed when rolled up from the Tract level
Content - Total cost of the contents in the college building(s)
Calculation: Summed when rolled up from the Tract level
Source: HAZUS

County – Name of county
State – State Abbreviation
FIPS – Federal Information Processing Standards

Declared – Y/N Indicating whether the county was declared a disaster (Boolean identifier field)
Source: FEMA

Declaration – Disaster Declaration number (if declared)
Source: FEMA

Year – Year of storm
Source: FEMA

APPENDIX F: List of Variables from the Disaster Assistance Data

Source: FEMA – National Emergency Management System, 2014

County Code (5-digit FIPS):
County and State name with corresponding State and County FIPS code

Disaster Title:
Name of incident assigned by the National Hurricane Center

Disaster Number:
Sequentially assigned number used to designate an event or incident declared as a disaster.

Total Amount from Federal Assistance (IA, PA, MA, SBA):
Combined amount for Individual Assistance, Public Assistance, Mitigation Assistance, and SBA disaster loans aggregated to the county level.

Sum of No Valid Registrations:
Count of FEMA registration owners within the state, county, zip where registration is valid. In order to be a valid registration applicant must be in an Individual Assistance declared state or county and registered within FEMA designated registration period.

Sum of Average Amount FEMA Inspected Damage:
The average inspected damage (based on FEMA's inspection guidelines) for valid registration owners within the state, county, zip that had a completed inspection.

Sum of No. Total Inspected:
The total FEMA applicants who received an inspection.

Sum of Total Damage Amount:

The total damage recorded by FEMA at the time of inspection.

Sum of No FEMA Inspected Damage:
The number of applicants who received an inspection but had no damage recorded by the inspector.

Sum of FEMA Inspected Damage between $1 and $10,000:
A count of valid registration owners within the state, county, zip that had a completed inspection (based on FEMA's guidelines) where the inspected damage fell between $1 and $10,000.

Sum of FEMA Inspected Damage between $10,001 and $20,000:
A count of valid registration owners within the state, county, zip that had a completed inspection (based on FEMA's guidelines) where the inspected damage fell between $10,001 and $20,000.

Sum of FEMA Inspected Damage between $20,001 and $30,000:
A count of valid registration owners within the state, county, zip that had a completed inspection (based on FEMA's guidelines) where the inspected damage fell between $20,001 and $30,000.

Sum of FEMA Inspected Damage > $30,000:
A count of valid registration owners within the state, county, zip that had a completed inspection (based on FEMA's guidelines) where the inspected damage was greater than $30,000.

Sum of No. Approved for FEMA Assistance:
The number of FEMA applicants who were approved for FEMA's IHP assistance.

Sum of Total Approved IHP Amount:
The total amount approved under FEMA's IHP program.

Sum of Repair/Replace Amount:
The total amount of Repair and/or Replacement approved for Housing Assistance (HA) under FEMA's IHP program (note that renters are not eligible for this type of assistance because they do not own the structure)

Sum of Rental Amount:
The total amount of Rental Assistance approved for Housing Assistance (HA) under FEMA's IHP program

Sum of Other Needs Amount:
The total amount of Other Needs (ONA) assistance approved under FEMA's IHP program (this could include, personal property, transportation, medical, dental, funeral, essential tools, moving/storage, miscellaneous and other needs).

Sum of No. Approved between $1 and $10,000:
A count of valid registration owners within the state, county, zip that received a financial grant from FEMA that fell between $1 and $10,000.

Sum of No. Approved between $10,001 and $25,000:
A count of valid registration owners within the state, county, zip that received a financial grant from FEMA that fell between $10,001 and $25,000.

Sum of Approved between $25,001 and Max:
A count of valid registration owners within the state, county, zip that received a financial grant from FEMA that fell between $25,001 and the maximum financial grant from FEMA.

Sum of No. Approved Total Max Grants:
A count of valid registration owners within the state, county, zip that received the maximum financial grant from FEMA.

Sum of No Valid Registrations (Renters):
Count of FEMA registration renters within the state, county, zip where the registration is valid. In order to be a valid registration the applicant must be in an Individual Assistance declared state and county and have registered within the FEMA designated registration period.

Sum of No. Total Inspected (Renters):
The total FEMA applicants who received an inspection.

Sum of No FEMA Inspected Damage (Renters):

Renters do not receive a full home inspection as they are only eligible for the items that they own. Instead a degree of damage is assigned. This is a count of valid registration renters who were deemed to have had no damage that the time of inspection.

Sum of No. Approved for FEMA Assistance (Renters):
The number of FEMA applicants who were approved for FEMA's IHP assistance

Sum of Total Approved IHP Amount (Renters):
The total amount of Rental Assistance approved for Housing Assistance (HA) under FEMA's IHP program

No. PA Projects:
Sum of the Number of PA projects aggregated to the county level.

Sum of PA Project Amount:
The estimated total cost of the Public Assistance grant project, without administrative costs. This amount is based on the damage survey.

Sum of Federal Share Obligated:

The Public Assistance grant funding available to the grantee (State), for sub-grantee's approved Project Worksheets.

Sum of Total Obligated:
The federal share of the Public Assistance grant eligible project amount, plus grantee (State) and sub-grantee (applicant) administrative costs. The federal share is typically 75% of the total cost of the project.

No Projects Damage Category A–Debris Removal:
Project worksheets approved for debris removal.

Sum of Project Amount Damage Category A:
Amount approved for debris removal.

Sum of Federal Share Obligated Damage Category A:
Amount of Federal share for debris removal.

Sum of Total Obligated Damage Category A:
Total amount obligated for debris removal.

No Projects Damage Category B–Protective Measures:
Project worksheets approved for protective measures.

Sum of Project Amount Damage Category B:
Amount approved for protective measures.

Sum of Federal Share Obligated Damage Category B:
Amount of Federal share for protective measures.

Sum of Total Obligated Damage Category B:
Total amount obligated for protective measures.

No Projects Damage Category C–Roads & Bridges:
Project worksheets approved for roads and bridges repairs.

Sum of Project Amount Damage Category C:
Amount approved for roads and bridges.

Sum of Federal Share Obligated Damage Category C:
Amount of Federal share for roads and bridges.

Sum of Total Obligated Damage Category C:
Total amount obligated for roads and bridges.

No Projects Damage Category D–Water Control Facilities:
Project worksheets approved for water control facility repairs.

Sum of Project Amount Damage Category D:
Amount approved for water control facilities.

Sum of Federal Share Obligated Damage Category D:
Amount of Federal share for water control facilities.

Sum of Total Obligated Damage Category D:

Total amount obligated for water control facilities.

No Projects Damage Category E–Public Buildings:
Project worksheets approved for public building repairs.

Sum of Project Amount Damage Category E:
Amount approved for public buildings.

Sum of Federal Share Obligated Damage Category E:
Amount of Federal share for public buildings.

Sum of Total Obligated Damage Category E:
Total amount obligated for public buildings.

No Projects Damage Category F–Public Utilities:
Project worksheets approved for public utility repairs.

Sum of Project Amount Damage Category F:
Amount approved for public utilities.

Sum of Federal Share Obligated Damage Category F:
Amount of Federal share for public utilities.

Sum of Total Obligated Damage Category F:
Total amount obligated for public utilities.

No Projects Damage Category G–Recreational or Other:
Project worksheets approved for recreational or other community facility repairs.

Sum of Project Amount Damage Category G:
Amount approved for recreation or other.

Sum of Federal Share Obligated Damage Category G:
Amount of Federal share for recreation or other.

Sum of Total Obligated Damage Category G:
Total amount obligated for recreation or other.

No Projects Damage Category Z–State Management:
Project worksheets approved for State Management.

Sum of Project Amount Damage Category Z:
Amount approved for state management.

Sum of Federal Share Obligated Damage Category Z:
Amount of Federal share for state management.

Sum of Total Obligated Damage Category Z:
Total amount obligated for state management.

No. of HM Projects:
Sum of the number of Hazard Mitigation projects at the county level.

Sum of HM Project Amount:
Total cost of a project as submitted in the project application.

No. HM Total Damage Cat 0_49%:
Amount of damage, expressed as a percentage, to a structure relative to the market value of the structure before the damage occurred.

No. HM Total Damage Cat 50_99%:
Amount of damage, expressed as a percentage, to a structure relative to the market value of the structure before the damage occurred.

No. HM Total Damage Cat 100%:
Amount of damage, expressed as a percentage, to a structure relative to the market value of the structure before the damage occurred.

Sum of HM Total Actual Amount Paid:
Total amount paid for the project.

No. HM Total Properties Acquired:
Sum of the number of properties acquired at the county level.

Source: Small Business Administration 2012

No. Loans:
Sum of the number of disaster loans awarded by SBA at the county level.

Sum of Total Gross Amount:
The amount of the loan guaranteed by the SBA.

No. Paid in Full:
No of loans that were fully paid by the applicants.

Sum of Total Amount Paid in Full:
Sum of the total amount paid in full for the loan.

No. Charged Off:
Number of loans that were charged off.

Sum of Total Amount Charged Off:
Sum of the total amount paid in charged off for the loan.

County – Name of county
State – State Abbreviation
FIPS – Federal Information Processing Standards

Declared – Y/N Indicating whether the county was declared a disaster (Boolean identifier field)
Source: FEMA

Declaration – Disaster Declaration number (if declared)
Source: FEMA

Year – Year of storm
Source: FEMA

APPENDIX G: Correlation Matrices

Bret

Correlation matrix (Pearson):

Variables	SOVI	HUNITS	POP2000	AREASQMI	POPDEN00	PERCAPINC	PCTPOV	AVEDISTC	TREEVOL	MAXSUSWIN
SOVI	**1**									
HUNITS	-0.428	**1**								
POP2000	-0.413	**0.996**	**1**							
AREASQM	-0.069	0.166	0.234	**1**						
POPDEN0	-0.474	**0.939**	**0.906**	-0.083	**1**					
PERCAPIN	-0.481	-0.174	-0.226	-0.352	0.008	**1**				
PCTPOV	**0.554**	0.247	0.290	0.236	0.090	**-0.893**	**1**			
AVEDISTC	0.233	0.098	0.162	**0.734**	-0.159	**-0.642**	0.490	**1**		
TREEVOL	0.236	-0.255	-0.256	0.045	-0.272	0.399	-0.334	-0.267	**1**	
MAXSUSW	-0.136	-0.174	-0.194	-0.371	-0.061	0.534	-0.281	-0.346	-0.117	**1**
BLDGLOSS	0.332	0.099	0.074	-0.190	0.182	-0.070	0.242	-0.284	0.495	-0.304
CNTLOSS1	0.172	0.263	0.229	-0.203	0.366	-0.069	0.215	-0.316	0.370	-0.343
NUMBRID	-0.513	**0.896**	**0.886**	0.252	**0.880**	-0.172	0.129	0.072	-0.326	-0.336
ROADMI	-0.440	**0.977**	**0.986**	0.281	**0.870**	-0.270	0.273	0.197	-0.275	-0.276
ERC_CNT	-0.147	**0.730**	**0.722**	-0.034	**0.688**	-0.291	0.224	0.048	-0.324	-0.267
FIRESTA_	-0.419	**0.911**	**0.882**	0.004	**0.906**	-0.046	0.056	-0.028	-0.237	-0.237
POLSTA_C	-0.254	**0.907**	**0.927**	0.209	**0.762**	-0.406	0.412	0.261	-0.257	-0.277
SCH_CT	-0.477	**0.965**	**0.967**	0.251	**0.861**	-0.165	0.200	0.153	-0.255	-0.245
MEDFAC_	-0.495	**0.887**	**0.853**	0.057	**0.902**	0.060	-0.003	-0.073	-0.185	-0.203
ERC_prob	0.429	-0.247	-0.244	0.150	-0.269	-0.278	0.102	0.268	-0.144	-0.109
Fire_prob	0.102	-0.134	-0.142	0.021	-0.107	-0.177	0.094	-0.031	-0.108	-0.170
Pol_prob	0.217	-0.252	-0.248	0.073	-0.273	0.420	-0.372	-0.219	**0.980**	-0.055
Sch_prob	0.332	-0.289	-0.284	0.055	-0.313	0.356	-0.264	-0.198	**0.980**	-0.069
Med_prob	-0.174	-0.214	-0.218	-0.166	-0.218	0.000	-0.064	-0.234	0.012	-0.118
Gra_prob	0.329	-0.289	-0.284	0.056	-0.312	0.358	-0.268	-0.196	**0.980**	-0.069
Gov_prob	0.325	-0.287	-0.283	0.057	-0.311	0.361	-0.273	-0.197	**0.981**	-0.069
GovE_prol	0.325	-0.288	-0.283	0.056	-0.311	0.360	-0.272	-0.197	**0.981**	-0.069
NH_prob	0.226	-0.255	-0.251	0.074	-0.277	0.417	-0.366	-0.215	**0.980**	-0.056
Nonp_pro	0.307	-0.282	-0.277	0.060	-0.305	0.372	-0.291	-0.201	**0.983**	-0.066
Hosp_prol	0.358	-0.298	-0.293	0.050	-0.322	0.339	-0.239	-0.189	**0.975**	-0.073
Coll_prob	0.325	-0.288	-0.283	0.056	-0.311	0.360	-0.272	-0.197	**0.981**	-0.069

Variables	BLDGLOSS1K	CNTLOSS1K	NUMBRIDGE	ROADMI	ERC_CNT	FIRESTA_CT	POLSTA_CT	SCH_CT	MEDFAC_CT	ERC_prob
SOVI										
HUNITS										
POP2000										
AREASQM										
POPDEN0										
PERCAPIN										
PCTPOV										
AVEDISTC										
TREEVOL										
MAXSUSW										
BLDGLOSS	**1**									
CNTLOSS1	**0.969**	**1**								
NUMBRID	0.064	0.247	**1**							
ROADMI	0.019	0.176	**0.914**	**1**						
ERC_CNT	-0.158	-0.036	**0.717**	**0.767**	**1**					
FIRESTA_	0.074	0.254	**0.897**	**0.882**	**0.799**	**1**				
POLSTA_C	0.038	0.153	**0.777**	**0.949**	**0.805**	**0.791**	**1**			
SCH_CT	-0.002	0.160	**0.900**	**0.968**	**0.726**	**0.926**	**0.886**	**1**		
MEDFAC_	0.147	0.335	**0.884**	**0.828**	**0.609**	**0.955**	**0.668**	**0.907**	**1**	
ERC_prob	-0.304	-0.322	-0.108	-0.181	0.277	-0.079	-0.105	-0.230	-0.244	**1**
Fire_prob	0.052	0.114	-0.100	-0.122	0.025	-0.112	-0.079	-0.184	-0.162	0.536
Pol_prob	0.377	0.244	-0.332	-0.264	-0.290	-0.256	-0.246	-0.263	-0.219	-0.129
Sch_prob	0.470	0.315	-0.376	-0.310	-0.330	-0.294	-0.271	-0.299	-0.253	-0.135
Med_prob	0.172	0.228	-0.227	-0.201	-0.352	-0.202	-0.177	-0.174	-0.142	-0.158
Gra_prob	0.466	0.311	-0.376	-0.310	-0.330	-0.294	-0.271	-0.299	-0.253	-0.136
Gov_prob	0.462	0.308	-0.375	-0.308	-0.328	-0.293	-0.271	-0.298	-0.252	-0.135
GovE_prol	0.463	0.309	-0.375	-0.308	-0.329	-0.293	-0.271	-0.298	-0.252	-0.135
NH_prob	0.380	0.245	-0.337	-0.268	-0.292	-0.259	-0.249	-0.266	-0.222	-0.125
Nonp_pro	0.448	0.297	-0.368	-0.301	-0.322	-0.287	-0.267	-0.293	-0.247	-0.133
Hosp_prol	0.488	0.328	-0.387	-0.321	-0.340	-0.303	-0.277	-0.308	-0.261	-0.137
Coll_prob	0.463	0.309	-0.375	-0.308	-0.329	-0.293	-0.271	-0.298	-0.252	-0.135

Variables	Fire_prob	Pol_prob	Sch_prob	Med_prob	Gra_prob	Gov_prob	GovE_prob	NH_prob	Nonp_prob	Hosp_prob	Coll_prob
SOVI											
HUNITS											
POP2000											
AREASQM											
POPDEN0											
PERCAPIN											
PCTPOV											
AVEDISTC											
TREEVOL											
MAXSUSW											
BLDGLOSS											
CNTLOSS1											
NUMBRID											
ROADMI											
ERC_CNT											
FIRESTA_											
POLSTA_C											
SCH_CT											
MEDFAC_											
ERC_prob											
Fire_prob	**1**										
Pol_prob	-0.197	**1**									
Sch_prob	-0.211	**0.983**	**1**								
Med_prob	**0.554**	-0.129	-0.140	**1**							
Gra_prob	-0.211	**0.984**	**1.000**	-0.141	**1**						
Gov_prob	-0.210	**0.985**	**1.000**	-0.140	**1.000**	**1**					
GovE_prol	-0.210	**0.985**	**1.000**	-0.140	**1.000**	**1.000**	**1**				
NH_prob	-0.194	**1.000**	**0.985**	-0.133	**0.986**	**0.987**	**0.987**	**1**			
Nonp_pro	-0.208	**0.990**	**0.999**	-0.139	**0.999**	**1.000**	**1.000**	**0.992**	**1**		
Hosp_prol	-0.214	**0.975**	**0.999**	-0.141	**0.999**	**0.998**	**0.999**	**0.977**	**0.996**	**1**	
Coll_prob	-0.210	**0.985**	**1.000**	-0.140	**1.000**	**1.000**	**1.000**	**0.987**	**1.000**	**0.999**	**1**

Values in bold are different from 0 with a significance level alpha=0.05

Charley

Correlation matrix (Pearson):

Variables	SOVI	HUNITS	POP2000	AREASQMI	POPDEN00	PERCAPINC	PCTPOV	AVEDISTC	TREEVOL	MAXSUSWIN	BLDGLOSS1K	CNTLOSS1K	NUMBRIDGE	ROADMI	ERC_CNT	FIRESTA_CT	POLSTA_CT	SCH_CT	MEDFAC_CT	ERC_prob	FIRE_prob	Pol_prob	Sch_prob	Med_prob	Gra_prob	Gov_prob	GovE_prob	NH_prob	Nonp_prob	Hosp_prob	Coll_prob
SOVI	**1**																														
HUNITS	**-0.567**	**1**																													
POP2000	**-0.577**	**0.989**	**1**																												
AREASQM	0.095	0.195	0.168	**1**																											
POPDEN0	**-0.668**	**0.852**	**0.869**	-0.198	**1**																										
PERCAPIN	**-0.455**	0.332	0.258	-0.008	0.338	**1**																									
PCTPOV	**0.656**	**-0.422**	-0.364	0.045	**-0.456**	**-0.771**	**1**																								
AVEDISTC	0.316	-0.177	-0.105	0.282	-0.139	**-0.578**	**0.389**	**1**																							
TREEVOL	-0.073	0.304	0.290	0.053	0.278	0.088	-0.254	0.001	**1**																						
MAXSUSW	0.084	**-0.369**	-0.350	-0.169	-0.300	-0.186	0.239	-0.109	**-0.481**	**1**																					
BLDGLOSS	0.067	0.106	0.081	-0.038	0.080	0.079	-0.228	-0.120	**0.860**	-0.302	**1**																				
CNTLOSS1	0.059	0.119	0.094	-0.039	0.095	0.084	-0.233	-0.117	**0.871**	-0.310	**1.000**	**1**																			
NUMBRID	**-0.430**	**0.890**	**0.893**	0.226	**0.716**	0.296	-0.263	-0.170	0.189	-0.215	0.079	0.088	**1**																		
ROADMI	**-0.464**	**0.905**	**0.874**	0.302	**0.684**	0.177	-0.317	-0.106	0.361	-0.347	0.177	0.189	**0.793**	**1**																	
ERC_CNT	-0.268	0.208	0.215	0.039	0.258	0.118	-0.120	-0.083	-0.025	0.084	-0.066	-0.067	0.257	0.247	**1**																
FIRESTA_	-0.282	0.290	0.236	**0.411**	0.071	0.077	-0.220	-0.117	0.067	-0.056	-0.064	-0.061	0.223	**0.458**	**0.443**	**1**															
POLSTA_C	-0.354	**0.557**	**0.538**	**0.555**	0.300	0.126	-0.234	0.089	0.273	**-0.409**	0.047	0.052	0.344	**0.601**	0.341	**0.548**	**1**														
SCH_CT	**-0.584**	**0.959**	**0.986**	0.170	**0.847**	0.200	-0.317	-0.062	0.245	-0.310	0.049	0.061	**0.880**	**0.831**	0.231	0.220	**0.552**	**1**													
MEDFAC_	**-0.443**	**0.914**	**0.913**	0.097	**0.759**	0.232	-0.318	-0.244	0.154	-0.246	0.060	0.067	**0.836**	**0.797**	0.217	0.161	**0.419**	**0.904**	**1**												
ERC_prob	-0.238	0.179	0.182	0.350	0.168	-0.044	-0.095	0.273	0.295	-0.205	0.147	0.148	0.043	0.238	**0.497**	0.362	**0.741**	0.216	0.005	**1**											
FIRE_prob	0.337	-0.217	-0.194	-0.068	-0.220	**-0.384**	**0.523**	0.219	0.186	-0.316	0.143	0.139	-0.153	-0.214	-0.107	-0.136	-0.029	-0.174	-0.207	0.092	**1**										
Pol_prob	0.318	-0.221	-0.196	-0.152	-0.198	-0.366	**0.561**	0.198	0.049	-0.232	0.015	0.011	-0.146	-0.231	-0.104	-0.163	-0.074	-0.176	-0.208	0.015	**0.964**	**1**									
Sch_prob	0.228	-0.151	-0.134	-0.098	-0.128	-0.256	0.238	0.138	**0.543**	-0.338	**0.617**	**0.614**	-0.092	-0.139	-0.121	-0.178	-0.091	-0.130	-0.158	0.059	**0.805**	**0.741**	**1**								
Med_prob	**0.386**	-0.184	-0.168	-0.151	-0.156	-0.216	0.326	-0.053	0.198	-0.215	0.254	0.250	-0.156	-0.208	-0.130	-0.203	-0.151	-0.154	-0.076	-0.048	**0.434**	0.302	0.266	**1**							
Gra_prob	0.313	-0.157	-0.143	-0.113	-0.140	-0.257	0.256	0.075	**0.606**	**-0.377**	**0.698**	**0.694**	-0.109	-0.142	-0.134	-0.199	-0.090	-0.139	-0.135	0.078	**0.775**	**0.656**	**0.926**	**0.590**	**1**						
Gov_prob	0.311	-0.155	-0.140	-0.110	-0.138	-0.258	0.257	0.079	**0.608**	**-0.380**	**0.695**	**0.691**	-0.108	-0.140	-0.133	-0.197	-0.087	-0.136	-0.134	0.081	**0.777**	**0.657**	**0.925**	**0.592**	**1.000**	**1**					
GovE_prol	0.311	-0.155	-0.141	-0.110	-0.138	-0.258	0.257	0.078	**0.607**	**-0.380**	**0.696**	**0.692**	-0.108	-0.141	-0.133	-0.198	-0.088	-0.137	-0.134	0.080	**0.777**	**0.657**	**0.925**	**0.592**	**1.000**	**1.000**	**1**				
NH_prob	0.315	-0.159	-0.146	-0.118	-0.142	-0.255	0.255	0.069	**0.604**	**-0.372**	**0.702**	**0.698**	-0.111	-0.144	-0.135	-0.202	-0.094	-0.142	-0.135	0.073	**0.771**	**0.655**	**0.927**	**0.587**	**1.000**	**1.000**	**1.000**	**1**			
Nonp_pro	0.318	-0.164	-0.152	-0.125	-0.147	-0.251	0.253	0.059	**0.600**	-0.364	**0.709**	**0.704**	-0.114	-0.147	-0.136	-0.206	-0.101	-0.148	-0.137	0.066	**0.765**	**0.653**	**0.928**	**0.580**	**0.999**	**0.998**	**0.999**	**1.000**	**1**		
Hosp_prol	0.302	-0.146	-0.130	-0.101	-0.128	-0.261	0.256	0.092	**0.617**	**-0.393**	**0.687**	**0.683**	-0.103	-0.134	-0.130	-0.191	-0.076	-0.126	-0.131	0.092	**0.782**	**0.657**	**0.922**	**0.597**	**0.999**	**0.999**	**0.999**	**0.998**	**0.996**	**1**	
Coll_prob	0.310	-0.154	-0.139	-0.108	-0.137	-0.259	0.257	0.081	**0.608**	**-0.381**	**0.694**	**0.690**	-0.108	-0.140	-0.133	-0.196	-0.086	-0.135	-0.134	0.082	**0.778**	**0.657**	**0.925**	**0.593**	**1.000**	**1.000**	**1.000**	**0.999**	**0.998**	**0.999**	**1**

Values in bold are different from 0 with a significance level alpha=0.05

Claudette

Correlation matrix (Pearson):

Variables	SOVI	HUNITS	POP2000	AREASQMI	POPDEN00	PERCAPINC	PCTPOV	AVEDISTC	TREEVOL	MAXSUSWIN	BLDGLOSS1K	CNTLOSS1K	NUMBRIDGE	ROADMI	ERC_CNT	FIRESTA_CT	POLSTA_CT	SCH_CT	MEDFAC_CT	ERC_prob	FIRE_prob	Pol_prob	Sch_prob	Med_prob	Gra_prob	Gov_prob	GovE_prob	NH_prob	Nonp_prob	Coll_prob
SOVI	**1**																													
HUNITS	**-0.765**	**1**																												
POP2000	**-0.768**	**0.994**	**1**																											
AREASQM	0.090	-0.083	-0.013	**1**																										
POPDEN0	**-0.590**	**0.890**	**0.839**	-0.389	**1**																									
PERCAPIN	**-0.660**	**0.509**	**0.484**	-0.218	**0.485**	**1**																								
PCTPOV	**0.823**	-0.467	-0.464	0.276	-0.349	**-0.654**	**1**																							
AVEDISTC	**0.564**	**-0.477**	-0.450	**0.574**	-0.458	-0.413	**0.609**	**1**																						
TREEVOL	-0.306	0.019	0.021	0.026	-0.109	0.110	-0.380	-0.346	**1**																					
MAXSUSW	0.168	0.181	0.163	0.064	0.331	0.153	0.451	0.224	-0.459	**1**																				
BLDGLOSS	-0.313	0.091	0.101	-0.019	-0.029	0.175	-0.350	-0.317	**0.943**	-0.334	**1**																			
CNTLOSS1	-0.313	0.093	0.103	-0.017	-0.028	0.174	-0.351	-0.311	**0.938**	-0.335	**1.000**	**1**																		
NUMBRID	**-0.692**	**0.644**	**0.698**	0.373	0.301	0.213	**-0.560**	-0.235	0.310	-0.265	0.298	0.302	**1**																	
ROADMI	**-0.763**	**0.803**	**0.841**	0.308	**0.526**	0.254	**-0.469**	-0.218	0.130	-0.052	0.134	0.136	**0.886**	**1**																
ERC_CNT	-0.101	0.229	0.281	0.337	-0.005	-0.115	-0.174	0.010	-0.154	-0.285	-0.127	-0.122	**0.482**	0.398	**1**															
FIRESTA_	**-0.601**	0.468	**0.530**	0.399	0.063	0.176	-0.438	-0.303	0.378	-0.401	0.288	0.284	**0.755**	**0.732**	0.376	**1**														
POLSTA_C	**-0.470**	0.332	0.405	0.407	-0.077	0.148	-0.422	-0.195	0.189	**-0.503**	0.136	0.136	**0.712**	**0.646**	**0.545**	**0.902**	**1**													
SCH_CT	**-0.503**	0.366	0.437	0.450	-0.023	0.038	-0.356	-0.139	**0.555**	-0.433	**0.563**	**0.567**	**0.790**	**0.703**	0.351	**0.821**	**0.777**	**1**												
MEDFAC_	-0.441	0.328	0.385	0.323	0.001	0.160	-0.393	-0.217	**0.737**	-0.388	**0.784**	**0.788**	**0.678**	**0.535**	0.202	**0.685**	**0.618**	**0.907**	**1**											
ERC_prob	0.087	-0.118	-0.127	0.139	-0.108	-0.033	-0.108	0.159	-0.115	-0.156	-0.123	-0.122	0.114	0.004	**0.542**	-0.146	0.050	-0.132	-0.189	**1**										
FIRE_prob	-0.164	-0.138	-0.164	-0.156	-0.142	0.037	-0.201	-0.426	**0.581**	-0.288	0.404	0.386	-0.076	-0.094	-0.214	0.261	0.083	0.050	0.109	-0.116	**1**									
Pol_prob	-0.155	-0.169	-0.192	-0.227	-0.153	0.057	-0.215	-0.421	0.467	-0.288	0.329	0.314	-0.129	-0.162	-0.213	0.176	0.054	-0.052	0.018	-0.115	**0.960**	**1**								
Sch_prob	-0.203	-0.120	-0.140	-0.203	-0.132	0.093	-0.265	-0.445	**0.726**	-0.327	**0.630**	**0.616**	-0.037	-0.109	-0.242	0.221	0.051	0.134	0.271	-0.132	**0.942**	**0.934**	**1**							
Med_prob	-0.176	-0.128	-0.154	-0.108	-0.140	0.035	-0.208	-0.434	**0.617**	-0.287	0.420	0.402	-0.043	-0.063	-0.214	0.281	0.092	0.089	0.149	-0.116	**0.986**	**0.914**	**0.906**	**1**						
Gra_prob	-0.226	-0.103	-0.121	-0.197	-0.124	0.115	-0.291	-0.440	**0.792**	-0.336	**0.725**	**0.713**	-0.004	-0.097	-0.250	0.212	0.038	0.187	0.354	-0.136	**0.893**	**0.883**	**0.990**	**0.862**	**1**					
Gov_prob	-0.227	-0.104	-0.122	-0.197	-0.124	0.115	-0.291	-0.440	**0.791**	-0.337	**0.724**	**0.712**	-0.005	-0.097	-0.250	0.212	0.038	0.186	0.353	-0.136	**0.893**	**0.884**	**0.990**	**0.862**	**1.000**	**1**				
GovE_prol	-0.226	-0.104	-0.121	-0.197	-0.124	0.115	-0.291	-0.439	**0.792**	-0.336	**0.724**	**0.713**	-0.005	-0.097	-0.250	0.212	0.038	0.186	0.354	-0.136	**0.892**	**0.883**	**0.990**	**0.861**	**1.000**	**1.000**	**1**			
NH_prob	-0.213	-0.111	-0.128	-0.193	-0.128	0.114	-0.273	-0.417	**0.777**	-0.318	**0.719**	**0.707**	-0.020	-0.105	-0.259	0.201	0.033	0.182	0.345	-0.142	**0.885**	**0.881**	**0.989**	**0.847**	**0.998**	**0.998**	**0.998**	**1**		
Nonp_pro	-0.226	-0.103	-0.121	-0.195	-0.123	0.118	-0.290	-0.437	**0.791**	-0.333	**0.727**	**0.715**	-0.006	-0.097	-0.250	0.211	0.038	0.188	0.355	-0.136	**0.890**	**0.881**	**0.990**	**0.858**	**1.000**	**1.000**	**1.000**	**0.999**	**1**	
Coll_prob	-0.226	-0.104	-0.121	-0.197	-0.124	0.115	-0.291	-0.439	**0.792**	-0.337	**0.724**	**0.712**	-0.005	-0.097	-0.250	0.212	0.038	0.186	0.353	-0.136	**0.893**	**0.883**	**0.990**	**0.862**	**1.000**	**1.000**	**1.000**	**0.998**	**1.000**	**1**

