A COMPARISON OF SELECTED WISCONSIN COUNTIES USING AN ATMOSPHERIC HAZARD VULNERABILITY ASSESSMENT

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ABSTRACT

Hazard, risk, and vulnerability assessments are vitally important to the communities for which they serve. Risk from natural hazards is unavoidable, but the consequences of a hazard event can be better managed when they are planned for. Using 1998-2008 data from the National Climatic Data Center, an assessment based on the Total Place Vulnerability Index (TPVI) and the Integrated Risk Assessment of Multi-hazards (IRAMH) was created to help communities in selected Wisconsin counties receive a better estimate of their vulnerability to atmospheric-related natural hazards at the county scale. This model used data compiled by the NCDC's Storm Events database to calculate damage and casualty scores for each of the selected counties. U.S. census data was then used to create a vulnerability statistic that looked at population demographics, type of housing, and median income. Based off scores created by ranking these statistics, the results show that the counties that are the most vulnerable are those in the southwestern and central parts of the state.

INTRODUCTION

The importance of hazard, risk, and vulnerability assessments cannot be understated. These are important tools for community officials, emergency personnel, spatial planners, insurers, and even homeowners. For planners, it is essential that they anticipate the consequences of planned actions so that future uncertainty can be reduced. Risks are unavoidable, but can be managed better when they are planned for. Thus, when long-term decisions are being made for a specific geographic area, all hazards must be considered, or else the uncertainty and risks associated with those decisions become larger and harder to manage (Greiving et al. 2006).

There are many good examples of research that are trying to actively reduce the risks to populations from natural hazards. Two important assessments form the basis for this research. These are the Total Place Vulnerability Index (TPVI) created by the Hazards Research Lab at the University of South Carolina (HVRI 2007; Greiving et al. 2006) and the Integrated Risk Assessment of Multi-hazards (IRAMH) developed by Greiving et al. (2006). The TPVI's approach looks at two parts of disaster proneness: physical and social. Physically, the TPVI looks at rates of hazard occurrence to quantify how often, and therefore vulnerable, a location is to being struck by a natural hazard. Socially, the TPVI looks at indicators derived from census data to quantify how vulnerable a population is to natural hazards. When the two parts are combined, the TPVI gives a total assessment of how vulnerable a place and its population are (Cutter et al. 2000; Greiving et al 2006).

The IRAMH uses more physical than social factors in determining disaster proneness. It ranks hazards based on intensity, not occurrence like the TPVI, to determine a location's vulnerability. The intensities are based on several indicators for each hazard. The IRAMH is

much broader in its use of social parameters since it uses indicators such as regional wealth, national wealth, and population density in order to quantify a population's vulnerability. The physical and social parts are normalized and then combined within a table in order to determine how vulnerable a location and its population are (Greiving et al. 2006).

The primary goal of both assessments is to decrease vulnerability and save lives through determining areas that could benefit from mitigation efforts. However, the TPVI enables the user to see not only the biophysical risks, but the risks that are inherent to the population. Social vulnerabilities are a cornerstone to this index so that all vulnerabilities to populations can be accounted for and effectively analyzed.

PURPOSE AND SCOPE

The Total Place Vulnerability Index has been shown to be effective at the county level (Cutter et al. 2000), the state level (SCEMD 2006), and partly at the national level (Cutter 1996; Cutter et al. 2003). However, this model has not been applied to the state of Wisconsin, where natural hazards occur with some frequency. The use of an assessment tool such as the Total Place Vulnerability Index could be important to local planners, officials, and emergency responders.

There is one major research question that will direct this research: what is the atmospheric-related natural hazards risk to populations within the state of Wisconsin? Atmospheric-related hazards were chosen over all hazards for three reasons. First, human-induced hazards such as chemical spills are not considered "natural" hazards. Second, Wisconsin does not suffer from very many geophysical hazards such as earthquakes or volcanoes, so the scope was narrowed to natural hazards that are known to have direct

impacts within the state. Last, by using atmospheric-related hazards, the data source (the NCDC Storm Events Database) will be consistent for all hazards within the research.

LITERATURE REVIEW

Historical Trends

Fatalities and economic losses due to natural hazards are rising (Mitchell et al. 2001). There is a direct relationship between the level of development and the type of losses that occur. For example, developing nations often have higher death tolls but developed nations often have higher economic costs (Mitchell et al. 2001). In a study period between 1975 and 1998, damages caused in the United States by atmospheric natural hazards totaled $266,204.3 million (out of a total $302,187.2 million) (in $1999). There were also 8,228 deaths and 60,324 injuries (Mitchell et al. 2001). New loss records were set for the U.S. in 1989 and in the years from 1992-1994 for all natural disasters (Mitchell et al. 2001). In fact, the decade of the 1990s was the most disastrous decade ever in the United States (this can partly be attributed to increases in population). However, it is important to note that approximately 75% of all these losses were not caused by a singular, defining event. This means that smaller events occurring more frequently are just as important (Mitchell et al. 2001). Weather-related events accounted for 89% of the total losses from natural hazards and 92% of the fatalities with floods topping the list as the most costly natural hazards in the nation. Floods led in both economic losses and in fatalities (Mitchell et al. 2001).

The Nature of Risk

Definitions

Humans have the capability to alter and respond to their environment. This power both creates and reduces risk (Slovic 1994). Risk, hazard, and disaster are three words that often get used interchangeably, yet there are fundamental differences between all three. While there are more general definitions of these terms, these definitions are specific to this research.

- *Hazard*: occurs where a natural event is likely to harm human life or property (Hyndman et al. 2006).
- *Disaster*: a singular event, caused by a hazard, that kills or injures large numbers of people, causes major property or infrastructure damage, or causes widespread damage to the environment (Cutter 2001; Hyndman et al. 2006).
- *Risk*: the possibility of a disaster affecting a population (Cutter 2001).
- *Susceptibility*: the degree to which a population is sensitive to hazards due to its demographics.
- *Vulnerability*: a population's potential for loss of property or life (risk) due to its susceptibility to hazards (Cutter et al. 2000; Hill et al. 2001).

Aspects of Risk

Risk is shaped by the interactions of many components in society, technology, and the environment. Greiving et al. (2006) write about a set of four influences on risk. The first is the threat of loss. These are things that people want to avoid losing; i.e. family, friends, their homes, etc (Greiving et al. 2006). Second is that vulnerability stems from attributes in individuals or communities that will increase damage from hazards. Examples include

greater harm due to the predispositions of people, buildings, and communities, lack of resilience, and inabilities to acquire means of protection or relief (Greiving et al. 2006). These predispositions are usually rooted in belief that an event could not occur in that community and therefore the members do less to prepare for such an event. The resilience of a community is often coupled with the wealth of a community. Wealthy communities can rebuild faster than less wealthy communities (Greiving et al. 2006).

The third influence identified is that of "intervening conditions of danger" or in simpler terms, secondary hazards. These elements could magnify or moderate the impact of a disaster. Examples of these include topography and tree cover (Greiving et al. 2006). A community that is in a topographically low area could not only suffer from a hurricane that comes through the community, but also could be affected by floods in low-lying areas. The final influence comes from human coping and adjustments to reduce the dangers of hazards and potentially reduce risk (Greiving et al. 2006). In other words, the final influence is mitigation. By mitigating the potential primary and secondary dangers associated with hazards, a community can also reduce their potential vulnerability.

Vulnerability

Definition

As stated earlier, vulnerability is a population's potential for loss of property or life (risk) due to its susceptibility to hazards. This definition can mean different things to different people because the type of loss and whose loss is being described depends on the circumstance (Cutter 1996). Vulnerability "is an essential concept in hazards research and is

central to the development of hazard mitigation strategies at the local, national, and international level" (Cutter 1996).

Key Themes in Vulnerability Research

There are three key themes in vulnerability research: vulnerability as risk/hazard exposure, vulnerability as social response, and vulnerability of place (Cutter 1996). Vulnerability as risk/hazard exposure focuses on the distribution of hazards, the spatial distribution of populations, and the degree of loss associated with an event (Cutter 1996). These studies often focus on the biophysical vulnerability side of the hazard-of-place model. Research in the theme of vulnerability as social response focuses on how human populations cope and show resistance and resilience to hazards (Cutter 1996). These studies often focus on the social vulnerability side of the hazard-of-place model, where human vulnerability is the main subject of research. The last major theme of research is vulnerability of place. This theme combines the other two by considering vulnerability as both a biophysical risk as well as a social response within a geographic area (Cutter 1996). Within the hazard-of-place model, place vulnerability is essential because it is incorporates both biophysical and social factors.

Types of Vulnerability

Cutter (1996) points out the there are many types of vulnerability but three are the most important. There are individual, social, and biophysical vulnerability. Individual vulnerability is the susceptibility or sensitivity of a person or structure to potential harm from hazards (Cutter 1996; Hill et al. 2001). For this research, individual vulnerability will generally not be relevant. Social and biophysical vulnerability are wider in scope, as they refer to entire social groups and landscapes (Cutter et al. 2000). Biophysical vulnerability

has already been discussed in some detail. In essence, it looks at the spatial characteristics of vulnerability. Biophysical vulnerability is synonymous with exposure. Variables related to exposure normally include: proximity to the source of the threat, incident frequency or probability, magnitude, duration, rapidity of onset, and spatial impact (Cutter 1996; Hill et al. 2001).

Social vulnerability is the most changing and hardest to use of these three types of vulnerability. Social vulnerability describes the demographic characteristic of social groups that make them more or less susceptible to the impact of hazards (Hill et al. 2001). Cutter suggests that social factors such as wealth and housing can contribute to greater vulnerability (Cutter et al. 2000). Actions such as population shifts from urban to suburban can result in more people living in areas of risk such as floodplains, where they are either unaware or uncaring of such a risk. At the same time, the decision to live in manufactured housing, as many do near the Gulf coast, means that more people could be living in homes that are more likely to be damaged by the next hurricane that comes through the Gulf region. Population shifts and housing decisions such as these suggest that vulnerability is created by people through their decisions and actions (Hill et al. 2001).

Social vulnerability is also partially the result of social inequalities. Inequalities can influence the susceptibility of groups to harm and govern their ability to respond (Cutter et al. 2003). Social vulnerability also is a factor of place inequalities. These inequalities include the characteristics of communities such as the level of urbanization, growth rates, and economic vitality (Cutter et al. 2003). For example, those same people living in the Gulf coast manufactured homes are often there because that is all they can afford due to low-income jobs in the region.

Key social and demographic characteristics that are indicators of social vulnerability are population density and distribution, socioeconomic status, age, experience, gender, age, race or ethnicity, and wealth (Hill et al. 2001). For example, age is important because the elderly and young are more difficult to evacuate than the average middle-aged person. The poor are more susceptible due to lack of resources, representation, and deficient housing. The rich could sustain higher material losses, although they will most likely be able to recover (Cutter et al. 2003).

At the end of Cutter et al. (2003), the authors note that social vulnerability can be combined with hazard event frequency and economic loss data to further examine those factors that are the most important contributors to dollar losses. It is this step that starts to bind social vulnerability with its biophysical side and starts to create an assessment of both hazards and vulnerability.

Natural Hazard Assessments

Types of Assessments

Broadly, risk assessments look to define the probability of a hazardous event occurring and where it is likely to occur. More narrowly, they tend to focus on one type of risk posed by one substance in a single medium (Hill et al. 2001). Vulnerability assessments are used to determine the potential damage and loss of life from extreme natural events (Cutter 1996). They are more difficult to undertake because they need to incorporate both risk and social factors in an attempt to recognize why some places are more susceptible to hazards than others. Vulnerability assessments include information on risks and hazards as well as on the population and infrastructure at risk (Hill et al. 2001). Many examples of each

model exist. Examples of risk estimation applications include: the EPA's Areal Locations of Hazardous Atmospheres and Computer-Aided Management of Emergency Operations models for hazardous airborne pollutant exposure, the National Weather Service's (NWS) Sea, Lake, and Overland Surges model for storm surge, National Hurricane Center hurricane strike forecasting and wind field models, the NWS's SKYWARN system for tornado risk estimation, and the Coastal Vulnerability Index for coastal risks from flooding and erosion (Hill et al. 2001).

Examples of vulnerability assessments include both single-hazard and multi-hazard approaches. A couple of the more advanced models developed of the single-hazard variety include the U.S. Agency for International Development's Famine Early Warning System and the U.N. Food and Agricultural Organization's Africa Real Time Environmental Monitoring Information System. Both provide data that evaluate national and international food security issues (Hill et al. 2001). Multi-hazard assessments are usually scaled to the local level and conducted by individual researchers.

National Hazard Index for Megacities

Three hazard assessments are critiqued in the article by Greiving et al. (2006). Two will be discussed here, while the third (the Total Place Vulnerability Index) will be discussed more thoroughly later in this paper. The first model discussed is the National Hazard Index for Megacities. This model was developed by the Munich Reinsurance Company and it measures the risk of material losses in the 50 largest cities in the world. Thus, it focuses on the economic side of risk and vulnerability. The main focus of this model is the measure of loss potential (Greiving et al. 2006). This is important because it can lead to the reduction of risks through mitigation efforts that can protect the economic investments within these cities.

Three components to this model are hazard exposure, vulnerability, and exposed values. First, hazard exposure is determined through the indicators of "average annual losses" and probable maximum loss" by a ratio of 80:20 (Greiving et al. 2006). The second component is vulnerability, for which there are three indicators. These are safeguards/building regulations, building class vulnerability, and general vulnerability as determined by population density and quality of construction within the city. Each of these indicators is defined by classes that are all weighted equally (Greiving et al. 2006). The third component is the exposed values. This component takes into consideration the importance of households and industrial facilities in relation to value of urban area. It also calculates the global economic significance of an urban area within the overall global context (Greiving et al. 2006). All indicators are then standardized and then combined by multiplying to get the overall risk index, as seen in Figure 2 (Greiving et al. 2006). The principle methodology of this model could be applied to towns, regions, or counties.

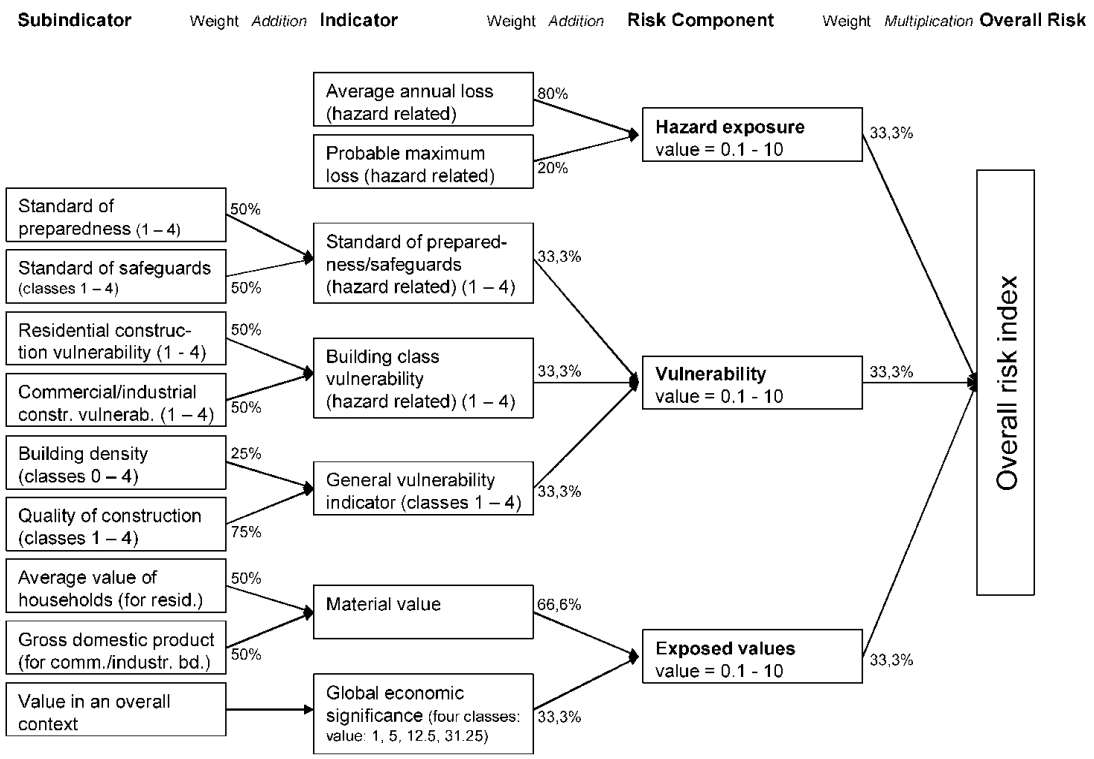

Figure 1. The National Hazard Index for Megacities. Greiving et al. 2006.

