Analyzing Climate Change and Extreme Weather Event Impacts on Human Migration and Vulnerability in the Southeastern United States (2004-2018)

by

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Abstract

There is growing concern about how extreme environmental events and climate change will impact communities, both urban and rural, in the Southeastern United States (SEUS). A changing climate is expected to force individuals within the southeast to migrate to seek refuge from rising seas, increasing temperatures, and other environmental consequences. This study analyzes migratory trends into seven southeast United States counties: Fulton County, Georgia, Mecklenburg County, North Carolina, Jefferson County, Alabama, Muscogee County, Georgia, Richland County, South Carolina, Houston County, Georgia, and Lowndes County, Georgia. Particularly, if any trends indicate migration influenced by climate hazards; and if individuals are moving into more, equally, or less climatically vulnerable destinations. Moreover, this study seeks to better understand the spatial and temporal trends in climatic vulnerability throughout the contiguous United States (CONUS). The results of this study can be used to bolster destination counties [and corresponding urban areas] to have adequate resources available and the adaptive capacity to integrate displaced individuals into their communities.

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List of Abbreviations

Abbreviation	Definition
CONUS	Contiguous United States
CVI	Climate Vulnerability Index
DFL	Distributive Flow Lines
EHSA	Emerging Hot Spot Analysis
EPA	Environmental Protection Agency
EVI	Exposure Vulnerability Index
FEMA	Federal Emergency Management Agency
FHH	Female-Headed Household
HVI	Hazard Vulnerability Index
IDP	Internally Displaced Person
IPCC	Intergovernmental Panel on Climate Change
IRS	Internal Revenue Service
PCA	Principal Component Analysis
MAUP	Modifiable Areal Unit Problem
NGO	Non-governmental organization
NLCD	National Land cover data
NRI	National Risk Index
NRT	National Science Foundation Research Traineeship
NSF	National Science Foundation
NYT	New York Times
SDM	Structured Decision Making
SEUS	Southeast United States
SOI	Status of Income
SVI	Social Vulnerability Index
UCA	Urban Climate Archipelago
UN	United Nations

NSF Reporting Statement

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Addendum

The lead author would like to make the reader aware that the data utilized to create the Climate Vulnerability Index (CVI) and perform migratory analysis spans between 2003-2018, rather than 2004-2018. Changes have been made within the table of contents, figures and paper body to reflect this. (BJR – 7.10.2023)

Chapter 1

Introduction and Literature Review

1.1 Introduction

A 2022 report by the Intergovernmental Panel on Climate Change (IPCC), concluded that humans have unequivocally, "warmed the skies, waters, and lands, and that widespread and rapid changes have already occurred in every inhabited region across the globe. Many of these changes are irreversible within our lifetimes" (Irfan 2021). Many scientists are throwing away the best-case scenario of RCP 1.9, limiting the global temperature to below 1.5 °C, due to continued "status-quo" of greenhouse gas emissions. These warming temperatures have been linked to an increase in climate-related disasters over the past decade, like the wildfires in California, deadly floods in China and Europe, and record heat waves in northern Siberia (Irfan 2021). Moreover, droughts are expected to become more frequent throughout the United States and the world in the future (Lee et al. 2016). Recent events across the United States and elsewhere around the world have shown that droughts can develop very rapidly if extreme weather anomalies persist over the same region for several weeks to months (Zargar et al. 2011).

This increase in climate-related weather events over the past decade, and into the future, are expected to force millions away from their homes. It is estimated that roughly 25 million to 200 million environmental migrants are expected to move within their countries and across borders by 2050 (Kamal 2017). In 2015 alone there were roughly 244 million migrants worldwide (International Committee of the Red Cross 2017). Many, not all, migrants are likely to be fleeing a vulnerable situation and while all migrants are not inherently vulnerable, they may experience poor transportation conditions while traveling, unwelcoming conditions at their destination, or due to personal characteristics such as age, gender identity, race, disability, or health status (Office of the High Commissioner for Human Rights 2022).

Figure 1.1. Central American migrants ride atop a freight train during their journey towards the U.S.-Mexico border, Tuesday, April 23, 2019. From Stevenson and Perez (2019)

Migrants in Mexico, for instance, frequently hop a train known as “La Bestia” (Figure 1.1), which is a 1,450-mile journey from the southern state of Chiapas northward to the state of Veracruz (Stevenson and Perez 2019). This forced migration stems from the United States and Mexico’s increased enforcement efforts on large caravans, the United States War on Drugs in Central America, and poor economic and agricultural production within the region. One important thing to know is that cracking down on migration does not inhibit people from moving, rather, it just forces people to take more dangerous methods of travel.

Migrants are also likely to find themselves in a vulnerable situation when they arrive at their destination. When migrants reach their destination, they are likely to be met with discrimination, inequality, and structural and societal dynamics that lead to diminished and unequal levels of power and enjoyment of rights (Office of the High Commissioner for Human Rights 2022). Furthermore, migrants may struggle to integrate or find social networks within their new community. Presently roughly 60% of the world's refugees reside in urban areas, and in some instances, they are a more representative population than "traditional" minority populations (Park 2016). According to the United Nations, roughly 70 percent of the world's population will be living in urban areas by 2050 (United Nations Department of Economic and Social Affairs 2018). These urban centers face threats of increased poverty, greater air pollution, and environmental degradation (National Geographic 2009). A report by the World Bank on cities and related flooding events emphasizes that urban flooding, for instance, is becoming more dangerous and economically damaging simply because of the huge population (Jha et al. 2012).

Currently, few studies attempt to show a relationship between extreme climatic events and migration (Black et al. 2013). Moreover, to our understanding, there are no studies that attempt to analyze the relationship between hazards, migration, and vulnerability. This study takes an interdisciplinary approach by combining the physical and social aspects of vulnerability and attempts to determine where vulnerable populations are within the United States through the creation of a novel Climate Vulnerability Index (CVI). This study also proposes the utilization of new methodologies and tools, such as the *Emerging Hot Spot Analysis (EHSA)* tool (ESRI 2021), which have never been previously employed in vulnerability and migration studies, as to the knowledge of the authors, to act as a foundation and catalyst for future studies.

1.2 Study Area

This project has two different study areas. For Chapter 2, climatic vulnerability was assessed at the county level for the contiguous United States (CONUS). Chapter 3 specifically focuses on seven Southeastern United States (SEUS) counties, which encompass varying urban center sizes. The seven counties, major urban area, state, metro population, and city classification, can be seen below in Table 1.1 and Figure 1.2. The seven counties of interest are Fulton County (Atlanta, Georgia), Mecklenburg County (Charlotte, North Carolina), Jefferson County (Birmingham, Alabama), Muscogee County (Columbus, Georgia), Richland County (Columbia, South Carolina), Lowndes County (Valdosta, Georgia), and Houston County (Dothan, Alabama). City size is based on The National Center for Education Statistics definition of, “a large city as an Urbanized Area with a population of 250,000 or more; medium cities have a population between 100,000 and 250,000 with small cities having a population below 100,000” (National Center for Education Statistics 2022). The seven counties of interest were chosen for this study as they are more urbanized counties and are more likely to be potential destinations for displaced individuals.

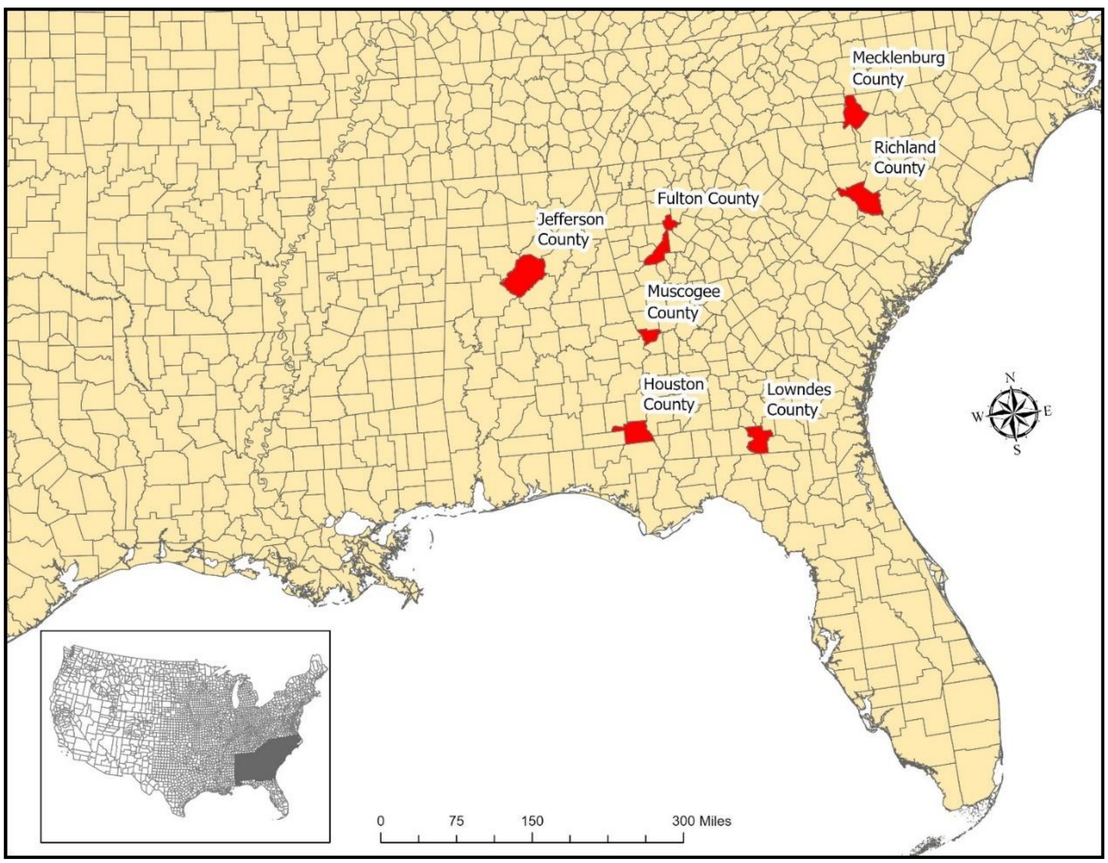
The SEUS, and these counties specifically, are of particular interest for vulnerability and migration studies due to the frequency of hazardous weather events in the region, the surging population within the southeast, and because it houses large populations of communities of color and those in poverty (Carter 2014). 2020 marked the slowest population growth in the United States, 7.4%, since 1930; however, specific regions of the United States have seen population growth over this period. Florida, Georgia, and South Carolina all saw their populations grow between 10-15% (Pendall 2010). This growth is also expected to continue into the future; Atlanta, Georgia could grow to 6.5 million residents by the year 2030, Raleigh and Charlotte, North Carolina, would top 2.7 million by 2030; and Birmingham, Alabama, and Columbia, South

Carolina, are expected to each exceed 1 million residents (Pendall 2010). This exponential population growth has put and will potentially put more people in high-risk disaster areas.

Table 1.1. List of the seven counties of interest, the corresponding urban center in the county, state, metro population of the urban center, and city size classification.

County	City	State	Metro Population	City Size
Fulton	Atlanta	Georgia	488,800	Large
Mecklenburg	Charlotte	North Carolina	857, 425	Large
Jefferson	Birmingham	Alabama	212,297	Medium
Muscogee	Columbus	Georgia	197,485	Medium
Richland	Columbia	South Carolina	133,273	Medium
Lowndes	Valdosta	Georgia	56,095	Small
Houston	Dothan	Alabama	57,894	Small

Figure 1.2. Area of interest map for the seven counties of interest. These are: Fulton County, Georgia; Jefferson County, Alabama; Mecklenburg County, North Carolina; Richland County, South Carolina; Muscogee County, Georgia; Houston County, Alabama; and Lowndes County, Georgia.



The southeast is also extremely susceptible to the effects of climate change, like sea-level rise and extreme heat, and is home to many populations who will disproportionately be impacted by climate change consequences. Temperatures in the Southeast are expected to rise by 2.2 °C through the next century, along with an increase in more intense droughts (KC Binita et al. 2015; Petkova et al. 2015). The southeast also has higher rates of those over the age of 65 and black Americans, compared to the national average, making it a region of extreme socioeconomic inequity. 142 of the 384 “persistent poverty counties”, whose average income is below the poverty line, are located within SEUS states (Petkova et al. 2015).

