FACTORS INFLUENCING INLAND PROPERTY DAMAGE FROM GULF OF MEXICO TROPICAL CYCLONES

by

SHAIKH ABDULLAH AL RIFAT

JASON SENKBEIL, COMMITTEE CHAIR
JOE WEBER
LAURA MYERS

A THESIS

Submitted in partial fulfillment of the requirements
for the degree of Master of Science
in the Department of Geography
in the Graduate School of
The University of Alabama

TUSCALOOSA, ALABAMA

2017

ABSTRACT

Landfalling tropical cyclones (TC) in the USA cost 5-10 billion dollars annually. Tropical cyclone related losses can be influenced by the characteristics of a tropical cyclone itself as well as the levels of social vulnerability of the population in the region impacted. Coastal areas generally receive the greatest economic losses; however, research suggests that losses in the inland zone could occasionally be higher than the coastal zone due to excessive inland flooding, wind, and tornadoes. In this research, these physical storm characteristics (wind, tornadoes, rain) from decaying tropical cyclones in inland counties and county social vulnerability (SOV percentile scores) were used to predict property damage and economic impact. Results from the Louisiana, Mississippi, and Alabama tri-state region are inconsistent and suggest some counter-intuitive relationships with previously published research. Hurricane Katrina dominated the results for this region, and this appears to have skewed the results. Hypothetical scenarios were created to determine what would happen if a Katrina type storm tracked over major inland metropolitan areas in the Southeastern United States. Hypothetical results show that property damage would be more in the densely populated areas for a storm like Hurricane Katrina.

ACKNOWLEDGMENTS

With utmost respect, I would like to express my gratitude from the core of my heart to my adviser, Prof. Jason C. Senkbeil, for his kind support throughout my research project. Without his continuous support, care, motivation, and guidelines, it would not be possible for me to complete this research. He always had his door open for me whenever I had questions or needed to discuss anything with him.

I would also like to thank my thesis committee members, Dr. Joe Weber and Dr. Laura Myers, for their timely reviews and comments on this thesis. I learned a lot from them. and they also helped me to think more critically about my research.

I am really grateful to the Department of Geography at the University of Alabama for believing in me and providing me the financial and technical support for the last two years. I also want to thank all the faculty members of the Geography Department; especially I am really grateful to Dr. Sagy Cohen for his kind help and support. I am also indebted to the Cartographic Research Lab at the Geography Department. Mr. Craig Remington and all my other colleagues at the Cartlab always treated me like family and helped me whenever I needed assistance.

And finally, I am very thankful to my parents, Mr. and Mrs. Azmol and my wife, Sadia Tasnin Jhumur. Without their inspiration and support, I would never be able to complete my work.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE: INTRODUCTION

Natural hazards research is one of the most important aspects of the human-environment interaction geographic theme (Paul 2011). Gilbert White was one of the first prominent researchers to investigate human-environment interactions and natural disasters, and he postulated that human behavior was one of the major contributing factors in natural disasters (Burton et al. 1993). Tropical cyclones are one of the most devastating forms of natural disasters. On average eighty to ninety tropical cyclones occur annually around the world causing billions of dollars of property damage and thousands of fatalities (Mendelsohn et al. 2012). In the USA, tropical cyclone (TC) intensity is assessed using the Saffir Simpson (SS) scale based on sustained winds (Table 1.1).

Table 1.1: Saffir-Simpson Scale of Hurricane Winds

Categories	Sustained Wind	Type of Potential Damage
Tropical Depression	0-38 mph	
Tropical Storm	39-73 mph	
Category 1 Hurricane	74-95 mph	Very dangerous winds will produce some damage
Category 2 Hurricane	96-110 mph	Extremely dangerous winds will cause extensive damage
Category 3 Hurricane	111-130 mph	Devastating damage will occur
Category 4 Hurricane	131-155 mph	Catastrophic damage will occur
Category 5 Hurricane	More than 155 mph	Catastrophic damage will occur

Source: National Hurricane Center, (http://www.nhc.noaa.gov/sshws.shtml)

Losses from extreme weather events have risen significantly over the past few decades and a notable portion of these losses have occurred in the USA as a result of tropical cyclones (Pielke et al. 2003, Senkbeil et al. 2011). With increasing population, this cost is projected to increase simultaneously with the projected increasing amount of tropical cyclones. Tropical cyclones in the North Atlantic basin are getting stronger which particularly makes the USA vulnerable to major damage (Elsner et al. 2008). Deadly hurricanes are likely to increase in the future (Mestre and Hallegatte, 2008). The 2005 season remains the most active season in recorded history in the USA. Hurricane Katrina, the costliest disaster in USA history, alone caused around 1833 deaths, both directly and indirectly, and $108 billion dollars of property loss in 2005 (Knabb et al. 2005, Blake et al. 2011). Rappaport (2014) showed that one out of every five or six Atlantic basin tropical cyclones caused loss of life in the USA. On average, two to three tropical cyclones per year caused U.S. fatalities. Around 2,544 people died in the USA, both directly and indirectly, from tropical cyclones in the last 50-year period of 1963–2012 (Rappaport 2014).

Tropical cyclones are also causing greater economic losses, and socio-economic characteristics of the people affected by these storms are strongly related to these losses (Schmidt et al. 2009). Hurricane Ivan in 2004 and Sandy in 2012 were particularly destructive, even though Sandy was not a hurricane while it made landfall. Hurricane Ivan caused 92 direct deaths and $14.2 billion dollars of property damage (Stewart 2005) and Hurricane Sandy caused 147 direct deaths and approximately $50 billion dollars of damages and losses in the USA (Blake et al. 2013).

Tropical cyclone related losses can be influenced by the characteristics of a tropical cyclone itself as well as the levels of physical and social vulnerability of the population in the

region impacted. People who are more socially and physically vulnerable are especially exposed to natural disasters. Several researchers have defined vulnerability in similar ways. Singha (2006) defined vulnerability to natural disasters as "the result of a complex range of variables that include not only the location of human settlements and the magnitude of the disaster itself, but also the socio-economic, institutional, demographic and environmental characteristics of the disaster area, as well as the quality of its basic infrastructure". Turner et al (2003) defines vulnerability as "the degree to which a system, subsystem, or system component is likely to experience harm due to exposure to a hazard, either a perturbation or stress/stressor." Vulnerability is often defined as the susceptibility of a place or people to a natural hazard and their potential losses (Cutter 1996).

There is a public misconception that losses due to tropical cyclones occur mostly in the coastal areas. However, losses due to land-falling TCs are not limited to coastal zones only, and research suggests that losses in the inland zone and outside of the land-falling areas could be higher than the coastal zone. In the USA, tropical cyclone impacts often extend far inland after landfall. For example, Hurricane Camille in 1969 caused around 150 casualties in Virginia which was 1300 km inland from where the storm made landfall (Kruk et al. 2010). About 80% of direct USA hurricane fatalities since 1970 occurred outside of landfall counties, with most of these fatalities caused by inland flooding (Czajkowski et al. 2011). The most fatal hazards associated with inland TC's are wind and rain. Rappaport (2013) showed that 82% of TC related fatalities from 1963 to 2012 are due to drowning, and 59% of all TC related deaths are due to freshwater flooding. Inland fatalities are also associated with tornadoes and wind-gusts, and falling trees from wind (Schmidlin et al. 2009). Czajkowski et al. 2011 found that the incidence of tropical cyclone fatalities in the USA is greater in inland areas than the coastal zones.

Although research found that losses due to tropical cyclone could be higher in the inland areas, no previous research concurrently assessed the vulnerability of tropical cyclones and tropical cyclone impacts in inland areas from both physical and social science perspectives. In the past, vulnerability of any place was assessed either for single hazards or from strictly physical or social perspectives of the hazards. The social perspectives of vulnerability hazards have been studied many times (Blaikie et al. 1994; Tierney et al. 2001; Cutter et al. 2000, 2003, 2011; Flanagan et al. 2011). Also, there is a lack of published research that shows the hazards associated with tropical cyclones (precipitation, wind, and tornado) for each county and metropolitan area beyond government websites. The combined social and physical approach makes this study unique and worthwhile.

The primary goal of this research is to predict inland property damage for Gulf of Mexico tropical cyclones. This research seeks to answer several questions about the relationships between tropical cyclones and cyclone-related property damage in the inland areas of Southeastern USA over the past 20 years (1995-2015). What makes the inland areas of this region vulnerable to tropical cyclone-related property loss? Does this vulnerability differ between urban and rural counties? Is the amount of property damage associated with tropical cyclones related to the level of vulnerability? Answers to these questions may help mitigate against future property damage in the study area.

Based on these questions, the objectives of this study are:

To understand the intersection of physical storm characteristics and social vulnerability for a combined influence on property damage

To create hypothetical “what if” scenarios for selected counties based on the influential and rare Hurricane Katrina

CHAPTER TWO: LITERATURE REVIEW

2.1 Vulnerability

Generally, vulnerability means potential for loss of property or life from environmental hazards. It is an integral part of hazards research. Vulnerability has many contradictory definitions as different field's measure vulnerability in different ways (Cutter, 1996). The concept of vulnerability was familiarized by O'keefe et al. (1976) within the context of natural hazards and disasters. They illustrated that the occurrence of disasters increased over the last 50 years, with an increase in loss of life. They also showed that the greatest losses of life are concentrated in developing countries, where the authors concluded that vulnerability is increasing. They also argued that vulnerability to disasters are more a consequence of socio-economic than natural factors. Research in natural hazards focuses on how and why places and people are vulnerable to natural disasters. Cutter (1996) showed three different sub-fields in vulnerability studies of natural hazards: 1) Vulnerability as risk/hazard exposure, 2) Vulnerability as social response, and 3) Vulnerability of places. The first sub-field of hazards research examines the source of natural or environmental hazards, human occupancy of the hazardous zone, and the amount of loss associated with a particular hazard. The second sub-group studies the coping responses with societal resistance and resilience to hazards. Third sub-field of vulnerability studies in natural hazards combine both natural hazards risk and social response. Liverman (1990) postulated vulnerability assessments due to global change based on drought and hunger. Vulnerability assessment should be a key concept of global change and

hazards research. In order to understand global change and the nature of the hazards, we need more research on vulnerability and vulnerability assessments. Vulnerability due to natural hazards can be divided into two broad categories: social vulnerability and physical vulnerability.

2.2 Social Vulnerability

Social vulnerability of people is not rigid and varies from place to place. Previous research has examined components of biophysical vulnerability and the vulnerability of the built environment (Mileti, 1999). Less attention has been paid towards the social aspects of vulnerability. It is mainly because of the difficulty in quantifying the social indicators of vulnerability (Cutter et al. 2003). People are considered as more or less socially vulnerable because of lack of access to resources and political power. Social vulnerability is defined by the possession of social attributes that increase susceptibility to disasters (Blaikie et al. 1994).

There are many factors that influence social vulnerability and according to Cutter et al. (2003), these include "lack of access to resources; limited access to political power and representation; social capital, including social networks and connections; beliefs and customs; building stock and age; weak and physically limited individuals; and type and density of infrastructure and lifelines." Cutter et al. (2003) first introduced the concept of social vulnerability to assess the vulnerability of people and locations by creating a Social Vulnerability Index (SoVI). The conventional indicators of social vulnerability are age, gender, race, and socioeconomic status. Other characteristics identified special needs populations or those that lack the normal social safety nets necessary in disaster recovery (Jonkman et al. 2009). These include the physically or mentally challenged, non-English-speaking immigrants, the homeless, transients, and seasonal tourists (Green et al. 2007).

The most common factors of social vulnerability are:

- Personal Wealth

Individual personal wealth and is measured by per capita income, percentage of households earning per year, median house values and median rents. Lack of wealth is a primary contributor to social vulnerability because fewer resources are available for recovery and it makes the community less resilient to hazard impacts (Morrow 1999; Heinz Center for Science, Economics, and the Environment 2000; Cutter et al. 2003; Holand et al. 2011).

- Age

Children are considered as the most vulnerable part of the population but they can also be part of the community resilience through schooling (Walker et al. 2012) and can be of assistance to the households during the recovery process (Kuhlicke et al. 2011). Elderly people are also considered as vulnerable people as both children and elderly people often need assistance to move and depend on others (O'Brien and Mileti 1992; Hewitt 1997; Cutter et al. 2000; Ngo 2001). Nevertheless, young people can also be vulnerable to disasters due to their risk-taking behavior (Ashley and Ashley 2008; Doocy et al. 2013).

- Gender

Gender is one of the most important factors in disaster vulnerability and preparedness (Enarson and Morrow 1998; Anderson 2000). Women can be more vulnerable during an extreme weather event than men because of their lack of access to resources and decision-making, lower wages, and their dependence on sector-specific employment (Vlassoff 1994; Cutter 1996; Hewitt 1997). Generally, women play the role of caregivers to the young and the old of the family, which also influence their vulnerability to disasters (Fothergill 1998; Enarson and Morrow 1998; Babugura 2010). Additionally, women, especially divorced and single mothers, may face

difficulty during the disaster recovery period (Blaikie et al. 1994; Bianchi and Spain 1996; Enarson and Morrow 1998; Morrow and Phillips 1999; Steinfuhrer and Kuhlicke 2007).

- Education

Education is another important factor of social vulnerability which reflects socioeconomic status and employment (Holand et al. 2011). Lower education impedes people's ability to understand disaster warnings which make them vulnerable to disasters and might cause difficulties in the recovery period (Cutter et al. 2003; Sund and Krokstad 2005; Wamsler et al. 2012). Higher level of education often direct to higher income and socio-economic status (Psacharopoulos and Patrinos 2002) and this higher income may lead to a better coping capacity during a disaster event (Muttarak and Lutz 2014). Also, people with higher education level understand the disaster warnings more effectively and can act accordingly which eventually put them in a lower risk zone during disaster period than the lower educated people (Cotten and Gupta 2004; Wen et al. 2011; Neuenschwander et al. 2012).

- Race and Ethnicity

Race and Ethnicity are also important factors in defining social vulnerability. Racial and ethnic minority groups often lack of access to resources, cultural differences, and the social, economic, and political marginalization which make them vulnerable to disasters (Cutter et al. 2003). Cutter et al. 2003 showed that African-American, Hispanics and Native American are the most socially vulnerable racial and ethnic groups. Language barriers, especially if the minorities are immigrants from non-English-speaking countries, can increase vulnerability to disaster and recovery (Gladwin and Peacock 1997; Peacock et al. 1997; Radford et al. 2013).

- Infrastructure Dependence

In the city, people usually depend on social and physical infrastructure, such as health and human services, public transportation, and utility networks such as water, electricity, and telecommunications (Dwyer et. al. 2004). Growing concentration on infrastructure with the threats and hazards also increases the potential loss in urban areas (Swiss Reinsurance Company Ltd. 2013). Moreover, the complex nature of infrastructure, a higher density of people and large numbers of socially vulnerable populations in cities causes the poor outcomes after the disaster events (Pelling 2003; Galea et al. 2005; Dickson et al. 2012). It is also expected that loss of sewers, bridges, water communications and transportation infrastructures compounds potential disaster losses (Cutter et al. 2003). The loss of infrastructure put the financial burden on smaller communities that lack the financial resources to rebuild (Platt 1995; Heinz Center for Science, Economics, and the Environment 2000; Cutter et. al. 2003).

2.3 Physical Vulnerability of Tropical Cyclones and Impacts

Direct losses from natural disasters are increasing in the USA and losses from hurricanes and floods have tripled over the last 50 years where losses from other natural hazards remained stable (Cutter et al. 2011). Per-capita losses due to natural hazards are increasing due to more frequent numbers of disasters, disasters of high magnitude, changes in social resilience, etc. (Cutter et al. 2011). In order to decrease losses from natural disasters, sustainable development, vulnerability reduction, and disaster mitigation must be given priority. Current loss reduction strategies need to be re-evaluated. Atmospheric hazards are more frequent in the southern region of the USA, and not all the people living in this part of the country have the same resilience and capacity to cope with extreme weather events (Cutter et al. 2011). The threats from tropical cyclone hazards to communities are well known (NOAA 2012; Davidson and Lambert 2002; Pompe and Haluska 2011). Tropical cyclone related mortality shows a downward trend (Figure

1) over the last few decades due to timely evacuations from storm surge flood zones (Rappaport 2000; Willoughby et al. 2007). However, when the number of deaths from inland fresh-water flooding is included, the trend for mortality remains stable or is even higher for these tropical cyclones (Czajkowski and Kennedy 2010). Although, great efforts have been made to decrease the fatalities of hurricanes near landfall (Kunkel et al. 1999; Rappaport 2000, 2014; Cjazkowski 2011), fewer endeavors were given to the inland communities. Tropical cyclone intensity is usually assessed by using minimum central pressure, wind, rain, and storm surge (Senkbeil et al. 2011). Senkbeil et al. (2011) showed that direct and indirect meteorological hazards of TCs include: "storm surge, heavy precipitation⁄flooding, sustained winds, wind gusts, falling trees, and tornadoes." Water hazards, such as storm surge and inland flooding, are more fatal than wind hazards, such as high winds and tornadoes. Storm surge is the primary hazard associated with TC in the coastal areas, and in the inland zones, the primary hazard is heavy precipitation (Senkbeil et al. 2011). Severe wind, tornadoes, and flooding due to heavy rainfall are the most fatal hazards associated with tropical cyclones as they move into inland (Czajkowski and Kennedy 2010). The most fatal hazard varies by location as a function of two variables; distance from the coast and elevation above sea level. Fatalities from freshwater flooding caused by heavy precipitation occur mainly in inland counties (Cjazkowski et al. 2011). About 63% of deaths due to tropical cyclones from 1970 to 1999 occurred inland (Rappaport 2000). Czajkowski et al. (2011) found that one-inch and one-knot increases in rainfall and wind increase total inland fatalities by 28% and 4% respectively. The same is also true for wind related fatalities. There were 407 deaths from wind-related tree failures in the United States from 1995–2007, and most were in inland counties (Schmidlin, 2009).

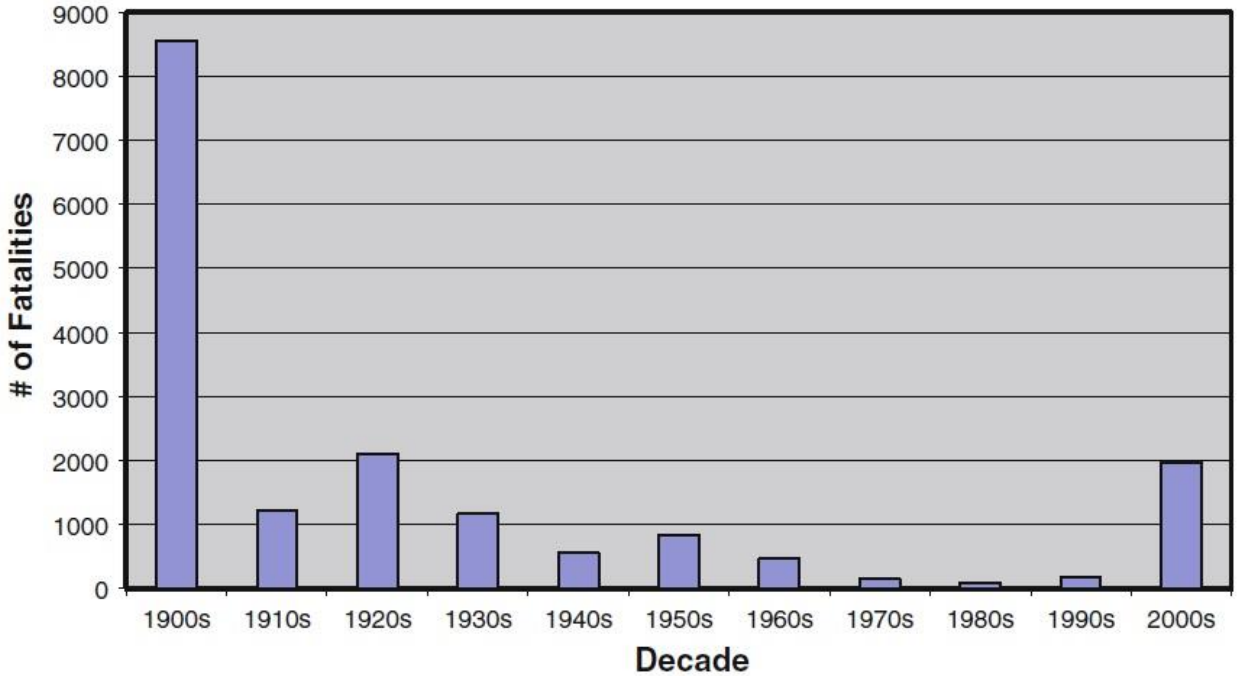

Figure 2.3.1: US hurricane fatalities by decade (Czajkowski et al. 2011)

2.3.1 Tropical Cyclone Tornadoes

One of the major threats from inland tropical cyclones is tornadoes (Rhodes and Senkbeil, 2014). Tropical cyclone tornadoes are quite difficult to predict and thus often cause unexpected damage. These tornadoes are usually brief and may sometimes go unwarned. There is a large amount of variability in the number of tornadoes produced by land-falling tropical cyclones with some rare occurrences of tornado outbreaks and over 100 total tornadoes. For example, Hurricane Beulah in 1967 spawned 115 tornadoes, Hurricane Frances in 2004 generated 103 tornadoes, and Hurricane Ivan in 2004 generated 117 tornadoes. Most of these hurricane-induced inland tornadoes are quite weak (F0 or F1 in Fujita or Enhanced Fujita scale), but stronger tornadoes have occasionally occurred. Tornadoes cause significant property damage and 5% of overall tropical cyclone related deaths (Rappaport 2000). An updated assessment of tropical cyclone tornado hazards is essential to decreasing potential property damage and fatalities.

2.3.2 Flooding

Freshwater flooding from heavy precipitation is the most fatal hazard associated with tropical cyclones. Freshwater flooding caused over 300 deaths from 1970 to 1999 in the United States, which is 52% of all tropical cyclone related deaths (Rappaport 2000). Of these flood-related deaths, 82% were a result of drowning. More recently, Rappaport (2014) showed that between 1963 and 2012, storm surge caused 50% of tropical cyclone related deaths and heavy-rainfall-induced flooding caused 27% of tropical cyclone fatalities. There are a number of factors that contribute to flood events such as: total rainfall, topography and land use of the region affected, soil type, watershed type, etc. (Ashley and Ashley 2008). Rainfall associated with TC depends on many factors including TC strength, forward speed of the TC, baroclinic extratropical transition, etc. Slow-moving TCs produce larger amounts of rainfall (Konrad et al. 2002).