An Integrated Risk Assessment of Multi-hazards

Greiving et al. (2006) propose their own method at the end of the paper called the Integrated Risk Assessment of Multi-hazards. The approach was developed at the Institute of Spatial Planning at the University of Dortmund, Germany. The purpose of this model is to determine total risk potential of sub-national regions with spatially relevant hazards (Greiving et al. 2006). There are four components to this model; they are hazards maps, an integrated hazard map, a vulnerability map, and an integrated risk map. In the hazard mapping stage, each hazard has a separate map to show the regions it is spatially relevant to and the intensity of the hazard. This intensity is based on the frequency and magnitude of the hazard. Then each hazard is classified separately on an ordinal scale using five relative

hazard classes. This step allows for different types of data to be used for the hazards (Greiving et al. 2006).

Creating an integrated hazard map is the next step. Here, individual hazards are integrated into one map. This is done by adding up the individual intensities (Greiving et al. 2006). Weighting is once again an issue, so the weighting scale used in this model is the Delphi method. This allows for multiple rounds of experts assigning weights to hazards anonymously so there is a more reasonable explanation for the weights chosen. The individual hazards are then weighted using the aggregate expert weights, added together, and reclassified on an ordinal scale into five classes (Greiving et al. 2006).

The third component is the vulnerability map. This is created using information on economic and social vulnerability and then combining them. These sub-components include: regional GDP per capita, population density, fragmented natural areas, and coping capability. Coping capability is acquired by looking at the population density of an area and the national GDP per capita (Greiving et al. 2006). The weighting is normative for this component and thus changed if needed. Each vulnerability component is then classified using the same five ordinal classes as the earlier maps. The last step is the integrated risk map. The two maps are combined into one and the risk matrix seen in Figure 3 helps determine regions that are hazardous against those that are instead risky or more vulnerable (Greiving et al. 2006).

Degree of vulnerability / Overall hazard intensity	1	2	3	4	5
1	2	3	4	5	6
2	3	4	5	6	7
3	4	5	6	7	8
4	5	6	7	8	9
5	6	7	8	9	10

Figure 2. The integrated risk matrix from the Integrated Risk Assessment of Multi-hazards. Lower numbers equate to lower risk. Greiving et al. 2006.

Perceived Problems with these Assessments

There are a few problems with each of these models. First, in the National Hazard Index for Megacities, the multiplication of hazards and social vulnerability creates large difference between economically rich cities and economically poor ones (Greiving et al. 2006). This is because if one factor is low, it keeps the end result for the city low. This could be avoided by adding instead of multiplying (Greiving et al. 2006). Secondly, the vulnerability component of the model is less important than the hazard and exposed loss components (Greiving et al. 2006). Both of these components are based on economic factors. This model requires very detailed data that few can obtain. Lastly, the model contains much normative weighting which makes the model less methodologically sound (Greiving et al. 2006).

The Integrated Risk Assessment of Multi-hazards model also has a few issues. The authors note that their model does not take into account interrelations between hazards that could cause more or lessen the effects to a community. However, this subject has been worked into few if any assessments (Greiving et al. 2006). There are also weighting

problems, even with the incorporation of the Delphi method. This method would need to be updated regularly as events occur and thus changing expert opinion of hazards (Greiving et al. 2006). The use of GDP per capita data will need to allow for changes of those parameters, both up and down and would also need to be updated (Greiving et al. 2006). Lastly, there are limits of measurability, especially when it comes to components such as coping capability. The model only allows for quantitative data and this component may require qualititative data (Greiving et al. 2006).

Total Place Vulnerability Index

This research uses the Total Place Vulnerability Index as a base for the end assessment. The TPVI was developed by the Hazards Research Lab and Dr. Susan Cutter, who is currently at the University of South Carolina. The TPVI's main goal is to identify areas that are most vulnerable to hazards. This index uses the three components of social, biophysical, and place vulnerability to recognize at risk areas (Greiving et al. 2006). It uses the scaffolding of the hazards-of-place model of vulnerability as its base.

The Hazards-of-Place Model of Vulnerability

The hazards-of-place model is the basic concept from which the TPVI stems. The model's outcome is an overall place vulnerability of the area in question. It starts with the interaction of risk, which is defined as the likelihood of a hazard event, and mitigation. These two factors create a hazard potential. The hazard potential is affected by two filters: geographic and social. The geographic filter is created by the site and situation of a place, the frequency of occurrence of hazards, and the proximity to hazardous events (Cutter et al. 2000). The social filter is concerned with community experience with and the ability to

respond and recover from hazards. This filter is affected by economic, demographic, and housing characteristics (Cutter et al. 2000).

Both of these filters result in the quantifying of vulnerabilities in both the biophysical and social realms. These two vulnerabilities interact to create the overall place vulnerability (Cutter et al. 2003; Cutter et al. 2000; Greiving et al. 2006). At the end of the model, there is a feedback loop that goes back to the beginning that allows for the enhancement or reduction of both the risk and mitigation factors (Cutter et al. 2000; Cutter 1996). Mitigation, or changes to an environment to minimize loss from a disaster (Hyndman et al. 2006), can either reduce or amplify risk. Good mitigation policies can help buffer a community from the worst a hazard has to offer, while poor or nonexistent policies can leave a community at the mercy of a hazard.

This entire process is illustrated in Figure 3 (Cutter et al. 2003). The Total Place Vulnerability Index essentially uses the last three aspects of this model: the biophysical and social vulnerabilities as well as the overall place vulnerability. This is illustrated in a case study of Georgetown, South Carolina (Cutter et al. 2000).

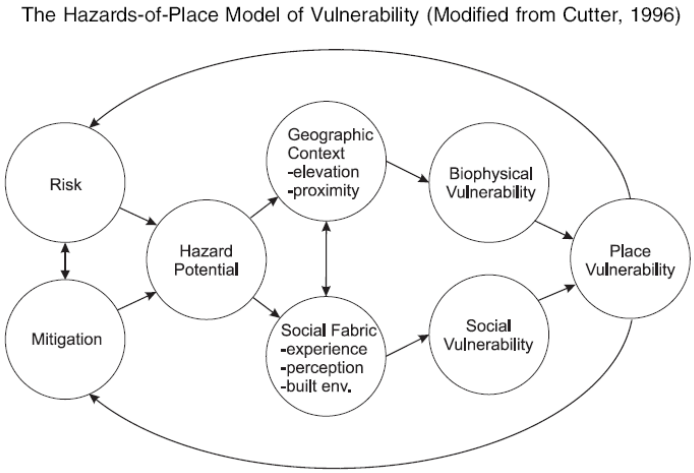

Figure 3. The Hazards-of-Place Model of Vulnerability. Cutter et al. 2003.

Georgetown, S.C.: A Case Study

The case study of Georgetown, South Carolina provides a good example of this index's use. The first step in Cutter et al. (2000)'s use of the Total Place Vulnerability Index was identifying the hazards that affected the county and as well as their frequency of occurrence. The frequency of occurrence was calculated by taking the number of hazard occurrences and dividing them by the number of years of record (Cutter et al. 2000).

The next step in the process was the delineation of each hazard zone and followed by the assignment of their rate of occurrences. If hazards were not spatially concentrated, such as tornadoes for example, they were assumed to have a random spatial distribution and thus the hazard events covered the entire county. Other, spatially concentrated hazards such as floods were delineated from data sources such as FEMA's Q3 flood data. To assess the total biophysical vulnerability, the layers were all combined and summed using GIS software (Greiving et al. 2006) and resulted in the composite map seen in Figure 4.

The third part of the case study defined the social vulnerability of the county. This was accomplished by using U.S. Census Bureau block datasets on: total population, total housing units, number of females, number of nonwhite residents, number of people under age 18, number of people over age 65, mean house value, and number of mobile homes (Cutter et al. 2000). In order to standardize the data, the ratio of each variable in each census block to the total number of that variable within the county was calculated. This value was then divided by the maximum value for that variable to create an index of 0 to 1 where higher values indicated greater vulnerability (Cutter et al. 2000). A composite map was created by summing up all the index values and then mapping them with a GIS program. This composite map can be seen in Figure 5.

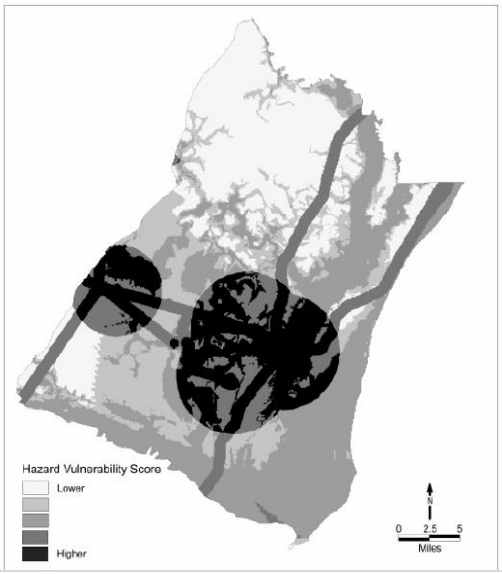

Figure 4. A composite map of hazard vulnerability scores. Cutter et al. 2000.

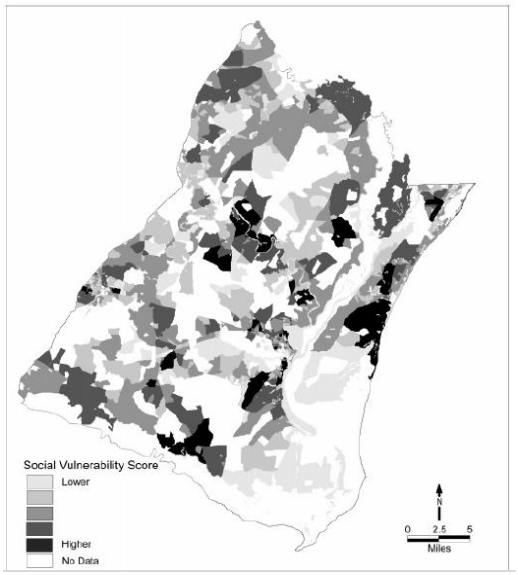

Figure 5. A composite social vulnerability map. Cutter et al. 2000.

The next step involved discovering the vulnerability of place by combining the two vulnerability maps. The hazard scores were multiplied by the vulnerability scores and then reclassified into five categories (Cutter et al. 2000). This place vulnerability map can be seen in Figure 6.

In the final step of the case study, the social and infrastructural context was put into place. This was done for mitigation and evacuation planning. Mapping features such as daycare centers, nursing homes, health centers, hospitals, and schools allowed for the identification and collection of special-needs population data. Mapping infrastructure such as emergency response stations, roads, utilities, railroads, bridges, dams, airports, seaports, and evacuation centers helped determine where key infrastructure and lifelines were located (Cutter et al. 2000). This can be seen in Figure 7.

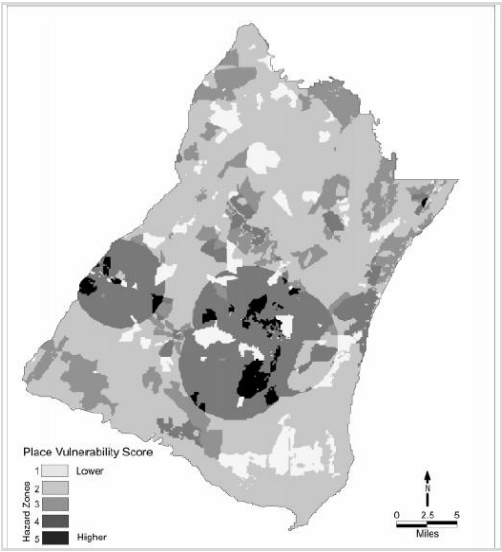

Figure 6. A composite map of place vulnerability derived from combining the hazard scores with the vulnerability scores. Cutter et al. 2000.

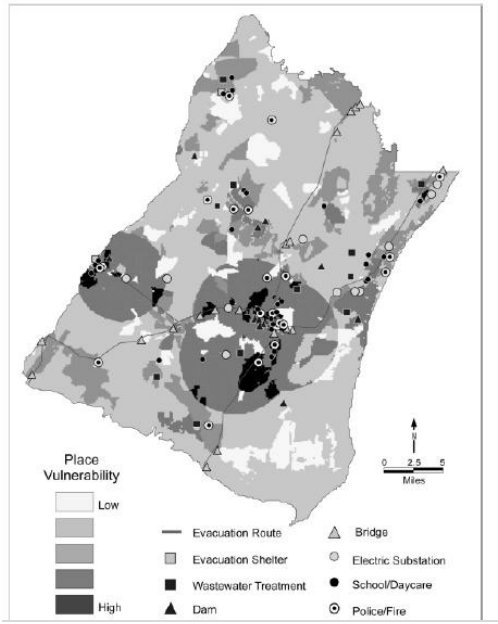

Figure 7. Establishing the lifelines and infrastructure on top of the place vulnerabilities. Cutter et al. 2000.

An analysis of this case study shows a few important facts. First, the maps created using GIS software enables users to visualize potentially vulnerable locations which allows for a better understanding of overall vulnerability in areas. Second, the maps help direct mitigation efforts to the areas that are most vulnerable not only biophysically, but also socially. GIS allows for numerical estimates of vulnerability of a potential population to a single or multiple hazards by social indicator (Cutter et al. 2000). Lastly, these maps allow emergency responders to work more efficiently because they now know the locations of more vulnerable populations such as the special-needs populations. This can help with first-response as well as evacuations.

Perceived Problems with this Index

There are a few problems within the Total Place Vulnerability Index. First, the interpretation of results can be hard to decipher. There is also no aspect of hazard intensity

or magnitude (Greiving et al. 2006). This could be avoided by including loss data and a minimum threshold for defining event as a hazard (Greiving et al. 2006). At the same time the weighting of population indicators is flawed, because the total population is weighted less than individual population indicators (Greiving et al. 2006). Some of these problems as well as those listed for the other two assessments will be attempted to be addressed in the completion of this research.

Selected Atmospheric Hazards

Hazards exist where natural events are likely to threaten and harm people or their property (Hyndman et al. 2006). Our world contains many hazards, yet for the purpose of this research the focus will be on atmospheric-related hazards: tornadoes, extreme wind events, lightning, hail, floods, drought, winter storms, ice storms, and temperature extremes. Each of these natural hazards poses a risk to human populations in the state of Wisconsin. As stated earlier, this project does not focus on geologic hazards such as earthquakes because they occur relatively infrequently in this area. This research also does not focus on human-induced hazards such as chemical spills because the goal of this research is to focus on natural events.

Tornadoes

The United States has the largest share of the world's tornadoes (Hyndman et al. 2006). There are approximately 800-1,400 tornadoes reported in the United States in any given year (Ashley 2007). The most active locations in the U.S. have an average of 1.00 to 1.25 tornado days a year, based on data from 1980-1999 (Brooks et al. 2003). A tornado day is a traditional 24-hour day in which at least one tornado occurs (Britt et al. 2009). Within a

tornado, winds can reach over 300 mph. Path lengths can range from less than one to more than 30 kilometers (Hyndman et al. 2006). The total amount of fatalities caused by tornadoes from 1880-2005 was 18,717 people (Ashley 2007).