Furthermore, these climate impacts are expected to force individuals to migrate away from the region in the future. Hurricane Katrina, for example, a category 5 storm, caused catastrophic damage across Louisiana and Mississippi resulting in over 1 million displaced people (Plyer 2016). The Groundswell report on the impact of climate change on migration estimated that climate change could force more than 143 million people to move within their countries by 2050 (Clement et al. 2021). This forced movement is likely to further exacerbate many of the inequities existing within the SEUS. The disparity between small and medium-sized (SMSCs) and large cities, for instance, will put a strain on migrant destination cities to have adequate resources available for incoming migrants.

Buffalo, New York, and Duluth, Michigan, both small-sized cities, have been deemed a climate haven for future migrants, yet lost 20% and $20 million, respectively, of their revenue due to the COVID-19 pandemic (Poon 2020). With these budget shortfalls, we can see how difficult it may be for SMSCs to ensure there are adequate resources available for displaced migrants. Residents of these smaller communities are generally more vulnerable in the event a disaster strikes due to their diminished emergency response capabilities, lack of emergency medical care, poor hazard warning and emergency management, and poor infrastructure, which is likely to buckle if the population were to drastically increase (Cross 2001).

1.3 Explanation of Spatial Methods

1.3.1 Create Space Time Cube from Defined Locations

The *Create Space Time Cube from Defined Locations* tool is a tool located within the *Space-Time Pattern Mining* toolbox. This tool takes panel or station data, data which the locations geography does not change, and structures it into a NetCDF data format (ESRI 2021). Defined locations can be any polygon, so long as the boundaries remain the same from year to year. The defined locations for this study are United States County cartographic boundaries. Within this study, the CVI score for each county will be the data input and analyzed within the space-time cube. The structure of the data can literally be thought of as a cube (Figure 1.3). Structuring the data this way allows for the addition of a temporal component into the study.

Each bin is indicative of a single point or feature of data and has a unique (x,y) or latitude/longitude coordinate, which occurs at a given instance in time (Kang, Cho, and Son 2018). For this study, an individual bin indicates a single county, for a given year. A time slice indicates all bins which encompass the same time duration, such as the light blue bins selected in Figure 1.4. This time slice highlights all the bins which had data for 2008. A bin time series allows for a single (x,y) location, or county, in this case, to be analyzed for trends over time. To create the space-time cube at least 10-time steps need to occur and each location must have its ID, date, and data attached to it. One benefit of this tool is the ability to set any time step interval; for this study, a time step interval of one year was chosen, with the lowest possible interval being 10 seconds (ESRI 2021).

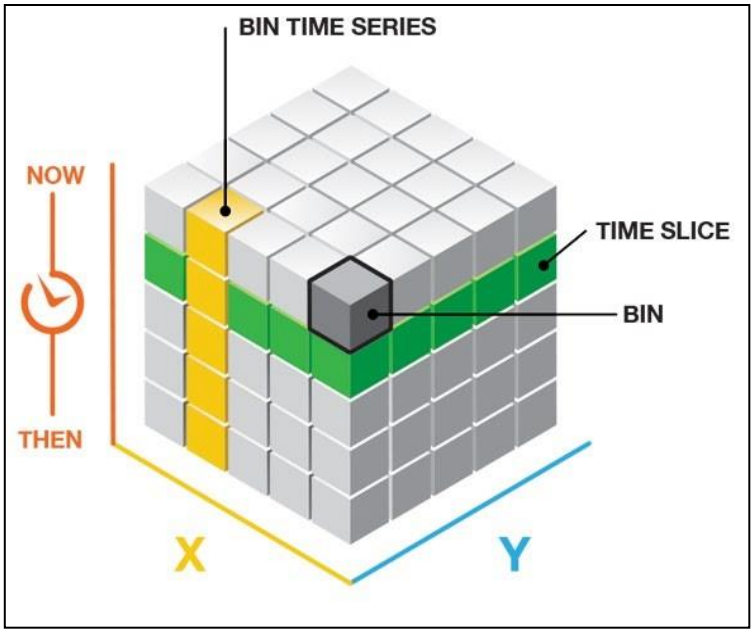


Figure 1.3. Visualization of the NetCDF output from the Create Space Time Cube from Defined Locations tool (ESRI 2021).

1.3.2 Emerging Hot Spot Analysis (EHSA)

The *Emerging Hot Spot Analysis* (EHSA) tool is another tool within the *Space-Time Pattern Mining* toolbox. This tool is based on *Getis-Ord Gi** statistic, which tells you where features with either high or low values cluster spatially (ArcGIS Pro 2.8). A statistically significant hot spot is one where a feature with a high value is surrounded by other features with high values. For this study, high areas of vulnerability will be indicated by hot spots, and low areas of vulnerability will be indicated by cold spots. This *Getis-Ord Gi** statistic outputs a z-score, the number of standard deviations above the mean, and a p-value, which tells us that certain features must be statistically significant and whether one can accept or reject the null hypothesis (Dahiru 2008; Iverson G.L.). The null hypothesis indicates that the underlying data occurs through complete spatial randomness, so a very high or low z-score with a very small p-value would indicate that we can reject the null hypothesis, or that we see statistically significant clustering. The tool compares each bin county to its temporal neighbors and determines where statistically significant hot and cold spots are within the cube for every year in the time series.

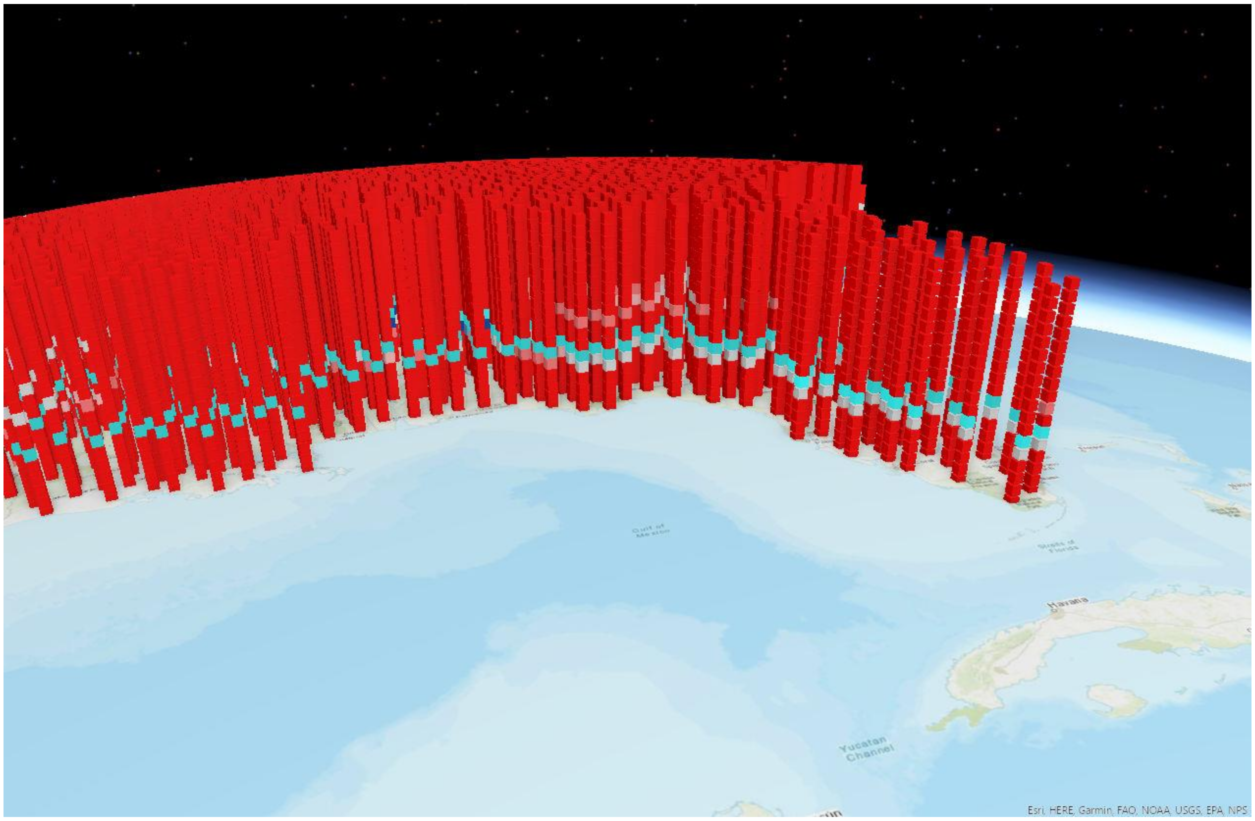


Figure 1.4. 3D ArcScene of the NetCDF output from the Create Space Time Cube from Defined Locations tool.

The EHSA then uses the Mann-Kendall statistic to determine statistically significant, temporal trends within the data. The tool begins by comparing the bin values of the same location, across two different periods. If the first period is smaller than the second, the result is +1. If the first is larger than the second, the result is -1, and if the two values ties, the result is zero (Mann 1945; Kendall 1990). To provide a more concrete example, after the *Getis-Ord Gi** statistic has been processed each bin county will either be assigned as a hot or cold spot. The Mann-Kendall statistic will then determine how the pattern of hot and cold spots within the bin, county, has changed from year to year. Let us say Lee County, Alabama has a CVI score of 0.7 in 2004 and a score of 0.75 in 2005. First, the *Getis-Ord Gi** statistic would likely determine that

Lee County, Alabama is a hot spot for both years. Then, the Mann-Kendall statistic would attribute that time step as a +1 since the data has increased between the two years. It then iterates this process for every bin in the cube, for each year in the time series.

Whether the trend is statistically significant is determined by summing up the results of the comparison of bin values. Each trend for each bin time series is given a z-score, if the trend is an increase in bin values (positive z-score) or a decrease in bin values (negative z-score), and a p-value, a small p-value indicates that the trend is statistically significant (ESRI 2021). Compared to the *Getis-Ord Gi** statistic, which only outputs if a location is a hot or cold spot with 90%, 95%, and 99% confidence intervals; EHSA, rather, outputs eight distinct hot and cold spot temporal trends, which indicate how the patterns of hot and cold spots have changed at a location, and how the underlying data at a particular location have changed over time.

To date, and the understanding of the authors, there have been few vulnerability studies that use EHSA. This tool has been used in previous studies within other disciplines, particularly within the forest conservation and wildlife management sectors. A study by Betty et al. (2020) used EHSA to analyze stranding data, an aquatic animal observed in an inappropriate location, of data-poor cetacean, marine mammal, species between 1978-2017. A similar study by Bass (2017) sought to use EHSA to understand manatee mortality rates in Florida between 1974-2012. Other studies which utilize EHSA include Harris et al. (2017); Golbon et al. (2019); Morckel and Durst (2021); Park et al. (2021); Fan et al. (2022); Roy (2022); and Xu et al. (2022). Although EHSA has not been used in vulnerability studies previously, the recent emergence of work utilizing the tool highlights the usefulness of EHSA, especially with datasets spanning long periods.

1.4 Vulnerability Background

1.4.1 Social Vulnerability

Vulnerability, defined as the potential for loss, is a predominant feature in hazard research (Cutter 1996). There are three distinct themes in which vulnerability can be categorized, vulnerability as a pre-existing condition, as a tempered response, or as a hazard of place. Vulnerability as a pre-existing condition examines the source of exposure to a biophysical hazard. Vulnerability as a tempered response analyzes the historical and cultural socioeconomic processes that influence a society's ability to cope with a disaster. Vulnerability as a hazard of place rather looks at vulnerability based on biophysical risk and social response (Cutter 1996).