2.3.3 Tropical Cyclone Wind

High winds associated with tropical cyclones are another lethal hazard. This strong wind associated with TC become weaker when the TC makes landfall. Sustained winds decrease significantly due to both friction from the land and loss of latent heat energy as it moves inland (Kaplan and De Maria 1995). However, maximum wind gust speeds can remain well above hurricane force for hundreds of kilometers inland from landfall (Powell et al. 1991). Hurricane Hugo produced 98 miles per hour wind gusts over 100 miles inland from landfall and 87 miles per hour wind gusts over 200 miles inland. A fast moving tropical cyclone produces strong wind and wind gusts farther inland (Kaplan and DeMaria 1995).

CHAPTER THREE: DATA AND METHODS

3.1 Study Area

The entire Southeastern United States was preliminarily selected as the study area for this research because it is routinely hit by tropical cyclones. The states of LA, MS, AL, GA, and SC were included. The state of Florida was not included because all Florida counties are coastal as defined by this research. Georgia and South Carolina had very little inland property damage due to Tropical Cyclones (TC) in the last 20 years period (from 1995 to 2015) due to a lack of stronger storms inland, so they were excluded from the list. The main reason behind using the last 20 years of data is that the storm event database (https://www.ncdc.noaa.gov/stormevents/choosedates.jsp?statefips=-999%2CALL) was used for property damage data. Storm data fails to successfully include all the tropical cyclone events beyond this 20 year period which could bias the results. For example, Hurricane Opal in 1995 caused notable damages in inland Alabama but there are no reported property damage values found for Hurricane Opal in the storm event database. This is why more recent (last 20 years) tropical cyclones were chosen for this study. For all these reasons, Alabama, Mississippi, and Louisiana were selected as the study area for this research.

3.1.1. Defining Inland

Although previous research found that inland areas could be more affected than coastal areas by tropical cyclones, the definition of inland is still not clear. Czajkowski et al. (2011)

identified inland counties as those that are adjacent to coastal counties and are not coastal counties according to the NHC definition.

In this study, the first task was to clearly identify the inland zones of tropical cyclones. Senkbeil et al. (2011) identified different zones and hazards in each zone (Surge zone, Coastal zone, Inland zone, and Continental zone) associated with a land-falling tropical cyclone based on the hours after landfall. They identified the inland zone as 6-12 hours after landfall based on the average forward speed of 10 miles per hour (NOAA, Senkbeil et al. 2011). Using Senkbeil et al. (2011), the average forward speed of a hurricane was multiplied by six (6) as they showed that hurricanes typically move into inland zones after 6 hours of landfall. Then a 60 mile buffer was created using Geographic Information System (GIS) from the lower state boundary of the three states: Alabama (AL), Mississippi (MS), and Louisiana (LA) to define the inland area. Counties that are located on the north side of this buffer line were marked as inland counties and these counties are the final study area of this research (Figure 3.1.1). If the 60 mile buffer line bisected a county, it was not included as an inland county. The buffer line was then rearranged according to the county boundaries.

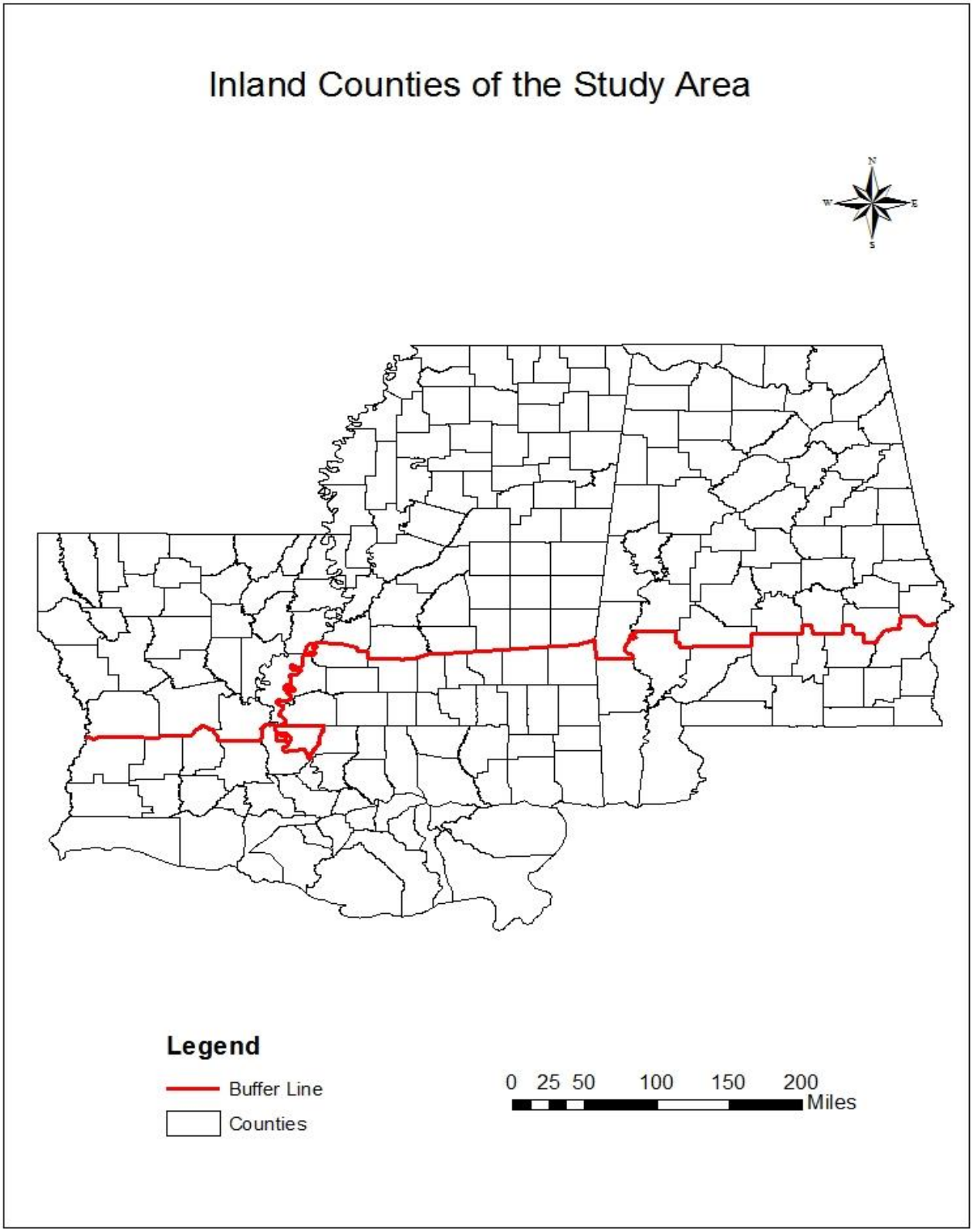

Figure 3.1.1: Map of the Study Area

3.2 Social Vulnerability Assessment

The social vulnerability assessment highlighted the areas where a high concentration of socially vulnerable people are located within the study area. For this study, Social Vulnerability Index (SOVI) created by the Hazards and Vulnerability Research Institute at University of South Carolina (http://artsandsciences.sc.edu/geog/hvri/sovi%C2%AE-0) was used for assessing the social vulnerability of the study area. To prepare a SOVI for the USA, they first identified 29 variables that reflect social vulnerability. After that, they used principal component analysis (PCA) on those 29 social vulnerability variables to reduce the number of factors. After doing PCA, they found eight significant components of social vulnerability that explain 78% of the variance in the dataset. These components of social vulnerability were discussed in section 2.2 of Chapter Two (Literature Review). Each component was given a score for each county in the USA and then summed together to get a composite social vulnerability score. Each county was given a percentile score (1 means least vulnerable and 100 means highest vulnerable) which represents that county's overall social vulnerability. In this research, this percentile score of county social vulnerability was used to assess the social vulnerability of the study area. GIS was used to produce an overall social vulnerability map. This map shows the areas of highest and lowest overall vulnerability in the study area.

3.3 Physical Vulnerability Assessment

For assessing the physical vulnerability of the study area, the tropical cyclone impact zone was determined first. In doing this, historical hurricane tracks from the NOAA website (ftp://eclipse.ncdc.noaa.gov/pub/ibtracs/v03r09/all/shp/basin) were downloaded as shapefiles for the last 20 years (1995-2015). Using the historical hurricane tracks, the 'select by location' tool was utilized in GIS to select only the tropical cyclones that made landfall along the Gulf of

Mexico and hit the study area in the given period. Then the selected hurricane tracks were exported and displayed using GIS. The Storm Event Database archives property damage data for several variables, hurricanes, tornadoes, tropical storms, floods, etc. from 1995 to 2015. The popular SHELDUS database from the University of South Carolina uses Storm Events data for its atmospheric hazards information. Again going back to hurricane tracks and using the 'select by attributes' tool in GIS, only the storms that had property damage in our previously selected study area (Map 2) were selected. Selected hurricane tracks were then exported and displayed in GIS. There were 15 different tropical cyclones that caused property damage in the study area as shown in Table 3.3.1.

Strong winds, hurricane-induced tornadoes, and freshwater flooding from heavy rainfall are the most lethal hazards associated with inland tropical cyclones. For this study, county rainfall data for each selected storm over the last 20 years were collected from the Tropical Cyclone Rainfall Data website (http://www.wpc.ncep.noaa.gov/tropical/rain/tcrainfall.html). They used radar and satellite imagery, daily weather maps (http://www.wpc.ncep.noaa.gov/dailywxmap/index.html), and tropical cyclone reports (http://www.nhc.noaa.gov/data/#tcr) for the rainfall data and quantitative precipitation estimates (QPE) to estimate the rainfall amount because weather stations are not available in each county. Coordinates of the counties in the study area were then used to record the rainfall amount by counties for each tropical cyclone in this research.

Wind data was collected from the hwind website (http://www.rms.com/perils/hwind/legacy-archive/). Hwind is a branch of NOAA's Hurricane Research Division who does real-time and historical hurricane wind analysis. They used different methods and analysis to estimate wind values for over 200 storms through 2013. In this

research, coordinates of the counties in the study area were used to record the wind value by county for each tropical cyclone. Hwind records and predicts hurricane wind by counties for different times in different days. The highest value of the wind for each county for each tropical cyclone was considered in this research. Tornado data was collected from the Storm Event Database website (https://www.ncdc.noaa.gov/stormevents/). While collecting tornado data, only the tornadoes that were generated for the selected tropical cyclones were considered. Also, only those counties were considered for tornado data which had property damage for the last 20 years of tropical cyclones.

This database was then joined with the hurricane track shapefile's attribute table. Then using the 'Statistics' tool in GIS, the property damage values for each individual county were summed to get the total amount of property damage for each county and stored in a different field in the attribute table. Also, the number of storms for which each county had property damage was calculated and stored in a different field in the attribute table. The 'Graduated Color' option in GIS was used to display the total amount of property damage and the total number of tropical cyclones in GIS.

Table 3.3.1: Names of the storms that hit the study area

Year	Name of the Storm	Intensity at Landfall (mph)	Total Fatalities	Property Damage (Billion Dollars)
1998	Georges	110	4	2.955
2002	Lili	92	2	0.925
2002	Isidore	63	5	0.330
2003	Bill	57	4	0.05
2004	Ivan	120	25	18.82
2005	Dennis	120	3	2.545
2005	Katrina	126	1833	108
2005	Rita	115	62	12.037
2007	Humberto	92	1	0.05
2008	Fay	63	5	0.56
2008	Gustav	103	52	4.618
2008	Ike	109	113	29.5
2009	Ida	---	7	0.3
2011	Lee	46	16	1.6
2012	Issac	80	5	2.35

Source: National Hurricane Center

The total amount of property damage for each individual county was then divided by the total number of storms for each county to get the average property damage per storm in each county. Again, the ‘Graduated Color’ option in GIS was used to display the average property damage for each storm in each county using GIS.

The same process was applied for county wind, rainfall, and tornado data. After completion of the entire process, the total and average amount of rainfall, wind, and tornadoes for each county were found. From these maps, inland counties that are most and least severely impacted were identified.

3.4 Predicting Property Damage

Before actually predicting the property damage for each county of the study area, the correlation between property damage and tropical cyclone hazards and social vulnerability was tested. Property damage was set as the dependent variable and wind, rainfall, tornadoes, and the selected social vulnerability indicator score were set as independent variables. Two different correlation matrices were created to see the relationships between property damage and TC hazards and social vulnerability using both the total and per storm values for each county.

After testing the degree of correlation between dependent and independent variables, multiple linear regression analysis was used to better understand the explained variance. Only independent variables with strong correlations were used. The 'Enter' method for multiple regression analysis was used to predict the property damage of the study area which is subject to increase or decrease by variation in the independent variables.

Hurricane Katrina (2005) had a skewing impact on the database as it alone caused around 1833 deaths, both directly and indirectly, and $108 billion dollars of property loss which make it the costliest storm in the history of United States (Knabb et al. 2005, Blake et al. 2011). Some counties along the inland hurricane Katrina track had an enormous amount of property damage because of this single storm. Since Katrina was such an anomalous storm, the property damage without including Hurricane Katrina in the database was also predicted to see the effects of removing that event.

3.5 Hypothetical Scenarios for Hurricane Katrina

As Hurricane Katrina exerted a strong influence on the results of inland property damage in the study area, it was decided to explore: what would happen if a storm like Hurricane Katrina tracked over major metropolitan areas in the study area? Hurricane Katrina tracked just east of Jackson, MS and impacted some of the more densely populated counties in central Mississippi. This research hypothesizes that Hurricane Katrina caused greater property damage in those counties in Mississippi where population density and median household income is greater. Multiple linear regression was used to predict property damage for Hurricane Katrina in Mississippi. In this secondary analysis, only those counties in Mississippi were taken into account which had the highest property damage for Hurricane Katrina. Population density, and median income along with the physical characteristics of Hurricane Katrina (wind and rainfall) were used as independent variables, and property damage was used as the dependent variable in this analysis. After doing the regression analysis, the regression model/equation for predicting property damage for Hurricane Katrina in Mississippi was found. Also, simple linear regression between property damage and individual independent variables was tested to see how the individual independent variables predicted property damage for Hurricane Katrina in Mississippi.

Then the hypothetical 'what if' scenarios were created to determine what would happen if a Katrina type storm tracked over major inland metropolitan areas in the Southeastern USA. The regression model created for Mississippi was used to predict the property damage in the metropolitan counties surrounding Birmingham, AL, Atlanta, GA, and Montgomery-Auburn, AL. The Hurricane Katrina track was changed accordingly to let it go through these metropolitan areas. In doing this, the coordinates of the Hurricane Katrina track were changed manually in the

attribute table in GIS. The wind value for Hurricane Katrina for these major metropolitan areas was overlayed according to the geographical location of the counties of Mississippi that received the highest property damage for Hurricane Katrina. For example, a county with a wind value of 50 knots per hour that was 50 miles east of the track was overlayed onto the Birmingham, AL metropolitan area to find a county 50 miles east of the hypothetical track. However, this overlaying of the wind values onto the major metropolitan areas was performed manually based on eye-estimation and the results could change slightly at the discretion of the user. A map was created showing the overlayed wind values for Hurricane Katrina around the Birmingham, AL metropolitan area to better understand how this overlay of wind values in these metropolitan areas was performed (Figure 3.5.1). Figure 3.5.1 shows the selected counties around Jackson, MS and Birmingham, AL for this secondary analysis. The numbers on the left side map are the wind values for the selected counties in Mississippi and the numbers on the right side map are the overlayed wind values for Hurricane Katrina in Alabama. Arrows are showing which county's wind value for Hurricane Katrina in Mississippi was overlayed onto which county in Alabama as an example without including an arrow for every county to avoid being too busy.

Simple linear regression with property damage and individual independent variables in these major metropolitan areas was also determined to predict the inland property damage in these metropolitan areas in the study area.

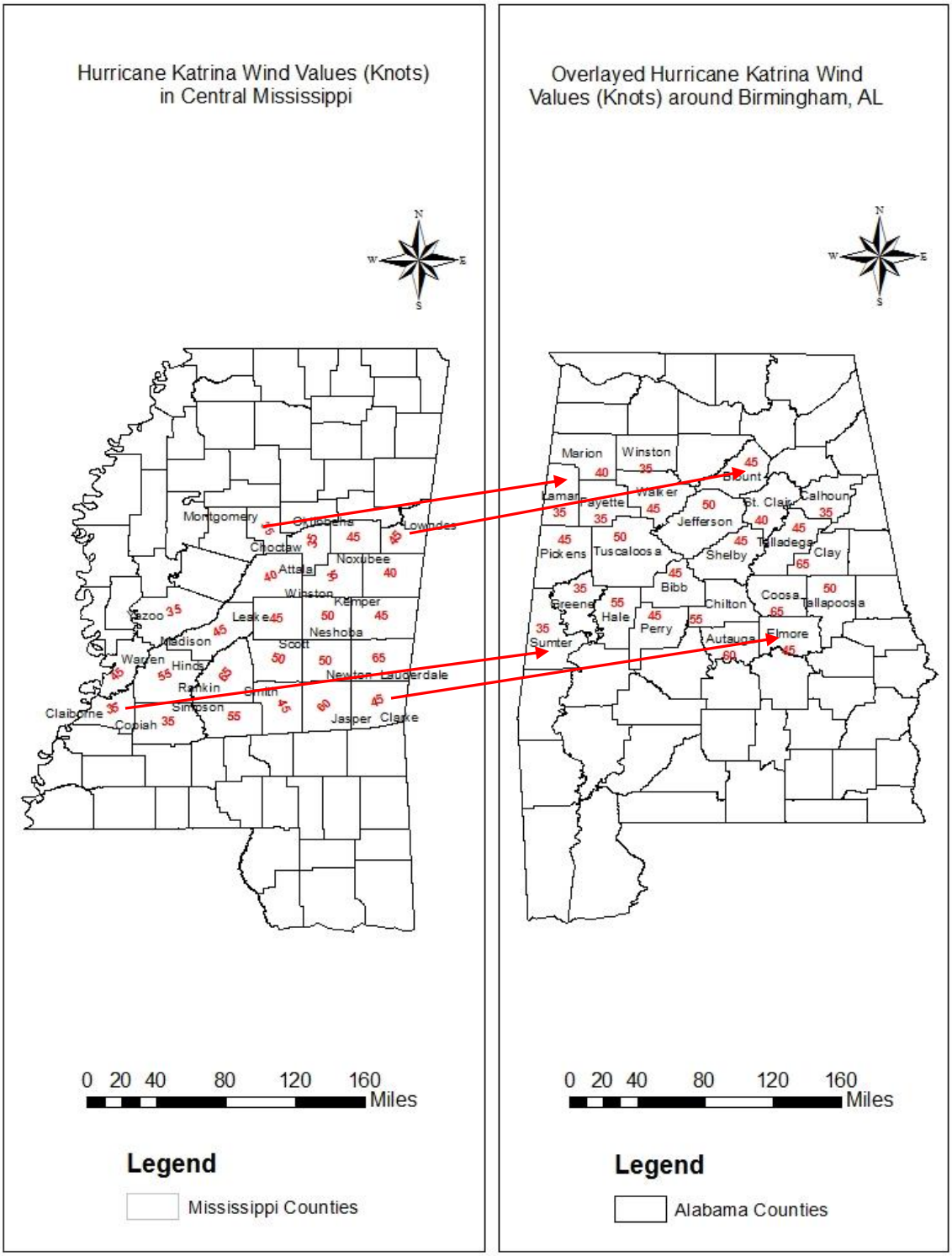

Figure 3.5.1: Overlaying Hurricane Katrina Wind Values around Birmingham Metropolitan Area

CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.1 Predicting Property Damage

The average inland property damage per storm for each inland county was calculated. In doing this, total property damage for each county was divided by the total number of storms that caused property damage. Likewise, the average amount of rainfall (inches), wind (knots), and average number of hurricane-induced tornadoes per storm for each inland county was calculated. There were 123 inland counties in the study area that recorded property damage from the last 20 years (1995-2015) of tropical cyclones. The mean value of average inland property damage in the study area was $9,370,000 (Table 4.1.1). The mean value of rainfall (inches), wind (knots), and tornadoes was 2.77, 18.87, and 0.44 per tropical cyclone respectively (Table 4.1.1).

Table 4.1.1: Descriptive Statistics

	Mean	Standard Deviation	N
Average Property Damage	$9,370,000	$26,280,000	123
Average Rain	2.77	1.408	123
Average Wind	18.87	6.114	123
Average Tornado	0.44	0.577	123
SoVI	56.598	27.0545	123

Maps were made using graduated color in GIS for average property damage, amount of rainfall, wind, hurricane-induced tornadoes per TC, and social vulnerability with the historical hurricane tracks over the study area (figure 4.1.1, 4.1.2, 4.1.3, 4.1.4, and 4.1.5 respectively). Property damage values were divided into six categories: counties that had zero or no property damage, counties that had property damage values between $1-$50,000; $50,001-$150,000; $150,001-$500,000; $500,001-$2,000,000; and $2,000,001-highest amount of property damage, in this case which is $166,840,000 (Figure 4.1.1). It is apparent from figure 4.1.1 that central inland Mississippi had the highest amount of average property damage per Tropical Cyclone (TC) in the study area. Counties in Northern Alabama had the lowest amount of average property damage per TC in terms of number of counties that have zero or no property damage values.

The average amount of rainfall per TC was divided into five categories: counties that had zero or no rainfall, counties that had 1-2.5, 2.51-3.75, 3.76-5.0, and 5.01-8.0 inches of rainfall (Figure 4.1.2). One county in inland Mississippi, three counties in inland Louisiana and two counties in Alabama had the highest amount of average rainfall per TC (5.01-8.0 inches).

Wind values were also divided into five categories in the study area: counties that had zero or no wind, counties that had 1-10, 10.01-15.0, 15.01-25.0, and 25.01-45.0 knots of wind per TC (Figure 4.1.3). Not surprisingly, central inland Mississippi had the highest amount of winds per TC, and Northern Alabama had the lowest amount of wind per TC regarding number of counties that have zero or no wind values.

Most of the inland counties in the study area had zero or no hurricane-induced tornadoes. Central Mississippi is the area mostly affected by these hurricane-induced tornadoes (Figure 4.1.4) and also had the highest number of average tornadoes per TC. Inland Alabama is the least affected area in terms of hurricane-induced tornadoes despite the outbreak associated with

Hurricane Ivan in 2004. Hurricane Ivan tornadoes were primarily in coastal counties to the northeast and east of landfall and that is why that was not captured in this study area. Also, discussions with state EMA revealed that in the rural areas, people do not often report tornado property damage to the concerning agencies and organizations and reconstruct their damaged houses and other goods on their own. This is one of the limitations of the dataset that was used in this research.

