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# Assessing Inland Hazards Associated With Hurricanes In The U.S. Atlantic Basin

Dereka LaTrese Carroll
*Purdue University*

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J. Eric Dietz

Robert J. Trapp

James Done

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# ASSESSING INLAND HAZARDS ASSOCIATED WITH HURRICANES IN THE U.S. ATLANTIC BASIN

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by

Dereka Carroll

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"I can do all things through Christ who gives me strength." -Philippians 4:13

This thesis is dedicated to my two guardian angels, Chrissie Mae Young and Sherry Vanessa Thomas, may they rest in peace.

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# ABSTRACT

Carroll, Dereka M.S., Purdue University, August 2014. Assessing Inland Hazards Associated with Hurricanes in the U.S. Atlantic Basin. Major Professor: Robert J. Trapp.

The skill of tropical-cyclone (TC) track forecasts has steadily improved over the past decades, as has the understanding of TC risk in coastal regions. However, there is still much to be learned about the TC risk in inland regions, which is complicated by the presence of coastal evacuees, and includes hazards such as inland flash flooding and tornadoes. This was exemplified by Hurricane Ivan (2004), which spawned 118 tornadoes and produced significant rainfall amounts contributing to flooding inland. Ivan was responsible for 25 deaths in the U.S. and $18.8 billion (2004 USD) in damages. As part of a larger effort to improve the decision support tools available to emergency managers, this project seeks to map the inland U.S. hazards associated with TCs in the Atlantic Basin.

The specific hazards of TC-associated flash flooding (TCFF) and tornadoes (TCT) are assessed over approximately the last two decades using GIS. The highest TCFF hazard is indicated in southern Mississippi, Alabama, North Carolina and the Mid Atlantic Region, and TCT hazard is highest in the same region as TCFF, including Florida; stream-gage data additionally show that the highest TC-flood potential is in southern Florida. The TCFF and TCT data are smoothed at a county/parish level and

then combined with a quantification of the social vulnerability of the exposed populations to derive a hurricane disaster risk index. The disaster risk index is also used in experiments with agent based modeling to assess evacuation behavior.

# CHAPTER 1. BACKGROUND INFORMATION

## 1.1 Defining Risk and Assessing Hurricane Fatalities

### 1.1.1 Definitions

Before one can begin to discuss disaster risk, it is important to identify what risk is in relation to its proposed use. For this thesis, the following definition of disaster risk as described in IPCC (2012) applies: Disaster risk is defined as the possible adverse effects deriving from interactions between social and environmental processes. The combined effects of the physical hazard and the vulnerability drive this risk. Hazard is the pending occurrence of a physical natural or man made event adversely effecting a vulnerable population or exposed element. Lastly, exposure references the population within the domain of the hazard. Using these definitions, disaster risk is therefore:

$$\text{Risk} = \text{Hazard} \times \text{Vulnerability} \times \text{Exposure} \tag{1.1}$$

Note that if the population and associated resources are not located or exposed to the hazard, then disaster risk would be nonexistent. IPCC (2012) also discusses the distinction between vulnerability and exposure, which are commonly, yet mistakenly interchanged. For example, low-income residents would have little ability to rebuild their homes if a disaster occurs, and thus would have high vulnerability. On the other hand, these same residents must live in a hazard-prone region, i.e., be exposed to a hazard in order to be deemed vulnerable. (IPCC 2012

For the purpose of this thesis, the hazards are the wind (implicitly defined in the domain), flooding and tornadoes associated with an Atlantic-Basin tropical system making landfall in the U.S. The exposed populations are considered all those within the hazard region. Vulnerability pertains to social aspects such as age, gender, income, and race.

### 1.1.2 Hurricane Fatalities

The hazards that hurricanes pose to communities are well known (NOAA 2012; Davidson and Lambert 2002; Pomp and Haluska 2011). Figure 1 shows a decline in the number of fatalities by decade with some credit given to well-timed evacuations from storm surge flood zones (Rappaport 2000; Willoughby et al. 2007). However, Czajkowski and Kennedy (2010) mention that when the number of inland deaths due to flooding is included, there is not a downward trend in the lethality of these tropical cyclones. Indeed, although great efforts have been made to decrease the lethality of hurricanes near landfall (Kunkel et al. 1999; Rappaport 2000; Sadowski and Sutter 2005; Baker et al. 2007), fewer efforts have focused on inland communities, being that the main impacts are along the coast. Strong winds, tornadoes and flooding rains accompany the tropical cyclone as it moves over land (Czajkowski and Kennedy 2010). The overall risk of inland communities is difficult to assess due to the omission of fatalities from freshwater flooding in the official statistics (Czajkowski et al. 2011). Despite this, research has shown that freshwater flooding is the cause of the majority of tropical cyclone related deaths. In fact, about 63% of deaths from 1970-99 occurred inland, at distances as much as hundreds of miles from the coast (Fig. 1.2; see Rappaport 2000).

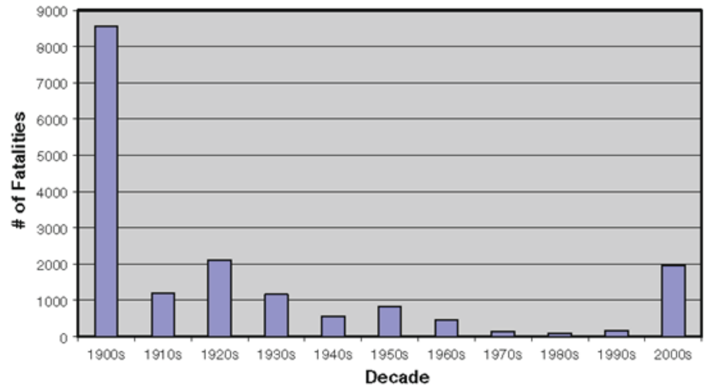



Figure 1.1 Tropical storm-related fatalities in the U.S. by decade. Fatalities exceeded 1000 in the first four decades of the twentieth century, and then gradually fell to under about 200 through the 1990s. In 2005, hurricane Katrina noticeably reversed this downward trend. (Czajkowski et al. 2000)

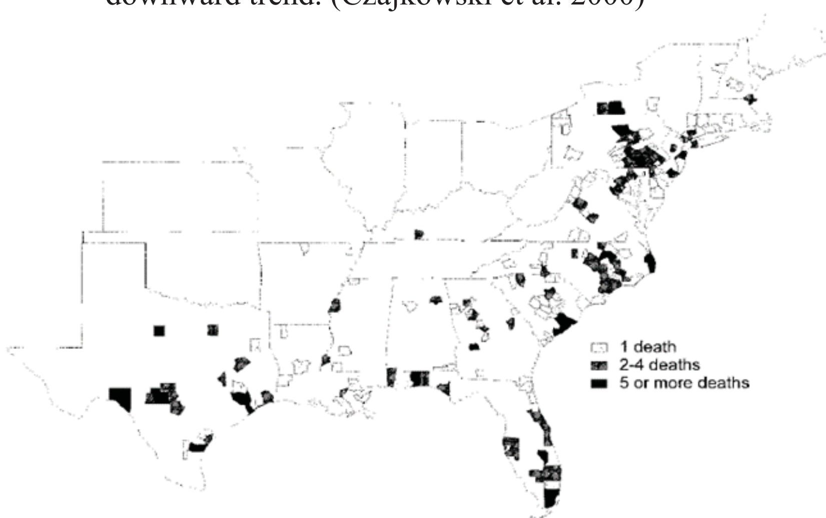



Figure 1.2 Geographical distributions of 468 deaths in the contiguous United States associated with Atlantic tropical cyclones during 1970-99. Map excludes remaining 132 cases occurring offshore or where county or parish could not be identified (Rappaport 2000).

## 1.2 Tropical Cyclone Hazards

### 1.2.1 Tornadoes

Tropical cyclone tornadoes (TCTs) are often unexpected and are difficult to forecast during tropical cyclone events. This is in part what makes this phenomenon interesting to the research community. One would think that TCTs are a relatively new discovery but records of TCT events date as far back as 1811. It is uncommon, however, to have more than a few tornadoes per tropical cyclone, and until Hurricane Beulah only a few TCT events per storm were recorded on average. There are a few anomalous cases in which over a hundred tornadoes were spawned, such as the aforementioned Hurricane Beulah 1967 (115 TCTs), Hurricane Frances 2004 (103 TCTs), and Hurricane Ivan 2004 (117 TCTs). Such events create major forecasting issues and can place evacuating populations in the path of TCTs. Although the majority of TCT events are on the lower end of the Fujita- and Enhanced-Fujita scale, stronger tornadoes have occurred. For this reason, an updated climatology and assessment of tornado hazard is essential to decreasing the lethality of Atlantic Basin hurricanes.

TCTs are commonly found in the outer rainbands, 200-400 km from the cyclone center. However, McCaul (1991) found that some tornadoes have formed within the eye wall and inner core. The right front quadrant (RFQ) of the TC is favored for tornado development due to its ample convective available potential energy (CAPE) and vertical wind shear (McCaul, 1991; Verbout et al. 2007). It is also found that TCs making landfall along the U.S. Gulf Coast are more likely to produce tornadoes since that coast is exposed to the RFQ longer than landfalling TCs in the Atlantic that obliquely strike the U.S. coast (Verbout et al. 2007). The curvature of TCs is also known to affect tornado development. Using synoptic composites of 83TCs, Verbout et al. (2007) showed that mid latitude troughs provide additional deep-layer and low-layer vertical wind shear to re-curving TCs which favor mesocyclogenesis and tornadogenesis respectively.

### 1.2.2 Flooding

Flooding is the second most fatal natural disaster in the U.S., after heat, with trends increasing since the mid-20th century (Kunkel et al. 1999; Pielke and Downton 2000; Pielke et al. 2002; Downton et al. 2005). Several factors contribute to flood events, including rainfall totals/rate, topography, land use of the affected region, soil type, watershed type, and prior moisture conditions in the flood region (Ashley and Ashley 2008). Orography also has an impact on flooding. Hart and Evans (2001) found there was minimal flooding in regions directly upwind and downwind of the Appalachian Mountains. In central Texas, the Balcones Escarpment results in a dramatic descent of the elevated topography into the flat lands. Less rainfall is required to reach peak discharge, and thereby causes this area to be prone to severe flooding (Abbott et al 1986).

Flooding is defined in three categories according to the National Weather Service (NWS): flash flooding, river flooding, and coastal flooding. Flash flooding occurs as a result of heavy rain over a short period of time; the convention is six hours. River flooding occurs due to an overflow of its natural banks, causing threatening damage. Lastly, coastal flooding is a result of storms pushing water onto land from an adjacent body of water.

Flooding has a range of socioeconomic impacts that contribute both to life loss and economic loss. Certain flood characteristics contribute to fatalities, such as the water depth, velocity of the flow, and rise rate. Socio-economic and behavioral factors also contribute to fatalities, such as reception of a flood warning, response (or lack thereof) in the form of evacuation and sheltering, and failure of structure (Jonkman et al 2009). Historically, roughly 90% of flood related fatalities are due to flash flooding, with roughly 40% of those related to vehicles that cross streams and standing water (French et a. 1983; Zevin 1994); this is suggestive of a disregard to, or lack of understanding of the danger posed by flooding. In Mooney's (1983) study, 60% of flood fatalities between 1977 and 1981 occurred in urban areas, with 75% of those fatalities occurring during evening and overnight hours. A more recent study by Ashley and Ashley (2008) shows that 63% of fatalities in which location of death was known, occurred in vehicles. The age group of victims are primarily less than 20 years of age and older than 60 years of age. In terms of gender, the majority of the victims were males, of which 35% were between the ages of 10 and 29 (Ashley and Ashley 2008).

Distinctive seasonal peaks in flooding fatalities were noted by Ashley and Ashley (2008). In June and July summer months, peak fatalities were seen in the eastern and central portions of the U.S. This finding is largely attributed to the amount of convective rainfall in this area, during this time period. The large number of fatalities in August and September are attributed to monsoon rains in the southwest, and to tropical cyclones in the southeast; over all months, 20% of all flood related fatalities are a result of tropical cyclones. What is interesting to note is that the peak month for tropical cyclones is in September, while the peak fatalities are in August (41%). East coast states in general, along with states along the Gulf of Mexico are most susceptible to the most tropical storm fatalities. Specifically focusing on TC-related fatalities (between 1970 and 1999), Rappaport (2000) found that 82% of deaths were a result of drowning, in particular, 52% of all TC related deaths were due to freshwater flooding. More recently, Rappaport (2013) showed that storm surge caused 50% of TC fatalities (between 1963 and 2012), and rain contributed to 27% of TC fatalities (Fig. 3b). However, the percent occurrence of rain fatalities (~47%) surpasses that of surge deaths (10%) for deadly cyclones (Fig. 3a); the same is true for all Atlantic TCs (~9.5% rain, ~2.1% surge). This information suggests that although more storm surge deaths have occurred, it is more likely to have fatalities as a result of rain events.

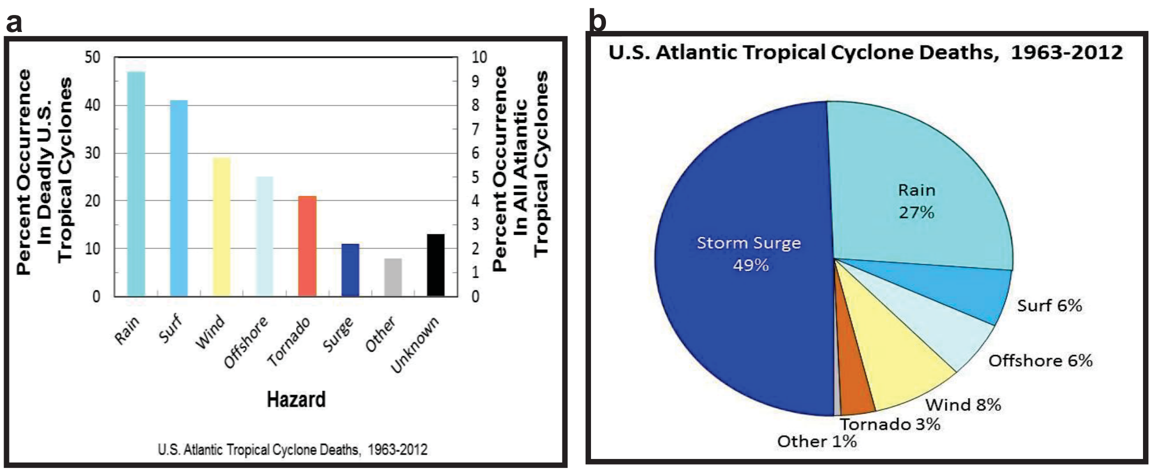



Figure 1.3 (a)Percent occurrences of fatalities from 1963 to 2012 due to Atlantic tropical cyclones (right scale) and deadly U.S. tropical cyclones (left scale) in which noted types of fatalities occurred in the United States. (b) Cause of death in the United States directly attributed to Atlantic tropical cyclones, 1963 to 2012. (Rappaport 2013)

Jonkman et al (2009) conducted a more detailed study on life loss due to flooding during Hurricane Katrina. Hurricane fatality studies have excluded fatalities due to Katrina, because the total number was unknown and there were ongoing investigations on the cause of deaths for many evacuees. This study, however, aimed to provide a link between flood characteristics (flow velocity, rise rate and flood arrival time) and mortality, defined here as the number of fatalities divided by the exposed population. The exposed population can be calculated as the difference of the original population at risk minus the evacuated and sheltering population. Mortality will be highest near the breaches, areas with large water depth, high rise rate, and large building collapses or infrastructure failure, which from the Ashley and Ashley (2008) study made up 12% of the fatalities as a low probability high impact event. Jonkman et al. (2009) suggest that mortality can be crudely estimated as at least 1% of the exposed population.

## 1.3 Decision Support Tools for Hurricane Preparedness and Disasater Management

### 1.3.1 Hurricane Disaster Risk Index

The significant decrease in hurricane losses have corresponded with the development of decision support tools such as the Hurricane Disaster Risk Index (HDRI) (Davidson and Lambert 2002). Commonly after natural disasters, an assessment of the social vulnerability of the impacted communities is performed so that the efficiency of emergency management capabilities can be enhanced in the future. These assessments can also aid in identifying areas most at risk for natural hazards (Tapsell et al. 2010). The HDRI is a composite index created to compare the risk of hurricane disasters in U.S. coastal counties. It was designed to support the local, state, and national agencies that: 1) make resource allocations and decisions, 2) make high-level planning decisions, and 3) raise public awareness of hurricane risks. The developers of HDRI identified the factors that contributed to economic and life loss during hurricanes in the U.S., such as geographic location, topography, and socio economic status. Next, measurable scalar indicators were chosen to represent each of the previously identified factors, based on their ability to be represented in the conceptual framework and on the availability of data in the U.S. After that, a mathematical index was developed to combine the indicators into two composite index values, one representing economic loss and the second representing life disaster risk. The four factors that were included in the HDRI are: 1) hazard, 2) exposure, 3) vulnerability, and 4) emergency response and recovery capability (Davidson and Lambert 2002). Since the HDRI is limited to coastal hazards and there are clear indicators of increased losses of lives inland due to tropical cyclones, an additional index is needed that will include both inland and coastal vulnerabilities.