Extreme Wind Events

Extreme wind events can range from straight-line winds associated with derechos (i.e. downbursts) (Coniglio et al. 2001) to unusually high wind gusts associated with severe thunderstorms. A downburst is an intense downdraft of air that induces an outburst of highly divergent, damaging winds on or near the ground (Coniglio et al. 2001). These winds can be as fast as 200 km/hr (Hyndman et al. 2006). In an 18-year period from 1986 to 2003, derechos were responsible for 153 deaths and over 2,600 injuries with a number of events exceeding $100 million in damages. Thunderstorm winds from 1993-2003 were responsible for 286 fatalities and over 4,300 injuries (Ashley et al. 2005).

Lightning

Lightning strikes kill an average of 86 people (Hyndman et al. 2006) and cause over 250 injuries per year (Livingston et al. 1996). According to the National Climatic Data Center's publication *Storm Data*, the United States sustained 3,239 fatalities, 9,818 injuries, and 19,814 occurrences of property damage due to lightning from 1959 to 1994 (Curran et al. 2000).

Hail

Hailstones are another atmospheric hazard associated with severe thunderstorms. They can range in size from pea-size to larger than golf balls (Ahrens 2003). Hail causes $2.9 billion in annual damages (Hyndman et al. 2006) as hailstones can break windows, dent

cars, and damage livestock and crops (Ahrens 2003). Although potentially fatal, only two documented fatalities have occurred in the United States since 1900 (Ahrens 2003).

Floods

In the United States, floods are responsible for one-quarter to one-third of the annual monetary losses and up to 80% of annual deaths from hazards (Hyndman et al. 2006). These losses are often exacerbated by populations that live within floodplain areas, who build protective dikes and dams, logged forests, and built large paved areas such as roads (Hyndman et al. 2006). While floods are often caused by short periods of high-intensity rainfall or from prolonged periods of rain lasting several days (Oliver et al. 2002), these human practices increase the risk of floods threatening life and limb while causing damage costs to rise year after year (Hyndman et al. 2006). By paving large swaths of land, populations increase impermeable surfaces where the rainfall cannot be soaked in, thus making it run into storm drains and move quicker to streams and rivers. This makes the water rise faster and longer and can flood those homes built in flood plains.

Droughts

Droughts are a danger to societies throughout the world and are one of the most damaging climactic hazards (Woodhouse et al. 1998). They impact both surface and groundwater resources, which can lead to reductions in water supply, diminished water quality, crop failures, diminished water-power generation, and can negatively affect recreation activities (Woodhouse et al. 1998). While droughts do not often lead to loss of life in developed countries, they often can result in causing dire consequences for the economic, social, and political structures of cities, states, and entire nations (Woodhouse et al. 1998). Ethiopia is a good example of a country that has been gravely affected by droughts. When a

large, widespread drought hit during the main growing season of 2002, the government declared that 11.3 million people were in need of emergency food aid, which was later revised to 13.2 million people. During a famine in 1984 and 1985, it is estimated that 600,000 to over one million people died (De Waal et al. 2006).

Winter Storms

Severe winter storms (both snow and ice) are considerable hazards as they cause disruptions in transportation networks, wind damage to buildings, closure of schools and businesses, losses of electricity and losses to local economies (Schwartz et al. 2002). They are hazardous to human health as they may cause death due to exposure or indirectly through car accidents or heart attacks from people overexerting themselves walking or clearing deep snow drifts (Schwartz et al. 2002). Economically, loss of retail sales could ensue in the immediate days after and livestock deaths during a winter storm may be in the tens of thousands. For example, one 5-day blizzard that occurred in Buffalo, NY in 1977 cost the city $250 million in damages, snow removal, and lost wages and production (Schwartz et al. 2002).

Temperature Extremes

Temperature extremes include both heat and cold waves. There is no agreed upon definition of a heat wave, but these events consist of several days of particularly hot, sustained temperatures sufficiently above normal that causes stress resulting in notable impacts on human mortality, regional economies, and ecosystems (Hunt 2007; Meehl et al. 2004). The loss of life from heat waves can be substantial. In two well documented cases, more than 500 people died in a 1995 Chicago heat wave, while over 30,000 people died in a

2003 heat wave over the whole of Europe (Nicholls et al. 2007). That same European heat wave was responsible for $13 billion (U.S.) in crop losses (Nicholls et al. 2007).

Documentation on cold waves is much harder to find. In essence, cold waves must meet similar criteria to that of heat waves, only on the opposite side of the spectrum. Most fatalities to be considered due to excessive cold are deaths due solely to exposure (Dixon et al. 2005). Often, if other weather conditions were present, such as a winter storm, any fatalities are listed under that event and not due to extreme cold (Dixon et al. 2005). From 1979 to 1999, there was an average of 748 deaths per year due to "excessive cold resulting from weather conditions" (Dixon et al. 2005).

STUDY AREA

The study area for this research consists of twenty-one Wisconsin counties. Counties throughout the state were use to avoid any spatial autocorrelation within the data, which could occur by selecting counties that were all within a similar geographic area. Instead, all 72 counties were grouped into four categories based on population density and severe weather event density (Figure 8). Five counties were randomly chosen from each group and Milwaukee County was added due to its significantly higher population size and density (Figure 10).

All Wisconsin counties were plotted on a scatterplot of these two variables (Figure 8). Population data were acquired from the U.S. Census Bureau using the 2008 population estimates for the counties (Available at: http://factfinder.census.gov). Event data were acquired from the National Weather Service using event data from 1982-2008 (Available at: http://www.crh.noaa.gov/mkx/?n=wi_severe_weather_climatology). This dataset was used

to determine the historical event density, even though the research only used data from 1998-2008. The scatterplot was then divided into four quadrants based on the median population and event densities: high population density/high event density, low population density/low event density, low population density/high event density, and high population density/low event density. Five counties from each quadrant were then randomly selected for use. Milwaukee County was also selected since it was an extreme outlier in population density giving the study a total of 21 counties.

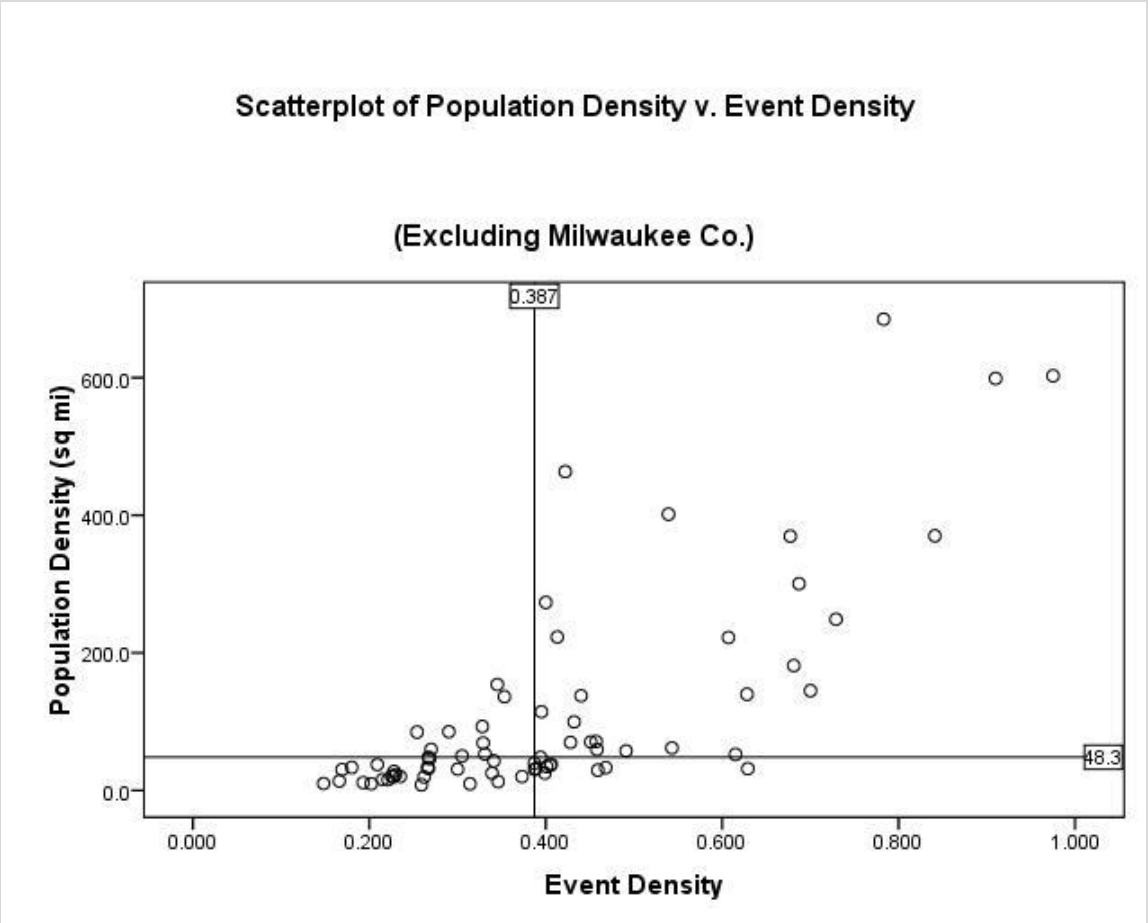

Figure 8. Scatter plot of population density and event density used to determine county groupings.

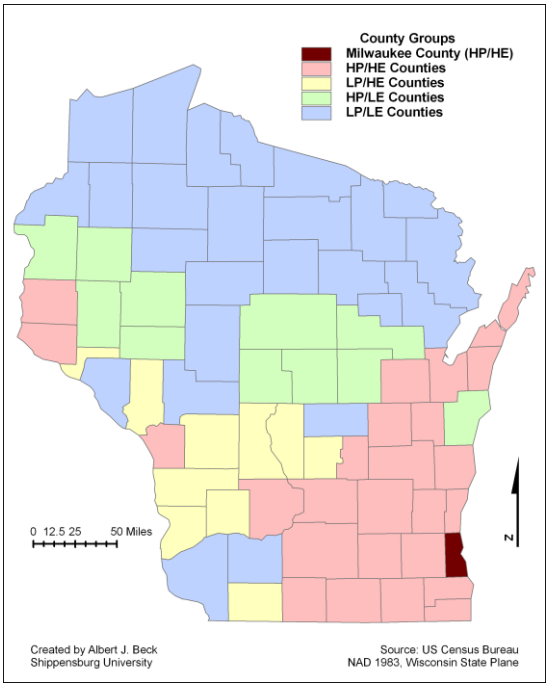

Figure 9. County groupings in the state of Wisconsin by population density v. event density

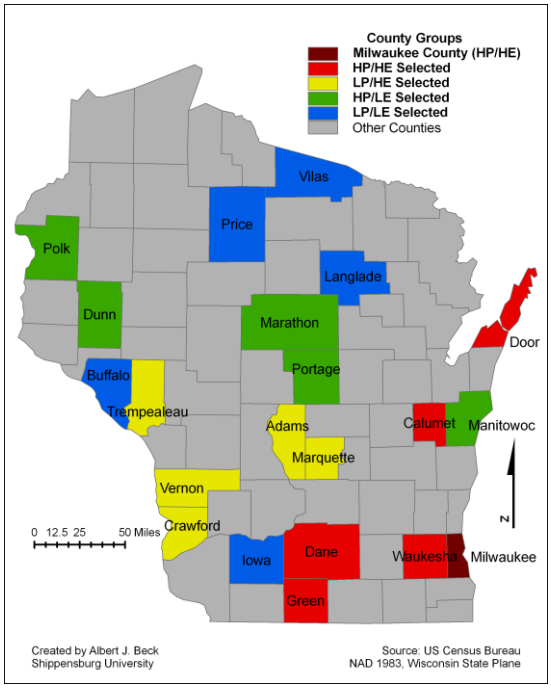

Figure 10. Counties selected for further study.

According to the United States Census Bureau, the 2008 population estimate for Wisconsin is 5,627,967. It has a land area of 54,310 square miles and a statewide population density of 103.6 people/sq. mi. Milwaukee County is the most populous county in the state with 940,164 people and has the highest population density in the state (3,946.5 people/sq. mi). The county chosen for this research that has the lowest population is Buffalo County with a total population of 13,741. However, the county chosen for this research that has the lowest population density is Price County (11.4 people/sq. mi).

Dane County has the highest number of events of the study period at 423. However, the county with the highest event density per year is Milwaukee County at 0.109 event density per year. The county within the study area that has the least number of events during the study period is Calumet County with 120 events. However, Price County has the lowest event density per year at 0.010.

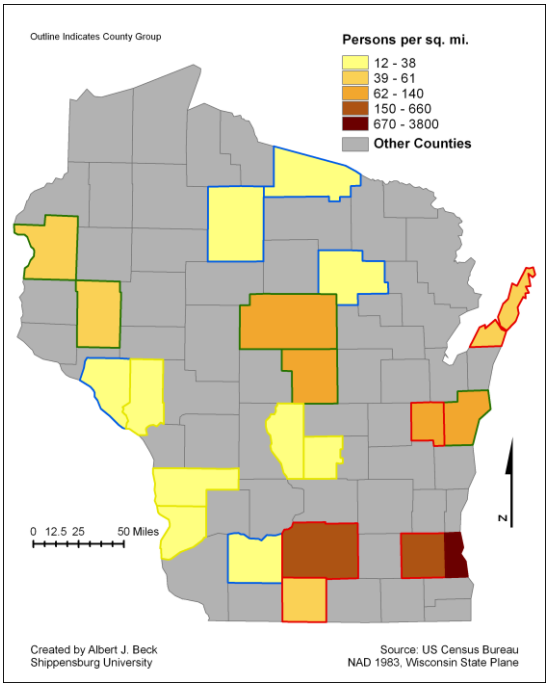

Figure 11. 2005 population densities by study area county.

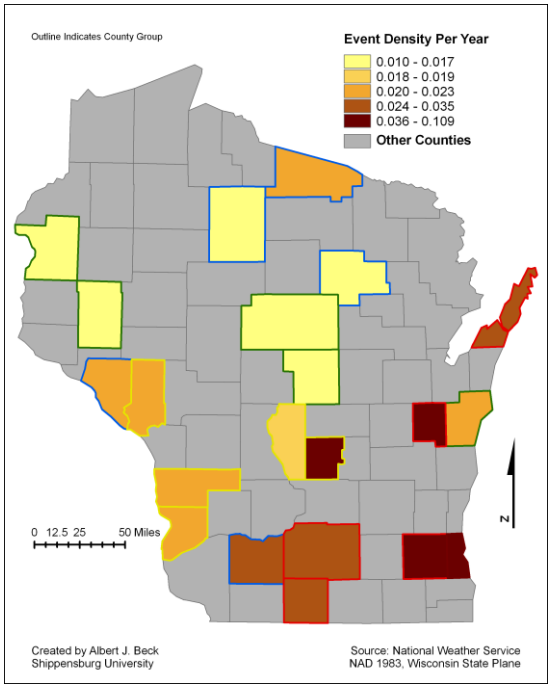

Figure 12. 1998-2008 event densities by study area county.

There are four major urban centers in the region delineated by the U.S. Bureau of the Census based on resident population and population density. These areas consist of a central core and adjacent densely settled area that together contain at least 50,000 people (SEWRPC 2000). The Milwaukee urbanized areas is the only one located within this research's defined study area. Yet there are other urban areas that are located within the selected counties. In addition to Milwaukee, these are the large cities of Waukesha, Madison, and Wausau (Figure 13).