Values in bold are different from 0 with a significance level alpha=0.05

Floyd

Correlation matrix (Pearson):

Variables	SOVI	HUNITS	POP2000	AREASQMI	POPDEN00	PERCAPINC	PCTPOV	AVEDISTC	TREEVOL	MAXSUSWIN	BLDGLOSS1K	CNTLOSS1K	NUMBRIDGE	ROADMI	ERC_CNT	FIRESTA_CT	POLSTA_CT	SCH_CT	MEDFAC_CT	ERC_prob	FIRE_prob	Pol_prob	Sch_prob	Med_prob	Gra_prob	Gov_prob	GovE_prob	NH_prob	Nonp_prob	Hosp_prob	Coll_prob
SOVI	**1**																														
HUNITS	**-0.288**	**1**																													
POP2000	**-0.326**	**0.992**	**1**																												
AREASQM	0.101	0.107	0.065	**1**																											
POPDEN0	-0.041	**0.480**	**0.457**	-0.034	**1**																										
PERCAPIN	**-0.702**	**0.551**	**0.571**	-0.109	0.104	**1**																									
PCTPOV	**0.815**	**-0.287**	**-0.305**	0.050	-0.040	**-0.767**	**1**																								
AVEDISTC	**0.211**	**-0.229**	**-0.233**	**0.278**	-0.087	**-0.343**	**0.227**	**1**																							
TREEVOL	0.093	-0.004	-0.027	0.096	-0.061	-0.081	0.088	**-0.279**	**1**																						
MAXSUSW	-0.014	-0.049	-0.034	0.009	-0.104	-0.044	-0.009	**0.209**	**-0.152**	**1**																					
BLDGLOSS	0.031	0.008	-0.009	0.027	-0.035	-0.016	0.012	**-0.215**	**0.899**	-0.109	**1**																				
CNTLOSS1	0.035	-0.010	-0.026	0.023	-0.035	-0.020	0.010	**-0.200**	**0.880**	-0.099	**0.996**	**1**																			
NUMBRID	**-0.220**	**0.685**	**0.680**	**0.286**	**0.421**	**0.431**	**-0.210**	**0.139**	-0.059	-0.049	-0.051	-0.063	**1**																		
ROADMI	**-0.228**	**0.718**	**0.708**	**0.435**	**0.290**	**0.436**	**-0.260**	**-0.187**	-0.059	-0.035	-0.065	-0.078	**0.690**	**1**																	
ERC_CNT	**-0.230**	**0.492**	**0.532**	-0.048	0.013	**0.496**	**-0.217**	**-0.142**	-0.046	-0.032	-0.017	-0.036	**0.541**	**0.466**	**1**																
FIRESTA_	**-0.303**	**0.668**	**0.691**	**0.185**	**0.282**	**0.511**	**-0.279**	-0.042	0.051	0.045	0.059	0.042	**0.764**	**0.701**	**0.618**	**1**															
POLSTA_C	**-0.275**	**0.736**	**0.748**	0.119	**0.379**	**0.553**	**-0.274**	-0.121	0.031	-0.095	0.033	0.018	**0.765**	**0.657**	**0.701**	**0.867**	**1**														
SCH_CT	**-0.247**	**0.912**	**0.916**	0.082	**0.482**	**0.483**	**-0.222**	-0.106	0.018	-0.046	0.038	0.026	**0.755**	**0.649**	**0.543**	**0.760**	**0.787**	**1**													
MEDFAC_	**-0.244**	**0.433**	**0.445**	-0.122	**0.144**	**0.318**	**-0.163**	**-0.225**	-0.035	0.022	-0.022	-0.038	0.006	0.058	0.073	0.072	**0.142**	**0.146**	**1**												
ERC_prob	0.027	-0.020	-0.020	0.035	-0.013	-0.024	0.008	-0.075	**0.365**	-0.037	**0.310**	**0.320**	-0.021	-0.037	0.009	-0.010	-0.004	-0.005	-0.018	**1**											
FIRE_prob	**0.142**	-0.097	-0.109	0.010	-0.048	-0.131	0.120	**-0.252**	**0.837**	**-0.139**	**0.795**	**0.805**	-0.128	**-0.165**	-0.105	-0.057	-0.044	-0.053	-0.088	**0.339**	**1**										
Pol_prob	0.134	-0.103	-0.113	0.009	-0.048	-0.135	0.121	**-0.251**	**0.821**	**-0.140**	**0.776**	**0.786**	-0.135	**-0.175**	-0.107	-0.064	-0.048	-0.057	-0.092	**0.341**	**0.985**	**1**									
Sch_prob	**0.149**	-0.105	-0.115	0.004	-0.049	**-0.144**	0.134	**-0.255**	**0.815**	**-0.142**	**0.768**	**0.779**	-0.136	**-0.171**	-0.107	-0.068	-0.051	-0.060	-0.094	**0.351**	**0.991**	**0.985**	**1**								
Med_prob	0.072	-0.052	-0.064	0.045	-0.037	-0.078	0.069	**-0.203**	**0.884**	-0.108	**0.899**	**0.908**	-0.076	-0.122	-0.073	-0.004	-0.007	-0.006	-0.059	**0.447**	**0.835**	**0.823**	**0.808**	**1**							
Gra_prob	**0.142**	-0.102	-0.112	0.011	-0.048	-0.138	0.124	**-0.253**	**0.829**	**-0.140**	**0.781**	**0.791**	-0.132	**-0.165**	-0.105	-0.063	-0.048	-0.057	-0.093	**0.352**	**0.993**	**0.990**	**0.998**	**0.818**	**1**						
Gov_prob	**0.143**	-0.102	-0.113	0.010	-0.049	**-0.139**	0.126	**-0.254**	**0.828**	**-0.141**	**0.778**	**0.788**	-0.133	**-0.167**	-0.106	-0.064	-0.049	-0.058	-0.093	**0.350**	**0.993**	**0.990**	**0.998**	**0.816**	**1.000**	**1**					
GovE_prol	**0.143**	-0.102	-0.113	0.010	-0.049	**-0.139**	0.126	**-0.254**	**0.828**	**-0.141**	**0.779**	**0.789**	-0.133	**-0.167**	-0.106	-0.064	-0.049	-0.057	-0.093	**0.351**	**0.993**	**0.990**	**0.998**	**0.816**	**1.000**	**1.000**	**1**				
NH_prob	**0.140**	-0.101	-0.111	0.011	-0.048	-0.136	0.121	**-0.251**	**0.828**	**-0.139**	**0.783**	**0.794**	-0.132	**-0.165**	-0.104	-0.062	-0.047	-0.056	-0.092	**0.353**	**0.993**	**0.990**	**0.997**	**0.820**	**1.000**	**1.000**	**1.000**	**1**			
Nonp_pro	0.136	-0.098	-0.109	0.011	-0.047	-0.132	0.116	**-0.248**	**0.827**	-0.136	**0.789**	**0.801**	-0.130	**-0.163**	-0.102	-0.059	-0.046	-0.054	-0.090	**0.356**	**0.992**	**0.988**	**0.996**	**0.825**	**0.999**	**0.999**	**0.999**	**1.000**	**1**		
Hosp_prol	**0.150**	-0.107	-0.117	0.010	-0.050	**-0.146**	0.135	**-0.259**	**0.830**	**-0.146**	**0.769**	**0.778**	-0.137	**-0.171**	-0.109	-0.068	-0.051	-0.061	-0.096	**0.344**	**0.992**	**0.991**	**0.997**	**0.809**	**0.999**	**0.999**	**0.999**	**0.998**	**0.996**	**1**	
Coll_prob	**0.144**	-0.103	-0.113	0.009	-0.049	**-0.140**	0.127	**-0.254**	**0.827**	**-0.141**	**0.777**	**0.787**	-0.134	**-0.168**	-0.106	-0.065	-0.049	-0.058	-0.093	**0.350**	**0.993**	**0.991**	**0.998**	**0.815**	**1.000**	**1.000**	**1.000**	**1.000**	**0.999**	**0.999**	**1**

Values in bold are different from 0 with a significance level alpha=0.05

Irene

Correlation matrix (Pearson):

Variables	SOVI	HUNITS	POP2000	AREASQMI	POPDEN00	PERCAPINC	PCTPOV	AVEDISTC	TREEVOL	MAXSUSWIN	BLDGLOSS1K	CNTLOSS1K	NUMBRIDGE	ROADMI	ERC_CNT	FIRESTA_CT	POLSTA_CT	SCH_CT	MEDFAC_CT	ERC_prob	FIRE_prob	Pol_prob	Sch_prob	Med_prob	Gra_prob	Gov_prob	GovE_prob	NH_prob	Nonp_prob	Hosp_prob	Coll_prob
SOVI	**1**																														
HUNITS	**-0.476**	**1**																													
POP2000	**-0.500**	**0.996**	**1**																												
AREASQM	0.129	0.422	0.378	**1**																											
POPDEN0	**-0.721**	**0.787**	**0.822**	-0.084	**1**																										
PERCAPIN	**-0.493**	0.301	0.263	0.109	0.244	**1**																									
PCTPOV	**0.733**	-0.241	-0.230	0.127	-0.350	**-0.737**	**1**																								
AVEDISTC	0.432	-0.248	-0.206	0.102	-0.145	**-0.715**	**0.578**	**1**																							
TREEVOL	-0.330	**0.918**	**0.896**	0.324	**0.669**	0.334	-0.194	-0.374	**1**																						
MAXSUSW	-0.115	0.412	0.368	0.197	0.181	**0.590**	-0.133	**-0.659**	**0.633**	**1**																					
BLDGLOSS	-0.250	**0.859**	**0.845**	0.239	**0.655**	0.217	-0.106	-0.265	**0.974**	**0.567**	**1**																				
CNTLOSS1	-0.252	**0.865**	**0.849**	0.249	**0.654**	0.225	-0.109	-0.270	**0.978**	**0.572**	**1.000**	**1**																			
NUMBRID	-0.431	**0.936**	**0.939**	**0.489**	**0.699**	0.344	-0.216	-0.198	**0.799**	0.390	**0.726**	**0.732**	**1**																		
ROADMI	-0.440	**0.918**	**0.917**	**0.558**	**0.674**	0.170	-0.178	-0.088	**0.712**	0.130	**0.625**	**0.632**	**0.892**	**1**																	
ERC_CNT	-0.343	**0.661**	**0.670**	-0.004	**0.699**	0.127	-0.140	-0.129	**0.730**	0.296	**0.829**	**0.820**	**0.512**	0.453	**1**																
FIRESTA_	**-0.493**	**0.781**	**0.770**	0.446	**0.554**	0.216	-0.286	-0.256	**0.688**	0.235	**0.646**	**0.647**	**0.641**	**0.773**	**0.601**	**1**															
POLSTA_C	-0.412	**0.784**	**0.763**	**0.635**	**0.480**	0.216	-0.207	-0.152	**0.621**	0.169	**0.546**	**0.553**	**0.704**	**0.876**	**0.475**	**0.866**	**1**														
SCH_CT	**-0.550**	**0.973**	**0.984**	0.384	**0.824**	0.236	-0.243	-0.164	**0.813**	0.272	**0.746**	**0.751**	**0.932**	**0.950**	**0.597**	**0.793**	**0.800**	**1**													
MEDFAC_	-0.358	**0.961**	**0.943**	0.398	**0.679**	0.287	-0.190	-0.325	**0.964**	**0.521**	**0.903**	**0.910**	**0.863**	**0.838**	**0.630**	**0.722**	**0.720**	**0.895**	**1**												
ERC_prob	-0.213	**0.705**	**0.709**	0.038	**0.642**	0.083	-0.046	-0.186	**0.828**	0.429	**0.920**	**0.911**	**0.569**	0.452	**0.930**	**0.572**	0.385	**0.608**	**0.707**	**1**											
FIRE_prob	-0.175	0.356	0.336	0.014	0.242	0.387	-0.203	-0.430	**0.556**	**0.765**	**0.561**	**0.557**	0.256	0.064	0.445	0.378	0.183	0.264	0.424	**0.543**	**1**										
Pol_prob	-0.220	**0.645**	**0.619**	0.182	0.433	0.385	-0.185	-0.430	**0.830**	**0.811**	**0.823**	**0.824**	**0.527**	0.354	**0.619**	**0.532**	0.401	**0.527**	**0.730**	**0.726**	**0.916**	**1**									
Sch_prob	-0.240	**0.714**	**0.690**	0.181	**0.502**	0.355	-0.178	-0.403	**0.890**	**0.770**	**0.892**	**0.892**	**0.583**	0.425	**0.689**	**0.580**	0.444	**0.595**	**0.792**	**0.796**	**0.864**	**0.989**	**1**								
Med_prob	-0.201	**0.643**	**0.621**	0.159	0.452	0.283	-0.123	-0.386	**0.824**	**0.771**	**0.830**	**0.829**	**0.518**	0.356	**0.648**	**0.516**	0.393	**0.530**	**0.733**	**0.753**	**0.888**	**0.987**	**0.976**	**1**							
Gra_prob	-0.236	**0.750**	**0.726**	0.218	**0.521**	0.341	-0.161	-0.387	**0.918**	**0.761**	**0.918**	**0.919**	**0.620**	**0.471**	**0.698**	**0.592**	**0.476**	**0.629**	**0.831**	**0.805**	**0.823**	**0.979**	**0.997**	**0.970**	**1**						
Gov_prob	-0.236	**0.750**	**0.726**	0.218	**0.521**	0.342	-0.161	-0.388	**0.919**	**0.762**	**0.917**	**0.918**	**0.620**	**0.471**	**0.697**	**0.592**	**0.476**	**0.629**	**0.831**	**0.804**	**0.822**	**0.979**	**0.997**	**0.969**	**1.000**	**1**					
GovE_prol	-0.236	**0.751**	**0.726**	0.218	**0.521**	0.342	-0.161	-0.388	**0.919**	**0.761**	**0.917**	**0.919**	**0.620**	**0.471**	**0.697**	**0.592**	**0.476**	**0.629**	**0.831**	**0.805**	**0.822**	**0.979**	**0.997**	**0.970**	**1.000**	**1.000**	**1**				
NH_prob	-0.236	**0.750**	**0.726**	0.216	**0.522**	0.340	-0.160	-0.387	**0.918**	**0.760**	**0.918**	**0.919**	**0.619**	**0.470**	**0.700**	**0.592**	**0.475**	**0.629**	**0.830**	**0.807**	**0.823**	**0.979**	**0.997**	**0.970**	**1.000**	**1.000**	**1.000**	**1**			
Nonp_pro	-0.236	**0.750**	**0.726**	0.215	**0.523**	0.337	-0.159	-0.385	**0.918**	**0.759**	**0.919**	**0.920**	**0.619**	**0.469**	**0.703**	**0.592**	**0.474**	**0.629**	**0.829**	**0.810**	**0.823**	**0.979**	**0.997**	**0.971**	**1.000**	**1.000**	**1.000**	**1.000**	**1**		
Hosp_prol	-0.236	**0.750**	**0.725**	0.220	**0.518**	0.347	-0.162	-0.392	**0.919**	**0.766**	**0.916**	**0.917**	**0.620**	**0.471**	**0.692**	**0.590**	**0.476**	**0.628**	**0.832**	**0.799**	**0.822**	**0.979**	**0.996**	**0.968**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1**	
Coll_prob	-0.237	**0.751**	**0.726**	0.219	**0.521**	0.343	-0.162	-0.388	**0.919**	**0.762**	**0.917**	**0.918**	**0.620**	**0.471**	**0.697**	**0.592**	**0.476**	**0.629**	**0.831**	**0.804**	**0.822**	**0.979**	**0.997**	**0.969**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1**

Values in bold are different from 0 with a significance level alpha=0.05

Isabel

Correlation matrix (Pearson):

Variables	SOVI	HUNITS	POP2000	AREASQMI	POPDEN00	PERCAPINC	PCTPOV	AVEDISTC	TREEVOL	MAXSUSWIN	BLDGLOSS1K	CNTLOSS1K	NUMBRIDGE
SOVI	**1**												
HUNITS	**-0.284**	**1**											
POP2000	**-0.318**	**0.994**	**1**										
AREASQM	0.081	0.075	0.073	**1**									
POPDEN0(	-0.126	**0.472**	**0.434**	**-0.456**	**1**								
PERCAPIN	**-0.750**	**0.446**	**0.456**	**-0.255**	**0.401**	**1**							
PCTPOV	**0.826**	**-0.186**	**-0.212**	0.132	-0.020	**-0.729**	**1**						
AVEDISTC	**0.185**	**-0.195**	**-0.185**	**0.317**	**-0.256**	**-0.325**	**0.162**	**1**					
TREEVOL	0.018	0.066	0.069	-0.028	0.016	-0.065	0.096	**-0.386**	**1**				
MAXSUSW	-0.036	0.145	0.129	0.067	-0.001	0.051	-0.052	**-0.246**	0.063	**1**			
BLDGLOSS	-0.063	**0.204**	**0.211**	**-0.218**	**0.264**	0.031	0.013	**-0.338**	**0.773**	0.040	**1**		
CNTLOSS1	-0.018	0.102	0.105	**-0.219**	**0.205**	-0.035	0.050	**-0.338**	**0.772**	0.046	**0.977**	**1**	
NUMBRID	**-0.203**	**0.606**	**0.609**	**0.498**	0.054	**0.171**	-0.099	**0.247**	-0.018	0.115	0.021	-0.044	**1**
ROADMI	**-0.329**	**0.761**	**0.768**	**0.502**	0.022	**0.322**	**-0.224**	0.021	-0.003	**0.195**	0.026	-0.052	**0.776**
ERC_CNT	-0.075	**0.321**	**0.313**	-0.036	**0.175**	0.156	-0.075	**-0.188**	0.141	**0.218**	**0.196**	**0.161**	**0.312**
FIRESTA_(	**-0.184**	**0.579**	**0.585**	**0.360**	0.013	**0.217**	-0.126	0.030	-0.062	0.092	-0.011	-0.035	**0.465**
POLSTA_C	-0.062	**0.727**	**0.708**	**0.244**	**0.274**	**0.214**	0.025	-0.102	0.016	**0.206**	0.091	0.021	**0.501**
SCH_CNT	**-0.239**	**0.979**	**0.969**	0.017	**0.525**	**0.405**	-0.138	**-0.207**	0.040	0.132	**0.195**	0.095	**0.567**
MEDFAC_(	-0.090	**0.846**	**0.812**	-0.029	**0.615**	**0.259**	0.030	**-0.188**	0.043	0.112	**0.206**	0.127	**0.474**
ERC_prob	0.013	0.053	0.056	**-0.229**	**0.280**	-0.006	0.007	**-0.171**	**0.264**	0.017	**0.534**	**0.509**	0.015
FIRE_prob	**0.160**	-0.102	-0.104	**-0.177**	0.013	**-0.167**	**0.187**	**-0.333**	**0.519**	0.057	**0.493**	**0.575**	**-0.171**
Pol_prob	**0.160**	-0.112	-0.112	**-0.186**	0.024	**-0.178**	**0.194**	**-0.364**	**0.555**	0.061	**0.499**	**0.567**	**-0.188**
Sch_prob	0.151	-0.128	-0.127	**-0.171**	-0.021	**-0.209**	**0.231**	**-0.365**	**0.525**	0.063	**0.463**	**0.556**	**-0.188**
Med_prob	0.139	0.018	0.023	**-0.248**	**0.223**	-0.137	**0.181**	**-0.251**	**0.443**	0.038	**0.661**	**0.668**	-0.037
Gra_prob	**0.162**	-0.131	-0.131	**-0.163**	-0.034	**-0.214**	**0.243**	**-0.364**	**0.553**	0.065	**0.472**	**0.576**	**-0.195**
Gov_prob	**0.162**	-0.131	-0.131	**-0.163**	-0.035	**-0.214**	**0.243**	**-0.363**	**0.552**	0.065	**0.471**	**0.575**	**-0.195**
GovE_prol	**0.162**	-0.131	-0.131	**-0.163**	-0.035	**-0.214**	**0.243**	**-0.363**	**0.551**	0.065	**0.471**	**0.575**	**-0.195**
NH_prob	**0.162**	-0.131	-0.131	**-0.162**	-0.036	**-0.213**	**0.243**	**-0.361**	**0.546**	0.064	**0.467**	**0.572**	**-0.194**
Nonp_pro	**0.160**	-0.131	-0.131	**-0.162**	-0.038	**-0.212**	**0.242**	**-0.358**	**0.541**	0.064	**0.464**	**0.570**	**-0.194**
Hosp_prol	**0.166**	-0.133	-0.133	**-0.166**	-0.032	**-0.216**	**0.245**	**-0.371**	**0.569**	0.066	**0.482**	**0.583**	**-0.196**
Coll_prob	**0.162**	-0.131	-0.131	**-0.163**	-0.035	**-0.214**	**0.243**	**-0.362**	**0.550**	0.065	**0.470**	**0.574**	**-0.195**

Variables	ROADMI	ERC_CNT	FIRESTA_C	POLSTA_C	SCH_CNT	MEDFAC_C	ERC_prob	FIRE_prob	Pol_prob	Sch_prob	Med_prob	Gra_prob	Gov_prob	GovE_prob	NH_prob	Nonp_prob	Hosp_prob	Coll_prob
ROADMI	**1**																	
ERC_CNT	**0.285**	**1**																
FIRESTA_(	**0.672**	0.105	**1**															
POLSTA_C	**0.633**	**0.285**	**0.674**	**1**														
SCH_CNT	**0.683**	**0.317**	**0.540**	**0.719**	**1**													
MEDFAC_(	**0.520**	**0.383**	**0.396**	**0.656**	**0.882**	**1**												
ERC_prob	-0.083	**0.373**	-0.102	0.015	0.076	**0.183**	**1**											
FIRE_prob	**-0.209**	-0.025	-0.098	-0.102	-0.093	-0.085	**0.196**	**1**										
Pol_prob	**-0.251**	0.003	-0.154	-0.110	-0.102	-0.079	**0.269**	**0.809**	**1**									
Sch_prob	**-0.233**	-0.036	-0.152	-0.132	-0.116	-0.096	**0.178**	**0.861**	**0.884**	**1**								
Med_prob	-0.122	0.132	-0.089	-0.035	0.036	0.142	**0.465**	**0.415**	**0.474**	**0.488**	**1**							
Gra_prob	**-0.241**	-0.046	-0.147	-0.127	-0.122	-0.102	0.156	**0.859**	**0.884**	**0.974**	**0.457**	**1**						
Gov_prob	**-0.240**	-0.047	-0.147	-0.127	-0.122	-0.102	0.155	**0.859**	**0.883**	**0.974**	**0.456**	**1.000**	**1**					
GovE_prol	**-0.240**	-0.047	-0.147	-0.127	-0.122	-0.102	0.155	**0.859**	**0.883**	**0.974**	**0.456**	**1.000**	**1.000**	**1**				
NH_prob	**-0.239**	-0.048	-0.146	-0.127	-0.122	-0.103	0.149	**0.859**	**0.879**	**0.974**	**0.453**	**1.000**	**1.000**	**1.000**	**1**			
Nonp_pro	**-0.237**	-0.049	-0.145	-0.127	-0.122	-0.103	0.145	**0.858**	**0.874**	**0.974**	**0.451**	**0.999**	**0.999**	**0.999**	**1.000**	**1**		
Hosp_prol	**-0.245**	-0.043	-0.151	-0.129	-0.124	-0.102	**0.168**	**0.861**	**0.892**	**0.974**	**0.467**	**0.999**	**0.999**	**0.999**	**0.998**	**0.997**	**1**	
Coll_prob	**-0.240**	-0.047	-0.146	-0.127	-0.122	-0.102	0.153	**0.859**	**0.882**	**0.974**	**0.455**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.999**	**1**

Values in bold are different from 0 with a significance level alpha=0.05

Ivan

Correlation matrix (Pearson):

Variables	SOVI	HUNITS	POP2000	AREASQMI	POPDEN00	PERCAPINC	PCTPOV	AVEDISTC	TREEVOL	MAXSUSWIN	BLDGLOSS1K	CNTLOSS1K	NUMBRIDGE
SOVI	**1**												
HUNITS	**-0.177**	**1**											
POP2000	**-0.209**	**0.995**	**1**										
AREASQM	0.015	**0.214**	**0.183**	**1**									
POPDEN0(	**-0.131**	**0.634**	**0.655**	-0.088	**1**								
PERCAPIN	**-0.538**	**0.537**	**0.536**	0.068	**0.246**	**1**							
PCTPOV	**0.615**	**-0.285**	**-0.284**	-0.015	**-0.185**	**-0.720**	**1**						
AVEDISTC	0.073	**-0.358**	**-0.347**	**-0.170**	-0.089	**-0.389**	**0.220**	**1**					
TREEVOL	-0.054	0.065	0.069	**0.217**	-0.049	0.025	-0.003	**-0.256**	**1**				
MAXSUSW	**0.154**	**-0.149**	**-0.142**	**-0.186**	-0.111	**-0.232**	**0.385**	**0.224**	-0.020	**1**			
BLDGLOSS	-0.041	0.086	0.089	**0.169**	-0.032	0.043	-0.026	**-0.244**	**0.951**	-0.010	**1**		
CNTLOSS1	-0.040	0.084	0.087	**0.169**	-0.032	0.042	-0.026	**-0.244**	**0.944**	-0.010	**0.999**	**1**	
NUMBRID	**-0.293**	**0.677**	**0.697**	**0.270**	**0.508**	**0.408**	**-0.232**	0.039	0.025	**-0.152**	0.036	0.034	**1**
ROADMI	**-0.221**	**0.751**	**0.735**	**0.529**	**0.360**	**0.477**	**-0.365**	**-0.254**	**0.148**	**-0.247**	**0.150**	**0.149**	**0.662**
ERC_CNT	**-0.259**	**0.180**	**0.207**	-0.082	**0.191**	**0.277**	-0.103	-0.022	-0.040	0.006	-0.030	-0.028	**0.278**
FIRESTA_(	**-0.356**	**0.601**	**0.618**	**0.198**	**0.611**	**0.450**	**-0.367**	-0.106	0.088	**-0.200**	0.093	0.092	**0.697**
POLSTA_C	**-0.263**	**0.710**	**0.721**	**0.190**	**0.710**	**0.431**	**-0.297**	**-0.157**	0.038	**-0.164**	0.049	0.048	**0.681**
SCH_CT	**-0.192**	**0.926**	**0.937**	**0.128**	**0.728**	**0.446**	**-0.233**	**-0.318**	0.070	**-0.160**	0.085	0.084	**0.705**
MEDFAC_(	**-0.131**	**0.860**	**0.865**	**0.149**	**0.730**	**0.371**	**-0.181**	**-0.263**	0.084	**-0.166**	0.080	0.077	**0.700**
ERC_prob	-0.025	0.005	-0.004	**0.209**	-0.020	0.033	-0.026	-0.098	**0.421**	-0.006	**0.440**	**0.464**	-0.008
FIRE_prob	-0.021	0.022	0.023	**0.220**	-0.046	-0.006	0.025	**-0.219**	**0.905**	-0.016	**0.796**	**0.792**	-0.016
Pol_prob	-0.020	0.024	0.025	**0.224**	-0.046	-0.007	0.026	**-0.213**	**0.909**	-0.016	**0.802**	**0.798**	-0.015
Sch_prob	-0.028	0.026	0.028	**0.218**	-0.047	-0.001	0.015	**-0.232**	**0.920**	-0.017	**0.816**	**0.812**	-0.014
Med_prob	-0.017	0.025	0.026	**0.223**	-0.046	-0.004	0.026	**-0.214**	**0.909**	-0.016	**0.801**	**0.795**	-0.016
Gra_prob	-0.024	0.023	0.025	**0.220**	-0.048	-0.007	0.024	**-0.229**	**0.915**	-0.017	**0.806**	**0.802**	-0.014
Gov_prob	-0.024	0.024	0.025	**0.220**	-0.048	-0.007	0.024	**-0.229**	**0.915**	-0.017	**0.807**	**0.803**	-0.014
GovE_prol	-0.024	0.024	0.025	**0.220**	-0.047	-0.007	0.024	**-0.229**	**0.915**	-0.017	**0.807**	**0.804**	-0.014
NH_prob	-0.022	0.026	0.027	**0.218**	-0.046	-0.004	0.022	**-0.223**	**0.916**	-0.016	**0.813**	**0.809**	-0.013
Nonp_pro	-0.025	0.026	0.027	**0.216**	-0.046	-0.003	0.019	**-0.231**	**0.918**	-0.016	**0.816**	**0.813**	-0.013
Hosp_prol	-0.023	0.020	0.022	**0.224**	-0.049	-0.012	0.030	**-0.228**	**0.910**	-0.018	**0.796**	**0.792**	-0.017
Coll_prob	-0.024	0.024	0.026	**0.219**	-0.047	-0.006	0.023	**-0.229**	**0.916**	-0.017	**0.809**	**0.805**	-0.014