#### 1.3.2 Hurricane Evacuation Tool

The HURRicane EVACuation tool (HURREVAC) is one of the current decision support tools for emergency managers. It was produced by the National Hurricane Program (NHP). NHP is a partnership between the Federal Emergency Management Agency (FEMA), U.S. Army Corps of Engineers (USACE), and the National Oceanic and Atmospheric Administration (NOAA). HURREVAC was developed and is maintained by Sea Island Software.

HURREVAC incorporates hurricane tracks, forecasts and advisories from the NOAA/National Hurricane Center, and individual state hurricane evacuation studies (HES). Information such as storm arrival time and potential hazards such as storm surge and wind are included. Emergency managers use this tool to keep track of the storm as it travels inland, and has the potential of becoming a threat to inland communities.

While HURREVAC is very effective in providing real time hurricane information, paired with risk information for the emergency region, it does not have the capability to track the risk and associated vulnerabilities as those residents move to safety. This serves as partial motivation for the work presented herein.

### 1.3.3 Modeling Hurricane Evacuations

#### 1.3.3.1 Agent Based Modeling

Following hurricane events, the evacuation behaviors and details are often assessed by organizations such as the USACE. Information collected in such assessments may include: distance traveled to flee danger, destination type, likelihood of evacuating, and source of evacuation and hurricane information (http://www.csc.noaa.gov/hes/about.html). This information allows decision makers to gain insight into the strengths and weaknesses of their evacuation procedures. It also offers insight into what future evacuations will be like should the event occur again, and what changes should be made to mitigate future disaster.

A common practice by emergency management agencies is to conduct full-scale exercises to practice procedures during emergency events. A full-scale exercise for hurricane evacuations is not feasible, however, due to the magnitude of the event and the scale on which evacuations for this weather phenomenon take place. Therefore evacuation simulation tools and models are developed using behavioral information from the aforementioned surveys, as well as from census data and risk assessments to test evacuation scenarios and behavior during hurricane events. An example of such a simulation is shown in Zou et al. (2005), who built an interactive emergency evacuation tool, or principle component model for Ocean, City Maryland. The principle model consists of five modules, the Input module, consisting of the control parameters and model base; the Optimization module generates the most optimal routes; the Simulation module analyzes traffic conditions based on the model input; the Database module stores the various scenarios from the input, as well as allow the user to load new scenarios while the simulation is still running; and lastly the Output module displays the custom output from the simulation runs. Essentially their tool is able to perform real-time simulations of traffic conditions integrated with an optimization model that assesses the best possible evacuation plan under the current traffic conditions.

Agent-based modeling has also been demonstrated as an effective tool in modeling hurricane evacuation decisions. This type of modeling tool allows one to simulate "interactions of autonomous agents in various environments" (Macal and North 2005). The agents are unique in that they can make decisions based on their pre-described environment; the agents can also interact with other agents in their environment (Zhang et al. 2009). Zhang et al. (2009) developed an agent-based model to capture how humans behave on the household level during the evacuation process. The main goal of their research was to assess how the proportion "normal" and "greedy" agents affected the efficiency of evacuation. Greedy agents were allowed to switch evacuation routes if their original route became congested, and normal agents followed a specified route regardless of the congestion on that route. Zhang et al. showed that greedy agent behavior can reduce the amount of time it takes for an individual agent to reach its destination. However, having a high percentage of greedy agents in the environment reduces the efficiency of overall evacuations. Another example of agent-based models of hurricane evacuations is that of Chen et al. (2006). The purpose of their study was to assess the ideal amount of time to evacuate 92,596 residents from the Florida Keys, and to determine how many evacuees would be stranded on the Overseas Highway (U.S. Highway 1) serving as the only route out of the Keys if it were to become impassable as a result of flooding. Along with the census data of residents in the Keys, the study included the number of tourists that would also need to evacuate. Chen et al. found that their clearance time of 20 hr and 14 min was less than the 24-hr clearance time mandated in Florida. Another interesting finding was that if people evacuated 48 hours ahead of the storm, with a traffic flow observed in a previous hurricane event, then only about 460 people would be stranded if the road became impassable after that period. However if that 48-hr period was reduced to 40 hours, then 14,000 evacuees would be stranded under the same traffic flow. In both examples of agent-based models, not only were agents assigned to the environment with allocated behavior (e.g. greedy, normal, tourist, motorists), but traffic information and rules such as stop lights, traffic speed, and congested roads were used to create realism of an event on a micro scale. The capabilities seen in agent based modeling are very beneficial in simulating large scale events that otherwise would not be able to be exercised.

These studies and others (e.g. Zhan 2008; Hasan et al. 2011; Hasan and Ukkusri 2011) show the benefit in agent based modeling and other simulation tools for hurricane evacuations. While the models are beneficial in their respected aspects, little is known about the dynamic behavior of evacuations. More specifically, there is a current lack of knowledge of how the evacuees change the vulnerability of the communities in which they inhabit. Resources such as shelter, food, and even mobility become limited in a community when there is an influx of evacuees. Disaster risk also changes in ways that are often overlooked in inland communities. Hurricanes not only pose a threat to coastal communities who may flee the storm, but inland communities as well due to tropical cyclone tornadoes and inland flooding. People seeking shelter can inherently increase the vulnerability, thereby possibly increasing the risk of disaster in the area to which they flee. This information is not well known and has not been included in the aforementioned risk surveys.

As will be shown in Chapter 6, the research herein will capitalize on AnyLogic (http://www.anylogic.com/use-of-simulation), a tool that will be used to model the dynamic variability in risk due to hurricane hazards. AnyLogic is a modeling tool with the functionality to use three dynamic simulation platforms independent of each other, or in combination. Systems Dynamic, Discrete Event and Agent Based modeling are common simulation methodologies that many different businesses and entities use to dynamically simulate the complexities of various economic and social and business systems.

## 1.4 Risk Assessment Procedures

According to Session 6-Handbook-GIS Based Hazard Assessment (Cutter et al. 1997), the schematic below represents the steps necessary in preparing a hazard assessment, which is the basic goal of the research presented herein. These steps are slightly modified and incorporate efforts to assess the inland hazards of hurricanes that make mainland U.S. landfall from the Atlantic Basin. It is expected that this research will be an addition to methods currently used to prepare for and mitigate against hurricane disaster.

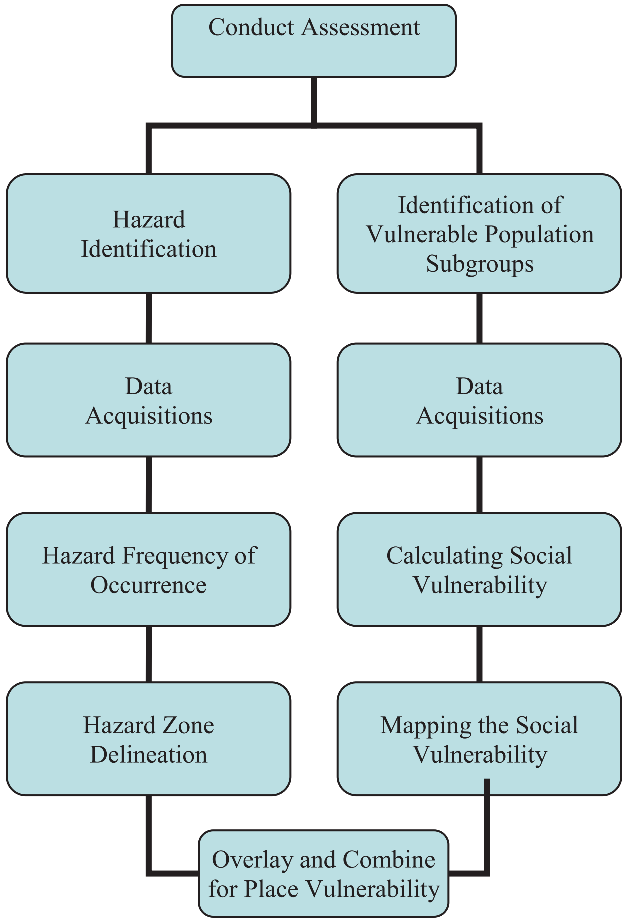



Figure 1.4 Risk assessment procedures adapted from Cutter et. al 1997

The first step in conducting an assessment is to identify the hazard as well as to determine the vulnerable populations and subgroups. Next, data from each category are acquired using available resources. Thirdly, an analysis of the hazard frequency and calculation of social vulnerability is done. The fourth step defines the hazard zone and maps the social vulnerability. Lastly both simultaneous processes are overlaid on one map to assess the hazard risk as defined for this research. The remaining steps listed in the hazard assessment procedures, which are beyond the immediate scope of the current research include: Identify special needs, identify lifelines and infrastructure, and add context to place vulnerability.

The components of the procedure in Fig. 1.4 frame the research to be presented in the subsequent chapters. The objective of this research is to develop a risk index that includes the main threats to inland communities. In Chapter 2, the social vulnerability is assessed. Chapter 3 develops the hazard map for tropical cyclone tornadoes. In Chapter 4, tropical cyclone flooding, particularly flash flooding is assessed and Chapter 5 brings together all of the aforementioned components into a risk map. Chapter 6 uses AnyLogic to show an example of the dynamic variability of risk. Chapter 7 summarizes this research, providing a brief discussion, conclusions and future work.

# CHAPTER 2. ASSESSNG THE EXPOSURE AND SOCIAL VULNERABILITY TO HURRICANES IN THE ATLANTIC BASIN

Development of the exposure and social vulnerability maps is discussed in this chapter. Compared to previous vulnerability maps, this map focuses solely on potential life loss in lieu of economic losses. The first step in the developmental process is to determine the impacted region, which is followed by a quantification of the spatial variability of social vulnerability. Implicitly, the impacted region is also the exposed region, and thus the methodology presented below also serves to develop the exposure map.

## 2.1 Methodology

### 2.1.1 Determining Hurricane Impact Regions

The hurricane impact region is assessed by identifying the TC-producing severe winds the farthest inland, in each region of the Atlantic. Once this is done, the severe wind swaths will be combined, forming the hazard domain, which will be large enough so that all possible tropical cyclone tornado and flash flood cases will be included. This process is further discussed below.

#### 2.1.1.1 50 kt Wind Extent

Vickery (2005) found that modeling the decay of storms is crucial to accurately assessing the vulnerability to wind damage. Instead of modeling the decay of wind speed as in Kaplan and DeMaria (1995; 2001), the decay of central pressure is modeled. Vickery (2005) also noted that hurricane models that simulate decaying central pressure are also able to give a mathematical representation of the hurricane wind field using the gradient wind balance equation combined with information on the characteristics of tropical cyclones (translation speed, central pressure and radius to maximum winds). Therefore, the steps taken here to determine the inland extent of damaging tropical cyclone winds are as follows:

1. Obtain the historical landfalling tropical cyclone track data from 1988-2010 using IBTrACS data (Knapp et al. 2010);
2. Extract storm variables (including pressure difference between the storm center and the environment, translation speed, and the radius of maximum winds) and calculate the storm decay rate (a), following Vickery (2005);

$$a = ao + a1(\Delta poVT/RMW) \qquad (2.1)$$

where VT is the translation speed, RMW is the radius of maximum winds, ao is the intercept, and a1 is the slope in this linear regression equation. The specific regression equations below are for different regions follow Vickery (2005):

| | | |
|---|---|---|
| Gulf Coast: | $a = 0.0413 + 0.0018\ (\Delta poVT/RMW)$; | (2.2) |
| Florida Peninsula Coast: | $a = 0.0225 + 0.0017\ (\Delta poVT/RMW)$; | (2.3) |
| Mid-Atlantic Coast: | $a = 0.0364 + 0.0016\ (\Delta poVT/RMW)$; | (2.4) |
| New England Coast: | $a = 0.0034 + 0.0010\ (\Delta poVT/RMW)$; | (2.5) |

3. Substitute the decay rate a from Eq. (2.2), (2.3), (2.4), or (2.5) into the Vickery (2005) filling model. The filling model is in the form of an exponential decay function:

$$\Delta p(t) = \Delta po \exp(-at) \tag{2.6}$$

where Δ p(t), is the central pressure difference in hPa between the storm center and the far field pressure (assumed to be a constant 1013mb) t hours after landfall. Δpo is the pressure difference (in hPa) at the time the storm makes landfall.

4. Convert the pressure decay to wind decay using gradient wind balance (see Holland et al. 2010 for details):

$$v_c = \left[ \frac{100 b \Delta p_s \left( \frac{r_{v_m}}{r} \right)^b}{\rho e^{\left[ \frac{r_{v_m}}{r} \right]^b}} \right]^{0.5} \tag{2.7}$$

where vc is the wind decay, b is the scaling parameter defining the proportion of pressure gradient near the radius of maximum winds, Δps is the pressure drop from a predefined external pressure to the center of the cyclone, ρ is the air density at the gradient level, r is the radius and rvm is the radius of maximum winds.

5. Extrapolate winds down to the surface using a constant factor of 0.72 and account for wind gusts using a constant factor of 1.25, both following Vickery (2005), and convert winds from storm relative to ground relative by adding the storm translation speed:

$$v = 1.25 \times (vc \times 0.72) + VT\_lf \tag{2.8}$$

where vc is the surface wind speed, and VT_lf is the storm translation speed.

6. Determine the farthest reach of 50 kt wind speed from the historical storm dataset for each of the four regions of the U.S. coast. The 50 kt threshold was chosen because it is the magnitude of wind that is defined as severe by the NWS. The historical storms by region and 50 kt wind maximum include:

New England: Hurricane Floyd 1999, 50kt winds 2100 km inland

Mid-Atlantic: Hurricane Hugo 1989, 50kt winds 1780 km inland

Florida Peninsula: Hurricane Gabrielle 2001, 50kt winds 990 km inland

Gulf Coast: Tropical Storm Opal 1995, 50 kt winds 930 km inland

Thus, the maximum inland extent of 50 kt winds for the four regions occurred between 930 and 2100 km reaching beyond the coast, well into the inland areas (Fig 2.1). This domain will be further modified cutting off Colorado, New Mexico, and the western portion of Texas, due to the 0 value of the TCT hazard (See Chapter 3).

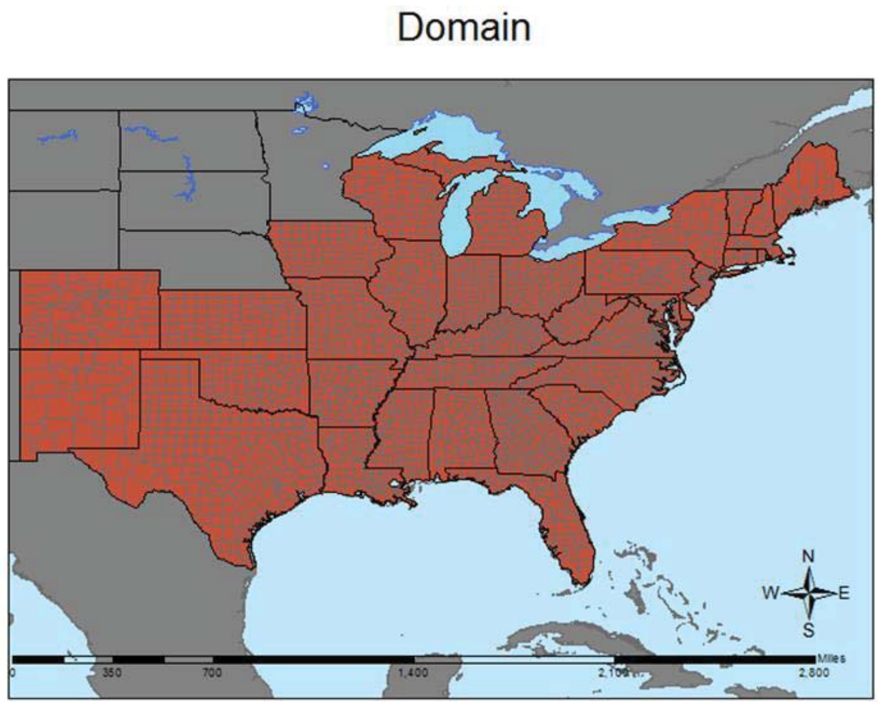



Figure 2.1 Hazard domain as defined by states impacted by severe winds.

### 2.1.2 Assessing and Mapping Social Vulnerability

Recalling from Chapter 1 that vulnerability here pertains only to social aspects, the following definitions for social vulnerability specifically will apply:

"The characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impact of a natural hazard … It involves a combination of factors that determine the degree to which someone's life, livelihood, property and other assets are put at risk by a discrete and identifiable event … in nature and in society." (Wisner et al. 2004)

"…social factors that place people in highly exposed areas, affect the sensitivity of people to that exposure, and influence their capacity to respond and adapt." (Yarnal 2007)

The former is a broader definition, whereas the latter is more specific to people and how society tends to place them in harm's way.