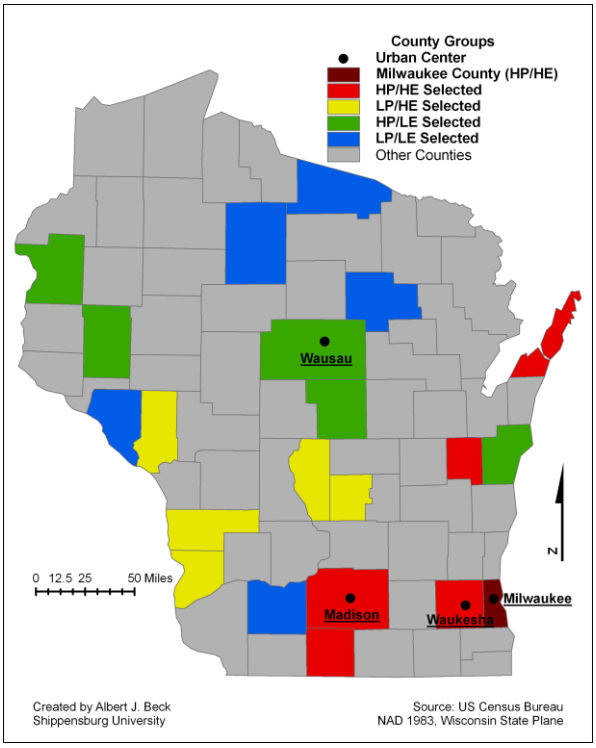

Figure 13. Large urban areas within the study area.

Table 1. Mean population and event densities and variables for each of the county groupings.

Mean Group Variable	HP/HE	HP/LE	LP/HE	LP/LE
Population Density[1]	301.5[3]	80.9	33.7	22.1
Females	156,663	35,802	10,524	9,439
Non-Whites	58,781	2,950	469	606
Persons Under 18	77,083	18,043	5,254	4,561
Persons Over 65	36,590	9,480	3,751	3,407
Mobile Homes	1,309	1,927	1,944	892
Median Income	$47,462	$42,375	$34,871	$36,379
Event Density[2]	241.00	155.00	152.20	149.60
Tornadoes Events	4.50	6.00	2.60	2.40
Hail Events	61.00	45.00	44.40	43.80
Lightning Events	11.83	4.60	0.40	1.20
Winter Events	27.00	26.60	30.40	36.20
Temperature Events	19.50	9.20	9.80	7.40
Wind Events	87.00	53.20	47.00	47.60
Flood Events	20.83	9.20	15.20	5.60
Drought Events	9.33	1.20	2.40	5.40

1. Population density is in people/square mile.
2. Event density is in events/square mile. Note that groups were divided using median event density, not the mean.
3. Excludes Milwaukee County.

Study Area Group Descriptions

High Population Density/High Event Density Counties

The high population density/high event density (HP/HE) county grouping contains the counties of Dane, Door, Calumet, Green, Milwaukee, and Waukesha (Figure 10). This group has a mean population density of 301.5 people/square miles (excluding Milwaukee County) and a mean event density of 241 events/square miles (Table 1). Dane County is the large county located in the south-central part of the state and is home to the state capital and urban area of Madison. Door County is located on the Door Peninsula that juts into Lake Michigan. Calumet County is located to the southwest of Door County. Green County is located south of Dane County along the Illinois border. Milwaukee County is located on the shore of Lake Michigan and is home to the City of Milwaukee, which is the largest urban center in the state. The City of Milwaukee currently contains over 600,000 occupants. Waukesha County is directly west of Milwaukee County. Waukesha County also contains another urban center, which is the City of Waukesha. These counties are represented by a red fill or red outline in any figure they are displayed in. All of the counties used in the study area are located in the southeast and eastern parts of the state. This is a sample of the larger group of HP/HE counties that can be seen in Figure 9.

High Population Density/Low Event Density Counties

The high population density/low event density (HP/LE) county grouping contains the counties of Dunn, Manitowoc, Marathon, Polk, and Portage (Figure 10). This group has a mean population density of 80.9 people/square miles and a mean event density of 155 events/square miles (Table 1). Dunn County is located in the northwest part of the state along with Polk County. Polk County is closer to the Wisconsin-Minnesota border, while

Dunn County is located just southeast of Polk County. These two counties have their populations influenced by the nearby metropolitan area of Minneapolis-St. Paul, located to the west across the Mississippi and St. Croix Rivers that make up the Wisconsin-Minnesota border. Marathon and Portage Counties are located in the north-central part of the state. Marathon County is the large county located to the direct north of Portage County. Marathon County contains one of the largest urban areas in northern Wisconsin, the City of Wausau. Manitowoc County is located in the eastern part of Wisconsin, on the shore of Lake Michigan. This county is the lone standout from the rest of the HP/HE counties that dominate this part of the state due to its lower event density. These counties are represented by a green fill or green outline in any figure they are displayed in. The counties used in the study area are located mainly in the northwest and north-central parts of the state, with Manitowoc being the only county in the eastern part of the state. These counties are on a slight diagonal running from northwest to the east. This is a sample of the larger group of HP/LE counties that can be seen in Figure 9.

Low Population Density/High Event Density Counties

The low population density/high event density county (LP/HE) grouping contains the counties of Adams, Crawford, Marquette, Trempealeau, and Vernon (Figure 10). This group has a mean population density of 33.7 people/square miles and a mean event density of 152.2 events/square miles (Table 1). Adams and Marquette Counties are located in the central part of the state. Adams County is located directly west of the smaller Marquette County. Crawford and Vernon Counties are located in the southwestern part of the state. Vernon County is located directly north of Crawford County. Both counties border the Mississippi River, which forms the border between Wisconsin and Iowa and Wisconsin and Minnesota.

Trempealeau County is also located in the western part of the state, although it is farther north than Crawford and Vernon Counties. Trempealeau's southern border is created by the Mississippi River, which is the border between Wisconsin and Minnesota. These counties are represented by a yellow fill or yellow outline in any figure they are displayed in. The counties used in the study area are located mainly in the west, southwest and central parts of the state. This is a sample of the larger group of LP/HE counties that can be seen in Figure 9.

Low Population Density/Low Event Density Counties

The low population density/low event density (LP/LE) county grouping contains the counties of Buffalo, Iowa, Langlade, Price, and Vilas. This group has a mean population density of 22.1 people/square miles and a mean event density of 149.6 events/square miles (Table 1). Buffalo County is located in the western part of the state and is directly west of Trempealeau County. The county shares it southern border with the Mississippi River and western border with Trempealeau County. Iowa County is located in the southwestern part of the state. It is directly west of and shares its eastern border with Dane County. The other three counties in this grouping are located in the northern part of the state. Langlade County is located northeast of Marathon County. Vilas County is located further north and its northern border is part of the Wisconsin-Upper Michigan border. Price County is located to the west and south of Vilas County. It shares part of its eastern border with Vilas county. These three counties are part of the "Wisconsin Northwoods," an unofficial term used to describe Wisconsin's northern counties. These counties are represented by a blue fill or blue outline in any figure they are displayed in. The counties used in the study area are located mainly in the northern parts of the state, with some counties in the west and south. This is a sample of the larger group of LP/LE counties that can be seen in Figure 9.

METHODOLOGY

In order to answer the research question: what is the atmospheric-related hazards risk to populations within the state of Wisconsin, this research interwove the Total Place Vulnerability Index (as described in HVRI (2007)) with the Integrated Risk Assessment of Multi-hazards (as described in Greiving et al. 2006) to create one multi-hazard assessment. The methods used in HVRI (2007) by the Hazard and Vulnerability Research Institute (HVRI) formed the base of this project while methods used by Greiving et al. (2006) were used to try to resolves some of the issues pointed out in their critique of the Total Place Vulnerability Index.

In order to answer the research question, seven objectives were completed. These objectives were:

- Determine the counties to be used in the study
- Determine the hazard potential of each country
- Calculate the rate of occurrence for each hazard
- Calculate the damage and casualty scores for each hazard
- Determine the social vulnerability of each county
- Apply the vulnerability scores
- Integrate the vulnerability scores with the hazard scores

This project covered the past ten years, from September 1998 to September 2008. Current data were important to use to avoid past trends in hazards that are not relevant today. These dates were also chosen due to the lack of dataset availability before 1993 for some hazards.

Selected County Determination

The methods for determining the selected counties within the study area are described in detail in the study area section of this paper.

Hazard Potential Determination

The next step in the project was to determine the hazard potential of the selected counties. These hazards included: tornados, extreme wind events, lightning, hail, floods, drought, winter storms, ice storms, and temperature extremes. All these events have occurred within the scope of the project and within the study area and each poses a risk to population or property within the study area.

The Storm Events database, which is managed by the National Climatic Data Center (NCDC), was the main source of datasets for each of these hazards. Data downloaded included: location, date, time, type of hazard, magnitude (if applicable), deaths, injuries, property damage, and crop damage (NCDC 2009). These datasets were downloaded for each hazard for each county and organized into a database. There was no minimum threshold for what was considered a hazard. Even if an event did not cause property damage, crop damage, injuries, or deaths, it was an event that needed to be recorded to have an accurate rate of occurrence.

The NCDC's *Storm Data* publication has been shown to have some flaws. *Storm Data* is where the NCDC's Storm Events Database is derived from and therefore has the same inherent flaws. *Storm Data* is compiled every month after every National Weather Service station in the country sends in lists a notable weather data to the NCDC headquarters (Curran et al. 2000). Thus to start, the information that is sent and complied into *Storm Data*

is not necessarily consistent from station to station. Data also comes from county, state, and federal emergency management officials, as well as local law enforcement officials, skywarn spotters, NWS damage surveys, the insurance industry, and the general public (NCDC 2006). Damage estimates, which were regarded as too inaccurate for one research paper (Ashley et al. 2005), also come from these sources as well as from the National Weather Service itself.

Curran et al. (2000) also note there is underreporting of lightning events within the publication (Curran et al. 2000). Ashley et al. (2005) suggests this is because certain events (hail, lightning, derechos) receive less attention that "large-scale" events such as floods, tornadoes, etc. (Ashley et al. 2005).

This research also had issues in using the Storm Events Database. Data between the tables created by using the database and the actual reports do not match. In many cases, the data given in the tables was a number rounded to the nearest $1000 whereas the data given in the reports was rounded to the nearest $100. This can cause some discrepancies to occur when calculating damage scores. For example, a county that had $400 of damage was listed as a county that had not sustained any damage at all. At the same time, casualties can be easily over predicted because the database lists some casualties by forecasting zone instead of by county. This means that if multiple counties were in the same forecasting zone, they would each have the same number of casualties. The only way to discover how many casualties actually occurred in a specific county, the report had to be read. In some cases, these reports are also unclear making it continually difficult to decipher how many casualties actually occurred within a county.

However, both papers mentioned earlier recognize that *Storm Data* (and thus the Storm Events Database) are the only consistent data source for damages and casualties for all

atmospheric-related natural hazards. Both studies used the database without modifications or alterations (Ashley et al. 2005; Curran et al. 2000). Because of this, this research also did not make any modifications of alterations to data from the Storm Events Database.

Calculation of Rate of Occurrence

Once the data were organized within a database, their rate of occurrence was calculated. The equation for this was $\frac{X}{10}$, where X equaled the number of occurrences and 10 was the number of years of record. This method was used for all hazards to ensure consistency. In the cases of winter/ice storms, floods, and droughts, these events are not confined to one specific area, but the NCDC's Storm Events Database records each as a singular event and thus they were able to be used.

Calculation of Damage and Casualty Scores

In order to incorporate loss data into the model, the categories of frequency of occurrence, property damage, crop damage, injuries, and deaths were compared. First, the data were quality controlled to make sure it represented the best and most accurate data. This required a line by line comparison of the data with their reports to look for inconsistencies. If an inconsistency was found, the numbers in the report were used.

Then, to allow for comparisons among the different hazards on a per event basis, each loss variable was divided by the number of events for that hazard. These values were subset into two scores, a damage score and a casualty score. The damage score was calculated using the equation:

$$Damage\ Score = \left(\frac{Crop\ Damage}{Events} + \frac{\mathrm{Pr}operty\ Damage}{Events} \right) \times Frequency$$

The casualty score was calculated using the equation:

$$Casualty\ Score = \left(\frac{Injuries}{Events} + \left(\frac{Deaths}{Events} \times 2 \right) \right) \times Frequency$$

Deaths were weighted by a factor of two to designate a more serious casualty than a non-fatal injury.

These damage and casualty scores allow the hazards to be compared and contrasted with less concern about fundamental differences among the hazards. Adding all the damage and casualty scores for each hazard resulted in county damage and casualty scores.

$$\begin{aligned} &County\ Damage\ Score = Tornado\ Damage\ Score + Hail\ Damage\ Score + \\ &Lightning\ Damage\ Score + ... + Drought\ Damage\ Score \end{aligned}$$

$$\begin{aligned} &County\ Casualty\ Score = Tornado\ Casualty\ Score + Hail\ Casualty\ Score + \\ &Lightning\ Casualty\ Score + ... + Drought\ Casualty\ Score \end{aligned}$$

These scores were then divided by the county population to create a per capita score that allowed each county to be compared to the other counties. These numbers were used later in conjunction with the vulnerability score.

Social Vulnerability Determination

The second step was to determine the social vulnerability of the 21 counties. Data were acquired from the U.S. Census Bureau for the identification of vulnerable population subgroups (Available at: http://factfinder.census.gov). The basic reasoning for use of each of these subgroups are explained, however more detail is available in HVRI (2007) and Cutter et al. (2000). The subgroups used include: the number of people less than 18, the number of

people 65 and older, the number of females, the number of non-whites, the number of housing units, the total population, the number of mobile homes, and median county income.

These variables were chosen because they are used by Cutter et al. (2000) and in HRVI (2007). Both research articles provide reasons for their inclusions of the specific population that are provided below. The rational for the use of these variables in the TPVI was decided to be sound enough for use within this research. Although other variables could very likely be used in conjunction with or instead of the variables used in the TPVI, none were included. This is in part because researching other variables would move beyond the scope of this research. However, these variables were used in this research mainly to see whether or not they could be applied in more regions of the United States other than just the original research location in South Carolina.

The number of housing units and the total population represent the population and structure of the study area. More specifically, the number of housing units input was chosen for use in the TPVI because it shows where the greatest number of people reside within a geographically chosen area. This becomes very important when combined with hazard frequency. The total population input was chosen for use in the TPVI for much the same reason as total number of housing units – it shows where the greatest number of people reside within the study area (HVRI 2007).

County median income represents wealth or poverty in the study area. The TPVI used mean house value instead because income data was not available at the census block scale. However, both of these inputs achieve the same ends. They are both a measure of economic status for the measured population. Lower house or median income values may

indicate a lack of resources, which can negatively impact a population's recovery from disasters or may indicate housing of lower structural quality (HVRI 2007).

The number of mobile homes represents the level of structural vulnerability within the study area. It is used in the TPVI because it is an indicator of housing of a lower structural quality. This type of housing is well know to be more susceptible to hazards with high winds than standard housing (HVRI 2007).

The number of people less than 18, the number of people 65 and older, the number of females, and the number of non-whites represent groups with access or lack thereof to resources or a higher susceptibility to hazards due to physical weakness (Cutter et al. 2000). More specifically, the variables of the number of people less than 18 and the number of people 65 and older were used in the TPVI because they both indicate the location of dependent populations. Both subgroups would need added assistance during and after a disaster and both may have a lower ability to recover from such an event (HVRI 2007). The variable of the number of females was used by the TPVI because the authors found it correlated with lack of resources and influence, limiting this population's options during and after a disaster. This group may also have a lower ability to recover from such disasters (HVRI 2007). Lastly, the variable of the number of non-whites was used by the TPVI because this population has also been correlated with lack of resources and other research notes that race can force some populations to live on or near less desirable land uses. This group may also have a lower ability to recover from such disasters (HVRI 2007).

These data were downloaded for the county level as opposed to the block level as seen in (HVRI 2007; Cutter et al. 2000). Because of this, county median income was used

instead of mean house value, which was used by Cutter et al. (2000) due to that research working at the census block level.

Application of Vulnerability Scores

Using the census data, two social vulnerability scores were calculated for each county. One score includes higher median income as beneficial to a population. Counties that have a higher median income respond better to and recover more quickly from an event. The other score includes higher median income as detrimental to a population. Counties that have a higher median income have more items to lose from an event.

