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Longitudinal Awareness: A Study of Vulnerability to Flooding in Polk County, Iowa

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Longitudinal Awareness: A Study of Vulnerability to

Flooding in Polk County, Iowa

by

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DEDICATION

I dedicate this thesis to my family: Mike, Doris, Derrick & Meridith Dickey. They never stopped supporting me even when times were hard, and they never stopped trusting me to do what I knew was right for myself. Thank you so much for a lifetime of encouragement and the wisdom you passed down to me. I would also like to recognize and dedicate this thesis to my secular/atheist community for supporting me through scholarship and for their continued unwavering support in science and critical thinking.

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ABSTRACT

Flooding has become a problem of national proportion and many scholars have started to take note of the human impacts in this area. This study will focus on the social vulnerability framework in tandem with the environmental justice theoretical frameworks being applied to Polk County Iowa so that information can be added to the body of works within a Midwestern U.S. context. This research will contribute to the current geographical knowledge in natural hazards, environmental justice, and vulnerability to flood hazards. Taking into consideration the scarcity of county or sub-county studies in the Midwest U.S. measuring spatial tendencies in hazards vulnerability, this thesis is fitting. This study examines Polk County Iowa for social vulnerability factors present today to the natural disaster of flooding and then looks longitudinally back to 1990 to see if similar individual variables were also prominent historically. This study utilizes block group census level data and creates from it a social vulnerability index (SoVI) following Cutter et al. (2003). The study then used FEMA flood risk level boundaries and the 100-year floodplain to create a comparison of vulnerability of higher flood risk areas and lower risk areas to see if exposure to flood prone areas coincides with an increase or decrease in social vulnerability. Findings of statistical tests and the bivariate choropleth map of the study area suggest that Polk County exhibits a spatial vulnerability paradox, where the persons most socially vulnerable do not necessarily always preside in the source area for flooding. Interestingly enough the study suggests that risk capable and risk resilient populations live in some of the most physically risky places. An examination of specific individual vulnerability factors from the present and historically in 1990 give the same picture of spatial paradoxical vulnerability, leading many variables to be inconclusive. However, four variables (QFAM, QMOBILE, QEXTRACT, and AVGTRVL) did show correlation to prolonged historical disenfranchisement within the flood boundaries. It is crucial

to take this information and widen the spatial location of risk from the present immobile boundary set forth and perpetuated by government entities, to a realistic flexible range of spatial locations that consider historical cultural forces and formulate new mitigation policies from these understandings. This thesis further highlights the need to use multiple interdisciplinary methods to understand what is happening within our space, place, and time. This thesis adds to the ever-growing literature in social vulnerability, and environmental justice but in a U.S. Midwestern context instead of a U.S. coastal context to a flood hazard situation.

CHAPTER ONE: INTRODUCTION

Flooding has become a problem of national proportion and many scholars have started to take note of the human impacts in this area (Moftakhari et al., 2015; Špitalar et al., 2014; Di Baldassarre et al., 2013; Smith, 2013). The importance of flooding has recently even been noted by the National Weather Service (NWS) who highlighted fatalities for 2015 for several weather-related hazards (*Figure 1*). The graph shows fatalities from weather related hazards over the last 30 years and it can be seen that flooding has consistently been the second deadliest event, but was the deadliest weather hazard in 2015 particularly due to several flash and river flood events in Texas, Missouri, Utah, Oklahoma, and Illinois (NWS Weather Fatality, Injury and Damage Statistics, 2016). Males accounted for 65% of deaths, and 64% of the deaths resulted from vehicles trying to cross flooded roadways, while the greatest number of deaths occurred among people from ages 30-50 (NWS Weather Fatality, Injury and Damage Statistics, 2016).

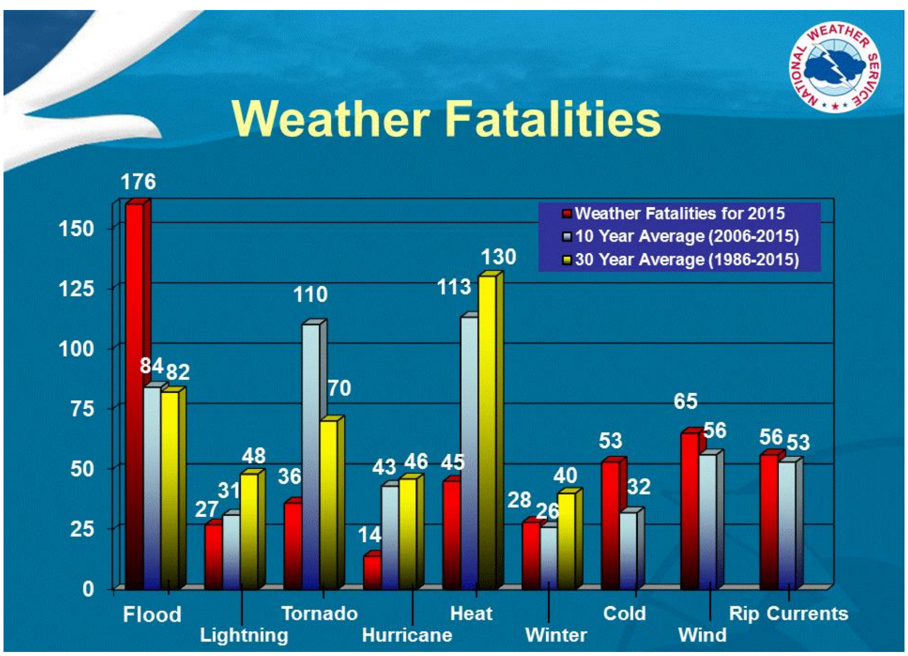

Figure 1: Weather Fatalities for 2015. Source: NWS Weather Fatality, Injury and Damage Statistics, 2016

Now, more than ever, there is an important push to study the social impacts of flooding as it gains attention and time in the national lime light. Flooding is a particularly important problem in the state of Iowa, and even more so in Polk County where the bulk of the population lives. Iowa's most impactful environmental hazards are those associated with severe weather, which includes heavy rains, flash flooding, urban and river flooding, tornadoes and high winds, as well as blizzards & heavy snow (Iowa Homeland Security and Emergency Management - Iowa Disaster History, 2016). The state of Iowa has received 40 Presidential Disaster Declarations (PDDs) in total from 1990 to 2016, and 58 PDDs since the first declaration in 1953 (Iowa Homeland Security and Emergency Management - Iowa Disaster History, 2016). When one looks deeper into the declarations one finds that 82.5% of all presidentially-declared disasters were flooding related, not to mention that historically out of 62 total PDDs for the entire state, 55 declarations are from flooding alone (Iowa Homeland Security and Emergency Management - Iowa Disaster History, 2016). Roughly 89% of all major disasters that warrant a state of emergency and a disaster declaration, including governor, federal and presidential, in the state of Iowa have a flooding component.

Flooding is not always directly attributed to a river, stream, or lake overflowing from its banks, though Polk County is highly susceptible to these events. For this area, it is the combination of excessive rainfall or snowmelt, saturated ground, and inadequate urban drainage. The water has no place to go, and naturally flows to the lowest elevations which are areas in the floodplain (Polk County, 2010). These types of flooding are becoming more dominant as development exceeds the ability to create efficient drainage infrastructure to appropriately carry and distribute the water flow away from populated areas on a floodplain (Polk County, 2010). Winter hazards are thus associated with flooding since precipitation can be either liquid or solid, and can occur rapidly or slowly over time. One event starting in 2007 and persisting to 2008 was the product of all the components of flooding, and was so devastating it totaled more than $126 million in federal aid (Iowa Homeland Security and Emergency

Management - Iowa Disaster History, 2016). The mapping of flood risk and social vulnerability in Polk County, Iowa, is of considerable importance since it is where the largest density of population occurs. As well, the State of Iowa stated in its 2013 Hazard Mitigation Plan, from the Polk County Multijurisdictional Risk Assessment documentation, that the jurisdictions with the most previous flash flood events were the City of Des Moines and the unincorporated county (Polk County Multijurisdictional Risk Assessment, 2009). In Polk County alone since 2007 there have been 102 flooding events, which is up from the ten-year span before it, with only 38 flooding events recorded in Polk County (Storm Events Database - National Centers for Environmental Information, 2016).

Mapping the flood risk allows one to know where the flooding is most likely to occur, but it is similarly important to find out who it is going to affect and if these people are socioeconomically more vulnerable to flooding and if they have been predisposed over time. It is possible to use a vulnerability index to find areas of concern and see if those areas align with flood exposure indicators while using an environmental justice framework to help define what vulnerability factors to investigate in the study area. With the recent concerns of sea level rise and climate change, many vulnerability analyses have focused more on coastal areas (Aerts et al., 2014; Balica et al., 2012; Lane et al., 2013; Balica et al., 2013). Considering the issues brought forth by Aerts et al., Balica et al., and Lane et al., this study will focus on the social vulnerability framework in tandem with the environmental justice theoretical frameworks being applied to Polk County so that information can be added to the body of works within a Midwestern U.S. context. This research will contribute to the current geographical knowledge in natural hazards, environmental justice, and vulnerability to flood hazards. Taking into consideration the scarcity of county or sub-county studies in the Midwest U.S. measuring spatial tendencies in hazards vulnerability, this thesis research is germane (Moftakhari et al., 2015; Špitalar et al., 2014; Di Baldassarre et al., 2013; Smith, 2013). It employs the prevailing methodology on social vulnerability metrics (Cutter et al. 2003) to evaluate the comparative vulnerability of populations in

Polk County Iowa in order to: enhance the understanding of the spatial relationships concerning vulnerable populations and areas of highest risk due to flooding; and to examine the resulting patterns of disproportionate vulnerability over time (Burton & Cutter, 2008).

1.1- Literature Review

1.1.1- Overview: Hazards Research in Geography

Geographers have always been involved with natural hazards, with early research focusing on physical developments and spatial distributions and designs (Montz & Tobin, 2011). Hazards research is a study that's birth is attributed to Harland Barrows during his AAG presidential address in 1923, where he emphasized the importance of the relationship between humanity and nature (Paul, 2011). This was a new alternative to the obsolete environmental determinism model and asked geographers to focus on the shared relationship between humans and the physical environment (Paul, 2011). In the 1940s and 1950s this approach enjoyed a rejuvenated awareness amongst geographers with the developing concerns over environmental problems (Paul, 2011). The pioneering work of Gilbert White's "Human Adjustment to Floods" (White, 1945) guided the discipline to monumental changes in hazards research (Montz & Tobin, 2011). Followed by his students Ian Burton and Robert Kates and later by their students, the White–Burton–Kates School of Natural Hazards emerged to oppose environmental determinism in geography (Paul, 2011). The methods have changed in complexity and have led to the growth of the human ecology approach to hazards research (Paul, 2011). As a result geography now has a tradition of applying geographic knowledge, techniques, and skills to the intricacy of matters allied with natural hazards (Montz & Tobin, 2011).

Hazards researchers are offering theoretical paradigms and integrative frameworks that attempt to reduce the tension between theory and practice (Montz & Tobin, 2011). Hazards research is now complexly incorporating thematic approaches, important elements of risk, socio-economic vulnerability, structural vulnerability, and individual or society resilience. With the latest technological advances, through GIS, remote sensing, and spatial analytical techniques, hazards research has been seriously supported (Montz & Tobin, 2011). Broadly defined social impacts are all impacts on humans and on all the ways in which people and communities interact with their socio-cultural, economic, and biophysical surroundings (Walker, 2006). To examine the impacts of flooding one must look at key demographic variables and determine if there is a connection to flood risk and vulnerability. Looking at the distribution of flood risk in a study area, the populations' ability to respond to flood warnings and cope with flood events is a large part of a vulnerability assessment. One needs to understand the vulnerability of an area that is not just framed on the where or focused on the geographical nature of impacts, and this is the study of social vulnerability.

1.1.2- Social Vulnerability

This section summarizes current relevant literature that emphasizes issues of social difference in addition to inequality and their importance even before flooding had become part of the environmental justice discourse. There is a stream of work on flooding and other forms of natural hazards that has long focused on questions of vulnerability and that seeks to understand the practices that lead to the poor and marginalized communities being more severely affected in countless ways than many others (Cutter et al. 2003; Wisner et al. 2004). Many scholars have drawn attention to the dimensions of inequality found in natural hazards like floods, droughts and other extreme weather events. In Europe and North America, the vulnerability perspective has independently become important in modeling research trajectories and stimulating disaster management practices and strategies (Wisner et al. 2004).

Vulnerability knowledge and investigation develops upon the multidisciplinary institution of hazards and disasters study. Theoretical and analytical methods have advanced to tackle vulnerability to disaster effects where the theories of exposure, resistance, and resilience are frequently beginning points (Burton & Cutter, 2008). These components also manufacture variants in vulnerability amongst clusters of people and amid places (Burton & Cutter, 2008). One personally has used the term vulnerability more than a few times in this thesis, as it has a conventional meaning: to be disposed to or predisposed to injury or harm (Wisner et al. 2004). To start, one poses a simple functioning definition of vulnerability. Social vulnerability is defined by Wisner et al. (2004, pg. 11) as "the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impact of an extreme natural event or process." Vulnerability is a vital concept for disaster risk, the term is employed in copious other contexts, for instance to refer to epidemiological and, environment sensitivity, or the circumstances that manufacture individual's susceptibility to natural and economic stressors. It seems that ordinarily one might hear widespread accounts of the aging, kids, or women as 'vulnerable,' without any suggestion as to what these groups are actually susceptible to (Cardona et al. 2012). It is imperative to recognize that vulnerability is highly connected with the deficiency of skills of an individual or society to foresee, manage with, oppose and recuperate from a flooding impact or natural disaster (Wisner et al. 2004; Cançado et al. 2008).

Vulnerability as a discipline has advanced in complex ways to calculate human exposure to injury, the disparate sensitivities of societal groups to injury and variances in adaptive capacity, the ability to bounce back after the harm occurs (Cutter, 2003 ; Boone, 2010). Such frameworks come from the different types of approaches one might take when studying vulnerability. Table 1 communicates the different approaches to vulnerability study that have been taken over the life of the concept. An example of vulnerability frameworks would be the MOVE framework proposed by Birkmann et al. (2013) which provides a conceptualization of the multi-faceted character of vulnerability as it attempts to give justification for crucial influences like exposure, susceptibility, lack of resilience to a disaster, and lack of communal reaction, as well as the thematic elements of vulnerability: material, communal, environmental, economic, cultural and institutional. The MOVE conceptual framework underlines that hazards are of natural or socio-natural origin, while vulnerability is multi-faceted in nature and is mainly linked to societal conditions and processes (Birkmann et al. 2013). These frameworks are vital to assist in visually understanding that vulnerability should not be looked at by just one variable but instead should use a multi-faceted approach that takes into consideration social and environmental factors.

Table 1: Vulnerability Approaches, adapted from Adger, 2006

Vulnerability Approach	Objectives	Authors
Antecedents		
Vulnerability to hazards	Identification & prediction of vulnerable groups, critical regions through likelihood & consequence to hazard. Applications in climate change impacts.	Burton et al. (1978, 1993); Smith (1996); Anderson & Woodrow (1998); Parry & Carter (1994)
Human Ecology	Structural analysis of underlying causes of vulnerability to natural hazards.	Hewitt (1983); O'Keefe et al. (1976); Mustafa (1998)
Pressure & Release	Further develop human ecology model to link discrete risks with political economy of resources & normative disaster management & intervention.	Blaikie et al. (1994); Winchester (1992); Pelling (2003)
Successors		
Vulnerability to climate change & variability	Explaining present social, physical or ecological system vulnerability to (primary)future risks, using wide range of methods & research traditions.	Klein & Nicholls (1999); Smit & Pilifosova (2001); Smith et al. (2001); Ford & Smit (2004); O'Brien et al. (2004)
Vulnerability of social-ecological systems	Explaining the vulnerability of coupled human environmental systems.	Turner et al. (2003); Luers et al. (2003); Luers (2005); O'Brien et al. (2004)

Previous researchers originally sought to reduce hazard impacts with approaches that only address physical events, like Wisner et al. (2004) who focused on the social vulnerability of places and people. Other reviews on social vulnerability have come to different deductions, for example, Cutter et al. (2003) classified research into vulnerability as exposure (conditions that make people or places vulnerable to hazard). Then into a social condition (measure of resilience to hazards), and finally they look at the "integration of potential exposures and societal resilience with a specific focus on places and spaces" (Cutter et al. 2003, p. 243; Adger, 2006). Geographical Information System (GIS) and statistical methods are used to relate the spaces specified on official Federal Emergency Management Agency (FEMA)/Environment Agency maps as being at risk for flooding with social data from a census. The many distinctive approaches for how to study populations which are distributed inside or outside of the floodplain were investigated by Fielding and Burningham (2005), demonstrating the necessities of results on the methodological choices made, and the doubts that exist within such studies (Walker & Burningham, 2011). Much study data can be obtained at various levels of aggregation from the U.S. Census Bureau and American Community Survey (ACS). Although quantitative measures derived from the U.S. Census and other secondary data sources are merely proxies for social vulnerability, these indicators can be analyzed statistically and compared (Cutter & Finch, 2008). There are also unjust socioenvironmental consequences which are actions that demote less powerful groups to hazardous living conditions without comparable protections which are afforded to elite classes. The political ecology approach to natural hazards enables understanding of the multifaceted qualities of areas associated with natural hazards and social vulnerability.

Distributional equity, is assessed by inspecting the present distribution of hazards regarding socially vulnerable groups; and procedural equity is concerned with fairness in the decision-making practices which affects the distribution of people across the hazard landscape (Fielding and Burningham, 2005; Walker and Burningham, 2011; Walker, 2012; Montgomery et al., 2015). Hazards research has a goal to study the disproportional impacts on socially and economically vulnerable people.

Susan Cutter (1995) has written a book about Hazards, Vulnerability, and Environmental Justice in which she noted challenges like how vulnerability metrics are usually descriptive and not predictive indices (Cutter, 1995). Furthermore, there is a lack of agreement in the scientific community about how to measure social vulnerability. Statistical methods for assessing social vulnerability include factor analysis techniques, which are employed to reduce multiple factors of vulnerability to a single index such as Cutter et al.'s (2003) Social Vulnerability Index (SoVI). Cutter et al. (2003) wrote Social Vulnerability to Environmental Hazards where the authors looked at county level socioeconomic and demographic data and could construct an index of social vulnerability to environmental hazards which they called the Social Vulnerability Index (SoVI). This idea bodes well with this study and is congruent with this study parameter; so, the way in which Cutter organizes vulnerability methods in terms of three theoretical frameworks makes the SoVI the logical choice of indices to utilize going forward (Cutter et al. 2000). This is the theoretical framework one will use in this thesis to pursue an understanding of vulnerability and integrate it with the environmental justice framework to assist in finding vulnerable populations to flooding over time. Social metrics make it possible to construct and scale the intersection of social and physical processes within a geospatial framework. The methods employed by Cutter et al. (2003) include using a factor analytic approach which places factors in an additive model and computes a summary score. In their study, there were 11 independent factors that accounted for about 76 percent of variance in the whole United States. Thus, the authors found distinct spatial patterns in the SoVI, with the most vulnerable counties clustered in metropolitan regions and near the coast. Their research suggests that factors contributing to overall scores varied widely from each county stressing the interactive nature of social vulnerability. Social vulnerability provides greater insight into the way in which the choices we make as a culture effect our differential experience of hazard episodes. Social vulnerability comes from incomplete access to sources and administrative power, societal capital, attitudes and traditions, material limitations of the populace, and features of the manufactured environment (Cutter et al. 2003).

The social vulnerability modeling approach, SoVI (Cutter et al. 2003), was developed to address many shortcomings. More recent examples of social vulnerability modeling have been based on limited representations of the social characteristics involved (Cutter et al. 2000; Chakraborty et al. 2005), considered only particular aspects of vulnerability, or focused on novel methodological approaches for one specific case study. Future goals from this research stress the importance of measuring places independently and noting how they change spatially and temporally which will require historical reconstructions of variables and the development of realistic scenarios of potential future vulnerabilities. A similar factor-analysis-based approach to characterizing social contributions to vulnerability was also used by Clark et al. (1998), who used a smaller enumeration unit (census block group) for one study area. The SoVI approach has been replicated in a number of studies in various geographic settings, at various spatial scales, and in differing time periods. SoVI has consistently illustrated its value by revealing both anticipated and unanticipated spatial patterns that conform to expert interpretations of social vulnerability. Though Cutter et al.'s research is pivotal, it is widely recognized in academia that there is currently no one best way to calculate social vulnerability and build it into an index. Works by Pelling and Uitto (2001); Birkmann (2006); Fekete (2009), and Flanagan et al. (2011) are all works which attempt to create or utilize an index to quantify vulnerability. Supplementary methods of quantitative analysis including chi-squared tests, *t*-tests, regression analyses, and spatial regression have all been used in vulnerability qualitative methods (Montgomery et al. 2015).

Despite a large body of natural hazards research, there is still a considerable lack of knowledge pertaining to social vulnerability to hazards and risk. Cutter et al. (2003) refers to this gap in knowledge as the "vulnerability paradox" (Cutter et al. 2003). Rufat et al. (2015), lists off both thematic indicators of vulnerability and more specific indicators under each sub section as seen in *Figure 2*.