For assessing social vulnerability, county percentile scores calculated by the Hazard and Vulnerability Research Institute at the University of South Carolina were used. County percentile score ranges from 1 to 100 where 1 means least socially vulnerable county and 100 means highest socially vulnerable county. These county percentile scores were then divided into five groups to show the level of social vulnerability in the study area: Not Vulnerable (percentile scores from 1 to 20), Low (percentile scores from 21 to 40), Moderate (percentile scores from 41 to 60), High (percentile scores from 61 to 80), and Very High (percentile scores from 81 to 100). Figure 4.1.5 shows the level of social vulnerability in this region. Louisiana and Mississippi have the highest number of counties which are socially vulnerable.

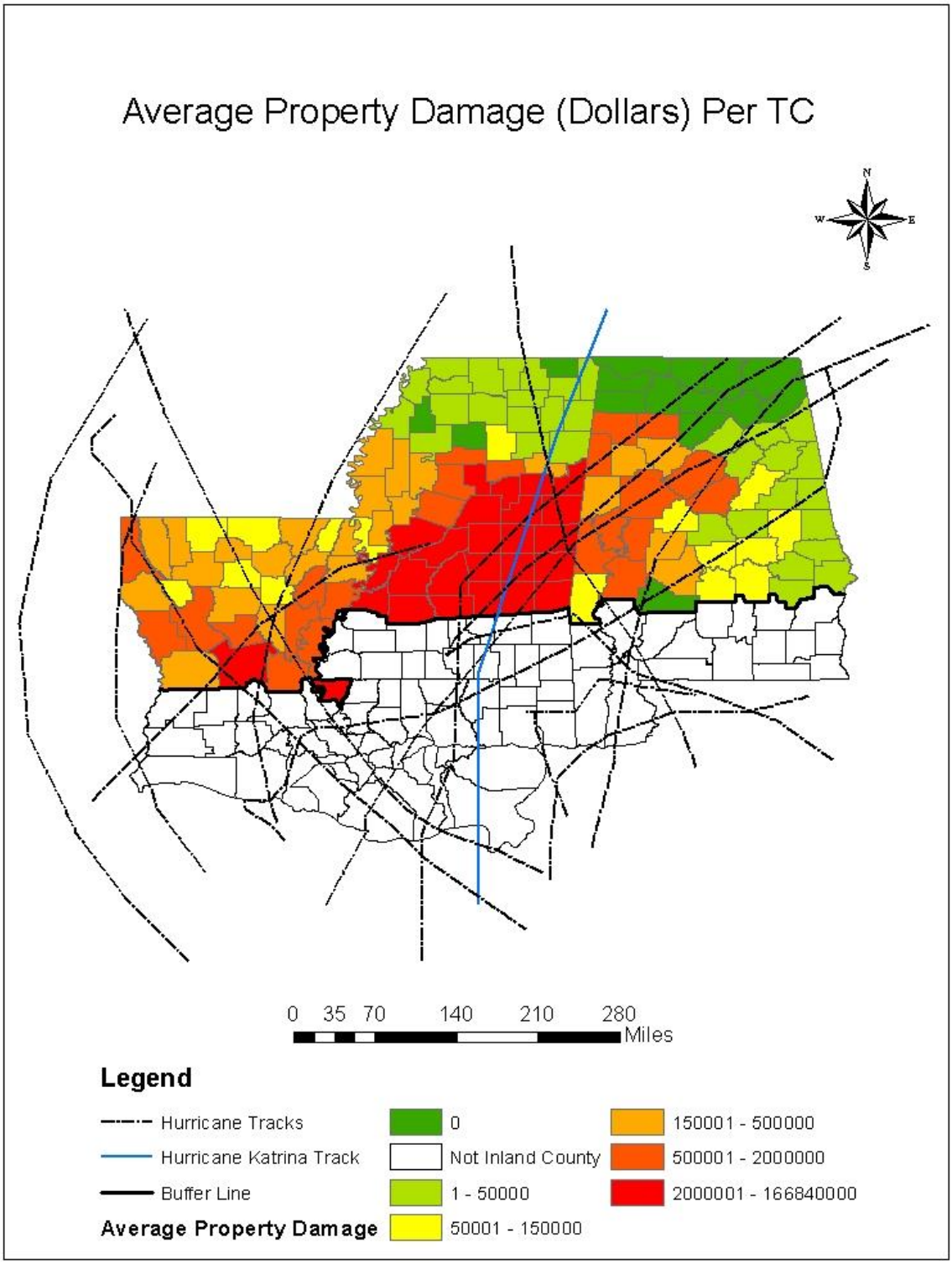

Figure 4.1.1: Average Property Damage per TC in the Study Area

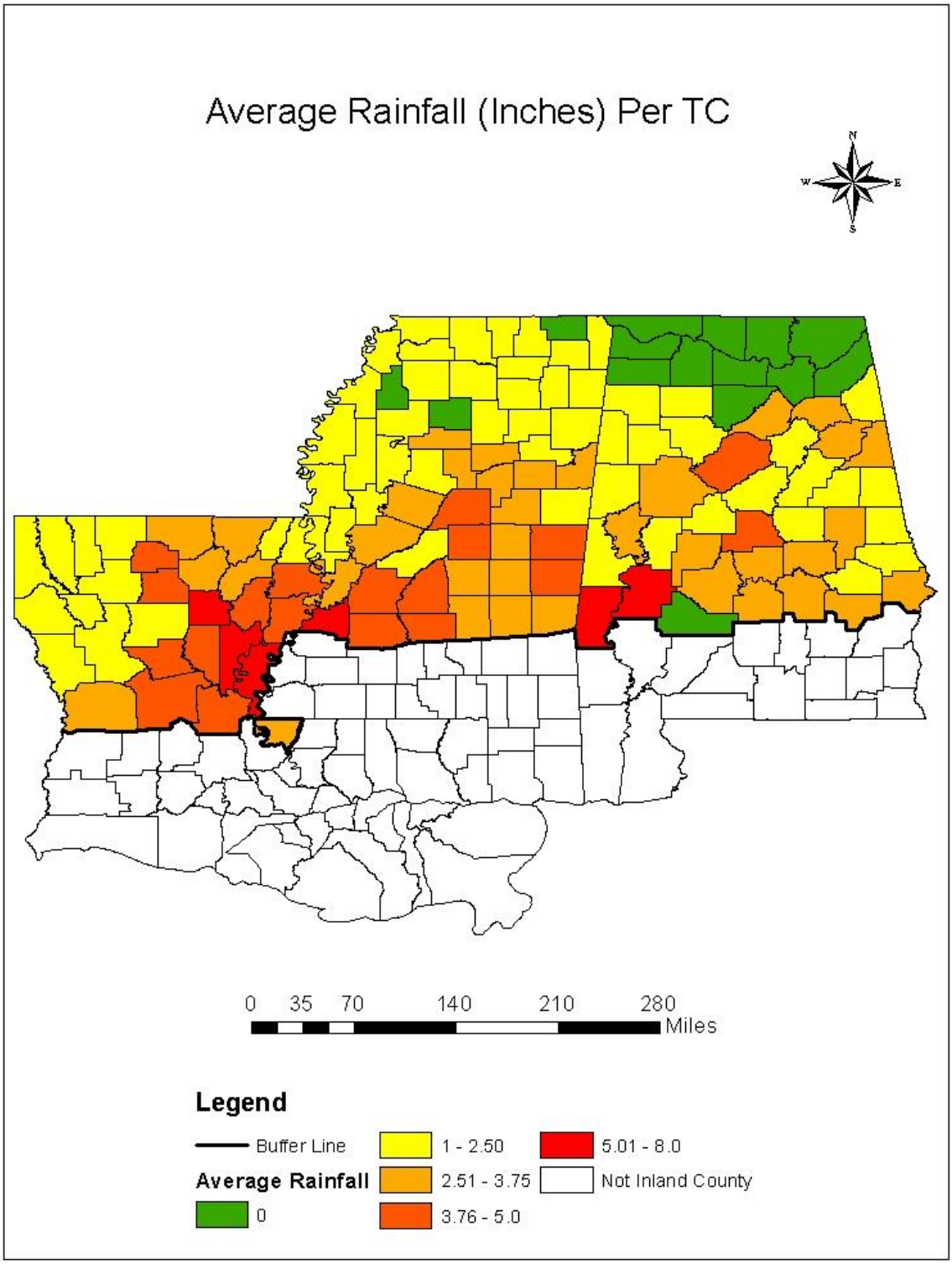

Figure 4.1.2: Average Rainfall per TC in the Study Area

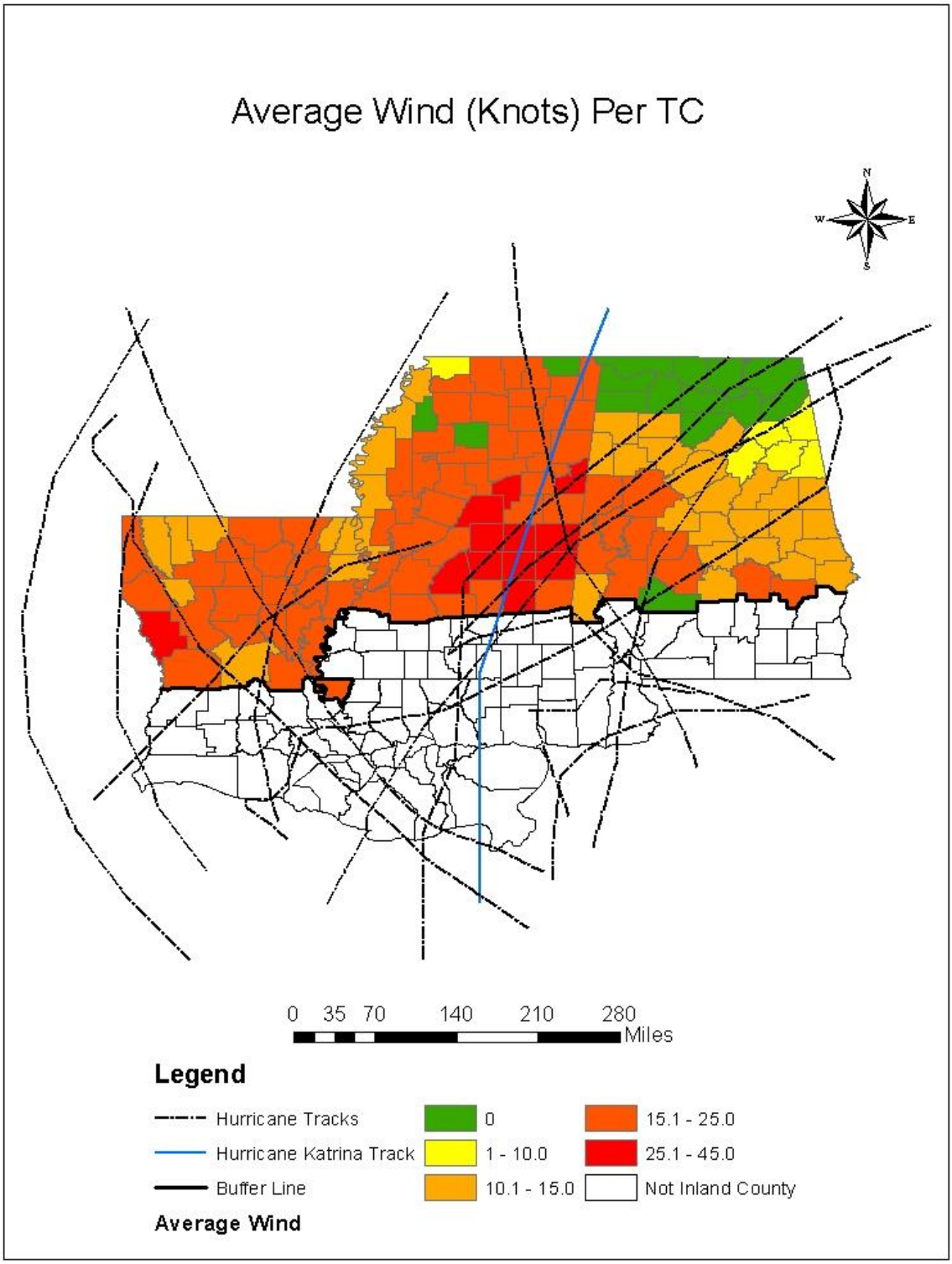

Figure 4.1.3: Average Wind per TC in the Study Area

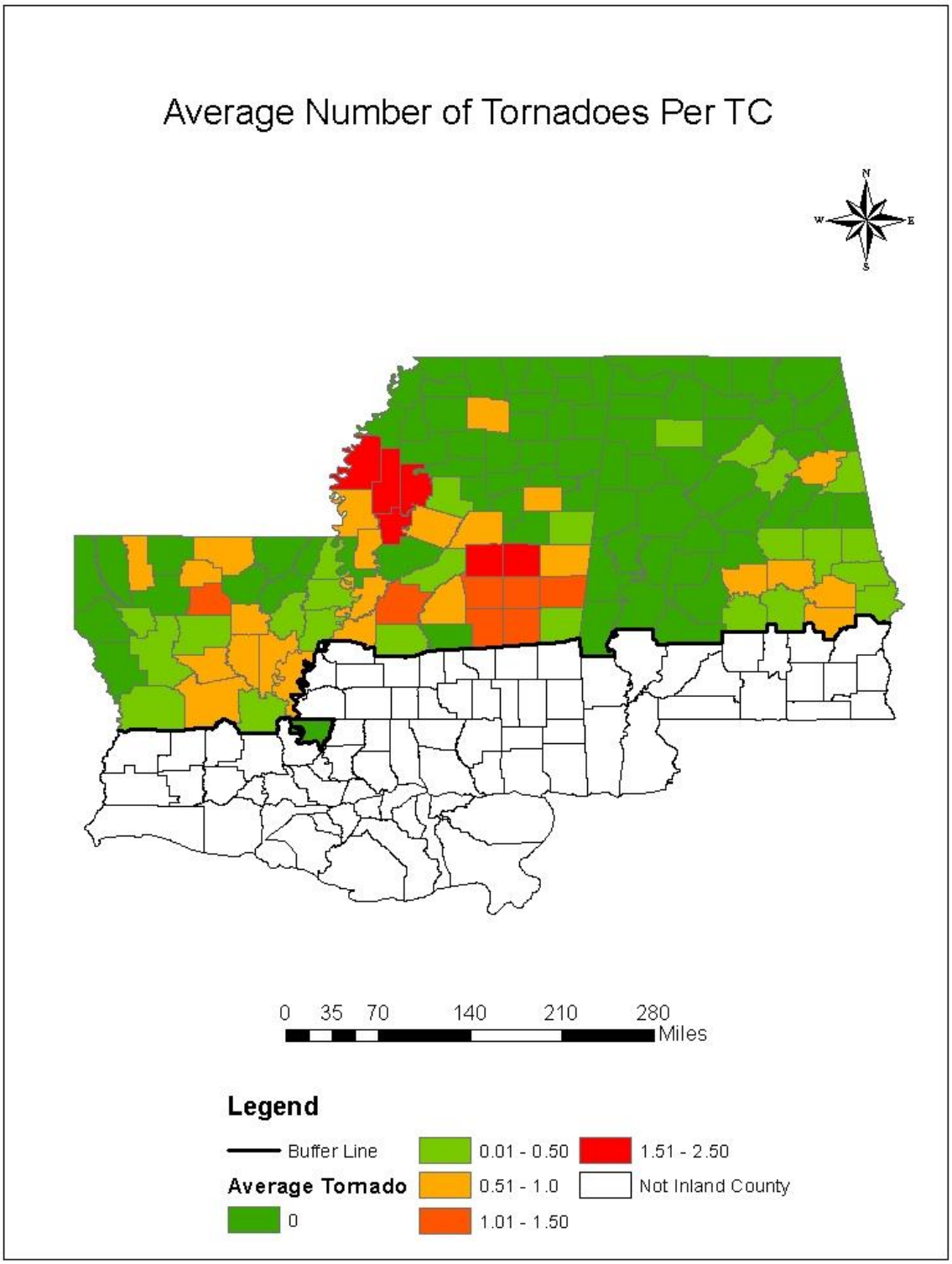

Figure 4.1.4: Average Number of Tornadoes per TC in the Study Area

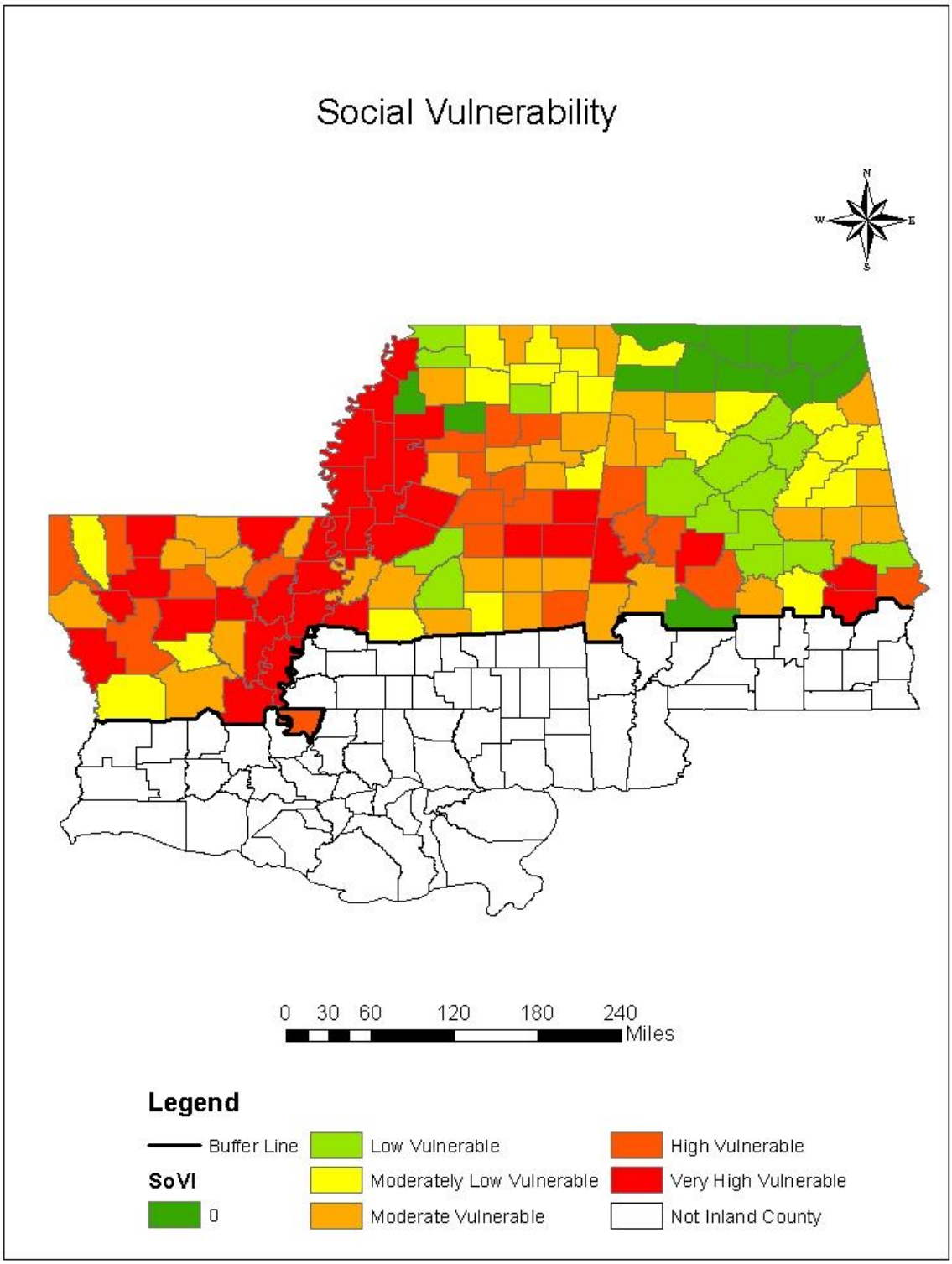

Figure 4.1.5: Level of Social Vulnerability in the Study Area

A regression model was built to predict the inland property damage based on physical storm characteristics (wind, rain, tornadoes) and social vulnerability percentile scores. Pearson correlations between property damage and physical storm characteristics and social vulnerability show that wind has the strongest relationship with property damage followed by tornadoes and rain. Social vulnerability was not significantly correlated with property damage.

Table 4.1.2: Correlation Matrix between Property Damage and Physical Characteristics and Social Vulnerability

		Average Rain	Average Wind	Average Tornado	SoVI
Average Property Damage	Pearson Correlation	0.265	0.640	0.371	-0.119
	Significance Level, *p*	0.002	< 0.001	< 0.001	0.095
	N	123	123	123	123

Multiple linear regression analysis was performed using just the physical variables that were statistically significantly correlated as independent variables and property damage for every county as the dependent variable. The r square value of the model (Table 4.1.3) shows the weak relationship between the dependent variable and independent variables.

Table 4.1.3: Result of Coefficient Analysis

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-4.422E7	6.310E6		-7.007	.000	-5.671E7	-3.172E7
	Avg. Rain	1.528E6	1.345E6	.082	1.137	.258	-1.134E6	4191202.141
	Avg. Wind	2.435E6	312824.859	.567	7.785	.000	1815932.171	3054781.099
	Avg. Tornado	7.747E6	3.355E6	.170	2.309	.023	1103205.793	1.439E7

Using the unstandardized coefficients value from the above table (Table 4.1.3), the constant value of the model is -4.422E7. The unstandardized coefficients indicate how much the dependent variable varies with an independent variable when all other independent variables are held constant. For this model, the unstandardized value of average rainfall per TC is 1.528E6 which means that for each inch increase of average rainfall, there will be an increase in average property damage per TC of 1.528 million USD. Each knot increase of average wind in the study area will cause an increased average property damage per TC of 2.435 million USD. Also, a single hurricane-induced tornado per TC in the study area will cause additional 7.747 million USD of average property damage per TC.

So, the final regression model for predicting average property damage per TC in the study area is:

Average Property Damage per TC = -44.22 + {1.528 * (Avg. Rain per TC) + 2.435 * (Avg. Wind per TC) + 7.747 * (Avg. Tornado per TC)} million USD.