Variables	ROADMI	ERC_CNT	FIRESTA_CT	POLSTA_CT	SCH_CT	MEDFAC_CT	ERC_prob	FIRE_prob	Pol_prob	Sch_prob	Med_prob	Gra_prob	Gov_prob	GovE_prob	NH_prob	Nonp_prob	Hosp_prob	Coll_prob
ROADMI	**1**																	
ERC_CNT	**0.151**	**1**																
FIRESTA_(	**0.616**	**0.357**	**1**															
POLSTA_C	**0.634**	**0.343**	**0.887**	**1**														
SCH_CT	**0.657**	**0.266**	**0.704**	**0.806**	**1**													
MEDFAC_(	**0.599**	**0.227**	**0.652**	**0.768**	**0.924**	**1**												
ERC_prob	0.096	0.060	0.036	0.017	-0.009	0.031	**1**											
FIRE_prob	0.100	-0.058	0.049	0.009	0.016	0.047	**0.429**	**1**										
Pol_prob	0.103	-0.055	0.052	0.012	0.018	0.049	**0.439**	**0.996**	**1**									
Sch_prob	0.105	-0.058	0.057	0.013	0.027	0.050	**0.424**	**0.992**	**0.994**	**1**								
Med_prob	0.103	-0.057	0.051	0.010	0.018	0.052	**0.426**	**0.994**	**0.998**	**0.993**	**1**							
Gra_prob	0.101	-0.059	0.054	0.010	0.024	0.048	**0.423**	**0.996**	**0.992**	**0.996**	**0.990**	**1**						
Gov_prob	0.101	-0.059	0.054	0.010	0.024	0.048	**0.424**	**0.996**	**0.993**	**0.996**	**0.991**	**1.000**	**1**					
GovE_prol	0.101	-0.059	0.054	0.010	0.024	0.048	**0.424**	**0.996**	**0.992**	**0.996**	**0.991**	**1.000**	**1.000**	**1**				
NH_prob	0.103	-0.057	0.053	0.012	0.022	0.050	**0.428**	**0.999**	**0.996**	**0.996**	**0.994**	**0.998**	**0.998**	**0.998**	**1**			
Nonp_pro	0.103	-0.057	0.055	0.012	0.026	0.049	**0.428**	**0.996**	**0.992**	**0.997**	**0.990**	**0.999**	**0.999**	**0.999**	**0.999**	**1**		
Hosp_prol	0.098	-0.060	0.052	0.007	0.023	0.046	**0.420**	**0.994**	**0.990**	**0.994**	**0.988**	**0.999**	**0.999**	**0.999**	**0.996**	**0.997**	**1**	
Coll_prob	0.102	-0.058	0.054	0.011	0.025	0.048	**0.424**	**0.996**	**0.992**	**0.997**	**0.990**	**1.000**	**1.000**	**1.000**	**0.998**	**0.999**	**0.999**	**1**

Values in bold are different from 0 with a significance level alpha=0.05

Jeanne

Correlation matrix (Pearson):

Variables	SOVI	HUNITS	POP2000	AREASQMI	POPDEN00	PERCAPINC	PCTPOV	AVEDISTC	TREEVOL	MAXSUSWIN	BLDGLOSS1K	CNTLOSS1K	NUMBRIDGE	ROADMI	ERC_CNT	FIRESTA_C	POLSTA_C	SCH_CT	MEDFAC_CT	ERC_prob	FIRE_prob	Pol_prob	Sch_prob	Med_prob	Gra_prob	Gov_prob	GovE_prob	NH_prob	Nonp_prob	Hosp_prob	Coll_prob
SOVI	**1**																														
HUNITS	-0.258	**1**																													
POP2000	-0.249	**0.990**	**1**																												
AREASQM	0.019	**0.500**	**0.500**	**1**																											
POPDEN0	**-0.306**	**0.733**	**0.690**	0.016	**1**																										
PERCAPIN	**-0.505**	**0.418**	**0.359**	0.226	**0.382**	**1**																									
PCTPOV	**0.536**	-0.247	-0.197	-0.010	**-0.304**	**-0.742**	**1**																								
AVEDISTC	**0.305**	**-0.408**	**-0.369**	-0.060	**-0.370**	**-0.645**	**0.490**	**1**																							
TREEVOL	-0.164	**0.410**	**0.365**	**0.398**	**0.306**	**0.343**	**-0.294**	-0.246	**1**																						
MAXSUSW	0.014	-0.030	0.018	-0.029	-0.115	-0.219	**0.326**	-0.002	-0.246	**1**																					
BLDGLOSS	-0.073	**0.300**	0.252	**0.373**	0.075	**0.405**	-0.218	-0.262	**0.714**	-0.119	**1**																				
CNTLOSS1	-0.078	**0.307**	0.259	**0.372**	0.086	**0.409**	-0.223	-0.268	**0.724**	-0.122	**1.000**	**1**																			
NUMBRID	**-0.333**	**0.726**	**0.677**	**0.319**	**0.571**	**0.440**	**-0.306**	**-0.331**	**0.585**	-0.214	**0.396**	**0.406**	**1**																		
ROADMI	**-0.287**	**0.606**	**0.537**	**0.428**	**0.472**	**0.350**	**-0.301**	**-0.278**	**0.588**	-0.269	**0.346**	**0.355**	**0.796**	**1**																	
ERC_CNT	**-0.274**	**0.438**	**0.409**	0.035	**0.417**	0.163	-0.054	-0.087	0.115	0.047	0.015	0.018	**0.418**	**0.338**	**1**																
FIRESTA_C	**-0.313**	**0.515**	**0.443**	**0.364**	**0.433**	**0.312**	**-0.284**	-0.198	**0.452**	-0.251	**0.304**	**0.309**	**0.513**	**0.666**	**0.473**	**1**															
POLSTA_C	-0.250	**0.622**	**0.564**	**0.550**	**0.413**	**0.319**	-0.263	-0.165	**0.666**	-0.239	**0.497**	**0.503**	**0.625**	**0.774**	**0.442**	**0.829**	**1**														
SCH_CT	**-0.429**	**0.783**	**0.732**	**0.340**	**0.673**	**0.445**	**-0.331**	**-0.319**	**0.605**	-0.227	**0.369**	**0.379**	**0.948**	**0.844**	**0.518**	**0.653**	**0.743**	**1**													
MEDFAC_	**-0.300**	**0.775**	**0.703**	0.269	**0.707**	**0.410**	**-0.291**	**-0.356**	**0.557**	-0.218	**0.451**	**0.461**	**0.858**	**0.772**	**0.560**	**0.637**	**0.706**	**0.907**	**1**												
ERC_prob	0.021	-0.035	-0.038	-0.057	-0.022	0.228	-0.136	-0.150	0.198	-0.050	**0.301**	**0.299**	0.015	-0.053	0.184	0.018	0.054	-0.014	-0.001	**1**											
FIRE_prob	0.247	-0.138	-0.138	0.066	-0.152	0.109	0.015	0.027	0.241	-0.155	**0.320**	**0.316**	-0.074	-0.185	-0.055	0.040	0.000	-0.109	-0.136	**0.307**	**1**										
Pol_prob	**0.278**	-0.117	-0.118	0.052	-0.143	-0.034	0.191	0.041	**0.271**	-0.155	**0.319**	**0.316**	-0.039	-0.129	-0.039	-0.012	0.058	-0.084	-0.090	**0.324**	**0.772**	**1**									
Sch_prob	0.213	-0.075	-0.083	0.088	-0.113	0.137	-0.040	-0.048	**0.430**	-0.170	**0.527**	**0.525**	0.012	-0.083	-0.036	-0.003	0.054	-0.028	-0.014	**0.422**	**0.791**	**0.785**	**1**								
Med_prob	**0.313**	-0.107	-0.109	0.066	-0.122	-0.024	0.097	-0.028	**0.298**	-0.157	**0.372**	**0.371**	-0.048	-0.123	-0.073	-0.118	-0.049	-0.075	-0.015	**0.299**	**0.403**	**0.489**	**0.774**	**1**							
Gra_prob	0.228	-0.061	-0.071	0.112	-0.109	0.144	-0.049	-0.070	**0.470**	-0.181	**0.574**	**0.573**	0.033	-0.068	-0.034	0.008	0.086	-0.007	0.012	**0.435**	**0.783**	**0.731**	**0.979**	**0.789**	**1**						
Gov_prob	0.229	-0.059	-0.070	0.116	-0.109	0.141	-0.047	-0.069	**0.474**	-0.182	**0.574**	**0.573**	0.035	-0.066	-0.034	0.011	0.090	-0.005	0.014	**0.431**	**0.785**	**0.735**	**0.978**	**0.789**	**1.000**	**1**					
GovE_prol	0.229	-0.060	-0.070	0.115	-0.109	0.142	-0.047	-0.069	**0.473**	-0.182	**0.574**	**0.573**	0.035	-0.066	-0.034	0.010	0.089	-0.005	0.013	**0.432**	**0.784**	**0.734**	**0.978**	**0.789**	**1.000**	**1.000**	**1**				
NH_prob	0.225	-0.062	-0.072	0.106	-0.109	0.147	-0.053	-0.073	**0.463**	-0.178	**0.574**	**0.572**	0.030	-0.072	-0.033	0.005	0.080	-0.010	0.010	**0.440**	**0.781**	**0.725**	**0.979**	**0.790**	**1.000**	**1.000**	**1.000**	**1**			
Nonp_pro	0.221	-0.065	-0.075	0.097	-0.109	0.153	-0.059	-0.077	**0.451**	-0.175	**0.572**	**0.570**	0.025	-0.078	-0.032	-0.002	0.070	-0.016	0.006	**0.448**	**0.777**	**0.714**	**0.979**	**0.791**	**0.999**	**0.998**	**0.998**	**1.000**	**1**		
Hosp_prol	0.235	-0.055	-0.065	0.127	-0.107	0.134	-0.041	-0.065	**0.490**	-0.188	**0.575**	**0.574**	0.043	-0.057	-0.035	0.019	0.103	0.004	0.020	**0.421**	**0.788**	**0.746**	**0.976**	**0.787**	**0.999**	**0.999**	**0.999**	**0.998**	**0.995**	**1**	
Coll_prob	0.230	-0.059	-0.069	0.117	-0.109	0.140	-0.046	-0.068	**0.476**	-0.183	**0.575**	**0.573**	0.036	-0.065	-0.034	0.012	0.092	-0.004	0.014	**0.430**	**0.785**	**0.737**	**0.978**	**0.788**	**1.000**	**1.000**	**1.000**	**0.999**	**0.998**	**0.999**	**1**

Values in bold are different from 0 with a significance level alpha=0.05

Lili

Correlation matrix (Pearson):

Variables	SOVI	HUNITS	POP2000	AREASQMI	POPDEN00	PERCAPINC	PCTPOV	AVEDISTC	TREEVOL	MAXSUSWIN	BLDGLOSS1K	CNTLOSS1K	NUMBRIDGE	ROADMI	ERC_CNT	FIRESTA_CT	POLSTA_CT	MEDFAC_CT	ERC_prob	FIRE_prob	Pol_prob	Sch_prob	Med_prob	Gra_prob	Gov_prob	GovE_prob	NH_prob	Nonp_prob	Hosp_prob	Coll_prob
SOVI	**1**																													
HUNITS	-0.083	**1**																												
POP2000	-0.107	**0.999**	**1**																											
AREASQM	-0.023	-0.125	-0.122	**1**																										
POPDEN0	-0.060	**0.944**	**0.936**	**-0.331**	**1**																									
PERCAPIN	**-0.672**	**0.605**	**0.625**	-0.097	**0.551**	**1**																								
PCTPOV	**0.841**	-0.120	-0.145	-0.087	-0.074	**-0.730**	**1**																							
AVEDISTC	**0.502**	**-0.324**	**-0.330**	0.015	**-0.317**	**-0.421**	**0.400**	**1**																						
TREEVOL	0.081	0.077	0.084	-0.007	0.125	-0.066	0.187	-0.117	**1**																					
MAXSUSW	0.215	-0.052	-0.056	-0.093	-0.062	-0.097	0.130	0.202	-0.106	**1**																				
BLDGLOSS	0.003	0.099	0.104	-0.084	0.213	0.082	0.054	-0.146	**0.897**	-0.055	**1**																			
CNTLOSS1	0.000	0.109	0.114	-0.086	0.222	0.089	0.051	-0.146	**0.898**	-0.057	**1.000**	**1**																		
NUMBRID	0.069	**0.571**	**0.576**	0.295	**0.411**	0.270	0.033	0.172	0.200	0.108	0.151	0.158	**1**																	
ROADMI	0.118	**0.315**	**0.312**	0.229	0.207	0.106	0.122	0.257	0.227	0.168	0.176	0.180	**0.780**	**1**																
ERC_CNT	0.204	0.214	0.212	-0.083	0.214	-0.119	**0.366**	0.144	0.091	-0.049	-0.060	-0.051	0.213	0.208	**1**															
FIRESTA_C	**-0.298**	**0.393**	**0.415**	**0.466**	0.181	**0.393**	**-0.317**	-0.272	0.163	-0.177	0.116	0.120	**0.585**	**0.333**	-0.123	**1**														
POLSTA_C	0.113	**0.749**	**0.739**	0.182	**0.616**	**0.300**	0.131	-0.162	0.220	-0.087	0.108	0.114	**0.722**	**0.588**	0.243	**0.548**	**1**													
MEDFAC_	0.025	**0.896**	**0.888**	-0.059	**0.842**	**0.545**	-0.032	-0.201	0.096	0.068	0.140	0.147	**0.678**	**0.471**	0.146	**0.374**	**0.824**	**1**												
ERC_prob	0.247	-0.113	-0.114	-0.048	-0.115	**-0.339**	**0.379**	0.089	0.263	-0.065	0.117	0.116	0.100	0.082	**0.520**	-0.020	0.129	-0.106	**1**											
FIRE_prob	0.216	-0.124	-0.125	0.107	-0.114	**-0.348**	**0.382**	-0.073	**0.795**	-0.089	**0.600**	**0.598**	0.037	0.115	0.171	0.053	0.174	-0.119	**0.549**	**1**										
Pol_prob	0.193	-0.115	-0.117	0.133	-0.113	**-0.322**	**0.341**	-0.097	**0.794**	-0.081	**0.586**	**0.585**	0.041	0.114	0.143	0.042	0.187	-0.114	**0.494**	**0.985**	**1**									
Sch_prob	0.156	-0.079	-0.078	0.071	-0.050	-0.246	0.282	-0.163	**0.900**	-0.080	**0.737**	**0.735**	0.042	0.100	0.098	0.063	0.167	-0.075	**0.407**	**0.953**	**0.960**	**1**								
Med_prob	0.233	-0.083	-0.083	0.055	-0.055	**-0.298**	**0.371**	-0.064	**0.842**	-0.081	**0.703**	**0.702**	0.099	0.162	0.125	0.075	0.180	-0.062	**0.524**	**0.975**	**0.948**	**0.948**	**1**							
Gra_prob	0.155	-0.060	-0.059	0.034	-0.014	-0.223	0.284	-0.146	**0.935**	-0.081	**0.806**	**0.804**	0.061	0.120	0.091	0.070	0.158	-0.047	**0.415**	**0.938**	**0.932**	**0.990**	**0.954**	**1**						
Gov_prob	0.154	-0.060	-0.058	0.035	-0.013	-0.222	0.283	-0.148	**0.935**	-0.081	**0.806**	**0.805**	0.061	0.120	0.088	0.071	0.158	-0.047	**0.412**	**0.938**	**0.932**	**0.990**	**0.954**	**1.000**	**1**					
GovE_prol	0.154	-0.060	-0.058	0.035	-0.013	-0.222	0.283	-0.148	**0.935**	-0.081	**0.806**	**0.805**	0.061	0.120	0.089	0.071	0.158	-0.047	**0.412**	**0.938**	**0.932**	**0.990**	**0.954**	**1.000**	**1.000**	**1**				
NH_prob	0.128	-0.044	-0.043	0.065	-0.005	-0.187	0.242	-0.182	**0.925**	-0.070	**0.810**	**0.808**	0.075	0.126	0.028	0.091	0.163	-0.032	**0.319**	**0.919**	**0.922**	**0.987**	**0.942**	**0.989**	**0.990**	**0.989**	**1**			
Nonp_pro	0.150	-0.057	-0.056	0.040	-0.012	-0.216	0.276	-0.154	**0.935**	-0.079	**0.808**	**0.807**	0.064	0.121	0.079	0.074	0.159	-0.044	**0.397**	**0.936**	**0.931**	**0.991**	**0.953**	**1.000**	**1.000**	**1.000**	**0.993**	**1**		
Hosp_prol	0.161	-0.064	-0.063	0.029	-0.016	-0.232	0.293	-0.137	**0.933**	-0.084	**0.803**	**0.801**	0.057	0.119	0.105	0.065	0.156	-0.051	**0.436**	**0.941**	**0.932**	**0.987**	**0.955**	**0.999**	**0.999**	**0.999**	**0.983**	**0.998**	**1**	
Coll_prob	0.154	-0.060	-0.058	0.035	-0.013	-0.222	0.283	-0.148	**0.935**	-0.081	**0.806**	**0.805**	0.061	0.120	0.089	0.071	0.158	-0.047	**0.412**	**0.938**	**0.932**	**0.990**	**0.954**	**1.000**	**1.000**	**1.000**	**0.989**	**1.000**	**0.999**	**1**

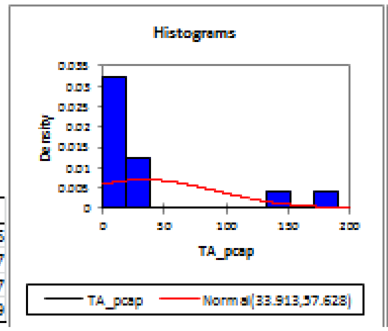
Values in bold are different from 0 with a significance level alpha=0.05

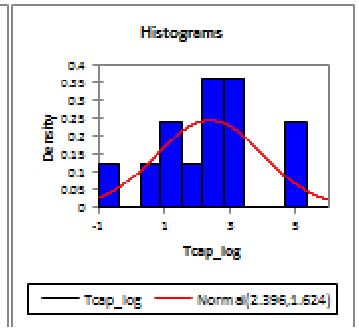
APPENDIX H: Log Transformations for Model Variables

Log transformation of Total Assistance per Capita (TA_PCAP)

Hurricane Bret

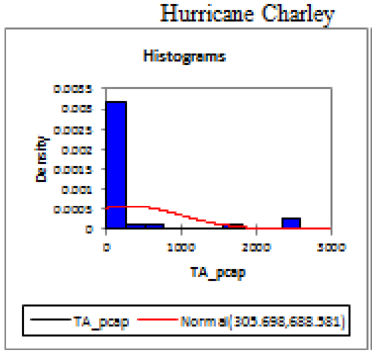
Statistic	Original	Log
Mean	33.913	2.396
Variance	3321.004	2.637
Skewness	1.752	0.047
Kurtosis	1.492	-0.779

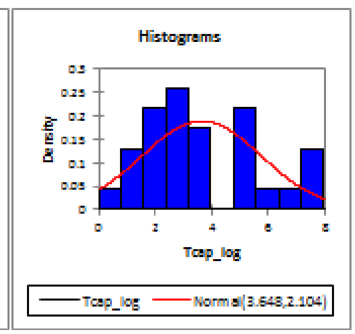




Hurricane Charley

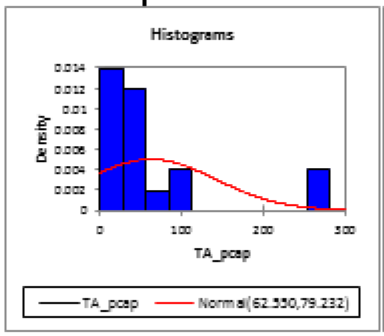
Statistic	Original	Log
Mean	305.698	3.648
Variance	474143.378	4.428
Skewness	2.494	0.524
Kurtosis	4.941	-0.897

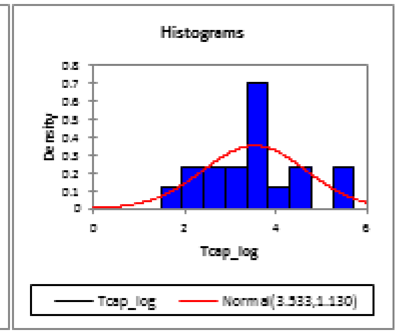




Hurricane Claudette

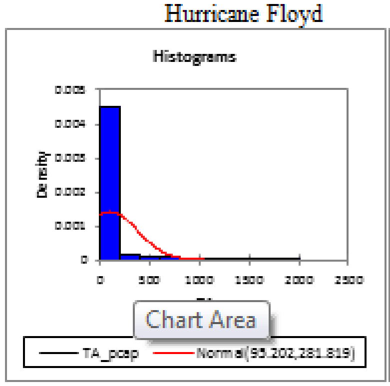
Statistic	Original	Log
Mean	62.550	3.533
Variance	6277.716	1.278
Skewness	1.785	0.156
Kurtosis	1.925	-0.766

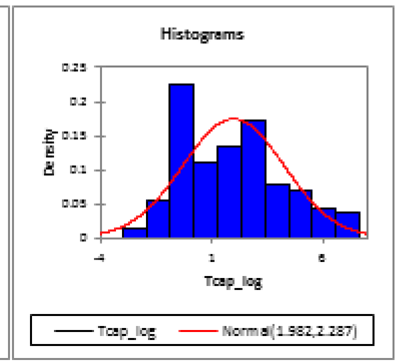




Hurricane Floyd

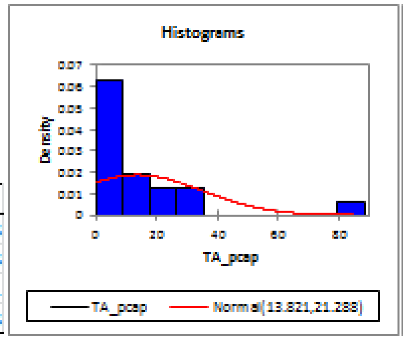
Statistic	Original	Log
Mean	95.202	1.982
Variance	79421.716	5.232
Skewness	4.219	0.499
Kurtosis	18.937	-0.487

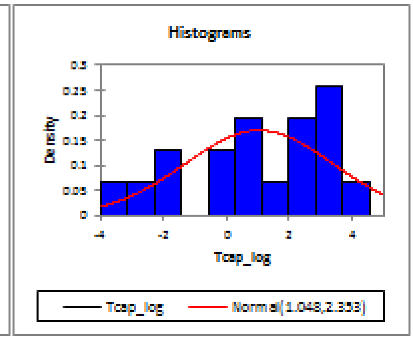




Hurricane Irene

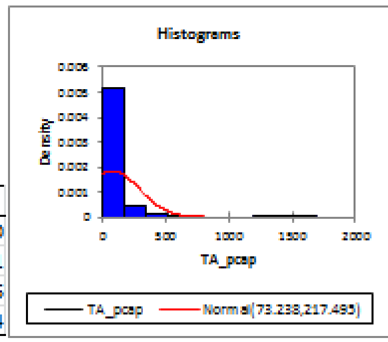
Statistic	Original	Log
Mean	13.821	1.048
Variance	453.199	5.538
Skewness	2.233	-0.431
Kurtosis	5.042	-1.138

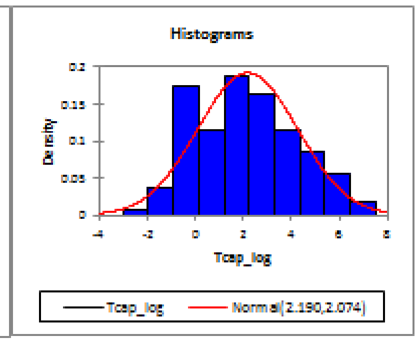




Hurricane Isabel

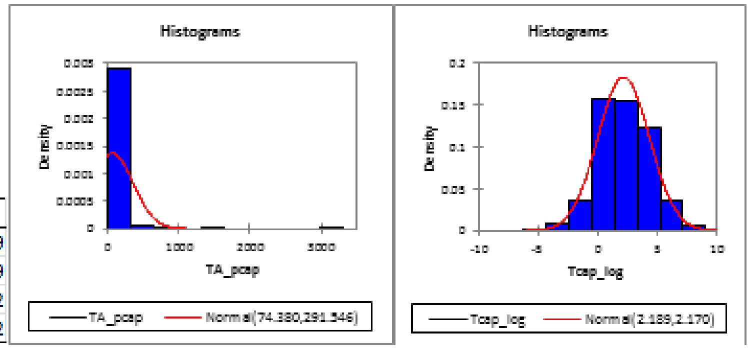
Statistic	Original	Log
Mean	73.238	2.190
Variance	47303.948	4.301
Skewness	5.353	0.396
Kurtosis	31.541	-0.604





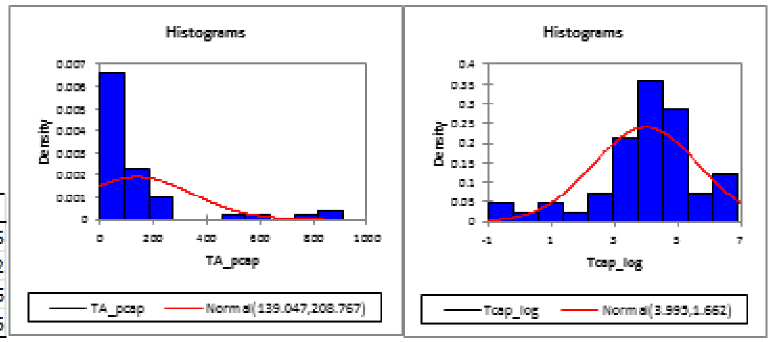
Hurricane Ivan

Statistic	Original	Log
Mean	74.380	2.189
Variance	84999.250	4.709
Skewness	8.784	-0.042
Kurtosis	86.429	-0.252



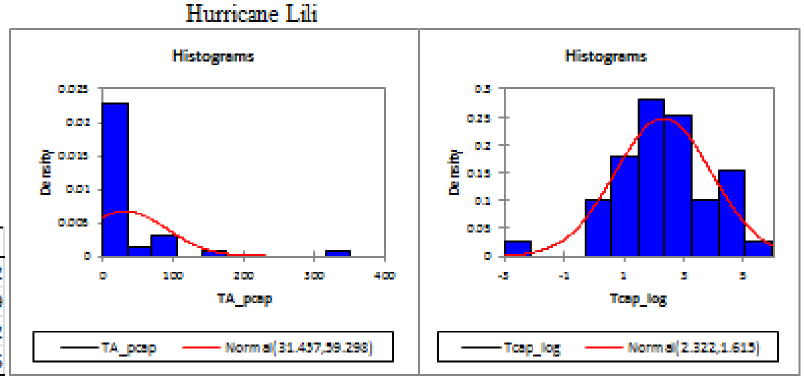
Hurricane Jeanne

Statistic	Original	Log
Mean	139.047	3.995
Variance	43583.684	2.762
Skewness	2.544	-0.966
Kurtosis	5.847	1.115



Hurricane Lili

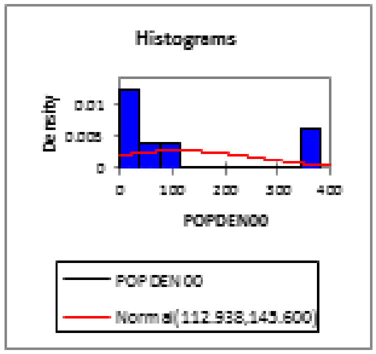
Statistic	Original	Log
Mean	31.457	2.322
Variance	3516.218	2.609
Skewness	3.680	-0.232
Kurtosis	15.886	0.255

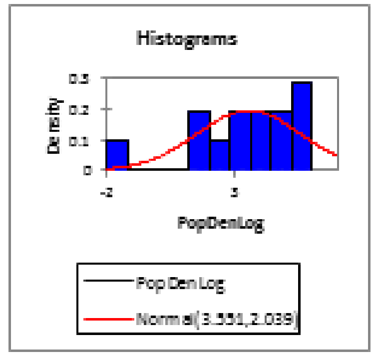


Log Transformations for FEMA Impact Model Variables

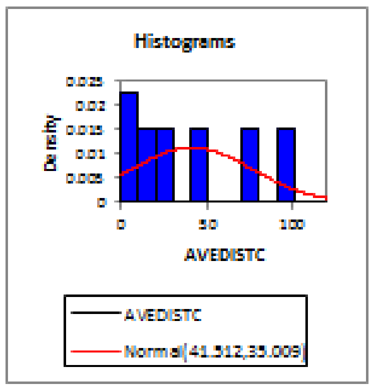
Hurricane Bret

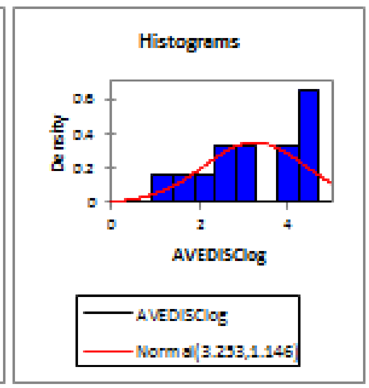
Statistic	Data	Data
Mean	112.938	3.551
Variance	21199.453	4.157
Skewness	1.006	-0.742
Kurtosis	-0.882	-0.195



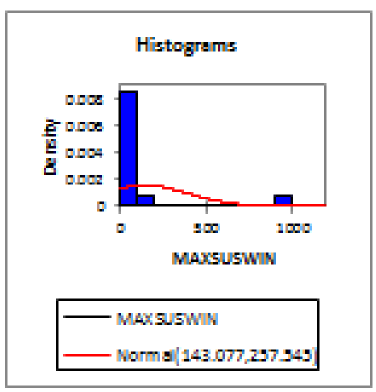


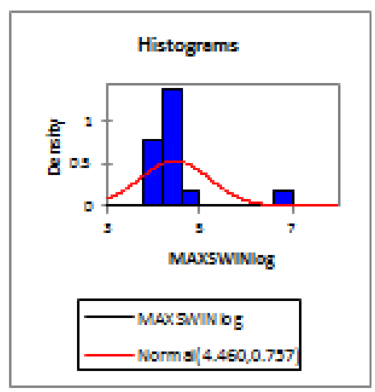
Statistic	Original	Log
Mean	41.512	3.253
Variance	1225.623	1.313
Skewness	0.454	-0.452
Kurtosis (I	-1.519	-1.099



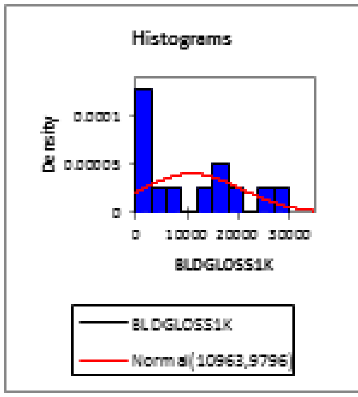


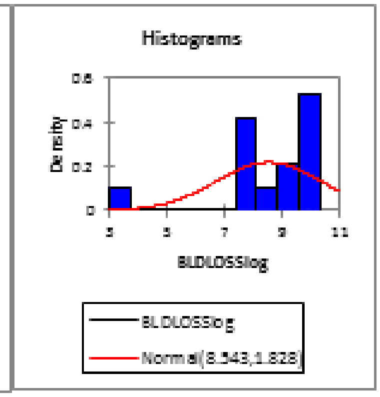
Statistic	Original	Log
Mean	143.077	4.460
Variance	66329.577	0.573
Skewness	2.802	2.545
Kurtosis	6.390	5.425