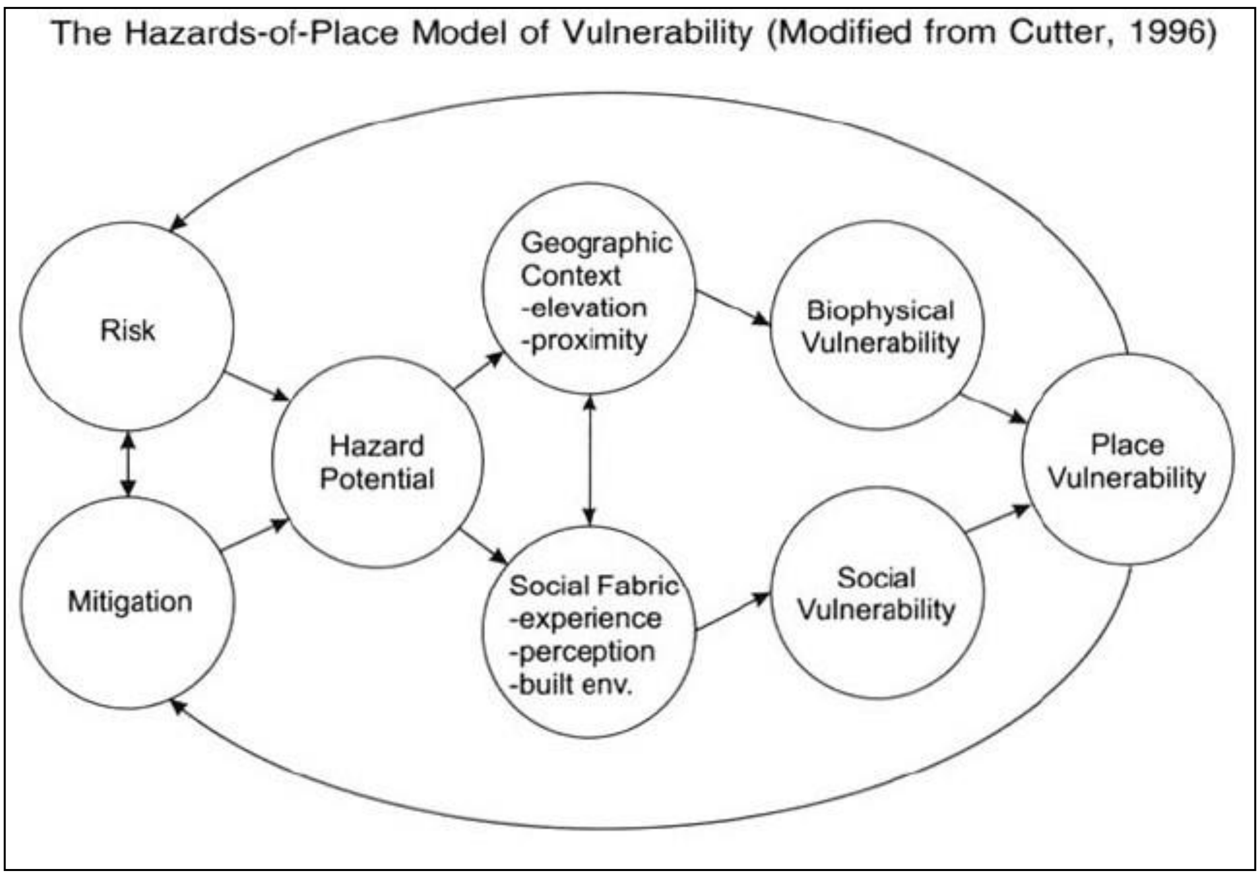


Figure 1.5. Visualization of the Hazards-of-Place Model from Cutter et al. (2003). This model posits that vulnerability stems from an individual's geographic or socioeconomic exposure to disaster risk.

As seen in Figure 1.5, this Hazards-of-Place model begins with risk or the likelihood of a certain event and the mitigation measures which are in place. Either there are enough mitigative measures in place to nullify the risk, or the risk is so great that it will overwhelm the mitigative measures. Geographic context encapsulates all the physical, biophysical, and manmade attributes which define a location. The social fabric consists of a community's experience with past risk, the demography, and the socioeconomic status of individuals which all contribute to one's vulnerability. Black Americans, for example, and other communities of color live in previous areas of historic redlining. Redlining was the racist housing practice in 1950 of outlining Black populations and deeming these areas more "hazardous" for mortgage lenders and other financial institutions to invest in (Shepherd 2020).

Comparatively, more white, affluent areas were outlined in green to indicate "safe" areas for institutions to invest in. This practice has since shaped the social, economic, and political status of neighborhoods today and has further exacerbated inequities in cities to this day. Many redlined neighborhoods today, like those in Dallas, Kansas City, and Baltimore, experience higher land surface temperatures and reduced amounts of exposure to greenness (Shepherd 2020). Other vulnerable populations include the economically disadvantaged, racial and ethnic minorities, the uninsured, low-income children, the elderly, the homeless, those with chronic health conditions, severe mental illness, and rural residents (American Journal of Managed Care 2006).

For this study, vulnerability will be defined according to the IPCC sixth assessment report which takes a different approach to vulnerability and risk. Whereas many vulnerability studies just focus on social vulnerability, the IPCC argues that climatic vulnerability and risk include weather and climate hazards, exposure of people to the hazards, and the vulnerability of exposed individuals (IPCC 2022). Climate hazards are direct consequences of climate change such as increased precipitation from hurricanes and prolonged drought. Exposure deals with who or what is at risk of climate change. Such as large amounts of coastal property, or dense populations in high-risk areas, like Californians residing in wildfire-prone areas. Lastly, the vulnerability of the exposed individuals is the socio-economic component. Marginalized communities already face many adverse health risks due to climate change or have been impacted in some way. Looking at all three components, although not a complete picture of the real world, paints a clearer example of vulnerability to climate change in the United States.

1.5 Previous Research

1.5.1 Migration & Mobility Studies

Migration and mobility studies encompass many different disciplines and topics due to the complex nature of migration, and the great impact it has on physical, economic, social, and political systems throughout the globe. The five main drivers of migration are push factors, a thing that force people away from their homes, pull factors, things that attract new people to a destination, network drivers, such as social or familial connections or transportation networks, national policies, and lastly, personal aspirations and motivations (Black et al. 2011; Semenza and Ebi 2019). While all these aspects of migration should be considered, many hazards and migration studies fall within the push and pull category since the environmental hazard itself is seen as the driving force behind the movement (Black et al. 2011). A study by Saldana-Zorilla and Sandberg (2009) for example, showed that emigration rates were higher between 1990 and 2000 for Mexican municipalities that had a higher frequency of disasters. Another study by Carvajal and Pereira (2010) found that households exposed to heavy rains associated with Hurricane Mitch, in Nicaragua, were more likely to have migrated afterward than those who were not exposed to heavy rains.

Other studies attempt to better understand how climate change consequences may be presently displacing individuals leading to a new type of ‘climate migrant.’ Gray and Mueller (2012) found that households living in an area impacted by crop failure were more likely to move, compared to those directly impacted by crop failure and those impacted by flooding. Whilst others, attempt to better predict how climate change will displace individuals in the future. Hauer, Evans, and Mishra (2016) investigate how future sea-level rise scenarios will impact growing populations along the United States coast. They found that roughly 4.2 million people could be at risk of 0.9 meters of flooding by 2100 due to population growth in vulnerable areas.

1.5.2 Vulnerability Studies

A review of literature by Jurgilevich et al. (2017) found that vulnerability assessments could be grouped into three major categories: 1.) publications discussing the concepts and methodologies of risk and vulnerability, 2.) Empirical case studies use an indicator or scenario-based methodologies, and 3.) studies that investigate the drivers and context behind vulnerability. Many studies, which fall under the second category, are largely influenced by the development of the SoVI® by Susan Cutter at the University of South Carolina. In 2003, they posited the idea to generate a quantifiable index to identify how socioeconomic status, and other social variables, impact an individual or communities’ capacity to be resilient to hazards and found that social vulnerability is influenced by an individual’s socioeconomic status, gender, race and ethnicity, age, or rural vs. urban (Cutter 2003). Other studies which utilize the SoVI®, or similar index, are Cutter and Finch (2008); Myers, Slack, and Singelmann (2008); Schmidtlein et al. (2008); Armaș and Gavriș (2013); Hardy and Hauer (2018); and Tellman et al. (2020).

There have been many attempts to push beyond the SoVI® index by generating new indices, hazard-specific indices, or by generating a multi-composite index with a social vulnerability component. A study by Cooley et al. (2012) attempted to better understand social vulnerability to potential climate impacts by generating a new vulnerability index. This index differs from SoVI® because it also integrates non-socioeconomic variables into itself. For example, Cooley et al. (2012) use impervious areas and tree canopy cover data, along with socio-economic variables, like those older than 86 and age under 18.

One major gap in vulnerability research studies assessing the temporal shifts in vulnerability. Many studies tend to look at a single year since assessments are used for planning and policy purposes, or because they are analyzing vulnerability to an event. Cutter and Finch (2008) sought to present empirical evidence on the spatial and temporal patterns of county-level vulnerability in the United States from 1960 to 2010; in which they generated a SoVI® index for 1960, 1970, 1980, 1990, 2000, and 2010. Another study by Monterroso-Rivas et al. (2018) attempted to discuss the scope of a multi-temporal vulnerability assessment by creating an agriculture-specific vulnerability index for Mexico from 1990 to 2010. Again, like Cutter and Finch (2008) the index was created at a decadal interval. While these studies are useful for gaining a broad understanding of how vulnerability has changed over time, it is not necessarily an accurate representation of this concept. Such large time steps between data can lead to a lot of errors and over-assumptions about how the vulnerability is changing over time. Moreover, a single year may have had an anomalous event or random population shift, which would make a county more vulnerable in that instance, but not for every year in the time frame.

1.6 Conclusion

Filippo Grandi, the UN High Commissioner for Refugees stated, “We need to invest now in preparedness to mitigate future protection needs and prevent further climate caused displacement. Waiting for disaster to strike is not an option” (United Nations High Commissioner for Refugees 2022). Hurricane Katrina alone impacted roughly 1.3 million people, and those that were socioeconomically disadvantaged or marginalized were more likely to relocate away from New Orleans, Louisiana after the storm. It is estimated that Houston, Texas, for instance, received an estimated 150,000 people from storm-affected areas in the year after Katrina (McLeman and Hunter 2010). If we can better understand where the at-risk communities are we can better-allocated resources and improve risk management and other services in these regions, so individuals are not forced from their homes. Moreover, if we know where individuals have migrated in the past as a response to these hazardous events, recipient cities can begin making infrastructure and policy and planning decisions to ensure that everyone, current residents, or new migrants, has equitable access to basic needs.

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Chapter 2

Analyzing the Spatial and Temporal Trends of Climatic Vulnerability throughout the Contiguous United States (2003-2018)

2.1 Introduction

The International Panel on Climate Change defines climatic risk as a consequence of climate hazards, exposure, and vulnerability (KC et al. 2021). The IPCC Sixth Assessment in 2022 highlights that there have been observed global changes in physical systems like land surface temperatures, sea levels, precipitation, droughts, and tropical cyclones. The report also states that many climate trends are projected to intensify across the globe, which increases the risk associated with physical systems (IPCC 2022). This increase in physical risk will then impact many other systems, such as the built, socioeconomic, and environmental. For instance, heat-related hazards are expected to affect humans' ability to work outdoors and disrupt global food chains and supplies (Pielke 2019). These impacts are not expected to be shared equally as communities of color, rural, coastal, and poor will face the brunt of climate impacts. Therefore, many scholars, non-governmental organization (NGOs), and governmental organizations have generated indices to attempt to quantify at-risk areas and populations. The Federal Emergency Management Agency (FEMA) has its own National Risk Index (NRI), which identifies the communities most at risk to 18 different natural hazards. Indices, like the NRI, can be extremely useful to inform decision-makers on where to prioritize resources, educate homeowners and communities, and enhance hazard mitigation plans (FEMA 2021).

A study by Borden et al. (2007) investigated the variability in vulnerability to natural hazards in 132 urban areas across the United States. To do this the study generated three separate vulnerability indices: social; comprised of gender, race, age, and socioeconomic variables, built environment; residential property, transportation infrastructure, and hazards/exposure; magnitude, hazard occurrence, and hazard type. They found that the top three most vulnerable cities were New Orleans, Louisiana, Baton Rouge, Louisiana, and Charleston, South Carolina all of which are in the American southeast. This study marks an early example of an index pushing beyond just social vulnerability and attempts to better replicate the dynamic nature of vulnerability to natural hazards.

Two studies by KC et al. (2015) and (2021), similarly, attempt to push beyond just analyzing social vulnerability, or looking at each aspect of vulnerability independently. Their 2015 study performed a decadal, county-level vulnerability analysis of the state of Georgia between 1975 to 2012. Here they created a composite index using variables such as temperature change, hazards, sensitivity, socio-economic drivers, education, per capita income, availability of physicians, and even irrigated land. They found that metro Atlanta, Georgia, southwest Georgia and coastal communities were at particular risk of the effects of climate change. Furthermore, in their 2021 study, they attempted to project climatic risk in the U.S. for 2040-2050. Again, a composite index was compiled using hazard; temperature, precipitation, heat waves, exposure; impervious surface, population; and social; socioeconomic drivers. They found that Florida, California, the Central Gulf Coast, and the North Atlantic will become the most at risk in the future.

The goal of this portion of the study is to showcase new methodological approaches for vulnerability assessments, which can be used by stakeholders, NGOs, and other academics. This was done by creating a novel, county-level Climate Vulnerability Index (CVI) for the contiguous United States and using EHSA to determine how vulnerability has changed over time from county to county. The objective of this study is to analyze and better understand the spatiotemporal trends in vulnerability to climate change throughout the United States. We seek to answer the research questions 1) Are there any clusters of climate vulnerability in CONUS between 2003-2018? Are there worsening, consistent, or new areas of climatic vulnerability, and why? And 2) Are individuals moving from climatically vulnerable counties into equally, less, or more vulnerable counties. Research Question 2 will be readdressed in Chapter 3.