The components of social vulnerability listed in Parker et al. (2009) and Tapsell et al. (2010) include security, economic, and social. Security includes the safety and stability of the built environment, along with effective response and minimal disruption in daily life. Economic refers to the access of resources available to communities that are considered socially vulnerable; conditions prior to a hazard have an effect on the quality of life post hazard event. Lastly, social characteristics include demographic factors (age, gender, disability etc.) that influence the sensitivity of a communities risk to hazards.

#### 2.1.2.1 Vulnerability Factors and Indicators

Most vulnerability assessments have been developed using the "top down" approach that makes general assumptions for the whole; this is the approach used here. Even though such an approach ignores small-scale or local drivers of vulnerability, factors are generally chosen to identify vulnerable populations within limitations posed by data restrictions and other factors. In this regard, assumptions about what makes a community vulnerable may be incorrect. For example, a community with a large population over age 65 may be deemed relatively more vulnerable under the assumption that the majority of these residents are immobile and cannot care for themselves. However, in the case of

Hurricane Andrew, many elderly residents did not evacuate because of “familiarity” to hurricanes, not because they had no means of leaving (Peacock et al. 1997, p. 66). Despite this limitation, this approach is useful in that it gives a detailed enough assessment on the county level that one could glean valuable information regarding the social vulnerability.

### 2.1.3 Developing the Social Vulnerability Map

The demographic factors discussed here and listed in Table 2.1 were chosen to be included in this study based on evidence from existing statistical and theoretical studies in the literature.

Age is one of the most commonly used vulnerability factors (Blaike et al. 1994; Davidson and Lambert 2002; Cutter, et al. 2000; O’Brien and Mileti 1992; Hewitt 1997; Ngo 2001; Cutter et al. 2003). Infants, defined as age 0-5 years, and elderly, defined as age $\geq$ 65 years, are relatively more likely to be at risk during severe weather events. For example, 36.7% of Americans age 65 and over are disabled compared to the 10% in the 18-64 brackets (2010 U.S. Census Bureau).

Gender plays a strong role in decision-making responsibilities. If a woman is a single parent, she will probably take more precaution in determining evacuation decisions. Statistics show men are more likely to be killed in hazardous weather than women. In a study by Rappaport (2010), out of 392 fatalities due to freshwater flooding in which gender was known, 71% were men and 29% were women. The reasons for this difference are unknown but possibly include chivalry, or not perceiving a weather event as “high risk.”

Race/ethnicity is a factor in vulnerability due to disparities in socioeconomic class, along with language and cultural barriers among the various groups within the U.S. However it cannot be presumed a culture is more at risk just because it is different. For example some Native Americans are able to interpret weather events and, based off their knowledge, make sound decisions for their community; this is not necessarily true for every culture. For instance, the majority of African Americans make up the poorer demographic in the U.S., and therefore often do not possess the resources to properly evade a hazard (evacuate) and otherwise educate themselves on hazards. Another example is Hispanic populations: with the growing number of immigrant and migrant Hispanics near the Mexican border, there may exist a language barrier preventing them from fully understanding their risk in certain hazards.

Education is important and it can be presumed that the more educated the community members, the more likely they are to be able to understand warnings and take action. It is also an indicator of wealth (U.S. 2010 Census), due to the high cost of private schooling and college. Personal wealth plays a role in many social issues. The wealthier the community members, the more likely they are to build a quality home that can be considered storm ready. Income also plays a role in the amount of resources available to a potential evacuee, and is linked to education as previously stated.

Renters, of apartments in particular, are vulnerable due to the typical lack of safe rooms and other durable shelters, and of severe weather planning (Mitchem 2003); a similar comment may be made about residents of mobile homes, who are likely at equal risk to hurricanes as are residents of apartments. Renters are also connected to the personal wealth factor. People who rent homes are probably less likely to be able to afford a home of their own and are also less likely to have home-owner's insurance. This puts them at risk of incurring large financial losses with no means of recovery.

If a state has poor building codes [as will be assessed using the Building Code Effectiveness Grading Schedule (BCEGS)], then the residents that inhabit that state would be considered highly vulnerable, as they do not have the proper shelter to protect them from certain hazards, such as severe wind, flooding and tornadoes. Mobile homes will also be a component of this factor due to their being the most vulnerable structures during weather events.

Special needs populations include those who are disabled, based on blindness, hearing impaired, mental health, and mobility. The higher the percentage of the population with special needs, the more resources are required during evacuation to ensure the safety of those individuals, and in turn an enhanced vulnerability.

Emergency planning is essential in understanding how well a community is prepared in the event of a disaster. This could include, but not limited to: the amount of information made available to the public, the ease of access to such information, and even programs and campaigns dedicated to severe weather. A similar factor is seen in the HDRI "public education factor" from Davidson and Lambert (2002). Population density will be an additional component to this factor as it relates to how many people are at risk who may need to evacuate and could possibly congest roads during the evacuation process.

Each factor contains one or more indicator as shown in Table 2.1. Within each factor, the indicators are given equal weights in the absence of information to suggest otherwise. The exception is the gender factor, in which males were weighted more than females. This is based on Rappaport (2010), who showed a much higher percentage (71%) of male fatalities due to freshwater flooding. Each factor is then normalized to a value between 0 and 1 using a standard approach (i.e., x-xmin/xmax-xmin, for each factor x). Finally all normalized factors are added together to give a total score of 1-10, with 10 being the most vulnerable.

| Factor | Indicators | Data Location |
|---|---|---|
| Age | 0-5<br>65+ | U.S. Census |
| Race/Ethnicity | Black or African American<br>Native Americans<br>Hispanic-Latino | U.S. Census |
| Gender | %male (accounts for female) | U.S. Census |
| Education | Pop 25 and older w/<br>Less than 9th grade<br>9-12 no diploma<br>H.S. Diploma | U.S. Census |
| Personal Wealth | Below Poverty Level | U.S. Census |
| Disability | Hearing<br>Ambulatory<br>Vision<br>Cognitive | U.S. Census |
| Renter | Apartments | U.S. Census |
| Building Grade codes and Mobile Homes | %1-2<br>%4-7<br>%8-10<br>% Mobile Homes | BCEG<br>U.S. Census |
| Emergency Planning and Population Density | Rate on accessibility<br>Population Density | Survey<br>U.S. Census |

Table 2.1 List of indicators and associated contributing factors to social vulnerability

## 2.2 Data Caveats

Limitations in the availability of data from both the physical and social perspectives presented numerous challenges to this study. When looking for data for the building codes, some states did not participate in the survey, so assumptions were made, and states with missing values were assigned the mean value over all states. Native American populations were difficult to assess because all tribes are not federally recognized, which means that during disasters, they would not receive federal or state funding. Some tribes, however, have signed treaties with certain states but this information would only be found by contacting each head tribal member (personal communication with Ma'Ko Qua Jones). For the emergency preparedness factor, there was little information that was publicly available pertaining to the preparedness of a particular state or county. Therefore this factor was assessed subjectively, in the absence of studies, through tests developed to determine the usability, available planning information, and length of time it took to find disaster such information in each state. Lastly, the census data had percentage errors (as the data is representative of a sample portion of the U.S.) that were not accounted for in this study.

## 2.3 Results

Examples of the indicators and their contributions to the index are shown in Figs. 2.2a-d. Note the use of different color scales to highlight the spatial variability of each indicator. For a given location, each indicator does not contribute equally to vulnerability; the contribution depends on the value of the indicator relative to the range of values of the indicator over all counties within the hazard prone region. For example, the Native American population in our domain is less than the Black/ African American population, so the Black/African American populations in areas where the contribution is highest will weigh more than Native Americans in the index.

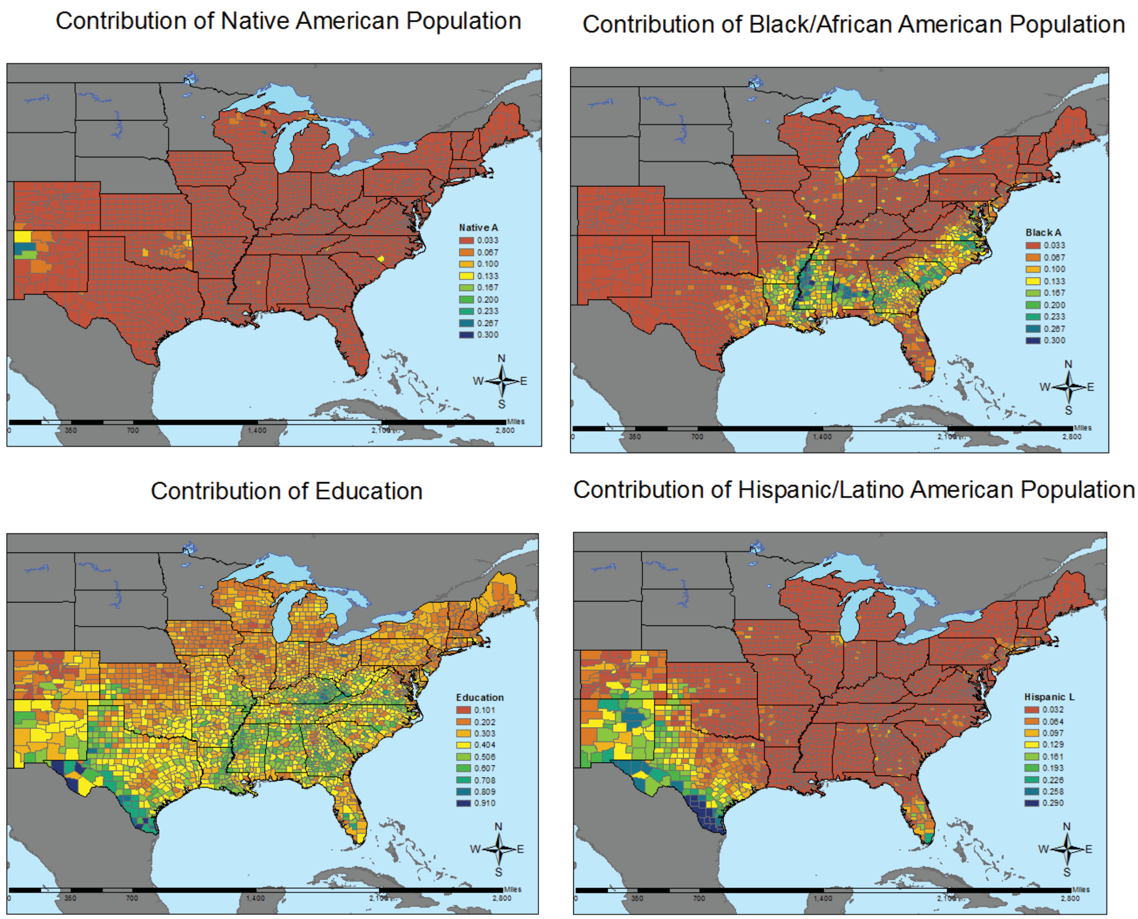



Figure 2.2 Spatial distribution of the contributions to vulnerability from four example indicators: (a) Native American population, (b) Black/ African American population, (c)Education, and (d) Hispanic/Latino population

A map of the social vulnerability is shown in Fig. 2.3. In general, the southern portions of the United States (from Texas to the Carolinas) have high vulnerability, with Arkansas having the most counties with high vulnerability. This is a result of the large contributions from lack of emergency preparedness and the BCEG in Arkansas. There is also high vulnerability in west Texas and New Mexico, especially along the Mexican border due to high contributions from lack of education and large Hispanic populations; however, a correlation cannot be made between the two without further research.

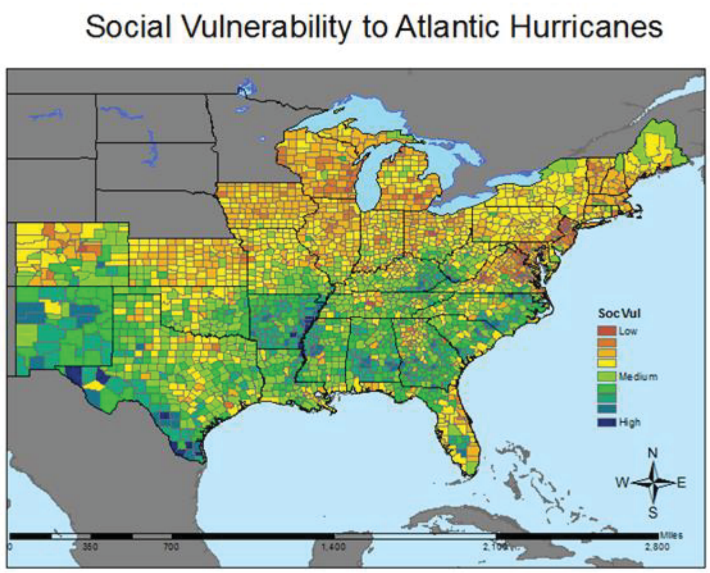



Figure 2.3 Spatial map of the vulnerability index. Here, “High” corresponds to index values of .511-.334, “Medium” to .333-.167, and “Low” to .166-0.

## 2.4 Summary

A social vulnerability index was developed in this study that includes both inland and coastal vulnerabilities to hurricanes making landfall in the Atlantic Basin. A major finding is that the most vulnerable communities are found inland, providing evidence that inland communities should be considered during planning in hurricane disaster prevention. It is found that the most vulnerable counties were located in portions of west

Texas, New Mexico, Arkansas and the Carolinas. The least vulnerable near-coastal area was near Washington, D.C.

To truly reduce the lethality of hurricanes, a thorough assessment of the communities that will be impacted is necessary. Emergency managers use various tools to aid them in determining when and where to allocate funding and resources to prevent hurricane disaster. The vulnerability index developed in this chapter presents additional important information on all counties within the hazard prone regions, not just coastal communities. It will be combined with exposure and hazard information developed in subsequent chapters, to culminate in a new risk index.

# CHAPTER 3. CLIMATOLOGICAL DISTRIBUTION OF TROPICAL CYCLONE TORNADOES

## 3.1 Methodology

### 3.1.1 Dataset

A record of tropical cyclone tornadoes that have occurred in the United States is obtained using the dataset developed by Edwards (2010) (who also continues to provide annual updates http://www.spc.noaa.gov/misc/edwards/TCTOR/tctor.xls). Relative to that used in previous TCT climatologies (e.g., Pearson and Sadowski 1965; Hill et al. 1966; Novlan and Gray 1974; McCaul 1991; Schultz and Cecil 2009; Edwards 2011), this more detailed and modern dataset "ameliorates impacts of systematic 'shocks' to the data record" (Edwards 2010) yet still offers enough data to analyze TCT events occurring between 1995 and 2011. Edwards' (2010) dataset is derived from the tornado-report database maintained by the NOAA Storm Prediction Center (SPC), which has been used in numerous studies of tornadoes (e.g., Brooks et. al 2003; Trapp and Brooks 2013; Rhodes and Senkbeil 2014). To determine the presence of a TCT within the circulation of a tropical cyclone or the remnants thereof, Edwards (2010) matched reports with imagery from archived NEXRAD Level II data (Kelleher et al. 2007). Qualifying TCTs were then separated from the SPC database and then assigned to their respective TCs by name.

There are a total of 1203 TCT events that occurred between 1995 and 2011 (Fig. 3.1). These have damage-based intensities that range from Enhanced-Fujita scale (EF)-0 to EF-4. Although both 2004 and 2005 hurricane seasons were active, the 2005 hurricane season produced significantly less TCTs compared to the 2004 season (Fig. 3.2). Thus, there is not necessarily a direct relationship between the number of Atlantic Basin TCs per year and the number of U.S. TCTs per year.

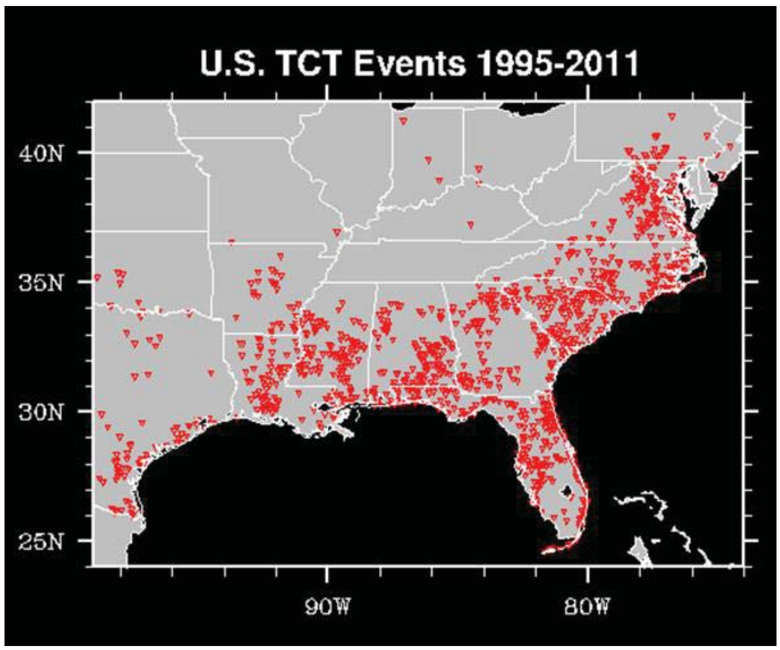



Figure 3.1 Geographical location of the 1203 TCTs that occurred during the interval 1995-2011.