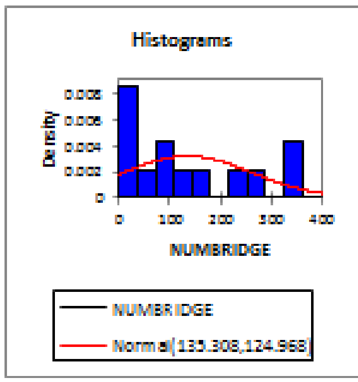


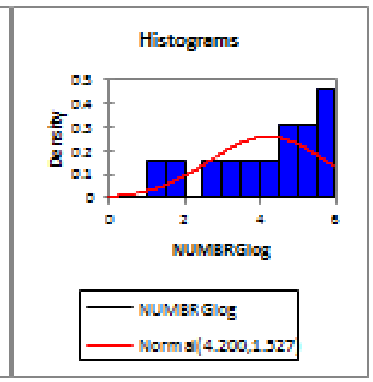
Statistic	Original	Log
Mean	10962.785	8.543
Variance	95957970.588	3.343
Skewness	0.490	-1.521
Kurtosis	-1.307	1.920





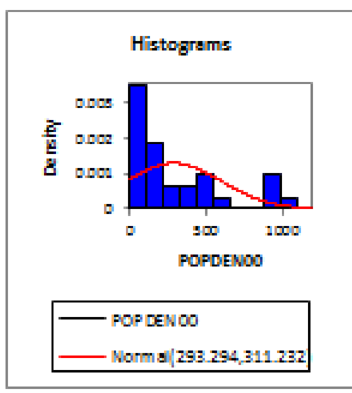
Statistic	Original	Log
Mean	135.308	4.200
Variance	15616.897	2.333
Skewness	0.528	-0.655
Kurtosis	-1.328	-0.959

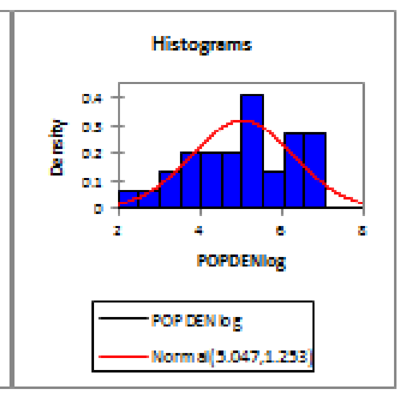




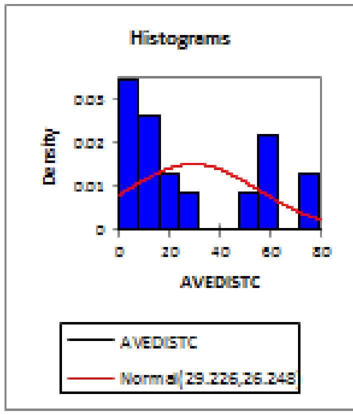
Hurricane Charley

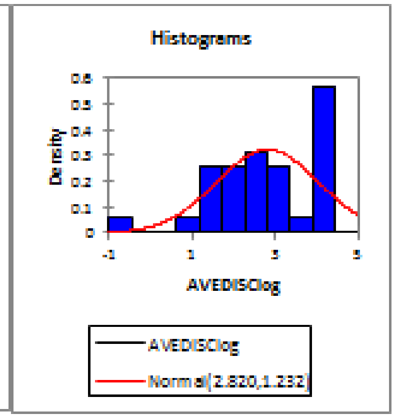
Statistic	Original	Log
Mean	293.294	5.047
Variance	96865.511	1.571
Skewness	1.178	-0.226
Kurtosis	0.104	-0.977



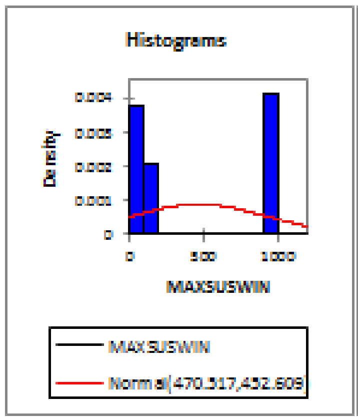


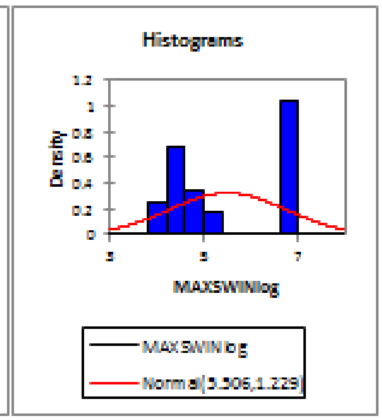
Statistic	Original	Log
Mean	29.226	2.820
Variance	688.937	1.519
Skewness	0.589	-0.626
Kurtosis	-1.330	-0.071



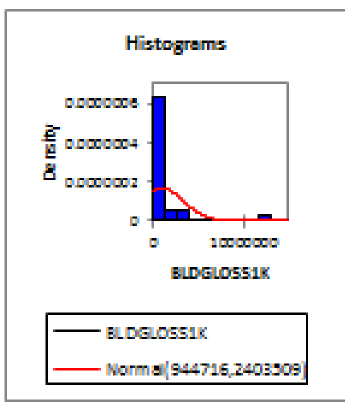


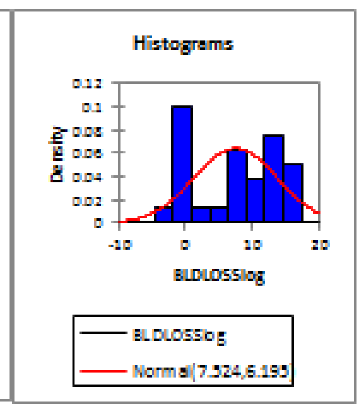
Statistic	Original	Log
Mean	470.517	5.506
Variance	204854.759	1.511
Skewness	0.323	0.184
Kurtosis	-1.948	-1.847



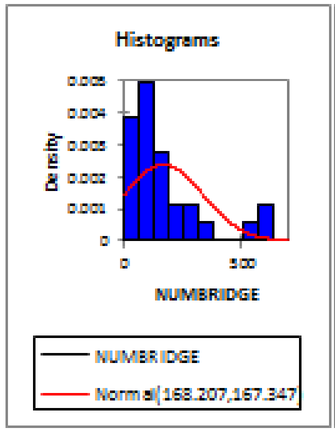


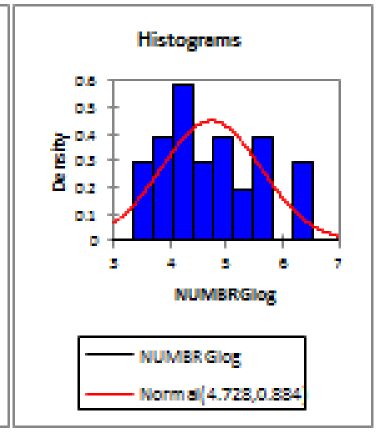
Statistic	Original	Log
Mean	944715.982	7.524
Variance	5776834888915.410	38.381
Skewness	3.788	-0.158
Kurtosis	15.058	-1.591





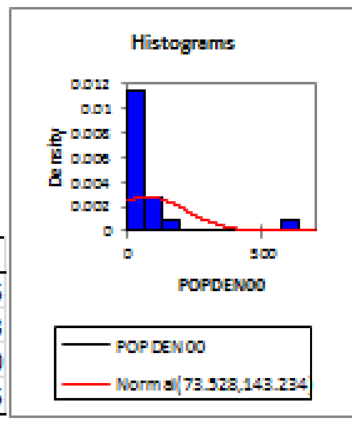
Statistic	Original	Log
Mean	168.207	4.728
Variance	28004.956	0.782
Skewness	1.538	0.406
Kurtosis	1.312	-1.029

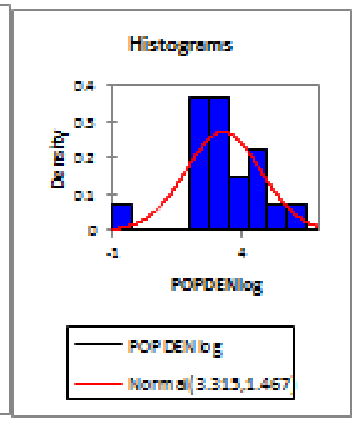




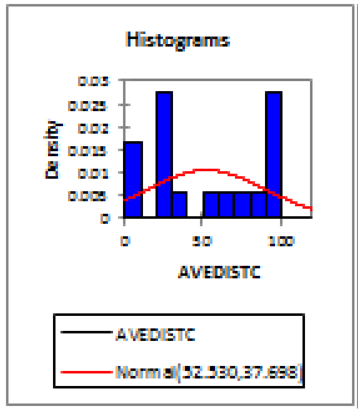
Hurricane Claudette

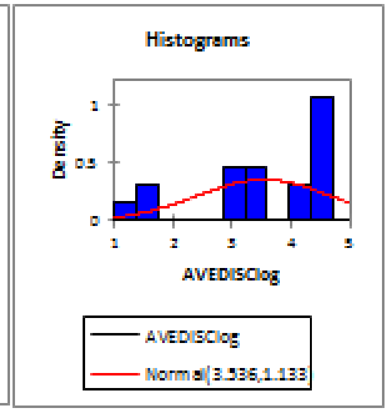
Statistic	Original	Log
Mean	73.528	3.315
Variance	20515.843	2.153
Skewness	3.061	-0.230
Kurtosis	8.818	0.585



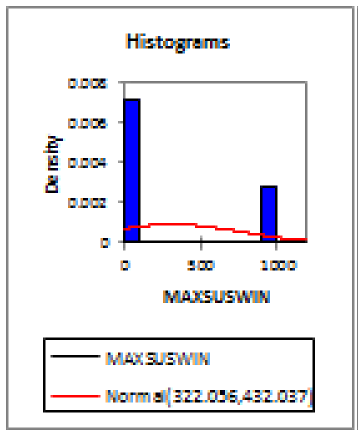


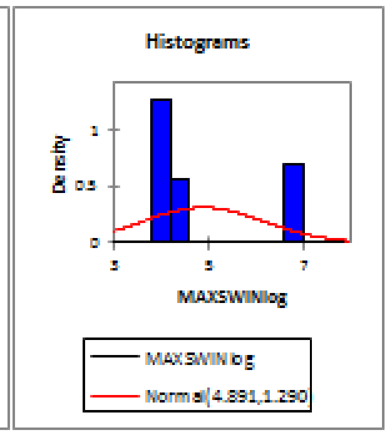
Statistic	Original	Log
Mean	52.530	3.536
Variance	1421.144	1.284
Skewness	0.097	-0.809
Kurtosis	-1.748	-0.656



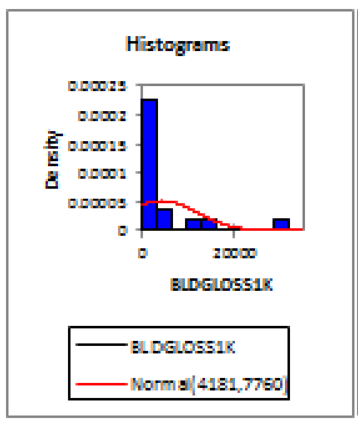


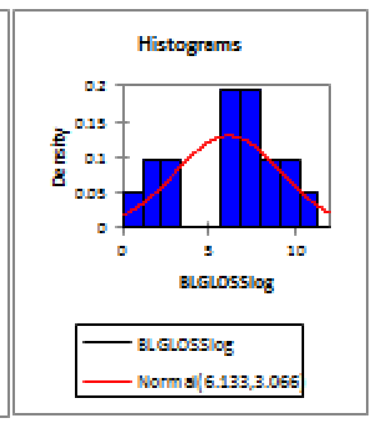
Statistic	Original	Log
Mean	322.056	4.891
Variance	186655.585	1.664
Skewness	0.910	0.893
Kurtosis	-1.230	-1.238

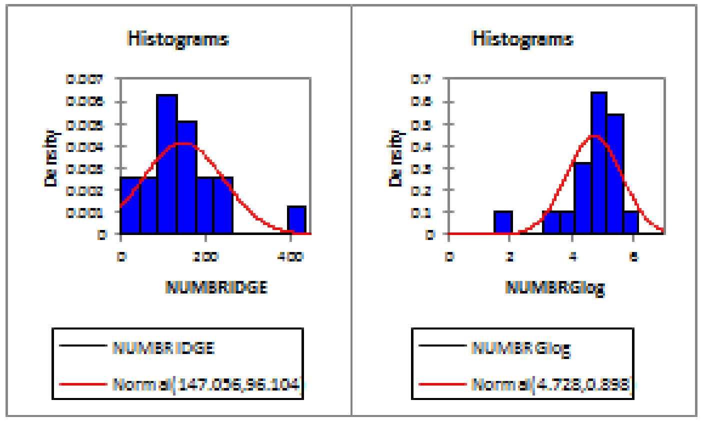




Statistic	Original	Log
Mean	4181.451	6.133
Variance	60214676.976	9.399
Skewness	2.388	-0.601
Kurtosis	5.255	-1.019

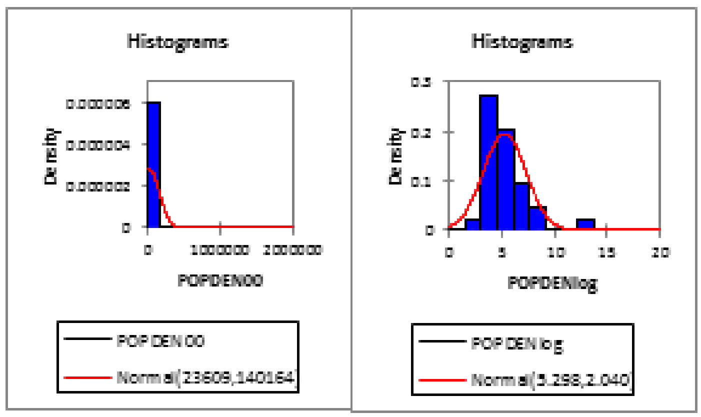




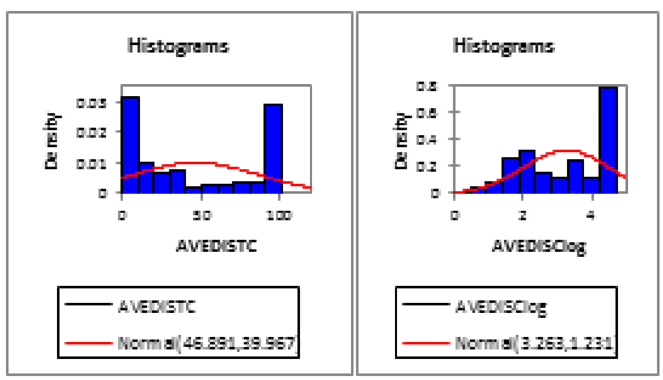


Statistic	Original	Log
Mean	147.056	4.728
Variance	9235.938	0.806
Skewness	1.247	-1.515
Kurtosis	1.986	2.641

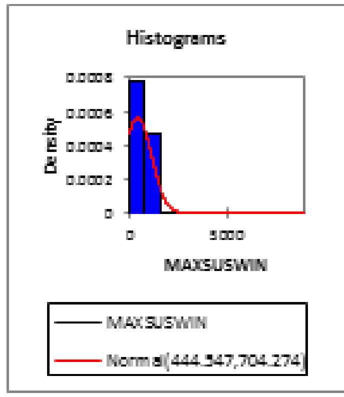
Hurricane Floyd

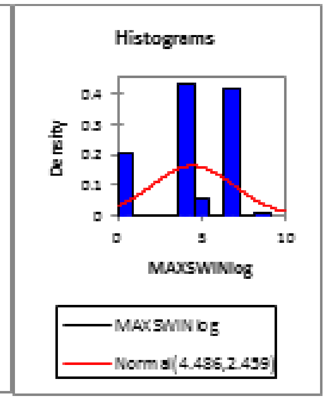


Statistic	Original	Log
Mean	23608.858	5.298
Variance	19645853687.168	4.163
Skewness	7.612	2.128
Kurtosis	67.585	5.881

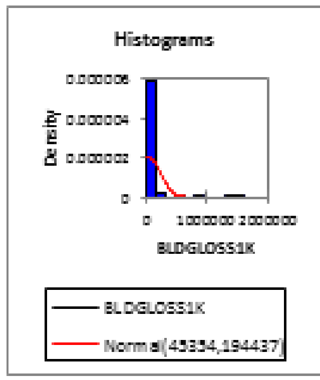


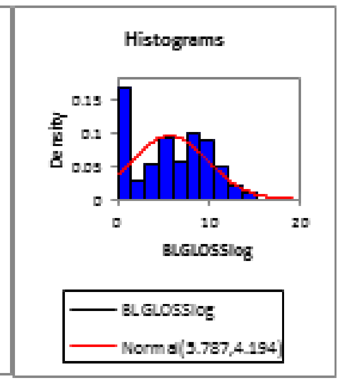
Statistic	Original	Log
Mean	46.891	3.263
Variance	1597.325	1.515
Skewness	0.312	-0.309
Kurtosis	-1.664	-1.400



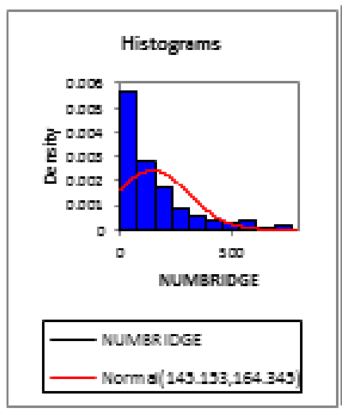


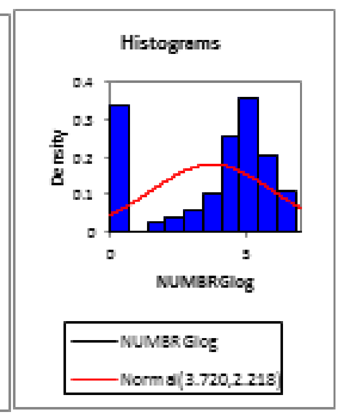
Statistic	Original	Log
Mean	444.547	4.486
Variance	496002.061	6.045
Skewness	6.151	-0.721
Kurtosis	62.423	-0.572





Statistic	Original	Log
Mean	45353.660	5.787
Variance	37805889592.073	17.593
Skewness	6.240	-0.067
Kurtosis	40.731	-1.203

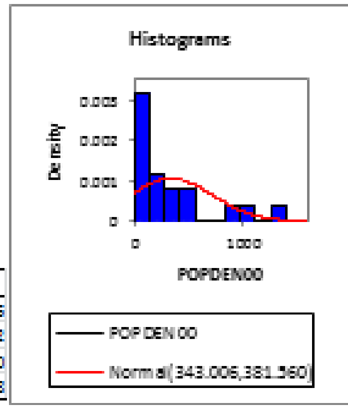


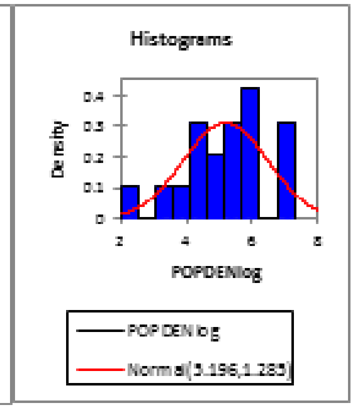


Statistic	Original	Log
Mean	145.153	3.720
Variance	27009.150	4.918
Skewness	1.561	-0.793
Kurtosis	2.199	-0.899

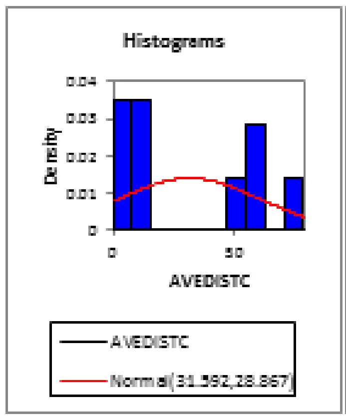
Hurricane Irene

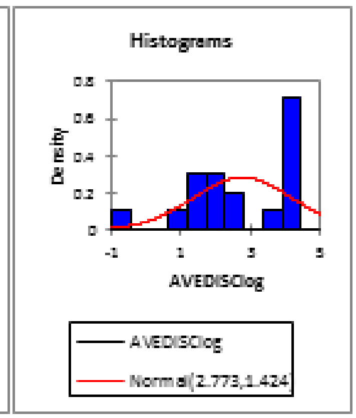
Statistic	Original	Log
Mean	343.006	5.196
Variance	145587.706	1.652
Skewness	1.324	-0.340
Kurtosis	0.540	-0.668



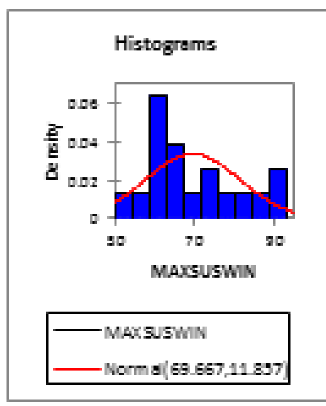


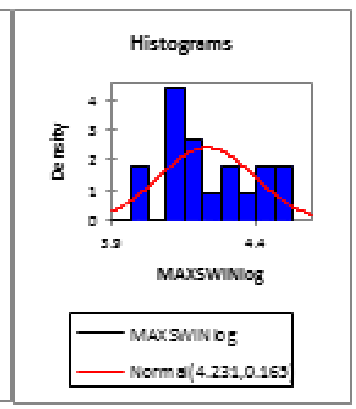
Statistic	Original	Log
Mean	31.592	2.773
Variance	833.314	2.029
Skewness	0.295	-0.575
Kurtosis	-1.811	-0.618



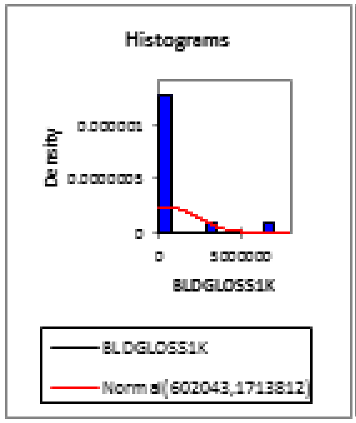


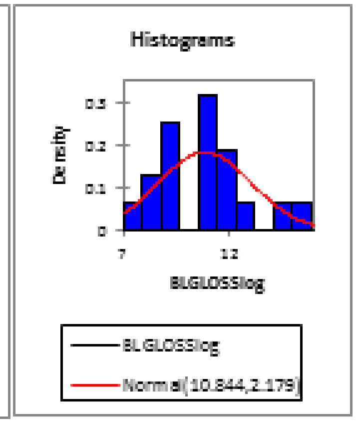
Statistic	Original	Log
Mean	69.667	4.231
Variance	140.588	0.027
Skewness	0.557	0.383
Kurtosis	-1.102	-1.222



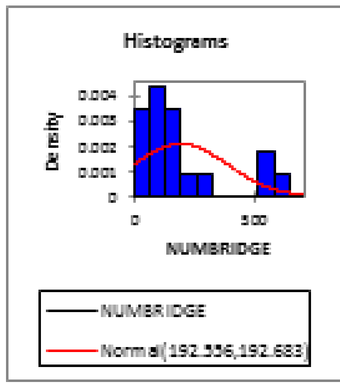


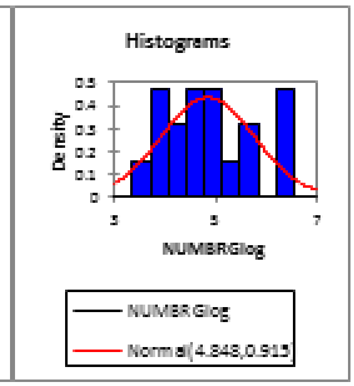
Statistic	Original	Log
Mean	602043.338	10.844
Variance	2937150956757.340	4.750
Skewness	2.901	0.515
Kurtosis	7.522	-0.212





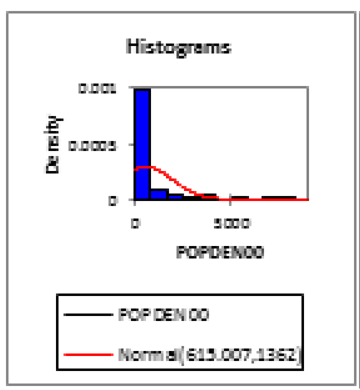
Statistic	Original	Log
Mean	192.536	4.848
Variance	37126.850	0.837
Skewness	1.255	0.386
Kurtosis	0.048	-1.172

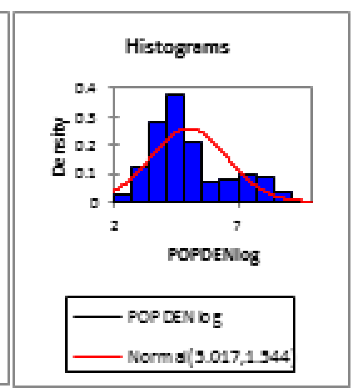




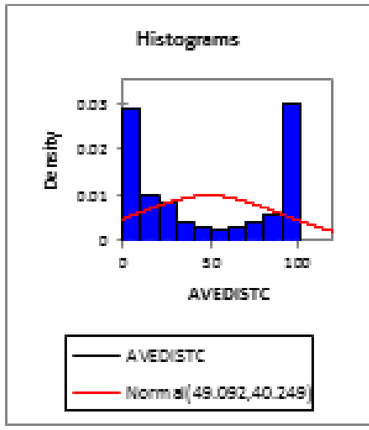
Hurricane Isabel

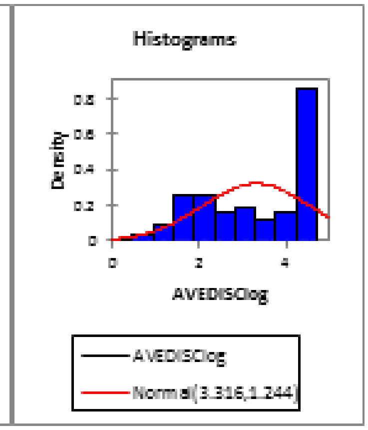
Statistic	Original	Log
Mean	615.007	5.017
Variance	1855850.231	2.383
Skewness	3.615	0.823
Kurtosis	14.590	-0.176



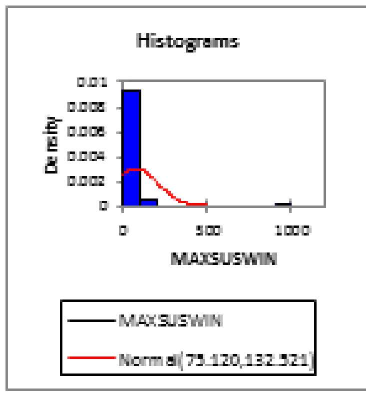


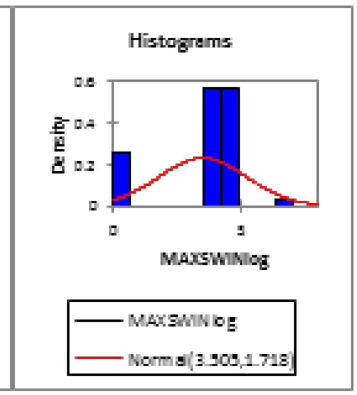
Statistic	Original	Log
Mean	49.092	3.316
Variance	1619.964	1.549
Skewness	0.189	-0.399
Kurtosis	-1.741	-1.360



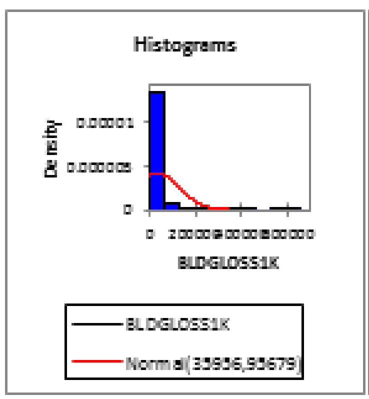


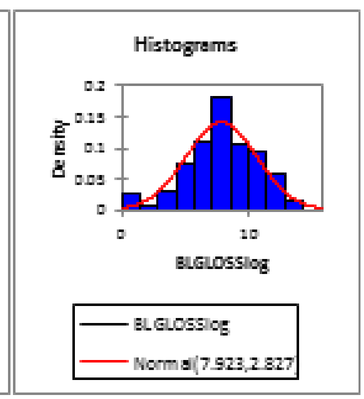
Statistic	Original	Log
Mean	75.120	3.505
Variance	17561.699	2.950
Skewness	6.400	-1.336
Kurtosis	41.872	0.516



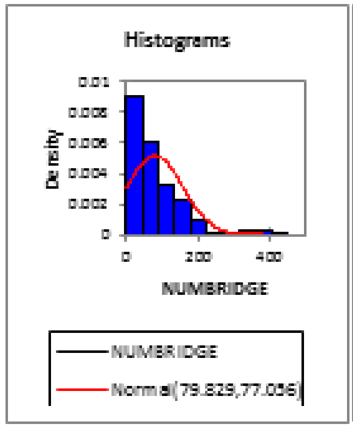


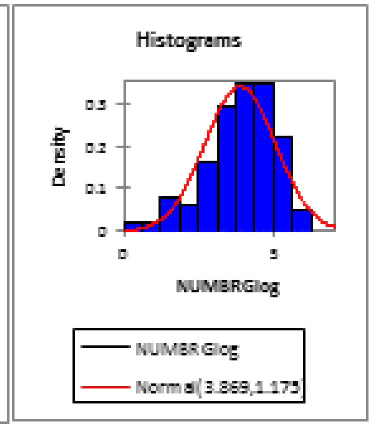
Statistic	Original	Log
Mean	35956.342	7.923
Variance	9154525287.177	7.991
Skewness	4.184	-0.612
Kurtosis	19.111	0.600





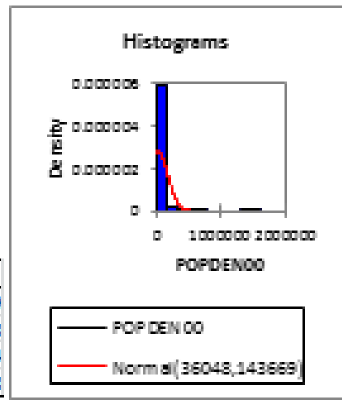
Statistic	Original	Log
Mean	79.829	3.869
Variance	5937.671	1.380
Skewness	2.037	-0.873
Kurtosis	5.542	0.732