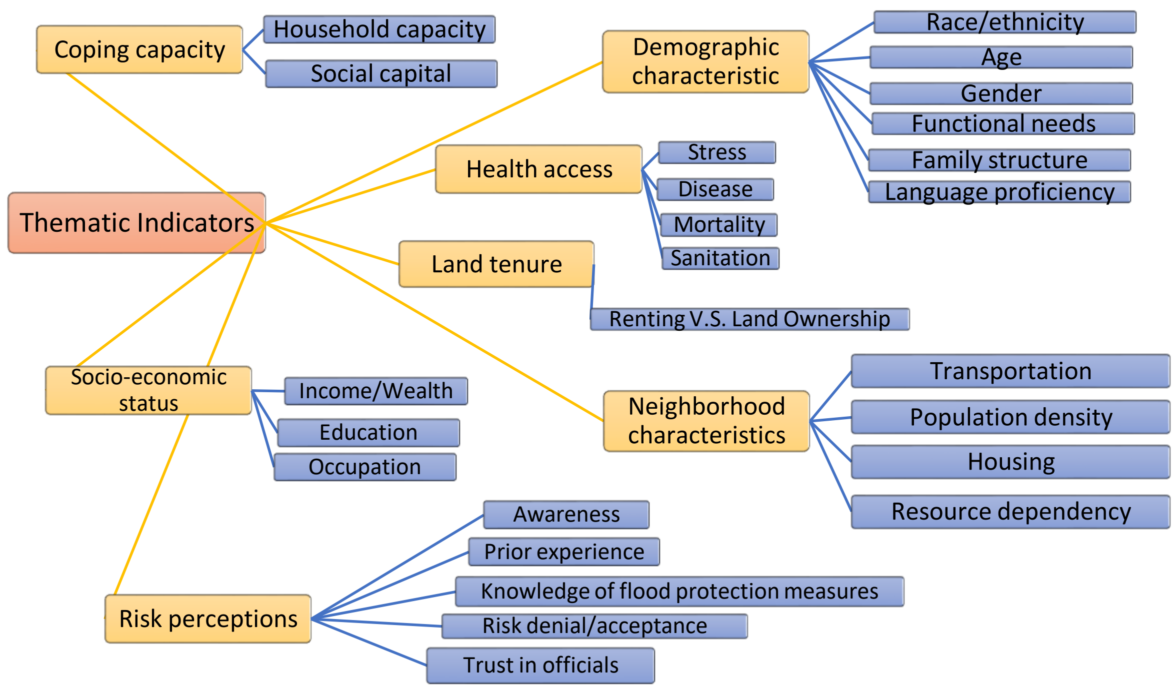

Figure 2: Thematic Indicators of social vulnerability. Adapted from-Source: Rufat et al. (2015)

1.1.3- Risk and Temporal Scale

One will start by defining what one means when talking about risk in the context of this thesis. Risk can be defined as "the possibility of adverse effects in the future happening, which is not only determined by the hazard but also by the exposure and vulnerability of persons to these hazards." Cardona et al., (2012). Attempts to reduce the exposure to a hazard and create disaster-resilient communities require the concept of risk and vulnerability between multiple disciplinary theories to intersect. Recognizing the different origins of disciplinary models will help us to intertwine economic, institutional, and vulnerability as well as risk so we can improve our understanding. A mixture of theoretical frameworks and interdisciplinary understandings will be the future of vulnerability studies (Fuchs, Birkmann, & Glade, 2012). This is a large reason for the completion of this social vulnerability analysis to be done with an assessment of environmental justice factors over time, as an effort to insert ideas from multiple disciplines. Wisner and Walt in 2005 emphasize that gathering data and information has to serve the aggregation of knowledge (the understanding of how things work or are supposed to work), which in turn is essential for being able to make the right choices (Birkmann, 2006). Wisner stresses the fact that the entire process always has to aim at the final level of what he calls "wisdom" which allows for sound decision-making, which means making value judgement based on experience, understanding and principle (Birkmann, 2006).

These vulnerability and risk indices require advanced study and refinement so that hazards researchers can improve their understanding of implications and challenges to comparative vulnerability assessments, including the assumptions and limitations associated with quantifying human vulnerability. One such implication and challenge with assessing flood vulnerability is comprised around FEMA and the National Flood Insurance Program (NFIP) which is managed by FEMA. The NFIP provides low-cost flood insurance to U.S. residents. NFIP is often been criticized because of its financial indebtedness as reported by the U.S. Government Accountability Office (U.S. GAO). The NFIP is intended to provide affordable flood insurance, but it is not designed to build a capital surplus (U.S. GAO, 2012). The premiums charged by FEMA are not consistent with the actual risk, additionally, the NFIP contains "grandfathered" rates that allow some proprietors to continue paying rates that do not call for reexaminations of their properties' flood risk (U.S. GAO, 2012). Conversely, private insurance companies must profit enough to have extra capital that can be used to recompense covered losses without entirely draining the financial reserves of the insurance company. Additionally, the NFIP does not drop high-risk contracts and those with recurring claims. Gilbert F. White forewarned shortly after the NFIP's foundation started that flood insurance could approve growth on the floodplains based on the moral hazard that the NFIP could produce with its grandfathered rates and not reassessing monetary risk (Montgomery et al. 2015). This idea of floodplains and insurance rates not being adequately updated comes twofold with the idea of time scale and vulnerability.

The last component to this thesis comes from the "Conclusions, future challenges and gaps in research" section from Tapsell et al. (2010). The social vulnerability field, as it concerns its self with natural hazards, should promote the idea that researchers need to stop just taking a snap shot of the present. Researchers in risk & vulnerability, as it pertains to natural hazards, must allow history to tell a tale and shed light onto the future to help us understand why vulnerabilities differ so much from one type of hazard to the next. Accordingly, this thesis will adopt a spatial and temporal approach for Polk County, Iowa. One needs to see if history is repeating its self, if information gathered indicates that indices have substantial biases over time to the same or similar groups of people. This type of study is not nearly as common in the vulnerability field as one might think, however, after reading and reviewing articles written on various spatial and temporal studies, it can be concluded that a sufficient time period to conduct a temporal study falls between 20-50 years' worth of data for a long term study (Beck & Katz, 1995). Almost half of the papers reviewed used 20 years, however, more recently published papers were commonly using 30, 40 or 50 years if the data was available. This seems to be in line with the kind of data that would be needed to conduct a social vulnerability study, as previously mentioned U.S. Census and the American Community Survey data, which are available every 1,5, and 10 years. Spans of time and timescales are vital cross-cutting ideas that warrant more consideration when dealing with the recognition and supervision of natural disasters. The primary issue when dealing with timescales is the point that distinctive hazards and their repetition intervals may essentially alter in terms of their time aspect. The classification and calculation of risk, exposure, and vulnerability needs to deal with changing time scales and in some cases, might need to reflect different spans of time. A crucial trial for improving knowledge of vulnerability as factors of risk necessitates better-quality data and methods to recognize different progress paths in demographic, socioeconomic, and political trends that can sufficiently demonstrate possible increases or decreases in vulnerability with time (Cardona et al. 2012).

1.1.4- Environmental Justice

Another complementary way to study social & economic vulnerability variables is to study environmental justice and see if these factors can help to eliminate some categories during a vulnerability study. Environmental Justice is the unbiased conduct and significant participation of all people irrespective of race, color, national origin, or income with respect to the growth, implementation, and execution of environmental rules and guidelines (Mohai, Pellow, & Roberts, 2009). Environmental justice research is concerned with distributional and procedural equity, even though originally, the emphasis of environmental justice was on race/ethnicity and economic class, and the indicators of social vulnerability, but it has since broadened its scope to include many other groups like women, elderly, disabled, transportation disadvantaged, and educational attainment inequality (Cutter et al. 2003; Mohai et al. 2009). Environmental justice is now being used as a screening method which is flexible and transparent in quantifying cumulative impacts and social vulnerability in metro areas using more than just income and race demographics. One can organize indicator metrics into three categories (1) hazard proximity and land use; (2) air pollution exposure and estimated health risk; and (3) social and health vulnerability. While the core of the environmental justice approach is focused on patterns of social-spatial distribution, it is also limited.

The environmental justice literature provides an inclusive set of social vulnerability indicators, since environmental justice researchers typically investigate disproportionate exposure to environmental hazards. Factors commonly used in environmental justice assessments of social vulnerability include racial and ethnic minorities, socioeconomic class, poverty thresholds, gender, single gendered (female) headed households, elderly, very young, disabled, infirm, immigration status, educational attainment level, transportation disadvantaged, and renters (Cutter 1996; Cutter et al. 2000; Cutter et al. 2003; Chakraborty et al. 2014). Having a hazard and the place where it will occur does not aid in defining and measuring vulnerability. Environmental justice can help to find inclusive sets of vulnerability indicators. Different interactions between flooding and socio-economic or deprivation status build up a picture that suggests that deprived or poorer households are likely to experience the impacts of flooding more severely than others. According to Walker and Burningham (2011), deprived people are at a reduced preparedness level, are less capable to retrieve economic resources to assist in revitalization and more prone to an assortment of health effects than those that are well off… but not all deprived communities are identical; signifying that some persons inside deprived neighborhoods might be additionally susceptible than others, and that larger susceptibility might originate separate of the influences of destitution or societal rank.

Privilege and power can be very successful at redirecting unwanted land uses or toxins as well as enticing environmental facilities such as clean air or parks and recreation spaces. A refocusing on social advantage and power can attract consideration to justice trepidations about equality of procedures. Early environmental justice work scrutinized and called in to focus the need for identifying causal mechanisms of injustice, not the standard race or ethnicity (Boone et al. 2009 ;Boone, 2010). Defining and finding indicators that are the most important to the study area will save valuable time and efforts in the future of vulnerability research and will help to give a quicker, more holistic vulnerability picture. One of the key stresses and impacts of environmental justice research has been to inspect and calculate patterns in the geography of risk or potential harm (Walker, 2009). Walker and Burningham (2011) argued that up until environmental justice activists and academics started to expose the environmental risks met by distinctive social groups there was slight methodical data about patterns of inequality in an environmental context. The risk of flooding is concentrated mainly on specific areas in the vicinity to rivers and other water bodies. It is thus subsequently relevant to ask who is living inside such 'at risk' spaces? (Walker & Burningham, 2011). Using a combined theoretical framework from both environmental justice and a social vulnerability index from hazard modeling it should be possible to incorporate the two to obtain a clearer image of the who, what, when, where and why's of vulnerability to flooding in Polk County, Iowa. Concepts from environmental justice will continue to provide a wide range of indicators and methods that can be used to further social vulnerability research for analysis and mapping.

1.2- Research Questions

The goal of this study is to answer the following research questions:

RQ1 – What are the current spatial vulnerability patterns based on demographic indicators in Polk County Iowa?

RQ2 – What is the relationship between social vulnerability and flood risk/exposure areas in Polk County Iowa?

RQ2.1 – How do key individual vulnerability variables compare for block groups that intersect with flood risk zones versus block groups that do not intersect with flood risk zones?

RQ3 – Using demographic data from 1990, how do these key individual vulnerability variables compare for block groups that intersect with the flood risk zones from 1990 versus block groups that do not intersect with the historical flood risk zones?

CHAPTER TWO: METHODOLOGY

In this next section, the study area will be described as well as the geo-hydrological cycle (rooted in the region's geological history) for Iowa's floodplain and then the section will move to quickly describe the data sets, exceptions, and challenges of the study before turning to the analysis portion where the section will move on to describe Polk County's hydrologic cycle as it relates to socioeconomic and sociodemographic factors. Then, the section will contain in detail how one creates a social vulnerability index in order to understand the spatial distribution of sociodemographic factors over the Polk County landscape. Then the study compares statistically, and adds a visual aid to the Polk County, IA SoVI and flood exposure/FEMA flood risk areas to determine if there is a local correlation between social vulnerability and the physical location of the economic flood variable. Lastly, the methodology for investigating the relationship between individual vulnerability variables and flood hazard areas using an environmental justice approach will be presented to see if variables have or had a correlation between flood risk and less-flood risk areas and the social vulnerability of the individual group.

2.1- Study Area

Polk County, Iowa, is located in the central region of the state and includes roughly 618 square miles in total area, of which 23 square miles is water (Flood Risk Report- Polk County, IA, 2016). Iowa is well known for its agriculture, because around 60% of Iowa's land is used for agriculture. Iowa, however, is home to more than 3 million people, 451,677 of whom live in Polk County (U.S. Census Bureau, 2013; USDA, 2014). *Figure 3* depicts the study region in red. Polk County, Iowa is located in the central region of the state and includes roughly 618 square miles in total area, of which 23 square miles is water (Flood Risk Report- Polk County, IA, 2016)

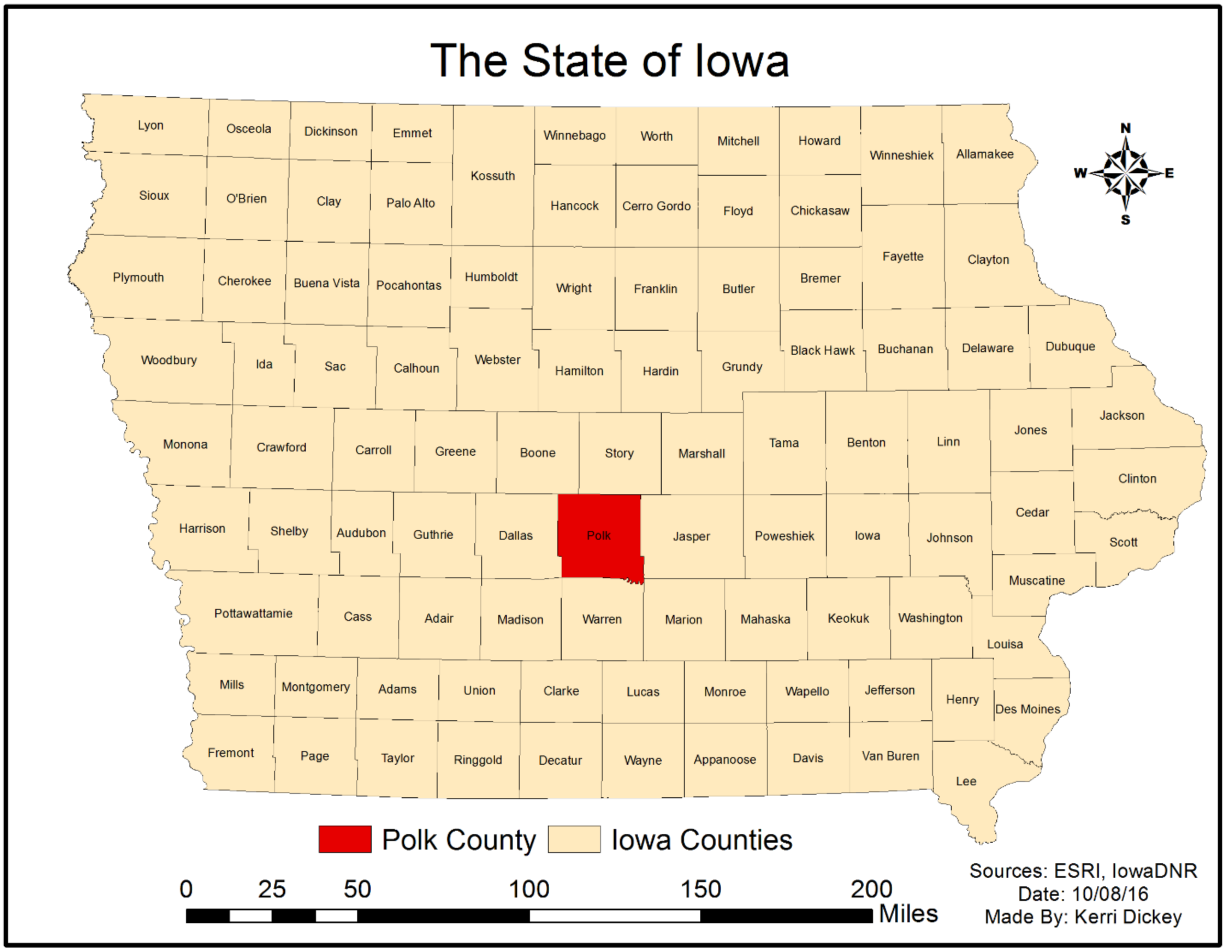

Figure 3: Study area, Polk County, Iowa

The study region encompasses the Digital Flood Insurance Rate Map (DFIRM) area which is produced by the Iowa Flood Center and Iowa DNR. DFIRMS map floodplains of various return periods according to FEMA guidelines. The Iowa Flood Center along with the Iowa DNR and FEMA produced the inundation maps of Polk County used in this study. The 100-year return period is the inundation level of interest for this study as not all historic mapping endeavors were at a high enough clarity to obtain other intervals of flooding. (*Figure 4*)

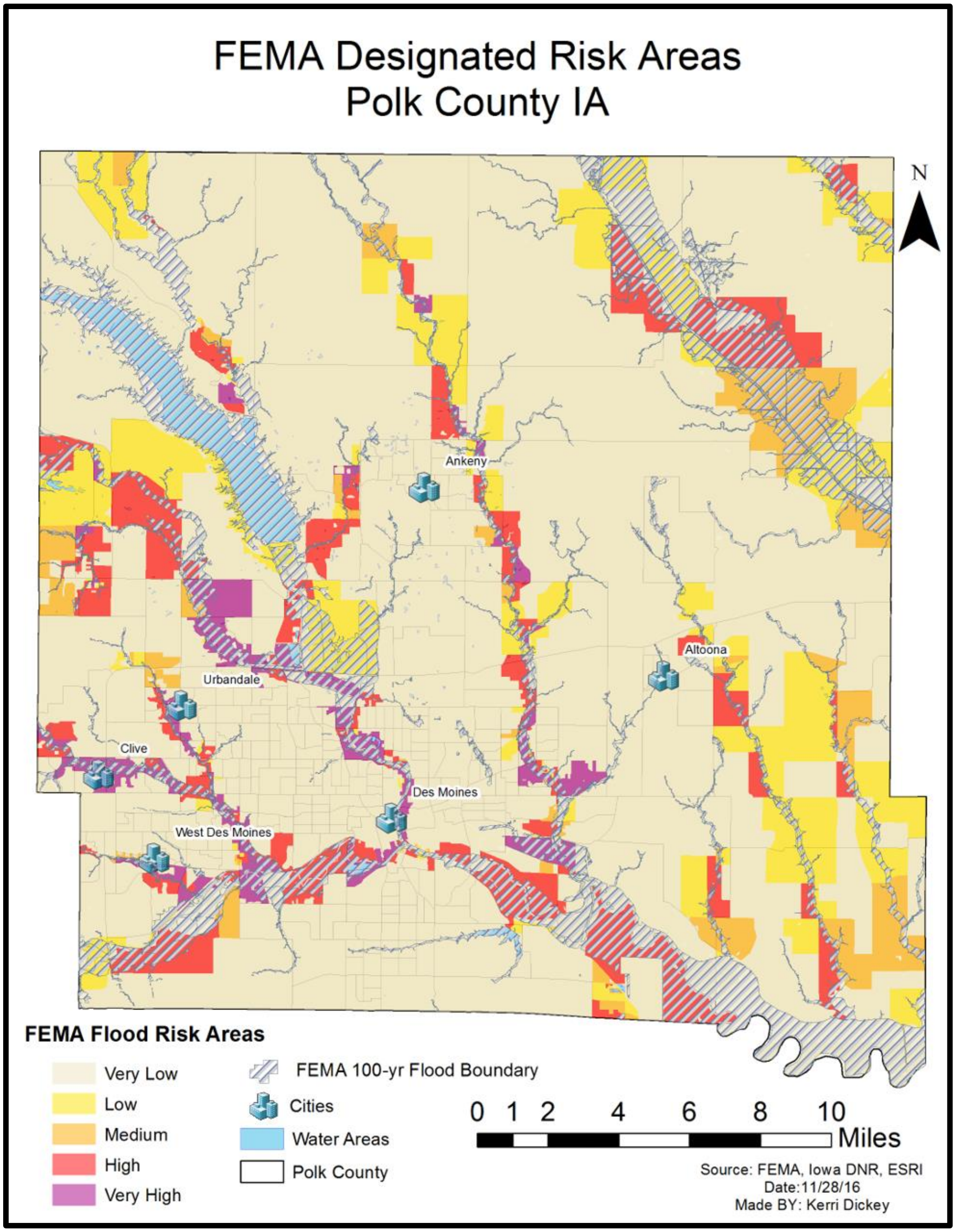

Figure 4: Polk County, Iowa 2014 100-year flood boundary & FEMA Hazard boundary. Source: Iowa DNR & FEMA

Polk County has an interesting and well documented geologic history, but for the purposes of this study it is only necessary to summarize the pertinent findings to provide a brief understanding of geologic processes that have shaped the way water drains from the county. The study area contains a large water body, the Saylorville Lake, which is located 11 miles northwest from Des Moines on the

Des Moines River. Saylorville Lake was dammed by the US Army Corps of Engineers (US ACE) in 1977 (Rock Island District, Media, Fact Sheets, 2016). The dam itself is earth-filled, 6,750 feet long, 105 feet high and 44 feet wide (Rock Island District, Media, Fact Sheets, 2016). It has 5,520 surface acres and stores 73,600 acre-feet of water for a distance of 24 miles upstream from the dam (Rock Island District, Media, Fact Sheets, 2016). At full flood-pool, Saylorville Lake has 16,100 surface acres and stores 641,000 acre-feet of water for a distance of 54 miles upstream from the dam (Rock Island District, Media, Fact Sheets, 2016). Since completion, the pool has reached the spillway six times: 1984, 1991, in April and July 1993, June 2008, and in July 2010 (Rock Island District, Media, Fact Sheets, 2016). Since 1977, it is assessed that by diminishing the water flow, the Saylorville reservoir has averted roughly $181,932,300 of flood damage to the surrounding area (Rock Island District, Media, Fact Sheets, 2016). This has a great deal to do with the fact that 3 of the 4 watersheds in Polk County fall near the Saylorville Lake or drain to rivers or streams leading to the lake. *Figure 5* shows the 4 watersheds that pass-through Polk County as depicted from the U.S. Environmental Protection Agency (EPA) website.

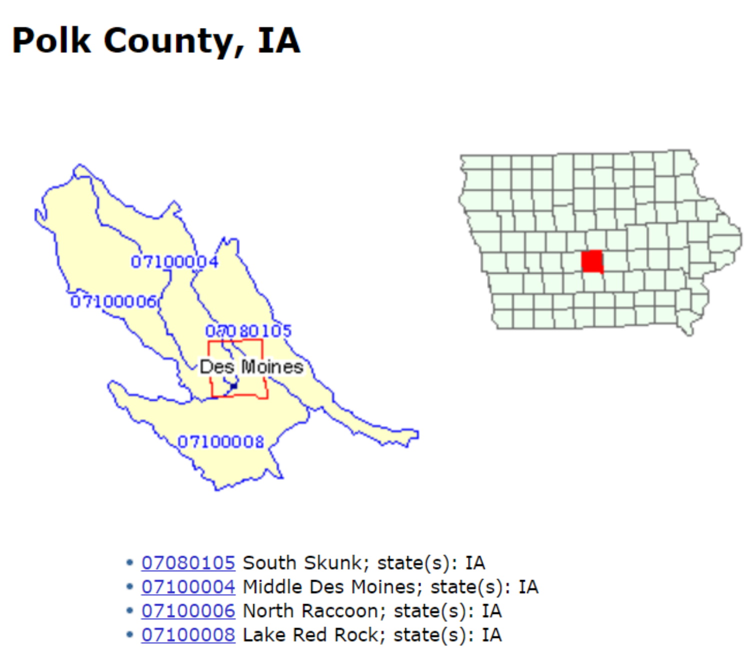

Figure 5: Polk County Watersheds (Polk County, Surf Your Watershed, US EPA, 2016)

More detailed geologic information is readily available from the Iowa Geological Survey Bureau and Iowa Department of Natural Resources. Polk County's geology in the context of flooding consists of surficial and bedrock features which combine over time and now effect the way water flows on and below the surface. The bedrock is predominantly marine sedimentary rocks deposited during the Carboniferous Period (roughly 354 to 290 million years ago) in the Paleozoic Era. Drainage patterns tend to be affected by the location and topography of the bedrock. Moreover, the nature of bedrock materials in relation to surficial deposits tends to control water as it flows above and below the ground surface (Polk County Comprehensive Plan, 2010).