4.2 Analysis without Hurricane Katrina

From the regression analysis, it was found that physical storm characteristics (average rain, wind, and tornado) are the main factors that influence property damage in the study area. Hurricane Katrina caused 108 billion USD of property damage alone in the USA (Knabb et al. 2005, Blake et al. 2011) and skewed the results. Therefore, regression analysis was performed again excluding Hurricane Katrina from the database.

After excluding Hurricane Katrina from the database, it was found that 21 counties in the study area had property damage only for Hurricane Katrina. As there was no positive correlation with property damage and social vulnerability found in the previous analysis, social vulnerability

was excluded from the database. Instead, only two factors of social vulnerability, population density per square miles and median income per households, were used in the analysis. Population density and median household income are two of the most important factors of social vulnerability (Cutter et al. 2003). There are a total of 102 counties found which had property damage for the last 20 years period excluding Hurricane Katrina. The mean value of average property damage per TC was found 334,000 USD. The mean values of rain, wind, and tornadoes per storm, median income, and population density were found as 3.12 inches, 14.44 knots, 0.49 tornado, 35,000 USD, and 65.825 per square miles respectively. Comparing these values with the previous mean values of average property damage, rain, and wind per TC it was clear that the mean value of average property damage and wind per TC decreased significantly. However, the mean value of average tornado and rainfall per TC increased slightly after excluding Hurricane Katrina from the database.

Table 4.2.1: Descriptive Statistics of Average Property Damage, Rain, Wind, and Tornado and Median Income and Population Density without Hurricane Katrina

	Mean	Std. Deviation	N
Average Property Damage	334000	1130779.444	102
Average Rain	3.12	1.720	102
Average Wind	14.44	4.380	102
Average Tornado	.49	.579	102
Median Income	35000	8579.192	102
Population Density	65.825	83.1594	102

Using GIS, maps for average property damage per TC, average rainfall, wind, tornado per TC, population density per square miles, and median income per households in the study area were created (Figure 4.2.1, 4.2.2, 4.2.3, 4.2.4, and 4.2.5 respectively). After excluding Hurricane Katrina from the database, Louisiana became the most affected state in the study area regarding

average property damage per TC (Figure 4.2.1). Inland Louisiana and Alabama received high amounts of average rainfall per TC (4.2.2). Louisiana also was mostly affected by high amounts of average wind per TC without considering Hurricane Katrina (Figure 4.2.3). Although, several counties in East Mississippi still received the highest amounts of average wind per TC after excluding Katrina from the list. Inland Alabama has the most counties with high population density and median household income in the study area (Figure 4.2.4 and 4.2.5 respectively).

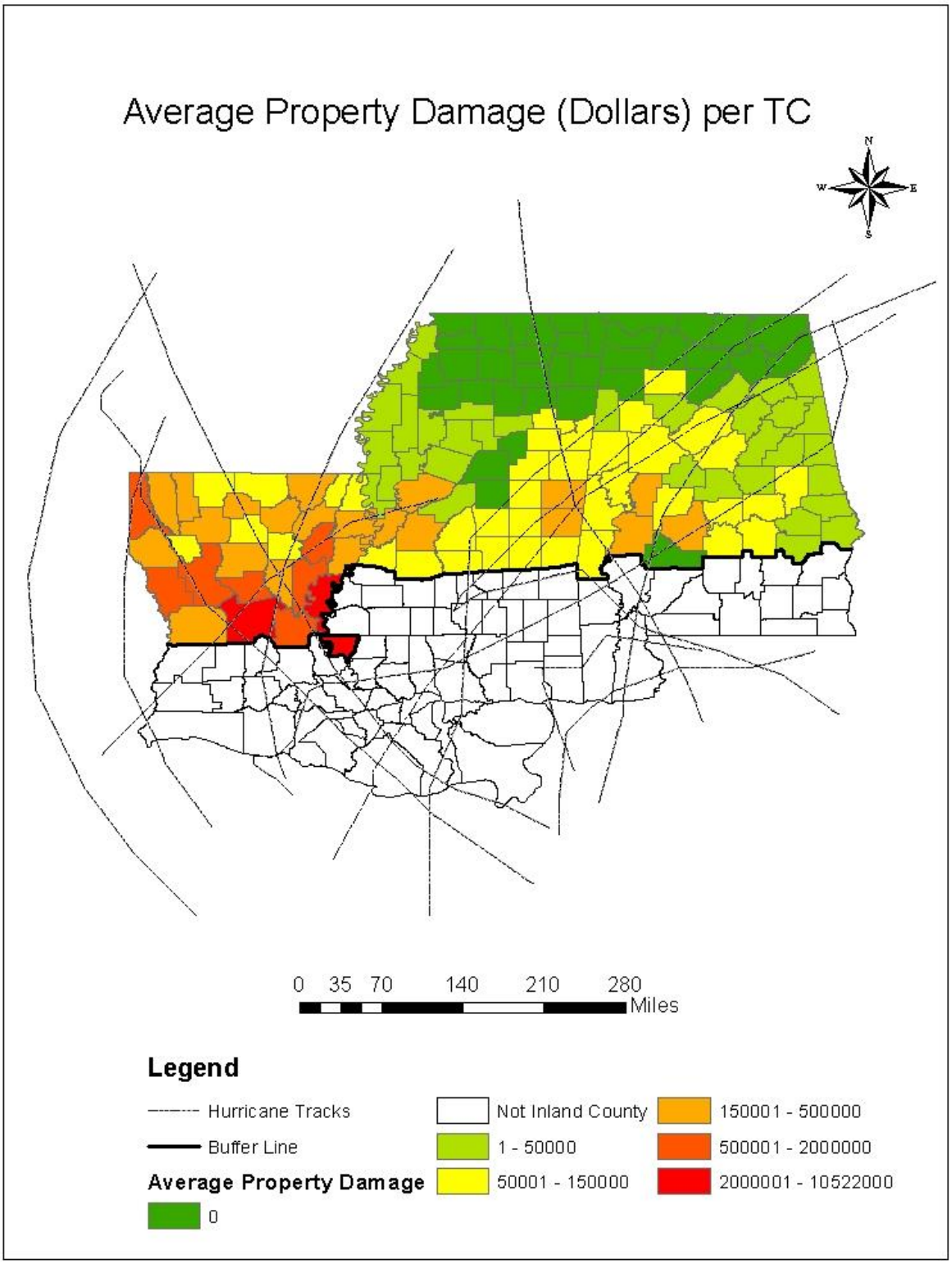

Figure 4.2.1: Average Property Damage per TC without Hurricane Katrina

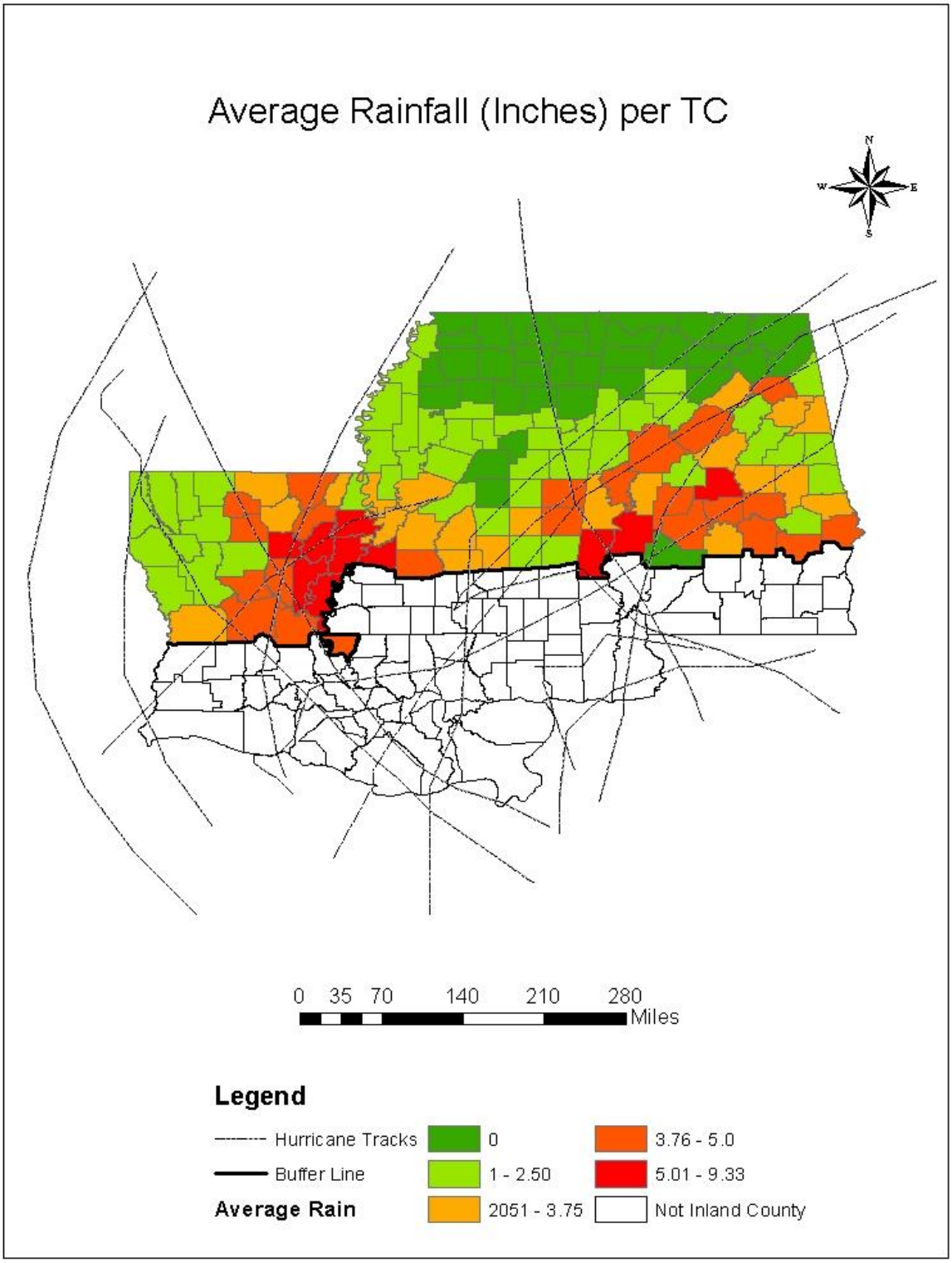

Figure 4.2.2: Average Rainfall per TC without Hurricane Katrina

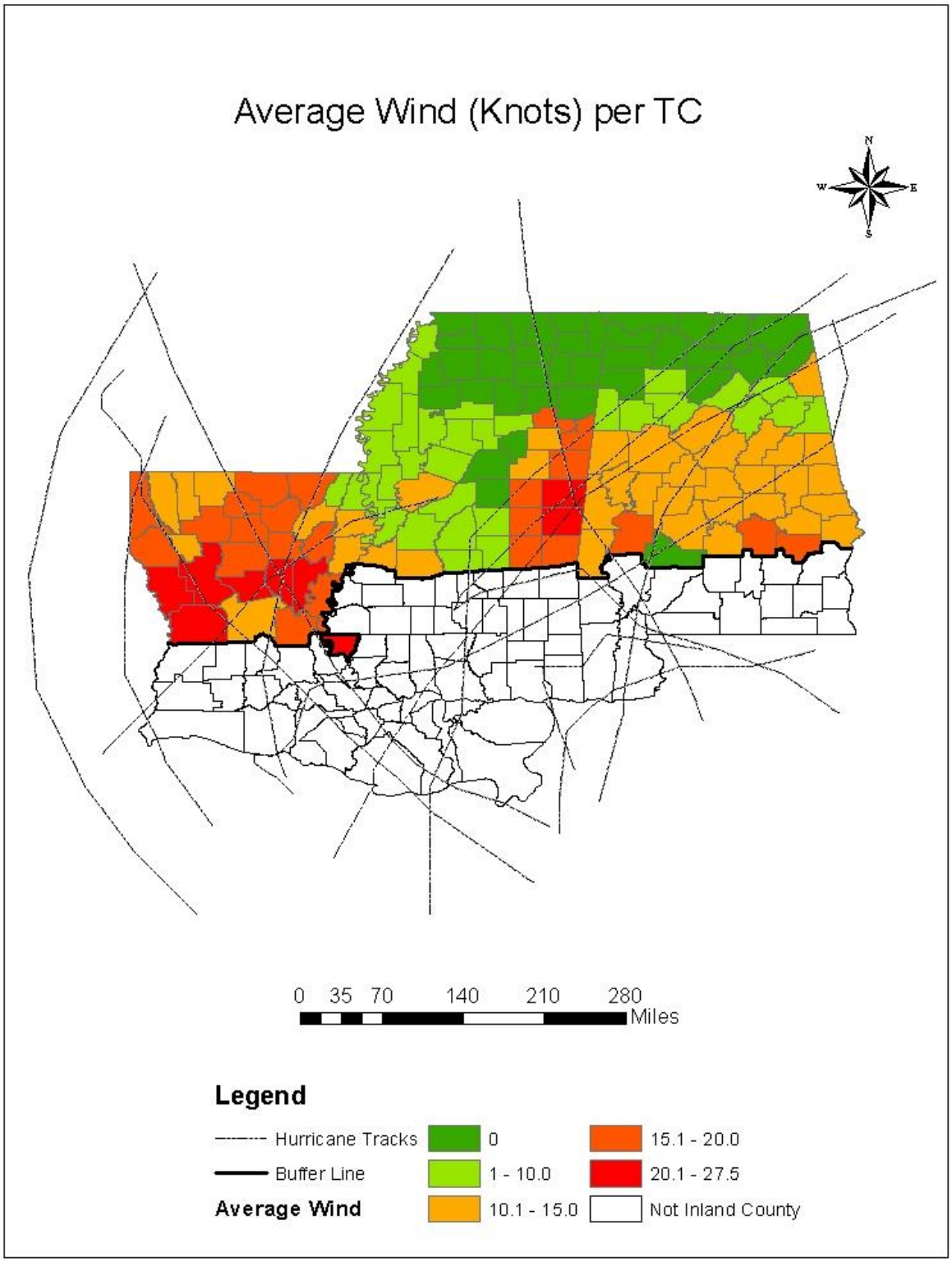

Figure 4.2.3: Average Wind per TC without Hurricane Katrina

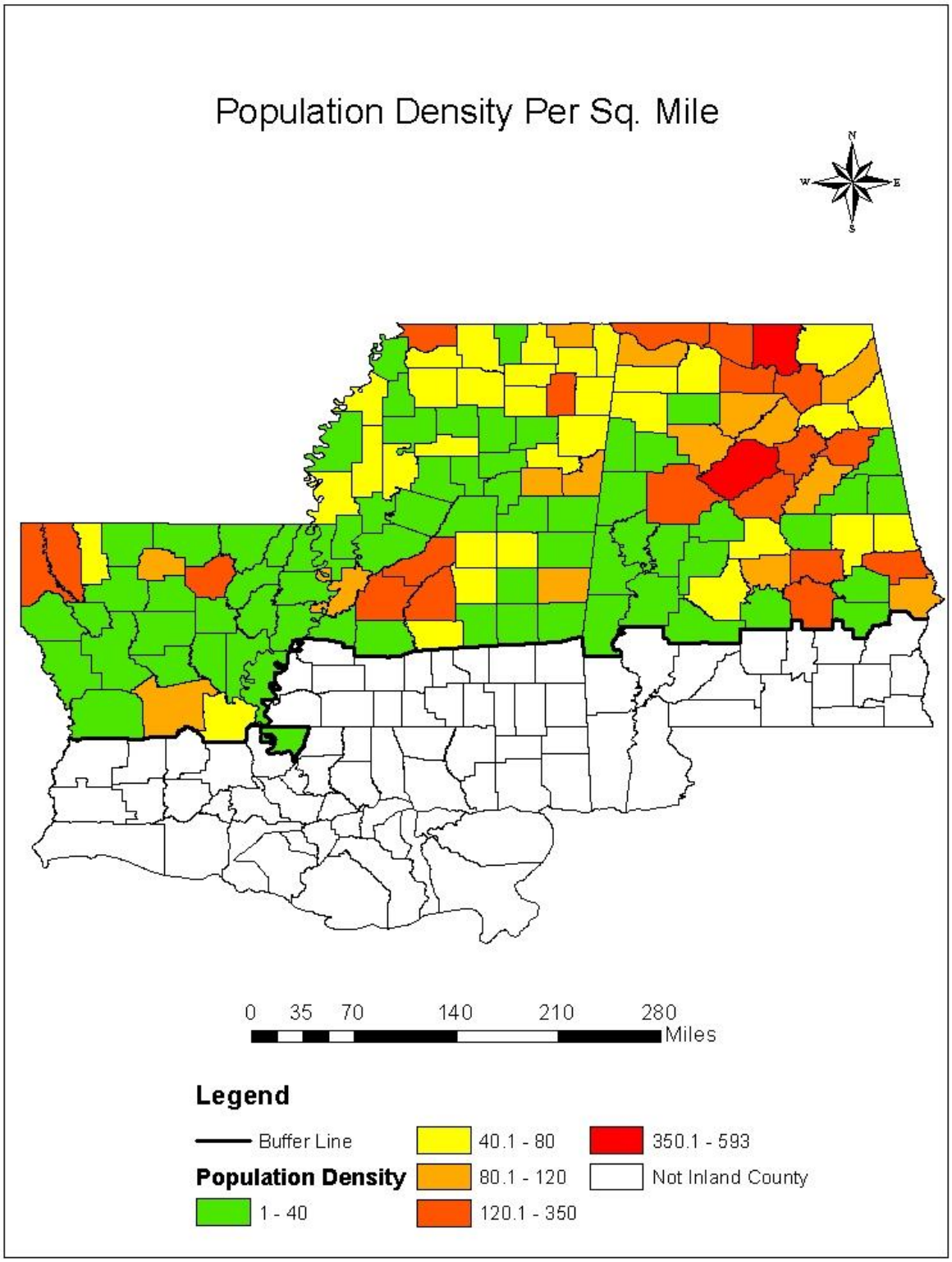

Figure 4.2.4: Population Density in the Study Area

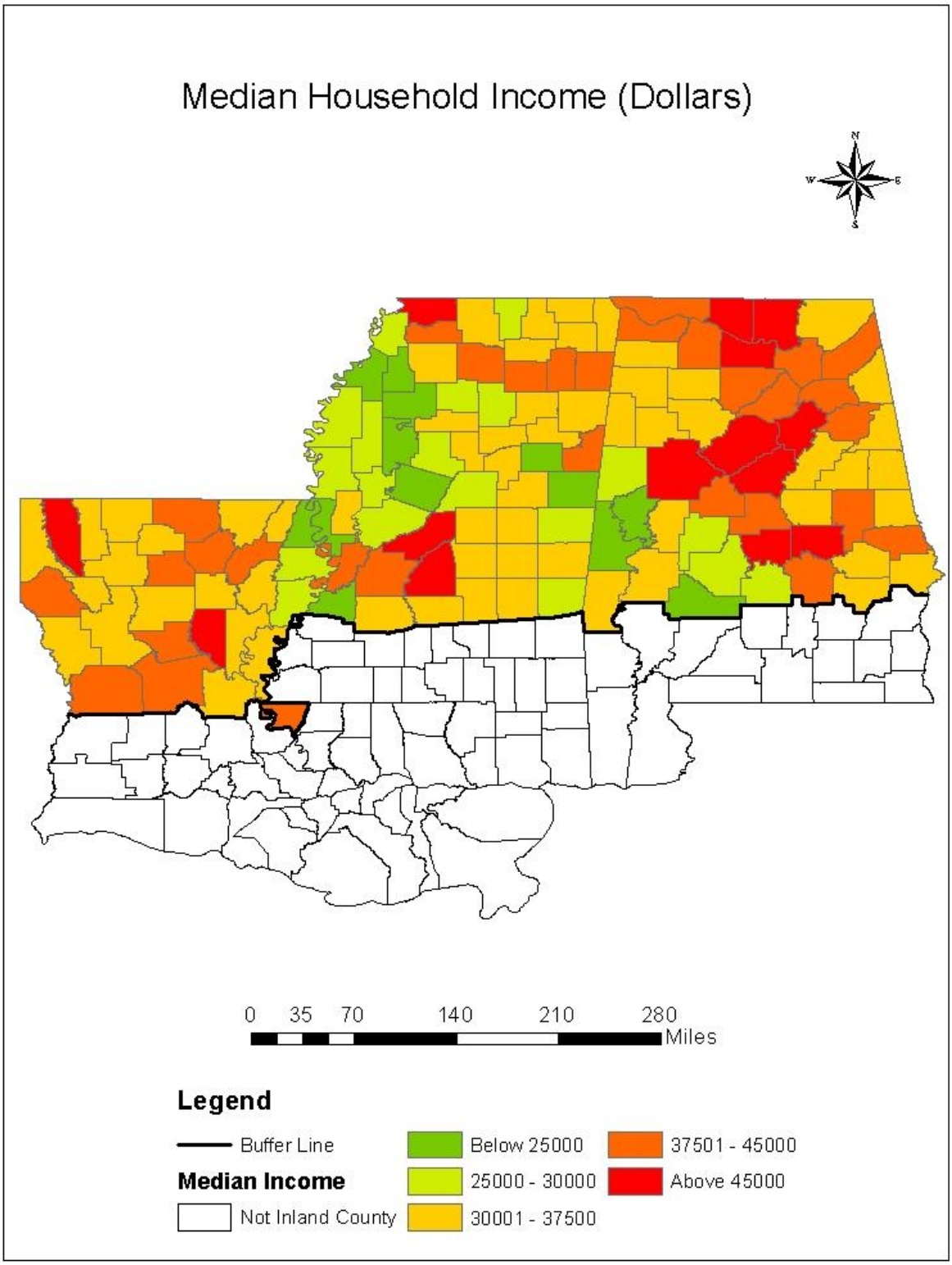

Figure 4.2.5: Median Household Income in the Study Area

Regression analysis was done to predict the average property damage per TC without including Hurricane Katrina, but these results were weaker than the analysis including Katrina.

So, it was clear that without Hurricane Katrina, the regression model became very weak and therefore, it is not possible to statistically significantly predict the average property damage per TC in this region with the database. Hurricane Katrina dominates the results and had an enormous influence on the data.

4.3 Hypothetical Analysis

Hurricane Katrina tracked through Mississippi and caused a large amount of property damage relative to Alabama and Louisiana. Regression analysis was performed with Hurricane Katrina data for Mississippi to first establish relationships between the predictor variables and property damage in the counties surrounding Jackson, MS where population density and income were highest. There were a total of 24 inland counties found in Mississippi which had property damage over 10 million USD for Hurricane Katrina (Table 4.3.1). Table 4.3.1 also shows the wind (knots) and rainfall (inches) for Hurricane Katrina in each of those counties along with population density per square mile and median income per household.