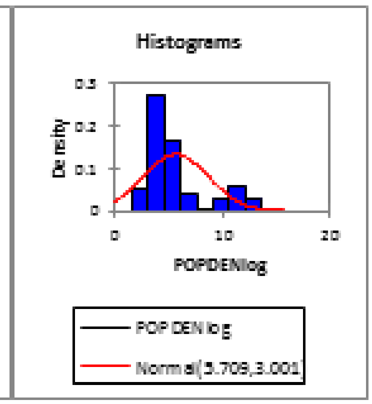




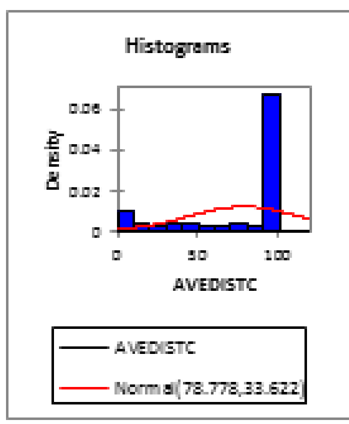
Hurricane Ivan

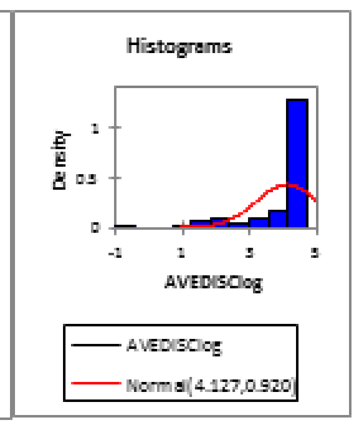
Statistic	Original	Log
Mean	36048.124	5.709
Variance	20640823778.213	9.008
Skewness	7.030	1.304
Kurtosis	59.119	0.368



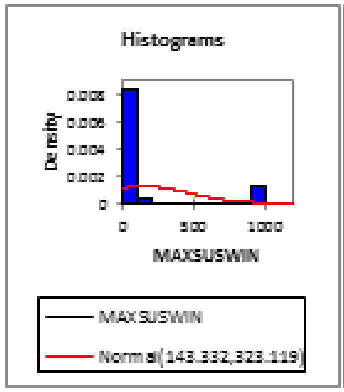


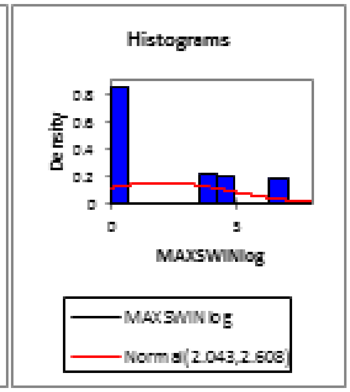
Statistic	Original	Log
Mean	78.778	4.127
Variance	1130.417	0.846
Skewness	-1.245	-2.129
Kurtosis	-0.088	4.045



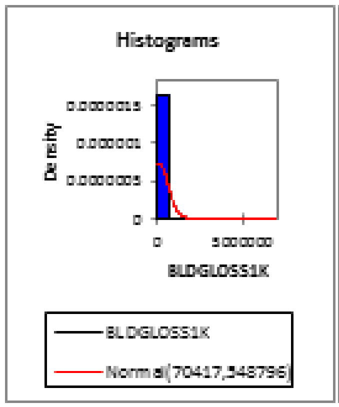


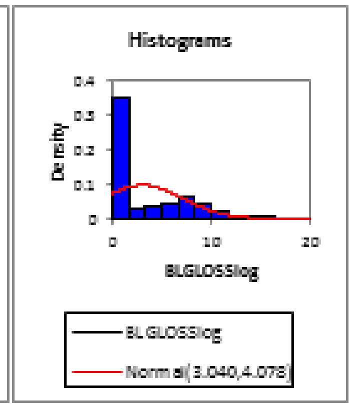
Statistic	Original	Log
Mean	143.332	2.043
Variance	104405.796	6.803
Skewness	2.234	0.688
Kurtosis	3.087	-1.132



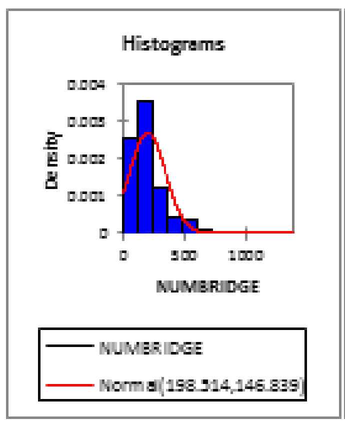


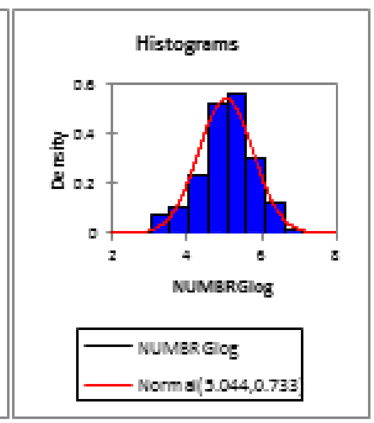
Statistic	Original	Log
Mean	70417.123	3.040
Variance	301177026493.943	16.631
Skewness	9.232	0.995
Kurtosis	87.511	-0.193



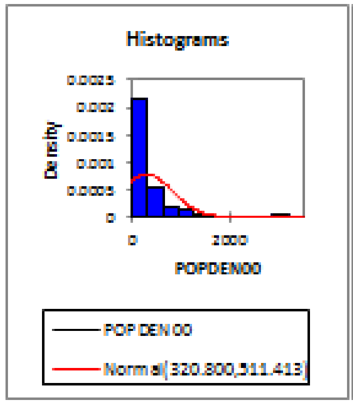


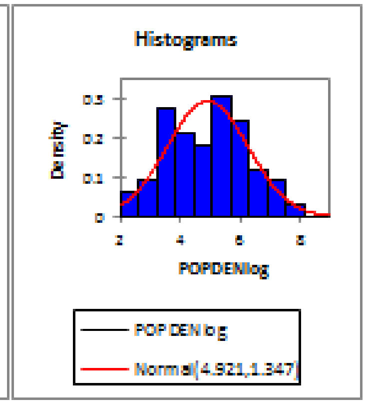
Statistic	Original	Log
Mean	198.514	5.044
Variance	21561.625	0.537
Skewness	1.989	-0.386
Kurtosis	6.210	0.341



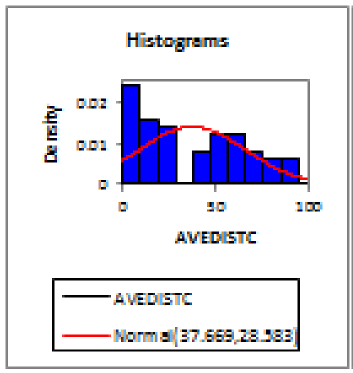


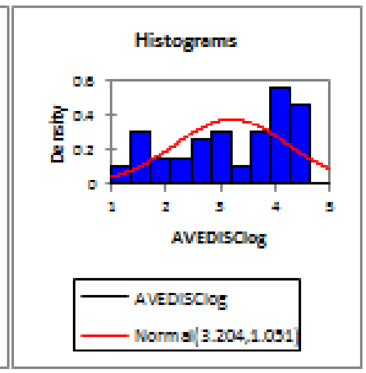
Statistic	Original	Log
Mean	320.800	4.921
Variance	261543.541	1.814
Skewness	3.543	0.115
Kurtosis	15.715	-0.840



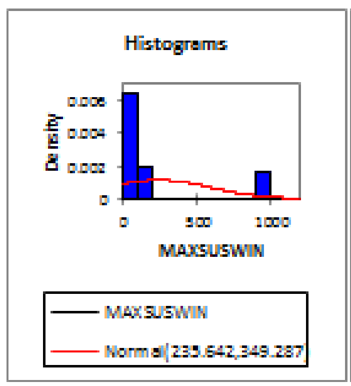


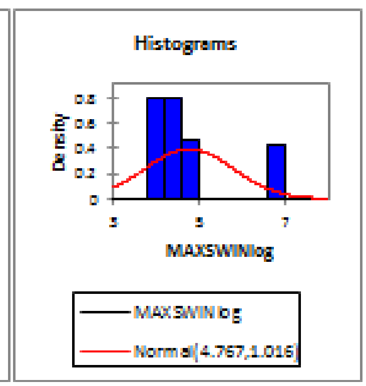
Statistic	Original	Log
Mean	37.669	3.204
Variance	816.987	1.106
Skewness	0.361	-0.476
Kurtosis	-1.269	-1.179



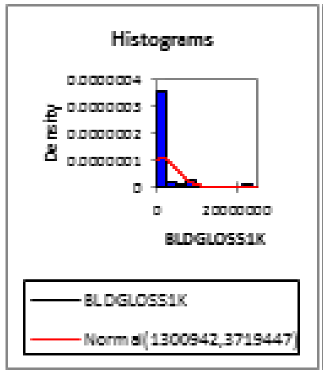


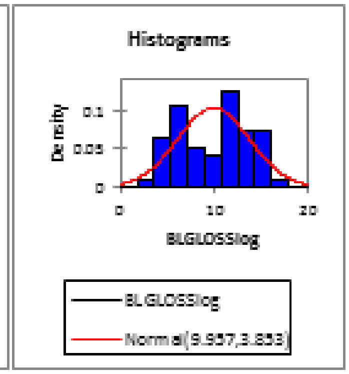
Statistic	Original	Log
Mean	235.642	4.767
Variance	122001.504	1.033
Skewness	1.693	1.429
Kurtosis	0.912	0.454



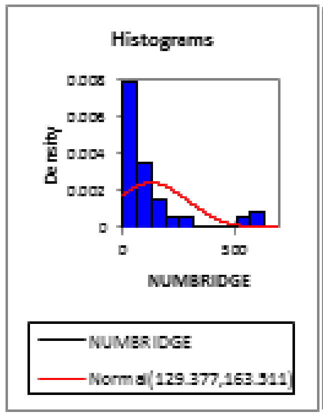


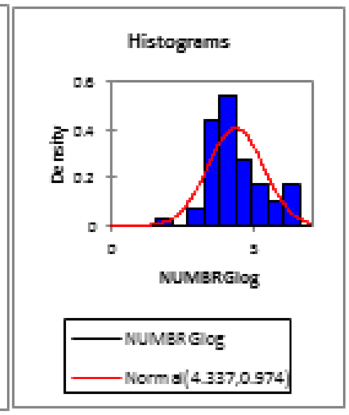
Statistic	Original	Log
Mean	1300942.080	9.957
Variance	13834285833837.500	14.844
Skewness	4.268	-0.046
Kurtosis	20.751	-1.207





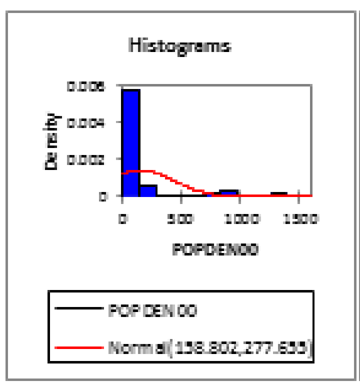
Statistic	Original	Log
Mean	129.377	4.337
Variance	26735.778	0.949
Skewness	2.091	0.518
Kurtosis	3.220	0.034

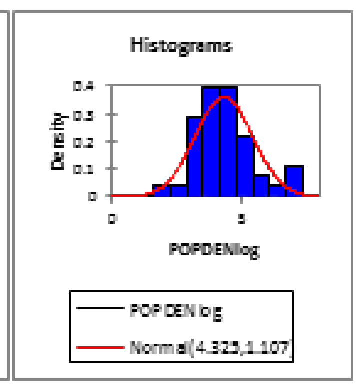




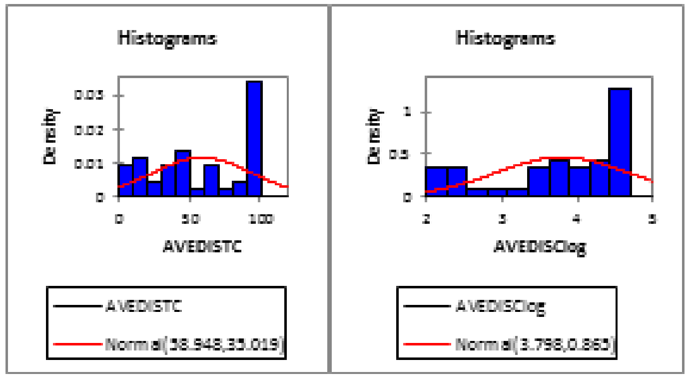
Hurricane Lili

Statistic	Original	Log
Mean	158.802	4.325
Variance	77092.092	1.226
Skewness	2.976	0.653
Kurtosis	8.429	0.603

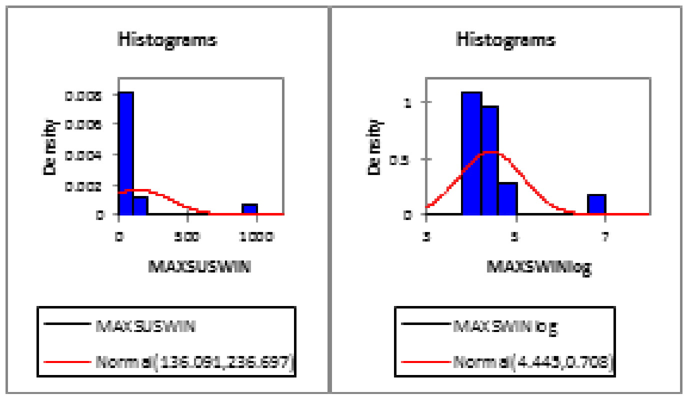




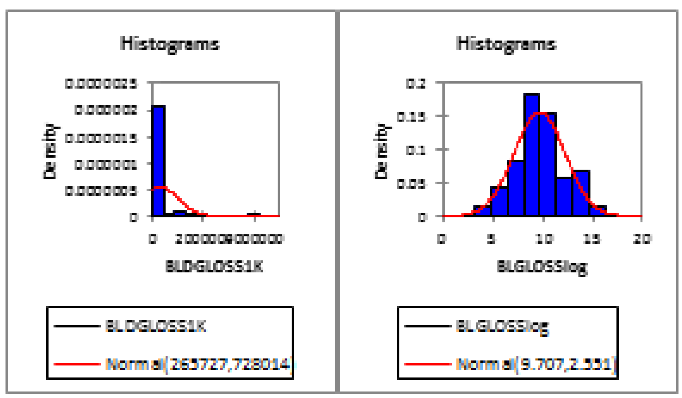
Statistic	Original	Log
Mean	58.948	3.798
Variance	1226.319	0.748
Skewness	-0.107	-0.792
Kurtosis	-1.570	-0.808



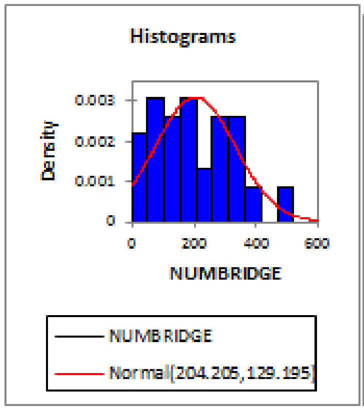
Statistic	Original	Log
Mean	136.091	4.445
Variance	56025.247	0.501
Skewness	3.282	2.797
Kurtosis	9.050	7.028

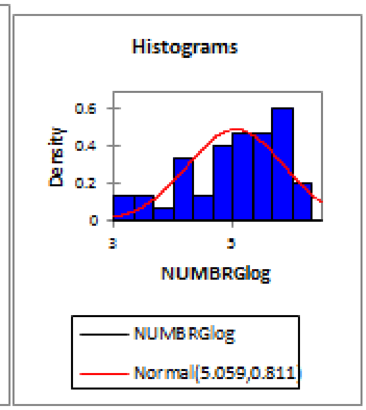


Statistic	Original	Log
Mean	265726.870	9.707
Variance	530004576054.637	6.505
Skewness	3.766	0.261
Kurtosis	15.625	-0.547



Statistic	Original	Log
Mean	204.205	5.059
Variance	16691.283	0.657
Skewness	0.484	-0.685
Kurtosis	-0.604	-0.504





APPENDIX I: Inventory of Spatial Regression Model Outputs

Regression Scenario 1

Hurricane Bret – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Bret_im
Dependent Variable  :        SOVI  Number of Observations:   13
Mean dependent var  :     4.59171  Number of Variables   :    7
S.D. dependent var  :     2.26675  Degrees of Freedom    :    6

R-squared           :    0.719110  F-statistic           :     2.56012
Adjusted R-squared  :    0.438221  Prob(F-statistic)     :    0.138735
Sum squared residual:     18.7623  Log likelihood        :     -20.831
Sigma-square        :     3.12705  Akaike info criterion :     55.6621
S.E. of regression  :     1.76835  Schwarz criterion     :     59.6167
Sigma-square ML     :     1.44325
S.E of regression ML:     1.20135

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      1.298284      2.419608       0.536568      0.61087
    POPDEN00  1.117766e-005    0.01046794     0.001067799     0.99921
      PCTPOV      16.39275      8.801997        1.86239      0.11185
   AVEDISTC    0.002656794    0.02185341      0.1215735     0.90721
   MAXSUSWIN  -0.001117758   0.003053671     -0.3660375     0.72690
  BLDGLOSS1K  5.254505e-005  7.279487e-005      0.7218236     0.49756
   NUMBRIDGE   -0.01207245    0.01259557     -0.9584678     0.37484
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   15.687955
TEST ON NORMALITY OF ERRORS
TEST                  DF            VALUE              PROB
Jarque-Bera            2              0.4536           0.79710

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF            VALUE              PROB
Breusch-Pagan test     6              3.8047           0.70308
Koenker-Bassett test   6              5.2221           0.51565

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Bret_im.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE           PROB
Moran's I (error)             -0.2490       -1.0214          0.30709
Lagrange Multiplier (lag)        1           0.1429          0.70542
Robust LM (lag)                  1           1.5386          0.21482
Lagrange Multiplier (error)      1           1.3347          0.24798
Robust LM (error)                1           2.7304          0.09845
Lagrange Multiplier (SARMA)      2           2.8733          0.23772
========================== END OF REPORT ==============================
```

Hurricane Charley – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Char_im
Dependent Variable  :        SOVI  Number of Observations:   29
Mean dependent var  :    0.695141  Number of Variables   :    7
S.D. dependent var  :     2.05749  Degrees of Freedom    :   22

R-squared           :    0.665421  F-statistic           :     7.29237
Adjusted R-squared  :    0.574172  Prob(F-statistic)     : 0.000220813
Sum squared residual:     41.0744  Log likelihood        :    -46.1965
Sigma-square        :     1.86702  Akaike info criterion :     106.393
S.E. of regression  :     1.36639  Schwarz criterion     :     115.964
Sigma-square ML     :     1.41636
S.E of regression ML:     1.19011

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     -1.045439       1.058318     -0.9878303      0.33398
    POPDEN00  -0.003504356    0.001323906      -2.646982      0.01473
      PCTPOV      19.82006       6.590629        3.00731      0.00648
    AVEDISTC    0.00630392     0.01115132      0.5653072      0.57758
   MAXSUSWIN -0.0005056676   0.0006459602     -0.7828154      0.44208
  BLDGLOSS1K     1.639e-007   1.154904e-007      1.419165      0.16986
   NUMBRIDGE  0.0005145664    0.002252511      0.2284413      0.82141
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   11.051014
TEST ON NORMALITY OF ERRORS
TEST                      DF           VALUE              PROB
Jarque-Bera                2             0.2497           0.88262

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                      DF           VALUE              PROB
Breusch-Pagan test         6             5.6038           0.46900
Koenker-Bassett test       6             4.7736           0.57316

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Char_im.gal
   (row-standardized weights)
TEST                           MI/DF         VALUE             PROB
Moran's I (error)              0.2846         2.2112           0.02702
Lagrange Multiplier (lag)        1            8.8333           0.00296
Robust LM (lag)                  1            6.9780           0.00825
Lagrange Multiplier (error)      1            2.9850           0.08404
Robust LM (error)                1            1.1298           0.28783
Lagrange Multiplier (SARMA)      2            9.9631           0.00686
========================== END OF REPORT ==============================
```

Hurricane Charley-Spatial Lag Model

```
SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set              : Char_im
Spatial Weight        : Char_im.gal
Dependent Variable    :        SOVI  Number of Observations:   29
Mean dependent var    :    0.695141  Number of Variables   :    8
S.D. dependent var    :     2.05749  Degrees of Freedom    :   21
Lag coeff.   (Rho)    :    0.457716

R-squared             :    0.781154  Log likelihood        :    -41.3257
Sq. Correlation       : -            Akaike info criterion :     98.6514
Sigma-square          :    0.926429  Schwarz criterion     :      109.59
S.E of regression     :    0.962512

-----------------------------------------------------------------------
    Variable    Coefficient      Std.Error       z-value    Probability
-----------------------------------------------------------------------
      W_SOVI       0.457716      0.1250493      3.660283      0.00025
    CONSTANT      -1.182848      0.7459256     -1.585746      0.11280
   POPDEN00   -0.002614162   0.0009480151     -2.757511      0.00582
      PCTPOV       15.64864       4.821974      3.245276      0.00117
   AVEDISTC     0.006707357    0.007866618     0.8526353      0.39386
   MAXSUSWIN  -0.0002761522   0.0004553456    -0.6064672      0.54420
  BLDGLOSS1K   5.627211e-008  8.266379e-008     0.6807346     0.49604
   NUMBRIDGE    0.000908497    0.001587263      0.572367      0.56707
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                                         DF      VALUE        PROB
Breusch-Pagan test                           6         2.9192     0.81892

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL LAG DEPENDENCE FOR WEIGHT MATRIX : Char_im.gal
TEST                                         DF      VALUE        PROB
Likelihood Ratio Test                        1         9.7416     0.00180
========================== END OF REPORT ==============================
```

Hurricane Claudette – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Clau_im
Dependent Variable  :        SOVI  Number of Observations:   18
Mean dependent var  :     2.72255  Number of Variables   :    7
S.D. dependent var  :     2.64404  Degrees of Freedom    :   11

R-squared           :    0.847958  F-statistic           :     10.2247
Adjusted R-squared  :    0.765026  Prob(F-statistic)     : 0.000586619
Sum squared residual:     19.1325  Log likelihood        :      -26.09
Sigma-square        :     1.73932  Akaike info criterion :     66.1801
S.E. of regression  :     1.31883  Schwarz criterion     :     72.4127
Sigma-square ML     :     1.06292
S.E of regression ML:     1.03098

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT    0.06801547       1.669191      0.04074757      0.96823
    POPDEN00  -0.004537018    0.003303207       -1.373519      0.19694
      PCTPOV      22.62535       7.488673        3.021277      0.01163
    AVEDISTC   0.002821272     0.01218392        0.231557      0.82113
   MAXSUSWIN -0.0007763676    0.001051869      -0.7380841      0.47592
  BLDGLOSS1K -1.900756e-005  4.693612e-005      -0.4049666      0.69327
   NUMBRIDGE  -0.008506885    0.004297922       -1.979302      0.07336
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   14.966859
TEST ON NORMALITY OF ERRORS
TEST                  DF           VALUE              PROB
Jarque-Bera            2            0.0334            0.98345

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF           VALUE              PROB
Breusch-Pagan test     6            5.2861            0.50768
Koenker-Bassett test   6            4.6683            0.58701

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Clau_im.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE              PROB
Moran's I (error)             -0.1095        0.5010             0.61636
Lagrange Multiplier (lag)        1           0.1290             0.71947
Robust LM (lag)                  1           0.0082             0.92777
Lagrange Multiplier (error)      1           0.3113             0.57688
Robust LM (error)                1           0.1905             0.66249
Lagrange Multiplier (SARMA)      2           0.3195             0.85235
========================== END OF REPORT ==============================
```

Hurricane Floyd – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :   floy_im
Dependent Variable  :        SOVI  Number of Observations:  203
Mean dependent var  :    -1.34016  Number of Variables   :    7
S.D. dependent var  :     2.53271  Degrees of Freedom    :  196

R-squared           :    0.669643  F-statistic           :     66.2162
Adjusted R-squared  :    0.659530  Prob(F-statistic)     :1.68156e-044
Sum squared residual:     430.181  Log likelihood        :    -364.271
Sigma-square        :      2.1948  Akaike info criterion :     742.542
S.E. of regression  :     1.48149  Schwarz criterion     :     765.734
Sigma-square ML     :     2.11912
S.E of regression ML:     1.45572

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     -5.961126     0.314324      -18.96491      0.00000
    POPDEN00  4.611029e-007  8.378609e-007     0.5503335     0.58272
      PCTPOV       36.3234     2.026812       17.92145      0.00000
    AVEDISTC   0.003438563   0.00290972        1.18175      0.23874
   MAXSUSWIN -5.905575e-005  0.0001528845    -0.3862769     0.69971
  BLDGLOSS1K  3.64845e-007  5.522471e-007    0.6606553     0.50961
   NUMBRIDGE  -0.001111609  0.0007416911     -1.498749      0.13555
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   7.379989
TEST ON NORMALITY OF ERRORS
TEST                  DF            VALUE              PROB
Jarque-Bera            2             17.9805           0.00012

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF            VALUE              PROB
Breusch-Pagan test     6               7.3112          0.29302
Koenker-Bassett test   6               5.2958          0.50647

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : floy_im.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE           PROB
Moran's I (error)              0.3251        6.9974         0.00000
Lagrange Multiplier (lag)        1          11.0443         0.00089
Robust LM (lag)                  1           2.3521         0.12511
Lagrange Multiplier (error)      1          40.4238         0.00000
Robust LM (error)                1          31.7316         0.00000
Lagrange Multiplier (SARMA)      2          42.7759         0.00000
========================== END OF REPORT ==============================
```

Hurricane Floyd – Spatial Error Model

```
SUMMARY OF OUTPUT: SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set             : floy_im
Spatial Weight       : floy_im.gal
Dependent Variable   :        SOVI  Number of Observations:  203
Mean dependent var   :   -1.340163  Number of Variables   :    7
S.D. dependent var   :    2.532711  Degrees of Freedom    :  196
Lag coeff. (Lambda)  :    0.515238

R-squared            :    0.747656  R-squared (BUSE)      : -
Sq. Correlation      : -            Log likelihood        : -344.817979
Sigma-square         :     1.61869  Akaike info criterion :     703.636
S.E of regression    :     1.27228  Schwarz criterion     :     726.828

-----------------------------------------------------------------------
    Variable     Coefficient      Std.Error       z-value    Probability
-----------------------------------------------------------------------
    CONSTANT      -6.099717      0.3892584      -15.6701     0.00000
    POPDEN00   9.34297e-007   9.804636e-007     0.9529134    0.34063
      PCTPOV      38.83513       2.159049       17.98715     0.00000
    AVEDISTC   -0.001631156    0.004263879    -0.3825522     0.70205
   MAXSUSWIN   3.229757e-005   0.0001437053    0.2247487    0.82217
  BLDGLOSS1K   1.569714e-007   5.578499e-007    0.2813865    0.77841
   NUMBRIDGE  -0.0008499803    0.0007766157    -1.094467    0.27375
      LAMBDA      0.5152376     0.06827846      7.546122    0.00000
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                                        DF       VALUE        PROB
Breusch-Pagan test                          6         7.3445      0.29016

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX : floy_im.gal
TEST                                        DF       VALUE        PROB
Likelihood Ratio Test                       1        38.9060      0.00000
========================== END OF REPORT ==============================
```

Hurricane Irene – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Iren_im
Dependent Variable  :        SOVI  Number of Observations:   18
Mean dependent var  :    0.645662  Number of Variables   :    7
S.D. dependent var  :     1.96918  Degrees of Freedom    :   11

R-squared           :    0.846996  F-statistic           :     10.1489
Adjusted R-squared  :    0.763539  Prob(F-statistic)     : 0.000606196
Sum squared residual:     10.6793  Log likelihood        :    -20.8423
Sigma-square        :    0.970848  Akaike info criterion :     55.6847
S.E. of regression  :    0.985316  Schwarz criterion     :     61.9173
Sigma-square ML     :    0.593296
S.E of regression ML:    0.770257

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     -1.040904       2.686476     -0.3874608     0.70581
    POPDEN00  -0.004143175     0.00104943      -3.948023     0.00228
      PCTPOV      19.73705       9.217274       2.141311     0.05548
    AVEDISTC    0.01393379     0.01534799      0.9078578     0.38341
   MAXSUSWIN   0.001436847     0.03661241      0.0392448     0.96940
  BLDGLOSS1K  4.513639e-007  2.588492e-007       1.743733     0.10905
   NUMBRIDGE  -0.0004742484    0.002020098      -0.234765     0.81870
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   35.336700
TEST ON NORMALITY OF ERRORS
TEST                  DF            VALUE              PROB
Jarque-Bera            2             0.4967            0.78009

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF            VALUE              PROB
Breusch-Pagan test     6             9.0168            0.17263
Koenker-Bassett test   6            12.3757            0.05409

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Iren_im.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE           PROB
Moran's I (error)             -0.1585       0.0208          0.98338
Lagrange Multiplier (lag)         1         0.1733          0.67723
Robust LM (lag)                   1         1.4712          0.22515
Lagrange Multiplier (error)       1         0.7062          0.40071
Robust LM (error)                 1         2.0042          0.15687
Lagrange Multiplier (SARMA)       2         2.1774          0.33665
========================== END OF REPORT ==============================
```

Hurricane Isabel – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Isab_im
Dependent Variable  :      SOVI  Number of Observations:  158
Mean dependent var  :   -1.4936  Number of Variables   :    7
S.D. dependent var  :   2.78906  Degrees of Freedom    :  151

R-squared           :  0.713583  F-statistic           :     62.7005
Adjusted R-squared  :  0.702202  Prob(F-statistic)     :1.53753e-038
Sum squared residual:   352.025  Log likelihood        :     -287.48
Sigma-square        :   2.33129  Akaike info criterion :     588.959
S.E. of regression  :   1.52686  Schwarz criterion     :     610.398
Sigma-square ML     :     2.228
S.E of regression ML:   1.49265

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     -6.282572      0.3686467      -17.04226      0.00000
    POPDEN00  -0.000157327   9.523184e-005     -1.652043      0.10060
      PCTPOV      40.32391       2.256171       17.87271      0.00000
    AVEDISTC    0.00495734     0.003661597      1.353874      0.17780
    MAXSUSWIN  0.0008653678   0.0009716648     0.8906032      0.37456
   BLDGLOSS1K -8.188883e-007   1.393156e-006    -0.5877939      0.55755
    NUMBRIDGE  -0.005158693    0.001708481     -3.019462      0.00297
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   7.209999
TEST ON NORMALITY OF ERRORS
TEST                      DF           VALUE              PROB
Jarque-Bera                2            42.3016           0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                      DF           VALUE              PROB
Breusch-Pagan test         6            19.8051           0.00300
Koenker-Bassett test       6             8.7754           0.18661

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Isab_im.gal
   (row-standardized weights)
TEST                              MI/DF        VALUE           PROB
Moran's I (error)                 0.2217        4.6528         0.00000
Lagrange Multiplier (lag)            1         15.2732         0.00009
Robust LM (lag)                      1          2.8047         0.09399
Lagrange Multiplier (error)          1         16.1145         0.00006
Robust LM (error)                    1          3.6459         0.05621
Lagrange Multiplier (SARMA)          2         18.9191         0.00008
========================== END OF REPORT ==============================
```