The surficial geology and landscapes of Polk County are primarily the result of recent glacial activity. *Figure 6* gives a general overview of the landforms that will be mentioned in this section. In Polk County, surficial evidence of glacial activity is primarily found in the form of Wisconsinan-stage deposits (60,000 to 10,000 years ago). The areas north of the Raccoon River are associated with the Des Moines Lobe region associated with late Wisconsinan glaciation. The areas in southern Polk County belong to the Southern Iowa Drift Plain landform region. As the glaciers slid over the land, they accumulated soil and rock. The depositions of this accumulation are glacial drift and are observed throughout the surficial geology of Polk County (Polk County Comprehensive Plan, 2010). The Des Moines Lobe of the glacier filled in the river valleys and, as the glacier melted it created a new drainage channel on the southern edge which is the present-day course of the Raccoon River. South of the Raccoon River in Polk County, surficial materials are comprised of windblown silty clays known as loess (Polk County Comprehensive Plan, 2010). An interglacial period followed the Wisconsinan glacial stage during which meltwater drained into valleys presently occupied by the Des Moines, Raccoon and Skunk Rivers (Polk County Comprehensive Plan, 2010). Drainage patterns within Polk County were totally reshaped by the Wisconsinan glacial stage. The Des Moines River south of the Des Moines city center follows an ancient river valley, while to the north of Des Moines it flows in a more recent post-glacial channel. The presence of the buried ancient river valley has consistently caused drainage problems on Des Moines's east side (Polk County Comprehensive Plan, 2010).

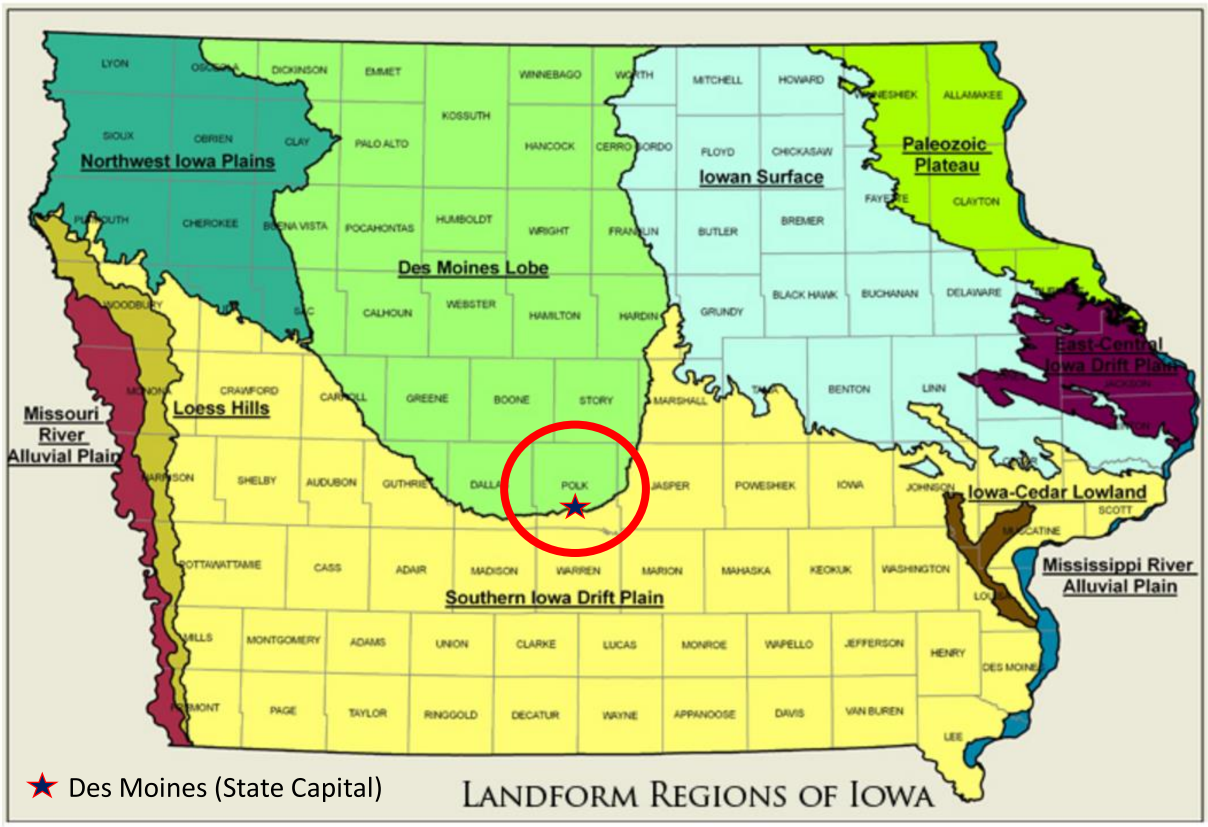

Figure 6: Landform Regions of Iowa. Source: Iowa DNR/Conservation

The topography of the Des Moines Lobe landform region is a recently glaciated and poorly drained landscape with many flat spaces punctuated by groups of bumpy ridges. Abundant ponds and marshes are located in the areas between ridges with no drainage channels. *Figure 7* shows the distribution of waterbodies and waterways in Polk County.

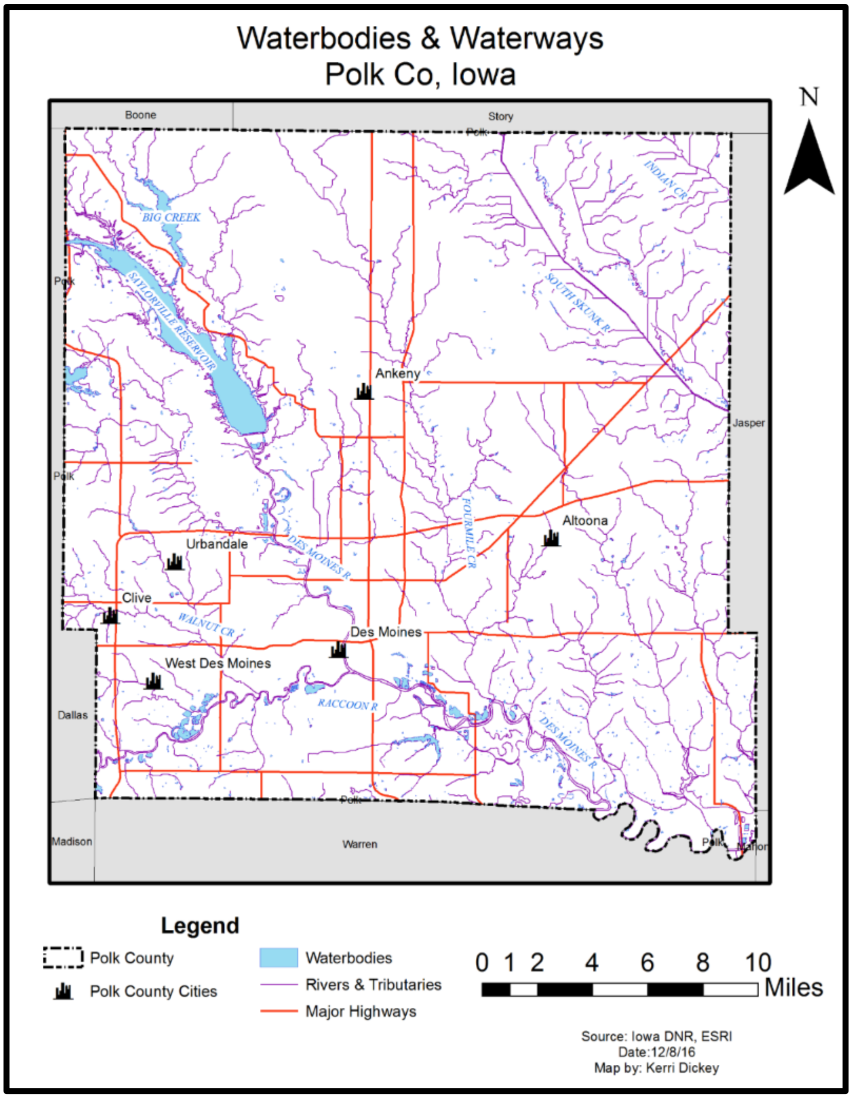

Figure 7: Waterbodies & Waterways in Polk Co. IA

2.2 Datasets

Geospatial data were collected from multiple sources to conduct this research. The Iowa DNR, Iowa Flood Center, US ACE, FEMA, and Natural Resources Geographic Information Systems (NRGIS) (Minnesota Population Center, 2011) repository provided the watershed boundaries, water area, rivers, and other physical data for Polk County. The Iowa DNR provided the current FEMA 100-year flood boundary and Flood Risk Report for Polk County as metadata. The United States Census Bureau contributed county and state boundaries data, and census block groups from the 2010

Census, and socioeconomic data from the 2010-2014 American Community Survey (ACS). All geo-referenced data is projected in Universal Transverse Mercator (UTM), Zone 15N, North American Datum 1983 (NAD83) (*Figure 8*). 2010 census data and 2010-2014 ACS data for Polk County was obtained using the online resource American FactFinder. All 1990 demographic data were obtained using the National Historical Geographic Information System (NHGIS) (Minnesota Population Center, 2011); summary file 1 data (100% counts) was utilized where possible, and otherwise summary file 3 (sample data) was used in the analysis.

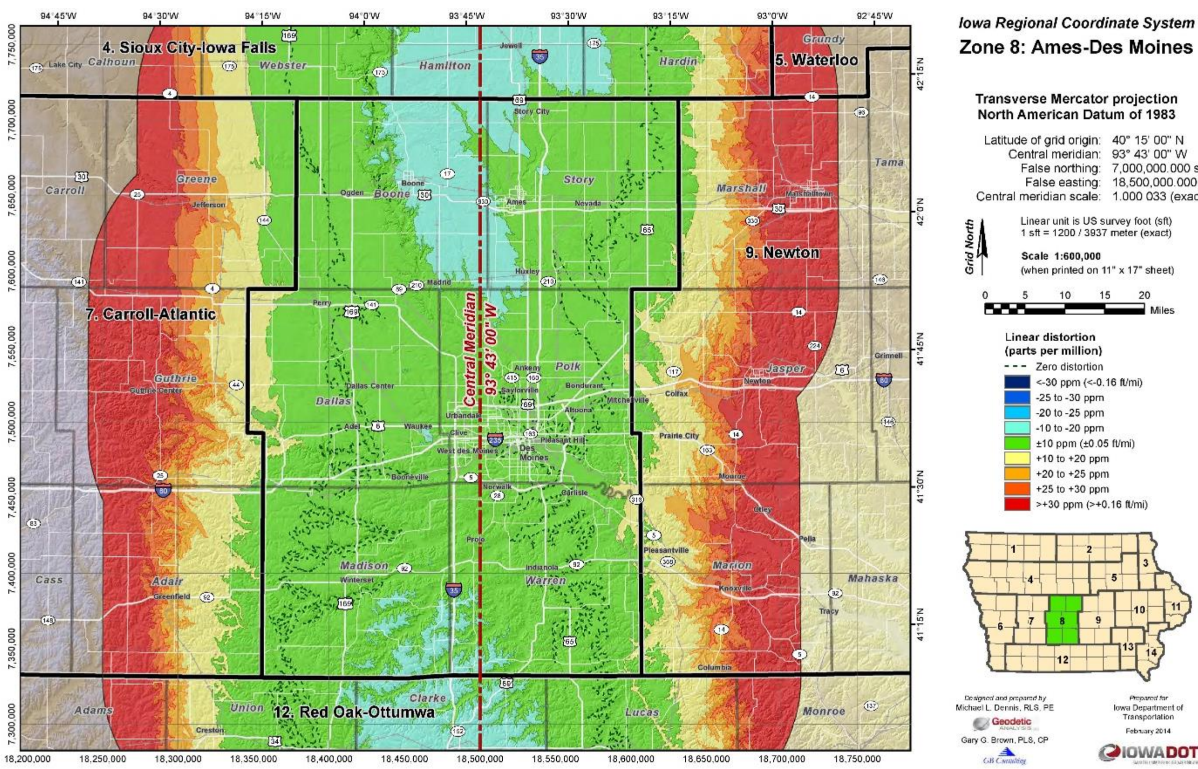

Figure 8: Polk County area of projection distortion. (Iowa DOT)

2.2.1- Data Exclusions

There were very few problems in obtaining the data required for the social vulnerability analysis and the subsequent comparisons based on proximity to the floodplain. The only historical variable that was not found pertained to health insurance, and it was thus excluded from the historical comparison because there was no way to obtain that information from the past. No information was missing from the present-day evaluation, but it should be noted that one specific block group in the southern part of the county encompasses the entirety of the Des Moines International Airport and is removed from calculations because the block group does not contain any permanent residents. Data not available at the block group level were not included in this analysis since block group level data were sufficiently available for use.

2.3- Analyses Methodologies

This study employs geospatial and statistical methods to analyze the relationship between flood exposure and social vulnerability for the years 2014 and 1990. Maps of the flood exposure areas for Polk County circa 1990 were obtained from FEMA's online archive (https://msc.fema.gov/portal/advanceSearch#searchresultsanchor). Using ArcGIS 10.5 software, flood/inundation maps for the 100-year floodplain with a 5% (0.05) significance level were georeferenced and flood areas were digitized and then merged into a single new shapefile. Using ArcGIS, the 1990 and 2014 flood areas were reviewed for similarities and differences. Differences in flood areas can be correlated with actual changes in the flood area and not changes in the flood mapping standards after corroborating information found in the *United States National Map Accuracy Standards from 1947* with information from *FEMA's Flood Hazard Mapping Program Guidelines and Specifications for Flood Hazard Mapping: Guidance for Aerial Mapping and Surveying*. FEMA currently designates multiple risk levels within the floodplain areas, which were derived from historical economic losses, and this information was received from Iowa DNR in a shapefile in order to use FEMA Risk Levels as one of the analysis inputs. The National Historical Geographic Information System (NHGIS) was utilized to gather historical demographic data corresponding to the SoVI individual variables for the year 1990.

2.3.1- Methodology for Creation of the Social Vulnerability Index (SoVI)

The creation of a social vulnerability index starts with creating variables from raw census data. *Table 2* shows the first step to answering research question one by using an assemblage of variables, chosen using previously confirmed knowledge in relevant literature, and compiling them into a list which will later be used to create the components for the Polk County, IA SoVI. *Table 2* shows the variable, short name used for reference, the exact table used from the census data, and any calculations or additional information needed to re-create the variable. One will notice for racial factors in the study, the choice was made to include a larger racial grouping within the census data than just one race with no combinations, which is offered. This reasoning is rooted in philosophy, environmental justice and qualitative research methods. There is a desire for "pure" or uncontaminated samples to define races or native people by "settlers" or Caucasians. It is the notion of trying to know and define the "other", however, the desire by native or ethnic people is to be self-defined and self-named, which is the desire to be free, to escape exterior definition, to be complicated, to develop, change, and to be deemed entirely human (Smith, 2005). There are also the extensive problems of disproportionately high levels of poverty and underdevelopment, high disease rates and premature death from preventable illnesses, unequal levels of incarceration, and other indicators of social marginalization suffered by most ethnic populations (Smith, 2005). It is this deep intrinsic understanding and self-description of racial identity, which the author of this thesis does not brave and cannot know as a Caucasian, but wanted to be assured was measured in this study. One will also note that in the variable PPUNIT, a choice was made to measure the total population in occupied housing units over occupied housing units, to remove any measure of institutionalized persons in the variable, as this variable is to focus on residential areas only.

Table 2: Polk County, IA SoVI Input Variables

Variable	Variable Short	Table Used	Specific Row Data used	Data Set	Denominator used for %
Percent Asian	QASIAN	B02011 ASIAN ALONE OR IN COMBINATION WITH ONE OR MORE OTHER RACES	NA	2010-2014 ACS	B02001 RACE Universe: Total population
Percent Black	QBLACK	B02009 BLACK OR AFRICAN AMERICAN ALONE OR IN COMBINATION WITH ONE OR MORE OTHER RACES	NA	2010-2014 ACS	B02001 RACE Universe: Total population
Percent Hispanic	QHISP	B03003 HISPANIC OR LATINO ORIGIN	NA	2010-2014 ACS	B02001 RACE Universe: Total population
Percent Native American	QNTAM	B02010 AMERICAN INDIAN AND ALASKA NATIVE ALONE OR IN COMBINATION WITH ONE OR MORE OTHER RACES	NA	2010-2014 ACS	B02001 RACE Universe: Total population
Percent of Population under 5 years or 65 and Over	QPOPAG EDEP	B01001 SEX BY AGE	Male & Female: - Under 5 years + Male & Female: - 65 years and over	2010-2014 ACS	Universe: Total population
Percent Children Living in Married Couple Families	QFAM	B11005 HOUSEHOLDS BY PRESENCE OF PEOPLE UNDER 18 YEARS BY HOUSEHOLD TYPE	Estimate; Households with one or more people under 18 years: - Family households: - Married-couple family	2010-2014 ACS	Universe: Households
Median Age	MEDAG E	B01002 MEDIAN AGE BY SEX	Median age - Total	2010-2014 ACS	NA
Percent of Households Receiving Social Security	QSSDEP	B19055 SOCIAL SECURITY INCOME IN THE PAST 12 MONTHS FOR HOUSEHOLDS	Total: - With Social Security income	2010-2014 ACS	Universe: Households
Percent Poverty	QPOVRT Y	B17021 POVERTY STATUS OF INDIVIDUALS IN THE PAST 12 MONTHS BY LIVING ARRANGEMENT	Income in the past 12 months below poverty level:	2010-2014 ACS	Universe: Population for whom poverty status is determined

Table 2 (cont.)

Variable	Variable Short	Table Used	Specific Row Data used	Data Set	Denominator used for %
Percent of Households earning greater than $150,000 Annually	QRICH	B19001 HOUSEHOLD INCOME IN THE PAST 12 MONTHS (IN 2014 INFLATION-ADJUSTED DOLLARS)	Total: - $150,000 or more	2010-2014 ACS	Universe: Households
Per Capita Income	PERCAP	B19301 PER CAPITA INCOME IN THE PAST 12 MONTHS (IN 2014 INFLATION-ADJUSTED DOLLARS)	NA	2010-2014 ACS	NA
Percent Speaking English as a 2nd language with Limited English Proficiency	QESL	B16002 HOUSEHOLD LANGUAGE BY HOUSEHOLD LIMITED ENGLISH SPEAKING STATUS	Rows:HD01_VD04 + HD01_VD07 + HD01_VD10 + HD01_VD13 = ESL/Households *100	2010-2014 ACS	Universe: Households
Percent Female	QFEMALE	B01001 SEX BY AGE	HD01_VD26 : Estimate Female	2010-2014 ACS	Universe: Total population
Percent Single Gendered (Female) Headed Households	QFHH	B09019 HOUSEHOLD TYPE (INCLUDING LIVING ALONE) BY RELATIONSHIP	HD01_VD06+ HD01_VD29	2010-2014 ACS	Universe: Total population
Percent Population living in nursing and skilled nursing facilities	QNURSRES	P42 GROUP QUARTERS POPULATION BY GROUP QUARTERS TYPE	Institutionalized population (101-106, 201-203, 301, 401-405): - Nursing facilities/Skilled-nursing facilities (301)	2010 Census	Universe: Total Population
Percent of Population without Health Insurance	QNOHLTH	B27010 TYPES OF HEALTH INSURANCE COVERAGE BY AGE	Under 18 years + 18 to 64 years + 65 years and over: - No health insurance coverage	2010-2014 ACS	Universe: Civilian noninstitutionalized population
Percent with less than 12th grade EDU	QEDU12LES	B15003 EDUCATIONAL ATTAINMENT FOR THE POPULATION 25 YEARS AND OVER	No Schooling + all grades to 12th, no diploma.	2010-2014 ACS	Universe: Population 25 years and over
Percent Civilian Unemployment	QCVUNEMPL	B23025 EMPLOYMENT STATUS FOR THE POPULATION 16 YEARS AND OVER	In labor force: - Civilian labor force: - Unemployed	2010-2014 ACS	Population 16 years and over in labor force: Civilian
People per Unit	PPUNIT	B25008: TOTAL POPULATION IN OCCUPIED HOUSING UNITS BY TENURE	B25008: Total population in occupied housing units/ B25009 Universe	2010-2014 ACS	B25009 Universe: Occupied housing units

Table 2 (cont.)

Variable	**Variable Short**	**Table Used**	**Specific Row Data used**	**Data Set**	**Denominator used for %**
Percent Renters	QRENTER	B25008 TOTAL POPULATION IN OCCUPIED HOUSING UNITS BY TENURE	Estimate; Total: - Renter occupied	2010-2014 ACS	Universe: Total population in occupied housing units
Median House Value	MEDHVAL	B25077 MEDIAN VALUE (DOLLARS)	NA	2010-2014 ACS	Universe: Owner-occupied housing units
Median Gross Rent	MEDRENT	B25064 MEDIAN GROSS RENT (DOLLARS)	NA	2010-2014 ACS	Universe: Renter-occupied housing units paying cash rent
Percent Mobile Homes	QMOBILE	B25032 TENURE BY UNITS IN STRUCTURE	Owner-occupied housing units: - Mobile home, Owner-occupied housing units: - Boat, RV, van, etc. Renter-occupied housing units: - Mobile home Renter-occupied housing units: - Boat, RV, van, etc.	2010-2014 ACS	B25033 Universe: Total population in occupied housing units
Percent employed in Extractive industry	QEXTRACT	C24030 SEX BY INDUSTRY FOR THE CIVILIAN EMPLOYED POPULATION 16 YEARS AND OVER	Male & Female: Agriculture, forestry, fishing, hunting, and mining	2010-2014 ACS	Universe: Civilian employed population 16 years and over
Percent Employment in Blue Collar Industries	QBLUECOL	C24030 SEX BY INDUSTRY FOR THE CIVILIAN EMPLOYED POPULATION 16 YEARS AND OVER	Male & Female: Construction, Manufacturing, Agriculture, forestry, mining, Transportation and warehousing, and utilities	2010-2014 ACS	Universe: Civilian employed population 16 years and over
Percent employed in Service industry	QSERVC	C24030 SEX BY INDUSTRY FOR THE CIVILIAN EMPLOYED POPULATION 16 YEARS AND OVER	Estimate; Male & Female: - Arts, entertainment, and recreation, and accommodation and food services: - Accommodation and food services.	2010-2014 ACS	Universe: Civilian employed population 16 years and over

Table 2 (cont.)