2.2 Data & Methods

2.2.1 Data Management

2.2.1.1 Social Vulnerability Index (SVI)

Variables for the social vulnerability index were chosen based on what reliable data was available for every year in the time series and ones that are known to be heavily impacted by the effects of climate change. The list of social variables (Table 2.1) and the reasoning behind the selected variables can be found below. Positively correlated variables are ones in which vulnerability increases as the variable itself increases. For instance, if a county has a 65% poverty rate it would be considered more vulnerable than a county with a rate of 45%. Conversely, negatively correlated variables increase in vulnerability as the variable decreases. Median Household Income, for instance, is negative because a smaller income means one has less adaptive capacity than someone with a higher income.

Table 2.1. List of social variables used in the creation of the SVI, the variables vulnerability relationship (+ indicating as the variable increase, so does vulnerability and – indicating that as the variable decreases, vulnerability increase), and the source of each variable.

Variable	Relationship	Source
Population Below Age 5	+	U.S. Census
Population Above Age 65	+	U.S. Census
Black Population	+	U.S. Census
Hispanic Population	+	U.S. Census
Indigenous American Population	+	U.S. Census

Poverty Rate	+	SAIPE
Median Household Income	-	SAIPE

***-Population Below Age 5*:** Young children lack the knowledge, resources, and capacity to respond in the case of a disaster. Children become even more vulnerable when their parents are away (Centers for Disease Control and Prevention 2015). On average, 1.6 million children between the ages of five to 14 are home alone daily (Phillips and Hewett, Jr. 2005). UNICEF went as far as to create a Children Climate Risk Index and found that roughly 1 billion children live in “extremely high-risk” countries. This risk is a combination of climate change, environmental disasters, and lack of access to basic needs, healthcare, and education (UNICEF 2021).

-***Population Above 65***: Elderly populations are considered vulnerable since they are more likely to have physical mobility issues, health conditions, or socioeconomic limitations which impact their ability to adapt and respond to climate change and natural disasters (Centers for Disease Control and Prevention 2015). A poll taken in 2005 found that 13 million people over the age of 50 would require assistance evacuating during a disaster, with half requiring assistance from someone outside their home (Benson n.d.).

-Black Population: Black Americans are disproportionately impacted by climate change. More than half of Black Americans live in the southern United States, which is expected to see stronger hurricanes and increased coastal flooding. Black Americans are also more likely to live near toxic facilities, in areas with significantly reduced tree canopy, and in areas with higher average land surface temperatures (Fernandez and Floyd 2017; Shepherd 2021). For instance, counties with large Black populations are currently exposed to 2-3 more extreme temperature days, than counties with a smaller Black population. By 2050 this number is expected to increase to roughly 20 additional extreme temperature days per year (EDF 2020).

-***Hispanic Population***: Like other communities of color, Hispanic Americans are disproportionately impacted by the effects of climate change. More than 55% of Hispanic and Latino Americans live in states experiencing historic drought, record-breaking temperatures, and increased flooding (EDF 2020). They are also overrepresented in industries like agriculture, manufacturing, and construction; and are 43% more likely to live in areas which will see a shortening of the work week due to increasing temperatures (Galvan and Franco 2021). Like Black Americans, Hispanic Americans live in areas prone to pollution, excess particulate matter, and asthma. Nearly 1 in 2 live in counties that are exposed to concerning levels of ozone, which is a key component in smog generation (Galvan and Franco 2021).

-***Indigenous American Population***: Indigenous nations have lost roughly 98% of their historical land since colonization (Farrell et al. 2021). A recent study found that the Mojave tribe, for instance, experiences 62 more days of extreme heat per year compared to when they lived on their historical land (Treisman 2021). Climate change also will further exacerbate many issues tribal communities are facing, such as reduced access to traditional foods, decreased water quality, and increasing health risks (U.S. Climate Resilience Toolkit 2020). Many tribal communities have also already been relocated due to climate change. The tribal community of Isle De Jean Charles, for instance, was relocated in 2016 due to coastal flooding, hurricanes, and land subsidization (Boyd 2019).

-***Poverty Rate***: Those in poverty suffer the greatest from a disaster. Those with a lower socioeconomic status, generally, occupy low-cost, affordable housing which may not be of quality construction. Impoverished citizens are more likely to die, suffer injuries or disease, have higher loss of property and assets, more psychological trauma and face many more obstacles on the road to recovery (Fothergill 2004; Masozera et al. 2007).

-***Median Household Income***: Roughly 40% of American households lack basic savings and would be extremely, economically vulnerable to income shocks like the COVID-19 pandemic (Prosperity Now 2019; Midões and Seré 2022). In 2020 Black households had the lowest median income of $45,870, followed by Hispanic households with an income of $55,321 (US Census Bureau 2021). Lower income also reduces an individual's adaptive capacity to a disaster and impacts one's ability to relocate or rebuild post-disaster.

2.2.1.2 Hazard Vulnerabilty Index (HVI)

Hazard vulnerability encompasses which hazards or disasters have impacted a particular region over time. Hazards come in many forms, but this index specifically investigates overall climatic trends and climatically induced weather events. The list of hazard variables (Table 2.2) and the reasoning behind the selected variables can be found below.

Table 2.2. List of hazard variables used in the creation of the HVI, the variables vulnerability relationship (+ indicating as the variable increase, so does vulnerability and – indicating that as the variable decreases, vulnerability increase), and the source of each variable.

Variable	Relationship	Source
Average Annual Precipitation (mm)	-	PRISM Climate Group (OSU)
Average Annual Temperature (°C)	+	PRISM Climate Group (OSU)
FEMA Disaster Declarations	+	FEMA

-***Average Annual Precipitation (mm)***: Availability of water has become a very apparent consequence of climate change, particularly within the American Southwest. Rapid population growth within the region has intensified the competition for water resources between states, and even local municipalities (Gober and Kirkwood 2010). The Ogallala Aquifer, which extends from South Dakota to Texas, today losses an annual volume of water equivalent to 18 Colorado Rivers, which far exceeds the natural restoration rate (Little 2009). Climate change is also expected to reinforce the idea that the "wet gets wetter" and the "dry gets dryer", likely further exacerbating water scarcity in already water-scarce regions (Staples and Beckwith 2017). At the other extreme, excessive precipitation events have increased throughout the United States, which has led to more flash flooding events, particularly in urban areas, death, and an increase in waterborne diseases (Centers for Disease Control and Prevention 2020).

-***Average Annual Temperature (°C):*** Today, roughly 1% of the globe is a barely livable hot zone, which is mainly the area of the Sahara Desert; but by 2070 roughly 30% of the world and 3.5 billion people will be living in parts of the world where the average temperature will exceed 29°C (84 °F) (Fleming 2020). Many studies consistently point to higher temperatures increasing the risk of heat-related illness and death in the future (EPA 2021). Across the United States heat has caused roughly 10,000 deaths between 1999 and 2016 – which was more than hurricanes, tornadoes, or flooding most years (Russell et al. 2020).

-***FEMA Disaster Declaration***: All federally declared disasters fall under the declaration types of major disasters and emergencies. The selected hazards for this study were: coastal storm, drought, fire, flood, hurricane, landslide, severe storm, and tornado.

2.2.1.3 Exposure Vulnerability Index (EVI)

Variables for the EVI were chosen based on what reliable data was available for every year in the time series. Exposure vulnerability deals with the "who" or "what" is impacted during a natural disaster. The list of exposure variables (Table 2.3) and the reasoning behind the selected variables can be found below.

Table 2.3. List of exposure variables used in the creation of the EVI, the variables vulnerability relationship (+ indicating as the variable increase, so does vulnerability and – indicating that as the variable decreases, vulnerability increase), and the source of each variable.

Variable	Relationship	Source
Total Population	+	U.S. Census
Housing Units	+	U.S. Census
Impervious Surface	+	NLCD

-***Total Population***: This is the total amount of people, within a geographic area, which may be exposed to and impacted by a potential hazard. Many coastal, and urban areas, for instance, are seeing increased concentrations in populations putting more people at risk in the event of a hurricane, coastal flooding, wildfires, earthquakes, and other hazards. In short, the more people within an area, the greater the potential for loss of life.

-***Housing Units***: The total number of built housing units, within a geographic area, which may be exposed and impacted by a potential hazard. Where structures are located, and the quality of housing impact how resilient infrastructure is to natural hazards. By 2045, roughly 300,000 homes and businesses throughout the United States will be chronically disrupted by flooding and sea-level rise (Sisson 2018). Climate Change is expected to exacerbate the worsening affordable housing market as well, with the number of affordable housing exposed to flooding tripling by 2050 (Buchanan et al. 2020). Variable used in Climate Central's Risk Screening Tool and studies by Borden et al. (2007), Buchanan et al. (2020), and KC et al. (2021).

-***Impervious Surface***: These are surfaces, such as concrete or asphalt, which inhibit water from infiltrating into the ground. According to the American Geophysical Union, there are more than 43,000 square miles of impervious surface in the United States, which is roughly the size of Ohio (Frazer 2005). These surfaces lead to increase surface water runoff, groundwater depletion, increase in flash flood potential, increase in urban heat, and can lead to an increase in pollution and particulate matter within urban centers (USGS n.d.; Frazer 2005). The two-year gaps in the dataset were filled in by assuming a 2% average growth rate for the United States between 1970-2010, for varying city sizes (Güneralp et al. 2020).

2.2.2 Index Methods and Weighting Schema

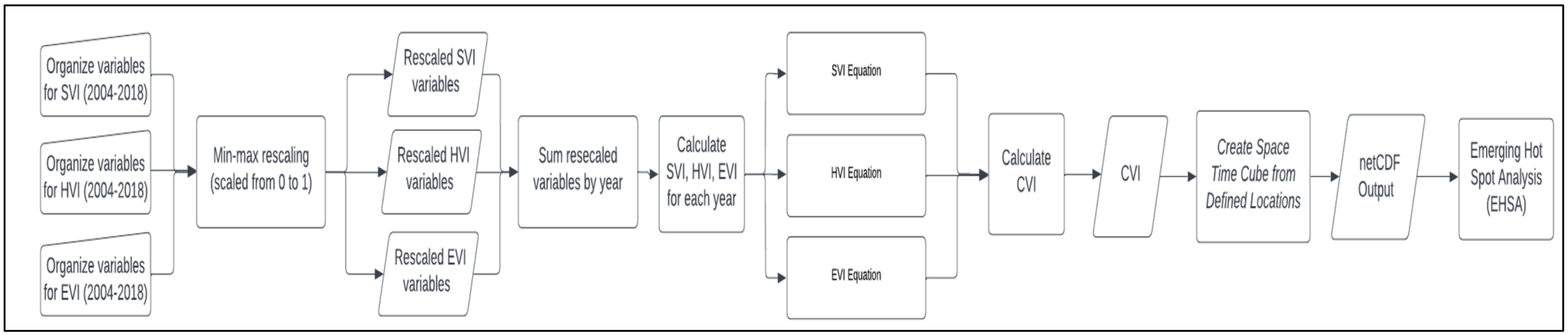


Figure 2.1. Flow Chart of Climate Vulnerability Index (CVI) creation methods.

To generate the three independent indices and the overall CVI, an index type and weighting must be chosen. There are many approaches in which an index can be created; and within the field of social vulnerability there are some established index creation methods. Table 2.4, from Reckien (2018) provides a list of some techniques.

Table 2.4. List of various index creation methods within vulnerability studies. Highlights the type of approach, a description of each approach, the methodological approach, and studies which use each technique. From Reckien (2018).