Vulnerability scores consisted of three factors: a population factor, a home factor, and an income factor. First, the total number of females, total number of non-whites, total number of people under 18, and total number of people over 65 were each divided by the total population to acquire the ratio of each within a county.

$$\frac{\#\ of\ [population\ input]\ in\ County}{Total\ County\ Population} = County\ [population\ input]\ Ratio$$

Second, the ratio of mobile homes was calculated:

$$\frac{\#\ of\ Mobile\ Homes\ in\ County}{Total\ County\ Homes} = County\ Mobile\ Home\ Ratio$$

Third, the ratio of county median income to the sums of the study area's county's median incomes was calculated:

$$\frac{County\ Median\ Income}{Sum\ of\ Study\ Area\ Median\ Incomes} = County\ Median\ Income\ Ratio$$

These ratios were then standardized on a 0-1 scale by dividing each ratio by the largest ratio among the counties. This helped keep the magnitudes of each input on the same scale. This was done using this calculation:

$$\frac{County\ [variable]\ Ratio}{Largest\ County\ [variable]\ Ratio} = Standardized\ [variable]\ Ratio$$

Finally, a vulnerability score was calculated. The vulnerability where median income was considered a negative influence was calculated:

$$\begin{aligned} &County\ Vulnerability\ Score\ (Negative) = Female\ Standardized\ Ratio \times \\ &Non-White\ Standardized\ Ratio \times Over\ 65\ Standardized\ Ratio \times Under\ 18\ Standardzied\ Ratio \times \\ &Mobile\ Home\ Standardized\ Ratio \times Median\ Income\ Standazardized\ Ratio \end{aligned}$$

This number, which was very small, was then multiplied by 100,000. This created a larger value that made it easier to compare the vulnerability scores. Multiplication was chosen to integrate these factors because each contains different units.

The vulnerability where median income was considered a positive influence was calculated:

$$County\ Vulnerability\ Score\ (Positive) = \frac{\left(\begin{array}{l} Female\ Standardized\ Ratio \times Non-White\ Standardized \\ Ratio \times Over\ 65\ Standardized\ Ratio \times Under\ 18 \\ Standardzied\ Ratio \times Mobile\ Home\ Standardized\ Ratio \end{array}\right)}{Median\ Income\ Standardized\ Ratio}$$

The number was multiplied by 100,000 for the same reasons described before. These numbers are able to be compared among the counties and later were used in conjunction with the per capita damage and casualty scores to calculate a final rank.

Delineation and Integration of Hazard and Vulnerability Scores

The third step in this project was to use ArcMap 9.3 to map the hazard and social vulnerability scores of each county. Since the scale for this project was the county, entire counties served as the hazards' bounds. Each county within the study area had its damage, casualty, and vulnerability scores mapped.

The last step in the project was creating a final ranking to determine which county is the most at risk from an atmospheric natural hazard. This was completed by ranking the counties in each of the three categories of damage, casualty, and vulnerability on a 1 to 21 scale. A ranking of 1 went the county with the lowest score and a ranking of 21 went to the county with the highest score. The three rankings were added together to receive an integrated score where the highest score was the county that was the most vulnerable. Due to the fact that this project was completed at the county scale as opposed to the census block level, the establishment of the social and infrastructure context as in HVRI (2007) and Cutter et al. (2000) was deemed not necessary.

Statistical Analysis

Using the statistical software PSAW 17, numerous statistical analyses were run to determine correlations and differences within the data. Spearman correlations were run instead of multi-variant regressions for two reasons. First, the data were non-parametric in nature and second, the sample sizes were very small. Using multi-variant regressions, while useful, would result in uncertainty within the results. For all tests used in this research, significance was measured at a 0.05 alpha level.

The first set of Spearman correlations run looked at the relationships between the counties' damage scores per capita and individual hazard damage scores per capita to determine which hazards had impacts on the counties' damage scores. The second set of correlations run looked at the relationships between the counties' casualty scores per capita and individual hazard casualty scores per capita to determine which hazards had impacts on the counties' casualty scores. The third set of correlations run looked at the relationships between the counties' positively influenced vulnerability scores and the individual demographic ratio inputs to determine which inputs had impacts on the counties' vulnerability scores. The same was done for the counties' negatively influenced vulnerability scores.

A fifth set of correlations run looked at the relationships between the counties' casualty scores per capita and the individual demographic ratio inputs to determine if there were any relationships between casualties and population vulnerabilities. The last two sets of correlations run looked at the relationships between the counties' damage and casualty scores per capita and the counties' population and event densities to determine which, if either, had an impact on the county scores.

To determine differences among county groups, two separate, non-parametric tests were used. To test for differences in population demographics between counties with populations greater than 80,000 people and counties with populations less than 20,000 people, a Mann-Whitney U Test was run.

To test for differences among the four county groups discussed earlier, a series of Kruskal-Wallis H Tests were run. The county groups were tested for differences among all scores and variables. These include: damage scores per capita, individual hazard damage

scores per capita, casualty scores per capita, individual hazard casualty scores per capita, vulnerability scores (both positive and negative influences), and all vulnerability inputs. To determine which county groupings were the most or least impacted by each score or variable, the mean ranks were used.

RESULTS AND ANALYSIS

Damage Scores

Hazard scores are broken into two different scores – damage and casualty. Figures 14 through 21 show the per capita damage scores for each individual hazard. The combination of these damage scores made up the total map in Figure 22. Table 1 shows each hazards correlation coefficient to the damage score per capita and its significance.

Table 2. Spearman correlations of county damage scores per capita and individual hazard damage scores per capita.

Damage Score Per Capita	Tornado Damage	Hail Damage	Lightning Damage	Winter Storm Damage	Extreme Temperature Damage	Extreme Wind Damage	Flood Damage	Drought Damage
Correlation Coefficient	0.290	0.590	0.055	0.415	.	0.060	0.938	0.474
Significance	0.203	0.005	0.814	0.061	.	0.797	0.000	0.030
Significant	N	Y	N	N	N	N	Y	Y

Figure 14 shows tornado damage scores. Marquette County had the highest per capita score at $12.95. Spatially, tornadoes hit all over the state, creating high damage scores in many different counties. However, the lowest scores are in the northwest part of the state and along the border of the state while the highest scores are in the center of the state. According to the correlation statistics, tornadoes were not significantly correlated to county damage scores per capita.

Figure 15 shows hail damage scores. Iowa County had the highest per capita score at $95.77. Most hail damage occurs in the southern and eastern parts of the state while most of the lower scores are located in the northern and western parts of the state. The correlation statistics noted that hail was the second highest correlated hazard event to county damage scores per capita within the study area.

Figure 16 shows lightning damage scores. Marathon County had the highest per capita score at $12.60. Most lightning damage came from the fires that resulted after a strike that destroyed homes and other property. Within the correlations statistics, lightning was determined to be not significantly correlated to county damage scores per capita.

Figure 17 shows winter storm damage scores. Interestingly, one would expect these scores to be higher in the northern part of the state due to the harsh winters. However, scores are instead higher in the central and southern part of the state. Dane County had the highest per capita score at $0.60. This is likely due to higher population amounts and thus more property that can be damaged. Winter storm damage was determined to be not significantly correlated to county damage scores per capita.

Figure 18 shows extreme wind event damage scores. Polk County had the highest per capita score at $11.09. Much like the tornado map, these scores are spread around the state such that no region was untouched. However, the bulk of high scores are located in the southern and southeastern parts of the state. Damage from extreme wind events was determined to be not significantly correlated to county damage scores per capita.

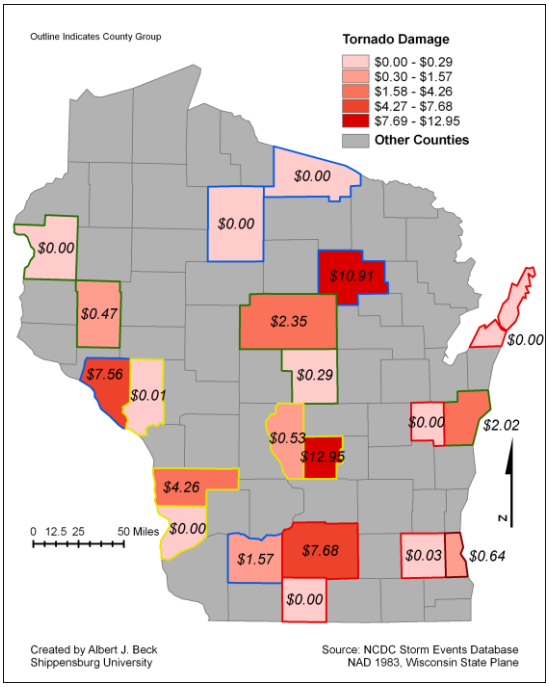

Figure 14. Tornado damage scores from 1998-2008. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

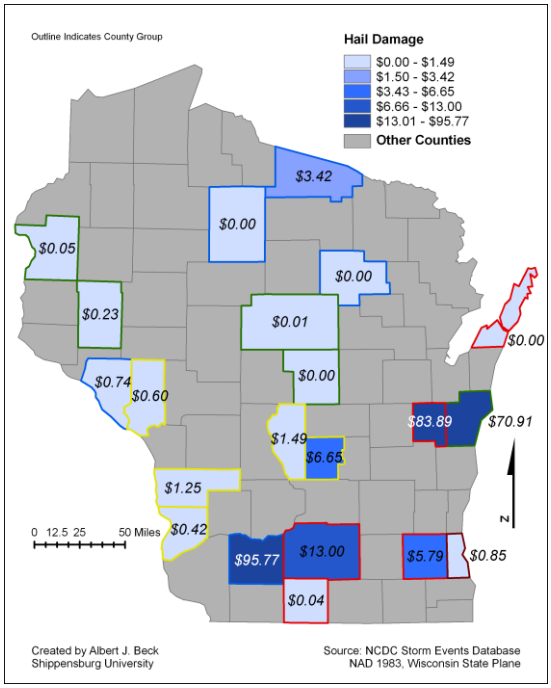

Figure 15. Hail damage scores from 1998-2008. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

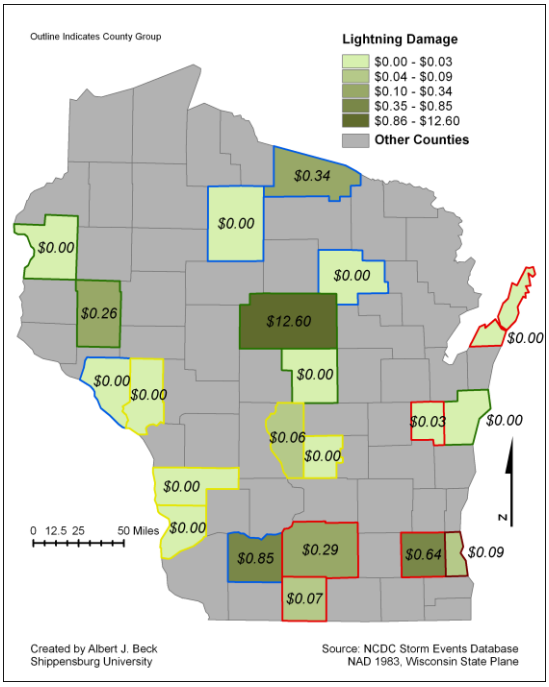

Figure 16. Lightning damage scores from 1998-2008. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

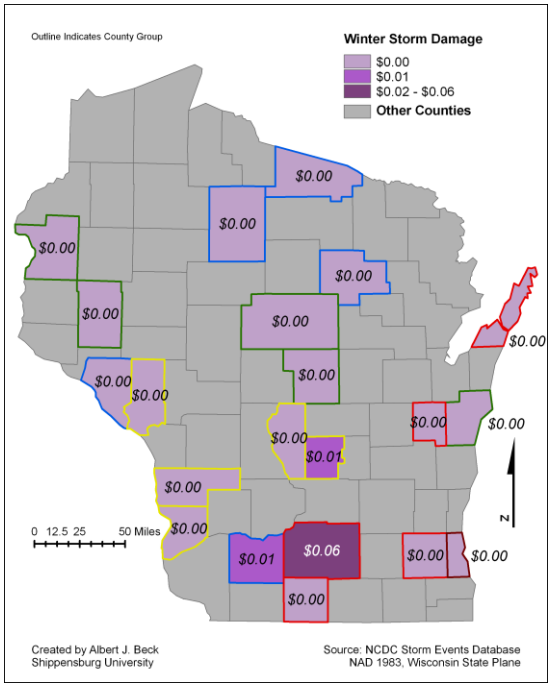

Figure 17. Winter storm damage scores from 1998-2008. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

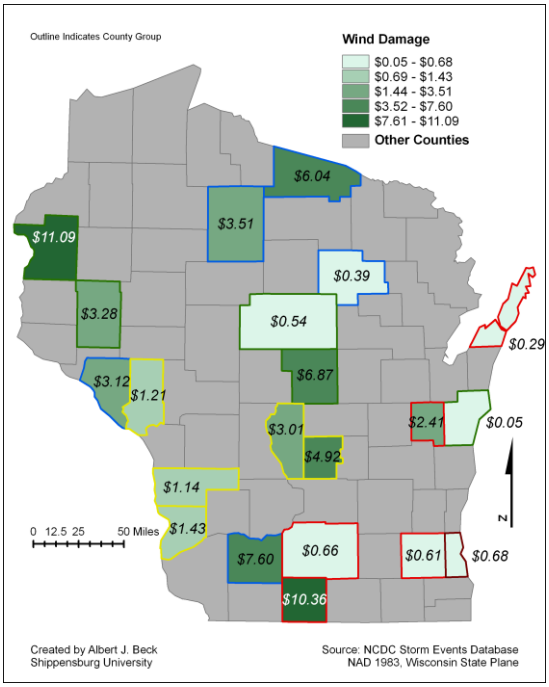

Figure 18. Extreme wind event damage scores from 1998-2008. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

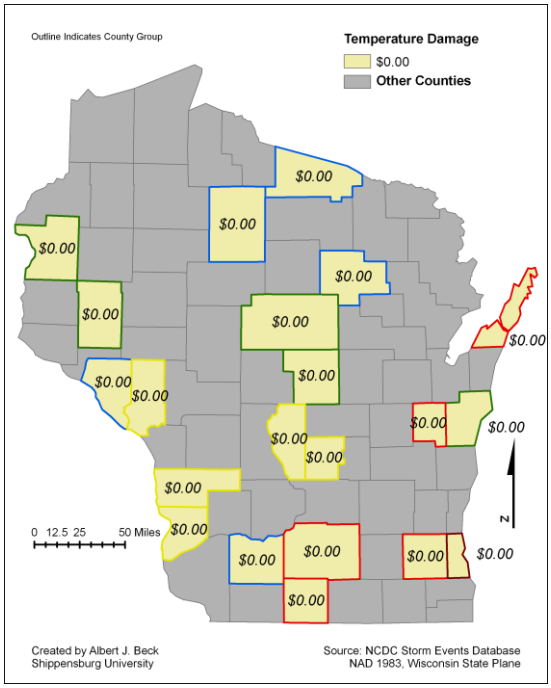

Figure19. Extreme temperature damage scores from 1998-2008. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

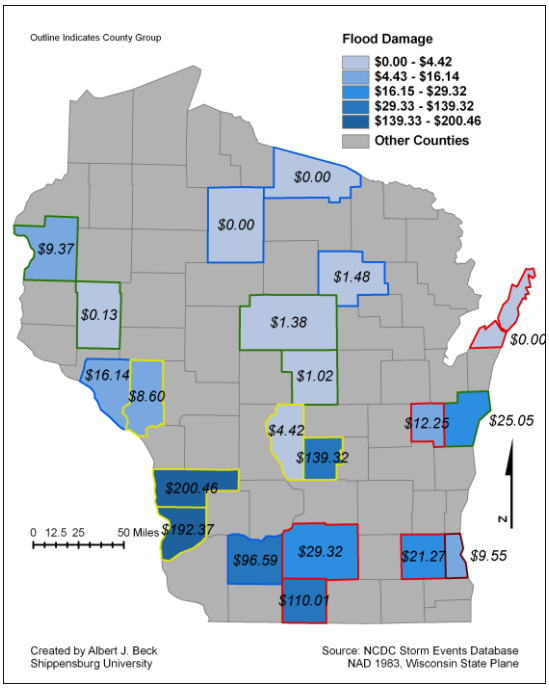

Figure 20. Flood damage scores from 1998-2008. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

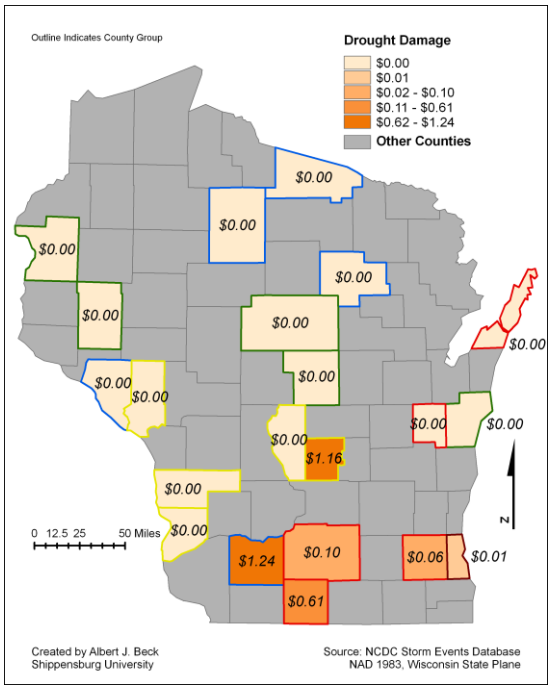

Figure 21. Drought damage scores from 1998-2008. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

Figure 19 shows extreme temperature damage scores. Due to very small damage totals, no county had a per capita score greater than $0.00. Iowa County had the highest overall score at $69.90. There were not many damage scores that resulted from extreme temperatures and it was determined to be not significantly correlated to county damage scores per capita. This hazard had more of an effect on casualties.