Table 4.3.1: Hurricane Katrina Data for Selected Counties in Mississippi

County Name	Property Damage (Million USD)	Wind (Knots)	Rain (Inches)	Population Density (per Sq. Miles)	Median Income (USD per Household)
Attala	50	40	5	26.6	28508
Choctaw	50	35	5	20.4	30994
Claiborne	20	35	5	19.7	24150
Clarke	100	45	5	24.2	29103
Copiah	80	35	5	37.9	36637
Hinds	500	55	6	282	39215
Jasper	150	60	5	25.2	30177
Kemper	100	45	5	13.6	25649
Lauderdale	450	65	5	114.1	33926
Leake	100	45	5	40.8	31986
Lowndes	100	45	5	118.3	37607
Madison	250	45	5	133.2	59730
Montgomery	10	35	5	26.8	31488
Neshoba	100	50	5	52.1	34905
Newton	100	50	5	37.6	36154
Noxubee	10	40	3	16.6	22178
Oktibbeha	100	45	6	104	19356
Rankin	300	65	5	182.6	56159
Scott	100	50	5	46.4	35765
Simpson	100	55	5	46.7	36739
Smith	100	45	5	25.9	37176
Warren	100	45	5	82.9	40404
Winston	50	35	5	31.6	30738
Yazoo	20	35	5	30.4	27356

Rainfall amounts were similar for each of the counties. There was high inland wind associated with decaying Hurricane Katrina varying from thirty five knots to sixty five knots. As in previous analyses, a correlation matrix was created to see which factors contributed more to property damage for Hurricane Katrina in Mississippi. Correlation results between property damage and rainfall, wind (for Hurricane Katrina in Mississippi), population density per square miles and median income per households are given in Table 4.3.2.

Table 4.3.2: Correlation Matrix between Property Damage and Physical Characteristics and Median Income and Population Density for Hurricane Katrina

		Rainfall	Wind	Median Income	Population Density
Property Damage	Pearson Correlation	0.391	**0.736**	0.499	**0.841**
	Significance Level, *p*	0.059	**< 0.001**	0.013	**< 0.001**
	N	24	24	24	24

From the correlation matrix (Table 4.3.2) it was found that wind and population density are highly correlated with property damage. Therefore, only wind and population density were considered as independent variables in the regression analysis for predicting the property damage for Hurricane Katrina in central Mississippi.

Table 4.3.3: Regression Model Summary for Hurricane Katrina

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.909	**.827**	.811	55.013

The regression model (Table 4.3.3) resulted in an r square value of 0.827 and an adjusted r square value of 0.811 which shows a much stronger relationship between the dependent and independent variables than the results for the entire study area. An ANOVA test was also performed with the dataset and found that the independent variables (wind and population density in this case) predict the property damage statistically significantly and also the model is a good fit for the dataset used.

From the results of the coefficient analysis (Table 4.3.5), it was found that the constant value for the model is -209.160 (using unstandardized coefficient value). The unstandardized coefficient value for wind and population density were found as 5.596 and 1.237 respectively.

Table 4.3.5: Results of Coefficient Analysis for Hurricane Katrina in Mississippi

Model		Unstandardized Coefficients		Standardized Coefficients	t	Significance	95% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-209.160	62.426		-3.351	.003	-338.983	-79.337
	Wind	5.596	1.471	.406	3.804	.001	2.537	8.655
	Population Density	1.237	.210	.628	5.883	.000	.800	1.674

Using the unstandardized coefficients, the final model for predicting the Hurricane Katrina property damage was found as:

Property Damage = -209.160 + 5.596 * Wind + 1.237 * Population Density

The total predicted property damage for all the selected Mississippi counties was found as 3040.245 million USD, and the total observed value of property damage (from the dataset) was 3040 million USD. The total observed value of property damage was then divided by the total predicted value of property damage in central Mississippi to determine the model accuracy. And it was found that the model predicted the property damage for Hurricane Katrina 99.99% accurately.

Table 4.3.6: Predicted Property Damage for Hurricane Katrina

County Name	Observed Property Damage (Million USD)	Wind (Knots)	Population Density (per Sq. Miles)	Predicted Property Damage (Million USD)
Attala	50	40	26.6	47.5842
Choctaw	50	35	20.4	11.9348
Claiborne	20	35	19.7	11.0689
Clarke	100	45	24.2	72.5954
Copiah	80	35	37.9	33.5823
Hinds	500	55	282	447.454
Jasper	150	60	25.2	157.7724
Kemper	100	45	13.6	59.4832
Lauderdale	450	65	114.1	295.7217
Leake	100	45	40.8	93.1296
Lowndes	100	45	118.3	188.9971
Madison	250	45	133.2	207.4284
Montgomery	10	35	26.8	19.8516
Neshoba	100	50	52.1	135.0877
Newton	100	50	37.6	117.1512
Noxubee	10	40	16.6	35.2142
Oktibbeha	100	45	104	171.308
Rankin	300	65	182.6	380.4562
Scott	100	50	46.4	128.0368
Simpson	100	55	46.7	156.3879
Smith	100	45	25.9	74.6983
Warren	100	45	82.9	145.2073
Winston	50	35	31.6	25.7892
Yazoo	20	35	30.4	24.3048
Total	**= 3040**			**= 3040.245**

Simple linear regression (SLR) analysis between predicted property damage and wind and population density for Hurricane Katrina was also performed individually (Figure 4.3.1 and 4.3.2 respectively) to see how wind and population density predict the property damage.

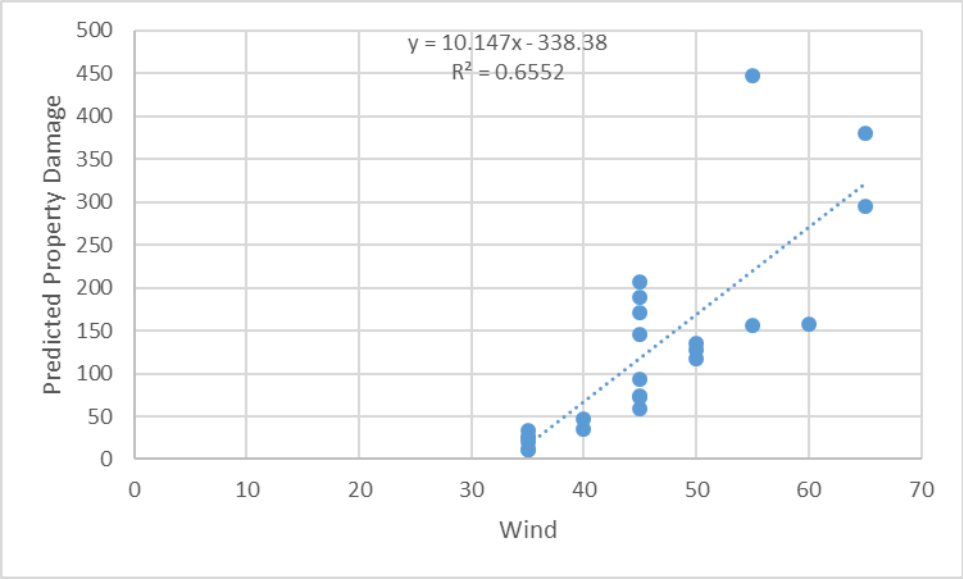

Figure 4.3.1: SLR between Property Damage and Wind for Hurricane Katrina

Figure 4.3.1 shows that the r square value between wind and the predicted property damage is 0.6552. It also shows that 10.147 million USD of property damage will be added for increasing every knot of wind after 35 knots.

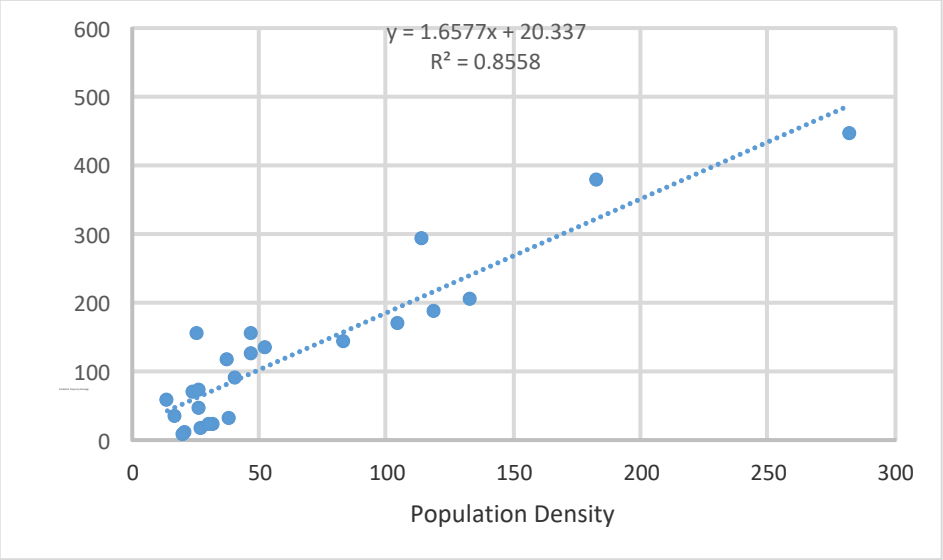

Figure 4.3.2: SLR between Property Damage and Population Density

Figure 4.3.2 shows that the r square value between the predicted property damage and population density is 0.8558. It is also found that 1.6577 million USD will be added for increasing every one person per square miles in this region.

It was apparent that Hurricane Katrina caused more damages in the densely populated areas in Mississippi with its devastating high wind. Rainfall associated with Hurricane Katrina was not found to be statistically significant for causing property damage in this region. Therefore, hypothetical scenarios were created to see what would happen if a Katrina type storm tracked over major metropolitan areas in the study area. In this regard, the Birmingham, Montgomery, and Atlanta Metropolitan areas were considered. Although Atlanta is not within the study area of this research, it was considered for the hypothetical scenario because of its very high population density and potential for being hit. Hurricane Katrina's track was moved in a way that it passed through these metropolitan areas by changing Hurricane Katrina's coordinates using GIS. Wind values for Hurricane Katrina in these metropolitan areas were matched with the wind values of Hurricane Katrina in selected 24 Mississippi counties based on their geographical location. The regression model that was created for predicting property damage for Hurricane Katrina in central Mississippi was used to predict the hypothetical property damage for Hurricane Katrina in these metropolitan areas.

4.4 Hypothetical Scenario: Birmingham, Alabama

24 counties around Birmingham area were selected for the analysis as the average area of a county in Alabama is more or less similar as the average county area in previously selected 24 counties in Mississippi. Then, the Hurricane Katrina track was overlayed onto Alabama so that it passed through Birmingham and wind values for those selected 24 adjacent counties in

Birmingham were matched according to the geographical location of the selected counties for Hurricane Katrina analysis in Mississippi (Table 4.4.1).

Table 4.4.1: Wind Values for Hurricane Katrina in Birmingham

Mississippi			Birmingham, Alabama		
County	Wind (Knots)	Population Density (per sq. miles)	County	Wind (Knots)	Population Density (per sq. miles)
Attala	40	26.6	Autauga	60	91.8
Choctaw	35	20.4	Bibb	45	36.8
Claiborne	35	19.7	Blount	45	88.9
Clarke	45	24.2	Calhoun	35	195.7
Copiah	35	37.9	Chilton	55	63
Hinds	55	282	Clay	65	23.1
Jasper	60	25.2	Coosa	65	17.7
Kemper	45	13.6	Elmore	45	128.2
Lauderdale	65	114.1	Fayette	35	27.5
Leake	45	40.8	Greene	35	14
Lowndes	45	118.3	Hale	55	24.5
Madison	45	133.2	Jefferson	50	592.5
Montgomery	35	26.8	Lamar	35	24.1
Neshoba	50	52.1	Marion	40	41.5
Newton	50	37.6	Perry	45	14.7
Noxubee	40	16.6	Pickens	45	22.4
Oktibbeha	45	104	Shelby	45	248.5
Rankin	65	182.6	St. Clair	40	132.3
Scott	50	46.4	Sumter	35	15.2
Simpson	55	46.7	Talladega	45	111.7
Smith	45	25.9	Tallapoosa	50	58.1
Warren	45	82.9	Tuscaloosa	50	147.3
Winston	35	31.6	Walker	45	84.7
Yazoo	35	30.4	Winston	35	39.9

Wind and population density values for these selected adjacent counties around Birmingham were joined in the attribute table in GIS and maps for Hurricane Katrina wind and population density were created with the Hurricane Katrina track over it (Figure 4.4.1 and 4.4.2 respectively).

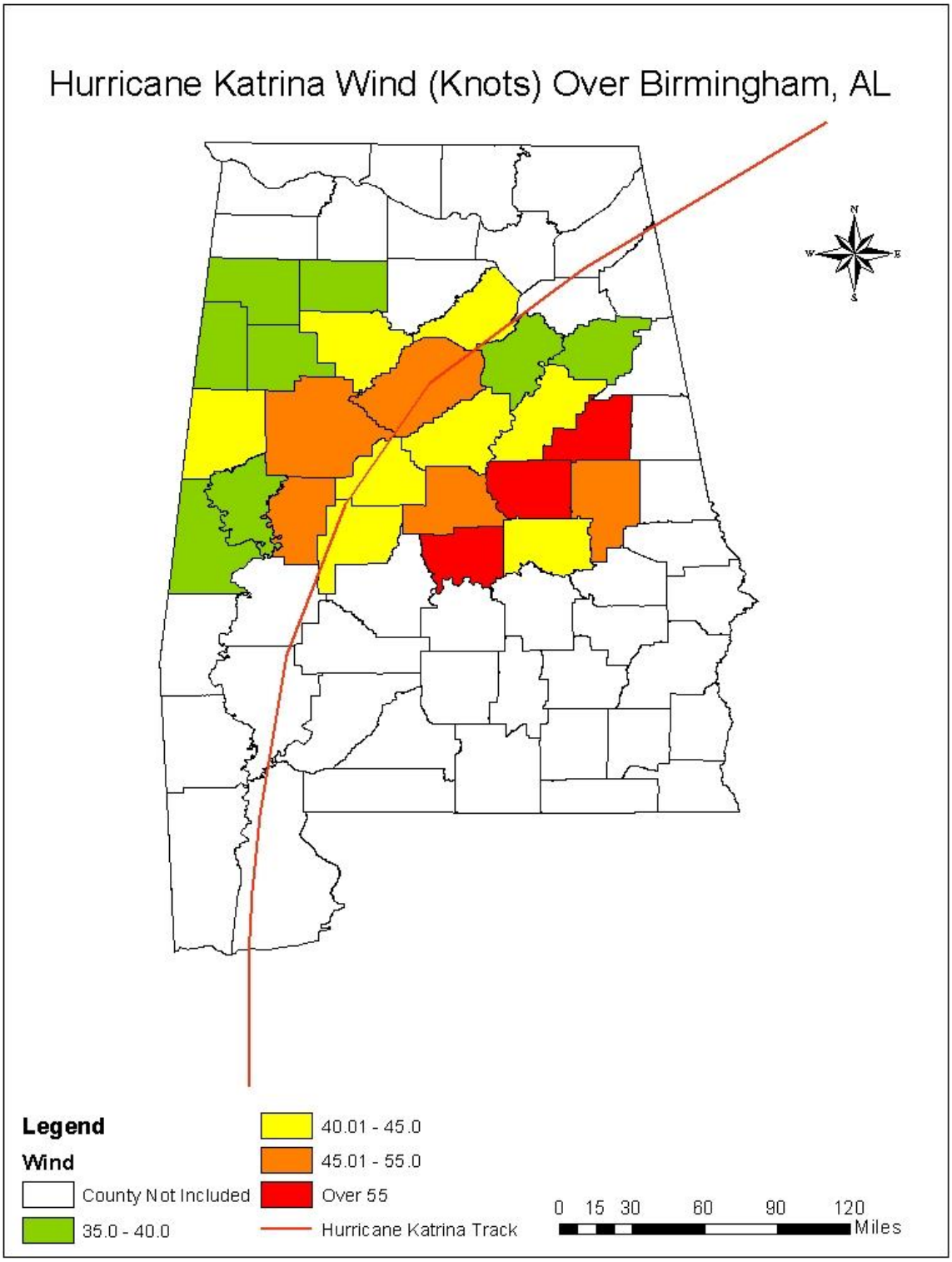

Figure 4.4.1: Hypothetical Wind Values for Hurricane Katrina over Birmingham Metropolitan Area

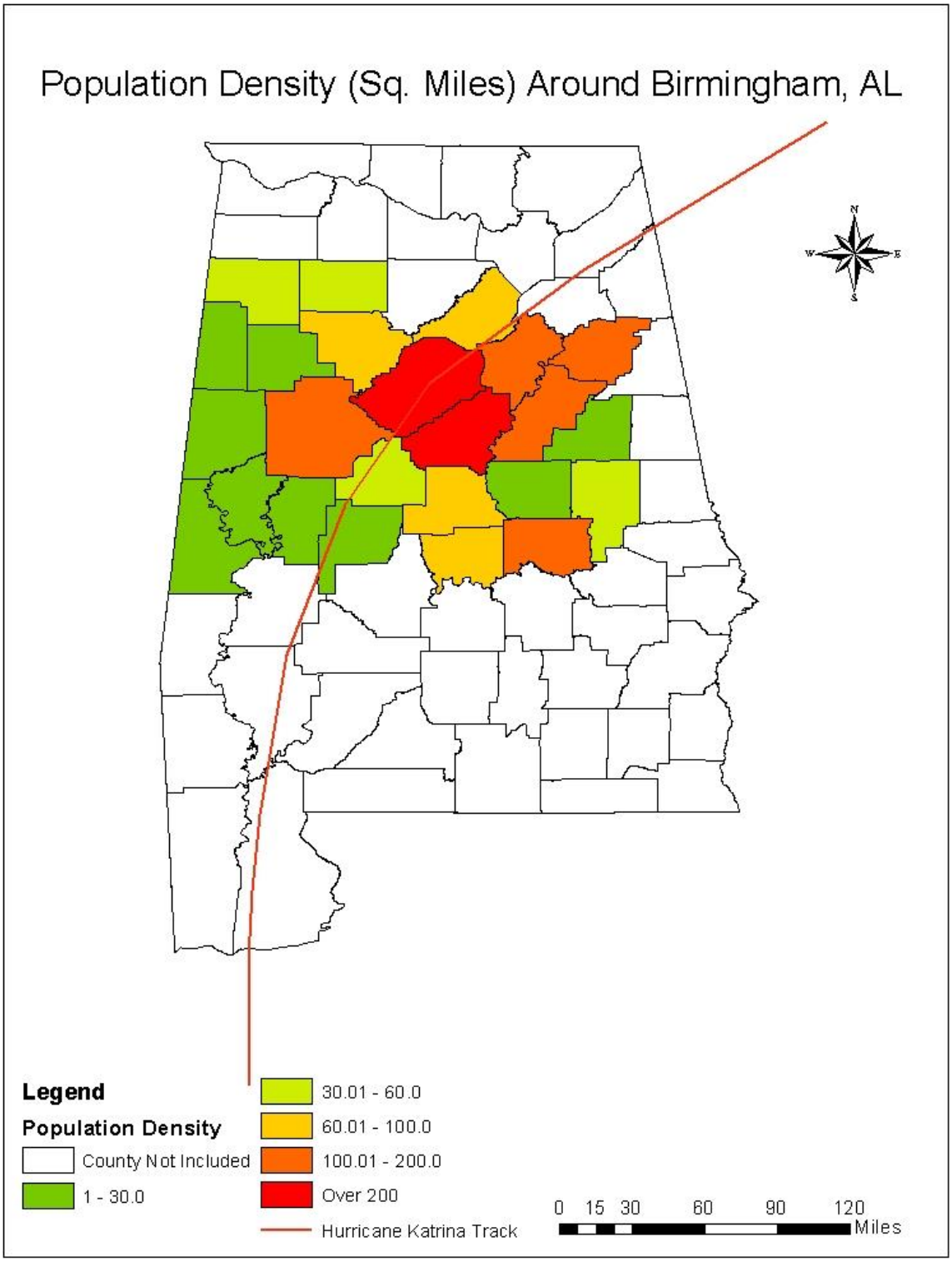

Figure 4.4.2: Population Density around Birmingham Metropolitan Area

These wind and population density values for Birmingham area were then used in the regression model that was created in the Hurricane Katrina Analysis section to predict the hypothetical property damage for Hurricane Katrina in Birmingham (Table 4.4.2 and Figure 4.4.3).