Name of approach/ technique	Description	Methods used	Examples in the literature
1. Variable reduction approach or inductive approach	A large number of variables are used that potentially have an influence. These are reduced to the most influential components by merging variables that are highly correlated into a number of new variables or components. These are then normalized to a similar unit or variability, and then mapped	Factor analysis; principal component analysis (PCA)	Abson et al. 2012; Cutter et al. 2003; de Sherbinin and Bardy 2015; Schmidtlein et al. 2008; Yoon 2012; Holand et al. 2011; Tate 2012
2. Variable addition approach or deductive or additive normalization approach • With weighting • Without weighting	Only those variables are used that are very likely influential or those that have been determined as influential in previous studies. These variables are normalized, added, and mapped	Normalization of data via z-scores, min-max rescaling or similar and addition of scaled variables	Abson et al. 2012; Yoon 2012; Tate 2012
3. Sub-index approach or hierarchical approach	Here, first, a number of variables are identified that contribute to sub-indices similarly (added to equal shares to form 100% likelihood of a sub-index). Sub-indices are, e.g., sensitivity, coping, and adaptation. These are then added to get to the overall variable of vulnerability	Likelihood measures of susceptibility, coping, and adaptation are added to arrive at vulnerability	Welle et al. 2012; Tate 2012
4.Fuzzy normalization approach	Variables of importance for vulnerability are selected and joined via fuzzy reasoning, i.e., fuzzy membership functions for degrees such as Bhigh^ or Blow^ and the definition of respective threshold values	Addition of fuzzified variables	Lissner et al. 2011

Widely used in social vulnerability assessments and utilized by Cutter (2003) in the creation of the original SoVI®, is the variable reduction and principal component analysis (PCA) method. PCA is an extremely useful tool because it can take many variables, and merge values that have high correlation into principal components, all while preserving as much information as possible (Reckien 2018; Jaadi 2021). Each principal component can act as its own indices and can be mapped to show patterns within the multivariate data, whereas aggregation and normalization alone generate a single index (Defne et al., 2020).

This study follows the methods used in KC et al. (2021), which employed the variable addition and min-max rescaling (without weighting) methods [number 2 in Table 2.4]. A flow chart of methods can be seen in Figure 2.1, which should help illustrate how the data was manipulated. This methodology is useful for these studies since 1) There are multiple indices and minimal variables, and 2) only variables highly influenced and impacted by climate change were selected. No weighting scheme was chosen since each variable is extremely impacted by climate change, therefore no variable needed to be weighed greater than the others. Not weighting any of the variables in the index also allows stakeholders the ability to amend the data and weigh variables, or indices based on their own needs.

To be compared, each variable must be normalized to a unitless number and rescaled. Each positively correlated variable, for each individual year, was rescaled from 0 to 1 using Equation 1:

$$X = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

Whereas negatively correlated variables, median household income, and average annual precipitation, were rescaled using Equation 2:

$$X = \frac{x - \max(x)}{\min(x) - \max(x)} \quad (2)$$

The rescaled variables are then grouped into their corresponding indices, for each, individual year. The variables are then summed and divided by the number of variables within each indices using:

$$\text{SVI} = \frac{\text{Age5} + \text{Age65} + \text{Black} + \text{Hispanic} + \text{IA} + \text{Poverty} + \text{MHH}}{7} \quad (3)$$

$$\text{HVI} = \frac{\text{Avg. Temp.} + \text{Avg. Precip.} + \text{FEMA Declerations}}{3} \quad (4)$$

$$\text{EVI} = \frac{\text{Population} + \text{Housing Units} + \text{Impervious Surface}}{3} \quad (5)$$

This means that there is a SVI, HVI, and EVI created for every year from 2003 to 2018. Once the three indices are created, they are added together (Equation 6) to generate the composite CVI. Again, there will be a CVI for every year from 2003 to 2018.

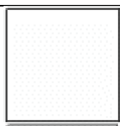
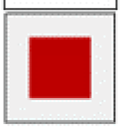
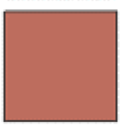
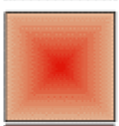
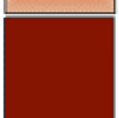
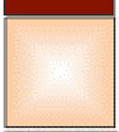
$$CVI = \frac{HI + EI + SVI}{3} \quad (6)$$

CVI scores are scaled between 0 and 1, where a CVI score approaching zero indicates a less vulnerable area, whereas a score approaching one indicates a more vulnerable area. The organized CVI data is then input into the *Create Space Time Cube from Defined Locations* tool, and the EHSA tool is run on the dataset.

2.2.3 Emerging Hot Spot Analysis (EHSA)

The EHSA toolkit enables for data in a space-time NetCDF file to be analyzed over space and time. It first takes this data and performs standard Getis-Ord Gi* statistics (Hot Spot Analysis) for each, individual bin within the space-time cube. Each bin is given a representative z-score and p-value and is determined to be either a hot or cold spot for the given year. Then using the Mann-Kendall trend test, the tool determines how hot and cold spots at a location have changed over time, and if those trends are statistically significant. The results and definitions of the Mann-Kendall trend test can be seen in Table 2.5 below.

Table 2.5. Legend of eight hot and cold spot outputs from EHSA. Provides the symbology used for each pattern type, the name of the pattern, and the statistical description of each hot or cold spot type. From ESRI (2021).

Symbol	Pattern Name	Definition
	No Pattern Detected	Does not fall into any of the hot or cold spot patterns defined below.
	New Hot Spot	A location that is a statistically significant hot spot for the final time step and has never been a statistically significant hot spot before.
	Consecutive Hot Spot	A location with a single uninterrupted run of statistically significant hot spot bins in the final time-step intervals. The location has never been a statistically significant hot spot prior to the final hot spot run and less than ninety percent of all bins are statistically significant hot spots.
	Intensifying Hot Spot	A location that has been a statistically significant hot spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of high counts in each time step is increasing overall and that increase is statistically significant.
	Persistent Hot Spot	A location that has been a statistically significant hot spot for ninety percent of the time-step intervals with no discernible trend indicating an increase or decrease in the intensity of clustering over time.
	Diminishing Hot Spot	A location that has been a statistically significant hot spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering in each time step is decreasing overall and that decrease is statistically significant.
	Sporadic Hot Spot	A location that is an on-again then off-again hot spot. Less than ninety percent of the time-step intervals have been statistically significant hot spots and none of the time-step intervals have been statistically significant cold spots.

Oscillating Hot Spot	A statistically significant hot spot for the final time-step interval that has a history of also being a statistically significant cold spot during a prior time step. Less than ninety percent of the time-step intervals have been statistically significant hot spots.
Historical Hot Spot	The most recent time period is not hot, but at least ninety percent of the time-step intervals have been statistically significant hot spots.
New Cold Spot	A location that is a statistically significant cold spot for the final time step and has never been a statistically significant cold spot before.
Consecutive Cold Spot	A location with a single uninterrupted run of statistically significant cold spot bins in the final time-step intervals. The location has never been a statistically significant cold spot prior to the final cold spot run and less than ninety percent of all bins are statistically significant cold spots.
Intensifying Cold Spot	A location that has been a statistically significant cold spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of low counts in each time step is increasing overall and that increase is statistically significant.
Persistent Cold Spot	A location that has been a statistically significant cold spot for ninety percent of the time-step intervals with no discernible trend, indicating an increase or decrease in the intensity of clustering of counts over time.
Diminishing Cold Spot	A location that has been a statistically significant cold spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of low counts in each time step is decreasing overall and that decrease is statistically significant.
Sporadic Cold Spot	A location that is an on-again then off-again cold spot. Less than ninety percent of the time-step intervals have been statistically significant cold spots and none of the time-step intervals have been statistically significant hot spots.
Oscillating Cold Spot	A statistically significant cold spot for the final time-step interval that has a history of also being a statistically significant hot spot during a prior time step. Less than ninety percent of the time-step intervals have been statistically significant cold spots.
Historical Cold Spot	The most recent time period is not cold, but at least ninety percent of the time-step intervals have been statistically significant cold spots.

Of particular interest for vulnerability studies are new, intensifying, consecutive, and persistent hot spots, as well as diminishing or intensifying cold spots. Let us think about what an intensifying hot spot would mean in the context of vulnerability. As defined, this type of hot spot, “is a location that has been a statistically significant hot spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of high counts in each time step is increasing overall and that increase is statistically significant” (ESRI n.d.). This means, in the context of this study, that an area has been determined to be a hot spot, or an area of high vulnerability, for 90% of the 15 years and this vulnerability is worsening over the time series. Comparatively, an intensifying cold spot is exactly like an intensifying hot spot except the area has been a cold spot for 90% of the time series. Rather than vulnerability worsening, in this case, vulnerability in these areas is decreasing over time.

Both provide a wealth of information for policy and planning purposes. Intensifying cold spots, for instance, could potentially indicate an area that may act as an ideal climate haven for potentially displaced individuals. Likewise, areas of consistent or worsening vulnerability will indicate counties that may need more immediate economic assistance under a changing climate.

2.3 Results

2.3.1 Climatic Vulnerability Rankings

The top 10 most vulnerable counties from the CVI can be seen in Table 2.6. The average CVI is averaged over the 15 years for each county. CVI scores are scaled from 0 to 1, meaning scores closer to 0 represents a less vulnerable, whereas scores closer to 1 represent a more vulnerable county.

Table 2.6. Table of the top 10 most climatically vulnerable counties in the United States from 2003-2018.

Rank	Major Urban Area	County	State	Average CVI
1	Los Angeles	Los Angeles County	California	0.72
2	Chicago	Cook County	Illinois	0.52
3	Houston	Harris County	Texas	0.47
4	New York City (Brooklyn)	Kings County	New York	0.45
5	Phoenix	Maricopa County	Arizona	0.43
6	Dallas	Dallas County	Texas	0.40
7	New York City (Bronx)	Bronx County	New York	0.40
8	Miami	Miami-Dade County	Florida	0.39
9	New York City (Queens)	Queens County	New York	0.39
10	San Diego	San Diego County	California	0.38

All the top 10 counties are major urban areas, with eight of the ten being coastal. Maricopa County (Phoenix, Arizona) and Dallas County (Dallas, Texas) were the only landlocked counties. These cities are the most vulnerable due to higher total populations, large impervious surface area, large populations of minority groups, and the frequency of coastal hazards.

2.3.2 Social Vulnerability Index (SVI)

Persistent hot spot clusters appeared throughout the Gulf Coast region to southern Missouri, a majority of New Mexico, the Carolina coast, Appalachia, and central South Dakota. Intensifying hot spots occur in parts of southeastern Appalachia, south-central Alabama and Georgia, southern California and Arizona, and southern Florida (Figure 2.2). These regions highlight areas of worsening or consistent social vulnerability throughout the time series.

A 2015 Pew Research Center report found that roughly 19.1% of Florida's population were aged 65 and older, and between 1995 and 2020 the population of those 85 and older was expected to double within Florida (Kent 2015; Gillen and Dwyer 2018). A 2017 study from Florida Building Resilience Against Climate Effects (BRACE) highlighted that within urban areas of Miami-Dade, Broward, and Palm Beach counties, roughly 76%, 31%, and 29%, respectively, of the population live in highly vulnerable areas, which matches with the intensifying hot spot cluster in southeastern Florida (FL BRACE 2017).

Similarly, the Appalachia region population was 18.4% age 65 and older in 2018. Rural Appalachia has also lagged other rural communities in educational attainment, household income, population growth, and labor force participation (Population Reference Bureau 2018). Likewise, the southeast and Black Belt region are composed of populations disadvantaged by race, poverty, ethnicity, and gender. Lowndes County, Alabama, for instance, is located south of

Montgomery and occurs just outside the intensifying hot spot cluster in Georgia-Alabama. Within unincorporated parts of Lowndes County, it is estimated that nearly 80% of households have no adequate wastewater treatment or septic system (Yamaguchi 2022). This means that raw sewage and fecal matter frequently flood households or leak into pools in residents' backyards, which has led to a reintroduction of hookworm to the U.S (Davies 2020).