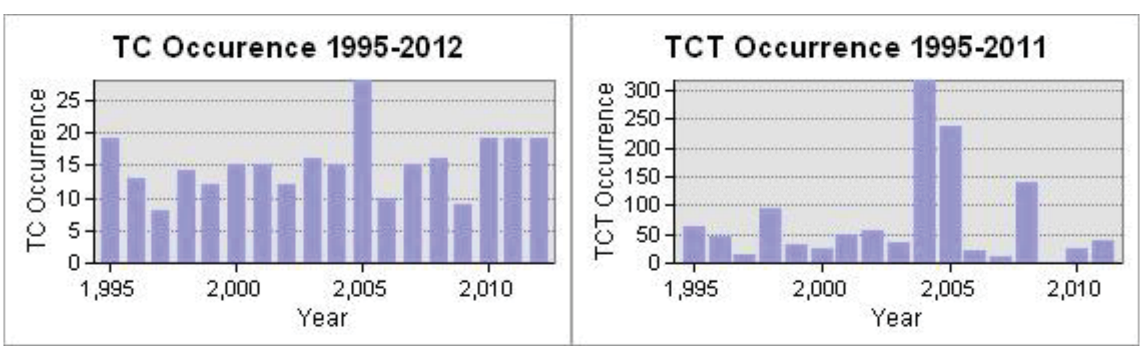



Figure 3.2 Comparison of TC (a) and TCT occurrence (b). Theses maps show there is not a connection between an active TC season and active TCT events. While the 2004 TC

season was moderately active, there was a high TCT occurrence, the opposite is true for the 2005 season.

### 3.1.2 Geospatial Analysis of the TCT Data: Interpolation and Smoothing

A multi-step procedure was used to prepare the TCT data for incorporation into the county-based risk index. This procedure included interpolation of the geo-referenced TCT reports ($\lambda$report, $\phi$report) to a uniform Cartesian grid (Xunigrid, Yunigrid) , and then an application of a spatial smoother within geographic information systems (GIS) using the ArcGIS software, which was then used to assign a TCT frequency to each county within the analysis domain.

The data were interpolated to a 3750 × 3750 km Cartesian grid assuming, for simplicity, a cylindrical equidistant projection, e.g.,

$$\text{Xunigrid} = \lambda\text{report} \times \text{re} \tag{3.1}$$

$$\text{Yunigrid} = \phi\text{report} \times \text{re} \tag{3.2}$$

and a grid spacing of 50 km; here, re is the radius of the Earth. To carry out the interpolation, uniform weighting was applied to all reports within a box surrounding the grid point (see Fig. 3.3); consequently, the grid point was assigned a value equaling the number of TCTs falling within that box.

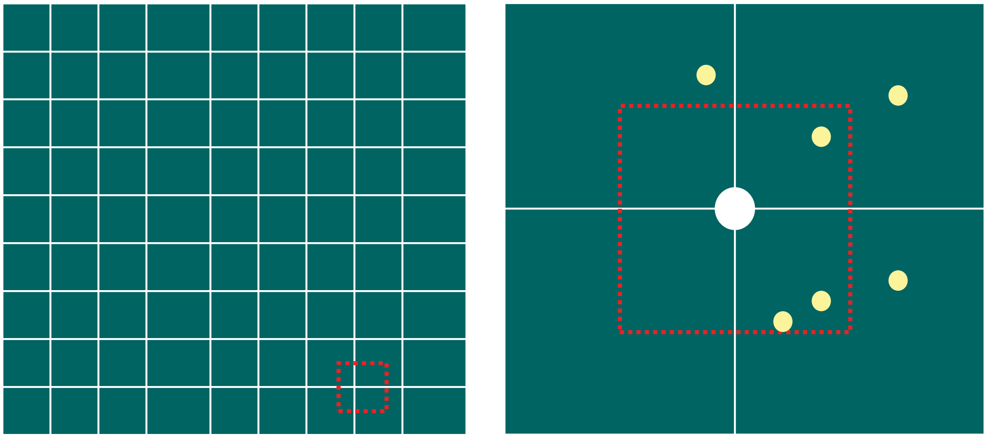


Figure 3.3 Example Cartesian grid used in the data interpolation (left panel); right panel shows a zoomed view of sample grid and data points. TCT events represent the smaller circles, and the white circle represents the grid point.

Figure 3.4 shows the gridded TCT report data at a county level. Note that the majority of TCT reports concentrated in the Southeastern and Mid-Atlantic states. This figure also reveals some of the potential representativeness errors inherent in data that derive from eyewitness reports. Thus, smoothing is applied to account for these potential errors (e.g., Brooks et al. 2003).

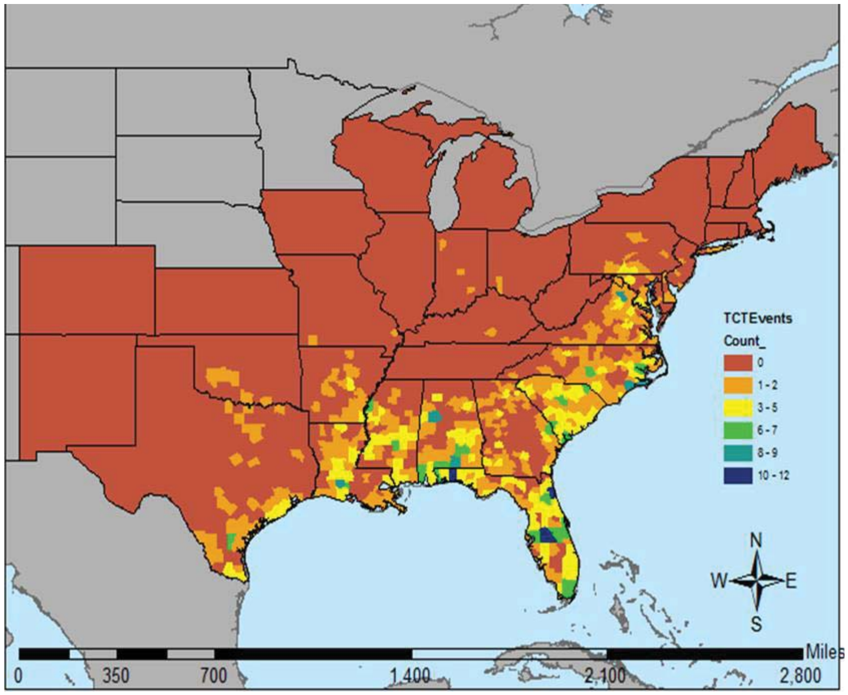



Figure 3.4 Unsmoothed county-level TCTs from 1995-2011.

As required for smoothing in GIS, the data were assigned latitude and longitude values using essentially an inverse of Eqs. 3.1-3.2, i.e.,

$$\lambda unigrid = Xunigrid/re \tag{3.3}$$

$$\phi unigrid = Yunigrid/re \tag{3.4}$$

where λunigrid and ϕunigrid is longitude and latitude, respectively. These data were imported into ArcGIS, and then a diffusion kernel smoother without barriers was applied to the TCT data (Silverman 1986; Brooks et al. 2003; Trapp and Brooks 2012). Note that this diffusion kernel behaves similarly to a kernel smoother with a Gaussian distribution, as used by Brooks et al. (2003) and Trapp and Brooks (2012). The steps taken within ArcGIS are outlined in Appendix A.

## 3.2 Results

The result here is presented as a smoothed mean annual occurrence, relative to the 16-y dataset of Edwards (2010). High TCT occurrence (0.135-0.208 TCTs per TC season) is shown in the Mid Atlantic Coastal States, Florida, southern Alabama, and central Mississippi, with decreasing probability farther inland (Fig. 3.5).

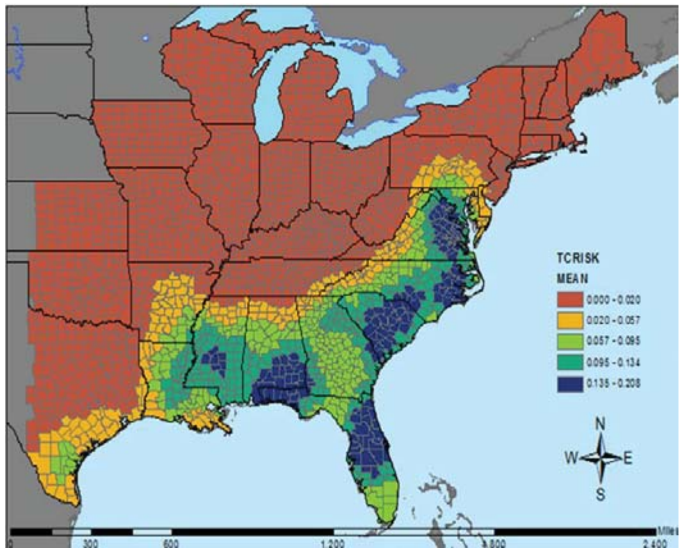



Figure 3.5 Smoothed TCT data from 1995-2011 using diffusion kernel without barriers

### 3.2.1 Summary

In summary, this chapter focused on developing an annual mean frequency of TCT events occurring between 1995 and 2011, to be included in a risk index for Atlantic Basin hurricanes (see Chapter 5). High TCT frequency is shown to occur in the Mid Atlantic Coastal States, Florida, southern Alabama, and central Mississippi.

# CHAPTER 4. CLIMATOLOGICAL DISTRIBUTION OF TROPICAL CYCLONE FLASH FLOODING

The purpose of this chapter is to develop a climatological distribution of tropical cyclone flash flooding (TCFF) that can be integrated with exposure and vulnerability data to assess TC risk. TC flash flooding is a particular hazard to inland communities. To date a TC flash-flood climatology has not been developed and is motivated by Ashley and Ashley's (2008) charge that national and regional studies should examine "localized [flooding], human perception and socio-economic characteristics of flood casualties."

## 4.1 <u>Methodology</u>

Villarini (2011, 2012) correlated tropical cyclone rainfall to stream-gauge data to develop a climatology of tropical cyclone flooding (TCF). Given this approach, the Villarini (2011, 2012) data necessarily includes river flooding but excludes coastal (surge) breaches. It may or may not include flooding associated with sub-diurnal-scale TC rainfall, especially within inland urban areas. Thus, in an effort to isolate such TC flash floods, a comparative study is conducted herein of flash-flood reports (FFRs) and flash flood warnings (FFWs) issued by the NWS. As detailed below, the FFR data are used to construct a TCFF hazard map.

### 4.1.1 Flash-flood Report and Warning Data Analysis

FFWs and FFRs were chosen here as a means to represent short-duration "freshwater" flooding, especially in inland urban areas, which may be well away from a major river or stream but still be affected by run-off from drains and small basins; such flash flooding is separate from river and coastal (surge) breaches, although inland flash flooding may eventually lead to river flooding. The respective FFW and FFR datasets have unique advantages and disadvantages in their use toward creation of a TC flash-flood climatology. For example, the FFW record is fairly long [a 28-yr archive is available through the Iowa Environmental Mesonet (IEM)] but there are questions as to how well a FFW serves as a proxy for an actual flash flood. On the other hand, a FFR is definitive evidence of a flash flood, but the archive is relatively short [a 17-yr archive is available directly through the NOAA National Climatic Data Center (NCDC)]. A comparison of analyses of both datasets follows.

The NWS "Flash Flood Warning Best Practices" can be found at: http://www.wdtb.noaa.gov/courses/ffw_bp/. Each NWS office issues FFWs based on their knowledge of prior and current weather conditions in their forecast area. They also closely monitor the thresholds of the various basins in their respective forecast areas and can quickly act if a weather system is expected to produce enough precipitation that will breach those basins. Forecasters are also aware of topographical features that may increase the likelihood of flash flooding, such as aforementioned urban development that may inhibit rain water from soaking into the ground. The specific topography of the Balcones Escarpment in Texas, for example, is responsible for a large number of flood related fatalities. Since these warnings incorporate information about location and time, they are useful to gain insight into inland flooding. To use the FFW data, two assumptions were made:

1. A flash flood occurred somewhere within the warning polygon.

2. The flash flood posed an immediate threat to the inhabitants within the warning polygon.

It is likely that a FFW does not always mean the event actually occurred, thereby bringing the first assumption into question; this is explored below using corresponding FFR data for a subset of the FFWs.

Archived FFWs were taken from the IEM, which is maintained by Iowa State University's Department of Agronomy. To be consistent with the TC rainfall cases analyzed below, only warnings from the years 1988-2012 were used in this analysis. Note that beginning 1 January 2002, the practice of issuing warnings over geographical polygons was adopted by the NWS. This means that warnings may apply to portions of a county rather than the entire county, although the polygons often span entire counties (Gourley et al. 2013). GIS was used to extract only those FFWs issued 24 hrs prior to and following the official international best track archive for climate stewardship (IBTRACS) of all TC events during the analysis period. As described in detail in Appendix A, GIS was then used to create county-level accumulations of all the TC-associated FFWs, from which FFW frequency maps were derived.

FFR data for the period 1988-2012 were extracted from the NCDC archive. In accordance with the NWS reporting procedures, each FFR concerns a storm that threatened life and property, and specifically identifies the occurrence of moving water with a depth greater than 6 inch, the amount of water presumed to affect moving vehicles, or of standing water with a depth greater than 3 feet (NWS 2007). Flash floods reported prior to 2007 were recorded at a county level, and thereafter, at point-specific locations. As done with the FFWs, GIS was used to create county-level accumulations of all the

TC-associated FFRs, from which FFR frequency map were derived (see also Appendix A). Only those FFRs during the 24 hrs prior to and following the passage of a tropical cyclone (as determined from the IBTRACS) were included in the analysis.

For consistency with the TCT analysis in Chapter 3, and implicitly to account for uncertainties in the report and warning data, a diffusion kernel smoother was applied (see Appendix A) to the accumulated county-level FFWs and FFRs (Silverman 1986; Brooks et al. 2003; Trapp and Brooks 2012). The resulting frequency maps are assessed in Section 4.2.

### 4.1.2 TC Rainfall Data and Analysis

To provide a quantitative, rainfall-based complement to the FFRs and FFWs, tropical cyclone rainfall was also analyzed, using data provided by David Roth from the NOAA/Weather Prediction Center (WPC). These data (see http://www.wpc.ncep.noaa.gov/tropical/rain/tcrainfall.html) are a compilation of rainfall totals collected by rain gauges at various locations and managed by NCDC. In 2004, "Katz" files were incorporated into the data set, which include NWS Cooperative Observer Program (COOP) and United States Geological Survey (USGS) rainfall reports (these are real time data from the NOAA/Climate Prediction Center rainfall collective). The WPC associates the rainfall data with a TC beginning with the formation of TC low pressure and continues until the TC low dissipates. In the instance that a tropical disturbance forgoes the formation of the low, the date of the TC rainfall event is extended. This is also done if there is a mesoscale convective vortex associated with a dissipating tropical system.

The analysis here includes rainfall associated with the 85 TC cases making U.S. landfall between 1988 and 2012. The rainfall totals were interpolated onto a 119° longitude x 29° latitude grid with 0.49° grid spacing, using iterative correction with radii of 0.3, 0.2, and 0.1 degree latitudes. The domain is centered about the continental U. S. and spans 24° to 53° latitude and -125° to -66° longitude. Using GIS, gridpoint values of the interpolated rainfall were then joined to the closest county center. If more than one rainfall total is near a county, then the sum total is assigned to that county.

## 4.2 Results and Discussion

### 4.2.1 TCFFW and TCFFR Analysis

To test the validity of using FFW as a proxy, a simple verification is conducted between warnings and reports over a 6-yr period 2006-2011. The FF report data comes from the flooded locations and simulated hydrographs (FLASH) project maintained by the NOAA National Severe Storms Laboratory. A total of 16 tropical systems occurred within this time frame, with 8 reaching hurricane intensity.

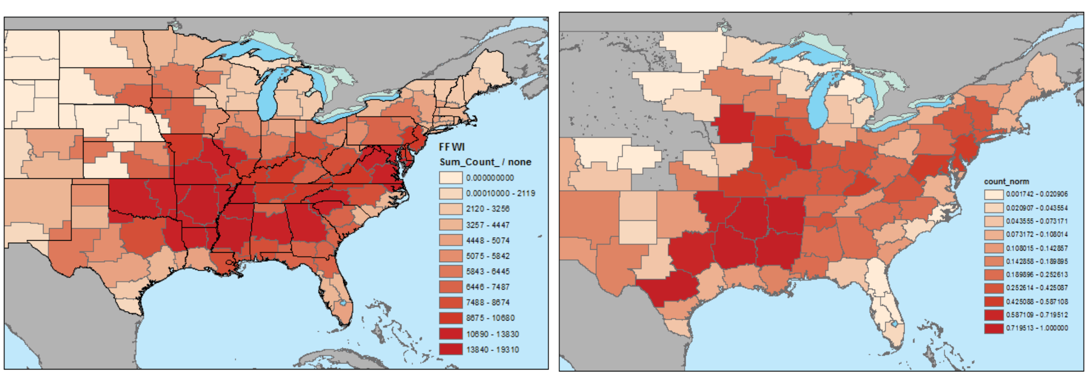



Figure 4.1 (a) All NWS flash flood warnings issued, and (b) All NWS flash floods reported, between 2006 and 2011 by NWS county warning area, regardless of flash flood source (e.g. thunderstorm, TC, etc).