Table 4.4.2: Predicted Hypothetical Property Damage for Hurricane Katrina in Birmingham

Mississippi		Birmingham, Alabama	
County	Predicted Property Damage (million USD)	County	Predicted Property Damage (million USD)
Attala	47.5842	Autauga	240.1566
Choctaw	11.9348	Bibb	88.1816
Claiborne	11.0689	Blount	152.6293
Clarke	72.5954	Calhoun	228.7809
Copiah	33.5823	Chilton	176.551
Hinds	447.454	Clay	183.1547
Jasper	157.7724	Coosa	176.4749
Kemper	59.4832	Elmore	201.2434
Lauderdale	295.7217	Fayette	20.7175
Leake	93.1296	Greene	4.018
Lowndes	188.9971	Hale	128.9265
Madison	207.4284	Jefferson	803.5625
Montgomery	19.8516	Lamar	16.5117
Neshoba	135.0877	Marion	66.0155
Newton	117.1512	Perry	60.8439
Noxubee	35.2142	Pickens	70.3688
Oktibbeha	171.308	Shelby	350.0545
Rankin	380.4562	St. Clair	178.3351
Scott	128.0368	Sumter	5.5024
Simpson	156.3879	Talladega	180.8329
Smith	74.6983	Tallapoosa	142.5097
Warren	145.2073	Tuscaloosa	252.8501
Winston	25.7892	Walker	147.4339
Yazoo	24.3048	Winston	36.0563

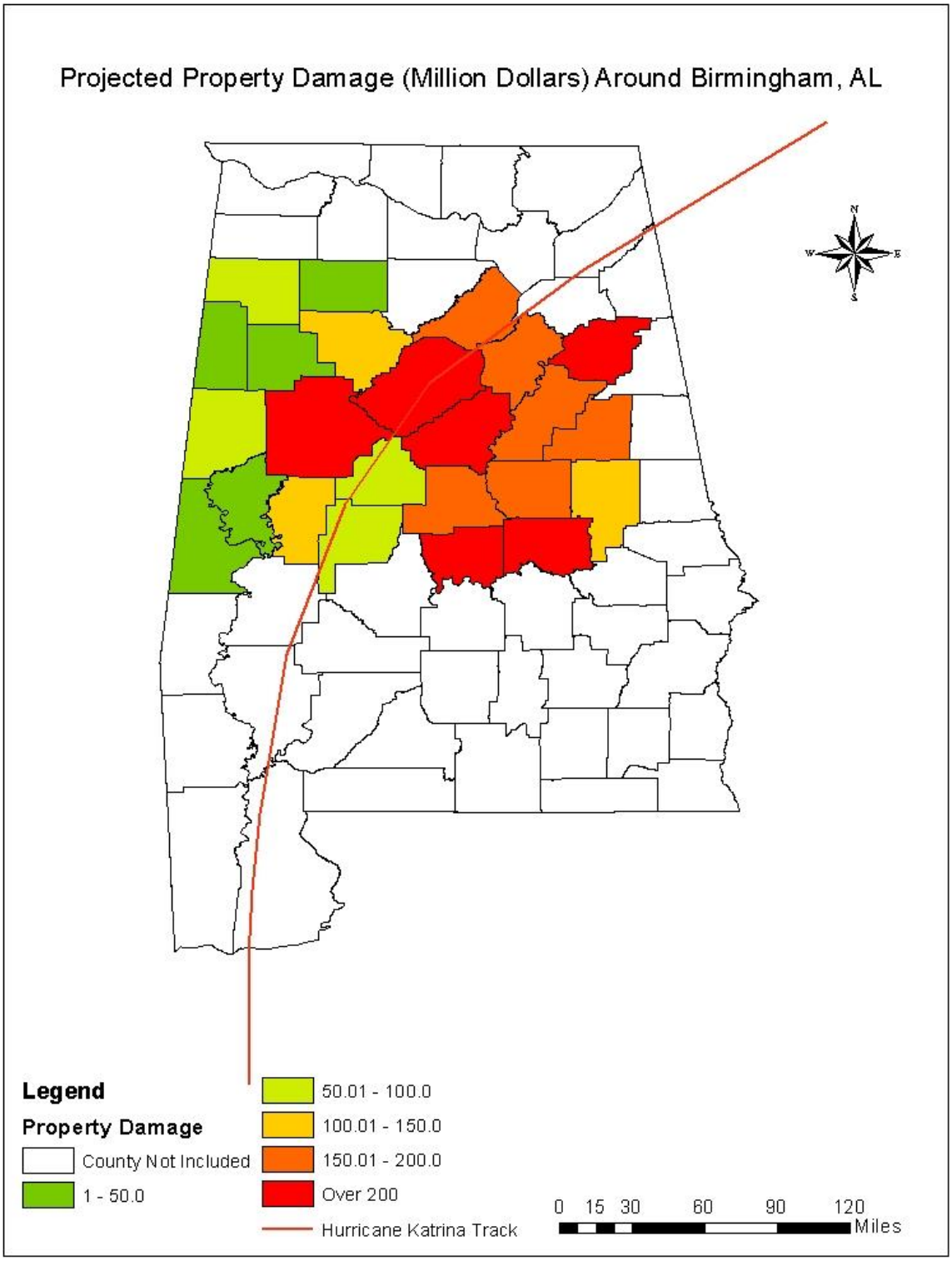

Figure 4.4.3: Predicted Property Damage for Hurricane Katrina around Birmingham Metropolitan Area

Correlation analysis was performed between the predicted property damage and wind and population density for Hurricane Katrina in Birmingham. The correlation matrix (Table 4.4.4) shows that there is a very high positive correlation between property damage and population density in Birmingham with an r square value of 0.949. Correlation between wind and property damage was found to be moderate.

Table 4.4.3: Correlation Matrix between Hypothetical Property Damage and Wind and Population Density in Birmingham, AL

		Wind (Knots)	Population Density (per sq. miles)
Predicted Property Damage	Pearson Correlation	.357	.949
	Significance Level, *p*	0.044	**< .001**
	N	24	24

Individual simple linear regression (SLR) between hypothetical property damage and wind and population density was also done to see how wind and population density influence property damage in Birmingham for Hurricane Katrina individually. It appeared that property damage would be increased 1.2555 million USD for increasing each one person per square miles in Birmingham (Figure 4.4.4) and property damage will be increased 6.3346 million USD for each knot of added wind after 35 knots per hour (Figure 4.4.5).

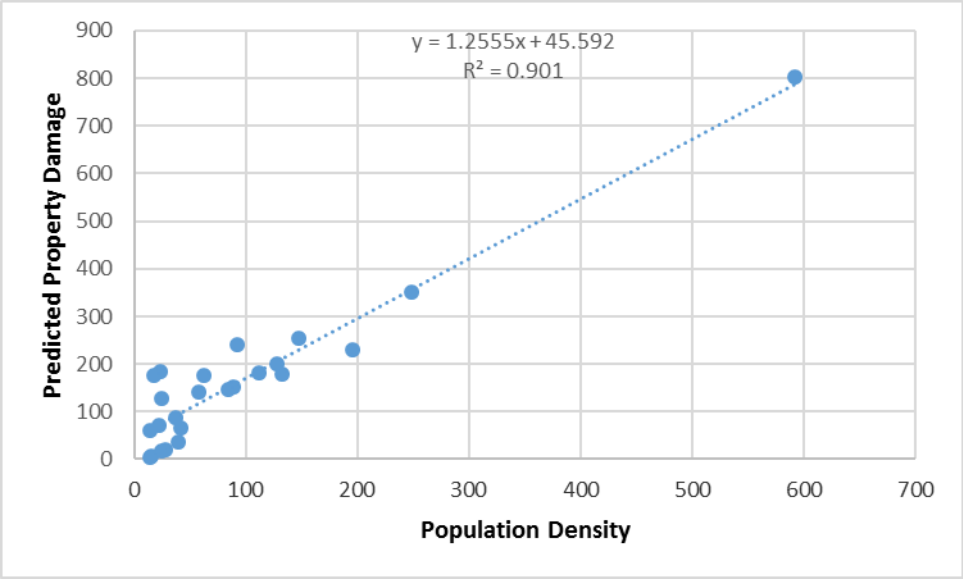

Figure 4.4.4: SLR between Hypothetical Property Damage and Population Density around Birmingham

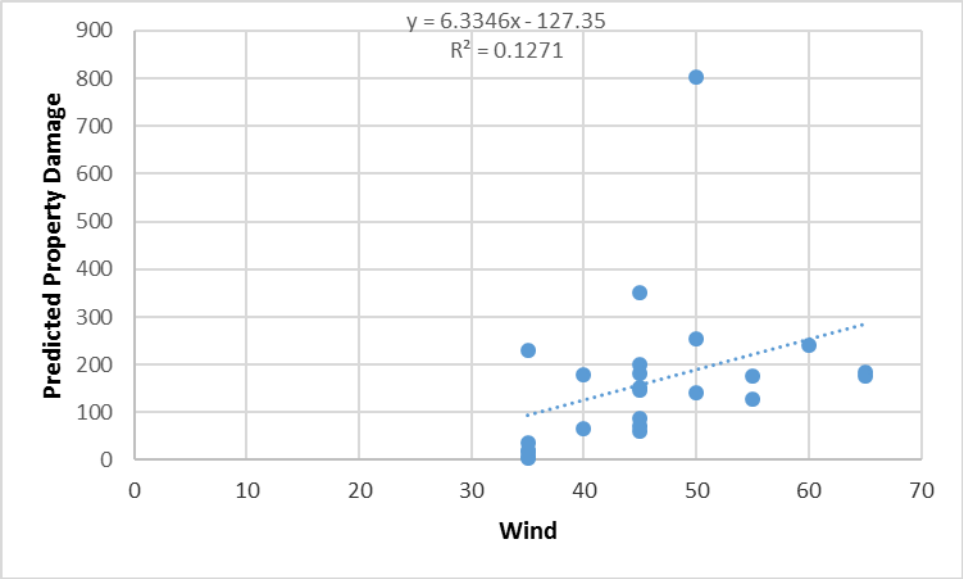

Figure 4.4.5: SLR between Hypothetical Property Damage and Wind around Birmingham

4.5 Hypothetical Scenario: Montgomery-Auburn, Alabama

The Hurricane Katrina track was moved to intersect the Montgomery and Auburn metropolitan area in Alabama by changing the coordinates of Hurricane Katrina using GIS. 24 adjacent counties around the Montgomery and Auburn metropolitan area were selected for this hypothetical analysis. Wind values for Hurricane Katrina for these 24 counties were then matched to the wind values for Hurricane Katrina in Mississippi counties based on their geographical location (Table 4.5.1). Some of the Montgomery and Auburn counties overlap with the Birmingham metropolitan area.

Population density per square miles for these selected 24 counties was collected from the census bureau website and then joined with the attribute table in a GIS shapefile along with their wind values. Maps for Hurricane Katrina wind and population density for these counties around Montgomery-Auburn metropolitan area were then created (Figure 4.5.1 and 4.5.2 respectively).

Table 4.5.1: Wind and Population Density for Hurricane Katrina in Montgomery-Auburn

Mississippi			Montgomery-Auburn, Alabama		
County	Wind (Knots)	Population Density (per sq. miles)	County	Wind (Knots)	Population Density (per sq. miles)
Attala	40	26.6	Autauga	65	91.8
Choctaw	35	20.4	Bibb	40	36.8
Claiborne	35	19.7	Bullock	45	17.5
Clarke	45	24.2	Calhoun	35	195.7
Copiah	35	37.9	Chambers	50	57.4
Hinds	55	282	Chilton	35	63
Jasper	60	25.2	Clay	45	23.1
Kemper	45	13.6	Cleburne	35	26.7
Lauderdale	65	114.1	Coosa	45	17.7
Leake	45	40.8	Dallas	55	44.8
Lowndes	45	118.3	Elmore	50	128.2
Madison	45	133.2	Hale	35	24.5
Montgomery	35	26.8	Lee	65	230.8
Neshoba	50	52.1	Lowndes	45	15.8
Newton	50	37.6	Macon	50	35.2
Noxubee	40	16.6	Marengo	35	21.5
Oktibbeha	45	104	Montgomery	60	292.5
Rankin	65	182.6	Perry	45	14.7
Scott	50	46.4	Randolph	45	39.5
Simpson	55	46.7	Russell	45	82.6
Smith	45	25.9	Shelby	35	248.5
Warren	45	82.9	Talladega	40	111.7
Winston	35	31.6	Tallapoosa	45	58.1
Yazoo	35	30.4	Wilcox	55	13.1

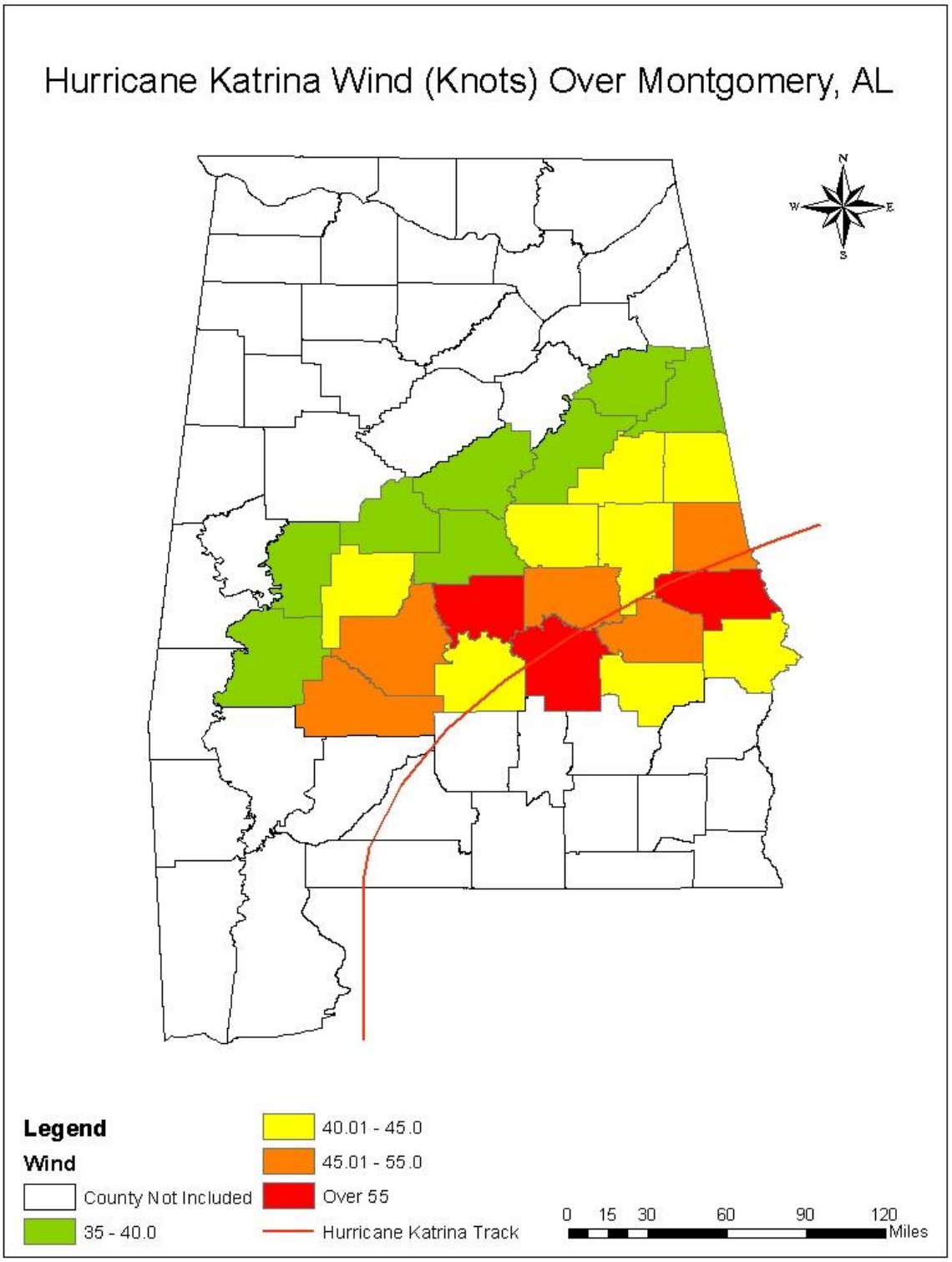

Figure 4.5.1: Hypothetical Wind Values for Hurricane Katrina over Montgomery Metropolitan Area

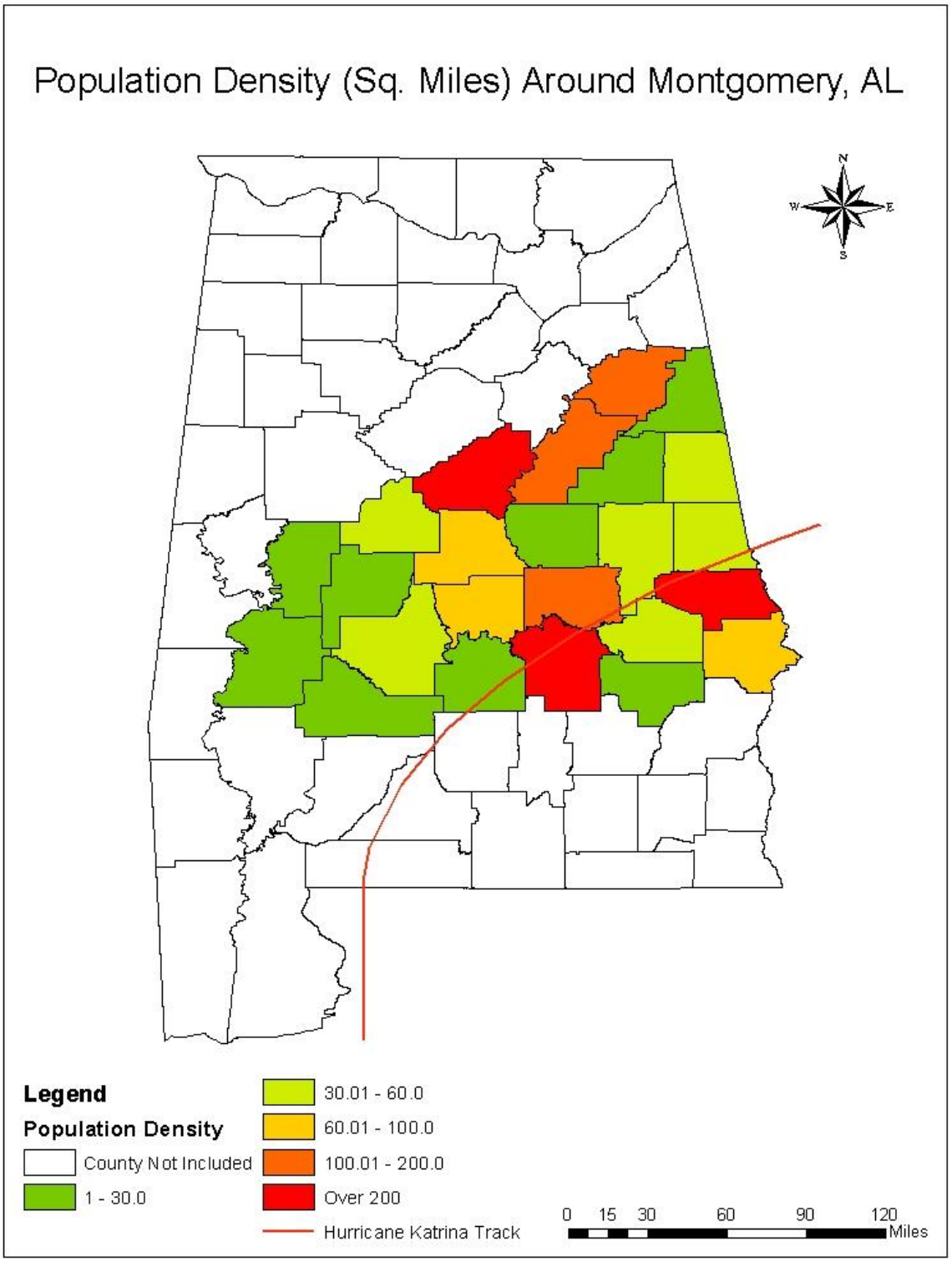

Figure 4.5.2: Population Density around Montgomery Metropolitan Area

As like Birmingham, these wind and population values for the selected 24 counties around Montgomery and Auburn, Alabama were then plotted into the regression model that was created for predicting the property damage for Hurricane Katrina in selected counties in Mississippi. Thus, property damage for Hurricane Katrina around Montgomery and Auburn metropolitan area were predicted (Table 4.5.2 and Figure 4.5.3).

Table 4.5.2: Predicted Property Damage for Hurricane Katrina in Montgomery and Auburn

Mississippi		Montgomery-Auburn, Alabama	
County	Predicted Property Damage (million USD)	County	Predicted Property Damage (million USD)
Attala	47.5842	Autauga	268.1366
Choctaw	11.9348	Bibb	60.2016
Claiborne	11.0689	Bullock	64.3075
Clarke	72.5954	Calhoun	228.7809
Copiah	33.5823	Chambers	141.6438
Hinds	447.454	Chilton	64.631
Jasper	157.7724	Clay	71.2347
Kemper	59.4832	Cleburne	19.7279
Lauderdale	295.7217	Coosa	64.5549
Leake	93.1296	Dallas	154.0376
Lowndes	188.9971	Elmore	229.2234
Madison	207.4284	Hale	17.0065
Montgomery	19.8516	Lee	440.0796
Neshoba	135.0877	Lowndes	62.2046
Newton	117.1512	Macon	114.1824
Noxubee	35.2142	Marengo	13.2955
Oktibbeha	171.308	Montgomery	488.4225
Rankin	380.4562	Perry	60.8439
Scott	128.0368	Randolph	91.5215
Simpson	156.3879	Russell	144.8362
Smith	74.6983	Shelby	294.0945
Warren	145.2073	Talladega	152.8529
Winston	25.7892	Tallapoosa	114.5297
Yazoo	24.3048	Wilcox	114.8247

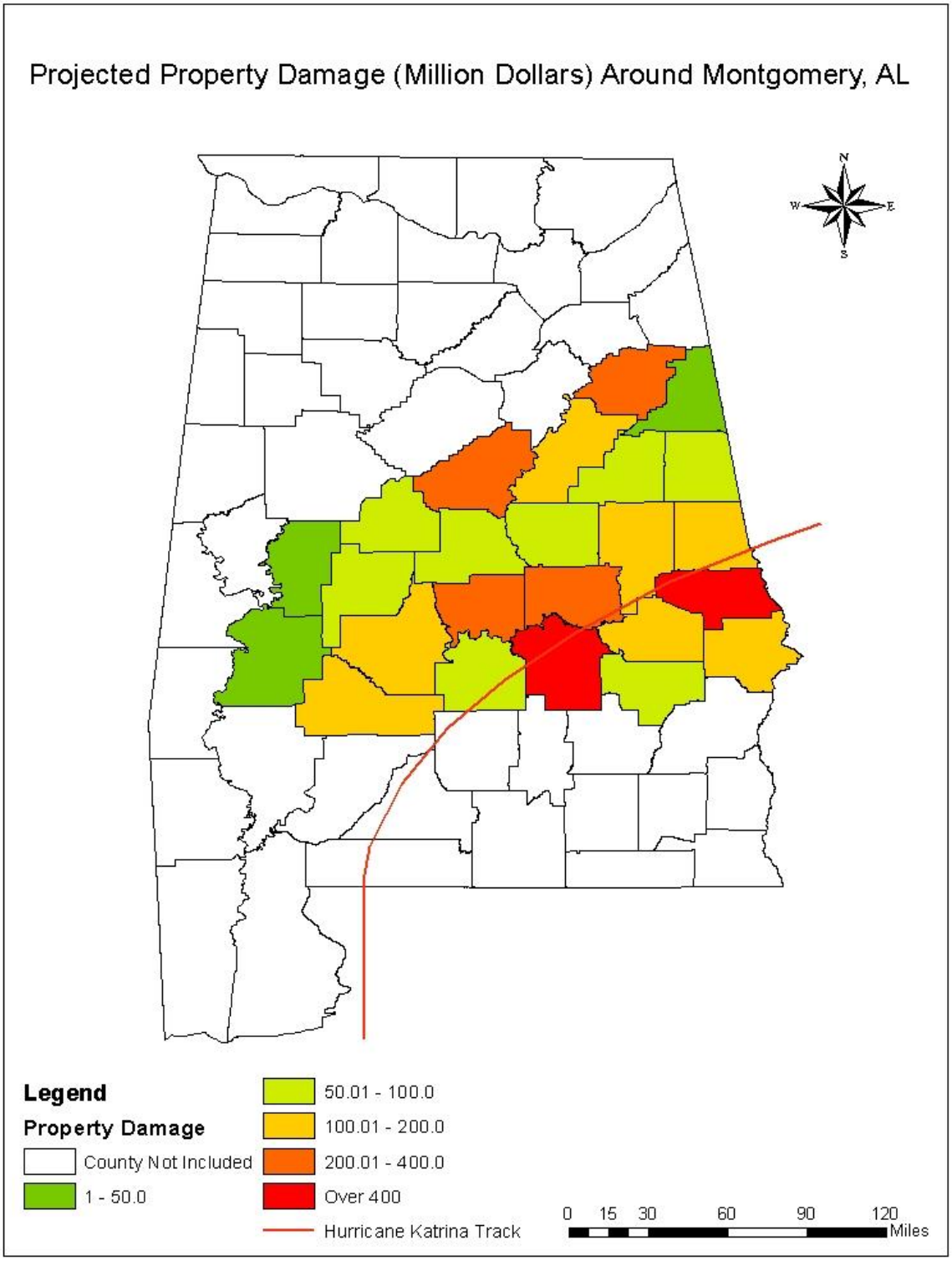

Figure 4.5.3: Hypothetical Property Damage for Hurricane Katrina around Montgomery Metropolitan Area

The correlation matrix (Table 4.5.3) between hypothetically predicted property damage and wind for Hurricane Katrina and population density per square miles in these 24 counties around Montgomery and Auburn metropolitan area suggest that there is a very strong and positive relationship between predicted property damage and population density and wind. The r square value for this correlation is 0.917 which is close to what we got for the predicted property damage and wind for Birmingham metropolitan area (0.949). The correlation coefficient between hypothetical property damage and wind is stronger (0.619) for this area than what we got for Birmingham metropolitan area (0.357).