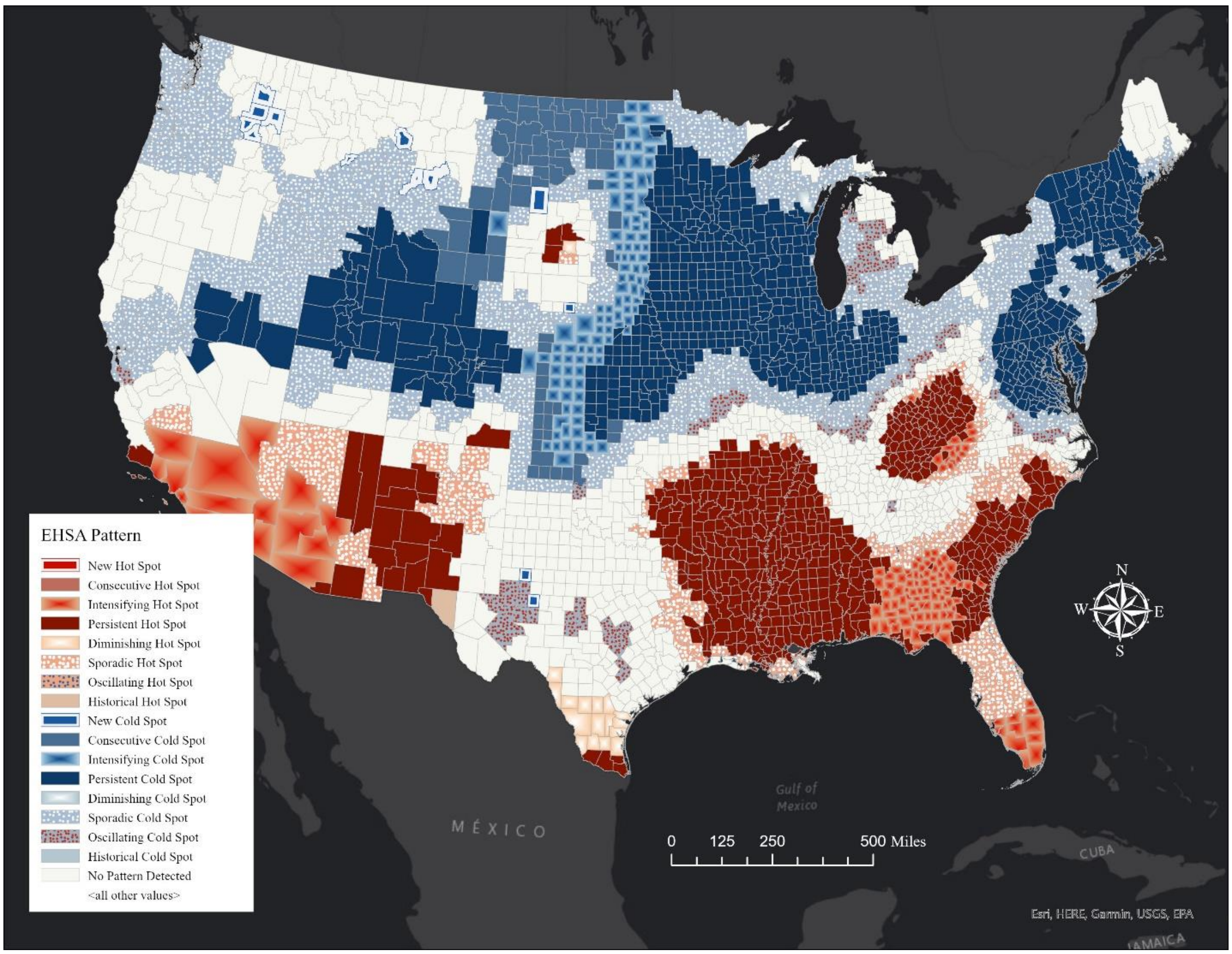


Figure 2.2. Map of EHSA results of the SVI for the Contiguous United States.

According to the 2018 Census, South Dakota is 12% American Indians and Alaska Natives (National Congress of American Indians 2020). Jackson County, South Dakota, just one of the persistent hot spots within the South Dakota cluster, had higher rates of poverty (44%), no high school diploma (15%), unemployment (6%), single-parent households (13%), persons 17 and younger (30%), minority populations (57%), housing with more people than rooms (12%), a household with no vehicle (9%), uninsured individuals (25%), mobile homes (24%), and those with disability (15%) compared to the entire state of South Dakota (South Dakota Department of Health 2019).

2.3.3 Hazard Vulnerabilty Index (HVI)

Over the time series the Gulf Coast region, majorly parts of southern Louisiana through southern Georgia and northern Florida were found to be a persistent hot spot for hazard vulnerability (Figure 2.3). A persistent hot spot, within this context, indicates a location that is consistently vulnerable to hazards; but detects no patterns of that vulnerability increasing or decreasing over time. The hot spot within the Gulf Coast is likely influenced by higher temperatures within the southeast, coupled with a high frequency of the selected hazards. Since 1970, average annual temperatures within the southeast have increased by roughly 2°F and the decade from 2011-2020 was the warmest on record for the region (US EPA 2016; WMO 2021).

The southeast has also seen a high rate of hurricanes impact the region during this time, with ones like Hurricane Katrina, Sally, Ida, and Delta. Coastal North Carolina, South Florida, and southeast Louisiana have the highest hurricane return rate in the United States at one striking these regions every 5 to 7 years (Michaels 2018). Moreover, within the past decade, the frequency of severe weather events and tornadoes has increased within the region (Gensini and Brooks 2018). Some speculate that the region termed “tornado alley”, an area of the Great Plains has shifted south or has even expanded into Arkansas and western Alabama. According to Brian Curren, Science and Operations Officer for the Midland National Weather Service, this shift is due to a greater number of exposed individuals, more reported tornadoes, an increase in coastal tropical storms, and persistent drought in the Midwest (France 2022).

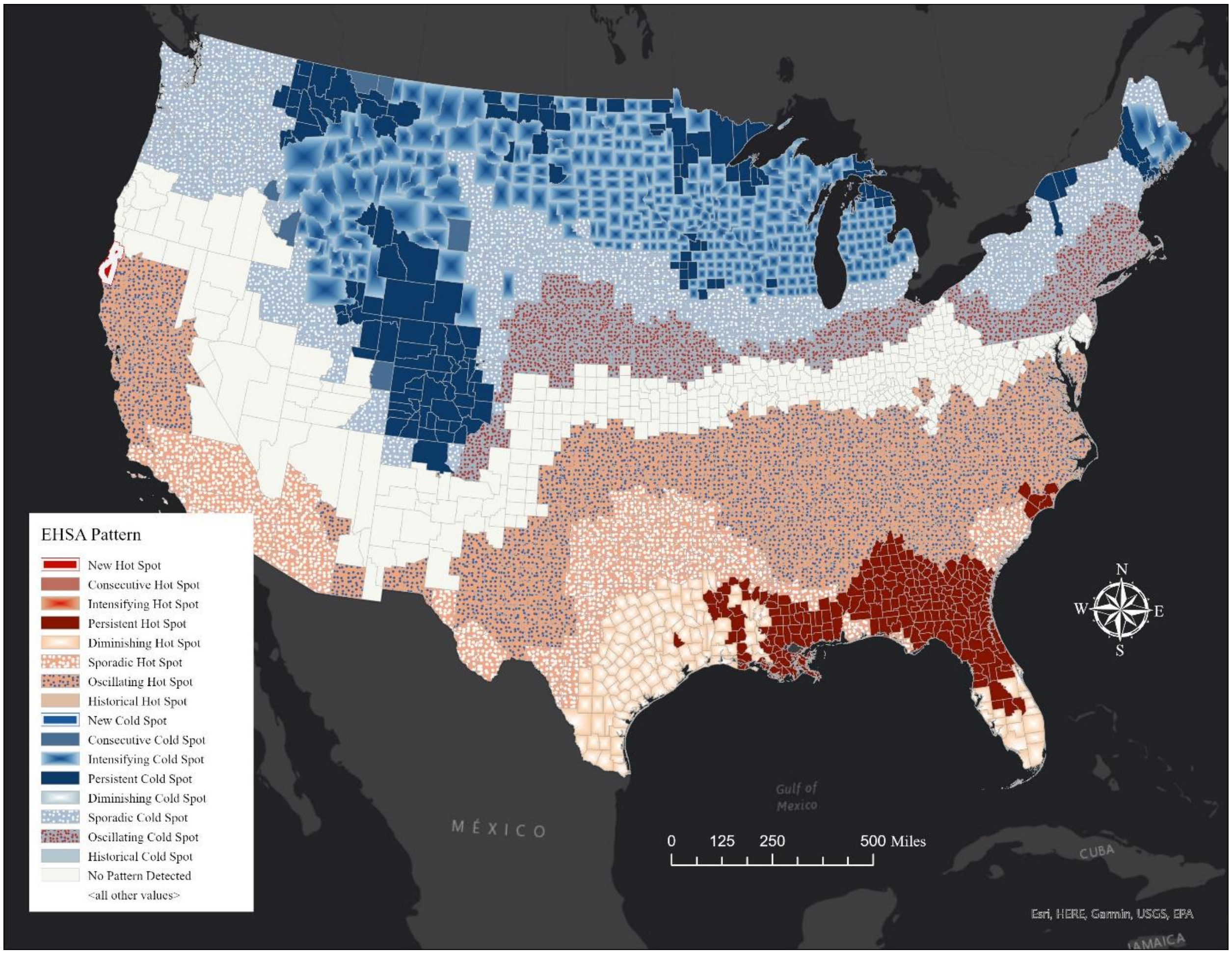


Figure 2.3. Map of EHSA results of the HVI for the Contiguous United States.

Another persistent hot spot cluster occurs between Myrtle Beach, South Carolina, and Wilmington, North Carolina. Like other portions of the southeast, this region is highly impacted by hurricanes and coastal flooding. Myrtle Beach has been impacted by many significant hurricanes over the past decade including Hurricane Florence in 2018 and Hurricane Matthew in 2016. On average, Myrtle Beach has a hurricane pass within 50 miles of it on an every other year basis (Stebbins 2021). These parts of North and South Carolina also see their fair share of wildfires and prescribed burns, with North Carolina averaging around 4,500 fires per year (Gellerstedt 2014). Much of the ecosystem in this region have adapted and are dependent on natural burning. With climate change and rising temperatures within this region, and the southeast, the risk of drought and lightning-induced fires are expected to grow under ideal conditions (Thompson 2016).

The only new hot spot occurred in Humboldt County, California. Presently Humboldt County experiences persistent flooding, which is expected to worsen as sea levels are anticipated to rise 1.0 meter by 2070 (Laird 2019). Much of the county, roughly 45%, is classified as having very high wildfire risk; with the county having a strong presence of interface fuels surrounding residential properties. Moreover, the North Coast Resource Partnership found in a study that there would be a 40% increase in wildfire probability across the region by 2100 (Humboldt County Fire Safe Council 2019).

2.3.4 Exposure Vulnerability Index (EVI)

Many areas of persistent hot spots occurred in counties around major urban centers. These clusters include the Florida peninsula, southern California, central California, northwest Washington, the Great Lakes region, New England, Appalachia, and the I-85 corridor (Figure 2.4). The New York-New Jersey-Connecticut urbanized area is the most populous and largest urban area in the United States, with 18,351,295 people and encompassing 3,450 square miles, according to the 2010 Census. Whereas the Los Angeles-Long Beach-Anaheim, California cluster has the highest urban population density, with roughly 7,000 persons per square mile (US Census Bureau 2021). Since 2000, more people have left rural counties for urban, suburban, or small-sized cities, which is on par with the trend that by 2050 roughly 70% of the world population will reside in cities (Parker et al. 2018; World Bank 2020).

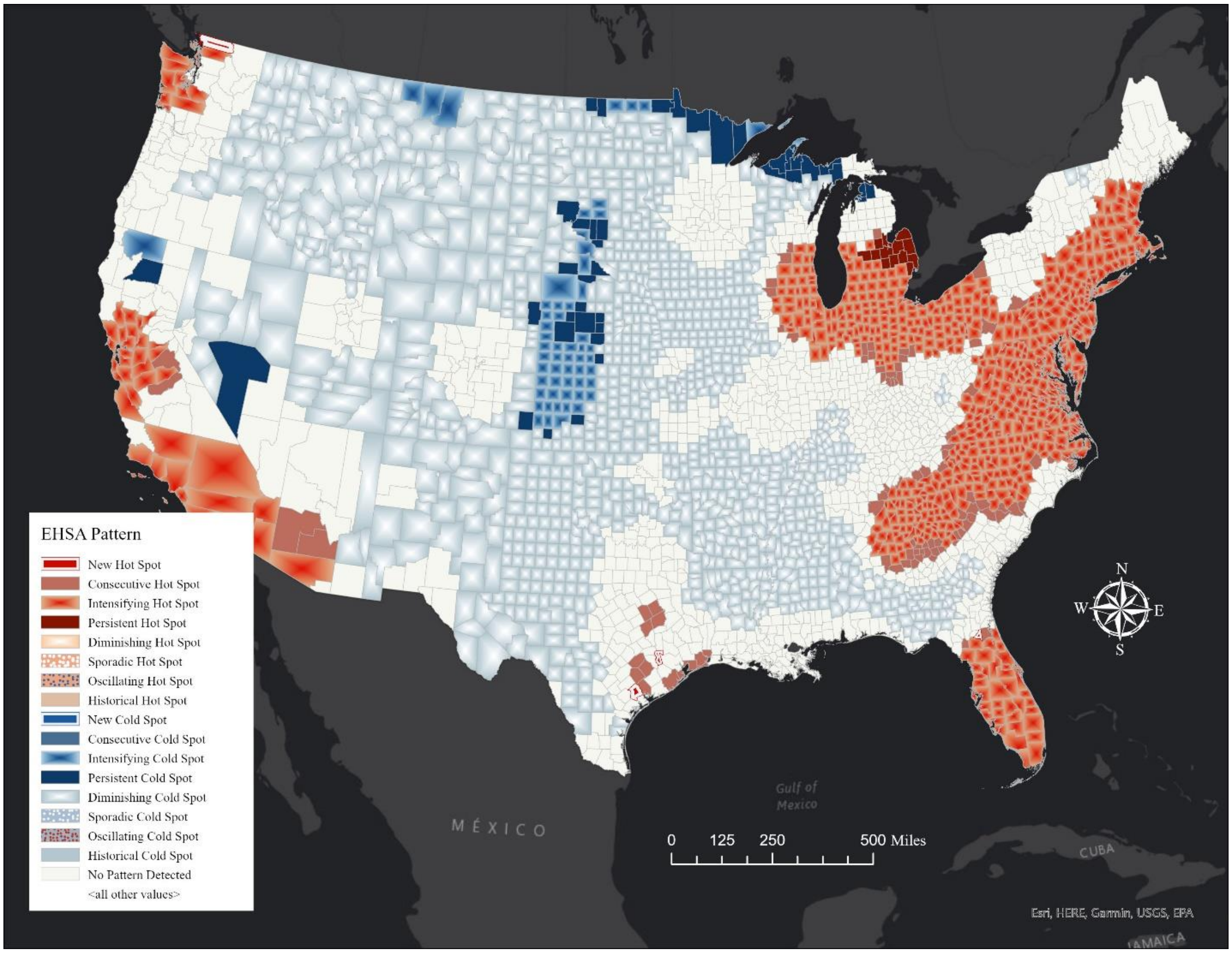


Figure 2.4. Map of EHSA results of the EVI for the Contiguous United States.