It was found that 90% of the FFWs were considered false alarms. Of the remaining 10%, 90% of the FFWs were actually verified (a report was recorded in an area in which a warning was issued), and 10% were classified as missed events (a report was recorded in an area in which a warning was not issued). The percentage of TCFFRs (Fig. 4.1a) to TCFFWs (Fig. 4.1b) in this period is 10%, compared to the overall total of FF reports to warnings regardless of source being 2.1%, and all events excluding TCT FF reports and warnings is 1.96%. Looking at the overall total of FFWs, regardless of cause, issued between 1996 and 2011, FFWs are mostly distributed in the southern states of Southwest Texas, Louisiana, and Mississippi. What is interesting is that there are more FFWs issued in the inland NWS county warning areas as compared to the coastal warning areas.

To further compare TC flash flood reports to warnings, and thus to complement the verification conducted above, the full TCFFR and TCFFW datasets are analyzed. Each normalized by their respective maximum values to facilitate this comparison.

In general, it is noted that large quantities of warnings and reports are located inland. Unexpectedly, large portions of Florida along the coast received few TCFFWs and TCFFRs for the period. There is also an area in central Georgia that received little to no FFWs and FFRs. This hole is also reflected in rain gauge data (Villarini 2011) and tropical cyclone tornado data. More insight into the demographics and geography of the location is needed for further assessment.

When comparing the TCFFW and TCFFR analyses (Fig. 4.2a and b), there is much agreement in the location of the flash flood events, however the magnitudes vary. One particular area of interest is the high concentration of TCFFW in Louisiana, Southern Mississippi and Southern Alabama. The TCFFR data however do not show a high number of reports in Louisiana compared to the TCFFW data. Another area of interest is the magnitude of TCFFR verses TCFFW in the coastal Mid-Atlantic region, where more reports are shown than actual warnings, signifying under reporting in the area. This can cause this region to be highly vulnerable if the residents are not warned in time to take the necessary safety precautions. Future studies should assess the fatalities in this region in particular.

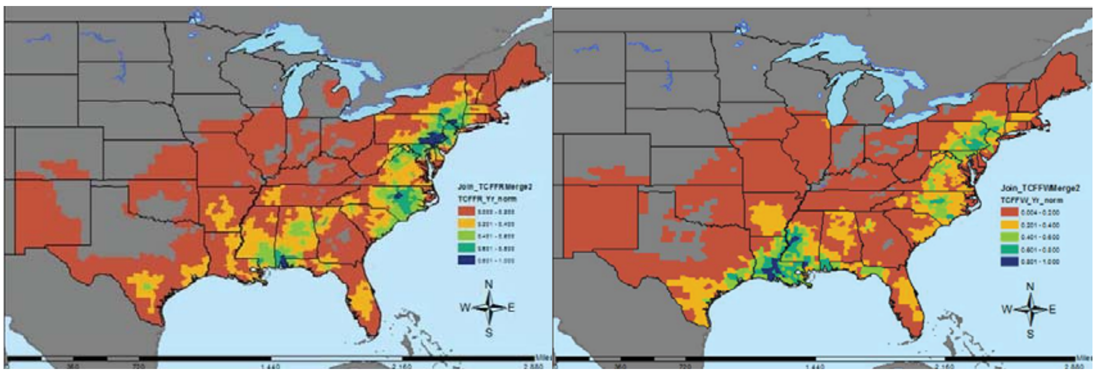


Figure 4.2 Mean, normalized, annual frequency of (a) TC related flash floods reported, and (b) TC related flash floods warnings issued. Both maps show high concentrations in the same general areas with higher concentrations seen in the flash flood warnings overall.

Despite the geographical similarities in the TCFFR and TCFFW analyses, the magnitude differences revealed in the verification statistics as well as in the un-normalized analyses lead to the conclusion that the TCFFRs are more suitable for use in the subsequent TC inland hazard maps and risk index.

As shown in Fig. 4.3, the highest concentration of tropical cyclone induced flash flood reports are seen in the mid-Atlantic and Appalachian Highland regions, along with the most southern tip of where Alabama and Mississippi meet. These areas have an average of 32 FFRs over the 16 yr period or about two reports per season. One can glean that these areas are highly susceptible to TC flash flooding. Although the aforementioned regions contained the highest number of reports, a significant number of reports are also located well inland with as many as 10 reports reaching as far as Tennessee on the southern end and New England on the northern tip of United States.

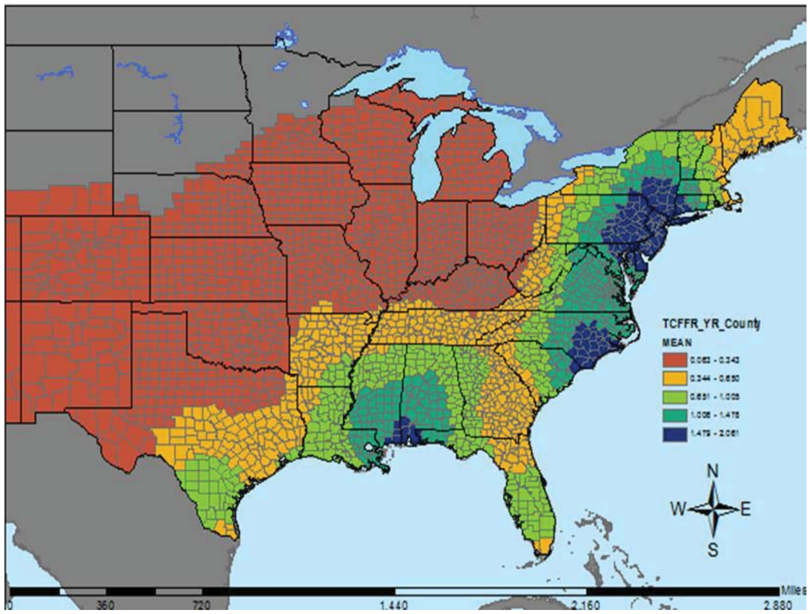



Figure 4.3 Smoothed mean frequency of TCFFRs based on data from the period 1988-2012.

### 4.2.2 TCR Analysis

Looking at the rainfall distribution from the 85 TC cases that occurred during the period 1988-2012, as expected, more rain occurred in the states bordering the Atlantic Basin (Fig. 4.4). Counties directly on the Gulf Coast, mid Atlantic and Florida Peninsula recorded the largest rainfall. Rain totals gradually decrease with distance from the coast. However, there are still relatively large amounts of TC rainfall well inland, on the county level. This supports the emphasis here on inland risk to TCs.

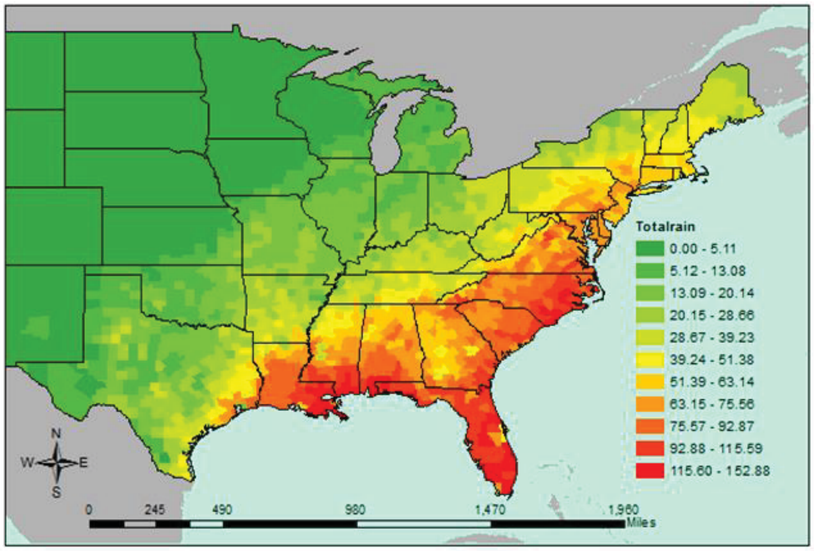



Figure 4.4 Tropical cyclone rainfall over the period 1988-2012.

## 4.3 Summary

In summary, tropical cyclones pose dangers to both inland and coastal communities. In particular inland flooding is a topic of discussion that still needs to be addressed to reduce loss of life during hurricane events. With most hurricane decision making tools focusing on coastal areas, this study sheds light on the potential risk of inland communities to flash flooding. To reiterate some of the key findings, there is relatively high potential risk in counties well inland from coastal areas, as evidenced by the concentration of flash flooding in the New England and Gulf Coast regions

# CHAPTER 5. DEVELOPING THE HURRICANE DISASTER RISK INDEX FOR TROPICAL CYCLONE TORNADOES AND FLASH FLOOD HAZARDS

In this chapter, the inland hazard risk index is formally developed, representing a culmination of the hazard (e.g. TCT and TCFF) analyses in Chapters 3-4, and the identification and quantification of the exposed and vulnerable populations in Chapter 2.

## 5.1 Methodology

From Chapter 1, risk is defined as a combination of exposure, vulnerability, and hazard (see Eq. 1.1). Accordingly, the inland-hazards hurricane disaster risk index (HDRI) is expressed as

$$\text{IHDRI} = \text{Exposure} \times \text{SocVul} \times \text{Hazard}\ , \tag{5.1}$$

where Exposure is the exposed population, SocVul is the measurement of the vulnerability of the overall population.(see Ch. 2), and Hazard is the sum of the TCT and TCFF probabilities (see Ch. 3 and 4, respectively). Each of these three contributions is normalized, and then combined using GIS.

## 5.2 Results

The highly exposed population and hazard likelihood contributes to the highest risk areas in the mid-Atlantic region (Figs. 5.1-5.3). Areas of moderate risk are seen in the Southeast, where the hazards probability peaks. One exception is in central Georgia, which is represented as relatively low risk despite the significant social vulnerability in the region, there still exists a risk "hole" in Georgia. This is due to the low contributions (and similar holes) from the TCT and TCFF hazards, and the relatively low exposed population. In the Midwest, the risk is also low, but because of low hazard and social vulnerability contribution, and despite of a high value of exposure. The exceptions in this region exist in counties with large urban areas, and inherently large populations (e.g. Chicago, Illinois).

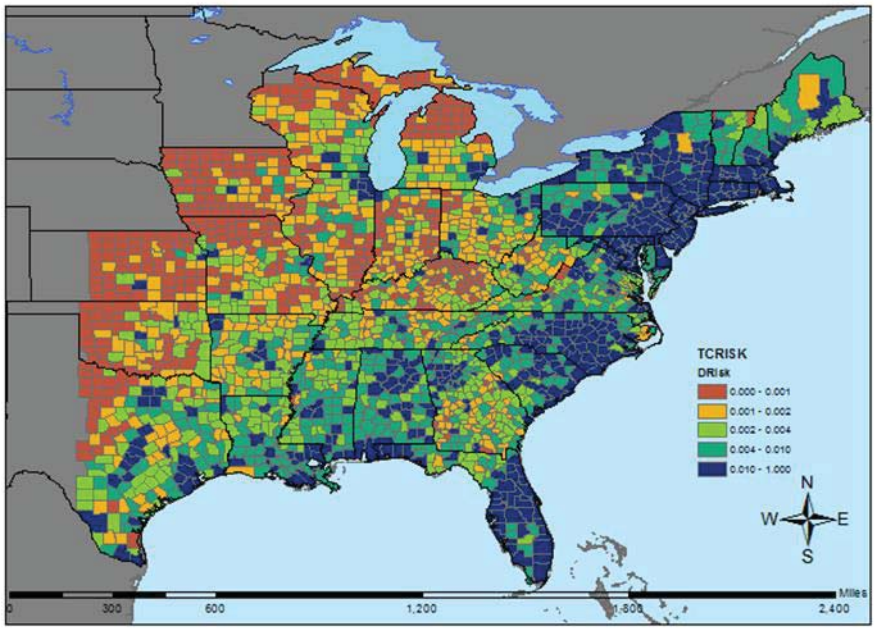



Figure 5.1 Geographical distribution of the Inland Hazard Hurricane Disaster Risk Index normalized by the maximum risk value of 0.201. This normalization is unique to this figure. “High Risk” corresponds to index values of .010-1.00, “Moderate Risk” to .002-.004, and “Low Risk” to 0.00-.001.

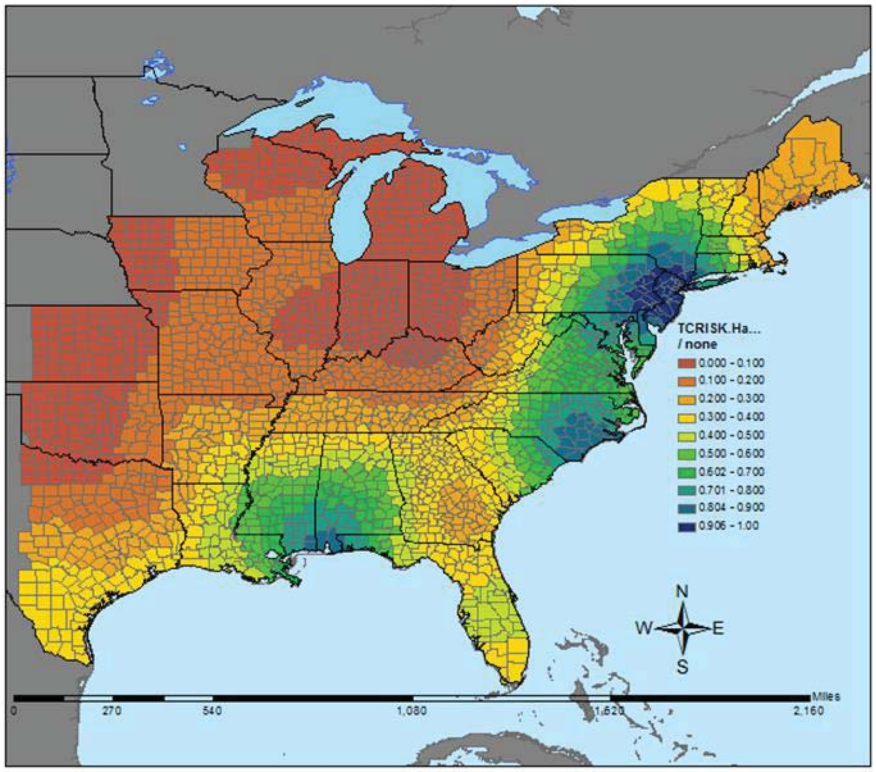



Figure 5.2 As in Fig. 5.1, except for the contribution of the TCT and TCFF hurricane hazards.

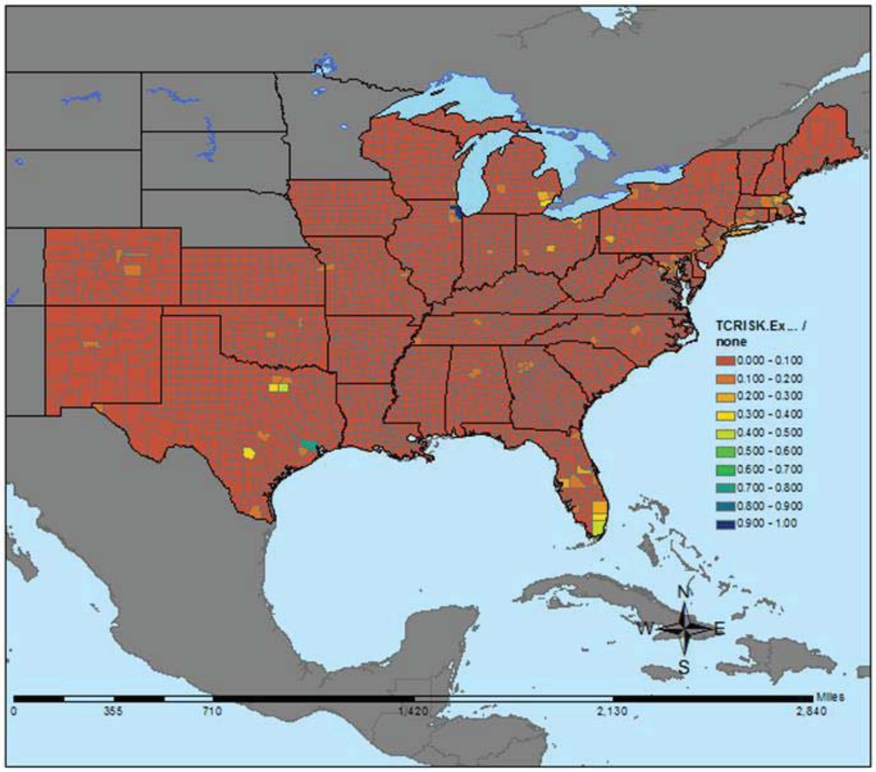



Figure 5.3 As in Fig. 5.1, except for the contribution of the exposed population.