Variable	Variable Short	Table Used	Specific Row Data used	Data Set	Denominator used for %
Percent female participation in Labor force	QFELABOR	B23022 SEX BY WORK STATUS IN THE PAST 12 MONTHS BY USUAL HOURS WORKED PER WEEK IN THE PAST 12 MONTHS BY WEEKS WORKED IN THE PAST 12 MONTHS FOR THE POPULATION 16 TO 64 YEARS	Estimate; Female:	2010-2014 ACS	C24030 Universe: Civilian employed population 16 years and over
Percent of housing units with no car	QHHNOCAR	B25044 TENURE BY VEHICLES AVAILABLE	Estimate; Owner occupied: - No vehicle available. Estimate; Renter occupied: - No vehicle available	2010-2014 ACS	Universe: Occupied housing units
Percent unoccupied housing units	QNOPPLHH	B25002 OCCUPANCY STATUS	Estimate; Total: - Vacant	2010-2014 ACS	Universe: Housing units
Average Travel Time to Work	AVGTRAVL	B08303 TRAVEL TIME TO WORK	Calculated the average time for each column, took the average time and multiplied it by the number of times it was recorded in that BLG, added all times together and divided by total number of records for that BLG.	2010-2014 ACS	NA

Utilizing IBM SPSS Statistics v23 (SPSS), the variables were added to the program to perform a standardization of each variable so the variables might be compared to one another on the same scale instead of their own individual scales. Thus, z-scores for each variable were calculated, after which a correlation matrix was compiled using the Pearson Correlation method. This method evaluates if there is statistical evidence for a linear relationship among the SoVI input variables for the study area (Rogerson, 2014). The first results gained from this thesis are from the standardization of variables and the correlation matrix at the start of the PCA. *Table 3* shows the Min, Max, Mean, and Standard Deviation of the variables so that one could be sure data was entered correctly and something was not skewing the data before one goes farther in the calculations. Thus *Table 3* only assists in assuring that data was not misread when brought into the SPSS program. The correlation matrix was examined to see if any variables were highly correlated above a threshold level of 0.80 (Appendix II). QRICH and PERCAP were correlated at 0.83, but since the author did not have a median income variable, one did not have sufficient information to remove either variable given that one's Per-Capita income does not necessarily place one in the $150,000+ income category used to represent the wealthiest percentage of households.

Table 3: Min, Max, Mean, Standard Deviation Statistics

	Minimum	Maximum	Mean	Std. Deviation
QASIAN	.00	36.32	4.27	5.81
QBLACK	.00	73.98	8.58	11.41
QHISP	.00	53.67	8.89	11.46
QNTAM	.00	14.23	0.89	2.01
QPOPAGEDEP	5.22	44.23	19.40	6.89
QFAM	.00	72.58	21.99	11.72
MEDAGE	16.80	59.90	36.47	7.43
QSSDEP	3.25	65.64	24.58	10.03
QPOVRTY	.00	61.57	13.99	13.11
QRICH	.00	65.56	7.95	10.43
PERCAP	9153.00	76023.00	29164.30	12298.86
QESL	.00	33.90	3.48	5.62
QFEMALE	33.91	74.51	50.96	5.81
QFHH	2.33	52.72	19.70	6.11
QNURSRES	.00	11.52	0.47	1.68
QNOHLTH	.00	37.57	8.71	7.10
QEDU12LES	.00	46.35	9.63	9.55
QCVUNEMPL	.00	42.67	6.81	6.478
PPUNIT	1.11	4.47	2.51	0.48
QRENTER	.00	100.00	29.73	22.74
MEDHVAL	.00	450000.00	142408.90	61187.90
MEDRENT	0	2000	714.59	364.31
QMOBILE	.00	41.05	.90	3.87
QEXTRACT	.00	15.65	.89	2.09

Table 3 (cont.)

	Minimum	Maximum	Mean	Std. Deviation
QBLUECOL	.00	49.34	20.14	9.47
QSERVC	.00	38.91	7.21	6.57
QFELABOR	30.00	158.13	65.05	15.35
QHHNOCAR	.00	47.82	6.18	7.85
QNOPPLHH	.00	38.17	6.90	6.80
AVGTRAVL	13.17	34.91	20.15	3.36

With the z-scores calculated, the next step was to perform the Principal Component Analysis (PCA). The extraction of components was based on eigenvalues greater than one, corresponding to its eigenvector, and allowing for a maximum of 100 iterations for convergence for all aspects of the analysis. The larger the eigenvalue the more the principal component explains the variance in the data, and a component with a value lower than one did not explain a useful portion of the variance in the data and was therefore not retained for analysis. The rotational method used was the orthogonal solution, Varimax, allowing one to obtain factors that are as dissimilar from each other as possible. Gorsuch (1983) recommends rotating with Varimax (orthogonal) or Promax (oblique) and Kim and Mueller (1978, p. 50) assert that, "beginners should choose one of the commonly available methods of rotation, such as Varimax if orthogonal rotation is sought." Tabachnick & Fiddell (2007) write in detail about determining the adequacy of a rotation method, but Varimax is the preferred method because of its simplicity. The Rotated Components Matrix was utilized to understand which input variables were most relevant for each component by noting the variables with moderate to strong factor loadings. A linear regression method was utilized to estimate and output the component factor scores for each block group.

After completion of the PCA and extraction of the components, it was necessary to name the components and then assign a negative or positive sign (or cardinality) to each per the components contribution to greater social vulnerability (positive) or reduced social vulnerability (negative) and was informed by the logic previously set forth in the seminal SoVI manuscript from Cutter et al. (2003). Following the determination of each component's cardinality, the Social Vulnerability Index (SoVI) for Polk County, Iowa was created by summing the factor scores for each block group across all retained components. The resulting index is a unit-less spatial quantity and its rank is derived from its comparative nature throughout the geographic locality (Cutter et al. 2000). Henceforth, the index will be referred to as the Polk Co, IA SoVI. Each component and the overall Polk County, IA SoVI will be presented in greater detail in Chapter 3.

2.3.2- Methodology for Exploring the Relationship Between Polk County, IA SoVI and Flood Hazard Areas

Comparing patterns from Polk Co, IA SoVI and overlaying the flood exposure area of the floodplain and FEMA designated levels of risk, one can statistically and visually investigate whether a relationship between Polk Co, IA SoVI and flood exposure exists, thus answering research question two. Using a social vulnerability approach, one can use a *t*-test to compare the Polk Co, IA SoVI scores of areas exposed to higher levels of flood risk and the scores of those areas exposed to less risk. However, the *t*-test assumes that data are normally distributed. The Polk County, IA SoVI Scores were not normally distributed in the Kolmogorov-Smirnov (K-S) test and a histogram, and thus the *t*-test would not be appropriate. Consequently, it was apparent for one to opt to use a nonparametric test for independent samples, the Mann-Whitney U test was thus used because it does not presuppose any specific data distribution or properties concerning the equal division of variables in an analysis and is mathematically indistinguishable to performing an independent sample *t*-test and is thus deemed the substitute to the *t*-test (Rogerson, 2014).

The Polk Co, IA SoVI and the flood risk levels were then mapped using a bivariate choropleth mapping technique to visually see any relationship between SoVI and the FEMA designated flood risk levels. This map complements the information found in the Mann-Whitney U test in a visual and easily digestible fashion, and it does not present any new or contradictory information from the group comparison test. The map is the intersection of FEMA designated Flood Risk Areas (*Figure 9*) with the study area block groups. The results of the Mann-Whitney U test and the accompanying bivariate choropleth map will be presented in Chapter 4.

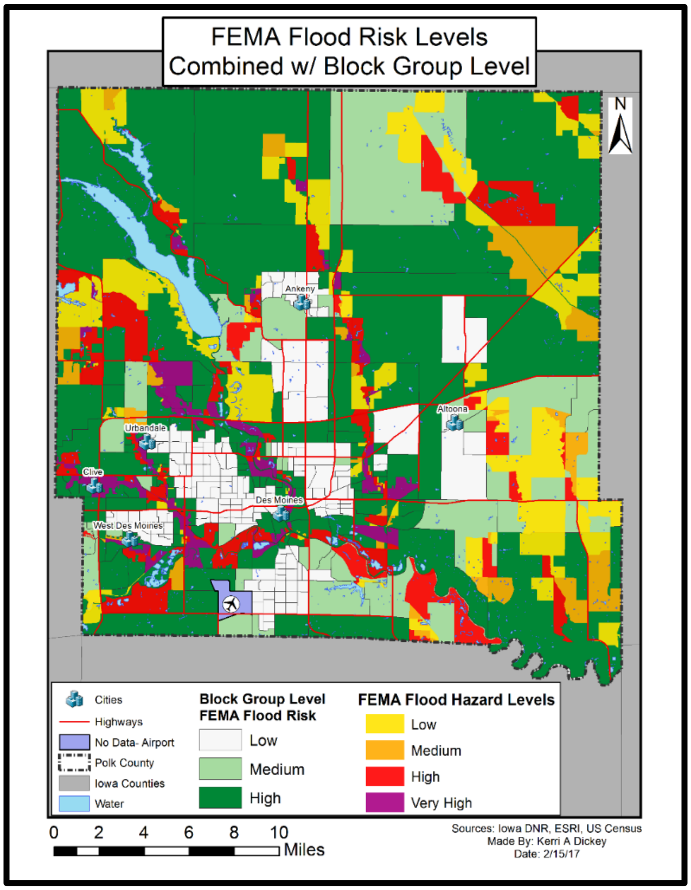

Figure 9: FEMA Flood Risk Levels joined via location on Polk County Block Group Level shapefile.

2.3.3 -Methodology for Inquiry: Link Between Individual Vulnerability Variables and Flood Hazard Areas: Environmental Justice Approach

An environmental justice approach was used to answer research questions 2.1 and 3 and complemented the vulnerability approach by disaggregating the SoVI and analyzing individual variables that represent large portions of the variance explained by the PCA. The Mann-Whitney U test is utilized in the analysis, comparing values of individual variables in block groups that intersect flood risk zones and in block groups that do not overlap with flood risk zones. Since several of the variables were (as with Polk County, IA SoVI) found not to be normally distributed, the Mann-Whitney test was used throughout for consistency in reporting of the results. This analysis was carried out using the original ACS 2010-2014 data to represent the present (research question 2.1) and using 1990 census data (research question 3) for a historical baseline. Variables chosen for in-depth analysis were those that scored high marks in their factor loadings in the PCA, and that have long histories in environmental justice research. The analysis included thirteen indicators of race and ethnic minorities, socioeconomic class, single gendered (female) headed households, age dependence (very young and advanced age), educational attainment level, transportation disadvantaged, and renters. The names of the thirteen vulnerability variables of interest which were run in the Mann-Whitney U tests included: QBLACK, QFAM, QRICH, PERCAP, QESL, QFHH, QNOHLTH, QRENTER, QMOBILE, QEXTRACT, QFELABOR, QHHNOCAR, and AVGTRAVL (*Table 2*). These were then tested against the FLD ZONE variable, which is a simplistic zero for any block groups not intersecting the flood zone and a one for block groups intersecting the flood zone, to see if scores of areas more exposed to flood risk were higher, lower, or the same in comparison to areas less exposed.

After conducting the comparisons with the 2010-2014 data, excluding QNOHLTH, one then needed to repeat the procedure using the historical 1990 census data and the digitized 1990 shapefile representing the historical 100-year flood zone. As before, one created a zero and one column for block groups in and out of the flood zone. This variable was called FldZONE90 and was used as the grouping variable in SPSS. The flood zone did not substantially change since the 1990s, however it was important to the author to use the most accurate zone for the historical period. *Table 4* below shows the calculations for the 1990 variables just as previously calculated for the 2010-2014 variables. Historical variables were calculated as close to the present day variable methods as possible. Readers will note what appears to be a significant change in the QRICH variable, but it is an adjustment for money equivalent to $150,000 in 1990. This was done by adjusting for inflation such that the threshold for QRICH was at $78,000. However, the closest category in the historical data was at $75,000 so that threshold was used instead. The results of the Mann-Whitney tests for both present and historical data will be presented and further interpreted in Chapter 4.

Table 4: Historical 1990 Variables

Variable	Variable Short	Table Used	Specific Row Data used	Data Set	Denominator used for %
Percent Black	QBLACK90	Table 4: Race Universe: Persons Source code: NP6 NHGIS code: EUY	EUY002: Black	1990 Census: STF 1 - 100% Data	Universe: Persons Source code: NP1 NHGIS code: ET1 ET1001: Total
Percent Children Living in Married Couple Families	QFAM90	Table 6: Household Size and Household Type Universe: Households Source code: NP16 NHGIS code: ET8	ET8003: 2 or more persons: Family households: Married-couple family: With related children ET8004: 2 or more persons: Family households: Married-couple family: Children, no related children	Dataset: 1990 Census: STF 1 - 100% Data NHGIS code: 1990_STF1	Universe: Households
Percent of Households earning greater than $75,000 Annually	QRICH90	Table 13: Household Income in 1989 Universe: Households Source code: NP80 NHGIS code: E4T	E4T022: $75,000 to $99,999 E4T023: $100,000 to $124,999 E4T024: $125,000 to $149,999 E4T025: $150,000 or more	1990 Census: STF 3 - Sample-Based Data	Universe: Households
Per Capita Income	PERCAP90	9. Per Capita Income in 1989 Universe: Persons Source code: NP114A NHGIS code: E01	E01001: Per capita income in 1989	Dataset: 1990 Census: STF 3 - Sample-Based Data NHGIS code: 1990_STF3	NA

Table 4 (cont.)

Variable	Variable Short	Table Used	Specific Row Data used	Data Set	Denominator used for %
Percent Speaking English as a 2nd language with Limited English Proficiency	QESL90	1. Age by Language Spoken at Home and Ability to Speak English Source code: NP28 NHGIS code: E26	Speak English "not well" or "not at all" E26004 E26007 E26010 E26014 E26017 E26020 E26024 E26027 E26030	1990 Census: STF 3 - Sample-Based Data	Universe: Households
Percent Female Head Households	QFHH90	Table 6: Household Size and Household Type Universe: Households Source code: NP16 NHGIS code: ET8	ET8002: 1 person: Female householder ET8007: 2 or more persons: Family households: Other family: Female householder, no husband present: With related children ET8008: 2 or more persons: Family households: Other family: Female householder, no husband present: No related children ET8010: 2 or more persons: Nonfamily households: Female householder	1990 Census: STF 1 - 100% Data	Universe: Persons Source code: NP1 NHGIS code: ET1 ET1001: Total
Percent Renters	QRENTER90	Table 2: Tenure Source code: NH3 NHGIS code: ES1	ES1002: Renter occupied	1990 Census: STF 1 - 100% Data	Universe: Occupied housing units
Percent Mobile Homes	QMOBILE90	Table 7: Tenure by Units in Structure Source code: NH43 NHGIS code: ETJ	ETJ009: Owner occupied >> Mobile home or trailer ETJ010: Owner occupied >> Other ETJ019: Renter occupied >> Mobile home or trailer ETJ020: Renter occupied >> Other	1990 Census: STF 1 - 100% Data	Universe: Occupied housing units

Table 4 (cont.)

Variable	Variable Short	Table Used	Specific Row Data used	Data Set	Denominator used for %
Percent Female Work Force	QFELABOR90	9. Sex by Employment Status Universe: Persons 16 years and over Source code: NP70 NHGIS code: E4I	E4I005: Female >> In labor force: In Armed Forces E4I006: Female >> In labor force: Civilian: Employed E4I007: Female >> In labor force: Civilian: Unemployed	1990 Census: STF 3 - Sample-Based Data	Universe: Employed population 16 years and over
Percent Employment in Extractive industry	QEXTRACT90	Table 10: Industry Universe: Employed persons 16 years and over Source code: NP77 NHGIS code: E4P	E4P001: Agriculture, forestry, and fisheries (000-039) E4P002: Mining (040-059)	1990 Census: STF 3 - Sample-Based Data	Universe: Civilian employed population 16 years and over
Percent of housing units with no car	QHHNOCAR90	Table 17: Tenure by Vehicles Available Universe: Occupied housing units Source code: NH37 NHGIS code: EYL	EYL001: Owner occupied >> None EYL007: Renter occupied >> None	1990 Census: STF 3 - Sample-Based Data	Universe: Occupied housing units
Average Travel Time to Work	AVGTRLV90	7. Travel Time to Work Universe: Workers 16 years and over Source code: NP50 NHGIS code: E3W	Calculated the average time for each column, took the average time and multiplied it by the number of times it was recorded in that BLG, added all times together and divided by total number of records for that BLG	1990 Census: STF 3 - Sample-Based Data	

Historical environmental justice literature suggests that marginalized populations tend to be disproportionately exposed to hazardous areas of all kinds, including flooding, but it does not say that these populations tend to be spatially exposed, though we assume their exposure will be higher. Thus, one might expect to see race/ethnic minorities and other disenfranchised communities such as lower income households, renters, mobile homes, single parents, and older adult persons heavily concentrated in flood areas. Thus, this thesis will examine how well I can explain the spatial relationships between flooding and vulnerability in Polk County Iowa, with vulnerability, historic, and environmental justice frameworks. Most notably I will be paying attention to the gentrification and expansion of the Des Moines area that started occurring in the 90's, as it might lead to findings from this study might suggesting that a spatial vulnerability paradox is occurring, and it might be important to consider historical cultural forces and formulate new mitigation policies from these understandings.

CHAPTER THREE: POLK COUNTY, IOWA SOCIAL VULNERABILITY INDEX

This chapter answers the first research question by presenting and discussing the results of the Polk County, IA SoVI. The findings will be discussed as they relate back to the literature of social vulnerability and environmental justice as well as contextualizing the findings into a local Midwest spatial view and how it relates to socioeconomic and sociodemographic factors. This chapter starts with information on the variables which assisted with the confidence & rationalization for continuing along the proposed line of testing in the thesis. Then the method for extraction and naming of components/factors found within the PCA will be described, as well as a discussion on the possible suppositions of the components as they pertain to the context of the local area. Lastly, this chapter will include any inferences about the final Polk County, Iowa SoVI composite and conclusions for the SoVI.

3.1- Suitability of the Data for PCA

To use the output of a PCA, it is necessary first to establish whether the data is suitable for the analysis technique. The Kaiser-Meyer-Olkin (KMO) Test is a measure of how suited a dataset is for factor analysis or PCA (Rogerson, 2014). The test measures sampling capability for each variable in the model and for the comprehensive model. KMO values between 0.8 and 1 indicate a selection that is satisfactory (Rogerson, 2014). The Bartlett's test of sphericity test indicates that a factor analysis may be useful with a given dataset if below 0.05 (Rogerson, 2014). The data in this study, with a KMO of .825 and a Bartlett sphericity test score of .000 significance value, are highly supported by these indicators and thus give high confidence and rationalization for continuing with interpretation of the PCA results.

3.2- Extraction and Naming of the Components

Using the criterion of keeping all components with eigenvalues greater than one, nine components were retained after performing the PCA (*Table 5),* reduced from the original set of thirty variables presented in Chapter 2. These nine components account for almost 70% of the variance in the data, with the first three components each accounting for more than 10% of the variance.

Table 5: Total Variance Explained

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.508	25.026	25.026	4.076	13.588	13.588
2	3.263	10.877	35.903	3.809	12.698	26.285
3	2.022	6.740	42.643	3.090	10.301	36.587
4	1.772	5.908	48.551	2.235	7.449	44.035
5	1.603	5.344	53.895	1.714	5.714	49.749
6	1.337	4.455	58.350	1.676	5.585	55.334
7	1.223	4.075	62.425	1.479	4.929	60.264
8	1.061	3.535	65.960	1.409	4.695	64.959
9	1.009	3.362	69.322	1.309	4.363	69.322
Extraction Method: Principal Component Analysis.						

The rotated component matrix (*Table 6)* is one of the most important outputs from the PCA as it helped determine what the components represent by providing the estimated correlation of each individual variable to each of the nine components. The table highlights minor loadings in grey, which are determined to be inappropriate for interpretive use because they do not exceed 0.5 or -0.5 and thus are not highly influential in determining the character of each component though they could have implications in a larger dataset. The estimates of 0.5 & -0.5 are common objectively determined thresholds for significant loadings and are appropriate for either correlation or covariance matrix PCA loadings. The moderate to strong loadings are highlighted in yellow and are most noteworthy due to correlations of 0.5 or -0.5 and greater/smaller. Each component is clarified more by the larger loadings and less by the smaller loadings. According to the variables which loaded highly on the components, all nine were named and given a mathematical sign indicating whether they increase or decrease social vulnerability to floods in Polk County, IA (*Table 6*).