These growing urban clusters are important as they point to previous research by Shepherd et al. and Terando et al. (2014). Shepherd et al. (2014) proposes a new definition for these urban agglomerations, by calling them Urban Climate Archipelagos (UCAs). UCAs are a chain of distinct urban entities with discernable impacts on the climate system (Shepherd et al. 2014). The study by Terando et al. (2014) furthers this idea by projecting urban growth in the SEUS by 2060. It is expected that the Piedmont ecoregion, which encompasses Atlanta and Charlotte, is expected to see a 165% increase in urban area by 2060, and southwest Appalachia is expected to see the highest increase of 261% (Terando et al. 2014). Growing urban clusters can enhance convective systems and precipitation rates which pass over; and centers have been found to cause temperature increases in smaller, downwind cities (Huang et al. 2019; Liu and Niyogi 2019). Urban growth will also increase the number of at-risk individuals, or force individuals into more vulnerable areas. In California, for example, nearly 10% of houses, and 11 million people, reside in “high” fire risk areas (Berger and Susskind 2018; Aarons 2021).

One interesting pattern to emerge were clusters with no hot or cold spots detected. These clusters seem to be concentrated around large urban areas, such as Dallas, St. Louis, Salt Lake City, Denver, and so on. The Dallas metro area, for instance, has had its suburbs grow faster than the urban center since 2010, which was likely due to the national economy recovering prompting a dispersal of the population away from metro areas (Frey 2020). Considering the underlying data, this likely means these cities may be experiencing slower growth, population or urban, compared to other areas of the United States; or the growth within these cities may not be confined to a particular county, or cluster of counties from year to year. The diminishing cold spot counties, like the intensifying hot spots, indicate areas of increasing exposure vulnerability, likely stemming from an increase in impervious surface or population in SMSCs.

2.3.5 Climate Vulnerability Index (CVI)

The final CVI (Figure 2.5) highlights areas of statistically significant vulnerability throughout the United States for the 15-year period. Much of the southeastern United States, including the entirety of Florida, southeastern South Carolina, southern Georgia, Mississippi, and Alabama, parts of central Louisiana, the Houston area, southern California, the San Francisco area, and coastal New Jersey were deemed persistent hot spots. The only area of intensifying hot spots was in counties surrounding Charleston, South Carolina. New hot spots occurred in counties in northern California and outside Las Vegas, Nevada.

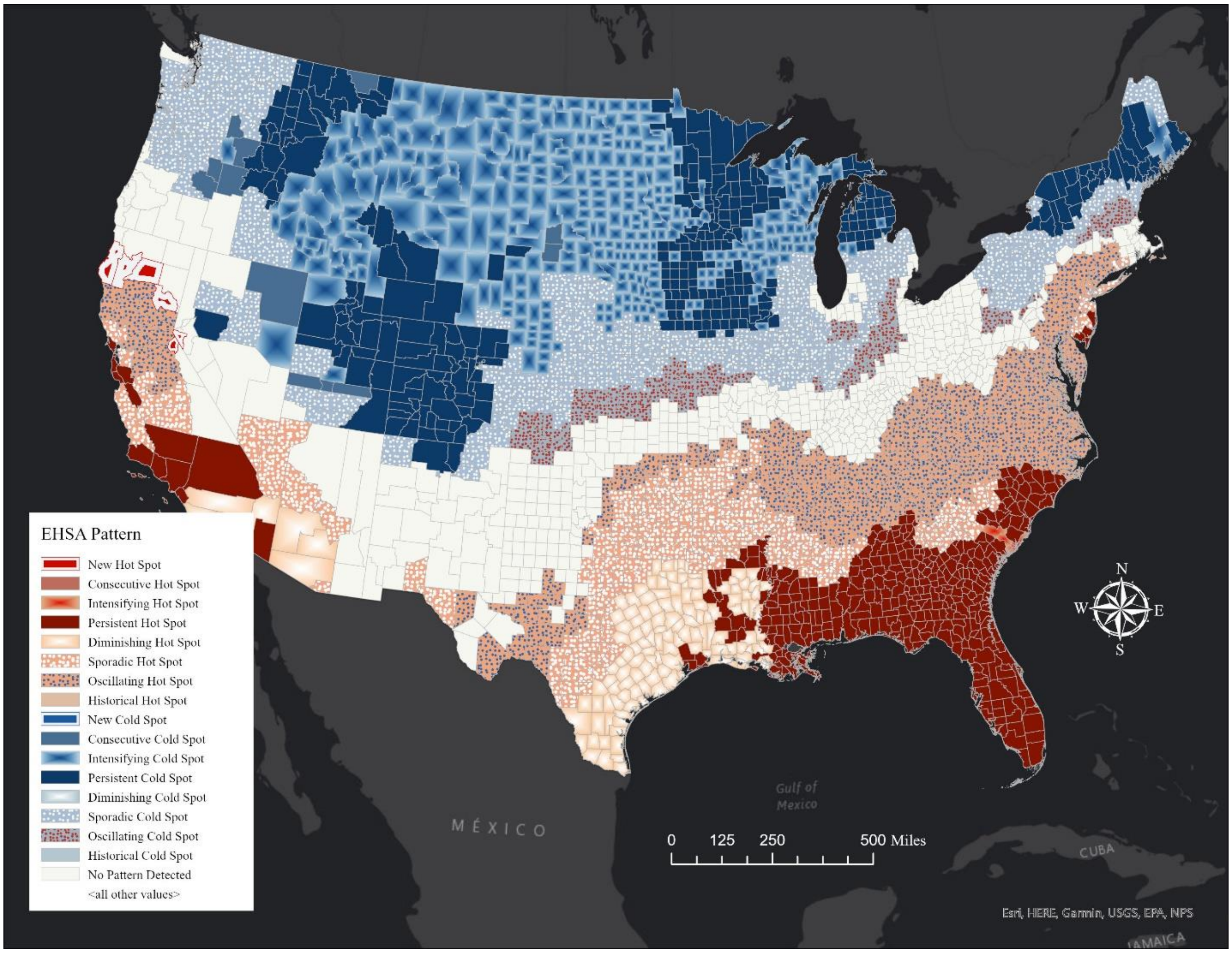


Figure 2.5. Map of EHSA results of the CVI for the Contiguous United States.

Again, the goal of this index is to highlight the counties most at risk and vulnerable to climate change in the United States. This is not to say counties labeled as cold spots are not vulnerable as well, they are just not as vulnerable as other parts of the United States. Many counties in the Great Lakes, and out west were determined to be vulnerable in the EVI and SVI. However, holistically, these are counties are less vulnerable since they are not frequently impacted by climate hazards. While the study period (15 years) is not on the same time scale as most climatological studies, 30 to hundreds of years, this study does focus on one of the worst, climatologically speaking, decades on record (NASA 2015). Hopefully, this provides new insight to stakeholders, NGOs, community leaders, and policymakers and allows effective action to take place in counties that are more likely to need immediate assistance or are already likely dealing with the consequences of climate change.

2.4 Discussion

Of the 3,143 counties, 367 were determined to be areas of new, intensifying, and persistent hot spots. This means that roughly 12% of the counties in the CONUS have been labeled highly vulnerable. This is not to say these counties were vulnerable for each year in the time series but highlights the overall trend of vulnerability for the 15 years. Below we will highlight Plumas County, California, which is one of six new vulnerability hot spots in the United States. This case study hopes to showcase why an index like CVI can be useful, and how the temporal component can be extremely beneficial and may be necessary, in future vulnerability assessments.

2.4.1 Case Study: Plumas County, California (Quincy)

Population: 1,706 (Small)

Vulnerability Rank: 2,773rd

Hazards: Earthquakes, Wildfires, Drought

Hot Spot Type: New

Plumas County emerged as another interesting case study, more specifically the town of Quincy, California, which resides within the county. Quincy is a historical mining camp, located in Northwest California; roughly 80 miles northwest of Reno, Nevada, and 120 miles southeast of Redding, California. Quincy is also located within the Plumas National Forest, which is roughly 1,146,000 acres. Quincy is rather small, with a metro population of 1,706 and a total population hovering around 5,000, which makes Quincy the largest township within Plumas

County (Sierra Trails 2021). It is roughly 80% White (Non-Hispanic), 6% Black (Non-Hispanic), 3% Indigenous American, and 11% Other Race/Ethnicity; and has a median household income of $69,073 and a poverty rate of 23.38% (Data USA 2019).

This region of the Sierra Nevada is mostly infamous for being a hot spot for seismic activity, while also being extremely susceptible to wildfires and drought. A 4.5- magnitude earthquake struck Quincy on December 26th, 2008; making it the largest earthquake to impact the area in decades. There is concern that the region is due for another severe earthquake, with USGS reporting an 83.97% chance of a major earthquake occurring within 50 km (31 miles) of Quincy within the next 50 years (HomeFacts 2021). Generally, though, the town is impacted by many, low-level seismic events [magnitude-2 or below] throughout the year (HomeFacts 2021).

According to a study by Li & Banerjee (2021), the frequency and spatial density of wildfires within California have increased significantly since 1920. Northern California had seen almost no human-caused wildfires from 1920-1999. However, there has been an emergence of human-caused wildfires; and a concentration of natural-caused wildfires, from 2000-2019 within the region (Li & Banerjee 2021). On August 17th, 2020, lightning sparked wildfires within Plumas National Forest. This storm sparked 21 separate fires with the largest being, the Sheep, Claremont, and Bear fires. The latter two merged on September 5th creating the North Complex Fire; and by September 8th, intense winds fueled the two fires resulting in the seventh largest [318,935 acres & 2,352 structures burned] wildfire in California history (The Press Democrat 2021). The Claremont and Bear fires started just 9 miles south of Quincy.

The morning of July 13, 2021, a Pacific Gas and Electric Company (PG&E) powerline met nearby trees, sparking a fire in roughly the same area as the origination of the 2020 Camp Fire (Romero 2021). This would result in the Dixie Fire, the second largest wildfire in California history, burning 963,309 acres of land and destroying nearly 1,329 structures. Greenville is a town located 26 miles north of Quincy, with a population hovering around 1,100; by August 5^{th} it would be a ghost town (Figure 2.6). In Plumas County alone, 7,000 individuals were forced to leave their homes; many of whom fled to Quincy, or neighboring Susanville (Williams et al. 2021).

Figure 2.6. Image of wildfire destruction. Buildings smolder as the Dixie fire rips through downtown Greenville, Calif., Aug. 4, 2021. From Jacobo (2021).

Many residents of Quincy and nearby towns are now facing a tough decision, stay and prepare for an earlier, and worsening wildfire season; or leave. Ally Bleese, a resident of Quincy her whole life, said about the fires, “It’s been crazy and really hard to deal with, everybody is panicking. My family and I have talked about giving it one more summer and then packing up and getting out” (Canon 2021). Leaving families also impact other aspects of life within rural communities, especially education. Quincy is home to the largest high school in Plumas County, but only had 301 students enrolled in grades 7-12 in 2021. This poses a problem since school funding in California is based on attendance, which means rural schools often receive less. This causes schools to have to lay off staff, cut after-school programs, or close entirely; and even that may not be an option if the school serves too large of a region.