Figure 20 shows flood damage scores. Vernon County had the highest per capita score at $200.46. Floods typically affected the southern and southwestern parts of the state the most. These counties are located next to the Mississippi River, which can cause excessive amounts of damage in years that it causes major flooding. Flooding was determined to be the most correlated hazard within the study area to county damage scores per capita.

Figure 21 shows drought damage scores. Iowa County once again had the highest per capita score at $1.24. These damage scores were driven by crop damages. While there is farming in the northern part of the state, there are also large tracts of forest in that area. The southern part of the state contains much more extensive agriculture. This part of the state is also has a greater frequency of drought events than many of the northern counties. Drought per capita damage scores were determined to be the third most significantly correlated hazard to county damage scores per capita.

These individual hazards help to clarify the overall damage score map (Figure 22). One of the reasons that the counties in the southwestern part of the state have higher damage scores is because of their proximity to a potential hazard every year – the Mississippi River. Counties located here have an inherent risk of flooding every year. Hail damage on the other hand, seems to be a key factor in higher damage scores in the eastern part of the state. The

best explanation is that since hail can affect small areas, those counties with higher population density are likely to have more people affected by a smaller event.

The county with the highest damage score was Dane County at $24,665,840. The county with the lowest damage score was Door County at $8,063. The mean damage score was $4,060,523 and the median damage score was $2,210,026. Ten counties had damage scores under $1,000,000. As damage is likely a function of population size, hazard scores were standardized as per capita scores (Figure 22). The county with the highest per capita damage score was Vernon County at $207.10 and the county with the lowest per capita damage score was Door County at $0.29.

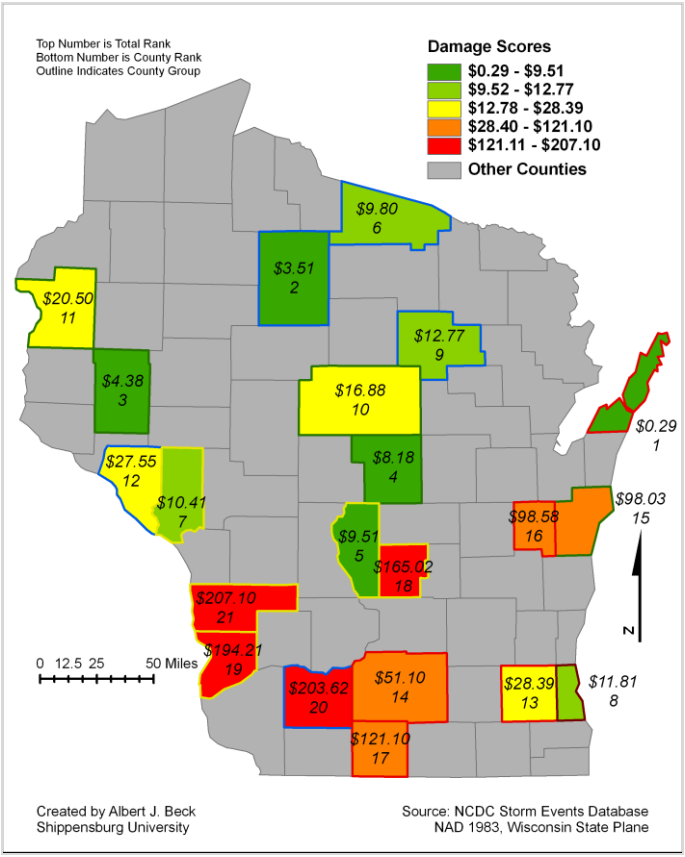

Figure 22. Damage scores per capita and ranks by county. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

Table 3. Spearman correlations of county damage scores per capita and population and event densities.

Damage Score Per Capita	Population Density	Event Density
Correlation Coefficient	0.062	0.477
Significance	0.788	0.029
Significant	N	Y

Table 4. Spearman correlations of county damage scores and population and event densities.

Damage Score	Population Density	Event Density
Correlation Coefficient	0.600	0.639
Significance	0.04	0.002
Significant	Y	Y

Table 5. Kruskal-Wallis H tests of differences in per capita damage scores among county groups.

Kruskal-Wallis H	Damage Score Per Capita	Tornado Damage	Hail Damage	Lightning Damage	Winter Storm Damage	Extreme Temperature Damage	Extreme Wind Damage	Flood Damage	Drought Damage
Significance	0.543	0.762	0.697	0.330	0.792	1.000	0.622	0.177	0.198
Significant	N	N	N	N	N	N	N	N	N
LP/LE Rank Mean	9.80	12.00	10.40	11.20	11.50	11.00	13.40	8.20	10.60
LP/HE Rank Mean	14.00	12.40	12.40	7.40	11.50	11.00	11.00	15.40	10.40
HP/LE Rank Mean	8.60	11.20	8.50	11.00	9.50	11.00	11.60	8.00	8.00
HP/HE Rank Mean	11.50	8.83	12.42	13.83	11.42	11.00	8.50	12.17	14.33

When considering damage scores, the most important factor is event density, not population density. In order to discover this, a Spearman test was run looking for correlations between county damage scores per capita, population density, and event density. This can be seen in Table 3, which shows that event density is significantly correlated to county damage scores per capita while population density is not. However, because damage scores per capita negate any influence from population, another Spearman test needed to be run looking for correlations between county damage scores, population density, and event density. This can be seen in Table 4, which shows that both event density and population density are correlated to county damage scores. In both cases, event density is highly correlated with damage scores – both raw and per capita.

In general, counties with higher event densities have higher damage scores per capita than counties that have lower event densities. For example, southwestern counties are located in areas of low population density but have medium to high event densities (Figures 11 and 12). Although not significantly different from the rest, the low population/high event (LP/HE) density county group had the highest mean rank of per capita damage scores of all four groups during a Kruskal-Wallis H-Test to test for differences in per capita damage scores among the groups (Table 5). This means these LP/HE counties have some of the highest damage scores in the study area. Thus, because there is a higher event density along with a low population density, events that occur in LP/HE counties (outlined in green in Figure 22) have a larger impact on communities.

The next highest scores are high population/high event (HP/HE) density counties (outlined in red) located in the southern and southeastern part of the state. This is where correlation seen in Table 4 between county damage scores and population density shows its importance. This correlation shows that larger population densities are correlated with larger county damage scores. This is likely due to the fact that higher population density counties simply have more items that can be damaged and have a greater chance of being damaged due to higher event densities in this area.

When looking at the overall damage scores per capita, the highest per capita damage scores correspond to LP/HE counties, followed by HP/HE counties, and then trending toward the middle and bottom of the rankings are high population/low event density (HP/LE) counties and low population/low event density (LP/LE) counties. Counties do not split exactly into these groups, but the LP/LE and HP/LE counties with higher per capita damage scores have higher event densities in their locations than the rest of their respective groups.

The one exception to this rule is Milwaukee County. This county is an HP/HE county yet its ranking is in the middle of all counties when comparing per capita damage scores. This is likely due to the fact that Milwaukee County's population density is nearly 4,000 persons per square mile, far above any other county in the state.

Counties with the highest damage amounts per capita are generally located in the south and southwestern parts of the state due to high event densities in these areas. Central and southern counties also have at least a minor to moderate impact from most of the individual hazards, which add up to higher scores. Northern counties, which are made up mainly of HP/LE (outlined in green) and LP/LE counties (outlined in blue), tend to have lower per capita damage scores than the rest of the study area. Within these northern counties there are lower event densities but the small amount of counties with higher pop densities (HP/LE counties) increase the likelihood of possible damage in those areas when an event occurs.

Casualty Scores

The county with the highest casualty score was Milwaukee County with a score of 9.41 casualties. The counties with the lowest casualty scores were Polk and Dunn Counties, both of which had a score of 0 casualties. The mean casualty score was 1.10 casualties and the median casualty score was 0.30 casualties. All but 4 counties had a casualty score below 1.00 casualties. Like the damage scores, casualty scores were determined to be a factor of population – the higher the density in a county, the more likely there will be casualties from severe weather events. The county with the highest per capita casualty score was Adams County at 1.067 casualties per 10,000 people. The county with the lowest per capita score

were Polk and Dunn Counties at 0 casualties per 10,000 people. All the county per capita casualty scores can be seen in Figure 23.

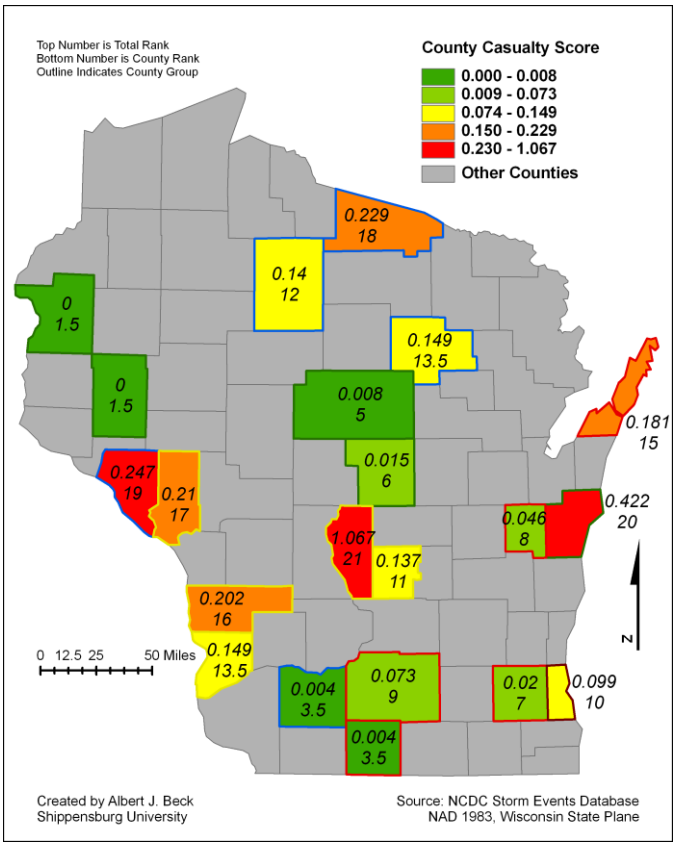

Figure 23. Casualty scores per capita and ranks by county. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

Table 6. Spearman correlations of county casualty scores per capita and population and event densities.

Casualty Score Per Capita	Population Density	Event Density
Correlation Coefficient	-0.372	-0.043
Significance	0.096	0.854
Significant	N	N

Table 7. Spearman correlations of county casualty scores and population and event densities.

Casualty Score	Population Density	Event Density
Correlation Coefficient	0.263	0.401
Significance	0.249	0.071
Significant	N	N

Table 8. Kruskal-Wallis H tests of differences in per capita casualty scores among county groups.

Kruskal-Wallis H	Casualty Score Per Capita	Tornado Casualties	Hail Casualties	Lightning Casualties	Winter Storm Casualties	Extreme Temperature Casualties	Extreme Wind Casualties	Flood Casualties	Drought Casualties
Significance	0.086	0.756	0.220	0.386	0.009	0.169	0.022	0.575	1.000
Significant	N	N	N	N	Y	N	Y	N	N
LP/LE Rank Mean	13.20	12.10	9.50	12.70	10.60	7.80	11.80	10.00	11.00
LP/HE Rank Mean	15.70	12.10	11.60	11.30	16.90	14.80	15.80	12.20	11.00
HP/LE Rank Mean	6.80	9.00	13.70	7.50	8.50	8.60	4.10	10.00	11.00
HP/HE Rank Mean	8.75	10.83	9.50	12.25	8.50	12.50	12.08	11.67	11.00

Casualty scores were determined mostly to be a function of county vulnerabilities. Spearman correlation tests run in Tables 6 and 7 show that event and population densities are not significantly correlated with casualty scores – both raw and per capita. Although not significant, the Spearman correlation test in Table 6 shows a slight correlation with population density. This test also shows that event density is not correlated to county casualty scores. However, although not significant, Table 7 shows that event density plays a role when determining casualty scores. In addition, the maps show the counties with the highest casualty scores generally have moderate event densities.

Table 7 shows positive correlation coefficients for both population and event density. This means that as population density and events increase, the overall number of casualties increase as well. At the same time, Table 6 shows a negative correlation coefficient, which means as population density reduces, casualty scores per capita increase. This means that as population density decreases casualties per capita increase. This makes sense because a county with a lower population density could lose a larger percent of its population to a disaster than a county a higher population density. Thus, when casualties occur, they have a much larger impact on the population. At the same time, the overall number of casualties in

a county with a high population density is likely to be higher than in a county with a low population density.

There is evidence of the non-significant correlation in Table 6 when examining the casualty rankings because the top half of the per capita casualty rankings contains most of the LP/HE and LP/LE counties while the bottom half is dominated by HP/HE and HP/LE counties. Although not significantly difference from the other groups, the LP/HE and LP/LE county groups had the highest mean rank of per capita casualty scores of all four groups during a Kruskal-Wallis H-Test to test for differences in per capita casualty scores among the groups (Table 8). LP/HE counties have the highest rank according to the same test. This may be in part because of the correlation shown in Table 5 between county casualty scores and event densities. However, all four county groupings are represented by at least one county in the top half of the casualty score per capita rankings, which may be an indication that anyone can be a victim of a hazard event no matter where they live.

Table 9. Spearman correlations of county casualty scores per capita and individual vulnerability inputs.

Casualty Score Per Capita	Female	Non-White	Under 18	Over 65	Mobile Home	Median Income
Correlation Coefficient	-0.123	-0.101	-0.277	0.679	0.242	-0.563
Significance	0.595	0.662	0.224	0.001	0.290	0.008
Significant	N	N	N	Y	N	Y

Two important inputs that helped drive the vulnerability scores were the persons over 65 and mobile home ratios. When put through a Spearman correlation test (Table 9) to see if vulnerability inputs were correlated to casualty scores, the only two inputs were the only significant were persons over 65 and median income. However, although there was no significant correlation between mobile homes and casualties, this was also felt to be an

important factor as the maps show the mobile home ratios tending to match up with higher per capita casualty rates. Combined with individual hazards such as tornadoes, extreme wind events, and extreme temperature events, all three of these variables make sense when considering the casualty scores.