Table 6: Rotated Component Matrix

	COMPONENT								
	1	2	3	4	5	6	7	8	9
Zscore(QASIAN)	-.081	.266	-.041	-.074	.102	-.030	.128	.694	.034
Zscore(QBLACK)	.581	.358	.073	-.140	.102	-.049	.039	.195	.091
Zscore(QHISP)	.386	.731	-.114	-.022	.046	-.100	.021	-.138	-.040
Zscore(QNTAM)	.394	.122	.173	.006	-.107	.095	.479	-.121	.146
Zscore(QPOPAGEDEP)	-.057	-.022	.058	.847	-.042	-.045	-.114	.082	-.088
Zscore(QFAM)	-.151	-.167	-.775	-.137	.076	.211	-.064	.121	.113
Zscore(MEDAGE)	-.405	-.245	.209	.543	-.080	.299	.000	-.228	.071
Zscore(QSSDEP)	.019	-.068	.062	.904	-.018	-.042	.062	-.098	-.023
Zscore(QPOVRTY)	.730	.348	.208	-.168	-.007	-.025	.115	.074	-.092
Zscore(QRICH)	-.324	-.297	-.369	-.048	-.311	.586	.049	-.008	.245
Zscore(PERCAP)	-.566	-.377	-.072	.041	-.349	.450	.038	-.025	.232
Zscore(QESL)	.038	.786	.035	-.094	.166	.041	.158	.234	.064
Zscore(QFEMALE)	.084	.036	.091	.067	-.107	.117	-.866	-.017	.106
Zscore(QFHH)	.062	.008	.808	.075	-.077	-.091	-.257	-.006	.011
Zscore(QNURSRES)	-.059	.156	.243	.383	.234	.240	-.029	.192	.297
Zscore(QNOHLTH)	.382	.651	.122	-.081	.172	-.039	.083	-.144	-.075
Zscore(QEDU12LES)	.522	.613	-.013	.073	.202	-.109	.060	.112	-.024
Zscore(QCVUNEMPL)	.784	.074	-.060	.042	.101	-.138	.042	.001	-.044
Zscore(PPUNIT)	.330	.109	-.854	-.079	.117	-.012	-.092	.042	.047
Zscore(QRENTER)	.344	.370	.528	-.285	-.025	-.123	.186	.313	.089
Zscore(MEDHVAL)	-.413	-.359	-.308	-.103	-.241	.423	-.006	-.059	.369
Zscore(MEDRENT)	-.006	.010	.094	-.032	-.039	-.762	.097	.084	.264
Zscore(QMOBILE)	-.030	.072	.052	.059	.062	.136	.049	.059	-.833
Zscore(QEXTRACT)	-.238	.112	-.012	-.058	.172	.083	.237	-.633	.135
Zscore(QBLUECOL)	.166	.181	-.045	.055	.747	-.111	.082	-.216	-.075
Zscore(QSERVC)	.090	.660	.093	-.093	-.123	.020	-.055	.049	-.222
Zscore(QFELABOR)	.748	.131	-.042	-.078	-.023	.076	-.419	-.081	.097
Zscore(QHHNOCAR)	.413	.244	.547	.118	.034	.160	.161	.209	.124
Zscore(QNOPPLHH)	.086	.570	.117	.059	-.060	-.107	-.132	.087	.100
Zscore(AVGTRAVL)	.039	-.069	-.161	-.093	.762	.023	.004	.140	.004

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization a. Rotation converged in 14 iterations

Table 7 shows the final component summary for the PCA and the cardinality that each component is given to calculate the Polk County, Iowa Social Vulnerability Index. Upon completion of the PCA, the component factor scores from the resulting orthogonal components found in *Table 7* were summed using the assigned cardinality to generate the final Polk Co, IA SoVI.

Table 7: Polk County, IA SoVI Component Summary

Component	Cardinality	Name	% Variance Explained	Dominant Variables	Component Loading
1	+	Unemployed & Low Income Working Women	13.588	QCVUNEMPL QFELABOR QPOVRTY QBLACK PERCAP QEDU12LES	.784 .748 .730 .581 -.566 .522
2	+	Ethnicity (Hispanic)	12.698	QESL QHISP QSERVC QNOHLTH QEDU12LES QNOPPLHH	.786 .731 .660 .651 .613 .570
3	+	Single Parent Households with No Transportation	10.301	PPUNIT QFHH QFAM QHHNOCAR QRENTER	-.854 .808 -.775 .547 .528
4	+	Older Adult Persons	7.449	QSSDEP QPOPAGEDEP MEDAGE QNURSES	.904 .847 .543 .383
5	+	Extended Travel for Blue Collar Workers	5.714	AVGTRAVL QBLUECOL	.762 .747
6	-	Wealth	5.585	MEDRENT QRICH PERCAP MEDVAL	-.762 .586 .450 .423
7	-	Gender (Male)	4.929	QFEMALE QFELABOR QNTAM	-.866 -.419 .479
8	-	Ethnicity(Asian) White Collar Workers	4.695	QASIAN QEXTRACT	.694 -.633
9	-	Lack of Mobile Homes	4.363	QMOBILE	-.833
Cumulative Variance Explained			**69.322%**		

3.3- Polk County, IA SoVI Components

Table 7 will assist in the understanding of the discussion about components found during the PCA, the author's analysis of them in greater detail, and discussions of the findings in a Midwest context. One would like to start this discussion by reminding the reader of the fact that all individual persons, regardless of information found in this PCA, SoVI, or other publications, have some degree of social vulnerability and that this analysis is to find larger underlying disenfranchised communities or sets of people who have above average amounts of vulnerability.

3.3.1- Component One

The first component identified was Unemployed & Low Income Working Women where the highest loaded variables were QCVUNEMPL, QFELABOR, & QPOVRTY. Unemployment and female labor were slightly positively correlated (0.54) after an examination of the correlation matrix, as was female labor with poverty (0.51), leading to the supposition that female labor workers might be being laid off more, or needing to leave the workforce after entering it, and making less money even when they are working. It is possible that the largest portion of component one that is being captured is gender discrimination or the gender wage gap in Polk Co, IA. Other variables loaded on the first component were Race (Black), per-capita income (negative) and less education which suggested that this component might also capture a large impoverished population, which might be racially divided. QBLACK did not load in its own category with QPOVERTY; however, there was a higher correlation between these two variables (0.62), which suggested that these two variables in the component go together. Similarly, lower levels of educational attainment, QBLACK, QPOVERTY/very low per-capita income were also slightly correlated seeming to suggest that not only is much of Polk County's African-American population in poverty, as well, they have lower levels of educational attainment. Accounting for 13.6% of the variance, this component is overloaded from a vulnerability and environmental justice standpoint. It is well established that poverty/low income is a large contributor in social vulnerability. Similarly, in environmental justice literature it is also one of the largest contributors to greater exposure to risks because of the lack of resources, and a sense of community to rebound from a disaster. With the gender discrimination/gender wage gap in this component, poverty is thus being unequally distributed onto working women who are already making less than their male counterparts but are working the same hours. For Polk County, women make only 70 cents for every dollar a man makes, while the state average is 77 cents and the national average is around 79 cents (American Community Survey, 2014). Thus, in Polk County it is likely that we might be looking at an older more "traditional" idea of lifestyles. The author's supposition on the situation simply points to male discrimination against females in a male dominated workforce. The idea that men should be working/making money and that women should be working in the home and tending to the family's needs is an older and historically biased, "traditional" way of thinking. It is quite possible that higher amounts of women are expected to quit their jobs to take on the caregiver role (because they make less money, even if they are equally qualified and educated for the position…one can see how this is a vicious cycle). In addition, these issues intensify when looking at women of ethnic and racial minorities, and women who have children to look after. *Figure 10* looks at the spatial distribution of this component, and with the exclusion of a few outlying block groups this component is well clustered. The highest concentration of this component is in the metropolitan city centers, and then just to the outside of those areas not too far away from main roadways, job areas, and one well-known impoverished area on the northwest side of Des Moines, which is historically where many African-Americans live (*Figure 11*). All of these issues are highly connected with the deficiency of skills of an individual to be able to foresee, manage with, oppose and recuperate from a natural hazard.

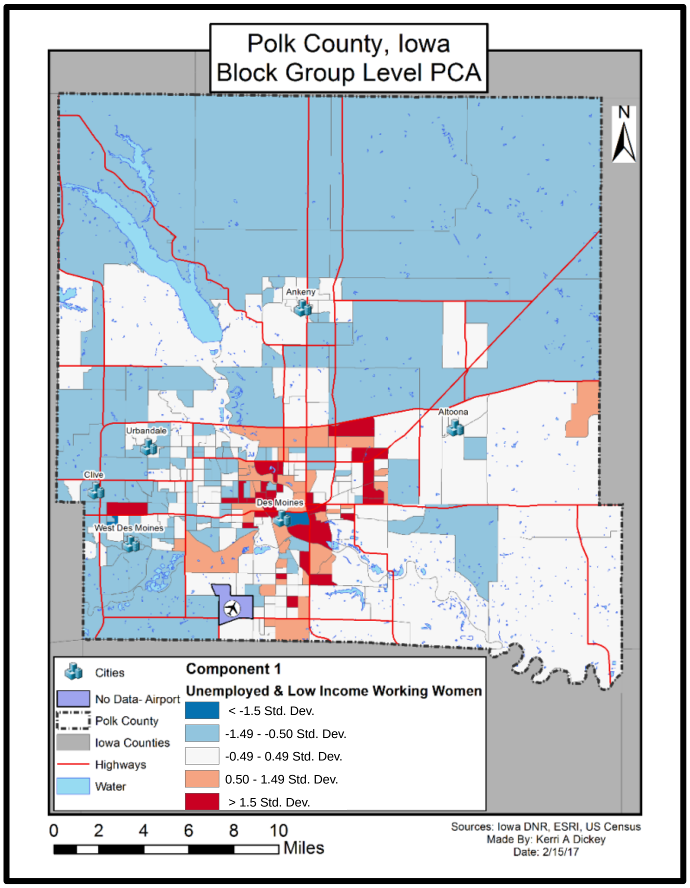

Figure 10: PCA Component One: Unemployed & Low Income Working Women

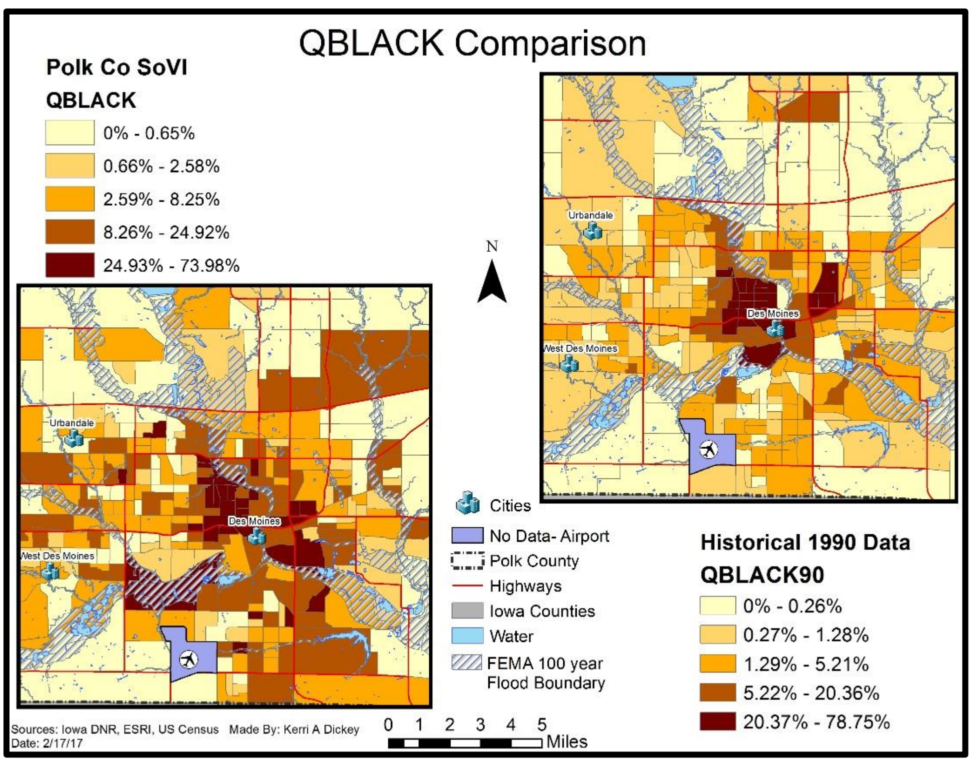

Figure 11: Visual Comparison of Historical QBLACK & Present QBLACK

3.3.2- Component Two

The second component identified was Ethnicity (Hispanic) and included the variable representing a reduced ability to speak English (QESL). This is important in a Midwestern U.S. context since this is an area where information in other languages is not usually readily available. Ethnicity is a distinctly defined social factor that weighs heavily on vulnerability, similar to how race contributes to vulnerability, with the lack of access to information, cultural dissimilarities, as well as historic economic, social and political marginalization. This marginalization is worsened by the inability to speak English language at a proficient level. Within the Des Moines Public Schools district there are over 6,100 English Language Learning (ELL) students. "There are more ELL students in the City of Des Moines than there are in the states of Vermont, West Virginia, North Dakota, Wyoming, Montana, New Hampshire, South Dakota and Maine." ("Learning Our Language: ELL Students In Des Moines Are Succeeding", 2017). Often, older persons rely on their younger children to inform them of situations or to translate for them since they might not speak any English. This is an issue in Polk County since this variable accounts for 12.7% of the variance, and most people in this area assume one should speak English, but since the amount of people speaking English as a second language is low, and not just one other language is dominant (for example like in Florida how there is a large Spanish speaking population), most hazard related reports are mostly, if not only, given in English. Reports in other languages are not readily available to the public and one would need to have the knowledge of where to obtain this information. Additional variables that loaded on this component contribute further to difficulty coping with flood hazards. The variables included persons with no healthcare, people with low educational attainment, and persons working in the service industry, all of which had higher than normal correlations to QHISP. These components together indicate a disregarded and excluded Spanish-speaking community that might not have the resources or time to find and fully comprehend information in their language when it comes to a natural hazard.

Spatially looking at this variable in *Figure 12*, it appears as though a density is found around the metropolitan center and major road ways. This could be linked to service industry job locations, potentially mass transit ability, lower housing costs or cost of living, and multi-room dwellings since PPUNIT indicated there are more persons living in each house with this component.

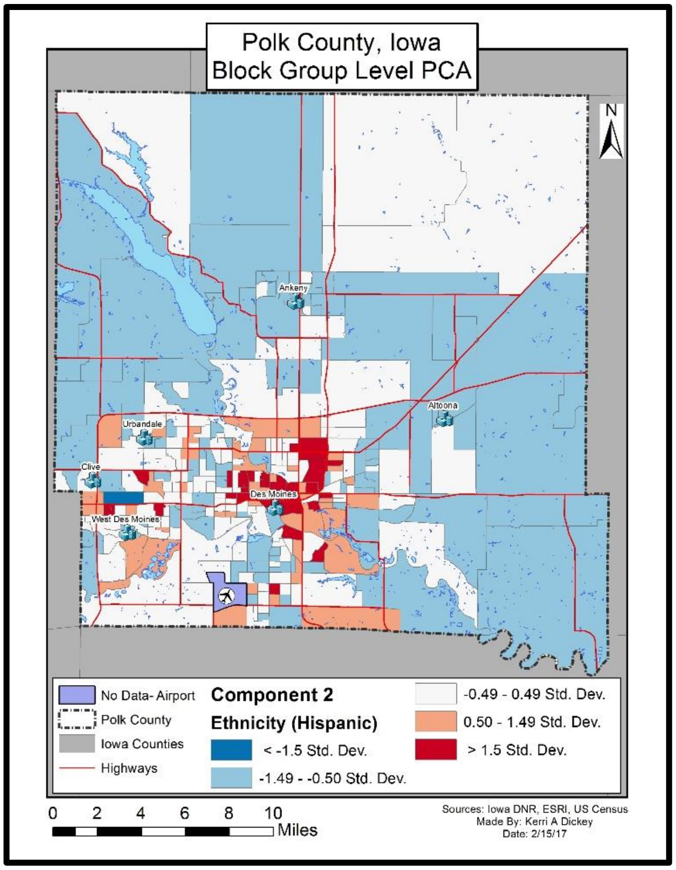

Figure 12: PCA Component Two: Ethnicity (Hispanic)

3.3.3- Component Three

The third component, Single Parent Households, heavily loaded on lower amounts of people per unit, higher percentages of women who are listed as the householder/head of house, and a lower percentage of households conforming to the traditional nuclear family model of two parents and their children living in the house. This component in Polk County accounted for 10.5% of the variance and captured the areas with non-traditional households, including single parent households (especially female), which suggests that non-traditional homes (not traditional nuclear families) might not be receiving community and personal support in this area of the country and could experience higher levels of vulnerability. QFHH and PPUNIT were moderately negatively correlated (Appendix II), which seems to suggest that when women are listed as the heads of a household, in certain locations, there are substantially less people living in that household (single/living alone, or living with someone they are not married to), and likewise we see a very negative QFAM score indicating that these single QFHH are still supporting persons in the household under the age of 18.

Greater percentages of persons with no car available and higher renter population could mean the component is also representing persons who must rely on spotty public transportation systems, cannot afford to own a car or a home without another person's income, or are possibly part of a transient community that does not stay in one place for a long period of time. Moving frequently disrupts the idea that one has social ties with their neighborhood, and feels a sense of community and familiarity with the area. Being transient equates to knowing and accessing less community resources and potentially not knowing the area very well in the event of a disaster. Mass transportation in America is already poor in comparison to Europe, but in a Midwest context it is just as bad. So much of the mass transit is vastly underutilized and most cities in Iowa do not have any mass transit to speak of, the major cities and many colleges have some sort of mass transit, however the transit on college campuses are only available to students. Thus, one skill that young adults obtain in the Midwest is driving, and with so many types of available recreational vehicles, farming equipment, and riding lawn mowers, one drives a lot. There also tends to be less congestion on the roadways, so owning a car is the fastest way to get from point A to point B and be independent in the process. Thus, not having a personal vehicle in the Mid-West is a transportation issue as it pertains to evacuating or getting to a safe location during an emergency. Spatially this component's higher vulnerability areas are confined around major roadways and areas less vulnerable are located farther away from mass transit points and the city center (*Figure 13*).

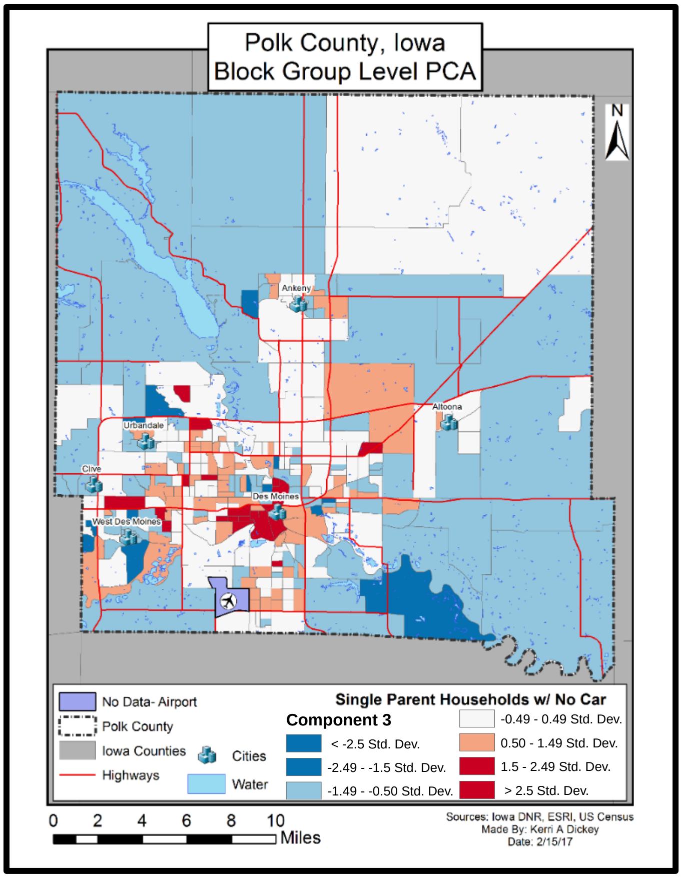

Figure 13: PCA Component Three: Single Parent (Female) Households

3.3.4- Component Four

Component four profoundly captured variables related to age such as social security dependent individuals, age dependent individuals (those below 6 or above 65 years of age) and a higher median age, which suggests the component represents older adult persons. Mapping of this component showed no clear groupings to suggest any significant spatial findings (*Figure 14*) This component accounts for 7.4% of the variance and is important for flood hazard vulnerability because older adult persons may have mobility constraints or concerns, income restrictions (especially those dependent on social security who might have been persons who were impoverished before retirement and have less money in their older age) and possible health complications when it comes to reacting and recovering from natural hazards. These concerns align with previous information found in social vulnerability and environmental justice literature.

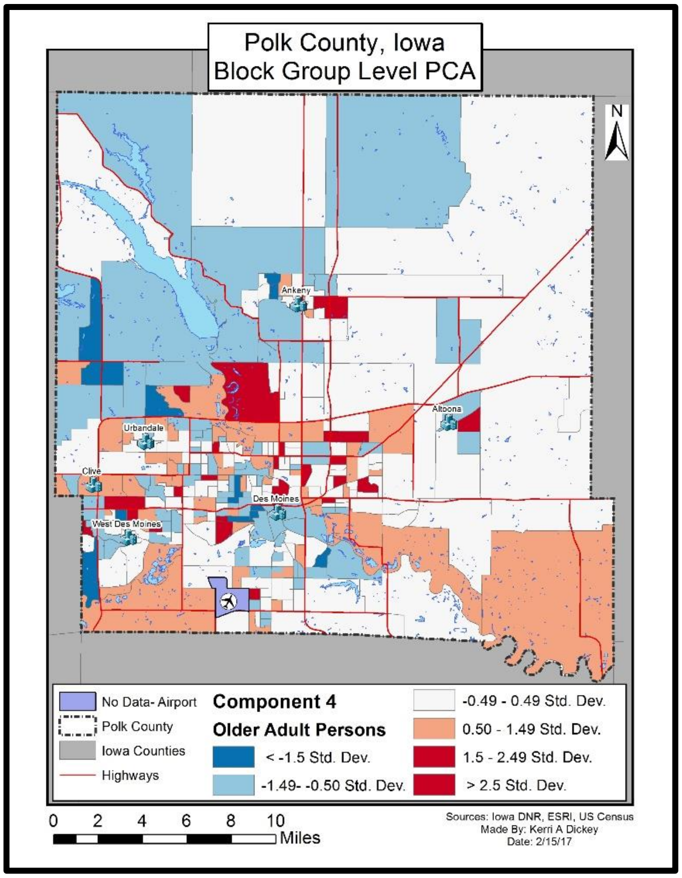

Figure 14: PCA Component Four: Older Adult Persons

3.3.5- Component Five

Component five is entirely captured by increased travel times to work and working in the blue-collar job sector. The literature suggests that occupation can be significant to vulnerability due to wage differences in occupation as well as wear and tear on mental and physical health. It is possible that what is being measured is that persons employed in the blue-collar sector (Construction, Manufacturing, Agriculture, Transportation, Warehousing, and Utilities) do not live close to their perspective places of employment, due to the correlation with lower per capita income, and thus must commute farther to work from more suburban and rural areas. Mapping of this component makes this point rather evident with large sections of blue collar work overlapping prominent flood areas, river, and streams as well as being geographically located farther away from the metropolitan town centers (*Figure 15*). Not only do these persons work in highly dangerous fields that might be more stringent on late or absences in work due to inclement weather, but they are potentially more exposed to flood hazards while commuting longer putting themselves in danger of being in an automobile accident, or outside during an event in which they might experience greater effects from a natural disaster. This component representing extended travel times to work for blue collar workers explained 5.7% of the variance in Polk County.