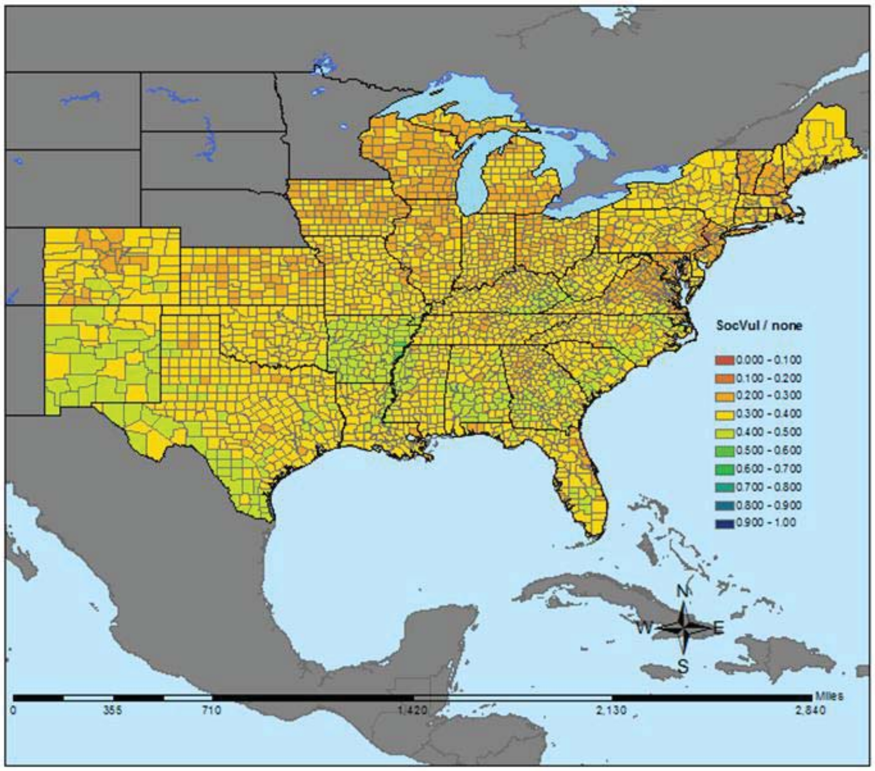



Figure 5.4 As in Fig. 5.1, except for the contribution of social vulnerability.

### 5.2.1 Sensitivity Tests

Note that in Eq. 5.1, all variables are intentionally weighted equally. However, a risk manager's preference (e.g., based on her/his protocols) might be that one variable should be weighted more than others when assessing risk. For example, the exposed population may not be of significant importance to this risk manager, who might make decisions simply based on the impact of the hazard; the same argument could be made for decisions driven mostly by vulnerable populations. Thus, the following section is devoted to tests of the sensitivity of risk to weights on exposure and social vulnerability.

#### 5.2.1.1 Exposure

Five sensitivity tests were conducted for exposure, the first being one in which all counties within the domain are given a uniform value of Exposure of one (Eq. 5.2). The next three tests reduce the weight of Exposure to 10%, 25% and 50%, respectively (see Eq. 5.3-5.5). Test five (Eq. 5.6) increases the contribution of Exposure by 1.5.

Geographically, creating a uniformly exposed population brings out similar features seen with the Hazard component of the map (see Fig. 5.4). This shows, not surprisingly, that the contribution of the exposed population has a major impact on the magnitude of risk. Furthermore, decreasing the contribution of the exposed population (Eq. 5.2-5.4) reduces the magnitude of risk but not necessarily the features that one would see in Fig. 5.1 (see Fig 5.5-5.6). Increasing the contribution of risk (Eq. 5.6) also showed little change in geographic distribution of risk.

$$\text{HDRI} = \text{SocVul} \times \text{Hazard}\,, \tag{5.2}$$

$$\text{HDRI} = (0.1 \times \text{Exposure}) \times \text{SocVul} \times \text{Hazard}\,, \tag{5.3}$$

$$\text{HDRI} = (0.25 \times \text{Exposure}) \times \text{SocVul} \times \text{Hazard}\,, \tag{5.4}$$

$$\text{HDRI} = (0.5 \times \text{Exposure}) \times \text{SocVul} \times \text{Hazard}\,, \tag{5.5}$$

$$\text{HDRI} = (1.5 \times \text{Exposure}) \times \text{SocVul} \times \text{Hazard}\,, \tag{5.6}$$

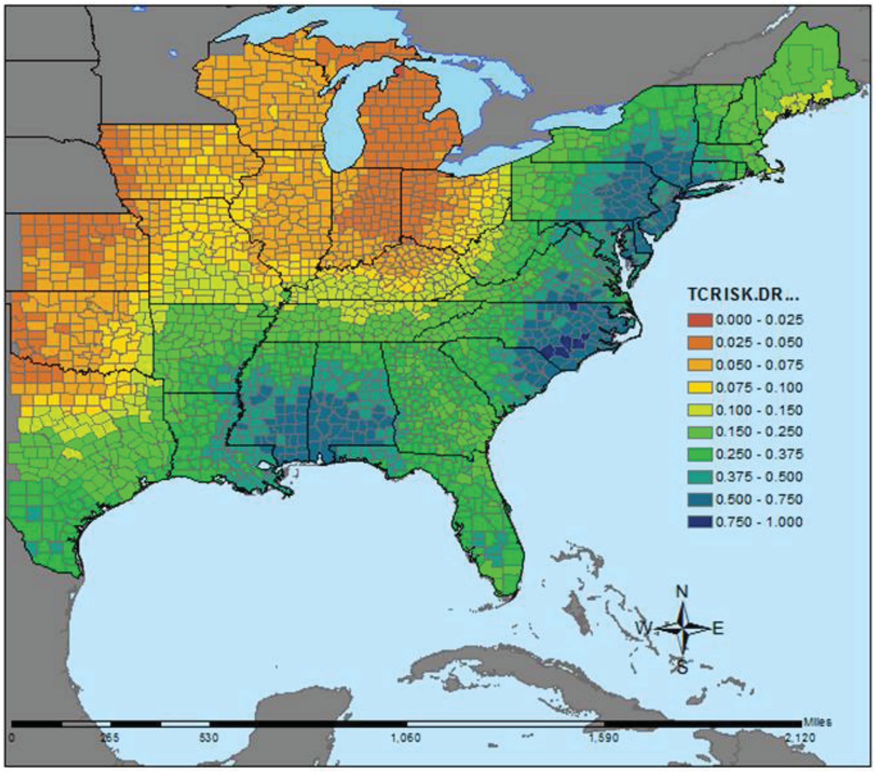



Figure 5.5 As in Fig 5.1, except for the contribution of a uniformly exposed population normalized by the maximum value of 0.464481.

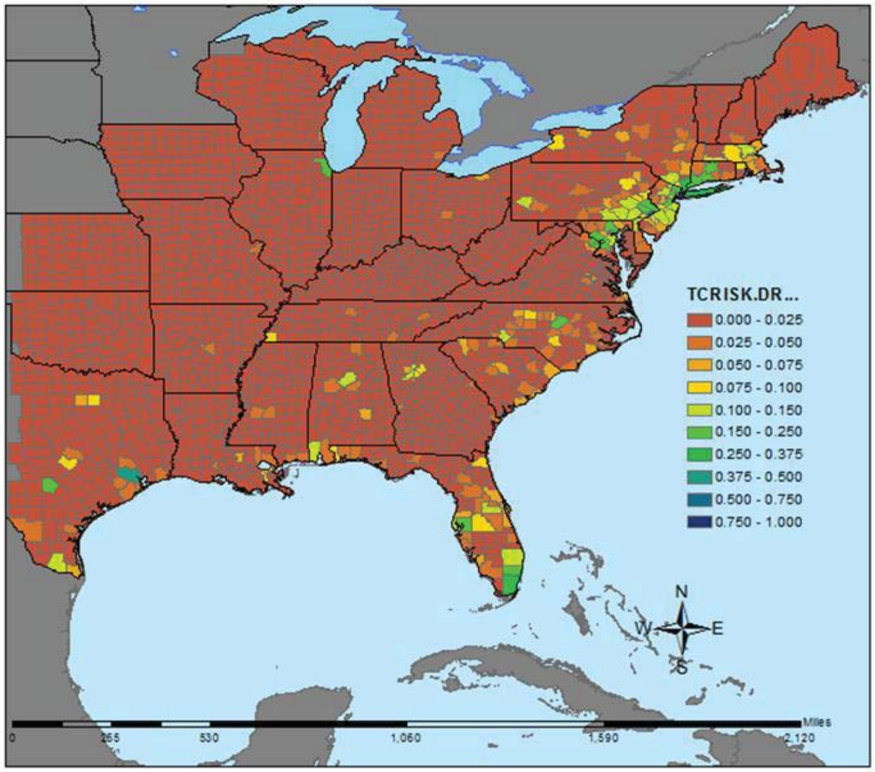



Figure 5.6 As in Fig 5.1, except for the contribution of 50% of the exposed population normalized by the maximum value of 0.100369.

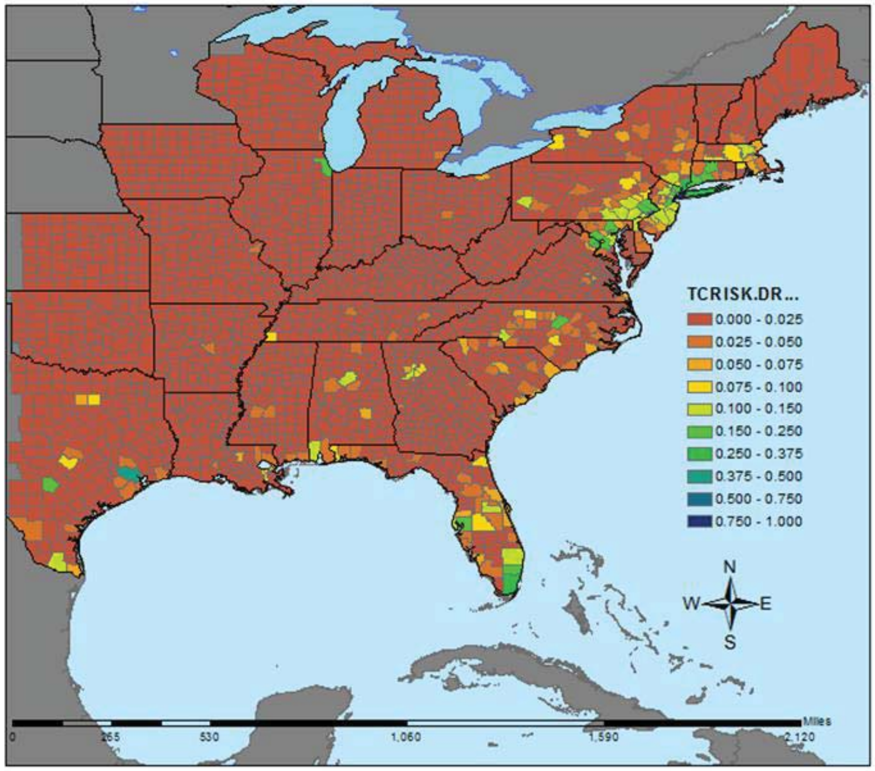
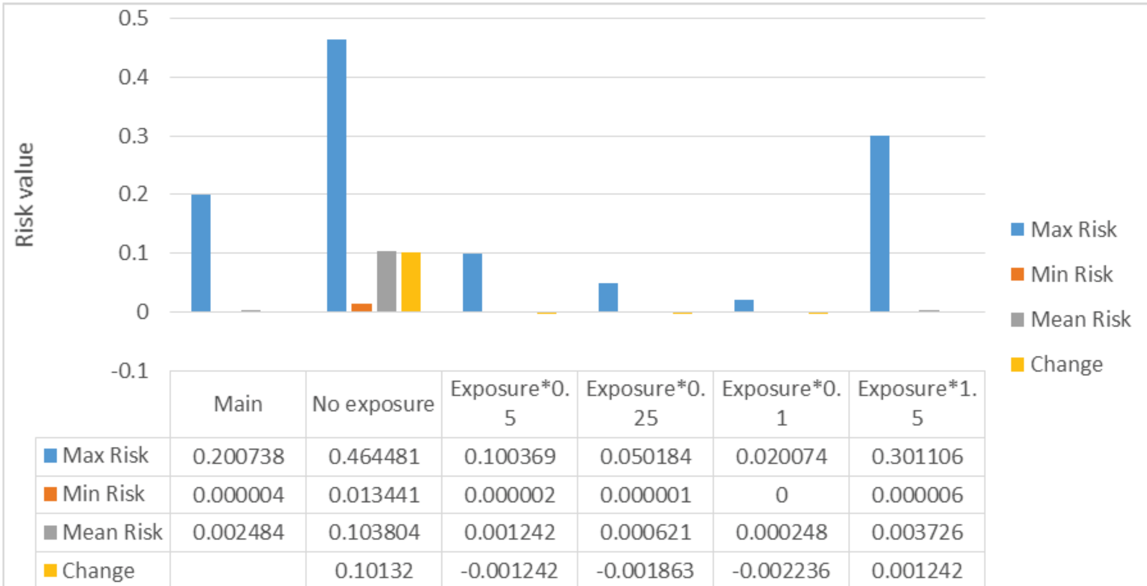



Figure 5.7 As in Fig 5.1, except for the contribution of 10% of the exposed population normalized by the maximum value of 0.020074.

Results in Table 5.1 show that the uniform exposure increases the risk in all the domain-wide statistics, doubling the maximum risk and increasing the mean risk by a factor 50. Reducing Exposure decreases the risk, however the main changes are seen in the mean risk when reducing this variable by 50%. Increasing the variable by 1.5 increased the max risk by 25% but produced little change in the mean risk.




| | Main | No exposure | Exposure*0.5 | Exposure*0.25 | Exposure*0.1 | Exposure*1.5 |
|---|---|---|---|---|---|---|
| Max Risk | 0.200738 | 0.464481 | 0.100369 | 0.050184 | 0.020074 | 0.301106 |
| Min Risk | 0.000004 | 0.013441 | 0.000002 | 0.000001 | 0 | 0.000006 |
| Mean Risk | 0.002484 | 0.103804 | 0.001242 | 0.000621 | 0.000248 | 0.003726 |
| Change | | 0.10132 | -0.001242 | -0.001863 | -0.002236 | 0.001242 |

Table 5.1 . Sensitivity tests for the exposure variable showing the maximum, minimum, mean and change in risk (‘Change;’ mean risk - “Main” mean risk). Main variable represents the control case (Eq. 5.1).

#### 5.2.1.2 Social Vulnerability Tests

Only two sensitivity tests were conducted for the SocVul parameter: increasing the variable to an equal contribution to the other two variables, and creating uniform vulnerability for all counties:

$$\text{HDRI} = \text{Exposure} \times (1.961 \times \text{SocVul}) \times \text{Hazard}\ , \qquad (5.7)$$

$$\text{HDRI} = \text{Exposure} \times \ \text{Hazard}\ , \qquad (5.8)$$

The former test (Eq. 5.7) is conducted to scale up the maximum value of social vulnerability. Owing to the way in which this variable is computed (see Chapter 2), the spatial maximum is only 0.52, and thus a factor of 1.96 scales this maximum to 1.0. The latter test (Eq. 5.8) forces the vulnerability to be equal amongst all counties. Although realistically this is not true (see Chapter 2), some decision makers may not take this aspect into account when considering risk.

As shown in Table 5.2, increasing SocVul by 1.96 nearly doubled the maximum, mean and minimum risk, while creating a uniform SocVul more than doubled the maximum risk (57%), tripled the minimum risk, and quadrupled the mean risk. Geographically, the double and uniform social vulnerability slightly increased the magnitude of the risk across the U.S. (Figs. 5.8 and 5.9).