Persons over 65 are more susceptible to events due to their age, while mobile homes are also more vulnerable to events due to their construction. Both of these factors can contribute to higher casualty rates. Both LP/HE and LP/LP county groups, which had the highest per capita casualty scores, had the highest mean rank of persons over 65 and mobile home scores of all four groups during a Kruskal-Wallis H-Test to test for differences in vulnerability inputs among the groups (See Table 12). Mobile homes are known to be susceptible to both tornadoes and extreme wind events (Ashley and Mote 2005; Ashley et al. 2008). Many of the top ranked counties with high per capita casualty scores have high tornado and extreme wind event casualty scores. When tested for correlations between county casualty scores per capita and individual hazard per capita casualties, extreme wind events were the highest correlated (Table 10).

Table 10. Spearman correlations of county casualty scores per capita and individual hazard casualty scores per capita.

Casualty Score Per Capita	Tornado Casualties	Hail Casualties	Lightning Casualties	Winter Storm Casualties	Extreme Temperature Casualties	Extreme Wind Casualties	Flood Casualties	Drought Casualties
Correlation Coefficient	0.360	0.120	0.403	0.582	0.472	0.594	0.038	.
Significance	0.109	0.606	0.070	0.006	0.031	0.005	0.869	.
Significant	N	N	N	Y	Y	Y	N	N

Extreme temperature events also can direly affect susceptible populations (these events were the third highest correlated to county casualty scores per capita). For example, Milwaukee County, which was ranked 10th, had a total of 68 casualties (40 injuries and 14

deaths, with deaths weighted x2) due to extreme temperature events. If Milwaukee County's population density was closer to the rest of the counties in the state, if would be ranked near the top of the casualty rankings. Five of the top six ranked counties with high per capita casualty scores have deaths related to these events. Generally, persons who are over the age of 65 are extremely susceptible to extreme temperature events (Knowlton et al. 2009; Rikkert et al. 2009). These counties also have moderate to high ratios of persons over 65. These factors can help explain the higher casualty rates in the top ranked counties.

Vulnerability Scores

The vulnerability scores for the study area can be explored more when each of the individual population ratios that comprise the scores are examined. All the vulnerability inputs were tested to see how well the inputs correlated to both the positively and negatively influenced vulnerability scores (Table 11). Figures 24 through 29 show the ratio per county for each vulnerability input. The combination of these inputs make up the vulnerability score maps in Figures 30 and 31.

Table 11. Spearman correlations of county vulnerability scores and individual vulnerability inputs.

Vulnerability Score (Positive)	Female	Non-White	Under 18	Over 65	Mobile Home	Median Income
Correlation Coefficient	-0.640	0.248	-0.422	0.521	0.658	-0.652
Significance	0.002	0.278	0.057	0.015	0.001	0.001
Significant	Y	N	N	Y	Y	Y
Vulnerability Score (Negative)	**Female**	**Non-White**	**Under 18**	**Over 65**	**Mobile Home**	**Median Income**
Correlation Coefficient	-0.657	0.423	-0.356	0.318	0.491	-0.425
Significance	0.001	0.056	0.113	0.161	0.024	0.055
Significant	Y	N	N	N	Y	N

The first of these demographic inputs was the ratio of females to county population seen in Figure 24. For the most part, this input did not seem to have that much impact on county vulnerabilities because the counties are all in a relatively small range. The range of ratios among the counties is only from 0.46 to 0.52. However, the Spearman correlation tests have this input as one of the largest correlations to vulnerability scores. The negative correlation means that counties with lower ratios of females have higher vulnerability scores. This is different than the results of the TPVI. Statistically, the female input has a very small standard deviation and almost no variance. This is likely influencing the correlation coefficient. In addition, the research conducted in the TPVI was completed for South Carolina. These results could also show demographic differences between the data for the Wisconsin study area and other study areas. It is beyond the scope of this research to speculate why this is the case.

Figure 25 shows the ratios of non-whites to the rest of the county population. The counties that were affected are mostly on the eastern half of the state. The correlation test determined that this input was not significantly correlated to either vulnerability score.

Figure 26 is a map of the ratios of persons under 18 to the rest of the county population. There are relatively high ratios of young people in the southwestern and north central parts of the state. However, this ratio was not considered to be significantly correlated to either vulnerability score.

Figure 27 shows the ratio of persons over 65 to the rest of the county population. The highest ratios are in the western, northern, and central parts of the state. Generally, except for counties in the southwest, counties with a high ratio of persons over 65 are the opposite of

counties with a high ratio of persons under 18. This input was determined to be significantly correlated to vulnerability scores only when median income was a positive influence.

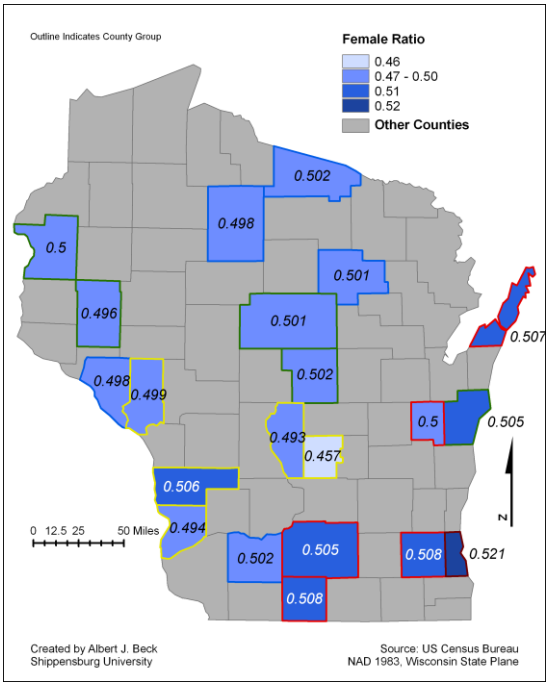

Figure 24. Ratio of females to total county population. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

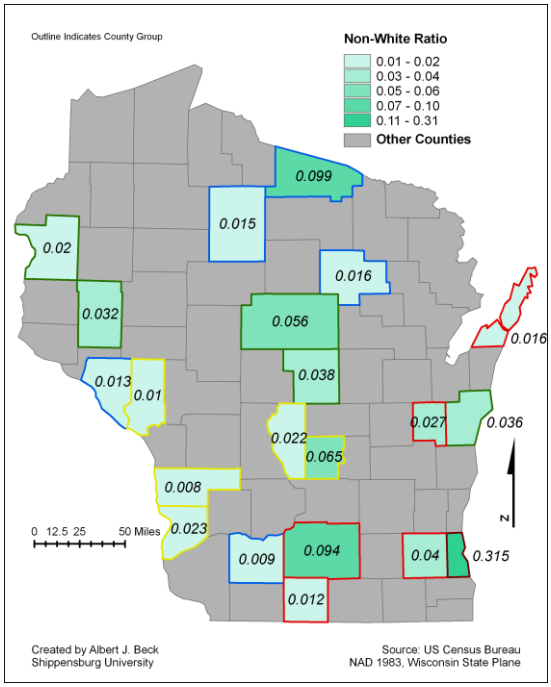

Figure 25. Ratio of non-whites to total county population. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

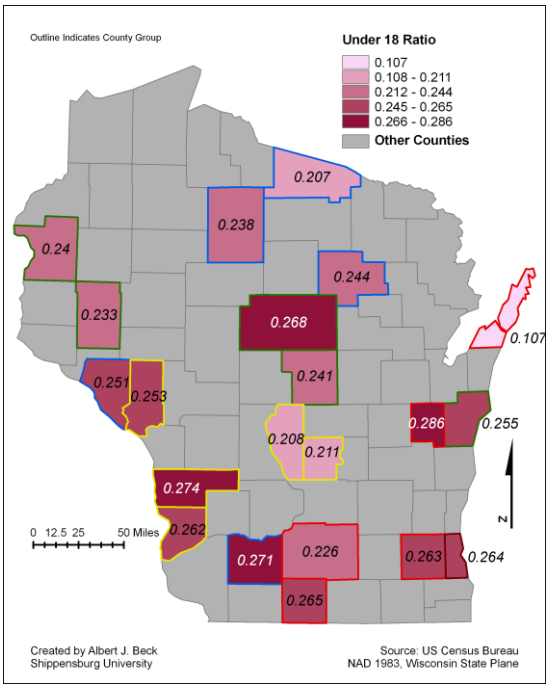

Figure 26. Ratio of persons under the age of 18 to total county population. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

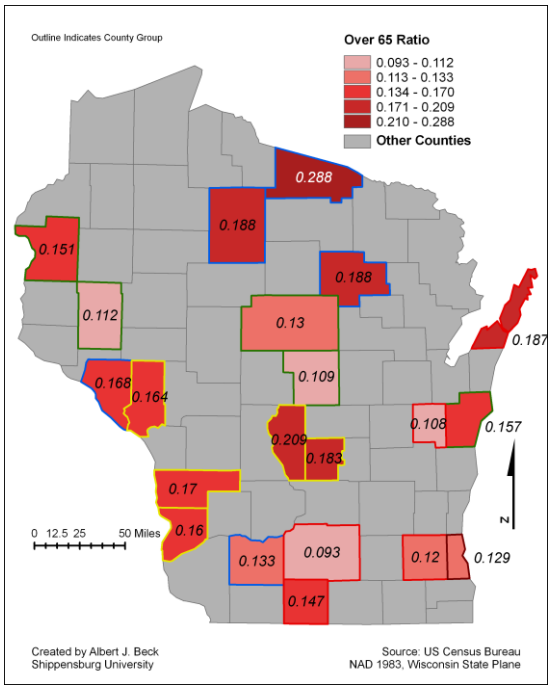

Figure 27. Ratio of persons over the age of 65 to total county population. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

Table 12. Kruskal-Wallis H tests of differences in vulnerability scores and inputs among county groups.

Kruskal-Wallis H	Vulnerability Scores (P)	Vulnerability Scores (N)	Female	Non-White	Under 18	Over 65	Mobile Home	Median Income
Significance	0.028	0.046	0.026	0.320	0.905	0.014	0.003	0.004
Significant	Y	Y	Y	N	N	Y	Y	Y
LP/LE Rank Mean	12.00	11.00	9.80	8.10	9.80	16.00	11.80	7.00
LP/HE Rank Mean	15.40	14.40	6.00	8.60	10.60	15.20	18.40	4.80
HP/LE Rank Mean	13.00	14.40	10.00	13.60	10.80	7.00	10.50	14.70
HP/HE Rank Mean	4.83	5.33	17.00	13.25	12.50	6.67	4.58	16.42

Figure 28 is a map of the ratio of mobile homes to total homes within the county. The highest ratios of mobile home use are located in the western and northern parts of the state. These are much the same locations of the high over 65 ratios. This input was determined to be significantly correlated to both vulnerability scores.

The last input was the ratio of county median income to the combined median incomes of the entire study area (Figure 29). This input could both positively and negatively influence the vulnerability scores of counties. A positive influence means that if county has a high median income, they will be able to recover faster from an event. A negative influence means that if a county has a high median income, they have more to lose from an event. Median income ratios were determined to be significantly correlated to positively influenced vulnerability scores.

In general, most HP/HE (outlined in red) and HP/LE (outlined in green) counties have higher median income ratios than LP/HE (outlined in yellow) and LP/LE (outlined in blue) counties. HP/HE and HP/LE counties had higher mean ranks of median income ratios in a Kruskal-Wallis H Test testing for differences in median income among the groups (Table 12). This can be seen in Figure 29, where the eastern and southeastern counties have higher ratios than counties in the northern and southwestern parts of the state. The counties with the

highest vulnerability scores also tend to be the counties that have lower median incomes. This makes sense when combined with the persons over 65 and mobile home inputs. Many persons over 65 do not make large amounts of money, often due to retirement, and if a county has a lower median income, one could expect less expense home purchases, which in this case, possibly means more mobile home purchases.

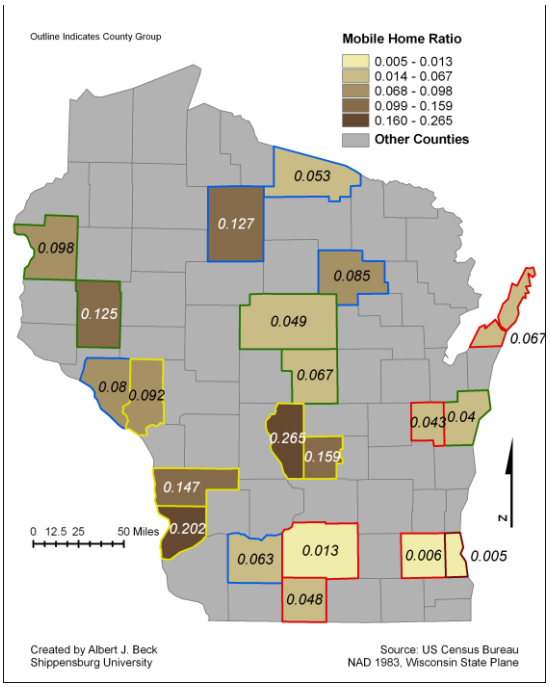

Figure 28. Ratio of mobile homes to total homes per county. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

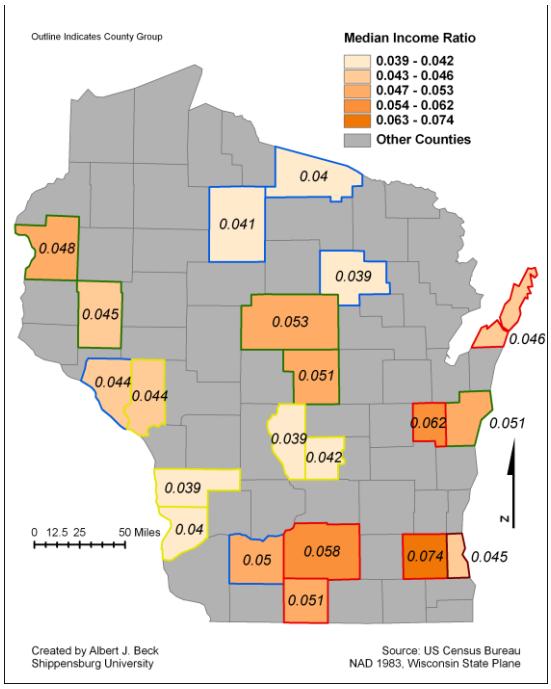

Figure 29. Ratio of county median income to total study area income. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

Vulnerability scores were divided into two separate categories based on median income (positive and negative influence). Each county was assessed a different vulnerability score according to the methods discussed previously. When median income was considered a positive influence, the county with the highest vulnerability score was Marquette County with a score of 436. The county with the lowest vulnerability score was Waukesha County with a score of 5. The mean vulnerability score was 107 and the median casualty score was 66. All the positive influence vulnerability scores and ranks can be seen in Figure 30.

When median income was considered a negative influence, interestingly the county with the highest vulnerability score was also Marquette County with a score of 7667. The county with the lowest vulnerability score was also Waukesha County with a score of 273. The mean vulnerability score was 2005 and the median casualty score was 1296. All the negative influence vulnerability scores and ranks can be seen in Figure 31.

While these counties did not change in rank, there were quite a few that did. Fourteen of the 21 counties in the study area changed at least one rank depending on the methodology used. Top among these were Langlade and Vernon Counties, which changed 4 ranks between the positive and negative rankings. Langlade County went from a positive influence rank of 14 to a negative influence rank of 10 and Vernon County went from a positive influence rank of 12 to negative influence rank of 8. Both of these counties had a median income ratio of 0.039. What these change in rankings mean is that these counties have a tougher time recovering from events (higher positive influence ranks) but they have less items that could potentially be damaged by events (lower negative influence ranks). On the other hand, Calumet County, which had a median income ratio of 0.062, changed 3 ranks. It went from a positive influence rank of 6 to negative influence rank of 9. This shows that this county had an easier time recovering from events because of its median income (lower positive influence ranking) but had more potential items to lose (higher negative influence ranking). The seven counties that did not have a change in rankings likely had more influential inputs than median income, chief among these being the ratio of mobile homes to total county homes discussed earlier.