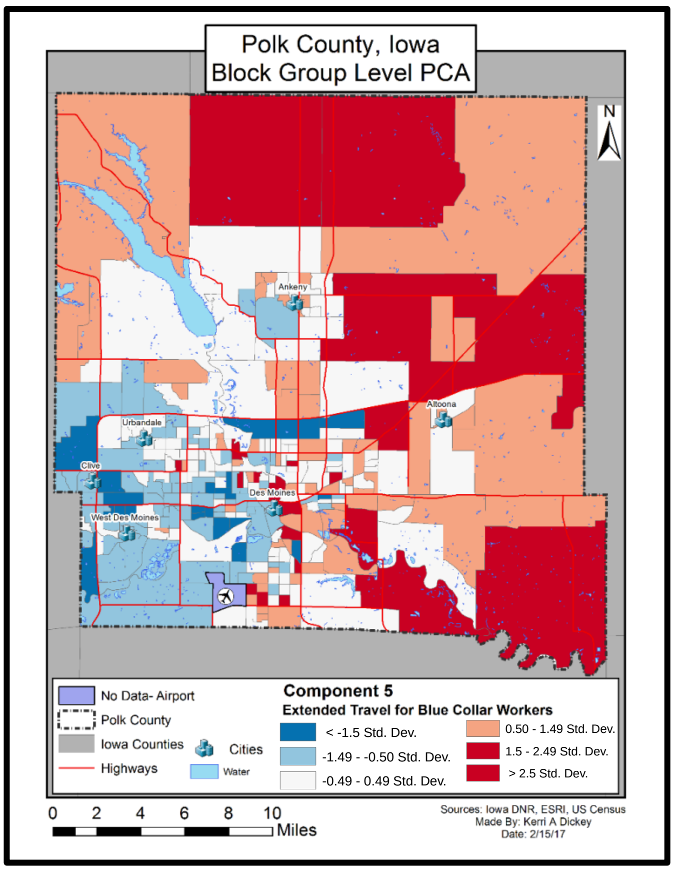

Figure 15: PCA Component Five: Extended Travel of Blue-collar Workers

3.3.6- Component Six

The sixth component seemed to capture a wealth component with higher percentages of households with income greater than $150,000, higher levels of income, household values and lower median rents, which makes sense geographically looking at *Figure 16* since most of the areas in bright blue and light blue, signifying higher wealth, are in areas where most people are purchasing very expensive homes and plots of land and there would be fewer places available to rent, if any. With most of the wealth factors loading in the positive, and a total lack of poverty variable it is easy to see how wealth can enable groups of populations to quickly adjust to a disaster, thus this variable explained roughly 5.6% of the variance in Polk County. Wealthier areas are more inclined to have a disposable income to help offset the cost of a disaster, as well they tend to have more than adequate insurance, so even though we might find losses in a high number because there are more expensive items damaged in a natural disaster, the amount that comes back out of the personal pocket is far less than a more disenfranchised community. It is found heavily in the literature and well agreed upon that a lack of wealth is a chief contributor to vulnerability since supplies become sparsely available, thus making the less wealthy a group less resistant to the effects of a natural disaster.

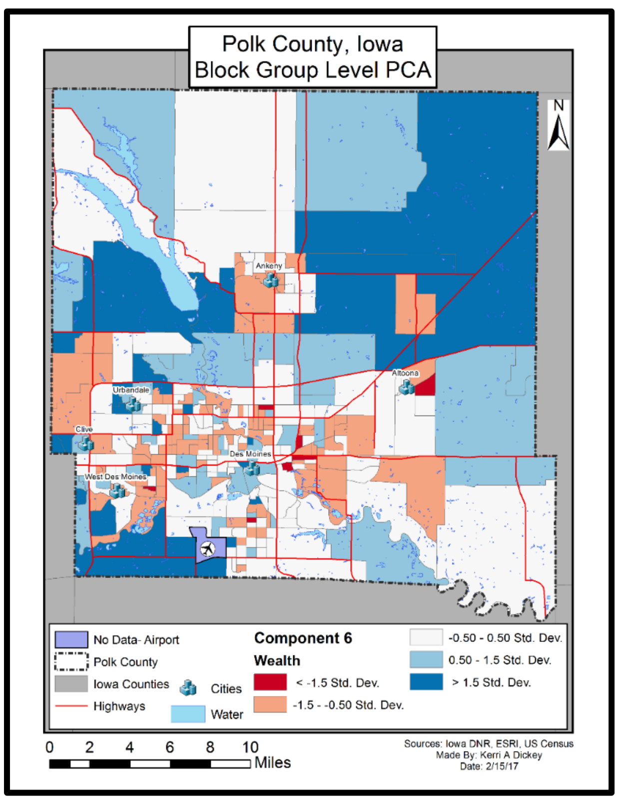

Figure 16: PCA Component Six: Wealth

3.3.7- Component Seven

The seventh component had negative loadings on variables pertaining to gender, specifically, a very high negative correlation with percentage of the population that is female, and with the percentage of females in the labor force. This variable represented 4.9% of the variance and is measuring the male population in Polk County. Mapping of this component showed no clear groupings to suggest any significant spatial findings (*Figure 17*). The literature in both social vulnerability and environmental justice agree that gendered issues are still problems today. Though some men might be more socially vulnerable on an individual basis, overall it is women who have historically faced marginalization, sexism, workplace discrimination, pay gaps, and lower graduation rates or educational attainment due to the expectation to maintain a family or be a caregiver. With this understanding, and a contextualized historical underpinning to the status of femininity in Polk County it follows that though this seventh component measured male gender, it does not add to vulnerability but decreases social vulnerability.

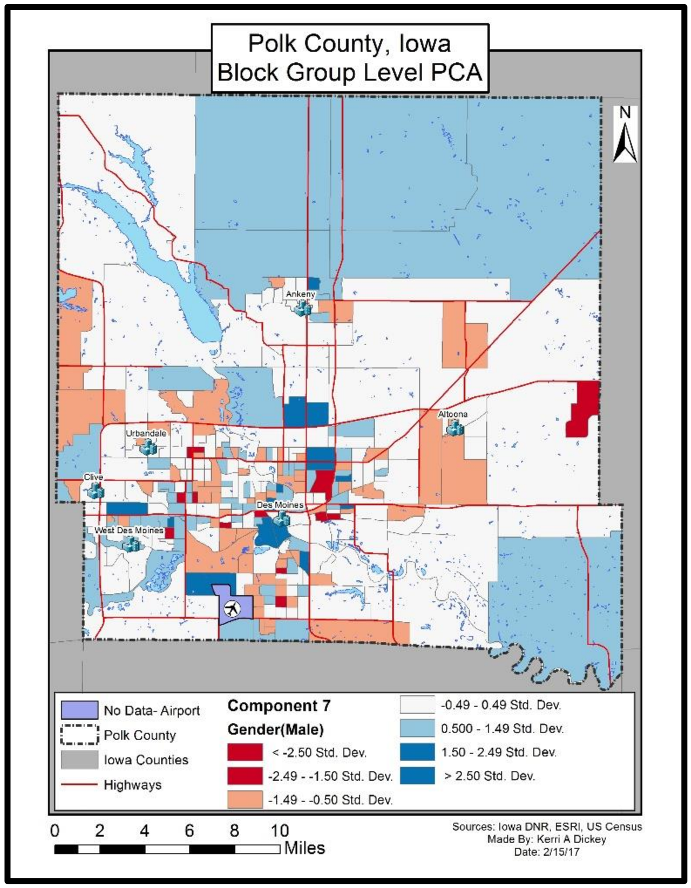

Figure 17: PCA Component Seven: Gender(Male)

3.3.8- Component Eight

The eighth component is very interesting, though it only captured roughly 4.7% of the variance, and the only variables that loaded in this component were the percentage of total population identifying as Asian (QASIAN) and a negative loading the percentage of employed persons working in extractive industries (QEXTRACT). What could be seen here is a recent influx of persons from Asia in Polk County, especially students and well educated workers. Mapping of this component showed no clear groupings to suggest any significant spatial findings (*Figure 18*). Just to the north of Polk County is the town of Ames, where one of Iowa's largest universities resides, Iowa State University (ISU). This university is largely known for having an advanced agricultural program, but it also boasts strong arts/graphic design programs, computer science, engineering, chemistry, and a well ranked business school. 51.9% is the percentage of Asians in 2014, age 25 and over, who have a bachelor's or higher degree education, so Asians have the highest proportion of college graduates of any race or ethnic group in Iowa ("ASIAN/PACIFIC AMERICANS IN IOWA,2016"). As well one finds that median income of households who report their race as Asian is $55,000 where median income reported for all Iowans is only $49,000("ASIAN/PACIFIC AMERICANS IN IOWA,2016"). Over the last decade there has been a dramatic uptick in international students and companies coming to Iowa, specifically from Asia ("Asian Population Growing In Iowa", 2015). A rise in international persons has brought several companies to the Polk County area like Syngenta, and Origin Agritech, both agricultural companies with connections to China ("Chinese Seed Company Expands To Des Moines", 2017). It is very possible that this component is seeing a boom in a tech savvy, highly educated, Asian population that does not work in the extractive services, even though Iowa has plentiful jobs in this area. It would seem just by looking at the surface value of this component that this might add to vulnerability, but when adding the Midwest context to the component one will find that the Asian population living in this area is highly educated, and most-have higher paying white collar jobs. The population is thus not working out in the fields in agriculture, and if they do work for an agricultural company it is in biology, chemistry, or genetic engineering making good money and surrounded by a community of peers that they may be very near to since they might have called ISU home during their college education.

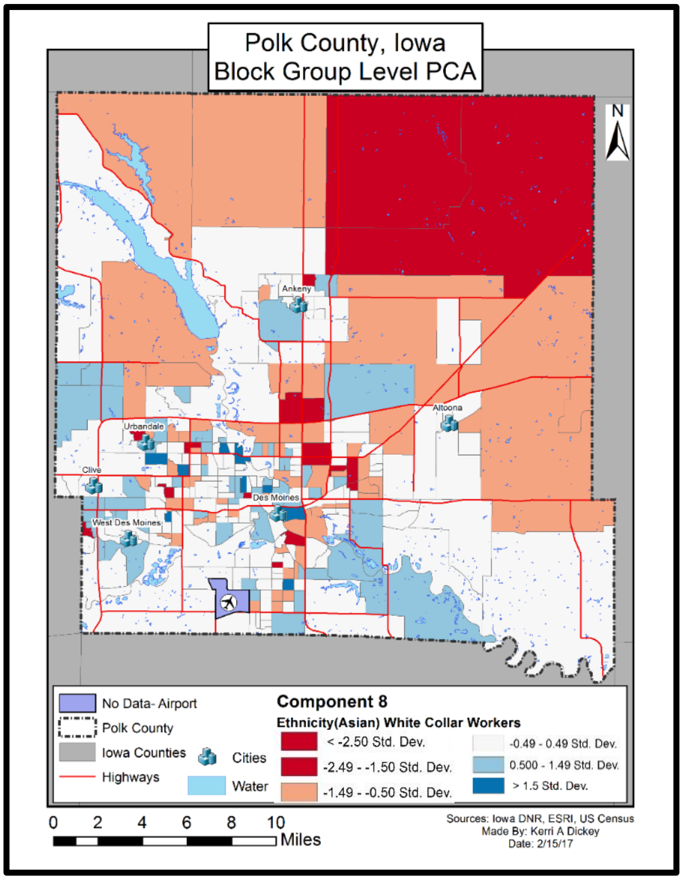

Figure 18: PCA Component Eight: Ethnicity(Asian) White-collar Workers

3.3.9- Component Nine

The ninth and final component captured roughly 4.4% of the variance and was a largely negative QMOBILE that suggested the absence of mobile homes. In a Midwestern context, this makes sense as there are many single-family homes with basements in Iowa and in cities there are diverse types of housing from single family to multi-family apartment complexes. This component is clearly noting the large difference in single family dwellings and mobile home parks in the Polk County area. Mobile home parks are not as widely found in the Polk County area as they are in the southern portion of the United States. Mobile home parks can still be found, but they are more few and far between. Thus, the lack of mobile homes equates to lower levels of vulnerability, and areas where there are more mobile homes equates to higher levels of vulnerability as represented in the literature (Cutter, 2008) since mobile homes tend to be cheaper, purchased by persons with less disposable money, and less structurally sound dwellings in the event of a disaster. Mapping of this component showed no clear groupings to suggest any significant spatial findings, though the densest groupings of mobile homes appear to be near water bodies or known flood areas so this will be a component to test later in the thesis (*Figure 19*).

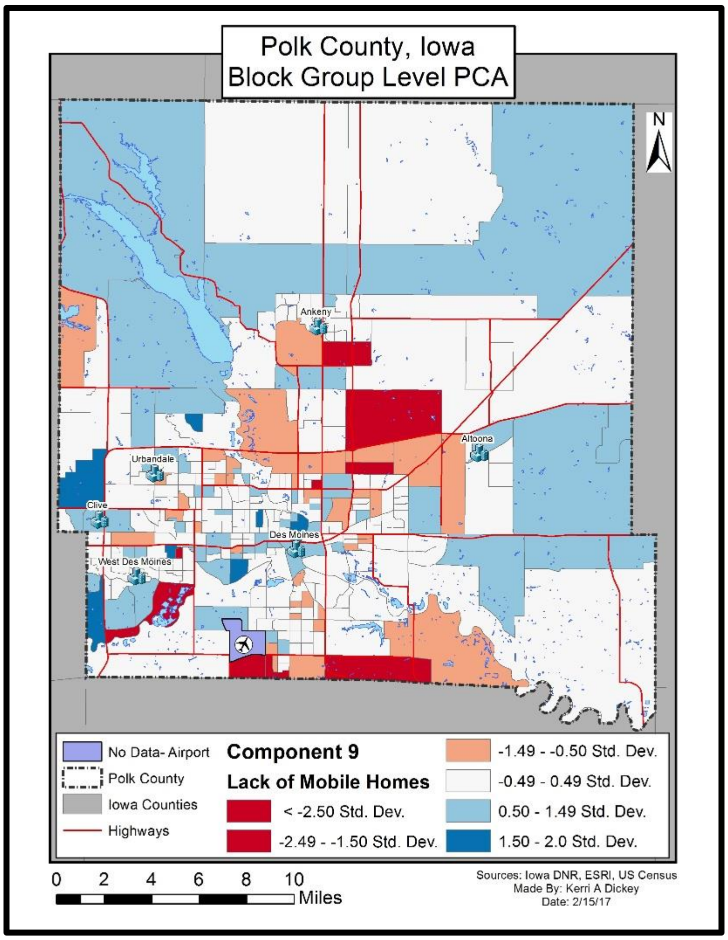

Figure 19: PCA Component Nine: Lack of Mobile Homes

3.4- Polk County, IA SoVI Composite

The completion of the PCA allowed for the creation of the SoVI for each block group in Polk County. The factor scores for all nine components were summed to create the composite index; those components with a positive cardinality (1-5) added to social vulnerability while those with a negative cardinality (6-9) reduced social vulnerability. According to the precedent set by Cutter et al. (2003), the components were not assigned any special weighting scheme as each component is assumed to theoretically contribute equally to social vulnerability, and there are only two decent ways to visualize the SoVI scores: Geometric Interval and Standard Deviation.

The division for classification shown in *Figure 20* is Geometric Interval: class breaks are based on class intervals that have a geometrical series which is created by an algorithm that minimizes the square sum of elements per class, thus ensuring that each class range has about the same number of values and that the change between intervals is comparatively constant (ESRI Online). Geometric intervals are better for visualizing predictive surfaces and data that are not normally distributed (ESRI Online). *Figure 21* below shows a histogram of SoVI scores so it is easy to see why the classification method of Geometric intervals is chosen to display the data. The data are not normally distributed and thus many other classification methods can visually appear highly skewed. In *Figure 20* below, one will see the resulting Polk Co, IA SoVI in map format. The legend does not show the values calculated for vulnerability, but it can be thought of as Very Low – White (-11.156 - -4.928), Low – Light Green (-4.929 - -2.158), Medium - Green (-2.157 - -0.924), High – Dark Green (-0.9243- 1.850). and Very High – Dark Peacock Green (1.851 - 8.074581).

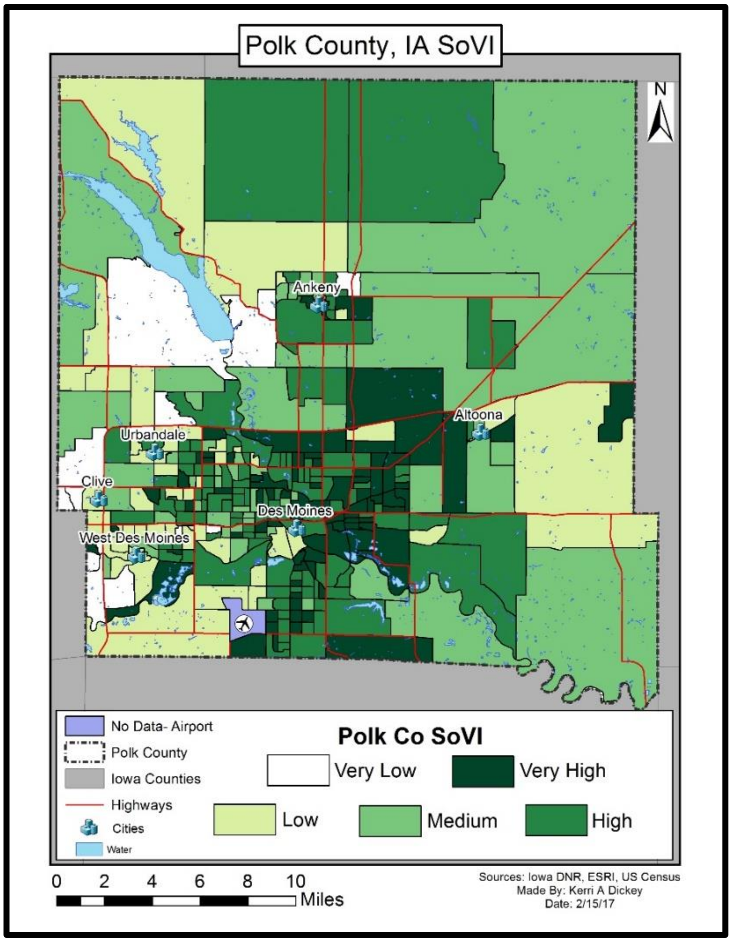

Figure 20: Polk County, IA SoVI - Geometric Interval

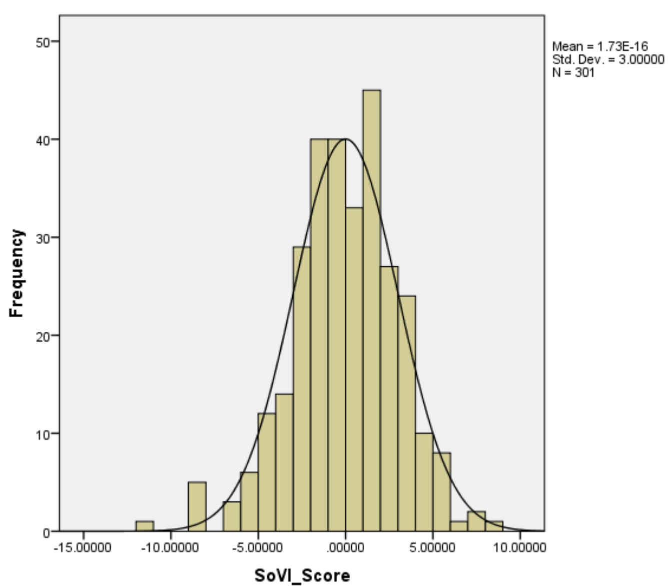

Figure 21: SoVI Score Histogram

Standard Deviation is the other way to visualize the data that are not normally distributed and can be seen in *Figure 22* below. This classification method visually shows the extremes of the data which are farther away from the calculated mean (-1.5 Std. Dev. to +1.5 Std. Dev is the Medium range, any values falling outside of these areas are placed in the (-) Low or (+) High section).

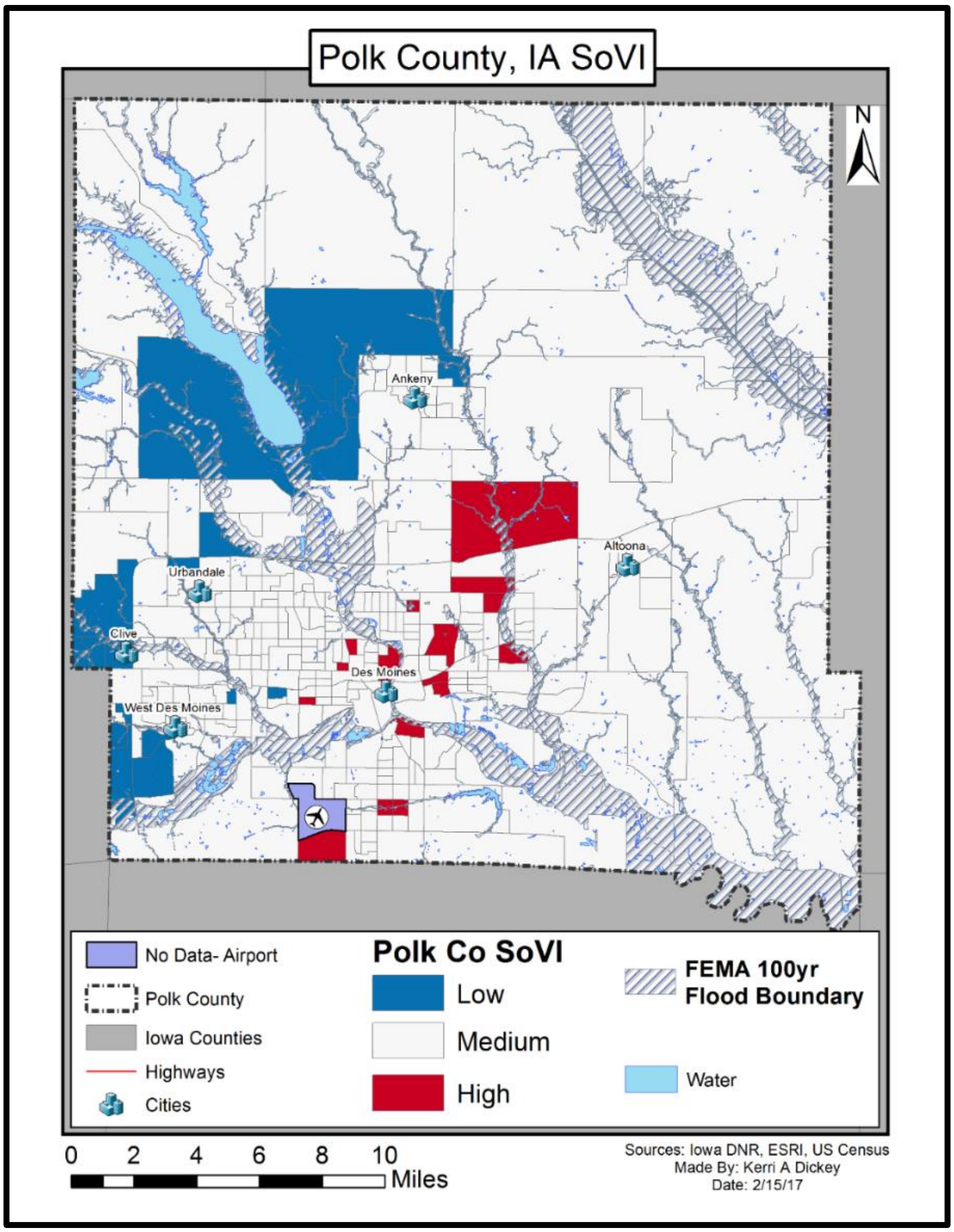

Figure 22: Polk Co, IA SoVI represented in one Standard Deviation classification method.