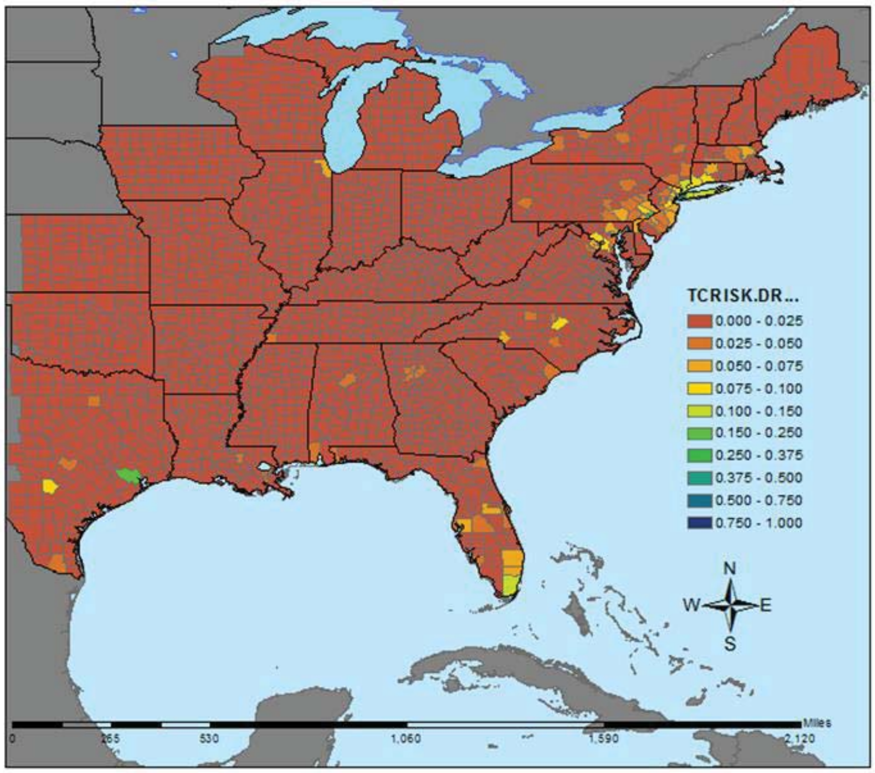



Figure 5.8 As in Fig 5.1, except for the contribution of 196% of social vulnerability.

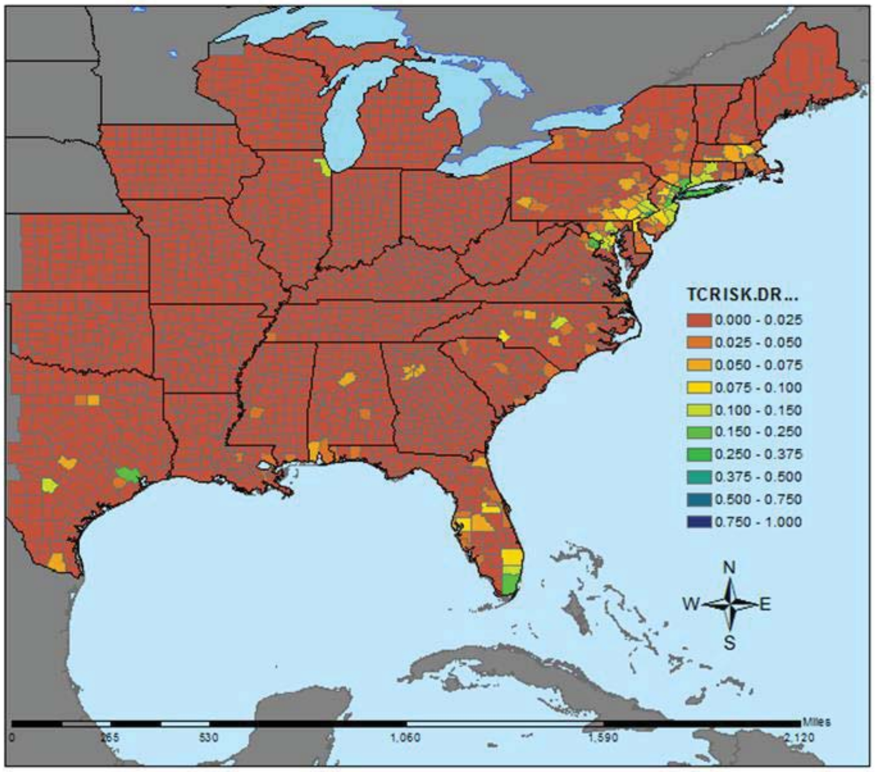
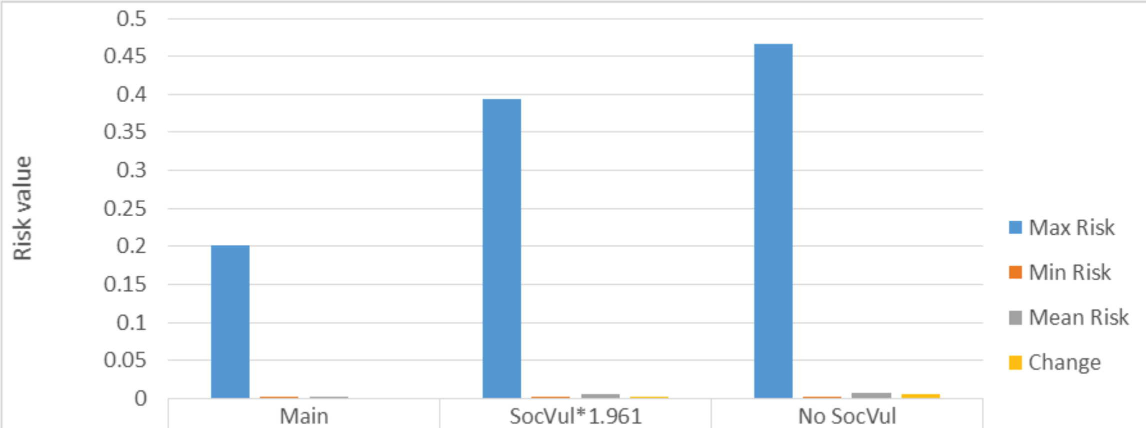



Figure 5.9 As in Fig 5.1, except for the uniform social vulnerability contribution.

Comparing the uniform Exposure and SocVul sensitivity tests, the effect of having a uniformly exposed population is greater than that of a uniformly vulnerable population. These findings suggest the importance of considering the exposed in risk analysis and the potential impacts the hazard will have on these communities. It does not suggest that social vulnerability is not important in such considerations.




| | Main | SocVul*1.961 | No SocVul |
|---|---|---|---|
| Max Risk | 0.200738 | 0.393646 | 0.465748 |
| Min Risk | 0.000004 | 0.000008 | 0.000012 |
| Mean Risk | 0.002484 | 0.004871 | 0.007628 |
| Change | | 0.002387 | 0.005144 |

Table 5.2 As in Table 5.1, except for the social vulnerability variable

Work is ongoing to investigate the different weights on the index variables. Additional work is aimed at testing different methods to normalize the index variables, each of which has disparate geographical distributions. These include “standardization” (which involve use of the mean and standard deviation of the variable distribution), and removal of outliers and therefore the use of a lower percentile value in the scaling.

## 5.3 Summary

An index was developed to help draw attention to the risk of inland communities to hurricane disaster. The combination of high probability of hazard occurrence and a large exposed population contributes the most to the high risk seen in the Mid-Atlantic. Other areas with high risk are shown in the southeast, where there is high social vulnerability, high hazard likelihood and moderate population exposure. Sensitivity tests were conducted on the Exposure and SocVul parameters, in which these variables were weighted differently. Creating a uniformly exposed population produced the most change in risk, suggesting the importance this variable could have in the decision making process. Risk information from this chapter will be used in Chapter 6 in the agent-based model simulations.

# CHAPTER 6. AGENT BASED MODELING OF TROPICAL CYCLONE HAZARD AND EVACUATION

The goal of this chapter is to demonstrate how an agent-based model can be used to simulate county-level changes in the probability of a TCT relative to a translating TC. Separate simulations are also performed of idealized county-level evacuations relative to the same translating TC. When combined, the two simulations are used to assess the time sensitive nature of evacuations ahead of an approaching TC.

## 6.1 *AnyLogic* Model

AnyLogic (AnyLogic North America, LLC 2014) is a commercial modeling system with the functionality of three different dynamic simulation platforms that can be used independently or in combination: “Systems Dynamic” modeling allows one to assess how a system behaves and its structure. The entities are modeled in quantities, however the individual properties of the entities are not included. “Discrete Event” modeling has the capabilities to approximate continuous real world processes with user-defined non-continuous processes. Finally, “Agent Based” modeling is a system of functions that allows user specific information to interact simultaneously in an environment. These modeling methods have been used to dynamically simulate the complexities of various economic, social, and physical systems, and hence have broad applicability.

Agent based modeling is the chosen modeling method here as it allows simulation of the effect of an agent, or active entity, on its environment. The agent is a TC that moves inland along a specified track. The environment consists of five counties.

## 6.2 Data and Methods

Using the TCT hazard analysis (see Chapter 3) as guidance, five cities/counties (see Fig. 6.1) have been chosen to represent the environment of the TC: Orange Beach/Baldwin, which is near the coast; Hattiesburg/Forrest and Meridian/Lauderdale, which are located inland and to the west of Baldwin County; and Montgomery/Montgomery and Birmingham/Jefferson, which are located inland and to the east of Baldwin County. As discussed below, Baldwin County also serves as the “evacuation” county. The modeling domain stretches 2124 km eastward across the southeastern United States. Five south-north TC tracks are specified, including a “main” track that flows directly through Baldwin County, and four additional tracks that are equally spaced on each side of the main track (Fig. 6.1). The simulated TC is constrained to move south-to-north at three different speeds, slow (8.05 km/hr), medium (16.09 km/hr), and fast (24.14 km/hr)

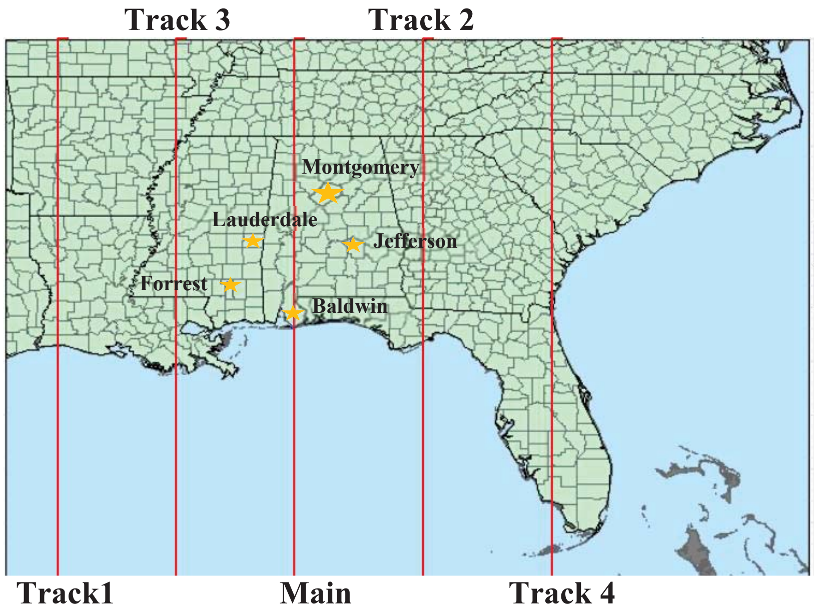



Figure 6.1 Agent-based modeling domain, showing the five different tracks of the TC (the agent), and the five counties (the environment).

TCT probability (TCTProb) is calculated on a hourly time step using the following equation, as the agent moves along one of the defined tracks:

$$TCTProb = StatP \times DistP \times QuadP \ . \qquad (6.1)$$

Here, StatP is the background or "static" probability of a TCT, as defined by the TCT hazard analysis:

Baldwin County = 0.147

Forrest County = 0.123

Lauderdale County = 0.115

Montgomery County = 0.152

Jefferson County = 0.062

DistP and QuadP are the "dynamic" probabilities of a TCT based on the distance d of the county (center) from the TC center, and on the county location relative to the TC quadrant, respectively.

Following Fig 7. of Edwards (2012), it is assumed that the probability of a TCT increases from a value of 0.25 at the TC center to 1.0 at 300 km, and then decreases thereafter. Specifically,

DistP = d/400 + 0.25, for $d \leq 300$ km,

DistP = (700-d)/400, for $300 < d \leq 700$ km,

DistP = 0, for $d > 700$ km.

The quadrant-relative TCT probabilities also follow Fig 7. of Edwards (2012). Letting X and Y be the coordinates of the county, and X0 and Y0 be the coordinates of the TC center, then

QuadP = 1.0, for X - X0 > 0, Y - Y0 > 0 (county is in Quadrant I),

QuadP = 0.5, for X - X0 < 0, Y - Y0 > 0 (county is in Quadrant II),

QuadP = 0.25, for X - X0 < 0, Y - Y0 < 0 (county is in Quadrant III),

QuadP = 0.75, for X - X0 > 0, Y - Y0 < 0 (county is in Quadrant IV).

## 6.3 Results

### 6.3.1 Change of TCTProb with Varied Speeds

The TCTProb maximum, minimum, mean, and change (MeanTCTProb-StaticTCTProb) is computed for each county and TC speed (fast, medium, and slow) over the Main Track (Tables 6.1-6.3). The expectation is that the faster the TC moves, the less time the county is subjected to the hazard. This is reflected somewhat in the mean TCTProb, particularly in Montgomery County, which accordingly also exhibited the greatest TCTProb variability or change during the simulations. One preliminary conclusion that can be extracted from these experiments is that the "dynamic" tornado hazard associated with a translating TC will become even more complicated with a nonlinear (i.e., curved) TC track.

| County | Static TCTProb | Max TCTProb | Min TCTProb | Mean TCTProb | Change of TCTProb |
|---|---|---|---|---|---|
| Jefferson | 0.062 | 0.06 | 0 | 0.029 | -0.033 |
| Montgomery | 0.152 | 0.149 | 0 | 0.064 | -0.088 |
| Forrest | 0.123 | 0.049 | 0 | 0.023 | -0.1 |
| Lauderdale | 0.115 | 0.057 | 0 | 0.023 | -0.092 |
| Baldwin | 0.147 | 0.049 | 0 | 0.022 | -0.125 |

Table 6.1 Tropical Cyclone Tornado Probability at slow speed (8.05 km/hr).

| County | Static TCTProb | Max TCTProb | Min TCTProb | Mean TCTProb | Change of TCTProb |
|---|---|---|---|---|---|
| Jefferson | 0.062 | 0.059 | 0 | 0.028 | -0.034 |
| Montgomery | 0.152 | 0.129 | 0 | 0.063 | -0.089 |
| Forrest | 0.123 | 0.048 | 0 | 0.023 | -0.1 |
| Lauderdale | 0.115 | 0.056 | 0 | 0.023 | -0.092 |
| Baldwin | 0.147 | 0.047 | 0 | 0.022 | -0.125 |

Table 6.2 Tropical Cyclone Tornado Probability at medium speed (16.09 km/hr).

| County | Static TCTProb | Max TCTProb | Min TCTProb | Mean TCTProb | Change of TCTProb |
|---|---|---|---|---|---|
| Jefferson | 0.062 | 0.055 | 0 | 0.028 | -0.034 |
| Montgomery | 0.152 | 0.126 | 0 | 0.061 | -0.091 |
| Forrest | 0.123 | 0.047 | 0 | 0.022 | -0.101 |
| Lauderdale | 0.115 | 0.057 | 0 | 0.023 | -0.092 |
| Baldwin | 0.147 | 0.046 | 0 | 0.022 | -0.125 |

Table 6.3 Tropical Cyclone Tornado Probability at fast speed (24.14 km/hr).