Hurricane Ivan – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Ivan_im
Dependent Variable  :       SOVI  Number of Observations:  292
Mean dependent var  :  -0.478615  Number of Variables   :    7
S.D. dependent var  :    2.09067  Degrees of Freedom    :  285

R-squared           :   0.417186  F-statistic           :     34.0012
Adjusted R-squared  :   0.404917  Prob(F-statistic)     :7.12525e-031
Sum squared residual:    743.849  Log likelihood        :    -550.852
Sigma-square        :       2.61  Akaike info criterion :      1115.7
S.E. of regression  :    1.61555  Schwarz criterion     :     1141.44
Sigma-square ML     :    2.54743
S.E of regression ML:    1.59607

-----------------------------------------------------------------------
    Variable   Coefficient       Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     -2.812156      0.3554974      -7.910482      0.00000
    POPDEN00  1.007793e-006  7.759867e-007       1.298724     0.19509
      PCTPOV      19.47506       1.571234       12.39475      0.00000
    AVEDISTC  -0.002141408     0.00306451     -0.6987765      0.48526
   MAXSUSWIN  -0.0006621157  0.0003230297      -2.049705      0.04131
  BLDGLOSS1K  -9.484704e-008   1.792436e-007     -0.5291517    0.59711
   NUMBRIDGE  -0.002784582   0.0007724331      -3.604949      0.00037
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   8.832847
TEST ON NORMALITY OF ERRORS
TEST                      DF           VALUE                PROB
Jarque-Bera                2            16.2786             0.00029

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                      DF           VALUE                PROB
Breusch-Pagan test         6            20.9303             0.00189
Koenker-Bassett test       6            13.5499             0.03509

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Ivan_im.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE              PROB
Moran's I (error)              0.4028       10.1713            0.00000
Lagrange Multiplier (lag)        1          51.5357            0.00000
Robust LM (lag)                  1           5.3409            0.02083
Lagrange Multiplier (error)      1          93.0241            0.00000
Robust LM (error)                1          46.8293            0.00000
Lagrange Multiplier (SARMA)      2          98.3651            0.00000
========================== END OF REPORT ==============================
```

Hurricane Ivan – Spatial Error Model

```
SUMMARY OF OUTPUT: SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set            : Ivan_im
Spatial Weight      : Ivan_im.gal
Dependent Variable  :        SOVI  Number of Observations:  292
Mean dependent var  :   -0.478615  Number of Variables   :    7
S.D. dependent var  :    2.090673  Degrees of Freedom    :  285
Lag coeff. (Lambda) :    0.609900

R-squared           :    0.615454  R-squared (BUSE)      : -
Sq. Correlation     : -            Log likelihood        : -506.379858
Sigma-square        :     1.68082  Akaike info criterion :     1026.76
S.E of regression   :     1.29646  Schwarz criterion     :      1052.5

-----------------------------------------------------------------------
    Variable    Coefficient      Std.Error        z-value    Probability
-----------------------------------------------------------------------
    CONSTANT      -4.106901      0.4505683      -9.114936      0.00000
    POPDEN00   1.49798e-006  7.902496e-007       1.895578      0.05802
      PCTPOV       24.32447       1.687685       14.41292      0.00000
    AVEDISTC  -0.0002629353    0.004360726    -0.06029623      0.95192
   MAXSUSWIN  -0.0003257375    0.000393971     -0.8268057      0.40835
  BLDGLOSS1K  -1.84222e-008  1.663083e-007     -0.1107714      0.91180
   NUMBRIDGE   -0.001214147   0.0006157855      -1.971705      0.04864
      LAMBDA      0.6098998     0.05080827       12.00395      0.00000
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                                     DF       VALUE          PROB
Breusch-Pagan test                       6         20.7428       0.00204

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX : Ivan_im.gal
TEST                                     DF       VALUE          PROB
Likelihood Ratio Test                    1         88.9450       0.00000
========================== END OF REPORT ==============================
```

Hurricane Jeanne – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set              :  Jean_im
Dependent Variable    :       SOVI  Number of Observations:   53
Mean dependent var    :   0.583392  Number of Variables   :    7
S.D. dependent var    :    2.05375  Degrees of Freedom    :   46

R-squared             :   0.371697  F-statistic           :     4.53551
Adjusted R-squared    :   0.289744  Prob(F-statistic)     :  0.00108701
Sum squared residual:      140.456  Log likelihood        :    -101.031
Sigma-square          :     3.0534  Akaike info criterion :     216.062
S.E. of regression    :     1.7474  Schwarz criterion     :     229.854
Sigma-square ML       :    2.65012
S.E of regression ML:      1.62792

-----------------------------------------------------------------------
    Variable   Coefficient       Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     -1.905861       0.8746205      -2.179072      0.03449
    POPDEN00  -0.0001890389   0.0006147374     -0.3075116      0.75984
      PCTPOV      23.28471        6.061421       3.841461      0.00037
    AVEDISTC   -0.002637679     0.01054695     -0.2500893      0.80363
   MAXSUSWIN   -0.001252838   0.0007608132       -1.64671      0.10643
   BLDGLOSS1K  6.223465e-008  7.427859e-008      0.8378545      0.40645
   NUMBRIDGE   -0.003002511    0.002028262      -1.480337      0.14560
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER    9.677308
TEST ON NORMALITY OF ERRORS
TEST                      DF            VALUE             PROB
Jarque-Bera                2              0.5546          0.75784

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                      DF            VALUE             PROB
Breusch-Pagan test         6              3.9282          0.68640
Koenker-Bassett test       6              4.1905          0.65091

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Jean_im.gal
   (row-standardized weights)
TEST                           MI/DF         VALUE           PROB
Moran's I (error)              0.2807         3.9264         0.00009
Lagrange Multiplier (lag)         1          11.7937         0.00059
Robust LM (lag)                   1           2.7847         0.09517
Lagrange Multiplier (error)       1           9.0318         0.00265
Robust LM (error)                 1           0.0228         0.88003
Lagrange Multiplier (SARMA)       2          11.8165         0.00272
========================== END OF REPORT ==============================
```

Hurricane Lili – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Lili_im
Dependent Variable  :        SOVI  Number of Observations:   44
Mean dependent var  :   -0.357499  Number of Variables   :    7
S.D. dependent var  :     2.02106  Degrees of Freedom    :   37

R-squared           :    0.750893  F-statistic           :     18.5884
Adjusted R-squared  :    0.710497  Prob(F-statistic)     :7.93991e-010
Sum squared residual:     44.7709  Log likelihood        :    -62.8154
Sigma-square        :     1.21002  Akaike info criterion :     139.631
S.E. of regression  :     1.10001  Schwarz criterion     :      152.12
Sigma-square ML     :     1.01752
S.E of regression ML:     1.00872

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      -7.081523       0.710707      -9.964054      0.00000
    POPDEN00   0.0006456772   0.0007418933      0.8703101      0.38974
      PCTPOV        29.3148       3.544336       8.270885      0.00000
    AVEDISTC     0.01266407    0.005991724       2.113593      0.04135
   MAXSUSWIN   0.0007010846   0.0007284458      0.9624388      0.34208
  BLDGLOSS1K  -4.222182e-008   2.402032e-007     -0.1757754      0.86143
   NUMBRIDGE  -0.0005669207    0.001543501     -0.3672954      0.71549
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   12.412321
TEST ON NORMALITY OF ERRORS
TEST                      DF           VALUE              PROB
Jarque-Bera                2             0.0463           0.97710

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                      DF           VALUE              PROB
Breusch-Pagan test         6             6.2596           0.39475
Koenker-Bassett test       6             6.4156           0.37828

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Lili_im.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE           PROB
Moran's I (error)              0.0346        1.2568         0.20881
Lagrange Multiplier (lag)        1           0.0661         0.79705
Robust LM (lag)                  1           0.0000         0.99800
Lagrange Multiplier (error)      1           0.1145         0.73508
Robust LM (error)                1           0.0484         0.82593
Lagrange Multiplier (SARMA)      2           0.1145         0.94436
========================== END OF REPORT ==============================
```

Regression Scenario 3

Hurricane Bret – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set              :  bret_sovi_tcap
Dependent Variable    :     Bret_TAP  Number of Observations:   13
Mean dependent var    :      33.9131  Number of Variables   :    2
S.D. dependent var    :      55.3673  Degrees of Freedom    :   11

R-squared             :     0.439954  F-statistic           :     8.64125
Adjusted R-squared    :     0.389041  Prob(F-statistic)     :   0.0134574
Sum squared residual:          22319  Log likelihood        :    -66.8598
Sigma-square          :         2029  Akaike info criterion :      137.72
S.E. of regression    :      45.0444  Schwarz criterion     :     138.849
Sigma-square ML       :      1716.84
S.E of regression ML:        41.4348

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     -40.47932        28.2227      -1.434283     0.17930
     US_SOVI      16.20146        5.51145         2.9396     0.01346
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   4.284751
TEST ON NORMALITY OF ERRORS
TEST                      DF             VALUE              PROB
Jarque-Bera                2               0.9148           0.63294

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                      DF             VALUE              PROB
Breusch-Pagan test         1               5.8078           0.01596
Koenker-Bassett test       1               6.5768           0.01033

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : bret_sovi_tcap.gal
   (row-standardized weights)
TEST                              MI/DF         VALUE            PROB
Moran's I (error)               -0.0241          0.4889          0.62491
Lagrange Multiplier (lag)          1             0.0691          0.79265
Robust LM (lag)                    1             0.0882          0.76644
Lagrange Multiplier (error)        1             0.0126          0.91080
Robust LM (error)                  1             0.0317          0.85873
Lagrange Multiplier (SARMA)        2             0.1008          0.95086
========================== END OF REPORT ==============================
```

Hurricane Charley – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  char_sovi_tcap
Dependent Variable  :    Char_TAP  Number of Observations:   69
Mean dependent var  :     130.085  Number of Variables   :    2
S.D. dependent var  :     463.439  Degrees of Freedom    :   67

R-squared           :    0.056787  F-statistic           :     4.03378
Adjusted R-squared  :    0.042709  Prob(F-statistic)     :   0.0486312
Sum squared residual:1.39779e+007  Log likelihood        :    -519.458
Sigma-square        :      208626  Akaike info criterion :     1042.92
S.E. of regression  :     456.756  Schwarz criterion     :     1047.38
Sigma-square ML     :      202579
S.E of regression ML:     450.088

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      91.09724       58.31293       1.562213      0.12295
     US_SOVI       53.9069       26.84036       2.008427      0.04863
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   1.413519
TEST ON NORMALITY OF ERRORS
TEST                  DF            VALUE               PROB
Jarque-Bera            2            954.1737            0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF            VALUE               PROB
Breusch-Pagan test     1             46.0704            0.00000
Koenker-Bassett test   1              5.0125            0.02517

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : char_sovi_tcap.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE           PROB
Moran's I (error)              0.2163        2.7906         0.00526
Lagrange Multiplier (lag)        1           7.4438         0.00637
Robust LM (lag)                  1           2.9693         0.08486
Lagrange Multiplier (error)      1           6.1126         0.01342
Robust LM (error)                1           1.6381         0.20059
Lagrange Multiplier (SARMA)      2           9.0819         0.01066
========================== END OF REPORT ==============================
```

Hurricane Claudette – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  clau_sovi_tcap
Dependent Variable  :    Clau_TAP  Number of Observations:   18
Mean dependent var  :     62.5502  Number of Variables   :    2
S.D. dependent var  :     76.9997  Degrees of Freedom    :   16

R-squared           :    0.024964  F-statistic           :     0.409658
Adjusted R-squared  :   -0.035975  Prob(F-statistic)     :     0.531202
Sum squared residual:      104057  Log likelihood        :     -103.502
Sigma-square        :     6503.56  Akaike info criterion :      211.004
S.E. of regression  :     80.6446  Schwarz criterion     :      212.784
Sigma-square ML     :     5780.94
S.E of regression ML:     76.0325

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     75.07755       27.28358       2.751748      0.01418
     US_SOVI    -4.601316       7.189047     -0.6400453      0.53120
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   2.465058
TEST ON NORMALITY OF ERRORS
TEST                  DF             VALUE                 PROB
Jarque-Bera            2              10.2135              0.00606

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF             VALUE                 PROB
Breusch-Pagan test     1               3.8271              0.05043
Koenker-Bassett test   1               1.8113              0.17835

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : clau_sovi_tcap.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE           PROB
Moran's I (error)              0.2706        2.1372         0.03258
Lagrange Multiplier (lag)        1           1.8280         0.17637
Robust LM (lag)                  1           0.0328         0.85633
Lagrange Multiplier (error)      1           1.9010         0.16797
Robust LM (error)                1           0.1058         0.74498
Lagrange Multiplier (SARMA)      2           1.9338         0.38027
========================== END OF REPORT ==============================
```

Hurricane Floyd – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  floy_sovi_tcap
Dependent Variable  :    Floy_TAP  Number of Observations:  182
Mean dependent var  :     106.509  Number of Variables   :    2
S.D. dependent var  :     294.823  Degrees of Freedom    :  180

R-squared           :    0.046563  F-statistic           :     8.79058
Adjusted R-squared  :    0.041266  Prob(F-statistic)     :  0.00343827
Sum squared residual:1.50829e+007  Log likelihood        :    -1288.83
Sigma-square        :     83794.1  Akaike info criterion :     2581.66
S.E. of regression  :     289.472  Schwarz criterion     :     2588.06
Sigma-square ML     :     82873.3
S.E of regression ML:     287.877

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      144.7687       25.03847       5.781849     0.00000
     US_SOVI      24.93917       8.411497       2.964891     0.00344
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   1.768304
TEST ON NORMALITY OF ERRORS
TEST                     DF            VALUE                PROB
Jarque-Bera               2          2481.7667              0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                     DF            VALUE                PROB
Breusch-Pagan test        1            30.7542              0.00000
Koenker-Bassett test      1             3.3482              0.06728

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : floy_sovi_tcap.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE            PROB
Moran's I (error)              0.4445        8.1813          0.00000
Lagrange Multiplier (lag)         1         65.7819          0.00000
Robust LM (lag)                   1          3.2968          0.06941
Lagrange Multiplier (error)       1         62.7938          0.00000
Robust LM (error)                 1          0.3087          0.57849
Lagrange Multiplier (SARMA)       2         66.0906          0.00000
========================== END OF REPORT ==============================
```

Hurricane Floyd – Spatial Lag Model

```
SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set            : floy_sovi_tcap
Spatial Weight      : floy_sovi_tcap.gal
Dependent Variable  :    Floy_TAP  Number of Observations:  182
Mean dependent var  :     106.509  Number of Variables   :    3
S.D. dependent var  :     294.823  Degrees of Freedom    :  179
Lag coeff.   (Rho)  :    0.574307

R-squared           :    0.379843  Log likelihood        :    -1259.68
Sq. Correlation     : -            Akaike info criterion :     2525.37
Sigma-square        :     53904.3  Schwarz criterion     :     2534.98
S.E of regression   :     232.173

-----------------------------------------------------------------------
    Variable     Coefficient     Std.Error       z-value    Probability
-----------------------------------------------------------------------
  W_Floy_TAP      0.5743071     0.06296652      9.120833     0.00000
    CONSTANT       61.65289       21.49955      2.867636     0.00414
     US_SOVI       12.89008       6.811172      1.892491     0.05843
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                                    DF      VALUE        PROB
Breusch-Pagan test                      1        27.7533     0.00000

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL LAG DEPENDENCE FOR WEIGHT MATRIX : floy_sovi_tcap.gal
TEST                                    DF      VALUE        PROB
Likelihood Ratio Test                   1        58.2862     0.00000
========================= END OF REPORT ==============================
```

Hurricane Irene – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set              :  iren_sovi_tcap
Dependent Variable    :     Iren_TAP  Number of Observations:   18
Mean dependent var    :      13.8209  Number of Variables   :    2
S.D. dependent var    :      20.6887  Degrees of Freedom    :   16

R-squared             :     0.000749  F-statistic           :   0.0119916
Adjusted R-squared    :    -0.061704  Prob(F-statistic)     :    0.914162
Sum squared residual:        7698.62  Log likelihood        :    -80.0667
Sigma-square          :      481.164  Akaike info criterion :     164.133
S.E. of regression    :      21.9354  Schwarz criterion     :     165.914
Sigma-square ML       :      427.701
S.E of regression ML:        20.6809

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      14.00658       5.441061        2.574238     0.02038
     US_SOVI    -0.2875174       2.625582      -0.1095061     0.91416
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   1.380266
TEST ON NORMALITY OF ERRORS
TEST                  DF            VALUE               PROB
Jarque-Bera            2             34.0137            0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF            VALUE               PROB
Breusch-Pagan test     1               1.7960           0.18019
Koenker-Bassett test   1               0.4479           0.50332

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : iren_sovi_tcap.gal
   (row-standardized weights)
TEST                          MI/DF         VALUE           PROB
Moran's I (error)            -0.0770         0.0443          0.96463
Lagrange Multiplier (lag)       1            0.1728          0.67768
Robust LM (lag)                 1            0.1877          0.66488
Lagrange Multiplier (error)     1            0.1667          0.68307
Robust LM (error)               1            0.1816          0.67000
Lagrange Multiplier (SARMA)     2            0.3544          0.83763
========================== END OF REPORT ==============================
```

Hurricane Isabel – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set              :  isab_sovi_tcap
Dependent Variable    :    Isab_TAP  Number of Observations:  158
Mean dependent var    :     83.8355  Number of Variables   :    2
S.D. dependent var    :     222.946  Degrees of Freedom    :  156

R-squared             :    0.018167  F-statistic           :     2.88649
Adjusted R-squared    :    0.011873  Prob(F-statistic)     :   0.0913194
Sum squared residual:7.71073e+006  Log likelihood        :    -1077.04
Sigma-square          :     49427.8  Akaike info criterion :     2158.08
S.E. of regression    :     222.324  Schwarz criterion     :      2164.2
Sigma-square ML       :     48802.1
S.E of regression ML:       220.912

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      101.8204       20.61294       4.939635     0.00000
     US_SOVI        10.784       6.347389       1.698966     0.09132
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   1.763927
TEST ON NORMALITY OF ERRORS
TEST                     DF          VALUE                PROB
Jarque-Bera               2        5171.9147              0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                     DF          VALUE                PROB
Breusch-Pagan test        1           5.3530              0.02069
Koenker-Bassett test      1           0.3780              0.53869

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : isab_sovi_tcap.gal
   (row-standardized weights)
TEST                           MI/DF         VALUE           PROB
Moran's I (error)              0.4268         8.9532         0.00000
Lagrange Multiplier (lag)         1          76.4974         0.00000
Robust LM (lag)                   1           4.6790         0.03053
Lagrange Multiplier (error)       1          72.9342         0.00000
Robust LM (error)                 1           1.1159         0.29081
Lagrange Multiplier (SARMA)       2          77.6133         0.00000
========================== END OF REPORT ==============================
```

Hurricane Isabel – Spatial lag Model

```
SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set              : isab_sovi_tcap
Spatial Weight        : isab_sovi_tcap.gal
Dependent Variable    :    Isab_TAP  Number of Observations:  158
Mean dependent var    :     83.8355  Number of Variables   :    3
S.D. dependent var    :     222.946  Degrees of Freedom    :  155
Lag coeff.   (Rho)    :    0.687356

R-squared             :    0.404802  Log likelihood        :    -1046.82
Sq. Correlation       : -            Akaike info criterion :     2099.64
Sigma-square          :     29584.3  Schwarz criterion     :     2108.83
S.E of regression     :     172.001

-----------------------------------------------------------------------
    Variable     Coefficient      Std.Error       z-value    Probability
-----------------------------------------------------------------------
  W_Isab_TAP       0.687356      0.06905727      9.953419      0.00000
    CONSTANT       33.22245        17.13588      1.938765      0.05253
     US_SOVI       4.663993        4.932469     0.9455697      0.34437
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                                        DF       VALUE         PROB
Breusch-Pagan test                          1          4.5153      0.03359

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL LAG DEPENDENCE FOR WEIGHT MATRIX : isab_sovi_tcap.gal
TEST                                        DF       VALUE         PROB
Likelihood Ratio Test                       1         60.4396      0.00000
========================== END OF REPORT ==============================
```

Hurricane Ivan – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set             :  ivan_sovi_tcap
Dependent Variable   :     Ivan_TAP  Number of Observations:  325
Mean dependent var   :       68.645  Number of Variables    :    2
S.D. dependent var   :      276.709  Degrees of Freedom     :  323

R-squared            :     0.000984  F-statistic            :     0.318148
Adjusted R-squared   :    -0.002109  Prob(F-statistic)      :     0.573113
Sum squared residual:   2.486e+007  Log likelihood         :     -2288.46
Sigma-square         :        76966  Akaike info criterion :      4580.92
S.E. of regression   :      277.427  Schwarz criterion      :      4588.49
Sigma-square ML      :      76492.3
S.E of regression ML:       276.572

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      70.74037       15.83095       4.468486     0.00001
     US_SOVI      4.081576       7.236249      0.5640458     0.57311
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   1.270127
TEST ON NORMALITY OF ERRORS
TEST                      DF           VALUE              PROB
Jarque-Bera                2        133056.4014           0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                      DF           VALUE              PROB
Breusch-Pagan test         1             5.7597           0.01640
Koenker-Bassett test       1             0.1159           0.73348

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : ivan_sovi_tcap.gal
   (row-standardized weights)
TEST                           MI/DF         VALUE             PROB
Moran's I (error)              0.5564       14.3813           0.00000
Lagrange Multiplier (lag)        1         200.9100           0.00000
Robust LM (lag)                  1           0.8764           0.34920
Lagrange Multiplier (error)      1         200.2098           0.00000
Robust LM (error)                1           0.1762           0.67465
Lagrange Multiplier (SARMA)      2         201.0862           0.00000
========================== END OF REPORT ==============================
```

Hurricane Jeanne – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  jean_sovi_tcap
Dependent Variable  :    Jean_TAP  Number of Observations:   53
Mean dependent var  :     139.047  Number of Variables   :    2
S.D. dependent var  :     206.788  Degrees of Freedom    :   51

R-squared           :    0.060907  F-statistic           :      3.3077
Adjusted R-squared  :    0.042493  Prob(F-statistic)     :   0.0748298
Sum squared residual:2.12832e+006  Log likelihood        :    -356.118
Sigma-square        :     41731.7  Akaike info criterion :     716.237
S.E. of regression  :     204.283  Schwarz criterion     :     720.177
Sigma-square ML     :     40156.9
S.E of regression ML:     200.392

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      124.5498       29.17063       4.269698     0.00009
     US_SOVI      24.84906       13.66302       1.818709     0.07483
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER    1.323625
                                       (Extreme Multicollinearity)
TEST ON NORMALITY OF ERRORS
TEST                     DF           VALUE             PROB
Jarque-Bera               2           149.9266          0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                     DF           VALUE             PROB
Breusch-Pagan test        1             0.0627          0.80226
Koenker-Bassett test      1             0.0149          0.90269

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : jean_sovi_tcap.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE           PROB
Moran's I (error)              0.4882        5.8302         0.00000
Lagrange Multiplier (lag)        1          28.0792         0.00000
Robust LM (lag)                  1           0.7623         0.38262
Lagrange Multiplier (error)      1          27.3229         0.00000
Robust LM (error)                1           0.0060         0.93802
Lagrange Multiplier (SARMA)      2          28.0852         0.00000
========================== END OF REPORT ==============================
```

Hurricane Lili – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  lili_sovi_tcap
Dependent Variable  :    Lili_TAP  Number of Observations:  44
Mean dependent var  :      31.457  Number of Variables   :   2
S.D. dependent var  :       58.62  Degrees of Freedom    :  42

R-squared           :    0.000376  F-statistic           :  0.0158134
Adjusted R-squared  :   -0.023424  Prob(F-statistic)     :   0.900532
Sum squared residual:      151140  Log likelihood        :   -241.552
Sigma-square        :     3598.58  Akaike info criterion :    487.105
S.E. of regression  :     59.9882  Schwarz criterion     :    490.673
Sigma-square ML     :     3435.01
S.E of regression ML:      58.609

-----------------------------------------------------------------------
    Variable   Coefficient       Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     31.25581        9.183952       3.403307      0.00147
     US_SOVI   -0.5626965        4.474669     -0.1257515      0.90053
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   1.192411
TEST ON NORMALITY OF ERRORS
TEST                  DF           VALUE              PROB
Jarque-Bera            2           619.1303           0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF           VALUE              PROB
Breusch-Pagan test     1             6.8699           0.00877
Koenker-Bassett test   1             0.7337           0.39169

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : lili_sovi_tcap.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE          PROB
Moran's I (error)              0.2427        2.8528         0.00433
Lagrange Multiplier (lag)        1           5.6053         0.01791
Robust LM (lag)                  1           0.1696         0.68046
Lagrange Multiplier (error)      1           5.6390         0.01757
Robust LM (error)                1           0.2033         0.65207
Lagrange Multiplier (SARMA)      2           5.8086         0.05479
========================== END OF REPORT ==============================
```

Regression Scenario 4

Hurricane Bret – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  bret_sovi_tcap
Dependent Variable  :    Bret_TAP  Number of Observations:   13
Mean dependent var  :     33.9131  Number of Variables   :    8
S.D. dependent var  :     55.3673  Degrees of Freedom    :    5

R-squared           :    0.811337  F-statistic           :     3.07176
Adjusted R-squared  :    0.547209  Prob(F-statistic)     :    0.117449
Sum squared residual:      7518.6  Log likelihood        :    -59.7874
Sigma-square        :     1503.72  Akaike info criterion :     135.575
S.E. of regression  :     38.7778  Schwarz criterion     :     140.094
Sigma-square ML     :     578.354
S.E of regression ML:      24.049

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     -62.5071       70.88957     -0.8817531      0.41828
      FAC1_1     18.42103       29.60951      0.6221322      0.56112
      FAC2_1    -8.849103       61.00827     -0.1450476      0.89034
      FAC3_1     16.32505       15.42014       1.058684      0.33819
      FAC4_1     24.02771       17.13152       1.402544      0.21969
      FAC5_1     70.28711       26.37743       2.664669      0.04463
      FAC6_1    -20.19778       93.77272     -0.2153908      0.83797
      FAC7_1    -3.155066       21.03121     -0.1500183      0.88661
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   16.198740
TEST ON NORMALITY OF ERRORS
TEST                      DF            VALUE             PROB
Jarque-Bera                2              0.8768          0.64506

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                      DF            VALUE             PROB
Breusch-Pagan test         7              4.3886          0.73409
Koenker-Bassett test       7              7.9683          0.33540

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : bret_sovi_tcap.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE            PROB
Moran's I (error)              0.0347        0.7798          0.43551
Lagrange Multiplier (lag)        1           1.1276          0.28829
Robust LM (lag)                  1           2.6468          0.10376
Lagrange Multiplier (error)      1           0.0259          0.87227
Robust LM (error)                1           1.5451          0.21386
Lagrange Multiplier (SARMA)      2           2.6727          0.26281
========================== END OF REPORT ==============================
```

Hurricane Charley – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  char_sovi_tcap
Dependent Variable  :    Char_TAP  Number of Observations:   69
Mean dependent var  :     130.085  Number of Variables   :    8
S.D. dependent var  :     463.439  Degrees of Freedom    :   61

R-squared           :    0.243238  F-statistic           :     2.80095
Adjusted R-squared  :    0.156397  Prob(F-statistic)     :   0.0135332
Sum squared residual:1.12148e+007  Log likelihood        :     -511.86
Sigma-square        :      183850  Akaike info criterion :     1039.72
S.E. of regression  :     428.777  Schwarz criterion     :     1057.59
Sigma-square ML     :      162534
S.E of regression ML:     403.155

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      392.0524      183.7814        2.133254      0.03694
      FAC1_1     -158.7568      115.6382       -1.372875      0.17482
      FAC2_1     -113.0124       75.5094       -1.496666      0.13964
      FAC3_1      58.86579      47.26453        1.245454      0.21773
      FAC4_1      186.9577      49.77168        3.756307      0.00039
      FAC5_1      246.1847      122.2753        2.013365      0.04849
      FAC6_1      133.3163      203.5911       0.6548238      0.51504
      FAC7_1     -12.59021        50.771      -0.2479803      0.80498
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER    9.115640
TEST ON NORMALITY OF ERRORS
TEST                      DF            VALUE                PROB
Jarque-Bera                2            914.7209             0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                      DF            VALUE                PROB
Breusch-Pagan test         7            120.5393             0.00000
Koenker-Bassett test       7             13.0950             0.06983

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : char_sovi_tcap.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE           PROB
Moran's I (error)              0.0695        1.3539         0.17576
Lagrange Multiplier (lag)        1           2.4108         0.12050
Robust LM (lag)                  1           6.0028         0.01428
Lagrange Multiplier (error)      1           0.6308         0.42707
Robust LM (error)                1           4.2228         0.03988
Lagrange Multiplier (SARMA)      2           6.6336         0.03627
========================== END OF REPORT ==============================
```

Hurricane Claudette – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  clau_sovi_tcap
Dependent Variable  :    Clau_TAP  Number of Observations:   18
Mean dependent var  :     62.5502  Number of Variables   :    8
S.D. dependent var  :     76.9997  Degrees of Freedom    :   10