One can now postulate suppositions and interpret the main ideas behind the SoVI results from the series of maps provided. Looking at *Figure 22*, one can see that the absolute highest values in the

SoVI are scattered across the social landscape and are not clustered in any discernable manner. Although, a few of these very high vulnerability areas coincide with mobile home parks which could contain persons with compounding vulnerability variables. However, referring to *Figure 23* allows one to see a more smoothed picture of SoVI scores and a slight pattern can be seen of higher vulnerability closer to city centers and older, more historic areas of the urbanite landscape. Areas farther away and more recently built suburbs of Des Moines, like West Des Moines, and Urbandale have lower levels of vulnerability and are trendy, up and coming areas of the county, so there is much wealth being spread around that area. Furthermore, the Des Moines downtown area, over the last 10 years or so, has had a push towards gentrification to renew life back in the city center which is why we see some slightly lower values around the downtown area. Sadly, the response to this gentrification is the exiling of impoverished communities out of downtown and to the northwest and east of Des Moines where property values have remained cheaper, houses are old and outdated, the public schools are in shambles, and the people living to the east have extremely low levels of educational attainment. Additionally, the waste management area for the city is contained just to the southeast of this high vulnerability area to the east.

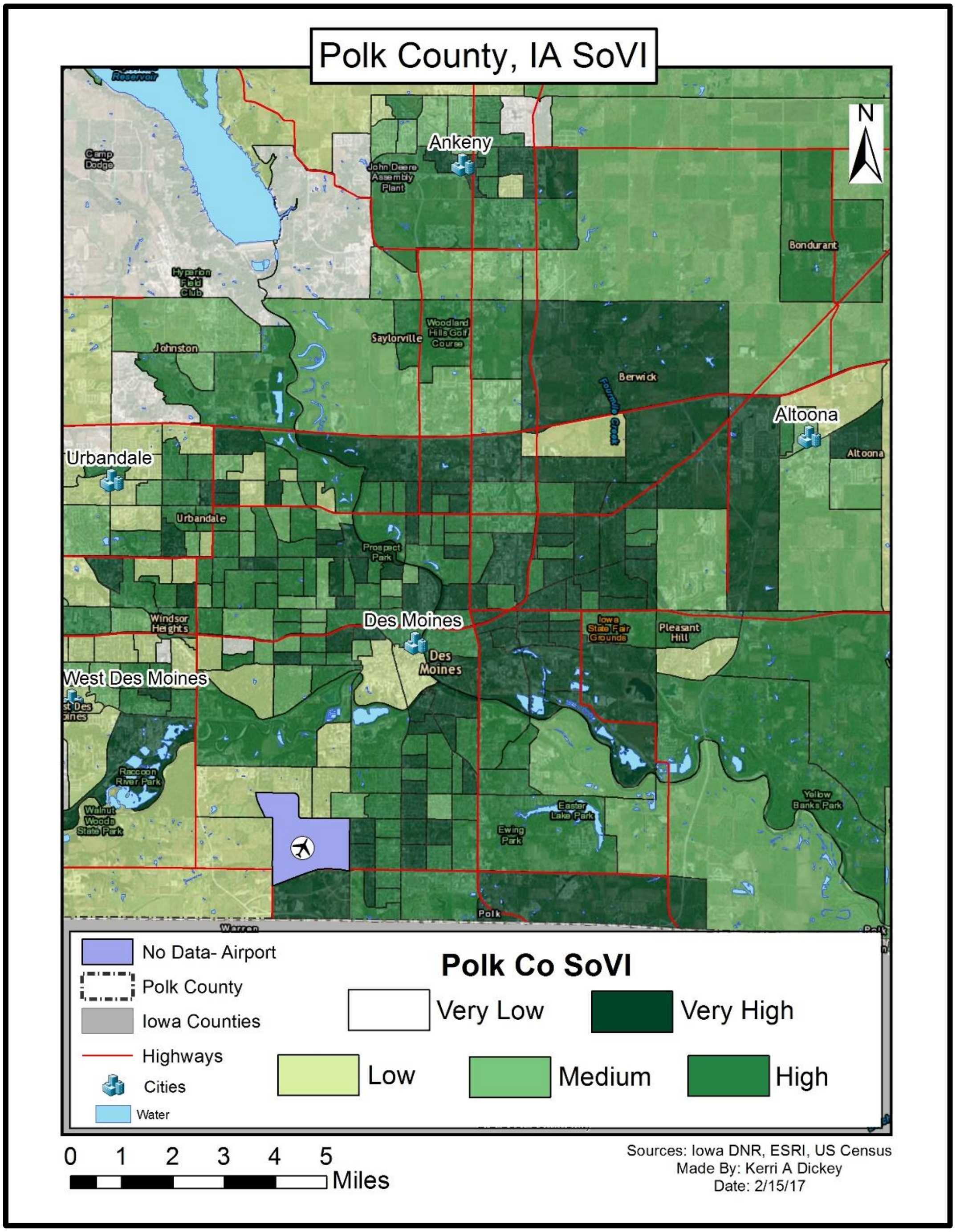

Figure 23: Zoom In View of High SoVI Variables, with added background spatial references.

3.5- Chapter 3 Conclusions

With the series of mapping in this chapter the first research question of the thesis is answered, and it can now be seen what the spatial patterns of social vulnerability based on demographic indicators in Polk County Iowa looks like. Key findings of the PCA and SoVI consist of: a possible gender pay gap & potential male discrimination against females in a male dominated workforce, which intensify issues even more when looking at women of ethnic and racial minorities, and women who have children to look after. A disregarded and excluded Spanish-speaking community that might not have the resources or time to find and fully comprehend information in their language when it comes to a natural hazard. Non-traditional homes (not traditional nuclear families) might not be receiving community and personal support in this area of the country and could experience higher levels of vulnerability, as well as transient persons and persons who rely on mass transportation. We also find that older adult persons and blue collar workers with extended travel times to work were all at risk for higher vulnerability in Polk County Iowa. Lastly, the conclusions for Polk Co, IA SoVI suggest that trendy newly built areas to the west and south of the metropolitan area had an influx of wealth and consisted mainly of risk capable populations. However, the historically black (slightly to the northwest of downtown), and entirely old and impoverished east side of Des Moines is where "at-risk" populations have been forced into with the rehabilitation and gentrification of the downtown area. At-risk populations are following mass transit routes as they are being pushed out of city centers and are moving into commercially used areas, and areas that are not well liked by their more affluent peers, like areas in proximity to waste facility plants and garbage dumps.

CHAPTER FOUR: POLK CO, IA SOVI & FLOOD RISK

This chapter answers the second & third research questions by presenting and discussing the author's interpretations of the results of statistical testing on the Polk County, IA SoVI and flood exposure/FEMA flood risk areas as it relates back to findings in the literature. Then to conclude one will create a discussion and mention suppositions for the meaning of statistical findings in the disaggregation of SoVI variables back into individual variables for both the present, 2014, and historical,1990, and the comparison for any similarities.

4.1- Relationship Between SoVI and Flood Risk

4.1.1- Flood Zone and Non-Flood Zone Comparison Approach

Promptly one moves to the analysis of the Polk Co, IA SoVI against the known flood zone and FEMA designated flood zone risk areas to determine if there is a correlation spatially between social vulnerability and the physical presence of the source point of flooding (rivers, streams, bodies of water). One started this assessment with a statistical test of Polk Co, IA SoVI scores versus the different levels of FEMA flood risk zones. *Figure 24* below shows the resulting hypothesis tested of Polk Co, IA SoVI scores exposed to higher FEMA flood hazard areas verses the lesser exposed areas to FEMA Flood Zones thus answering research question 2: What is the relationship between social vulnerability and flood risk/exposure areas in Polk County Iowa? Since the Mann-Whitney U test was not within a high enough significance level, one can postulate that there is no strong relationship between SoVI and higher or lower flood risk exposure. *Table 8* helps to understand the resulting test by looking at maximum total losses (from FEMA) and the correlation to SoVI scores using the Spearman's Rho which is a non-parametric test of association between two variables. A value of 1 would be a textbook positive association, and a -1 would be an absolute negative relationship, but this test was slightly negative, meaning that there is not a large defining correlation between the two variables. This line of testing is supported by one's informed suspicion of how events occur and where they tend to do the most damage, as well as, where vulnerable populations might be expected to live.

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of SoVI_Score is the same across categories of FldZone.	Independent-Samples Mann-Whitney U Test	.206	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Figure 24: SoVI Scores VS Flood Zone Mann-Whitney U Test

Table 8: Bivariate Correlation Test -Spearman's Rho Results

Correlations

			SoVI_Score	Max_TOT_LO
Spearman's rho	SoVI_Score	Correlation Coefficient	1.000	-.177**
		Sig. (2-tailed)	.	.002
		N	302	302
	Max_TOT_LO	Correlation Coefficient	-.177**	1.000
		Sig. (2-tailed)	.002	.
		N	302	302

**. Correlation is significant at the 0.01 level (2-tailed).

4.1.2- Flood Losses Correlation Approach

Figure 25 below shows a bivariate choropleth map that is a visual representation that complements the Spearman's Rho correlation test of Polk Co, IA SoVI scores versus the FEMA Flood Hazard Total Losses. This map is a result of FEMA designated Flood Risk Areas and past flood losses, and the Geometric Interval classification of the Polk Co, IA SoVI is overlaid.

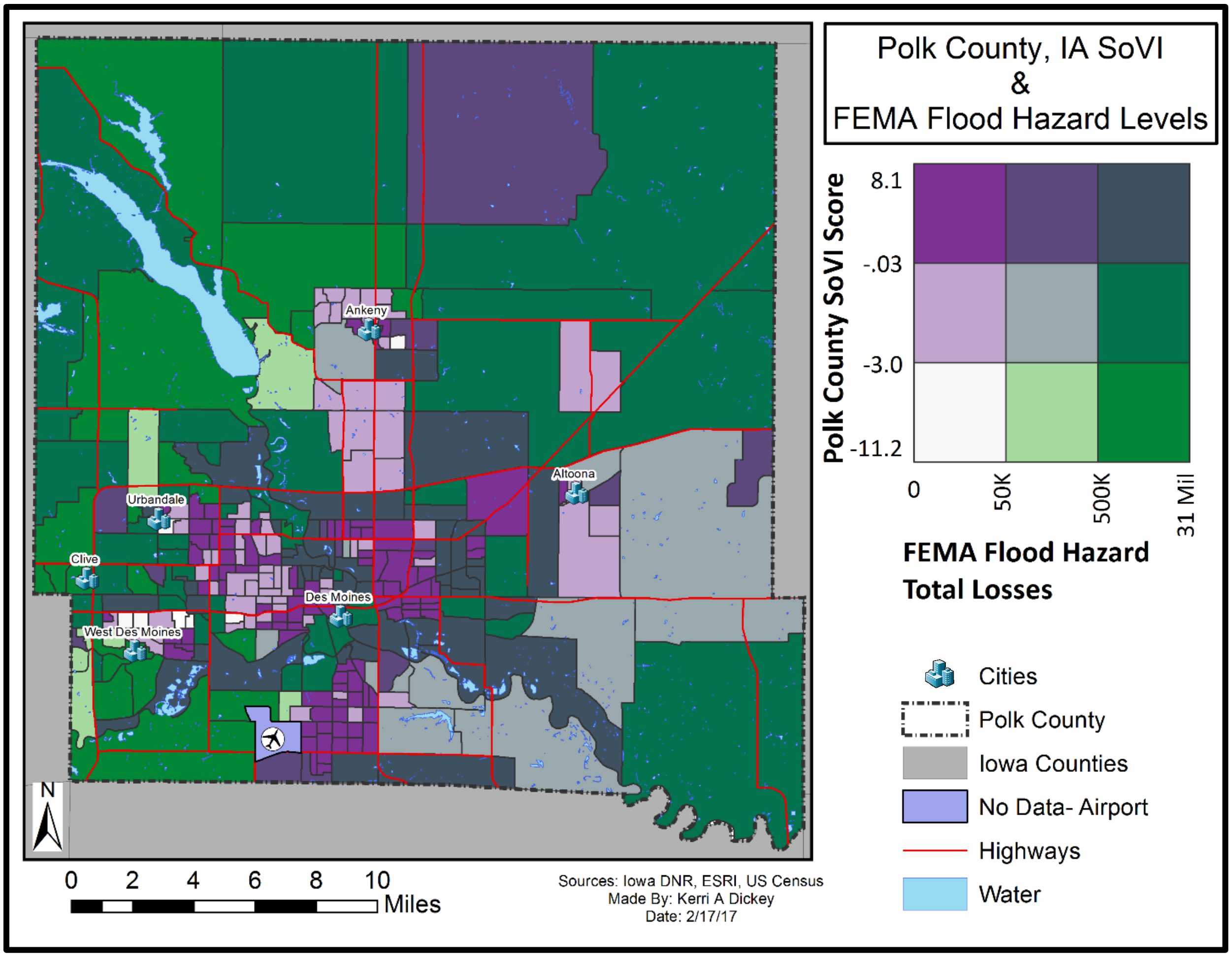

Figure 25: Bivariate choropleth map of Polk Co, IA SoVI and FEMA Flood Hazard Levels.

The findings from the statistical test, correlation and geospatial overlay suggest that the most socially vulnerable places in Polk County and the physical locations most exposed to flooding do not always spatially intersect. The correlation test even seems to suggest that to some extent when economic losses are the highest SoVI scores decrease. This finding is effectively congruent with findings from the literature in social vulnerability and environmental justice. These results concur specifically with the results from the Cutter and colleagues' (2000) Georgetown County, South Carolina case study as well as conclusions from Wisner et al, 2003 and other's asserting that "potential high damages do not represent high vulnerability. Vulnerability is most related with the lack of skills of an individual or a community to anticipate, cope with, resist and recover from the flooding impact"

(Cançado et al. 2008, p. 8). The FEMA flood risk areas are determined by reported economic losses (the maximum total losses), which are very large in some areas which coincide with populations who have more financial resources and insurance to assist in recovering from a flood. Thus, although monetary damages might be greater in these areas of high FEMA flood risk, the findings are compatible with previous findings that the populations residing in these areas have lower social vulnerability (a spatial vulnerability paradox). Correspondingly, one can theorize that it would only take a nominal to moderate flood event to displace the security and welfare of the majority of the medium to high level socially vulnerable populations. These populations might not reside directly in the highest area of FEMA designated risk based on past loss amounts, but their lack of skills and abilities to cope with and overcome a flood event thwart their continuing recuperation efforts from previous and or future disasters, and could result in higher casualty rates. This is the difference between the forces of nature and the forces of culture, of social, political, and historic power. There is an old saying that "water flows uphill to power and money" and in this a good example of how the physical expression of something is not always what ends up hurting our population the most. What hurts people for longer is the social expression of a natural disaster.

Given the lack of quality data on exact locations and causes of casualties associated with flood events, these assumptions cannot be tested directly in this study. Other information gathered off of spatial boundaries as it pertains to flood risk and vulnerability will be very inconclusive because of the finding in this paper suggesting that in Polk County Iowa there is a spatial paradox occurring with flood disparities. It is now imperative that Polk County's hazard mitigators, legislators, and policy creators change the way they think about flood mitigation if they want to help the most vulnerable populations recover. One would also seriously caution FEMA from producing their flood risk level boxes unless they start explicitly suggesting that these maps are only showing physical flood risk, because as we have found here the source of the hazard is not always where the most destruction is found.

4.2- Environmental Justice Approach: Present Data

Whereas the previous section outlined broad relationships between the composite social vulnerability index and flood hazard areas, this section addresses research question 2.1 by exploring how key individual vulnerability variables compare for block groups that intersect with flood risk zones versus block groups that do not intersect with flood risk zones. This methodology applies an approach typically seen in environmental justice research, which does not use composite indices. Variables chosen for in-depth analysis were those that were highly correlated with the nine retained components from Chapter 3, and that have been historically associated with environmental justice contexts involving unequal exposure to a range of environmental hazards. Thirteen variables were tested against the Flood Zone variable, and the tests resulted in eight variables that had significantly different values (at the 5% significance level) depending on their spatial intersection with the flood zone: QBLACK, QFAM, QRICH, PERCAP, QFHH, QMOBILE, QEXTRACT, AVGTRAVL. Three additional variables were valuable at the 10% significance level: QESL, QNOHLTH, and QRENTERS (*Table 9*). As mentioned in Chapter 2, the Mann-Whitney U test for independent samples was used to determine statistically significant differences between block groups intersecting the flood zones and block groups that do not intersect the flood zones.

Table 9: Mann-Whitney U Test & 2014 Individual Variable Correlation test.

Variable	Null Hypothesis	Sig.	Decision	FLDZone – NO Mean- Median		FLDZone – YES Mean -Median	
QBLACK	The distribution of the variable is the same across FLDZone	.018**	Reject	10.53	5.59	6.77	2.97
QFAM	The distribution of the variable is the same across FLDZone	.046**	Reject	20.02	20.00	23.63	22.17
QRICH	The distribution of the variable is the same across FLDZone	.000**	Reject	5.63	2.61	9.99	6.64

Table 9 (cont.)

Variable	Null Hypothesis	Sig.	Decision	FLDZone – NO Mean- Median		FLDZone – YES Mean -Median	
PERCAP	The distribution of the variable is the same across FLDZone	.007**	Reject	26,944	26,045	30,977	29,879
QESL	The distribution of the variable is the same across FLDZone	.091*	Retain Null	3.82	1.65	3.16	0.00
QFHH	The distribution of the variable is the same across FLDZone	.036**	Reject	20.31	19.60	19.03	18.13
QNOHLTH	The distribution of the variable is the same across FLDZone	.077*	Retain Null	9.34	8.56	8.08	5.86
QRENTER	The distribution of the variable is the same across FLDZone	.066*	Retain Null	31.36	25.84	28.08	22.50
QMOBILE	The distribution of the variable is the same across FLDZone	.000**	Reject	0.00	0.46	0.00	1.30
QEXTRACT	The distribution of the variable is the same across FLDZone	.001**	Reject	0.00	0.46	0.00	1.27
QFELABOR	The distribution of the variable is the same across FLDZone	.785	Retain Null	64.63	61.92	65.01	61.01
QHHNOCAR	The distribution of the variable is the same across FLDZone	.136	Retain Null	6.30	4.17	6.03	2.93
AVGTRAVL	The distribution of the variable is the same across FLDZone	.041**	Reject	19.58	19.37	20.54	20.20
Statistical significance: one asterisk significance at 10% and two for 5%.							

The tests for the individual variables largely corresponded with the results for the analysis of the SoVI composite QFAM, QRICH, PERCAP, QMOBILE, QEXTRACT, and AVGTRVL and were consistently higher for block groups that intersect the flood zones. The most interesting results are for QFAM, QMOBILE, QEXTRACT, and AVGTRVL since previous knowledge from research question 2 in this matter would suggest persons with higher incomes are more resilient to flooding thus QRICH was not investigated further in this study. These variables are of interest specifically because QFAM consists of age dependent persons who would need assistance in the case of an emergency. QMOBILE is of interest because the lack of mobile homes was noted in the PCA meaning that areas where mobile homes are found could contain, older adult persons, and persons trying to save money who might need tremendous financial support and could be low income. Finally, QEXTRACT & AVGTRVL were included in Component 5 & 8 in the PCA potentially increasing their vulnerability to natural disasters. It is also important to note that even though some of the variables were not found inside the floodplain as anticipated by classic environmental justice understandings, QBLACK, QESL, QFHH & QFELABOR are still variables of high importance. These variables are potentially experiencing the same spatial paradox as exhibited in the SoVI testing, and thus it is difficult at this time to suggest any solid conclusions about these variables, based on the testing completed in this thesis. In general, the findings seem to run counter to a classic environment justice premise that discrimination and poverty are found in higher risk zones. It is possible that when the hazard has to do with flooding/water, it does not matter if one is on the coast or near a river, risk capable populations can flock to more risky areas because they can mitigate that risk. The "at-risk" populations leave the riskiest water areas because it is the most intelligible thing to do to mitigate the risk of losing everything. It is possible that this creates a chain reaction. Disenfranchised people, maybe they do move into high risk flood areas, but after a flood they cannot afford to move back leaving all of the rather cheap land sitting vacant. Risk capable populations move in and buy up the land, build expensive homes on high risk areas and now economic losses and damages skyrocket the next time there is a flood because this area appears to be more at risk then it previously was. This is just one possible scenario of what could be happening to cause this spatial paradox.