### 6.3.2 Change of TCTProb with Varied Tracks

The TCTprob maximum, minimum, mean, and change (StaticTCTProb-MeanTCTProb) are also computed for each county and track, for a fixed TC speed; the medium speed is chosen but represents the basic effects of track change on the TCTProb. One observation of interest is the identical probability changes on Tracks 2 and 3 whose locations are directly to the east and west, respectively, of the Main Track (see Fig. 6.1). Observed changes from Track 1, located on the far west of the Main Track, are slightly lower than Track 4, however the maximum TCTprob from Track 1 is much higher. This is also true for Track 3 compared to Track 2. These findings illustrate how distance and quadrant combine to modify the dynamic hazard.

| County | Static TCTProb | Max TCTProb | Min TCTProb | Mean TCTProb | Change of TCTProb |
|---|---|---|---|---|---|
| Jefferson | 0.062 | 0.06 | 0 | 0.044 | -0.018 |
| Montgomery | 0.152 | 0.147 | 0 | 0.112 | -0.04 |
| Forrest | 0.123 | 0.123 | 0 | 0.067 | -0.056 |
| Lauderdale | 0.115 | 0.109 | 0 | 0.069 | -0.046 |
| Baldwin | 0.147 | 0.144 | 0 | 0.101 | -0.046 |

Table 6.4 Tropical cyclone tornado probability on Track 1

| County | Static TCTProb | Max TCTProb | Min TCTProb | Mean TCTProb | Change of TCTProb |
|---|---|---|---|---|---|
| Jefferson | 0.062 | 0.029 | 0 | 0.015 | -0.026 |
| Montgomery | 0.152 | 0.075 | 0 | 0.032 | -0.065 |
| Forrest | 0.123 | 0.058 | 0 | 0.033 | -0.076 |
| Lauderdale | 0.115 | 0.055 | 0 | 0.031 | -0.064 |
| Baldwin | 0.147 | 0.05 | 0 | 0.026 | -0.075 |

Table 6.5 Tropical cyclone tornado probability on Track 2

| County | Static TCTProb | Max TCTProb | Min TCTProb | Mean TCTProb | Change of TCTProb |
|---|---|---|---|---|---|
| Jefferson | 0.062 | 0.059 | 0 | 0.036 | -0.026 |
| Montgomery | 0.152 | 0.15 | 0 | 0.087 | -0.065 |
| Forrest | 0.123 | 0.093 | 0 | 0.047 | -0.076 |
| Lauderdale | 0.115 | 0.112 | 0 | 0.051 | -0.064 |
| Baldwin | 0.147 | 0.11 | 0 | 0.072 | -0.075 |

Table 6.6 Tropical cyclone tornado probability on Track 3

| County | Static TCTProb | Max TCTProb | Min TCTProb | Mean TCTProb | Change of TCTProb |
|---|---|---|---|---|---|
| Jefferson | 0.062 | 0.031 | 0 | 0.019 | -0.043 |
| Montgomery | 0.152 | 0.076 | 0 | 0.044 | -0.108 |
| Forrest | 0.123 | 0.06 | 0 | 0.042 | -0.081 |
| Lauderdale | 0.115 | 0.056 | 0 | 0.039 | -0.076 |
| Baldwin | 0.147 | 0.073 | 0 | 0.039 | -0.108 |

Table 6.7 Tropical cyclone tornado probability on Track 4

### 6.3.3 Example Vulnerability Case

The final set of experiments is used to show how vulnerability, and inherently risk changes during evacuations. During each simulation, each county is assumed to start with some risk, but thereafter experiences an increase in risk depending on the magnitude of the hazard (TCT) probability, exposed population and social vulnerability of that population:

$$DRisk = StaticRisk + (TCTProb \times Exposure \times SocVul) \quad (6.2)$$

where StaticRisk for each county is:

Baldwin County = 0.051

Forrest County = 0.030

Lauderdale County = 0.029

Montgomery County= 0.075

Jefferson County = 0.157

TCTProb is the same as in section II, SocVul for each county is:

Baldwin County = 0.405

Forrest County = 0.697

Lauderdale County = 0.555

Montgomery County= 0.546

Jefferson County = 0.465

and Exposure is the exposed population in these counties:

Baldwin County = 0.008

Forrest County = 0.008

Lauderdale County = 0.555

Montgomery County= 0.023

Jefferson County = 0.068

For simplicity, the variables of Baldwin County are equally distributed between the four destination counties as the TC moves northward (e.g. SocVul for Forrest county is 0.697 + (0.405/4) and Exposure is 0.008 + (0.008/4)). This suggests that the evacuees and associated vulnerability and exposure from Baldwin County are split equally between the destination counties. Disaster risk for each county varied according to the table below showing the maximum, minimum, mean, and the change of risk (Static Risk-Mean Risk). Only the main track at medium speed is presented.

| County | Static Risk | Max Risk | Min Risk | Mean Risk | Change of Risk |
|---|---|---|---|---|---|
| Jefferson | 0.01 | 0.12 | 0 | 0.011 | 0.001 |
| Montgomery | 0.009 | 0.11 | 0 | 0.01 | 0.001 |
| Forrest | 0.002 | 0.002 | 0 | 0.002 | 0 |
| Lauderdale | 0.002 | 0.023 | 0 | 0.01 | 0.008 |
| Baldwin | 0.004 | 0 | 0 | 0 | -0.004 |

Table 6.8 Disaster risk

Results in Table 6.9 show that disaster risk increased as the TC propagated on its south-north track. Furthermore, the change in risk is contingent on the magnitude of the exposed population in combination with the hazard and social vulnerability. On the other hand, Baldwin County has a risk of 0, if there is no exposed population, then there is no risk, despite having a potential for TCTs (Table 6.7).

## 6.4 Summary

AnyLogic agent-based modeling was used to simulate evacuation behavior and the changes in risk and associated hazards during an idealized hurricane event. Information gleaned from this example case will hopefully educate decision makers on the complex interactions between inland hazards such as TCTs and evacuations.

# CHAPTER 7. SUMMARY, DISCUSSION, AND FUTURE WORK

## 7.1 Summary

The purpose of this research was to assess the disaster risk associated with tropical cyclones in the Atlantic Basin. This was done by assessing the three components associated with risk: vulnerability, hazard and exposure. "Vulnerability" refers to social and demographic characteristics influencing a person's ability to mitigate and or recover from disaster. "Hazard" refers to the hazards associated with the tropical storm (e.g. wind, surge, flooding etc.), this research focuses explicitly on tropical cyclone tornadoes, and flash flooding, and implicitly on wind. Lastly, "Exposure" is the exposed population within the domain defined by the wind hazard

A social vulnerability index was developed in this study that includes both inland and coastal vulnerabilities to hurricanes making landfall in the Atlantic Basin. A major finding is that the most vulnerable communities are found inland, providing evidence that inland communities should be considered during planning in hurricane disaster prevention. It is shown that the most vulnerable counties were located in portions of west Texas, New Mexico, Arkansas and the Carolinas. The least vulnerable region was in the Washington D.C. area.

The hazard component to the risk index consisted of tornadoes and flash flooding. On average, TCTs are on the lower end of intensity using the EF scale (EF0-EF2). The right front quadrant of the TC and the outer rainbands are favored locations for TCT production, but they are still difficult to forecast. Using data from the TCTOR database, an updated hazard map of TCTs was developed for the purpose of incorporating into a hurricane disaster risk index. After smoothing the data using a diffusion kernel, high TCT probability is shown in the Mid Atlantic Coastal States, Florida, southern Alabama, and central Mississippi.

Inland flooding is a topic of discussion that still needs to be addressed to reduce loss of life during hurricane events. With most hurricane decision making tools focusing on coastal areas, this study sheds light on the vulnerability of inland communities to flash flooding. Flash flooding is a major contributor to inland fatalities, causing 80% of total tropical cyclone related flood fatalities. To analyze this hazard, flash flood reports were extracted from NCDC between 1995 and 2012. After acquiring the data, a smoothed frequency map of the annual flash flood occurrence was developed. A key finding is the relatively high probability in counties well inland from coastal areas, as evidenced by the concentration of flash flooding in inland New England and gulf coast regions.

The risk map was developed using the product of the hazard, exposure and vulnerability. The combination of high probability of hazard occurrence and a large exposed population contributes the most to the high risk seen in the Mid-Atlantic. Other areas with high risk are shown in the southeast, where there is high social vulnerability, high hazard likelihood and moderate population exposure. Counties with large populations show high vulnerability in unlikely hurricane risk areas such as Cook County, near Chicago, IL. Sensitivity tests were conducted on the Exposure and SocVul parameters to test the effects of weighting the variables, showing the impacts to the resulting risk map. Ultimately creating a uniformly exposed population produced the most change in risk, suggesting the importance this variable could have in the decision making process.

A potential means of testing how the risk index might be applied, and of evaluating the time-dependency of hurricane risk, was provided by agent-based modeling. In particular, AnyLogic agent-based modeling software was used to simulate evacuation behavior and the changes in risk and associated hazards during an idealized hurricane event. Information gleaned from this example case will hopefully educate decision makers on the complex interactions between inland hazards such as TCTs and evacuations.

## 7.2 Discussion and Conclusions

To truly reduce the lethality of hurricanes, a thorough assessment of the communities that will be impacted is necessary. Emergency managers use various tools to aid them in determining when and where to allocate funding and resources to prevent hurricane disaster. The risk index developed in this study presents additional important information on all counties within the hazard prone regions, not just coastal communities. In addition to the inclusion of the vulnerability of inland communities, a new approach using the tropical cyclone tornado and flash flood hazard maps gives a new perspective to assessing hurricane disaster risk. This is partly because storm surge and wind are considered the biggest threats causing mass evacuations. Now decision makers can have a more complete hazard analysis to assess the threats and make even more appropriate evacuation decisions. The use of agent based modeling, as demonstrated in Chapter 6, shows potential in aiding large scale evacuations, which is unrealistic to accomplish otherwise in full scale exercises. Although this tool is still in development, it is hoped that information gleaned from this research will aid in future hurricane evacuation preparations.

### 7.3 Future Work

There are several opportunities to expand on this research, which include addressing the data limitations described in Chapter 4. Initial testing (not presented here) showed that different combinations of factors strongly influenced the overall vulnerability of a county. Therefore conducting comprehensive sensitivity tests would allow for a better understanding of detailed factors that increase social vulnerability. It is also important to get a further break down of the indicators to pinpoint specific needs to specific demographics. Conducting more surveys to get a better analysis of emergency preparation for each county is necessary due to the limited information provided which was on the state level instead of county level. Finally a more integrated approach that will expand beyond the "top-down" approach would give more comprehensive vulnerability assessments and help communities prepare for disaster.

Another key addition to this research would be a statistical assessment to see the change in TCT activity over the years, especially during seasons producing unusually high TCT events. Also, a comparison of TCT frequencies to overall tornado events may be effective. For instance, during relatively high tornado event seasons, what are the implications for TCT events? Would one expect higher TCT events when there are fewer tornado events during the severe weather season?

To continue the flood hazard work, an assessment of stream flooding, storm surge and flood mortality would be beneficial in acquiring a complete knowledge of the tropical cyclone flood hazard. It would also be interesting to look for indicators on how this flooding will change in the future. Information from this portion of the research can be incorporated into an application tool such as HURREVAC, and be updated based on the projected rainfall during hurricane events. Finally, a physical assessment of rainfall and storm type (e.g. major, minor hurricane, tropical storm), and their percentage to the total contribution to the total annual rainfall would be valuable. In addition, the role of precursor conditions, such as drought, on flash flooding may be important to account for in hurricane risk assessments.

In continuing development of the hurricane disaster risk index, future research will include wind distribution and storm surge. These hazards are essential in obtaining a full assessment of the risk potential of landfalling Atlantic Basin Hurricanes. It is also beneficial to consider using weights on the various components to ensure that one factor is not driving down the risk to minute values. For example, sensitivity tests were conducted on the "Exposure" variable as this variable was so small due to normalizing with the maximum value. Because of the range of small values, many counties with high hazard likelihood and high social vulnerability are shown to have low risk.

Ultimately it would be beneficial to expand the agent based model to include all counties within the hazard domain. This will allow the user to assess various real time scenarios and make planning decisions based on real time forecasts and the dynamic variability in the dynamic variables.

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# APPENDIX

# APPENDIX

## FFW Climatology

A python script was written to loop through the following process for all 85 cases using GIS:

1. Add tracks data and make XY event layer.
2. Convert the points to a line using "Points to Line tool."
3. Create a buffer around the TC tracks layer using the buffer tool setting the distance of the buffer to 500km.
4. Add individual flash flood warning shape files.
5. Use the select tool, "new selection," to filter flash flood warnings
6. Use the "select from current selection" and filter warnings occurring within the buffer
7. Using "select from current selection" again filter the warnings occurring only within the continental U.S.
8. Store the filtered flash flood warnings in a designated geodatabase using the TC name as a unique file identifier

After looping this process for all cases, the "Merge" tool was used to merge the newly created files from step 8, to create one file to conduct the analysis. After the files are merged, the new shapefile is joined to counties based off a spatial location, where the polygon will be given the attributes of the line intersecting it. A count field is included in the table consisting of the number of flash flood warnings intersecting the county field.

**FFR Climatology**

Flash Flood reports are also analyzed in GIS with the same criteria as the FFW analysis:

1. Export individual files to a .dbf format
2. Join to county using FIPS attribute
3. Using the select by location tool, select features from counties that intersect the associated TC buffer
4. Create a new layer from the selected features
5. Copy features from (5) and store with TCYRReports
6. Using Merge Tool, merge the TCYRReports

**Smoothing the FFW and FFR Data**

The smoother is applied as follows:

1. Select Diffusion Kernel in the Geographical Analyst tool

   -input dataset and associated z field

   -No barriers
2. Use the Export to Raster tool

   -Input geostatistical layer from (1)

   -Change cell size 0.01330948
3. Use the Zonal Statistics as Table tool

-input counties for zone features

-input FIPS as zone field

4. Join zone table to counties using FIPS attribute

**Geospatial Analysis of TCT Data**

For reference, the smoother was applied within ArcGIS as follows:

1. Select Diffusion Kernel in the Geographical Analyst tool

   -input TCT dataset and associated z field

   -No barriers

2. Use the Export to Raster tool

   -Input geostatistical layer from (1)

   -Change cell size 0.01330948

3. Use the Zonal Statistics as Table tool

   -input counties for zone features

   -input FIPS as zone field

4. Join zone table to counties using FIPS attribute

VITA

# VITA

Dereka Carroll
Graduate School, Purdue University

Education
B.S., Meteorology, 2012, Jackson State University, Jackson, MS
M.S., Atmospheric Science, 2014, Purdue University, West Lafayette, IN

Research Interests
Modeling severe weather hazards, societal impacts of severe weather, agent based modeling and evacuation behavior.

Memberships
American Geophysical Union, 2011-present
SACNAS, 2010-present
American Meteorological Society, 2008-Present

Honors
Golden Key international Honour Society Nov 2011-Present
Minorities Striving to Pursue Higher Degrees of Success in Earth System Science(MSPHD) 2011-2013 Cohort 8, Oct 2011- Present
Phi Kappa Phi Honor Society, Apr 2011- Present
Alpha Chi Honor Society, Apr 2011- Present
Alpha Lambda Delta Honor Society, Apr 2008- Present
W.E.B DuBois Honors College, Apr 2008- Present

Awards
"Best Student Presentation" in the Ninth symposium on Science Policy and Socioeconomic research, 2014, American Meteorological Society 94th Annual Meeting
National Science Foundation Graduate Research Fellow, Sept 2013
David M. Knox Fellowship, Apr 2012, Purdue University
Higher Education Appreciation Day Working for Academic Excellence (HEADWAE) 2011-2012 Student Honoree, 2011, Jackson State University
Who's Who among students in American Universities and Colleges 2011
Who's Who among students in American Universities and Colleges 2012
3rd place: NOAA Enterprise-Capabilities Presentation, 2011

3rd place: Delta Sigma Theta Sorority Inc. Profound Essay, Scholarship and Service Competition, 2011

Experience

Teacher's Assistant, 2011-2012, Jackson State Meteorology Department

Research Assistant,2011-2012, Jackson State Meteorology Department

Mentor for IMAS-RAP (Increasing Minorities in Atmospheric Science through Research Application and Partnership), 2011-2012

This program is designed to increase the amount of minorities in the geoscience field, establishing a sustainable geoscience pipeline between the local area k-12 public schools and JSU geoscience department.

Ernest F. Hollings Scholarship Program, 2010 –2012

A ten- week summer internship designed to increase undergraduate training in the oceanic and atmospheric science, research and technology fields.

SOARS (Significant Opportunities in Research and Science), 2010-2014

An undergraduate-to-graduate bridge program designed to broaden participation in the atmospheric and related sciences.

LSMAMP (Louis Stokes Mississippi Alliance for Minority Participation), 2008

A five-week program that focuses on the enhancement of skills in both the areas of Science (specifically Chemistry) and Mathematics.

Presentations

American Meteorological Society, 2014, Atlanta, GA, 93th Annual Meeting, “Towards a better understanding of tropical cyclone flooding: Flash floods”

Great Lakes Meteorology Conference, 2013, Valparaiso, IN, “Mapping social vulnerability to landfalling hurricanes in the Atlantic Basin”

American Meteorological Society, 2013, Austin, TX, 93rd Annual Meeting “Mapping social vulnerability to landfalling hurricanes in the Atlantic Basin”

American Meteorological society, 2012, Nashville, TN, Severe and Local Storm Conference “Mapping social vulnerability to landfalling hurricanes in the Atlantic Basin”

National Conference on Undergraduate Research 2012, Ogden, Utah, “WRF Optimization for Forecasting Wet Microburst Potential” American Meteorological Society, 2012, New Orleans, LA, 92th Annual Meeting 11th Annual Student Conference “WRF Optimization for Forecasting Wet Microburst Potential”

American Geophysical Union Fall Meeting, 2011, San Francisco, CA, “WRF Optimization for Forecasting Wet Microburst Potential”

NOAA Student Scholarship Science Symposium, 2011, Silver Spring, MD, “WRF Optimization for Forecasting Wet Microburst Potential”

National Conference on Undergraduate Research, 2011, Ithaca, New York. “Model Verification and analysis of intense Mesoscale Convective Vortices (MCVs) at the surface: Simulation of Tropical Cyclone Erin (2007)”

American Meteorological Society, 2011, Seattle, WA, 91th Annual Meeting 10th Annual Student Conference “Model verification and analysis of intense Mesoscale

Convective Vortices (MCVs) at the surface: Simulation of Tropical Cyclone Erin (2007)"

SACNAS 2010 National Conference 2010, Anaheim, CA, “Model verification and analysis of intense Mesoscale Convective Vortices (MCVs) at the surface: Simulation of Tropical Cyclone Erin (2007