R-squared           :    0.247376  F-statistic           :    0.469549
Adjusted R-squared  :   -0.279461  Prob(F-statistic)     :    0.836032
Sum squared residual:     80320.9  Log likelihood        :    -101.172
Sigma-square        :     8032.09  Akaike info criterion :     218.343
S.E. of regression  :      89.622  Schwarz criterion     :     225.466
Sigma-square ML     :     4462.27
S.E of regression ML:     66.8003

-----------------------------------------------------------------------
    Variable   Coefficient       Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     220.9864        116.4032       1.898457      0.08684
      FAC1_1    -33.21251        40.35069     -0.8230965      0.42964
      FAC2_1    -90.92908        86.45378      -1.051765      0.31766
      FAC3_1    -7.606049        25.71445     -0.2957889      0.77344
      FAC4_1    -68.98087        53.88035       -1.28026      0.22935
      FAC5_1     21.37039        62.88533       0.339831      0.74101
      FAC6_1     203.4527        176.0714       1.155513      0.27474
      FAC7_1     12.60276        27.57346      0.4570611      0.65740
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   14.393334
TEST ON NORMALITY OF ERRORS
TEST                  DF            VALUE              PROB
Jarque-Bera            2             6.6618            0.03576

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF            VALUE              PROB
Breusch-Pagan test     7             8.2130            0.31419
Koenker-Bassett test   7             4.4616            0.72533

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : clau_sovi_tcap.gal
   (row-standardized weights)
TEST                          MI/DF        VALUE          PROB
Moran's I (error)             0.1994       2.6054         0.00918
Lagrange Multiplier (lag)       1          2.2274         0.13558
Robust LM (lag)                 1          4.5988         0.03199
Lagrange Multiplier (error)     1          1.0321         0.30966
Robust LM (error)               1          3.4035         0.06506
Lagrange Multiplier (SARMA)     2          5.6309         0.05988
========================== END OF REPORT ==============================
```

Hurricane Floyd – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  floy_sovi_tcap
Dependent Variable  :    Floy_TAP  Number of Observations:  182
Mean dependent var  :     106.509  Number of Variables   :    8
S.D. dependent var  :     294.823  Degrees of Freedom    :  174

R-squared           :    0.150531  F-statistic           :     4.40484
Adjusted R-squared  :    0.116357  Prob(F-statistic)     : 0.000158171
Sum squared residual:1.34382e+007  Log likelihood        :    -1278.32
Sigma-square        :       77231  Akaike info criterion :     2572.64
S.E. of regression  :     277.905  Schwarz criterion     :     2598.27
Sigma-square ML     :     73836.3
S.E of regression ML:     271.728

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      32.93055       52.24209      0.6303452     0.52930
      FAC1_1      84.82981       29.14904       2.910209     0.00408
      FAC2_1     -16.43821       20.24254     -0.8120627     0.41787
      FAC3_1     -18.35038        22.1122     -0.8298758     0.40774
      FAC4_1      8.479094       36.54125      0.2320417     0.81678
      FAC5_1      -40.2303       37.23126      -1.080552     0.28139
      FAC6_1     -114.5657       50.61356      -2.263537     0.02484
      FAC7_1      -15.9015       26.28111     -0.6050541     0.54593
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   5.324153
TEST ON NORMALITY OF ERRORS
TEST                  DF          VALUE             PROB
Jarque-Bera            2         1992.8547          0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF          VALUE             PROB
Breusch-Pagan test     7           94.5985          0.00000
Koenker-Bassett test   7           11.3342          0.12469

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : floy_sovi_tcap.gal
   (row-standardized weights)
TEST                         MI/DF        VALUE           PROB
Moran's I (error)            0.3788        7.3463         0.00000
Lagrange Multiplier (lag)      1          50.2299         0.00000
Robust LM (lag)                1           4.8850         0.02709
Lagrange Multiplier (error)    1          45.5882         0.00000
Robust LM (error)              1           0.2433         0.62185
Lagrange Multiplier (SARMA)    2          50.4732         0.00000
========================== END OF REPORT ==============================
```

Hurricane Floyd – Spatial Lag Model

```
SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set              : floy_sovi_tcap
Spatial Weight        : floy_sovi_tcap.gal
Dependent Variable    :     Floy_TAP  Number of Observations:  182
Mean dependent var    :      106.509  Number of Variables   :    9
S.D. dependent var    :      294.823  Degrees of Freedom    :  173
Lag coeff.    (Rho)   :     0.527127

R-squared             :     0.396760  Log likelihood        :     -1255.35
Sq. Correlation       : -             Akaike info criterion :       2528.7
Sigma-square          :      52433.9  Schwarz criterion     :      2557.53
S.E of regression     :      228.984

-----------------------------------------------------------------------
    Variable     Coefficient     Std.Error        z-value    Probability
-----------------------------------------------------------------------
  W_Floy_TAP      0.5271268     0.06649425       7.927404       0.00000
    CONSTANT       8.269609       43.11194      0.1918172       0.84789
      FAC1_1       47.89302       24.39474       1.963252       0.04962
      FAC2_1      -10.78034       16.72586     -0.6445313       0.51923
      FAC3_1      -3.899944       18.24084     -0.2138029       0.83070
      FAC4_1       8.352444       30.13012      0.2772124       0.78162
      FAC5_1      -19.99205       30.94987     -0.6459492       0.51831
      FAC6_1      -53.95854       42.14066      -1.280439       0.20039
      FAC7_1      -17.11401       21.73219     -0.7874956       0.43099
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                                     DF        VALUE          PROB
Breusch-Pagan test                       7          96.2585       0.00000

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL LAG DEPENDENCE FOR WEIGHT MATRIX : floy_sovi_tcap.gal
TEST                                     DF        VALUE          PROB
Likelihood Ratio Test                    1          45.9449       0.00000
========================== END OF REPORT ==============================
```

Hurricane Irene – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  iren_sovi_tcap
Dependent Variable  :     Iren_TAP  Number of Observations:  18
Mean dependent var  :      13.8209  Number of Variables   :   8
S.D. dependent var  :      20.6887  Degrees of Freedom    :  10

R-squared           :     0.625050  F-statistic           :     2.38146
Adjusted R-squared  :     0.362584  Prob(F-statistic)     :    0.103372
Sum squared residual:      2888.76  Log likelihood        :    -71.2448
Sigma-square        :      288.876  Akaike info criterion :      158.49
S.E. of regression  :      16.9964  Schwarz criterion     :     165.613
Sigma-square ML     :      160.487
S.E of regression ML:      12.6683

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      17.46534       20.83455      0.8382875      0.42145
      FAC1_1     -16.78226        21.7214     -0.7726143      0.45762
      FAC2_1      3.222512       5.798451      0.5557539      0.59060
      FAC3_1      8.169451       5.272423       1.549468      0.15231
      FAC4_1     -1.912594       4.653061     -0.4110399      0.68971
      FAC5_1      4.047105       15.91444      0.2543039      0.80441
      FAC6_1      24.08988       32.82886      0.7338021      0.47992
      FAC7_1      13.59014       8.601604       1.579954      0.14520
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   14.791849
TEST ON NORMALITY OF ERRORS
TEST                      DF            VALUE                PROB
Jarque-Bera                2              0.5449             0.76151

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                      DF            VALUE                PROB
Breusch-Pagan test         7              5.5847             0.58899
Koenker-Bassett test       7              7.1872             0.40965

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : iren_sovi_tcap.gal
   (row-standardized weights)
TEST                           MI/DF         VALUE            PROB
Moran's I (error)             -0.2875       -0.9076          0.36409
Lagrange Multiplier (lag)        1           1.0848          0.29763
Robust LM (lag)                  1           0.9477          0.33031
Lagrange Multiplier (error)      1           2.3247          0.12733
Robust LM (error)                1           2.1876          0.13912
Lagrange Multiplier (SARMA)      2           3.2724          0.19472
========================== END OF REPORT ==============================
```

Hurricane Isabel – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set              :  isab_sovi_tcap
Dependent Variable    :    Isab_TAP  Number of Observations:  158
Mean dependent var    :     83.8355  Number of Variables   :    8
S.D. dependent var    :     222.946  Degrees of Freedom    :  150

R-squared             :    0.123081  F-statistic           :     3.00764
Adjusted R-squared    :    0.082158  Prob(F-statistic)     :  0.00551747
Sum squared residual: 6.8868e+006  Log likelihood        :    -1068.11
Sigma-square          :       45912  Akaike info criterion :     2152.22
S.E. of regression    :     214.271  Schwarz criterion     :     2176.72
Sigma-square ML       :     43587.3
S.E of regression ML:       208.776

-----------------------------------------------------------------------
    Variable   Coefficient       Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      29.50832        40.81962      0.7228955      0.47087
      FAC1_1      19.63703        22.76507      0.8625949      0.38974
      FAC2_1      17.48149        14.80994       1.180389      0.23971
      FAC3_1      65.37948        18.18147       3.595939      0.00044
      FAC4_1     -2.367885        34.50893     -0.0686166      0.94537
      FAC5_1     -56.24415        29.42423      -1.911491      0.05785
      FAC6_1      -19.5651        40.61727     -0.4816942      0.63072
      FAC7_1      47.47223         21.4938       2.208648      0.02872
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   4.974666
TEST ON NORMALITY OF ERRORS
TEST                    DF           VALUE              PROB
Jarque-Bera              2          3748.8675           0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                    DF           VALUE              PROB
Breusch-Pagan test       7          133.1736           0.00000
Koenker-Bassett test     7           10.9425           0.14115

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : isab_sovi_tcap.gal
   (row-standardized weights)
TEST                           MI/DF         VALUE           PROB
Moran's I (error)              0.3721         8.2860         0.00000
Lagrange Multiplier (lag)        1           65.2672         0.00000
Robust LM (lag)                  1           10.9561         0.00093
Lagrange Multiplier (error)      1           55.4315         0.00000
Robust LM (error)                1            1.1203         0.28985
Lagrange Multiplier (SARMA)      2           66.3876         0.00000
========================== END OF REPORT ==============================
```

Hurricane Isabel – Spatial lag Model

```
SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set             : isab_sovi_tcap
Spatial Weight       : isab_sovi_tcap.gal
Dependent Variable   :    Isab_TAP  Number of Observations:  158
Mean dependent var   :     83.8355  Number of Variables   :    9
S.D. dependent var   :     222.946  Degrees of Freedom    :  149
Lag coeff.    (Rho)  :    0.651686

R-squared            :    0.435693  Log likelihood        :    -1041.44
Sq. Correlation      : -            Akaike info criterion :     2100.89
Sigma-square         :     28048.9  Schwarz criterion     :     2128.45
S.E of regression    :     167.478

-----------------------------------------------------------------------
    Variable     Coefficient      Std.Error       z-value    Probability
-----------------------------------------------------------------------
  W_Isab_TAP      0.6516857     0.07214579        9.0329      0.00000
    CONSTANT       10.69585       32.40395     0.3300787      0.74134
      FAC1_1        3.12961       17.80015     0.1758193      0.86044
      FAC2_1       11.71271       11.58768       1.01079      0.31212
      FAC3_1       37.09653       14.40984      2.574388      0.01004
      FAC4_1        7.00652       26.98443     0.2596505      0.79513
      FAC5_1      -29.17302        23.0005     -1.268365      0.20467
      FAC6_1       1.048861       31.74735    0.03303775      0.97364
      FAC7_1       34.26034       16.93313      2.023273      0.04304
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                                       DF       VALUE        PROB
Breusch-Pagan test                         7        154.3529     0.00000

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL LAG DEPENDENCE FOR WEIGHT MATRIX : isab_sovi_tcap.gal
TEST                                       DF       VALUE        PROB
Likelihood Ratio Test                      1         53.3335     0.00000
========================== END OF REPORT ==============================
```

Hurricane Ivan – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  ivan_sovi_tcap
Dependent Variable  :    Ivan_TAP  Number of Observations:  325
Mean dependent var  :      68.645  Number of Variables   :    8
S.D. dependent var  :     276.709  Degrees of Freedom    :  317

R-squared           :    0.020751  F-statistic           :    0.959624
Adjusted R-squared  :   -0.000873  Prob(F-statistic)     :    0.460836
Sum squared residual:2.43681e+007  Log likelihood        :    -2285.21
Sigma-square        :       76871  Akaike info criterion :     4586.42
S.E. of regression  :     277.256  Schwarz criterion     :     4616.69
Sigma-square ML     :     74978.8
S.E of regression ML:     273.823

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      24.16408       31.63938      0.7637343      0.44559
      FAC1_1      26.44319       16.55868       1.596938      0.11128
      FAC2_1      18.13911       18.56493      0.9770631      0.32928
      FAC3_1       4.63209       17.96412      0.2578523      0.79669
      FAC4_1     -30.90694       30.54499       -1.01185      0.31238
      FAC5_1     -56.30303       27.80467      -2.024949      0.04371
      FAC6_1      4.793672       41.65274      0.1150866      0.90845
      FAC7_1      13.02428       15.66784      0.8312742      0.40645
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   4.175867
TEST ON NORMALITY OF ERRORS
TEST                      DF            VALUE                PROB
Jarque-Bera                2        133706.8697              0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                      DF            VALUE                PROB
Breusch-Pagan test         7            85.6772              0.00000
Koenker-Bassett test       7             1.7202              0.97369

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : ivan_sovi_tcap.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE            PROB
Moran's I (error)              0.5477       14.5491          0.00000
Lagrange Multiplier (lag)        1         197.2243          0.00000
Robust LM (lag)                  1           3.3234          0.06830
Lagrange Multiplier (error)      1         193.9547          0.00000
Robust LM (error)                1           0.0537          0.81669
Lagrange Multiplier (SARMA)      2         197.2781          0.00000
========================== END OF REPORT ==============================
```

Hurricane Jeanne – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  jean_sovi_tcap
Dependent Variable  :    Jean_TAP  Number of Observations:    53
Mean dependent var  :     139.047  Number of Variables   :     8
S.D. dependent var  :     206.788  Degrees of Freedom    :    45

R-squared           :    0.158187  F-statistic           :      1.20801
Adjusted R-squared  :    0.027238  Prob(F-statistic)     :      0.31815
Sum squared residual:1.90784e+006  Log likelihood        :      -353.22
Sigma-square        :     42396.5  Akaike info criterion :      722.441
S.E. of regression  :     205.904  Schwarz criterion     :      738.203
Sigma-square ML     :     35997.1
S.E of regression ML:     189.729

-----------------------------------------------------------------------
    Variable   Coefficient       Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     -20.08771       114.9032     -0.1748229      0.86200
      FAC1_1    -0.7741545       80.87974   -0.009571675      0.99242
      FAC2_1      42.30104       46.55971      0.9085331      0.36844
      FAC3_1      23.23788        27.9893      0.8302415      0.41079
      FAC4_1      42.57783       25.89297       1.644378      0.10707
      FAC5_1     -41.76317       76.02075     -0.5493655      0.58547
      FAC6_1     -135.2852       156.8521     -0.8625018      0.39298
      FAC7_1     -8.751855       34.74775     -0.2518683      0.80229
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   10.513313
TEST ON NORMALITY OF ERRORS
TEST                  DF           VALUE              PROB
Jarque-Bera            2           127.5966           0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF           VALUE              PROB
Breusch-Pagan test     7             9.8604           0.19662
Koenker-Bassett test   7             2.4380           0.93169

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : jean_sovi_tcap.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE           PROB
Moran's I (error)              0.4605        5.9780          0.00000
Lagrange Multiplier (lag)        1          25.2844          0.00000
Robust LM (lag)                  1           1.0961          0.29511
Lagrange Multiplier (error)      1          24.3013          0.00000
Robust LM (error)                1           0.1131          0.73667
Lagrange Multiplier (SARMA)      2          25.3974          0.00000
========================== END OF REPORT ==============================
```

Hurricane Lili – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  lili_sovi_tcap
Dependent Variable  :    Lili_TAP  Number of Observations:   44
Mean dependent var  :      31.457  Number of Variables   :    8
S.D. dependent var  :       58.62  Degrees of Freedom    :   36

R-squared           :    0.443381  F-statistic           :     4.09659
Adjusted R-squared  :    0.335149  Prob(F-statistic)     :  0.00211858
Sum squared residual:     84159.4  Log likelihood        :    -228.671
Sigma-square        :     2337.76  Akaike info criterion :     473.343
S.E. of regression  :     48.3504  Schwarz criterion     :     487.616
Sigma-square ML     :     1912.71
S.E of regression ML:     43.7346

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     19.42739       23.00031      0.8446578     0.40388
      FAC1_1     2.317433       13.42825      0.1725789     0.86395
      FAC2_1    -5.829686       13.84514     -0.4210638     0.67621
      FAC3_1    -36.01001       16.54467      -2.176532     0.03616
      FAC4_1     36.71307       16.87826       2.175169     0.03627
      FAC5_1     4.848822       14.70495      0.3297409     0.74351
      FAC6_1     106.9539       30.52776       3.503495     0.00125
      FAC7_1     6.704872       9.411051      0.7124467     0.48078
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   6.578687
TEST ON NORMALITY OF ERRORS
TEST                      DF           VALUE                PROB
Jarque-Bera                2           189.6747             0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                      DF           VALUE                PROB
Breusch-Pagan test         7            91.1314             0.00000
Koenker-Bassett test       7            16.4129             0.02160

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : lili_sovi_tcap.gal
   (row-standardized weights)
TEST                              MI/DF        VALUE           PROB
Moran's I (error)                 0.0784        1.5633         0.11797
Lagrange Multiplier (lag)           1           0.9172         0.33821
Robust LM (lag)                     1           0.3462         0.55630
Lagrange Multiplier (error)         1           0.5888         0.44290
Robust LM (error)                   1           0.0177         0.89419
Lagrange Multiplier (SARMA)         2           0.9349         0.62659
========================== END OF REPORT ==============================
```

Regression Scenario 5

Hurricane Bret – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Bret_im
Dependent Variable  :     TA_pcap  Number of Observations:   13
Mean dependent var  :     33.9131  Number of Variables   :    7
S.D. dependent var  :     55.3673  Degrees of Freedom    :    6

R-squared           :    0.718711  F-statistic           :     2.55506
Adjusted R-squared  :    0.437421  Prob(F-statistic)     :    0.139224
Sum squared residual:       11210  Log likelihood        :    -62.3837
Sigma-square        :     1868.33  Akaike info criterion :     138.767
S.E. of regression  :     43.2241  Schwarz criterion     :     142.722
Sigma-square ML     :     862.304
S.E of regression ML:      29.365

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     -5.246791       59.14311     -0.08871348     0.93220
    POPDEN00    -0.1694157      0.2558707      -0.6621142     0.53249
      PCTPOV      12.64448       215.1496      0.05877066     0.95504
    AVEDISTC     0.1488498      0.5341686       0.2786569     0.78986
   MAXSUSWIN    0.02478131      0.0746417       0.3320035     0.75118
  BLDGLOSS1K   0.004690546    0.001779344        2.636109     0.03874
   NUMBRIDGE   -0.04616112      0.3078769      -0.1499337     0.88573
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   15.687955
TEST ON NORMALITY OF ERRORS
TEST                      DF            VALUE              PROB
Jarque-Bera                2              0.8916           0.64032

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                      DF            VALUE              PROB
Breusch-Pagan test         6              3.7187           0.71468
Koenker-Bassett test       6              5.6119           0.46804

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Bret_im.gal
   (row-standardized weights)
TEST                           MI/DF         VALUE            PROB
Moran's I (error)             -0.1459       -0.1450          0.88470
Lagrange Multiplier (lag)        1           0.0010          0.97500
Robust LM (lag)                  1           0.8010          0.37080
Lagrange Multiplier (error)      1           0.4580          0.49856
Robust LM (error)                1           1.2580          0.26203
Lagrange Multiplier (SARMA)      2           1.2590          0.53287
========================== END OF REPORT ==============================
```

Hurricane Charley – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Char_im
Dependent Variable  :      TA_pcap  Number of Observations:   29
Mean dependent var  :      305.698  Number of Variables   :    7
S.D. dependent var  :      676.604  Degrees of Freedom    :   22

R-squared           :     0.712898  F-statistic           :     9.10463
Adjusted R-squared  :     0.634597  Prob(F-statistic)     :4.63031e-005
Sum squared residual:3.81157e+006  Log likelihood        :     -212.05
Sigma-square        :       173253  Akaike info criterion :      438.1
S.E. of regression  :      416.237  Schwarz criterion     :    447.671
Sigma-square ML     :       131434
S.E of regression ML:      362.538

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     -448.9981        322.391      -1.392713     0.17762
    POPDEN00     0.1998049       0.403296        0.49543     0.62521
      PCTPOV       8412.27       2007.676       4.190054     0.00038
    AVEDISTC     -5.935837       3.396979      -1.747387     0.09452
   MAXSUSWIN    -0.5036774      0.1967762      -2.559647     0.01787
  BLDGLOSS1K  0.0001821471   3.518137e-005      5.177375     0.00003
   NUMBRIDGE    -0.9562007      0.6861729      -1.393527     0.17738
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   11.051014
TEST ON NORMALITY OF ERRORS
TEST                  DF           VALUE              PROB
Jarque-Bera            2            6.6375            0.03620

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF           VALUE              PROB
Breusch-Pagan test     6           24.6944            0.00039
Koenker-Bassett test   6           12.8552            0.04539

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Char_im.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE           PROB
Moran's I (error)              0.0765        0.9489          0.34268
Lagrange Multiplier (lag)        1           0.0004          0.98480
Robust LM (lag)                  1           0.1974          0.65686
Lagrange Multiplier (error)      1           0.2157          0.64236
Robust LM (error)                1           0.4127          0.52062
Lagrange Multiplier (SARMA)      2           0.4130          0.81341
========================== END OF REPORT ==============================
```

Hurricane Claudette – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Clau_im
Dependent Variable  :     TA_pcap  Number of Observations:  18
Mean dependent var  :     62.5502  Number of Variables   :   7
S.D. dependent var  :     76.9997  Degrees of Freedom    :  11

R-squared           :    0.381908  F-statistic           :    1.13278
Adjusted R-squared  :    0.044767  Prob(F-statistic)     :   0.404807
Sum squared residual:     65963.5  Log likelihood        :   -99.3993
Sigma-square        :     5996.68  Akaike info criterion :    212.799
S.E. of regression  :     77.4383  Schwarz criterion     :    219.031
Sigma-square ML     :     3664.64
S.E of regression ML:     60.5363

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      201.1681       98.01037        2.052518     0.06469
    POPDEN00    -0.1877198      0.1939554      -0.9678503     0.35392
      PCTPOV     -328.1253       439.7147      -0.7462233     0.47118
    AVEDISTC    -0.7301913       0.715407       -1.020666     0.32934
    MAXSUSWIN   0.01148286      0.0617629       0.1859184     0.85589
  BLDGLOSS1K   0.002779199    0.002755962        1.008432     0.33492
   NUMBRIDGE    -0.2561595      0.2523624       -1.015046     0.33189
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   14.966859
TEST ON NORMALITY OF ERRORS
TEST                  DF          VALUE              PROB
Jarque-Bera            2            4.1727           0.12414

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF          VALUE              PROB
Breusch-Pagan test     6           10.7050           0.09793
Koenker-Bassett test   6            5.6528           0.46318

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Clau_im.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE          PROB
Moran's I (error)             -0.1441       0.2273         0.82021
Lagrange Multiplier (lag)         1         0.0867         0.76846
Robust LM (lag)                   1         2.5045         0.11352
Lagrange Multiplier (error)       1         0.5395         0.46263
Robust LM (error)                 1         2.9574         0.08549
Lagrange Multiplier (SARMA)       2         3.0440         0.21827
========================= END OF REPORT ==============================
```

Hurricane Floyd – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  floy_im
Dependent Variable  :     TA_pcap  Number of Observations:  203
Mean dependent var  :     95.2018  Number of Variables   :    7
S.D. dependent var  :     281.124  Degrees of Freedom    :  196

R-squared           :    0.097917  F-statistic           :     3.54581
Adjusted R-squared  :    0.070302  Prob(F-statistic)     :  0.00234879
Sum squared residual:1.44723e+007  Log likelihood        :    -1422.26
Sigma-square        :     73838.2  Akaike info criterion :     2858.52
S.E. of regression  :     271.732  Schwarz criterion     :     2881.71
Sigma-square ML     :     71292.1
S.E of regression ML:     267.006

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     -15.89882       57.65284     -0.2757682     0.78302
   POPDEN00 -9.384413e-005  0.0001536792     -0.6106496     0.54214
      PCTPOV      1273.465       371.7548        3.42555     0.00075
    AVEDISTC    -0.3886535      0.5336966     -0.7282294     0.46734
   MAXSUSWIN   -0.05996387     0.02804184      -2.138371     0.03372
  BLDGLOSS1K  7.57586e-005   0.0001012923      0.7479203     0.45540
   NUMBRIDGE   -0.04965806      0.1360399     -0.3650258     0.71548
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   7.379989
TEST ON NORMALITY OF ERRORS
TEST                    DF           VALUE              PROB
Jarque-Bera              2         3331.5419            0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                    DF           VALUE              PROB
Breusch-Pagan test       6           84.3248            0.00000
Koenker-Bassett test     6            8.3583            0.21301

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : floy_im.gal
   (row-standardized weights)
TEST                           MI/DF         VALUE            PROB
Moran's I (error)              0.3604         7.7093          0.00000
Lagrange Multiplier (lag)        1           63.7313          0.00000
Robust LM (lag)                  1           23.2758          0.00000
Lagrange Multiplier (error)      1           49.6591          0.00000
Robust LM (error)                1            9.2037          0.00242
Lagrange Multiplier (SARMA)      2           72.9350          0.00000
========================== END OF REPORT ==============================
```

Hurricane Floyd – Spatial Lag Model

```
SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set            : floy_im
Spatial Weight      : floy_im.gal
Dependent Variable  :     TA_pcap  Number of Observations:  203
Mean dependent var  :     95.2018  Number of Variables   :    8
S.D. dependent var  :     281.124  Degrees of Freedom    :  195
Lag coeff.   (Rho)  :    0.639329

R-squared           :    0.431873  Log likelihood        :     -1388.51
Sq. Correlation     : -            Akaike info criterion :      2793.02
Sigma-square        :     44899.3  Schwarz criterion     :      2819.52
S.E of regression   :     211.895

----------------------------------------------------------------------
    Variable    Coefficient      Std.Error       z-value    Probability
----------------------------------------------------------------------
   W_TA_pcap     0.6393288     0.05546335      11.52705     0.00000
    CONSTANT     -4.052111       45.13348   -0.08978061     0.92846
    POPDEN00  -5.149201e-005  0.0001199013   -0.4294534      0.66759
      PCTPOV      605.1354       291.4276      2.076452     0.03785
    AVEDISTC    -0.3154588       0.417109    -0.7562983     0.44947
    MAXSUSWIN   -0.02826436    0.02187917     -1.291839     0.19641
   BLDGLOSS1K -0.0002168545  7.924997e-005    -2.736335      0.00621
    NUMBRIDGE   -0.01876017     0.1062033    -0.1766439     0.85979
----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                                        DF       VALUE        PROB
Breusch-Pagan test                          6         78.0027     0.00000

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL LAG DEPENDENCE FOR WEIGHT MATRIX : floy_im.gal
TEST                                        DF       VALUE        PROB
Likelihood Ratio Test                       1         67.5026     0.00000
========================== END OF REPORT ==============================
```

Hurricane Irene – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Iren_im
Dependent Variable  :     TA_pcap  Number of Observations:   18
Mean dependent var  :     13.8209  Number of Variables   :    7
S.D. dependent var  :     20.6887  Degrees of Freedom    :   11

R-squared           :    0.562145  F-statistic           :     2.35375
Adjusted R-squared  :    0.323316  Prob(F-statistic)     :    0.103727
Sum squared residual:      3373.4  Log likelihood        :    -72.6406
Sigma-square        :     306.673  Akaike info criterion :     159.281
S.E. of regression  :     17.5121  Schwarz criterion     :     165.514
Sigma-square ML     :     187.411
S.E of regression ML:     13.6898

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     -60.31108       47.74688      -1.263142      0.23266
    POPDEN00   0.002420859     0.01865158      0.1297937      0.89907
      PCTPOV      -114.831       163.8191     -0.7009624      0.49789
    AVEDISTC   -0.02065465      0.2727807    -0.07571889      0.94100
   MAXSUSWIN      1.407761      0.6507143       2.163409      0.05339
  BLDGLOSS1K -3.442071e-006  4.600541e-006     -0.7481883      0.47004
   NUMBRIDGE   -0.04237766     0.03590332      -1.180327      0.26276
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   35.336700
TEST ON NORMALITY OF ERRORS
TEST                     DF           VALUE               PROB
Jarque-Bera               2            0.1009             0.95079

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                     DF           VALUE               PROB
Breusch-Pagan test        6           13.7004             0.03317
Koenker-Bassett test      6           11.3034             0.07944

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Iren_im.gal
   (row-standardized weights)
TEST                           MI/DF          VALUE            PROB
Moran's I (error)             -0.3908        -1.4300          0.15271
Lagrange Multiplier (lag)         1           3.4064          0.06494
Robust LM (lag)                   1           0.5028          0.47827
Lagrange Multiplier (error)       1           4.2948          0.03823
Robust LM (error)                 1           1.3912          0.23820
Lagrange Multiplier (SARMA)       2           4.7977          0.09082
========================== END OF REPORT ==============================
```

Hurricane Isabel – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set              :  Isab_im
Dependent Variable    :     TA_pcap  Number of Observations:  158
Mean dependent var    :     73.2376  Number of Variables   :    7
S.D. dependent var    :     216.805  Degrees of Freedom    :  151

R-squared             :    0.185420  F-statistic           :     5.72859
Adjusted R-squared    :    0.153052  Prob(F-statistic)     :2.15526e-005
Sum squared residual:6.04966e+006   Log likelihood        :    -1057.87
Sigma-square          :       40064  Akaike info criterion :     2129.75
S.E. of regression    :      200.16  Schwarz criterion     :     2151.18
Sigma-square ML       :       38289
S.E of regression ML:       195.676

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      144.8826       48.32694        2.997967     0.00318
    POPDEN00   -0.03910202     0.01248421       -3.132118     0.00208
      PCTPOV      404.9204       295.7679        1.369048     0.17302
    AVEDISTC     -1.805775      0.4800091        -3.76196     0.00024
    MAXSUSWIN  -0.06457486      0.1273783      -0.5069535     0.61293
    BLDGLOSS1K 0.0003464189   0.0001826327        1.896807     0.05976
    NUMBRIDGE    -0.2123174      0.2239696      -0.9479741     0.34466
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   7.209999
TEST ON NORMALITY OF ERRORS
TEST                     DF           VALUE              PROB
Jarque-Bera               2         7165.6886            0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                     DF           VALUE              PROB
Breusch-Pagan test        6         113.2788            0.00000
Koenker-Bassett test      6           6.7856            0.34113