4.3- Environmental Justice Approach: Historical 1990 Data

Lastly, this thesis examines the results in order to answer research question 3 on how key historical individual vulnerability variables compare for block groups that intersect with flood risk zones versus block groups that do not intersect with flood risk zones. Using the same variables for the previous run, minus the QNOHLTH, the historic variables were tested against the FldZone90 variable, and the test presented 9 variables displaying a significance level of at least 5%: QBLACK,

QFAM, QRICH, QFHH, QRENTERS, QMOBILE, QFELABOR, QEXTRACT, and QHHNOCAR (*Table 10*). Other variables in the 6%-10% significance range were: QESL and AVGTRAVL (*Table 10*).

Table 10: Mann-Whitney U Test & Historic 1990 Individual Variable Correlation test.

Variable	**Null Hypothesis**	**Sig.**	**Decision**	**FLDZone – NO Mean- Median**		**FLDZone – YES Mean -Median**	
QBLACK90	The distribution of the variable is the same across FLDZone90	.000**	Reject	8.61	1.77	3.12	0.87
QFAM90	The distribution of the variable is the same across FLDZone90	.000**	Reject	49.19	52.33	57.44	57.14
QRICH90	The distribution of the variable is the same across FLDZone90	.007**	Reject	5.14	2.30	8.71	3.66
PERCAP90	The distribution of the variable is the same across FLDZone90	.148	Retain Null	13,849	13,265	15,158	13,231
QESL90	The distribution of the variable is the same across FLDZone90	.082*	Retain Null	3.48	0.93	2.32	0.00
QFHH90	The distribution of the variable is the same across FLDZone90	.000**	Reject	13.56	12.79	10.57	9.97
QRENTER90	The distribution of the variable is the same across FLDZone90	.001**	Reject	35.64	27.72	28.66	23.17
QMOBILE90	The distribution of the variable is the same across FLDZone90	.008**	Reject	2.09	0.66	5.87	0.93
QFELABOR90	The distribution of the variable is the same across FLDZone90	.020**	Reject	46.28	47.35	43.18	46.23
QEXTRACT90	The distribution of the variable is the same across FLDZone90	.042**	Reject	3.06	0.00	5.27	1.28
QHHNOCAR90	The distribution of the variable is the same across FLDZone90	.000**	Reject	9.40	6.83	6.66	2.89
AVGTRAVL90	The distribution of the variable is the same across FLDZone90	.071*	Retain Null	18.35	18.37	18.34	18.97
Statistical significance: one asterisk significance at 10% and two for 5%.							

Yet again, the test for the historical individual variables seem to be corresponding with the two previously run tests and the idea that a spatial paradox is and has been occurring. QFAM90, QRICH90, QMOBILE90, QEXTRACT90, AVGTRVL90 are variables occurring inside of the flood zone historically, and as one previously noted the main interest to draw any conclusions from this method is in the variables QFAM, QMOBILE, QEXTRACT, and AVGTRVL. Finally, one can perform a comparison of the environmental justice variables for 1990 and the present and can thus suggest that given the data in this experiment married couples with dependent children, persons living in mobile homes, persons working in extractive services and persons with increased travel times to work have been historically vulnerable groups with increased exposure to flood hazards for the last 27 years. Due to the findings of research question two and the understanding that there is a spatial paradox occurring with vulnerability variables and physical flood risk indicators, the results for the other environmental justice indicators are inconclusive at this time, but it is important to continue to advance the hypothetical and abstract understandings of the spatial elements of vulnerability though the interdisciplinary merger of multiple techniques.

4.4- Chapter 4 Conclusions

Findings in this chapter concluded that from the statistical test, correlation and geospatial overlay suggest that the most socially vulnerable places in Polk County and the physical locations most exposed to flooding do not always spatially intersect and that to some extent when economic losses are the highest SoVI scores decrease. Though, classic environmental justice ideas might have one expecting to see race/ethnic minorities and other disenfranchised communities such as lower income households, renters, mobile homes, single parents, and older adult persons would logically be closer to the origin of the disaster. But this study suggests there is a spatial vulnerability paradox occurring. Thus, the only findings this section of the study can suggest is, that given the data in this thesis, married couples with dependent children, persons living in mobile homes, persons working in extractive services and persons with increased travel times to work have been historically vulnerable groups with increased exposure to spatial/physical location of flood hazards for the last 27 years.

Previous findings in environmental justice literature suggest that there needs to be more research to inspect and calculate the potential harm associated with geographic risk as it pertains to "risk capable" and "at-risk" communities. Walker and Burningham (2011) note that spatial patterns of physical vulnerability to a hazard found in research data do not always accurately expose the inequalities that "at-risk" communities face. When beginning a study to find where there is a potential risk of flooding, we tend to concentrate on specific areas in the vicinity to rivers and other water bodies, spatial/geographic vulnerability, and it is easy to find who is living inside this easy to spot 'at risk' space and call it a day. Sometimes there are "at-risk" persons living in these areas, but who we tend to find living in these risky spaces are in fact not "at-risk" communities, because "at-risk" populations cannot afford to take such a reckless risk to live in such a place. This thus presents to us a spatial vulnerability paradox that can occur when one is looking at vulnerability as it pertains to natural hazards. When one looks at spatial/geographic vulnerability one is using informed judgment about the nature of a hazard (i.e. the hardest hit places will be closer to the origin). However environmental justice framework asks us to not only look at the forces of nature, but also the forces of culture.

Risk capable populations can afford to be reckless and put themselves at risk, because they can bounce back from a hazard and their recklessness is mitigated. Though these risk capable populations might live spatially closer to a natural disaster, the risk they end up taking on is actually less. Literature and research in environmental justice does suggest that over time "at-risk" populations move away from risky places in an attempt to mitigate risk, or because an event occurred and they could not recuperate from the losses and were forced to leave. One can start to study where a disaster originates, but if one finds that "at-risk" populations do not live in these areas, then one must confront the issue that we cannot continue to focus on where the disaster originates, but instead focus on how it travels through space and time across the cultural landscape. The author of this thesis will not make conjecture about the possible nature or linkages between present and historical variables that did not present themselves in this study as it pertains to the physical dissemination of flood risk and to concretely make a statement about any of those variables one would have needed to study the social, political, cultural, and historical issues of these variables not found in the flood area.

CHAPTER FIVE: CONCLUSIONS & FUTURE WORK

Vulnerability defined considering physical exposure or social-economical determinants alone cannot encompass the complexity of effects caused by the impact of a natural hazard on a group at risk. This study's effort was to encompass an interdisciplinary way of looking at social vulnerability to obtain a more holistic view of what is and was happening and consider new evidence of inequalities in flood exposure. This analysis is unavoidably preliminary due to the limitations of available historical data, the need to cover a sizable amount of diverse ground with block group level data, and underreporting of census information. Even with these limitations the study successfully identified factors in the statistical exploration that are analogous with current social vulnerability and environmental justice literature. This methodology explained almost 70% of the statistical variance using only 9 independent components and produced the first SoVI for Polk County Iowa and thus has expanded the available social vulnerability literature to include a Midwestern context. It would have been nice to have been able to weight some variables more heavily than others during the SoVI based on regional and local differences, but somehow seminal texts in vulnerability suggested that there was no justifiable logic in unequal weighting. It would seem that historically that there has never really been anything "equal" either spatially temporally, politically, or anything else for that matter in U.S. history. Something always comes before something else, so risk does not just spring forth and it most assuredly has not affected all persons equally throughout history. All things have history that is alive and we need to study how that history manifests itself in our world. The author thinks that there is ample historical prejudice to suggest in an American context that non-Caucasian persons and women have been systematically disenfranchised for so long that these categories should be weighted more heavily. Our present must be understood by our past, and sadly America has a long past in discrimination, biased treatment and prejudice against certain races and genders. This is a substantially large gap in the current literature in vulnerability, though it is not a gap in history and environmental justice and it requires further study.

This study was also capable of adding to the literature by way of adding a longitudinal component, with the comparison of the change of individual variables over time. This is something specifically that seminal social vulnerability literature called for in future works, and though many of the variables in this study were inconclusive at this point in time, it is possible that more conclusive answers can be found with continued historical reconstructions of variables. The gentrification and expansion of the Des Moines area has been occurring since the 90's so findings from this study suggest that a spatial vulnerability paradox is /has been occurring. It is imperative if this is the case, that one must widen the spatial location of risk from the present immobile boundary set forth and perpetuated by government entities, to a realistic flexible range of spatial locations that consider historical cultural forces and formulate new mitigation policies from these understandings. These findings are the exact reason why sometimes numbers do not always tell the full truth, and that they are not always the best language to communicate social phenomena like vulnerability, which is multi-faceted. This thesis also points to the use of multiple interdisciplinary methods being necessary to understand what is happening at this place and time. The numbers, statistics, and maps help us to understand that something is happening, but they are not explanations of the underlying issues. Other methods must be used moving forward to understand the perceptions and behaviors which are the root of the problems. Future work in this area would advance greatly from an ethnographic participant observation of the areas determined to be within the highest deviation of social vulnerability. This would help to create a triangulation of the multitude of interdisciplinary methods for studying protected populations and hopefully start a dialog with the populations that need the most assistance instead of the creation of more data. By the submersion of a researcher into the lives of the most socially vulnerable, we might be able to make hard, factual claims about what can be done to assist and continue to identify socially vulnerable populations. As preliminary as the work was, the implications of the work did suggest that a few variables (QFAM, QMOBILE, QEXTRACT, and AVGTRVL) represented vulnerable groupings of people that have been subjected to years and years of flood disasters with little assistance to become more resilient communities, decrease risk, and economic impact over time. It is important to note that even though some of the variables were not found inside the floodplain as the author might have anticipated based on environmental justice ideas, QBLACK, QESL, QFHH & QFELABOR were variables of high importance. But, because these variables were not found in the floodplain and this thesis was purely limited to studying what was found in the floodplain the author cannot make suppositions about variables which were not identified. Future research is needed in this area to research what cannot be seen from physical boundaries and there should be an ethnographic study of these vulnerable populations. Such findings can still be given back to the community and can be used to inform Polk County and City risk decision makers of the issues at hand. Recently the Iowa Flood Center (IFC) has built up a continuous surge guaging and data dispersal framework for use by all Iowans(Krajewski et al., 2016). The framework supplements the operational estimating issued by the National Weather Service, and depends on sound logical standards of surge beginning and spatial association, and incorporates numerous innovative advances. At its center is a consistent rainfall–runoff demonstrate in light of scene disintegration into hillslopes and channel joins(Krajewski et al., 2016). By using this SoVI, policy makers can use both the real time flood forecasting tool and social vulnerability information to change where assistance is dispatched first, where mitigation efforts are targeted in the future, and where community outreach information sessions should be held so that they can start making stronger, more resilient communities, today.

5.1- Limitations & Challenges

In addition to the challenges in expressing, measuring, analyzing, and likening social vulnerability, there are some specific considerations that are exclusive to flood hazard examination and vulnerability mapping. During the historical reconstruction of social vulnerability, changes in the spatial enumeration unit and the consistency of variables throughout time is a challenge that all studies that utilize the U.S. Census data run into. Self-reported data can be plagued with inconsistency, and it is close to impossible to obtain information in the study area about social vulnerability arising from social isolation and discrimination directed at persons identifying as gender fluid or sexuality minorities, or for persons or groups isolated and discriminated against based on lack of religious beliefs. Similarly, estimates of illegal immigrants, homeless, or LGBT youth discrimination are not widely available in the U.S. Moreover, the boundaries of flood hazard zones are necessarily easily compatible with those of census data containing socio-demographic information. As with any study using historical data, the data might not contain information that is currently gathered in the census, or to the level of detail that is required for the area. It is common for the census to add and subtract questions over many years, as well as changing of the boundaries in which the data was recorded. These types of challenges with historical data can never be truly overcome in future studies since we must work with the data that was obtained in the past. Nevertheless, studies using historical data help to provide a vital picture of how the study area once looked and if biases to groups of socially vulnerable people have persisted throughout time.

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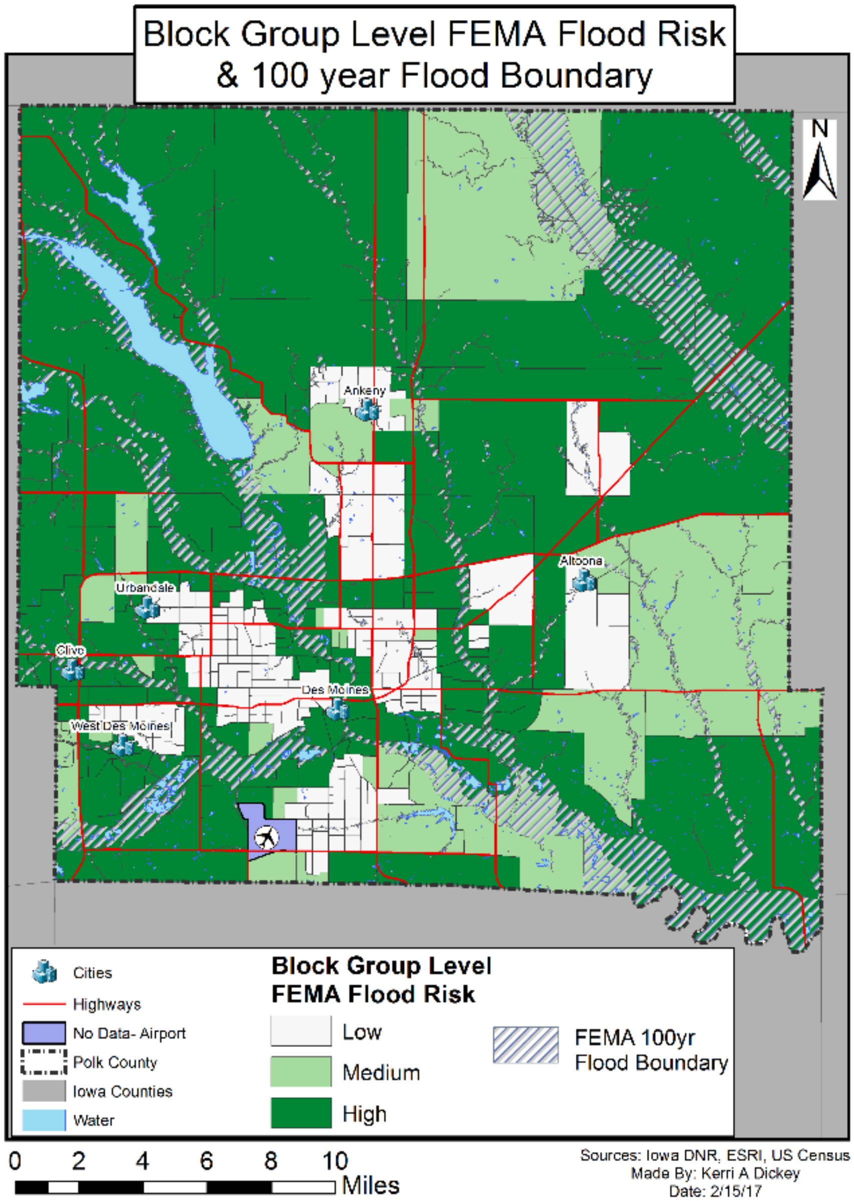
APPENDIX I – BLOCK GROUP LEVEL FEMA FLOOD RISK



Block Group Level (BGL) map with the FEMA Flood Risk levels integrated into the BGL for analysis, with the present 2014 FEMA 100 year flood boundary.

APPENDIX II - FULL CORRELATION MATRIX

	QNURSRES	QNOHLTH	QEDU12LES	QCVUNEMPL	PPUNIT	QRENTER	QMOBILE	QEXTRACT	QBLUECOL
QASIAN	.011	.086	.247**	.035	.048	.244**	.012	-.127*	.007
QBLACK	.035	.439**	.556**	.415**	.224**	.441**	-.043	-.134*	.229**
QHISP	-.001	.641**	.677**	.343**	.290**	.340**	.086	-.008	.276**
QNTAM	.112	.266**	.236**	.184**	-.052	.254**	-.048	.015	.015
QPOPAGEDEP	.242**	-.145*	-.004	-.060	-.139*	-.148*	.103	-.040	-.013
QFAM	-.108	-.268**	-.200**	-.122*	.616**	-.451**	-.093	.024	-.043
MEDAGE	.187**	-.279**	-.366**	-.293**	-.406**	-.445**	-.019	.110	-.147*
QSSDEP	.197**	-.076	.024	.031	-.141*	-.218**	.053	.045	.059
QESL	.110	.505**	.548**	.130*	.059	.433**	.050	-.006	.215**
QFEMALE	.078	-.042	-.006	-.058	.015	-.085	-.054	-.159**	-.145*
QFHH	.116*	.127*	.065	.044	-.612**	.352**	.018	-.082	-.096
QNURSRES	1	.051	.048	-.062	-.141*	.098	-.017	-.073	.079
QNOHLTH		1	.594**	.426**	.090	.405**	.081	-.026	.326**
QEDU12LES			1	.470**	.240**	.397**	.058	-.068	.278**
QCVUNEMPL				1	.272**	.263**	-.007	-.160**	.253**
PPUNIT					1	-.255**	-.061	-.053	.164**
QRENTER						1	-.005	-.140*	.051
QMOBILE							1	-.025	.091
QEXTRACT								1	.150**
QBLUECOL									1

Appendix II cont.

	QASIAN	QBLACK	QHISP	QNTAM	QPOPAGEDEP	QFAM	MEDAGE	QSSDEP	QESL	QFEMALE	QFHH
QASIAN	1	.183**	0.068	0.009	-0.059	0.05	-.193**	-0.094	.371**	-0.054	-0.025
QBLACK		1	.391**	.209**	-0.104	-.208**	-.422**	-.164**	.365**	0.006	0.102
QHISP			1	.237**	-0.075	-.135*	-.373**	-0.067	.566**	0.025	-0.016
QNTAM				1	-0.101	-.208**	-0.076	0.005	.134*	-.138*	0.059
QPOPAGEDEP					1	-.134*	.345**	.695**	-0.1	.156**	.158**
QFAM						1	-0.101	-.211**	-0.108	-0.024	-.567**
MEDAGE							1	.486**	-.272**	0.057	.173**
QSSDEP								1	-.142*	0.026	.119*
QESL									1	-0.087	-0.026
QFEMALE										1	.267**
QFHH											1

	QSERVC	QFELABOR	QHHNOCAR	QNOPPLHH	AVGTRAVL	QPOVRTY	QRICH	PERCAP	MEDHVAL	MEDRENT
QASIAN	.144*	-.039	.113	.097	.094	.109	-.092	-.110	-.109	.082
QBLACK	.260**	.359**	.314**	.296**	.047	.621**	-.331**	-.482**	-.393**	.090
QHISP	.379**	.371**	.256**	.307**	.030	.486**	-.348**	-.520**	-.426**	.109
QNTAM	.155**	.123*	.220**	.038	-.018	.302**	-.163**	-.205**	-.158**	.061
QPOPAGEDEP	-.063	-.107	.082	.020	-.083	-.121*	-.077	.039	-.055	-.051
QFAM	-.183**	-.062	-.378**	-.226**	.170**	-.342**	.469**	.243**	.451**	-.198**
MEDAGE	-.213**	-.316**	-.065	-.166**	-.137*	-.487**	.326**	.525**	.283**	-.208**
QSSDEP	-.114*	-.060	.131*	.009	-.072	-.127*	-.048	.056	-.085	-.015
QESL	.385**	.097	.325**	.337**	.092	.362**	-.261**	-.348**	-.302**	.065
QFEMALE	.035	.406**	-.049	.033	-.096	-.014	.004	.014	.042	-.077
QFHH	.090	.066	.391**	.113	-.181**	.144*	-.328**	-.110	-.243**	.145*
QNURSRES	.067	-.043	.195**	.111	-.010	-.010	-.050	.005	-.033	-.003
QNOHLTH	.434**	.290**	.299**	.304**	0.085	.497**	-.434**	-.532**	-.451**	0.072
QEDU12LES	.379**	.400**	.383**	.299**	.179**	.570**	-.453**	-.631**	-.536**	.123*

Appendix II cont.

	QSERVC	QFELABOR	QHHNOCAR	QNOPPLHH	AVGTRAVL	QPOVRTY	QRICH	PERCAP	MEDHVAL	MEDRENT
QCVUNEMPL	.176**	.549**	.247**	.167**	0.105	.526**	-.345**	-.520**	-.405**	.119*
PPUNIT	0.026	.301**	-.285**	0.006	.237**	0.11	.144*	-.230**	0.071	-0.064
QRENTER	.333**	.205**	.572**	.304**	-0.036	.601**	-.411**	-.394**	-.389**	.267**
QMOBILE	.129*	-0.045	-0.017	-0.02	0.056	.117*	-0.095	-0.106	-.232**	-0.071
QEXTRACT	-0.067	-0.112	-0.082	-0.074	0.016	-0.074	0.098	0.11	.142*	-0.04
QBLUECOL	0.034	0.09	0.046	0.069	.335**	.191**	-.352**	-.427**	-.324**	0.056
QSERVC	1	.170**	.204**	.302**	-0.031	.300**	-.289**	-.330**	-.316**	0.006
QFELABOR		1	.286**	.186**	0.027	.515**	-.195**	-.396**	-.250**	0.018
QHHNOCAR			1	.246**	-0.044	.463**	-.280**	-.287**	-.391**	0.038
QNOPPLHH				1	-0.016	.289**	-.230**	-.246**	-.328**	0.047
AVGTRAVL					1	-0.021	-0.101	-.191**	-0.079	0.048
QPOVRTY						1	-.407**	-.575**	-.493**	0.095
QRICH							1	.828**	.783**	-.360**
PERCAP								1	.760**	-.244**
MEDHVAL									1	-.223**
MEDRENT										1

ABOUT THE AUTHOR

Kerri Dickey moved to Florida in 2012 after graduating Magna Cum Laude at the University of Northern Iowa with her Bachelor's in Earth Science and minors in Meteorology and Geography. Working in Parks & Recreation in Orlando Kerri disliked the injustice she saw unfolding in disenfranchised communities near her and it prompted her to pursue her master's degree. Kerri was born in to a working-class family in a small town that is predominantly white, religious, male dominated, and anti-gay. Despite these early obstacles Kerri, as a Secular-Gay-Woman, is an outspoken advocate for racial justice, human rights, secular government & policies, and LGBT+ rights which continues to push her to work on social vulnerability and environmental justice issues. Kerri looks forward to starting work in her career field, and eventually moving back to a four-season state with her fiancée, Jillian, and her two grey cats. She wishes to continue working, advocating, and writing wherever life might take her and is currently pursuing careers in intelligence and geospatial sciences in both the private and government sectors.