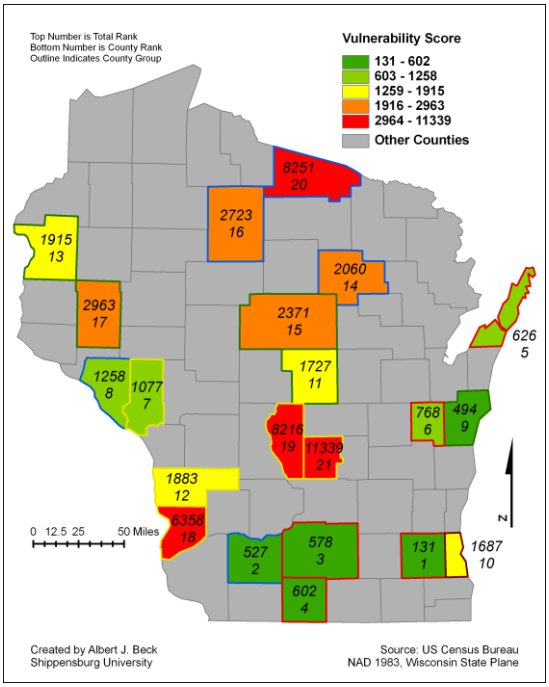

Figure 30. Vulnerability scores and ranks by county where median income is considered a positive factor. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

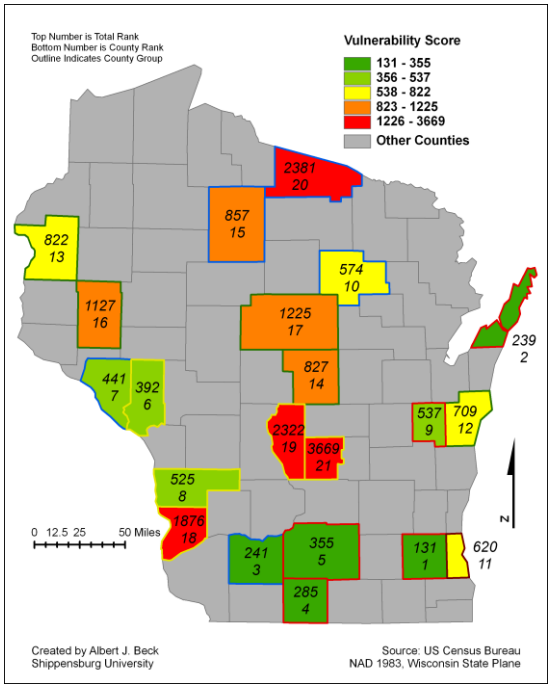

Figure 31. Vulnerability scores and ranks by county where median income is considered a negative factor. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

The overall vulnerability scores were products of the multiple ratios that took different individual population demographics into consideration. Unlike the damage scores where LP/HE and HP/HE county groups were located near the top of the rankings, the vulnerability rankings are not as affected by population and event densities. The vulnerability rankings show that LP/HE (outlined in yellow) and HP/LE (outlined in green) counties have the some of the highest scores while HP/HE (outlined in red) counties have some of the lowest scores. LP/LE (outlined in blue) counties have scores spread throughout the rankings. Having LP/HE counties with higher scores along with HP/LE counties shows a lack of influence by population and event densities. Instead, as intended, population demographics are the driving factor behind the vulnerability scores.

Even though there is clearly a spatial difference among the counties vulnerability scores, this difference does not change much whether median income is seen as a positive or

negative influence. The northwestern and central parts of the state are the most susceptible while the southeastern part of the state is the least susceptible. This is interesting because the southeastern counties would have been expected to have higher vulnerability scores when median income was a negative and lower vulnerability scores when median income was positive. Yet the change is not that dramatic. While median income does had an effect on county susceptibility, it affect is not overwhelming. This means that if a county's population is inherently susceptible or inherently not susceptible, median income will not drastically reduce or increase those susceptibilities.

Final Rankings

The final rankings of the counties can be seen in Figures 32 and 33. These final rankings are the combination of the damage, casualty, and vulnerability rankings and are indicators of how vulnerable a county is from atmospheric hazards. There are two sets of rankings because the vulnerability scores were divided into two separate categories – where county median income was considered a positive influence and where county median income was considered a negative influence. Looking at Figure 32, where median income was considered a positive influence, the county with the highest total ranking and therefore most vulnerable, was Crawford County with a total rank of 50.5. The county with the lowest total ranking, and therefore least vulnerable, was Door County with a total rank of 18. Looking at Figure 33, where median income was considered a negative influence, the county with the highest total ranking was Crawford County with a total rank of 50.5. The counties with the lowest total ranking were Door, Waukesha, and Portage Counties with a total rank of 21.

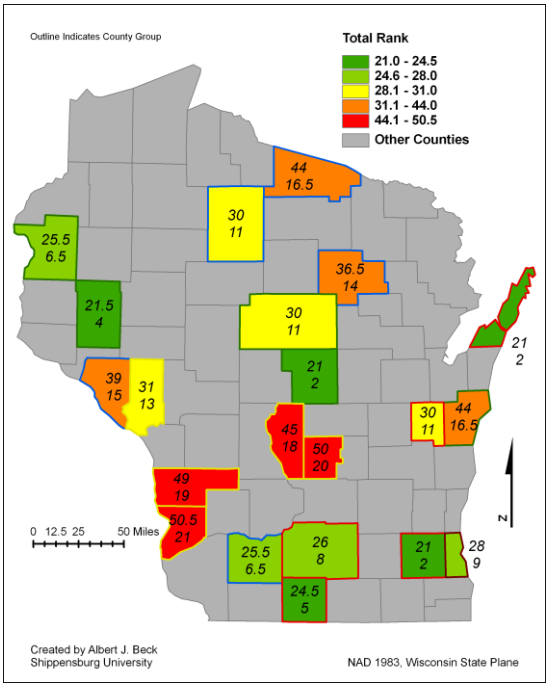

Figure 32. Total and final rankings by county where median income is a positive influence. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

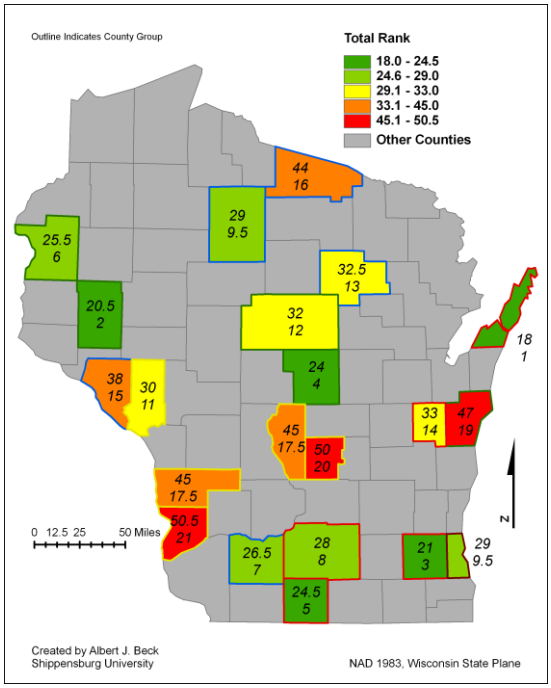

Figure 33. Total and final rankings by county where median income is a negative influence. (HP/HE=red, HP/LE=green, LP/HE=yellow, LP/LE=blue)

While Crawford and Door Counties did not change their final rankings at the top and bottom respectively, depending on the methodology used, there were a few counties that did change. The largest change between the positive and negative rankings was in Calumet County, which went from positive influence rank of 11 to negative influence rank of 14. This is a change of 3 ranks. Four other counties had rank changes of 2 or greater. These were Manitowoc County, which had a change of 2.5 ranks, and Dunn, Portage, and Trempealeau Counties, which all had rank changes of 2. Manitowoc County went from positive influence rank of 16.5 to negative influence rank of 19. Dunn County went from positive influence rank of 4 to negative influence rank of 2. Portage County went from positive influence rank of 2 to negative influence rank of 4. Trempealeau County went from positive influence rank of 13 to negative influence rank of 11. These changes in ranking

show just how important vulnerability scores were to the final rankings and beyond that, how important county median income could be in determining county vulnerability scores.

When looking at the overall rankings, a few points stand out. One would expect that counties with high population densities and high event densities (HP/HE counties) would be near the top of the final rankings. This is because there are more people in these counties, which would attribute to higher damage totals and therefore hazard scores. Higher population densities in these counties would contribute to higher casualty scores and the diversity of larger populations would contribute to higher vulnerability scores. Putting all three of these together would result in higher rankings and therefore more risk to those counties. However, the HP/HE counties are located in the bottom half of both the positive and negative influence rankings along with the HP/LE counties. The LP/HE and LP/LE counties tended to be in the top half of both rankings. These rankings show that even though high population density counties may have more overall damage or casualties due to having higher densities, high population density counties are able to buffer the effects of disasters while disasters that occur in low population density counties have a much larger impact. When a disaster occurs in low population density counties, it will have deeper consequences for the population.

These differences in population density also show themselves geographically. Both maps, either where median income is positive or negative, show that the counties in the southeastern part of the state are the least at risk. This area has low casualty and vulnerability scores and only moderate damage scores. With these low ranks combined, this area has the lowest overall ranks and is the area least at risk. This is contrasted by the southwestern and central part of the state. These areas have low population density and

therefore are not able to buffer damage and casualty scores. These areas have moderate to high casualty scores and high damage and vulnerability scores. Combined, this has led to these areas having higher total ranks and therefore these areas are more at risk. The northern half of the state is a mix of counties with high and low rankings. These rankings are driven by the counties vulnerability scores because the damage and casualty scores in this part of the state are relatively low.

CONCLUSION

Hazard, risk, and vulnerability assessments are important tools for community officials, emergency personnel, spatial planners, insurers, and even homeowners. For planners, it is essential that they anticipate the risks to a given population. As noted before, risks are unavoidable but can be mitigated better when they are planned for. The Total Place Vulnerability Index (TPVI) and the Integrated Risk Assessment of Multi-hazards (IRAMH) are good examples of assessment that aim to help anticipate risk and vulnerability. However, they are not without their faults. The TPVI's approach looks at the social aspect of vulnerability while the IRAMH uses more physical than social factors in determining disaster proneness. The atmospheric-hazard vulnerability assessment this research provides is an attempt to bridge the gap between the two assessments and help foster the development of a more inclusive approach to planning for risk and vulnerability from natural hazards.

The results presented by this research show that southwestern and central Wisconsin are the most vulnerable to atmospheric hazards while southeastern and northwestern Wisconsin are the least vulnerable. Southwestern Wisconsin is on the banks of the Mississippi River, a major source of natural disasters. Beyond that, these counties have

medium to high event densities which means these counties have more opportunities to be affected by natural hazards. Southwestern and central Wisconsin counties are also some of the lower populated counties in the state, which means that when hazards do occur, they can affect larger portions of the populations in these counties. At the same time, the populations in these counties generally have lower incomes, larger populations of persons over 65, and more of the population lives in mobile homes. This makes these populations more susceptible to natural hazards. When you combine all these factors, the counties are the most vulnerable in the state.

Counties in the southeastern and northwestern parts of the state, on the other hand, are much less vulnerable, but for different reasons. In the southeastern part of the state, there are many more people than any other region of Wisconsin. This, combined with higher event densities has lead to these counties having the highest per capita damage scores in the state. However, even though there are a lot of people, these counties have low per capita casualty scores. In many regards, this is due to the fact that these counties have low vulnerability scores. If the vulnerability scores are low, it is not a coincidence that the casualty scores are low as well. However, the northwestern counties have lower vulnerability levels for a different reason. These counties are located in an area of low event density. Despite the fact that the populations in these counties have higher vulnerabilities, the lack of events means that there are fewer opportunities for natural disasters to create damage or casualties.

The model created in this research does a decent job of integrating both social vulnerabilities inherent to populations with the physical risk posed by natural hazards. Instead of generalizing physical risk created by hazards into simple frequency of occurrence, this model takes into account the impact a hazard can have on communities. This was done

by creating both damage and casualty scores that quantify the impact hazards have on populations into hard numbers that can be measured and studied. On the other hand, human susceptibility is not generalized either. Important population demographics that were used by the TPVI were included and combined to create vulnerability scores within this assessment. Combining rankings, while simple, proved to be the best way to integrate all scores and determine which counties were the most vulnerable, from both a population and disaster standpoint.

However, this model does have some very important limitations. It should be noted that the results of the research should be read and interpreted within those limitations. This model is a relative assessment as opposed to an absolute assessment meaning that the results and comparisons are meant first and foremost for the defined study area. Conclusions about how these results translate beyond the study area are very limited but are based on reasonable hypotheses.

The first limitation of this model is that it is not a good predictive tool. While it may be reasonable to discern that the counties that are ranked the most and least vulnerable may perceivably still be higher or lower vulnerable counties in the near future, it is not a certainty. This model is a snapshot of ten years of hazard and population data. Weather patterns and population may change in the future, which in turn means this model would need to be constantly updated.

Secondly, the study area used for this research is conceivably too small to attain meaningful results outside the state of Wisconsin. While it is likely that the results of this research will apply throughout the state, this is because the state itself is a relatively similar

geographic region. These results may not in fact translate to another region of the United States or for the entire United States.

Third, it is difficult to prove the results of an assessment such as this. There is no overarching vulnerability assessment to compare the results to and while the numbers are certainly calculated rationally, they are in many ways still arbitrary numbers. The vulnerability scores in this research are simply representative of the susceptibility of county populations to natural hazards. These numbers could change based on the way they are calculated and/or what inputs are used in their creation. In many ways, the only way to test a model such as the TPVI or the one in this research would be to compare the results with data accumulated after the end date of the model's time frame.

Lastly, the social vulnerability inputs used in both this model and the TPVI are, in many ways, too general at the regional scale. To receive an accurate assessment of the vulnerability to hazards in a specific region, the susceptible population demographics must be known. Further, these susceptible populations are subject to change from one region another. For example, while the social vulnerability variable of females may have been an important input in South Carolina where the original research for the TPVI was conducted, in Wisconsin, it was found that the variable of females does not behave in the same fashion. Thus having general demographic inputs to calculate social vulnerability at a regional level is not as useful as it would be at a national level. At the national level, more general social inputs may want to be used instead of stitching together regional assessments with their unique vulnerability inputs because it would allow for comparisons across the regions and would help to determine where these demographic inputs were relevant.

This research leaves avenues for further research in many areas. First, if a better comprehensive natural hazard database of could be developed on the county scale, research such as this would be much easier to complete. This comprehensive database would need detailed information such as property and crop damage estimates to the nearest dollar amount and deaths and injuries per county as opposed to forecast zone for some hazards (winter storms and extreme temperatures for example). Complete reports for each event would also be an excellent inclusion to the database. Having all this information in one place would allow for better and faster use of the storm data.

Second, the research in this paper could be expanded to the entire state of Wisconsin for a much more comprehensive assessment. The groupings used in this research reflect larger areas within the state (see Figures 8 and 9). This research made generalizations based on random counties from these groups. With more time, research could be completed that would give a complete assessment of the state of Wisconsin. This research could also be used for other states and other hazards. All that is required are county-level census data and natural hazard data to use this assessment in a different state. Non-atmospheric hazards could also be included such as earthquakes if the hazard and damage/casualty data were available. A countrywide assessment would allow for a more comprehensive comparison of counties and as well as more certainty in the results due to an increase in sample size.

Lastly, the social demographic variables used in the TPVI, and therefore this research, could be studied further to allow for the best choices to include in the model. Currently, these choices seem to be the most useful variables for inclusion within these two models. However, currently there is no way to prove whether they are the best variables for inclusion. For example, the social variable of females was useful to the original research in

South Carolina, but when applied to the research in Wisconsin, it was found that the female variable was not as useful. Further research should be dedicated to identifying social demographics that can be proven to increase or decrease a population's susceptibility to natural hazards in all regions of the United States.

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