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Isab_im.gal
   (row-standardized weights)
TEST                           MI/DF        VALUE           PROB
Moran's I (error)              0.3139        6.3943          0.00000
Lagrange Multiplier (lag)        1          36.0616          0.00000
Robust LM (lag)                  1           4.6853          0.03042
Lagrange Multiplier (error)      1          32.2877          0.00000
Robust LM (error)                1           0.9114          0.33973
Lagrange Multiplier (SARMA)      2          36.9730          0.00000
========================== END OF REPORT ==============================
```

Hurricane Isabel – Spatial lag Model

```
SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set            : Isab_im
Spatial Weight      : Isab_im.gal
Dependent Variable  :     TA_pcap  Number of Observations:  158
Mean dependent var  :     73.2376  Number of Variables   :    8
S.D. dependent var  :     216.805  Degrees of Freedom    :  150
Lag coeff.   (Rho)  :    0.615131

R-squared           :    0.427216  Log likelihood        :    -1038.27
Sq. Correlation     : -            Akaike info criterion :     2092.54
Sigma-square        :     26923.4  Schwarz criterion     :     2117.05
S.E of regression   :     164.084

-----------------------------------------------------------------------
    Variable    Coefficient     Std.Error       z-value    Probability
-----------------------------------------------------------------------
   W_TA_pcap     0.6151315     0.07067802      8.703292     0.00000
    CONSTANT      78.45225        40.7959      1.923042     0.05447
    POPDEN00    -0.0187007     0.01037899     -1.801785     0.07158
      PCTPOV      40.37421       243.1927     0.1660173     0.86814
    AVEDISTC    -0.7313487      0.4100859     -1.783404     0.07452
   MAXSUSWIN   -0.05115778      0.1044214    -0.4899168     0.62419
  BLDGLOSS1K  0.0001808775   0.0001507928      1.199511     0.23033
   NUMBRIDGE    -0.1237791      0.1837432    -0.6736526     0.50053
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                                     DF       VALUE        PROB
Breusch-Pagan test                       6        106.0217     0.00000

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL LAG DEPENDENCE FOR WEIGHT MATRIX : Isab_im.gal
TEST                                     DF       VALUE        PROB
Likelihood Ratio Test                    1         39.2008     0.00000
========================== END OF REPORT ==============================
```

Hurricane Ivan – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set              :  Ivan_im
Dependent Variable    :     TA_pcap  Number of Observations:  292
Mean dependent var    :     74.3802  Number of Variables   :    7
S.D. dependent var    :     291.047  Degrees of Freedom    :  285

R-squared             :    0.371064  F-statistic           :     28.0244
Adjusted R-squared    :    0.357823  Prob(F-statistic)     :2.92593e-026
Sum squared residual:1.55566e+007    Log likelihood        :    -2003.28
Sigma-square          :     54584.5  Akaike info criterion :     4020.57
S.E. of regression    :     233.633  Schwarz criterion     :      4046.3
Sigma-square ML       :       53276
S.E of regression ML:       230.816

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      78.42662       51.41044          1.5255     0.12824
    POPDEN00  5.936724e-005  0.0001122197       0.5290268     0.59720
      PCTPOV      349.0358       227.2249        1.536081     0.12563
    AVEDISTC    -0.4378213      0.4431757      -0.9879181     0.32403
   MAXSUSWIN   -0.07452257     0.04671511       -1.595256     0.11176
  BLDGLOSS1K  0.0003112918   2.59214e-005        12.00906     0.00000
   NUMBRIDGE    -0.1957384      0.1117058       -1.752267     0.08080
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER    8.832847
TEST ON NORMALITY OF ERRORS
TEST                  DF           VALUE               PROB
Jarque-Bera            2        133715.7818            0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF           VALUE               PROB
Breusch-Pagan test     6          1093.2477            0.00000
Koenker-Bassett test   6            20.6700            0.00210

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Ivan_im.gal
   (row-standardized weights)
TEST                          MI/DF         VALUE            PROB
Moran's I (error)             0.3065         7.8203          0.00000
Lagrange Multiplier (lag)       1          121.6113          0.00000
Robust LM (lag)                 1          103.2595          0.00000
Lagrange Multiplier (error)     1           53.8657          0.00000
Robust LM (error)               1           35.5140          0.00000
Lagrange Multiplier (SARMA)     2          157.1253          0.00000
========================= END OF REPORT ==============================
```

Hurricane Ivan – Spatial Lag Model

```
SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set            : Ivan_im
Spatial Weight      : Ivan_im.gal
Dependent Variable  :     TA_pcap  Number of Observations:  292
Mean dependent var  :     74.3802  Number of Variables   :    8
S.D. dependent var  :     291.047  Degrees of Freedom    :  284
Lag coeff.   (Rho)  :    0.772217

R-squared           :    0.705622  Log likelihood        :    -1922.42
Sq. Correlation     : -            Akaike info criterion :     3860.83
Sigma-square        :     24936.2  Schwarz criterion     :     3890.24
S.E of regression   :     157.912

-----------------------------------------------------------------------
    Variable     Coefficient      Std.Error       z-value    Probability
-----------------------------------------------------------------------
   W_TA_pcap      0.7722167     0.03256317       23.71442     0.00000
    CONSTANT       31.11019       35.08732      0.8866506     0.37527
    POPDEN00   3.796675e-005  7.585993e-005      0.5004848     0.61673
      PCTPOV       85.95267       154.2573      0.5572031     0.57739
    AVEDISTC     -0.2186342      0.3031962     -0.7210982     0.47085
   MAXSUSWIN    -0.01947949     0.03162208     -0.6160091     0.53789
   BLDGLOSS1K  0.0001605805   1.807024e-005      8.886459      0.00000
   NUMBRIDGE    -0.08823713      0.0756257      -1.166761     0.24331
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                                    DF      VALUE        PROB
Breusch-Pagan test                      6      1029.0638     0.00000

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL LAG DEPENDENCE FOR WEIGHT MATRIX : Ivan_im.gal
TEST                                    DF      VALUE        PROB
Likelihood Ratio Test                   1       161.7359     0.00000
========================== END OF REPORT ==============================
```

Hurricane Jeanne – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Jean_im
Dependent Variable  :     TA_pcap  Number of Observations:    53
Mean dependent var  :     139.047  Number of Variables   :     7
S.D. dependent var  :     206.788  Degrees of Freedom    :    46

R-squared           :    0.326322  F-statistic           :     3.71365
Adjusted R-squared  :    0.238451  Prob(F-statistic)     :  0.00429527
Sum squared residual:1.52679e+006  Log likelihood        :    -347.316
Sigma-square        :     33191.1  Akaike info criterion :     708.632
S.E. of regression  :     182.184  Schwarz criterion     :     722.424
Sigma-square ML     :     28807.4
S.E of regression ML:     169.727

-----------------------------------------------------------------------
    Variable   Coefficient      Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      149.5866       91.18821        1.640416     0.10774
    POPDEN00    -0.0132418     0.06409271      -0.2066039     0.83723
      PCTPOV      423.3061       631.9656       0.6698245     0.50632
    AVEDISTC    -0.5058492       1.099628      -0.4600185     0.64767
   MAXSUSWIN    -0.1414331     0.07932262       -1.783011     0.08118
  BLDGLOSS1K  3.108941e-005  7.744309e-006       4.014485     0.00022
   NUMBRIDGE    -0.4133252      0.2114672       -1.954559     0.05673
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   9.677308
TEST ON NORMALITY OF ERRORS
TEST                  DF             VALUE              PROB
Jarque-Bera            2             92.8380            0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF             VALUE              PROB
Breusch-Pagan test     6             40.9463            0.00000
Koenker-Bassett test   6             11.0414            0.08711

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Jean_im.gal
   (row-standardized weights)
TEST                           MI/DF         VALUE            PROB
Moran's I (error)              0.2258         3.2720          0.00107
Lagrange Multiplier (lag)        1           15.3195          0.00009
Robust LM (lag)                  1           16.1074          0.00006
Lagrange Multiplier (error)      1            5.8431          0.01564
Robust LM (error)                1            6.6310          0.01002
Lagrange Multiplier (SARMA)      2           21.9505          0.00002
========================= END OF REPORT ==============================
```

Hurricane Jeanne – Spatial Lag Model

```
SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set            : Jean_im
Spatial Weight      : Jean_im.gal
Dependent Variable  :     TA_pcap  Number of Observations:   53
Mean dependent var  :     139.047  Number of Variables   :    8
S.D. dependent var  :     206.788  Degrees of Freedom    :   45
Lag coeff.   (Rho)  :    0.672155

R-squared           :    0.581213  Log likelihood        :    -338.256
Sq. Correlation     : -            Akaike info criterion :     692.511
Sigma-square        :     17907.9  Schwarz criterion     :     708.274
S.E of regression   :      133.82

-----------------------------------------------------------------------
    Variable     Coefficient      Std.Error       z-value    Probability
-----------------------------------------------------------------------
   W_TA_pcap      0.6721547      0.1058241       6.35162     0.00000
    CONSTANT       32.72172       68.37008     0.4785971     0.63223
    POPDEN00    0.002340384      0.0471014    0.04968819     0.96037
      PCTPOV       272.4395       465.1199     0.5857403     0.55805
    AVEDISTC     0.01111171      0.8078388    0.01375486     0.98903
   MAXSUSWIN    -0.06304514     0.05913031     -1.066207     0.28633
  BLDGLOSS1K   1.698047e-005  5.780039e-006      2.937779     0.00331
   NUMBRIDGE     -0.2744275      0.1554972     -1.764838     0.07759
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                                     DF        VALUE          PROB
Breusch-Pagan test                       6          22.7649       0.00088

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL LAG DEPENDENCE FOR WEIGHT MATRIX : Jean_im.gal
TEST                                     DF        VALUE          PROB
Likelihood Ratio Test                    1          18.1206       0.00002
========================== END OF REPORT ==============================
```

Hurricane Lili – OLS

```
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  Lili_im
Dependent Variable  :     TA_pcap  Number of Observations:   44
Mean dependent var  :      31.457  Number of Variables   :    7
S.D. dependent var  :       58.62  Degrees of Freedom    :   37

R-squared           :    0.224036  F-statistic           :     1.78044
Adjusted R-squared  :    0.098205  Prob(F-statistic)     :    0.130105
Sum squared residual:      117324  Log likelihood        :     -235.98
Sigma-square        :     3170.91  Akaike info criterion :     485.961
S.E. of regression  :     56.3108  Schwarz criterion     :      498.45
Sigma-square ML     :     2666.45
S.E of regression ML:     51.6376

-----------------------------------------------------------------------
    Variable    Coefficient       Std.Error     t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      31.02146        36.38193       0.8526612     0.39933
    POPDEN00   -0.06753945      0.03797839       -1.778366     0.08356
      PCTPOV      162.1774        181.4387        0.893841     0.37718
    AVEDISTC    -0.7068278       0.3067234       -2.304447     0.02691
   MAXSUSWIN  -0.008643242         0.03729      -0.2317845     0.81798
   BLDGLOSS1K  2.210631e-005   1.229628e-005       1.797805     0.08037
   NUMBRIDGE    0.07567288      0.07901361       0.9577195     0.34442
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   12.412321
TEST ON NORMALITY OF ERRORS
TEST                  DF           VALUE              PROB
Jarque-Bera            2         1063.3480            0.00000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF           VALUE              PROB
Breusch-Pagan test     6          21.2486             0.00166
Koenker-Bassett test   6           1.7359             0.94232

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Lili_im.gal
   (row-standardized weights)
TEST                           MI/DF          VALUE           PROB
Moran's I (error)              0.1032          2.0279          0.04257
Lagrange Multiplier (lag)        1             1.5854          0.20799
Robust LM (lag)                  1             1.0666          0.30171
Lagrange Multiplier (error)      1             1.0206          0.31239
Robust LM (error)                1             0.5018          0.47871
Lagrange Multiplier (SARMA)      2             2.0872          0.35219
========================= END OF REPORT ==============================
```

REFERENCES

Adger, W. Neil, Nick Brooks, Graham Bentham, Maureen Agnew, and Siri Eriksen. 2004. New indicators of vulnerability and adaptive capacity. Technical Report, 7, January 2004. Norwich, UK: Tyndall Centre for Climate Change Research.

Alexander, David. 2006. Globalization of Disaster: Trends, Problems, and Dilemmas. Journal of International Affairs, Spring/Summer 2006, Vol 59, no. 2.

Anderson, M. B. 2000. Vulnerability to Disaster and Sustainable Development: A General Framework for Assessing Vulnerability. Pp. 11–25 in R. Pielke, Jr. and R. Pielke Sr., eds. Storms (Vol. 1). London: Routledge.

Andrews, Clinton J., David M. Hassenzahl, and Branden B. Johnson. 2004. Accommodating uncertainty in comparative risk. Risk Analysis 24 (5):1323-1335.

Arima, Masahiro, Takuya Ueno, and Michitaka Arima. 2014. Spatial Distribution of Consent Forms from Residents Vulnerable to Disasters. Graduate School of Applied Informatics, University of Hyogo.

Armstrong, M. 2000. “Back to the Future: Charting the Course for Project Impact.” Natural Hazards Review 1 (3): 138-144.

Berke, P.R., J. Kartez, and D. Wenger. 1993.“Recovery after Disaster: Achieving Sustainable Development, Mitigation and Equity.” Disasters 17 (2): 93-108.

Blaikie, P., T. Cannon, I. Davis and B. Wisner. 1994. At Risk: Natural Hazards, People’s Vulnerability and Disasters. Routledge: London.

Birkmann, J. 2007. Risk and Vulnerability Indicators at Different Scales: Applicability, Usefulness and Policy Implications. Environmental Hazards 7: 20-31.

Bohle, H. G., T. E. Downing, and M. J. Watts. 1994. Climate change and social vulnerability: the sociology and geography of food insecurity. Global Environmental Change 4:37-48.

Boullé, P., L. Vroklijks, and E. Palm. 1992. “Vulnerability Reduction for Sustainable Urban Development.” Journal of Contingencies and Crisis Management 5 (3): 179-99.

Britton, N.R. 1999. “Whither the Emergency Manager?” International Journal of Mass Emergencies and Disasters 17 (2): 223-235.

Britton, N.R. and G.J. Clarke. 2000. “From Response to Resilience: Emergency Management Reform in New Zealand.” Natural Hazards Review 1 (3): 145-150.

Brunsdon, Chris, A. Stewart Fotheringham, and Martin E. Charlton. 1996. Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. Geographical Analysis 28 (4): 281-298.

Buckle, Philip, Graham Mars, and Syd Smale. 2000. “New Approaches to Assessing Vulnerability and Resilience.” Australian Journal of Emergency Management 15 (2): 8-14.

Burby, R, R.E. Deyle, D.R. Godschalk, and R. B. Olshansky. 2000. “Creating Hazard Resilience Communities Through Land-Use Planning.” Natural Hazards Review 1 (2): 99-106.

Burton, Ian, Robert W. Kates, and Gilbert F. White. 1993. The environment as hazard. 2nd ed. New York: Guildford Press.

Cannon, T. 1994. Vulnerability analysis and the explanation of natural disasters, in A. Varley (ed) Disasters, Development and Environment, John Wiley and Sons. New York, p 13-29.

Cardona, Omar D. 2005a. Indicators of Disaster Risk and Risk Management. Summary Report, July 2005. Washington D.C.: Inter-American Development Bank.

Cardona, Omar D. 2005b. System of Indicators for disaster risk management. Main Technical Report, August 2005. Washington D.C.: Instituto de Estudios Ambientales (IDEA), Universidad Nacional de Colombia, Inter-American Development Bank. Available from http://idea.unalmzl.edu.co/.

Chang, Stephanie E. and Masanobu Shinozuka. 2004. Measuring Improvements in the Disaster Resilience of Communities. Earthquake Spectra: August 2004, Vol. 20, No. 3, pp. 739-755.

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

Cobb, Clifford 2000. Measurement Tools and the Quality of Life. Redefining Progress. San Francisco, Ca.

Cobb, C. and C.Rixford. 1998. Lessons Learned from the History of Social Indicators. San Francisco: Redefining Progress.

Cuny, F.C. 1983. Disaster and Development. New York: Oxford University Press.

Cutter, Susan L. 1996. Vulnerability to environmental hazards. Progress in Human Geography 20 (4):529-539.

Cutter, Susan L., Jerry T. Mitchell, and Michael S. Scott. 2000. Revealing the vulnerability of people and places: a case study of Georgetown County, South Carolina. Annals of the Association of American Geographers 90 (4):713-737.

Cutter, Susan L. 2001. A research agenda for vulnerability science and environmental hazards [Internet]. International Human Dimensions Programme on Global Environmental Change [cited August 18 2006].

Cutter, S.L ed. 2001b. Charting a Course for the Next Two Decades. p. 159-165 in S.L Cutter Ed. American Hazardscapes: The regionalization of Hazards and Disasters. Washington, D.C.: Joseph Henry Press.

Cutter, Susan L. 2003. The vulnerability of science and the science of vulnerability. Annals of the Association of American Geographers 93 (1):1-12.

Cutter, Susan, B.J. Boruff, and W.L. Shirley. 2003. Social Vulnerability to Environmental Hazards. Social Science Quarterly. Vol. 84 (1): pp. 242-261.

Cutter, Susan L., Lindsey Barnes, Melissa Berry, Christopher Burton, Elijah Evans, Eric Tate, and Jennifer Webb. (2008) A place-based model for understanding community resilience to natural disasters. Global Environment Change (2008) 18 : 598-606.

Davidson, Rachel A. and Kelly B Lambert 2001. Comparing the Hurricane Disaster Risk of U.S. Coastal Counties. <u>Natural Hazards Review</u> 2(3).

Diener, Ed, and Eunkook Suh. 1997. Measuring quality of life: Economic, social, and subjective indicators. Social Indicators Research 40 (1-2):189-216.

DHS. 2013. Homeland Security Geospatial Concept of Operations v. 5. US Department of Homeland Security. Washington, DC.

Dow, Kirsten. 1992. Exploring differences in our common future(s): the meaning of vulnerability to global environmental change. Geoforum 23:417-436.

Downton, M. and R.A. Pielke, Jr., 2001. Discretion Without Accountability: Politics, Flood Damage, and Climate, Natural Hazards Review, 2(4):157-166.

Drucker, Peter F. 1954. The Practice of Management. New York: Harper & Brothers.

Dwyer, A., Zoppou, C., Nielsen, O., Day, S. and Roberts, S. 2004. Quantifying Social Vulnerability: A methodology for identifying those at risk to natural hazards. Geoscience Australia Record, 14.

Eakin, Hallie, and Amy Lynd Luers. 2006. Assessing the vulnerability of social-environmental systems. Annual Review of Environment and Resources 31:365-394.

Emrich, Christopher. 2005. Social Vulnerability in US Metropolitan Areas: Improvements in Hazard Vulnerability Assessment. Ph.D. Dissertation. Columbia, S.C.: University of South Carolina.

Emrich, Christopher T. and Susan L. Cutter. 2016. Developing and Maintaining Mission Critical Datasets and Analytics for National Preparedness and Resilience. A White Paper to DHS. Hazards Vulnerability Research Institute, University of South Carolina.

ESPON Hazards project 2003. The spatial effects and management of natural and technological hazards in general and in relation to climate change. 1rd Interim Report.

FEMA. 2009. HAZUS-MH User Guide 2009. The POLIS Center.

FEMA. 2012. FEMA Geospatial Standard Operating Procedure. FEMA. Washington, DC.

FEMA. 2013. “About Hurricane Katrina” webpage, http://www.fema.gov/response-recovery/about-hurricane-katrina. FEMA website.

FEMA. 2013. “NIMS Fact Sheet”, National Incident Management System webpage. http://www.fema.gov/pdf/emergency/nims/NIMSFactSheet.pdf. FEMA website

FEMA. 2013. “NRF Fact Sheet”, National Response Framework webpage. http://www.fema.gov/national-response-framework. FEMA website

Fotheringham, A. Stewart, Chris Brunsdon, and Martin Charlton. 2002. Geographically Weighted Regression: the analysis of spatially varying relationships. Newcastle, UK. John Wiley & Sons, Ltd.

Gall, Melanie. 2007. Indices of Social Vulnerability to Natural Hazards: A Comparative Evaluation. Doctoral Dissertation. Department of Geography, University of South Carolina.

Garrett, Thomas A. and Russell S. Sobel. 2002. The Political Economy of FEMA Disaster Payments. Working Paper 2002-012B, FEDERAL RESERVE BANK OF ST. LOUIS.

Garrett, Thomas A. and Russell S. Sobel. 2003. "The Political Economy of FEMA Disaster Payments," Economic Inquiry, 41(3): 496-509.

Geis, Don. 2000. "By Design: The Disaster Resistant and Quality of Life Community." Natural Hazards Review 1 (3): 151-160.

Hazards Vulnerability Research Institute 2013. Social Vulnerability Index webpage. http://webra.cas.sc.edu/hvri/products/sovi.aspx. HVRI, University of South Carolina website.

Hazards Vulnerability Research Institute 2012. Spatial Hazard Events and Losses Database for the United States webpage. *http://webra.cas.sc.edu/hvri/products/sheldus.aspx*. HVRI, University of South Carolina website.

Heinz Center 2002 Human Links to Coastal Disasters. Washington, DC: The H. John Heinz III Center for Science, Economics, and the Environment.

Hecht, Brent and Emily Moxley 2009. Terabytes of Tobler: Evaluating the First Law in a Massive, Domain-Neutral Representation of World Knowledge. Spatial Information Theory
Lecture Notes in Computer Science (2009) Volume 5756, pp 88-105 (1-17)

Hewitt, K. 1997. Regions of Risk: A Geographical Introduction to Disasters. Essex, U.K.: Longman.

Hilhorst, Dorothea and Greg Bankoff. 2008. Introduction: Mapping Vulnerability in Mapping Vulnerability: Disasters, Development and People, edited by Greg Bankoff, Georg Frerks, and Dorothea Hilhorst. Sterling Va: Earthscan Publications, 1-9.

Hill, Arleen A., and Susan L. Cutter. 2002. Methods for determining disaster proneness. In American Hazardscapes: the Regionalization of Hazards and Disasters, edited by S. L. Cutter. Washington D.C.: Joseph Henry Press, 13-36.

Investigative Reporters and Editors, Inc. 2013. SBA Disaster Loans data, National Institute for Computer Assisted Reporting (NICAR) database. http://www.ire.org/nicar/. IRE website.

Johnston, J. and DiNardo, J. (1997) Econometric Methods Fourth Edition. New York, NY: The McGraw-Hill Companies, Inc.

Kahane, Leo H. 2008. Regression Basics (2nd Ed.). Thousand Oaks, Ca.: Sage Publications, Inc.

Kasperson, J. X., R. E. Kasperson, and B. L. Turner, eds. 1995. Regions at Risk: Comparisons of Threatened Environments. Tokyo: United Nations University Press.

Kates, R. W. 1985. The interaction of climate and society. In Climate impact assessment, SCOPE 27, edited by R. W. Kates, J. H. Ausubel and M. Berberian. New York: Wiley, 3-36.

King, David. 2001. Uses and limitations of socioeconomic indicators of community vulnerability to natural hazards: data and disasters in northern Australia. Natural Hazards 24 (2):147-156.

Kumpulainen, Satu. 2006. Vulnerability Concept in Hazard and Risk Assessment. Natural and Technological Hazards and Risks Affecting the Spatial Development of European Regions edited by Philipp Schmidt-Thome. Geological Survey of Finland, Special Paper 42: pp. 65-74

Lavell, Alan. 2008. The Lower Lempa River Valley, El Salvador: Risk Reduction and Development Project in Mapping Vulnerability: Disasters, Development and People, edited by Greg Bankoff, Georg Frerks, and Dorothea Hilhorst. Sterling Va: Earthscan Publications, 67-82.

LeSage, James P. The Theory and Practice of Spatial Econometrics. Department of Economics. University of Toledo. 1999.

Menard, S. (1995). Applied Logistic Regression Analysis: Sage University Series on Quantitative Applications in the Social Sciences. Thousand Oaks, CA: Sage.

McEntire, David A. 2004. The Status of Emergency Management Theory: Issues, Barriers, and Recommendations for Improved Scholarship. Paper Presented at the FEMA Higher Education Conference, June 8, 2004, Emmitsburg, MD.

McEntire, D.A., C. Fuller, C.W. Johnston, and R. Weber. 2001. “A Comparison of Disaster Paradigms: The Search for a Holistic Policy Guide.” Public Administration Review 62 (3): 267-281.

McEntire, D.A. and M. Marshall. 2003. Epistemological Problems in Emergency Management: Theoretical Dilemmas and Implications. ASPEP Journal 10: 119-129.

Mileti, D. 1999. Disasters by Design: A Reassessment of Natural Hazards in the United States. Joseph Henry Press: Washington, D.C.

Mitchell, J. K. 1989. Hazards research. In Geography in America, edited by G. L. Gaile and C. J. Willmott. Columbus, OH: Merrill, 410-424.

National Geospatial-Intelligence Agency. 2012. Homeland Security Infrastructure Data Product (HSIP) GOLD Fact Sheet. Available from Homeland Infrastructure Foundation Level Working Group (HIFLD) website. https://www.hifldwg.org

National Hurricane Center (NHC) 2016. "See, Lake, and Overland Surges from Hurricanes (SLOSH)" webpage, http://www.nhc.noaa.gov/surge/slosh.php. NHC website.

Neal, David M. 1997. "Reconsidering the Phases of Disaster." International Journal of Mass Emergencies and Disasters 15 (2): 139-264.

Obama, Barack. 2011. Presidential Policy Directive / PPD-8 National Preparedness Whitehouse Policy Memorandum. The White House, United States Government.

O'Brien, Robert M. 2007. A Caution Regarding Rules of Thumb for Variance Inflation Factors. Quality & Quantity (2007) Vol. 41: 673–690.

Petak, W. J. and A.A. Atkinson. 1982. Natural Hazard Risk Assessment and Public Policy. New York. Springer-Verlag.

Piegorsch, Walter W., Susan L. Cutter, and Frank Hardisty. 2007. Benchmark analysis for quantifying urban vulnerability to terrorist incidents. Risk Analysis (2007) Vol. 27, No. 6: 1411-1425.

Pine, John C. 2009. Natural Hazards Analysis: Reducing the Impacts of Disaster. Boca Raton, Fl. CRC Press.

Rygel, Lisa, David O'sullivan And Brent Yarnal. 2005. A Method For Constructing A Social Vulnerability Index: An Application To Hurricane Storm Surges In A Developed Country. Mitigation and Adaptation Strategies For Global Change (2006) 11: 741–764

Samson, J., D. Berteaux, B.J. McGill, and M.M. Humphries. 2011. Geographic disparities and moral hazards in the predicted impacts of climate change on human populations. Global Ecology and Biogeography (2011) : 2-13. Blackwell Publishing Ltd.

Schmidtlein, M. C., R. C. Deutsch, W. W. Piegorsch, and S. L. Cutter, 2008. Building indexes of vulnerability: a sensitivity analysis of the social vulnerability index, Risk Analysis: 28 (4): 1099-1114.

Shi, Haijin, Lianjun Zhang, and Jianguo Liu. 2006. A new spatial-attribute weighting function for geographically weighted regression. Canada Journal for Research. (2006) 36: 996-1005

Simpson, David M. 2001. “Creating a Preparedness Measure (PM) Methodology: Initial Development, Application and Consideration in a Two Test Case for Carbondale, Illinois and Sikeston, Missouri.” Mid-America Earthquake (MAE) Center Publication Series. Univ.of Illinois: MAE.

Simpson, David M. 2006. Indicator Issues and Proposed Framework for a Proposed Framework for Disaster Preparedness Index. Center for Hazards Research and Policy Development University of Louisville.

Small Business Administration. 2012. Disaster Loans Program webpage. http://www.sba.gov/category/navigation-structure/loans-grants/small-business-loans/disaster-loans. SBA website.

Smith, Michael J. de, Michael F. Goodchild, and Paul A. Longley. 2007. Geospatial Analysis: A Comprehensive Guide to Principles, Techniques, and Software Tools (2nd Ed.). Leicester, England: Matador.

Sobel, Russell S., Christopher J. Coyne, and Peter T. Leeson, 2007. “The Political Economy of FEMA: Did Reorganization Matter?” Journal of Public Finance and Public Choice 17, No. 2/3, pp. 49-65.

Sylves, Richard Terry. 2008. Disaster Policy and Politics: Emergency Management and Homeland Security. Washington, DC. CQ Press.

Tapsell, S.M., Penning-Rowsell, E.C., Tunstall, S.M. and Wilson, T. 2002. Vulnerability to flooding: health and social dimensions. Phil. Trans. R. Soc. Lond. 360. 1511-1525.

UNDP/BCPR. 2004. Reducing disaster risk: a challenge for development. New York: United Nations Development Programme (UNDP), Bureau for Crisis Prevention and Recovery (BCPR).

UN/ISDR. 2004. Living with risk: A global review of disaster reduction initiatives. Geneva: United Nations Inter-Agency Secretariat of the ISDR (UN/ISDR).

United States Government Accountability Office. 2008. Actions Taken to Implement the Post-Katrina Emergency Management Reform Act of 2006. Washington, DC.

United States Government. 2003. National Response Framework: Emergency Support Function #5 Information and Planning Annex. Washington, DC.

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

Wong, David S. and Jay Lee. 2005. Statistical Analysis of Geographic Information with ArcView GIS and ArcGIS. Hoboken, New Jersey: John Wiley & Sons, Inc.

Wu, S-Y, Yarnal, B., and Fisher, A. 2002. Vulnerability of coastal communities to ea-level rise: A case study of Cape Cod County, New Jersey. Climate Research 22: pp. 255-270.

Yodmani, Suvit. 2001. Disaster Risk Management and Vulnerability Reduction: Protecting the Poor. Asian Disaster Preparedness Center. Paper presented at the Social Protection Workshop 6: Reforming Policies and Institutions for Poverty Reduction. Manila.

BIOGRAPHY

David Jean-Paul Alexander received his Bachelor of Arts in History from the University of South Carolina-Aiken in 1993. He went on to receive a Master of Science in Geography from the University of South Carolina in 1997, concentrating in physical geomorphology. After finishing his Doctor of Philosophy in Earth Systems and Geoinformation Sciences at George Mason University in 2016, he continued his civil service with the U.S. federal government as the Geospatial Information Officer for the Department of Homeland Security.