Table 4.5.3: Correlation Matrix between Hypothetical Property Damage and Wind and Population Density in Montgomery-Auburn, AL

		Wind (Knots)	Population Density (per sq. miles)
Predicted Property Damage	Pearson Correlation	.619	.917
	Significance Level, p	**< 0.001**	**< .001**
	N	24	24

Also, SLR between hypothetical property damage and wind and population density were done individually which shows that there will be an 8.4144 million USD of increased property damage for each knot of wind increase after 35 knots per hour (Figure 4.5.4) and 1.3967 million USD of property damage for adding 1 person per square miles in population density (Figure 4.5.5) in this region.

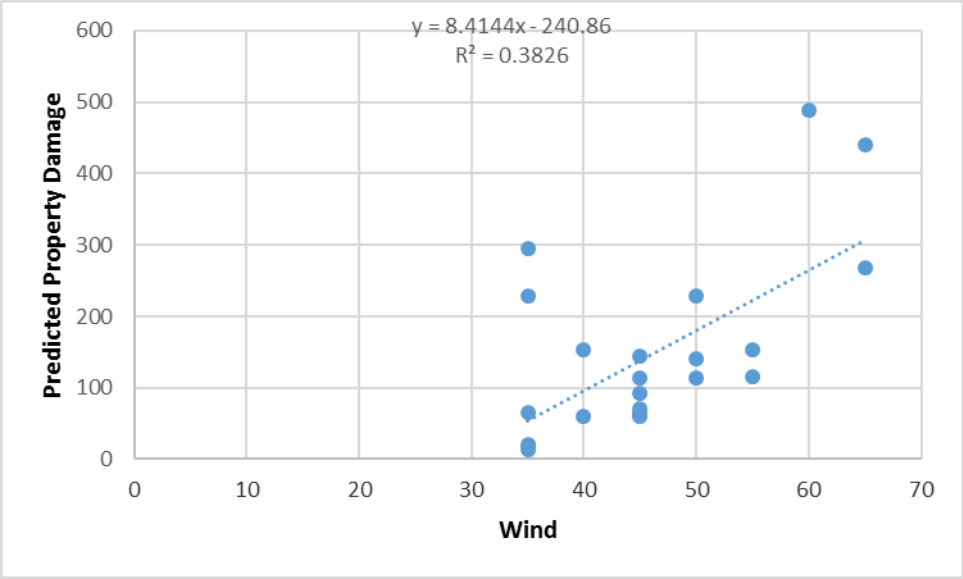

Figure 4.5.4: SLR between Hypothetical Property Damage and Wind for Hurricane Katrina in Montgomery and Auburn

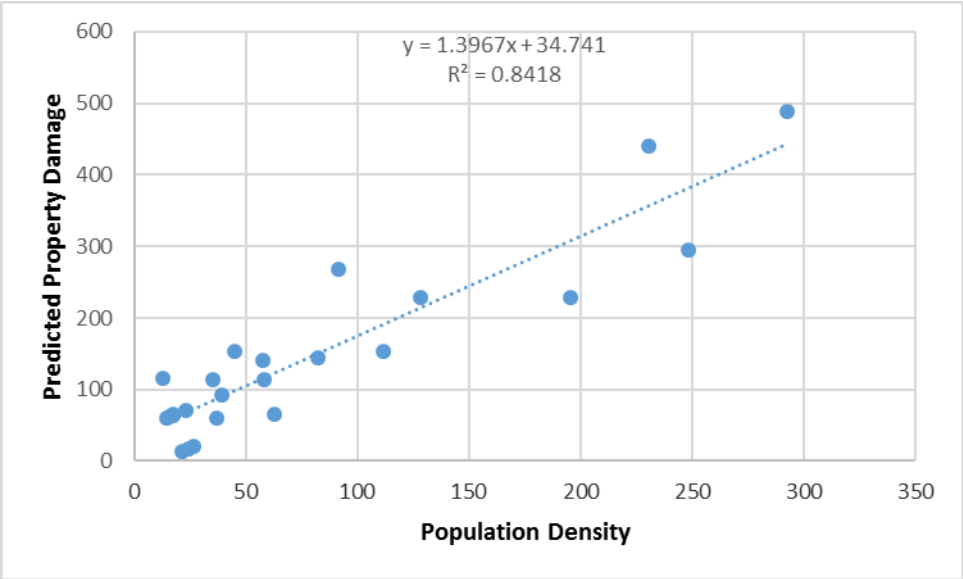

Figure 4.5.5: SLR between Hypothetical Property Damage for Hurricane Katrina and Population Density in Montgomery and Auburn

4.6 Hypothetical Scenario: Atlanta, Georgia

As like Birmingham and Montgomery-Auburn, the Hurricane Katrina track was moved to pass through Atlanta metropolitan area in Georgia. As the counties in Georgia are small relative to counties in Mississippi, 43 counties around Atlanta metropolitan area were selected instead of 24, and their wind values for Hurricane Katrina were matched in the same way that was done for Birmingham and Montgomery (Table 4.6.1).

Maps showing the wind values for Hurricane Katrina and the population density per square miles in these selected 43 counties around Atlanta were created using GIS (Figure 4.6.1 and 4.6.2 respectively).

These values for wind and population density were used in the same regression model that was created for predicting property damage for Hurricane Katrina in Mississippi and property damage for Hurricane Katrina were predicted for Atlanta metropolitan area (Table 4.6.2) and shown on a map using GIS (Figure 4.6.3).

Table 4.6.1: Wind and Population Density for Hurricane Katrina around Atlanta, Georgia

Mississippi		Atlanta, Georgia		
County	Wind (Knots)	County	Wind (Knots)	Population Density (Sq. Miles)
Montgomery	35	Chattooga	35	81.27
Montgomery	35	Gordon	35	155.47
Choctaw	35	Pickens	35	126.98
Choctaw	35	Dawson	35	104.94
Oktibbeha	45	Hall	45	431.68
Lowndes	45	Jackson	45	177.58
Noxubee	40	Oconee	40	181.19
Lowndes	45	Clarke	45	988.81
Noxubee	40	Barrow	40	434.96
Noxubee	40	Gwinnett	40	1927.97
Winston	35	Forsyth	35	765.94
Winston	35	Cherokee	35	510.93
Attala	40	Bartow	40	214.35
Attala	40	Floyd	40	185.44
Yazoo	35	Polk	35	132.15
Yazoo	35	Paulding	35	463.08
Madison	45	Cobb	45	2057.72
Leake	45	Walton	45	258.72
Leake	45	Morgan	45	50.38
Kemper	45	Newton	45	363.55
Neshoba	50	Rockdale	50	652.97
Neshoba	50	Dekalb	50	2608.18
Lauderdale	65	Fulton	65	1809.95
Madison	45	Douglas	45	671.74
Scott	50	Harralson	50	100.87
Newton	50	Carroll	50	222.04
Scott	50	Heard	50	38.77
Rankin	65	Coweta	65	294.78
Rankin	65	Fayette	65	541.49
Hinds	55	Clayton	55	1830.66
Hinds	55	Henry	55	640.24
Simpson	55	Spalding	55	320.39
Kemper	45	Butts	45	124.81
Warren	45	Jasper	45	36.54
Warren	45	Putnam	45	58.85
Claiborne	35	Troup	35	153.32
Copiah	35	Meriwether	35	42.41
Simpson	55	Pike	55	81.22
Smith	45	Lamar	45	97.55
Smith	45	Monroe	45	67.34
Jasper	60	Jones	60	72.79
Jasper	60	Baldwin	60	171.47

Table 4.6.2: Predicted Property Damage for Hurricane Katrina around Atlanta, Georgia

County	Predicted Property Damage (Million USD)
Chattooga	87.23099
Gordon	179.01639
Pickens	143.77426
Dawson	116.51078
Hall	576.64816
Jackson	262.32646
Oconee	238.81203
Clarke	1265.81797
Barrow	552.72552
Gwinnett	2399.57889
Forsyth	934.16778
Cherokee	618.72041
Bartow	279.83095
Floyd	244.06928
Polk	150.16955
Paulding	559.52996
Cobb	2588.05964
Walton	362.69664
Morgan	104.98006
Newton	492.37135
Rockdale	878.36389
Dekalb	3296.95866
Fulton	2393.48815
Douglas	873.60238
Harralson	195.41619
Carroll	345.30348
Heard	118.59849
Coweta	519.22286
Fayette	824.40313
Clayton	2363.14642
Henry	890.59688
Spalding	494.94243
Butts	197.04997
Jasper	87.85998
Putnam	115.45745
Troup	176.35684
Meriwether	39.16117
Pike	199.08914
Lamar	163.32935
Monroe	125.95958
Jones	216.64123
Baldwin	338.70839
Hancock	66.02693

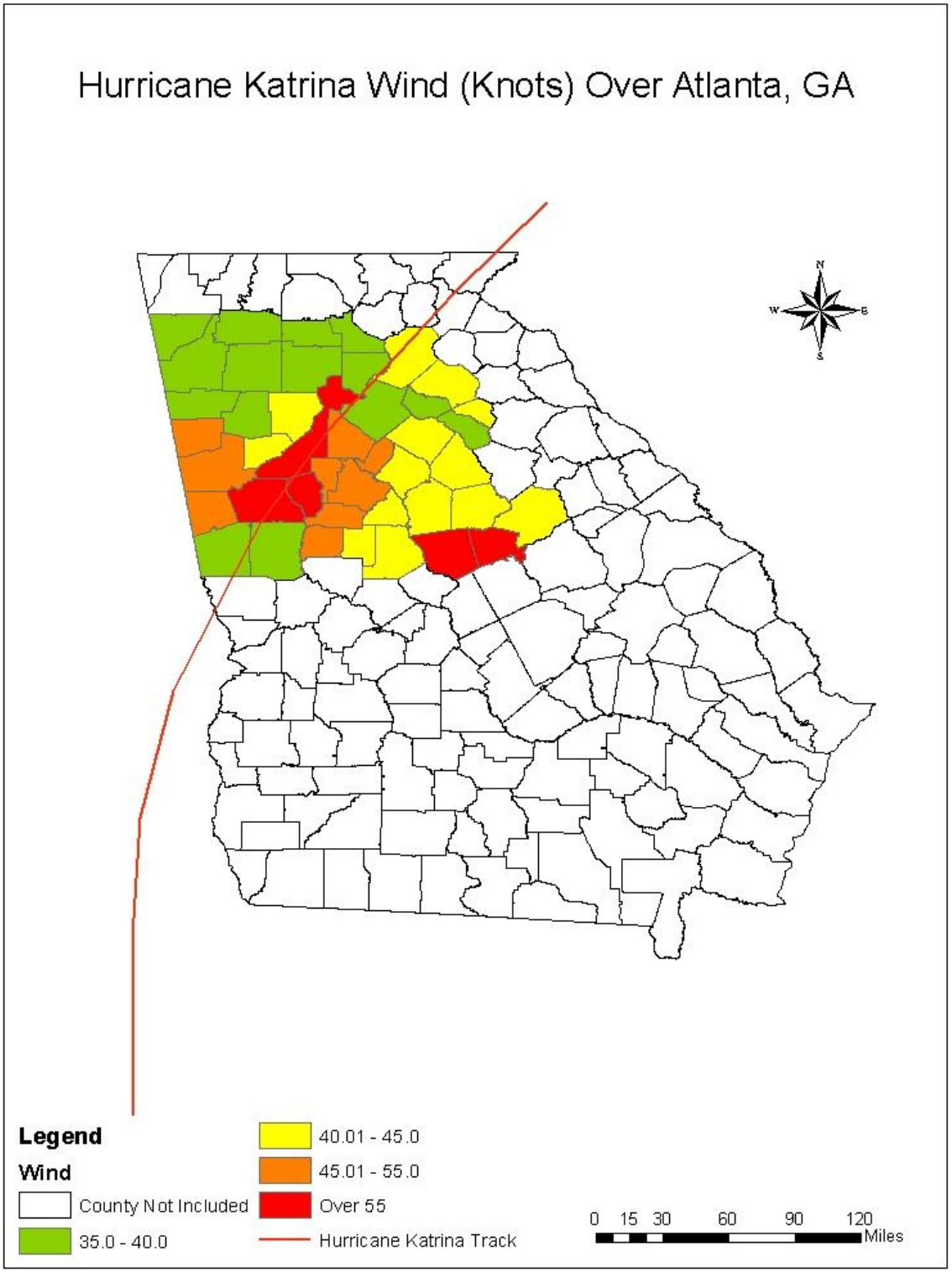

Figure 4.6.1: Hypothetical Wind Values for Hurricane Katrina over Atlanta Metropolitan Area

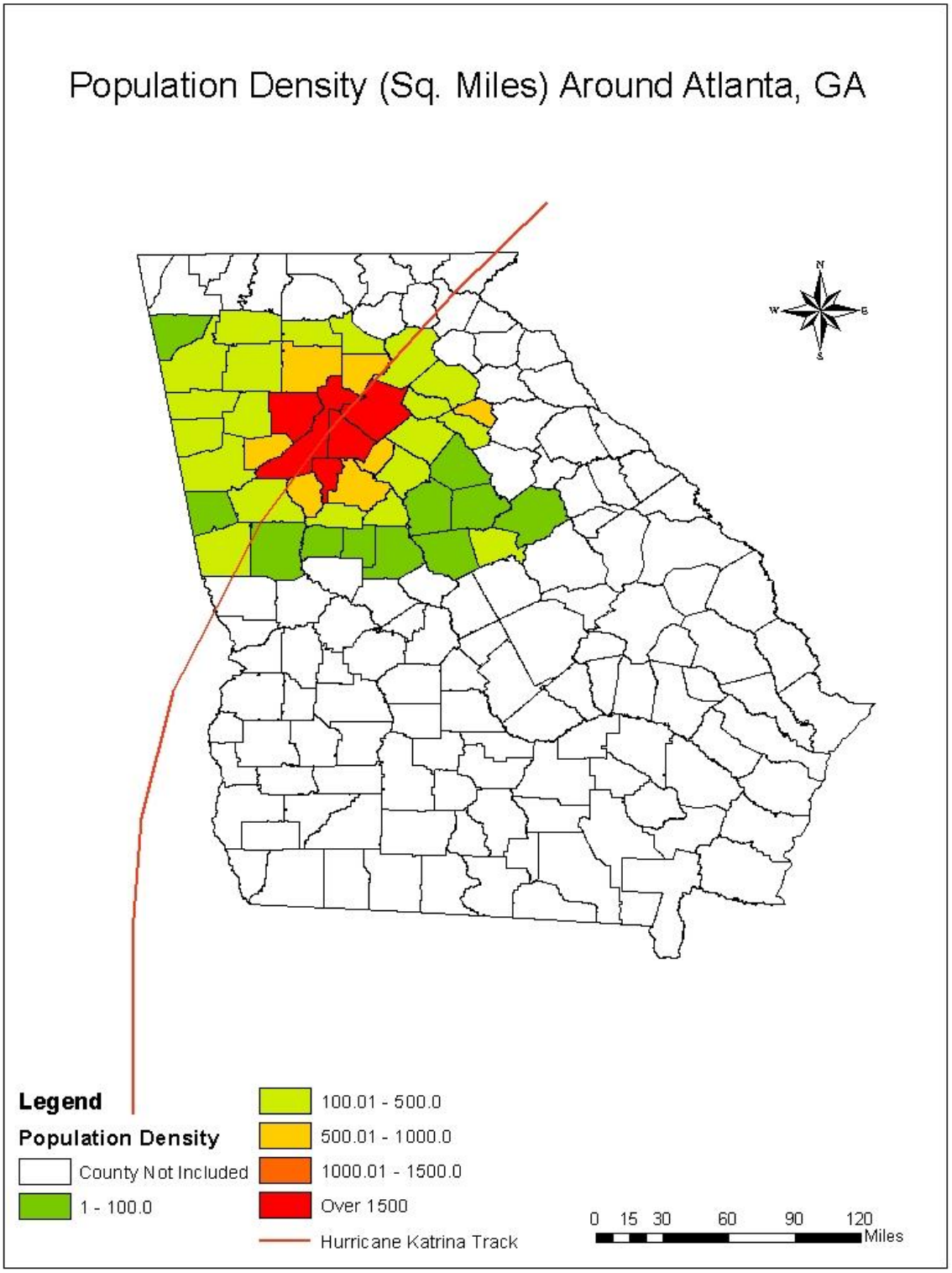

Figure 4.6.2: Population Density around Atlanta Metropolitan Area

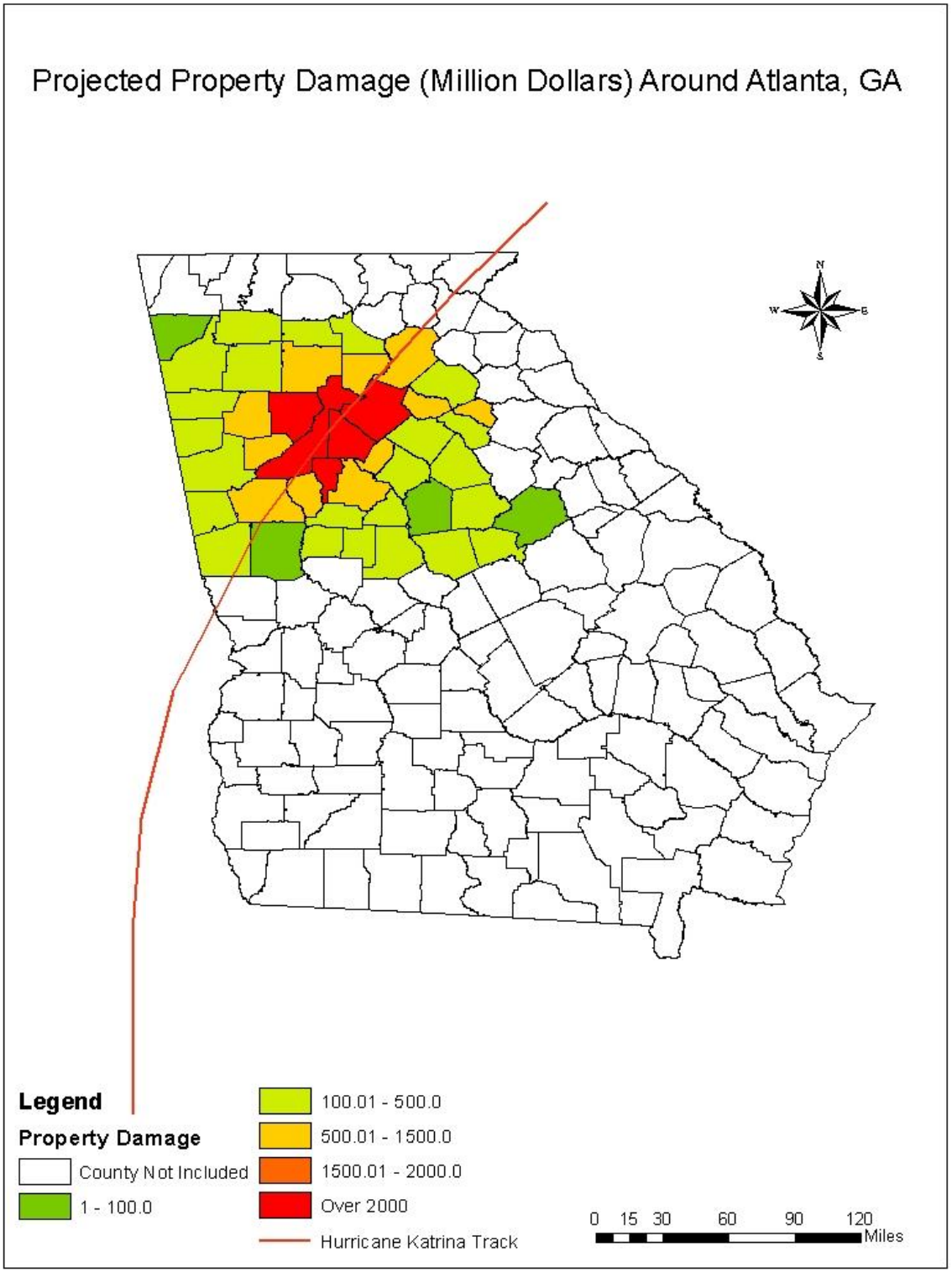

Figure 4.6.3: Hypothetical Property Damage for Hurricane Katrina around Atlanta Metropolitan Area

The correlation matrix (Table 4.6.3) between hypothetical property damage and wind and population density for Hurricane Katrina around Atlanta metropolitan area shows that there is a nearly perfect correlation exists between predicted property damage and population density (r square value of 0.998) which is statistically significant (significance level below 0.001). That means a slight increase in population density will increase property damage dramatically. Correlation between wind and predicted property damage was found weak (0.270) for this region.

Table 4.6.3: Correlation Matrix between Hypothetical Property Damage and Wind and Population Density around Atlanta Metropolitan Area

		Wind (Knots)	Population Density (per sq. miles)
Predicted Property Damage	Pearson Correlation	.270	.998
	Significance Level, *p*	0.40	**< 0.001**
	N	43	43

Individual SLR with hypothetical property damage and wind and population density showed that there will be a 24.157 million USD of increased property damage for each knot of wind increase after 35 knots per hour (Figure 4.6.4) and 1.2536 million USD of property damage for increasing population density of 1 person per square miles (Figure 4.6.5) in this region.

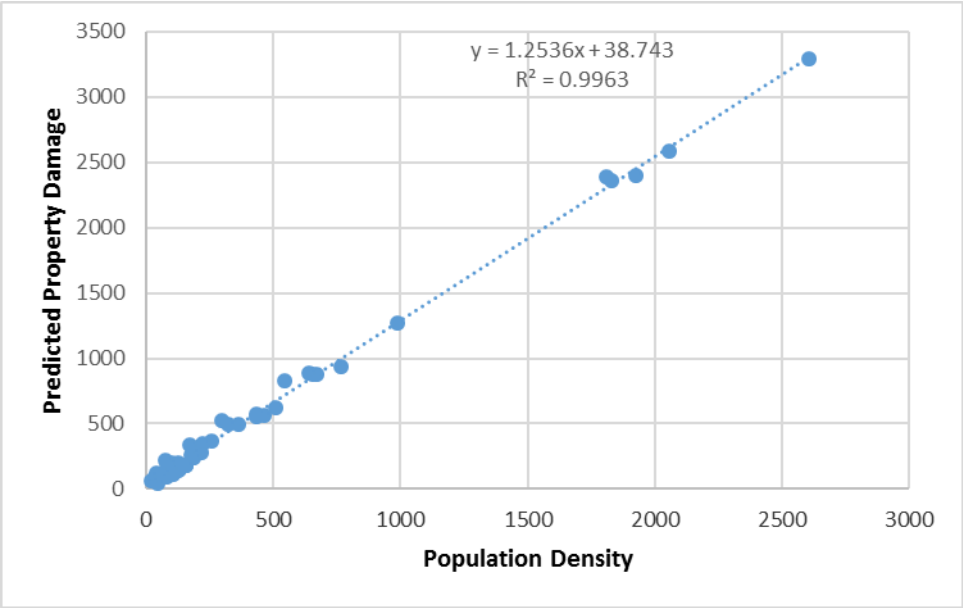

Figure 4.6.4: SLR between Hypothetical Property Damage and Population Density around Atlanta

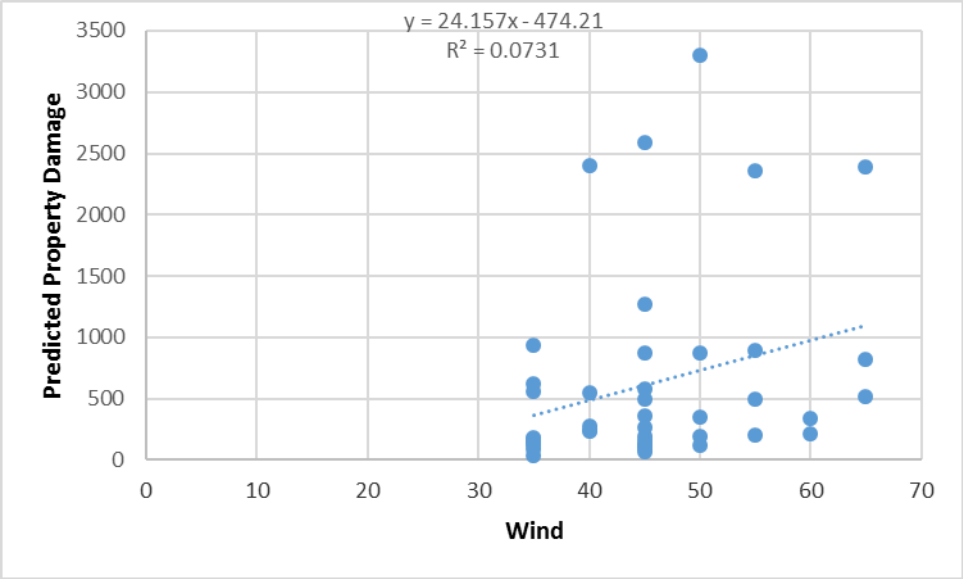

Figure 4.6.5: SLR between Hypothetical Property Damage and Wind around Atlanta

CHAPTER FIVE: CONCLUSION

The purpose of this research was to determine the physical hazards and social characteristics that explain property damage for Gulf of Mexico tropical cyclones. A number of research questions were proposed at the beginning of this thesis in order to analyze the relationship between tropical cyclone property damage and social and physical vulnerability. What makes the inland areas of this region vulnerable to tropical cyclone-related property loss? Does this vulnerability differ between urban and rural counties? Is the amount of property damages associated with tropical cyclones related to the level of vulnerability?

The first research question was answered by performing correlation and regression analysis between property damage and physical storm characteristics (rain, wind, and tornado) and social vulnerability. It was found from the analysis that tropical cyclone wind is the most significant factor behind property damage followed by hurricane-induced tornadoes and tropical cyclone rainfall in this region. However, these findings contradict previous research where fresh-water flooding from heavy rain associated with tropical cyclones is the main factor behind inland damage.

For the second research question, it was found that vulnerability regarding property damage differs between urban and rural counties. The level of vulnerability was found to be different among the inland counties of Louisiana, Mississippi, and Alabama. Mississippi was found as the most affected state regarding property damage. It is mainly because of Hurricane Katrina as this storm went right through Mississippi and had a huge impact on the results.

Overall, urban counties and surrounding metropolitan areas had more property damage than the rural counties.

For the third research question, vulnerability was assessed from both social and physical perspectives in this research. Physical vulnerability was assessed by analyzing the physical characteristics of the last 20 year's tropical cyclones (rain, wind, and tornado) and social vulnerability was assessed through the indicators of social vulnerability. Despite many counties being socially vulnerable, it was found that property damage was highest in the areas where the level of physical vulnerability was more. No significant results were found between property damage and social vulnerability.

One of the reasons behind this could be the low median household income in the study area. The mean value of average household income of this region was found $35,000 which is considerably lower than the average median household income of the entire USA. According to the census bureau, in 2014, average median household income in the USA was $51,939. However, if casualties due to tropical cyclones would have been taken into account, social vulnerability would have most likely played a larger role.

Hurricane Katrina had a huge influence on the dataset and dominated the results. This was illustrated through the correlation and regression analysis with property damage and physical storm characteristics and social vulnerability indicators. Without Hurricane Katrina included in the dataset, no significant relationship was found between property damage and social and physical vulnerability indicators.

Central Mississippi was directly affected by Hurricane Katrina, and this part of the study area had high property damage from this storm. The higher population density near Jackson, MS along with heavy wind associated with Hurricane Katrina were the main reasons for the extreme

property damage from Hurricane Katrina in Mississippi. Results of hypothetical analyses also showed that property damage would be enormous if an intense storm like Hurricane Katrina tracked over an area with high population density. The findings of this research are beneficial to the policy makers and emergency managers in the Southeastern USA region. The results help explain the intersection between physical storm characteristics and social vulnerability for predicting future tropical cyclone property damage. The results suggest high-density areas could face an enormous amount of property damage if a big storm like Katrina passes over major metropolitan areas in this region. The dollar values provided for these hypothetical scenarios establish a reasonable estimate of economic loss. This might be helpful in mitigation and preparedness planning and implementation prior to an intense inland tropical system.

REFERENCES

Ashley, S. T., and W.S. Ashley. 2008. Flood fatalities in the United States. *Journal of Applied Metereology and Climatology* 47: 805-818.

Anderson, M. B. 2000. Understanding the disaster-development continuum: gender analysis is the essential tool. *Gender & Development* 2 (1): 7-10.

Babugura, A. 2010. Gender and Climate Change: South Africa Case study. *Southern Africa*: https://www.boell.de/sites/default/files/assets/boell.de/images/download_de/ecology/south_africa.pdf (Last accessed February 16, 2017).

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

Blake, E. S. and E. J. Gibney. 2011. NOAA Technical Memorandum NWS NHC-6 , *The Deadliest, Costliest, and Most Intense United States Tropical Cyclones from 1851 to 2010 (And other frequently requested hurricane facts*. Last accessed February 24, 2017.

Bianchi, S.M. and D. Spain. 1996. Women, work, and family in America. Population Reference Bureau. *Population Bulletin* 51(3): 48.

Blake, E. S., T. B. Kimberlain, R. J. Berg, J. P. Cangialosi, and J. L. Beven II. National Hurricane Center, *Tropical Cyclone Report Hurricane Sandy 22-29 October 2012*. Last accessed February 24, 2017.

Burton, I., R. W. Kates, and G. F. White. 1993. *The Environment as Hazard*. New York, NY: The Guilford Press.

Cotten, S. R., and S. S. Gupta. 2004. Characteristics of online and offline health information seekers and factors that discriminate between them. *Social Science & Medicine* 59(9): 1795–1806.

Cutter, S. L. 1996: Vulnerability to environmental hazards. *Progress in Human Geography*, 20 (4): 529-539.

Cutter, S., J. Mitchell, and M. Scott. 2000. Revealing the Vulnerability of People and Places: A Case Study of Georgetown County, South Carolina. Annals of the Association of American Geographers 4: 713-737.

Cutter, S. L., B. J. Boruff, and W. L. Shirley. 2003. Social vulnerability to environmental hazards. *Soial Science Quarterly* 84 (2): 242-261.

Cutter, S. L. and C. T. Emrich. 2011. Social Vulnerability to Climate-Sensitive Hazards in the Southern United State. Weather Climate And Society 3(3): 193-208.

Czajkowski, J. and E. Kennedy. 2010. Fatal Tradeoff? Toward a better understanding of the costs of not evacuating from a hurricane in landfall counties. Population and Environment 31(1-3): 121-149.

Czajkowski, J., K. Simmons, and D. Sutter. 2011. An analysis of coastal and inland fatalities in landfalling US hurricanes. *Natural Hazards* 59: 1513-1531.

Davidson, R., and K. Lambert. 2002. Comparing the Hurricane Disaster Risk of U.S. Coastal Counties. *Natural Hazards Review*: 132-142.

Doocy, S., A. Daniels, S. Murray, and T. D. Kirsch. 2013. The human impact of floods: a historical review of events 1980-2009 and systematic literature review. *PLOS Currents* 5: doi:10.1371/currents.dis.f4deb457904936b07c09daa98ee8171a.

Dickson, E., J. L. Baker, and D. Hoornweg. 2012. *Urban Risk Assessments: Understanding Disaster and Climate Risk in Cities*. Washington, D.C.: World Bank Publications, 118-149.

Dwyer, A., C. Zoppou, O. Nielsen, S. Day, and S. Roberts. 2004. Quantifying social vulnerability: a methodology for identifying those at risk to natural hazards. *Geoscience Australia Record* 14: 1-5.

Elsner, J. B., J. P.Kossin, and T. H. Jagger. 2008. The increasing intensity of the strongest tropical cyclones, *Nature* 455: 92-95.

Enarson, E. and B. Morrow. 1997. A gendered perspective: The voices of women, in W.G. Peacock, B.H. Morrow and H. Gladwin, (eds.), Hurricane Andrew: Ethnicity, Gender, and the Sociology of Disasters, International Hurricane Center, Laboratory for Social and Behavioral Research, Miami, FL, 116–140.

Enarson, E., and B. Morrow. 1998. *The Gendered Terrain of Disaster*. New York, NY: Praeger, 226-242.

Flanagan, B. E., E. W. Gregory, E. J. Hallisey, J. L. Heitgerd, and B. Lewis. 2011. A Social Vulnerability Index for Disaster Management, *Journal of Homeland Security and Emergency Management*, 8(1): doi: https://doi.org/10.2202/1547-7355.1792

Fothergill, A. *The neglect of gender in disaster work: An overview of the literature', in E. Enarson and B.H. Morrow (eds.), The Gendered Terrain of Disaster: Through Women's Eyes.* (Westport, CT: Praeger Publishers, 1998), 11–25.

Galea, S., N. Freudenberg, and D. Vlahov. 2005. Cities and population health. *Social Science and Medicine* 60 (5): 1017–1033.

Gladwin, H. and W.G. Peacock. 1997. Warning and evacuation: A night for hard houses, in W.G. Peacock, B.H. Morrow and H. Gladwin (eds.), Hurricane Andrew: Ethnicity, Gender, and the Sociology of Disasters, International Hurricane Center, Laboratory for Social and Behavioral Research, Miami, FL, 52–74.

Green, R., L. K. Bates, A. Smyth. 2007. Impediments to recovery in New Orleans upper and lower Ninth Ward: one year after Hurricane Katrina. *Disasters* 31 (4): 311–335.

Hewitt, K. Regions of Risk: A Geographical Introduction to Disasters. (Essex, U.K.: Longman: 1997), 378.

Heinz Center for Science, Economics, and the Environment. *The Hidden Costs of Coastal Hazards: Implications for Risk Assessment and Mitigation.* (Covello, Cal.: Island Press, 2000).

Holand, I. S., P. Lujala, and J. K. Rod. 2011. Social vulnerability assessment for Norway: A quantitative approach. *Norsk Geografisk Tidsskrift - Norwegian Journal of Geography* 65(1): 1-17.

Jonkman, S. N., B. Maaskant, E. Boyd, and M. L. Levitan. 2009. Loss of life caused by the flooding of New Orleans after Hurricane Katrina: analysis of the relationship between flood characteristics and mortality. *Risk Analysis* 29 (5): 676-698.

Kaplan, J., M. DeMaria. 1995. A Simple Empirical Model for Predicting the Decay of Tropical Cyclone Winds After Landfall. *Journal of Applied Meteorology* 34(11): 2499-512.

Knabb, R. D., J. R. Rhone, and D. P. Brown. National Hurricane Center, Tropical Cyclone Report Hurricane Katrina 23-30 August 2005. Last accessed March 12, 2017.

Konrad C., M. F. Meaux, and D. A Meaux. 2002. Relationships between Tropical Cyclone Attributes and Precipitation Totals: Considerations of Scale. *International Journal of Climatology* 22(2): 237-247.

Kruk, M. C., E. J. Gibney, D. H. Levinson, and M. Squires. 2010. A Climatology of Inland Winds from Tropical Cyclones for the Eastern United States. *Journal of Applied Meteorology and Climatology* 49: 1538-1547.

Kuhlicke, C., A. Scolobig, S. Tapsell, A. Steinführer, and B. De Marchi. 2011. Contextualizing social vulnerability: findings from case studies across Europe. *Natural Hazards* 58 (2): 789-810.

Kunkel K., R. Pielke, and S. Changnon. 1999. Temporal fluctuations in weather and climate extremes that cause economic and human health impacts: a review. *Bulletin of the American Meteorological Society* 80(6): 1077-1098.

Liverman, D. M. 1990. Vulnerability to global environmental change. *Environmental Risks and Hazards*. Prentice-Hall, Englewood Cliffs, NJ, USA, pp. 326–342.

Mendelsohn, R., K. Emanuel, S. Chonabayashi, and L. Bakkensen. 2012. The Impact of Climate Change on Global Tropical Cyclone Damage. *Nature Climate Change* 2: 205-209.

Mestre, O. and S. Hallegatte. 2008. Predictors of Tropical Cyclone Numbers and Extreme Hurricane Intensities over the North Atlantic Using Generalized Additive and Linear Models. *American Meteorological Society*: doi: 10.1175/2008JCLI2318.1

Mileti, D. 1999. *Disasters by Design: A Reassessment of Natural Hazards in the United States*. Washington, D.C.: Joseph Henry Press.

Morrow, B. H., and B. Phillips. 1999. What's Gender 'Got to Do With It'? *International Journal of Mass Emergencies and Disasters* 17(1): 5–11.

Muttarak, R. and W. Lutz. 2014. Is education a key to reducing vulnerability to natural disasters and hence unavoidable climate change? *Ecology and Society* 19(1): 42.

Ngo, E. B. 2001. When Disasters and Age Collide: Reviewing Vulnerability of the Elderly. *Natural Hazards Review* 2(2): 80–89.

Neuenschwander, L. M., A. Abbott, and A. R. Mobley. 2012. Assessment of low-income adults' access to technology: implications for nutrition education. *Journal of Nutrition Education and Behavior* 44(1):60–65.

O'Brien, P., and D. Mileti. 1992. Citizen Participation in Emergency Response Following the Loma Prieta Earthquake. *International Journal of Mass Emergencies and Disasters* 10: 71–89.

O´Keefe, P. K. Westgate, and B. Wisner. 1976. Taking the naturalness out of natural disasters. *Nature*: 260.

Peacock, W., B. H. Morrow, and H. Gladwin. 1997. *Hurricane Andrew and the Reshaping of Miami: Ethnicity, Gender, and the Socio-Political Ecology of Disasters.* Miami, FL: Florida International University, International Hurricane Center, 60-66.

Paul, B. *Environmental Hazards and Disasters*. 2011. West Sussex, UK : John Wiley & Sons, Ltd.

Pelling, M. Vulnerability in Cities. 2003. London, UK: Earthscan Publications, 60-66.

Pielke, R. Jr., J. Rubiera, C. Landsea, M. Fernández, and R. Klein. 2003. Hurricane Vulnerability in Latin America and The Caribbean: Normalized Damage and Loss Potentials. *Natural Hazards Review*: doi: 10.1061/(ASCE)1527-6988(2003)4:3(101), 101-114.

Platt, R. 1995. Lifelines: An Emergency Management Priority for the United States in the 1990s. *Disasters* 15:172–76.

Pompe, J., and J. Haluska. 2011. Estimating the Vulnerability of U.S. Coastal Areas to Hurricane Damage, Recent Hurricane Research - Climate, Dynamics, and Societal Impacts. ISBN: 978-953-307-238-8.

Powell M. D., P. Dodge, and M. L Black. 1991. The Landfall of Hurricane Hugo in the Carolinas: Surface Wind Distribution. *Weather and forecasting* 6: 379.

Psacharopoulos, G., and H. A. Patrinos. 2002. Returns to investment in education: a further update. *Education Economics* 12(2): 111-118.

Radford, L., J. C. Senkbeil, and M. Rockman. 2013. Suggestions for alternative tropical cyclone warning graphics in the USA. *Disaster Prevention and Management: An International Journal* 22(3): 192-209.

Rappaport, E. N. 2000. Loss of life in the United States associated with recent Atlantic tropical cyclones. *Bulletin of the American Meteorological Society* 8(9): 2065-2073.

Rappaport, E. N. 2014: Fatalities in the United States from Atlantic Tropical Cyclones: New Data and Interpretation. *Bulletin of the American Meteorological Society* 95: 341–346.

Rhodes, C. L., and J. C. Senkbeil. 2014. Factors contributing to tornadogenesis in landfalling Gulf of Mexico tropical cyclones. *Meteorological Applications* 21(4): 940-947.

Schmidlin, T. W. 2009. Human fatalities from windrelated tree failures in the United States, 1995–2007. *Natural Hazards* 50: 13-25.

Schmidt, S., C. Kemfert, and P. Höppe. 2009. Tropical cyclone losses in the USA and the impact of climate change — A trend analysis based on data from a new approach to adjusting storm losses. *Environmental Impact Assessment Review* 29: 359 –369.

Senkbeil, J. C., D. M. Brommer, and I. J. Comstock. 2011. Tropical Cyclone Hazards in the USA. *Geography Compass* 5(8): 544-563.

Singha, P. C. 2006. *Disasters Vulnerabilities and Risks*. New Delhi, India: SBS Pulishers & Distributors.

Steinführer, A., and C. Kuhlicke. 2007. Social vulnerability and the 2002 flood: country report Germany (Mulde River). FLOODsite Report T11-07-08.

Stewart, Stacy. Nation Hurricane Center, *Tropical Cyclone Report Hurricane Ivan 2-24 September 2004*. Last accessed February 17, 2017.

Sund, E.R., and S. Krokstad. 2005. *Sosiale ulikheter i helse i Norge – en kunnskapsoversikt*. S*osial- og helsedirektoratet, rapport.* (Social inequalities in health in Norway – a review of knowledge.) Oslo. *Sosial og Helsedirektoratet.*

Swiss Reinsurance Company Ltd. 2013. Mind the Risk: A global ranking of cities under threat from natural disasters. Zurich, 5-27.

Tierney, K. J., M. K. Lindell, and R. W. Perry. 2001. *Facing the Unexpected: Disaster Preparedness and Response in the United States*. Washington, D.C.: Joseph Henry Press.

Turner, B. L., R. E. Kasperson, and P. A. Matson et al. 2003. A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences* 14: 8074-8079.

Vlassoff, C. 1994. Gender inequalities in health in the third world: Uncharted ground. *Social Science & Medicine* 39(9): 1249-1259.

Walker, M., R. Whittle, W. Medd, K. Burningham, J. Moran-Ellis, and S. Tapsell. 2012. 'It came up to here': learning from children's flood narratives. *Children's Geographies* 10 (2): 135-150.

Wamsler, C., E. Brink, and O. Rantala. 2012. Climate change, adaptation, and formal education: The role of schooling for increasing societies' adaptive capacities in El Salvador and Brazil. *Ecology and Society* 17(2): 2.

Wen, L. M., C. Rissel, L. A. Baur, E. Lee, and J. M. Simpson. 2011. Who is NOT likely to access the Internet for health information? Findings from first-time mothers in southwest Sydney, Australia. *International Journal of Medical Informatics* 80(6): 406–411.

Willoughby, H., E. Rappaport, and F. Marks. 2007. Hurricane forecasting: the state of the art. *Natural Hazards Review* 89(3): 45-49.

http://hurricanes.noaa.gov (Last accessed April 20, 2017).

http://www.nhc.noaa.gov/data/#hurdat (Last accessed April 27, 2017)

http://www.hwind.co/legacy_data/ (Last accessed May 6, 2017)

http://www.noaa.gov/ (Last accessed April 22, 2017)

http://www.nhc.noaa.gov/ (Last accessed May 7, 2017)

http://www.wpc.ncep.noaa.gov/tropical/rain/tcrainfall.html (Last accessed April 25, 2017)

http://www.census.gov/ (Last accessed April 17, 2017)

https://www.ncdc.noaa.gov/stormevents/ (Last accessed April 24, 2017)