Plumas County has a CVI rank of 2,773 of 3,143 and was deemed a statistically significant, new hot spot. Again, a new hot spot indicates that the county is a statistically significant hot spot for the final time step and has never been a statistically significant hot spot before (ESRI 2021). Comparatively, Plumas County was deemed a sporadic cold spot within the SVI, no pattern detected within the EVI, and an oscillating hot spot within the HVI. This highlights the importance of the CVI and looking at vulnerability more dynamically.

Social vulnerability indexes have been used in countless studies when analyzing hazard risk; however, social vulnerabilities alone do not explain the fluid nature of vulnerability, and the complexity of the real world. Again, Plumas County was deemed a sporadic cold sot, which is when “less than ninety percent of the time-step intervals have been statistically significant cold spots and none of the time-step intervals have been statistically significant hot spots” (ESRI 2021). This means that this location, based on this study’s SVI, has never been socially vulnerable over the time series.

In each, individual case (HVI, EVI, SVI), Plumas County would likely not be an area of interest for disaster or economic relief efforts. Yet, the CVI, which is composed of all three indices, tells a different story. The CVI highlights a new, potential region of vulnerability to climate change starting in 2018, prior to both the North Complex Fire and Dixie Fire. Ranking in the 12th percentile, Plumas County, similarly, may not be of interest solely based on its vulnerability ranking. This highlights another important aspect of vulnerability assessments, especially with an index like the CVI. Large, urban centers will dominate the dataset and bury small, rural counties, like Plumas County.

2.4.2 Limitations

One major limitation and bias within this study stems from an aspect of the Modifiable areal unit problem (MAUP). The MAUP occurs when point-based data are aggregated into differing areal units. For example, the aggregate number of COVID-19 cases at the county level would be different than the same analysis at the census tract level. While this study does not aggregate point data, the choice of selecting the county as the "modifiable areal unit" induces its own bias. In this case, vulnerability becomes extremely generalized at the county level and assumes that each portion of the county experiences the same vulnerability, which we know not to be true. A smaller geographic areal unit, such as the block group, would have been ideal, but there is no availability of migration data at that level.

Another limitation was the availability of data that covered the entire time series. Much of the SVI data, for instance, comes from the U.S. Census and becomes increasingly difficult to find every year prior to 2010. Due to this, many of the variables within the HVI, EVI, and SVI had to be created specifically for this study. In turn, since there is only one researcher on the project, a lot of time was spent on data organization and aggregation. Therefore, the limited number of variables for each index was largely due to the unavailability of data, and what could be reasonably compiled by a single individual. Alaska, Hawaii, and Puerto Rico were also not analyzed in the study due to a lack of impervious surface data and social vulnerability variables. Data is this study should also be considered a limitation.

Many of the social variables are based on population estimates, prior to 2010, therefore these totals could be an overestimation or underestimation of populations. The average annual temperature and rainfall data were joined to county boundaries, although boundaries change year to year, potentially leading to an overestimation or underestimation of that data. Percent of variables were also used for Poverty and the NLCD data. While normalizing the data twice does not induce any error numerically, a percent and whole count do represent two different things, particularly in the context of vulnerability. Percent poverty, for example, is a comparison of the total people in poverty compared to the number of people in the county. When this is rescaled through min-max we are looking at how the percent of poverty compares to the highest percent in the United States. Comparatively, a whole count of poverty just compares the total to the highest total in the United States. Percent poverty represents a more local scale comparison, which is then compared to the entire United States, whereas the total count is just a comparison to the entire United States. This issue is present in other studies by Borden et al. (2007) and KC et al. (2021) which use urban density in the creation of built and exposure indexes, which was grouped with total count, non-density variables. While this may have led to some bias in the data, we argue that the results and utilization of these variables still paint a realistic picture of vulnerability throughout the United States.

2.4.3 Future Research

One goal of this study is to showcase a potential methodology to create a CVI. The CVI developed by KC (2021), was the first multi-component approach for the entire CONUS at the county level. This highlights a need to move away from a single year, single index research and analysis. The CVI developed in this study highlights how current empirical and survey data can be used to create a more robust vulnerability index. Studies frequently use the SoVI® or similar indices to identify vulnerable areas, but the complexity of vulnerability cannot be quantified by one index. A study by Cooley et al. (2012), for example, attempted to create a robust climate vulnerability index for the state of California. This study compiled social variables which are directly related to hazards, extreme heat, air quality, and infectious disease. Although only socioeconomic variables were used, this highlights how more discrete, complex indices can be generated and used for policy and response.

In theory, there will never be an index that perfectly reflects real-world vulnerability; however, the goal should be to create one which attempts to encompass all aspects of vulnerability. The CVI within this study is by no means exhaustive or complete, but hopefully acts as a starting point for policymakers, stakeholders, community leaders, and other academics to begin generating their own CVI's. Hopefully, like the SoVI®, a standardized CVI can be generated to be used in future hazard studies, policy, and planning.

This study, to our understanding, also marks the first utilization of EHSA to assess vulnerability. One of the most similar studies to date is Summers et al. (2022), which used EHSA to analyze changes in the frequency and intensity of natural hazards in the United States from 2000 to 2019. Vulnerability studies can benefit greatly from EHSA and the whole Space Time Pattern Mining toolbox for many reasons. One, the Space-Time Cube can be created using any type of geography; therefore, it can be used to conduct vulnerability studies at any census boundary level. The cube also incorporates a temporal aspect into the study, allowing the user to determine how frequently the time-step occurs. Certain vulnerability assessments, like those analyzing pollution, may benefit from a shorter, more frequent time step; whereas larger studies such as this, benefit from a larger time step. Here are some suggested topics and areas of research potential:

1. Creation of a reviewed, standardized CVI

2. Creation of an even more robust index than the CVI, incorporating other aspects of climate change such as health inequities or access to basic needs (internet access, proximity to health care, food deserts, etc.).

3. A smaller spatial scale EHSA study for specific cities. Birmingham, for example, could be a great study to use EHSA to better understand where and how rates of pollution in the city have changed over time.

The time for inaction has long run out, climate change is on our doorstep and there is no turning back. This study highlights how lack of foresight, poor urbanization and building practices, entrenched systemic issues, and continued ‘status-quo’ mindset has led vulnerability to compound itself in many regions of the United States. It also highlights a need for a rapid improvement in climate-related science communication. Likely, many residents of hot spot counties know they are vulnerable or have already been feeling the brunt of climate change. It is our responsibility, as researchers and scientists, to supply those who are most at risk with the knowledge and capacity to elicit change for the betterment of society.

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Chapter 3

Investigating Human Mobility Patterns into Seven Southeast United States Counties and its Relationship to Climatic Vulnerability

3.1 Introduction

Storms, including hurricanes, cyclones, and storm surges, killed nearly 200,000 people between 2000 and 2019, making storms the deadliest type of weather-related disaster in the past 20 years (Centre for Research on the Epidemiology of Disasters 2020). Since 1980 there have been approximately $2.155 trillion in damages from United States weather and climate disasters. In 2021, alone, there were 20 different billion-dollar climate disasters making 2021 the third costliest year on record (Office for Coastal Management 2021). Of these disasters, tropical cyclones have cost, $1.1 trillion, and caused the most damage since 1980. As these disasters get worse and the climate continues to change, it is anticipated that hot spots of climate migration may emerge as soon as 2030 (Viviane et al. 2021).

In the United States alone, there have been roughly 10.5 million Internally Displaced Persons (IDPs), due to natural hazards, between 2008-2021. According to the UN Refugee Agency, an IDP is someone who moves involuntarily, and this movement takes place within national borders (UNHCR 2022). An IDP is not a refugee because they have not crossed an international border, and therefore, do not obtain the legal protections a refugee may have. In the United States, communities already on the move due to hazardous weather and climate change include residents fleeing Hurricane Katrina in 2005, Hurricane Sandy in 2012, Hurricane Harvey in 2017, and the tribal communities of Isle De Jean Charles, Shishmaref, and Newtok, which have already begun relocation efforts (Hurdle 2022). With this increase in migration expected to continue and worsen, within the United States, it is important to understand where these displaced individuals may have migrated to. This way destination cities can better prepare for migrants in the future, so policymakers can make informed decisions about relocation efforts, or so plans can be put in place to increase the adaptive capacity of residents so no relocation has to occur.

The objective of this section of the study is to better understand mobility patterns into the SUES counties of Fulton County (Atlanta, Georgia), Mecklenburg County (Charlotte, North Carolina), Jefferson County (Birmingham, Alabama), Muscogee County (Columbus, Georgia), Richland County (Columbia, South Carolina), Houston County (Dothan, Alabama), and Lowndes County (Valdosta, Georgia). This was done utilizing Internal Revenue Service Status of Income Tax Migration data, for 2003-2018, and the Distributive Flow Line tool created by Bob Gerlt. We hope to better understand 1.) From which regions and states did the seven SEUS counties see the most migration? Are they potentially moving due to hazardous weather events? and, readdressing Question 2, Chapter 2, 2.) Are individuals moving from climatically vulnerable counties, into equally, less, or more vulnerable counties? The goal of this section of the study is to highlight new methodology and approaches which attempts to correlate migration and hazards and relate migration to vulnerability. We hope that this interdisciplinary approach supplies stakeholders, NGOs, community leaders, and the public with usable data to make informed policy decisions; opens the door for new potential avenues of research and begins a dialogue on how interdisciplinary research and mixed methods can aid in tackling big picture problems like climate change.

3.2 Data & Methods

3.2.1 Data Management

3.2.1.1 IRS SOI Tax Migration Data

The United States Internal Revenue Service Status of Income (IRS SOI) division provides migration data for the entire United States at the state and county levels. This data is based on year-to-year address changes reported on individuals' tax return forms (Service Status of Income 2022). To determine if an individual has migrated for a given year the address, state, and zip code are compared between tax returns for the current and previous years. If the returns contain the same information, the individual is labeled a "non-migrant," whereas if any of the contained information is different the individual is classified as a "migrant" (Gross 1999).

Migration rates are determined based on the "filing" year of the income tax return. This is because the "filing" year is almost always one year behind the tax year in which the income was earned. For instance, one would file their taxes for 2020 income in the year 2021, but the information reported is for the year 2020. Migration data organized for 2020 to 2021 would represent migration that occurred in 2020, not both 2020 and 2021. For this study, the 'number of exemptions,' the number of individuals who have migrated into or from an area, will be used to estimate the total migration which occurred into the seven SEUS counties of interest (Gross 1999). Something to note, this study does not include migration data for tribal nations, Puerto Rico, and other United States territories.

This dataset does have a few limitations, however. Those who are not required to file income tax returns are not included in the file, which may lead to an underrepresentation of the poor, homeless and elderly. Migration data before 2011 also excludes a small percentage of tax returns filed after September, due to Census deadlines, many who file this late have either been granted an extension by the IRS or are high-income earners with complex returns, meaning that the extremely wealthy may also be excluded (Gross 1999). Data after 2011, however, has been significantly improved since the SOI division is now in charge of constructing this dataset. These improvements include migration data being based on full-year data, as opposed to filings after September being excluded, and the number of total matched returns has increased by 5% (Pierce 2015). While the accuracy of the data has improved since the IRS took over, another issue has arisen within the dataset. A study by DeWaard et al. (2022) found that data after the IRS took over, is not as volatile as expected with, minimal variations for in versus out-migration. This is concerning since this pattern cannot be explained by the methods the IRS uses to prepare the data. While it is recommended this dataset not be used until the IRS rectifies the issue, or is more transparent about its methods, researchers are required to develop ad-hoc adjustments or use the dataset as is (DeWaard et al. 2022). Another limitation is that data output is lagged by roughly two years or may be potentially due to the COVID-19 pandemic. At the start of this study in the Spring of 2021, for example, the most recently available data was for 2017 to 2018; whereas data for 2019 to 2020 only became available in 2022.

Many studies have been conducted using post-2011 data since the error within the data has only recently been found. In Hauer (2017) he used the IRS data and Migration Systems Theory to project future destinations for individuals displaced by future sea-level rise scenarios. Golding and Winkler (2020) used the dataset to analyze annual migration patterns across the rural-urban continuum, in which they found individuals preferred urban adjacency. More recently, a study by Winkler & Rouleau (2021) used the dataset to investigate the relationship between fire events and extreme heat on county-level migration between 1990-2015. Even with the limitations of the dataset, it is the largest, free-to-use, county-to-county dataset which tracks both household and individual migration (Gross 1999).

3.2.2 Methods

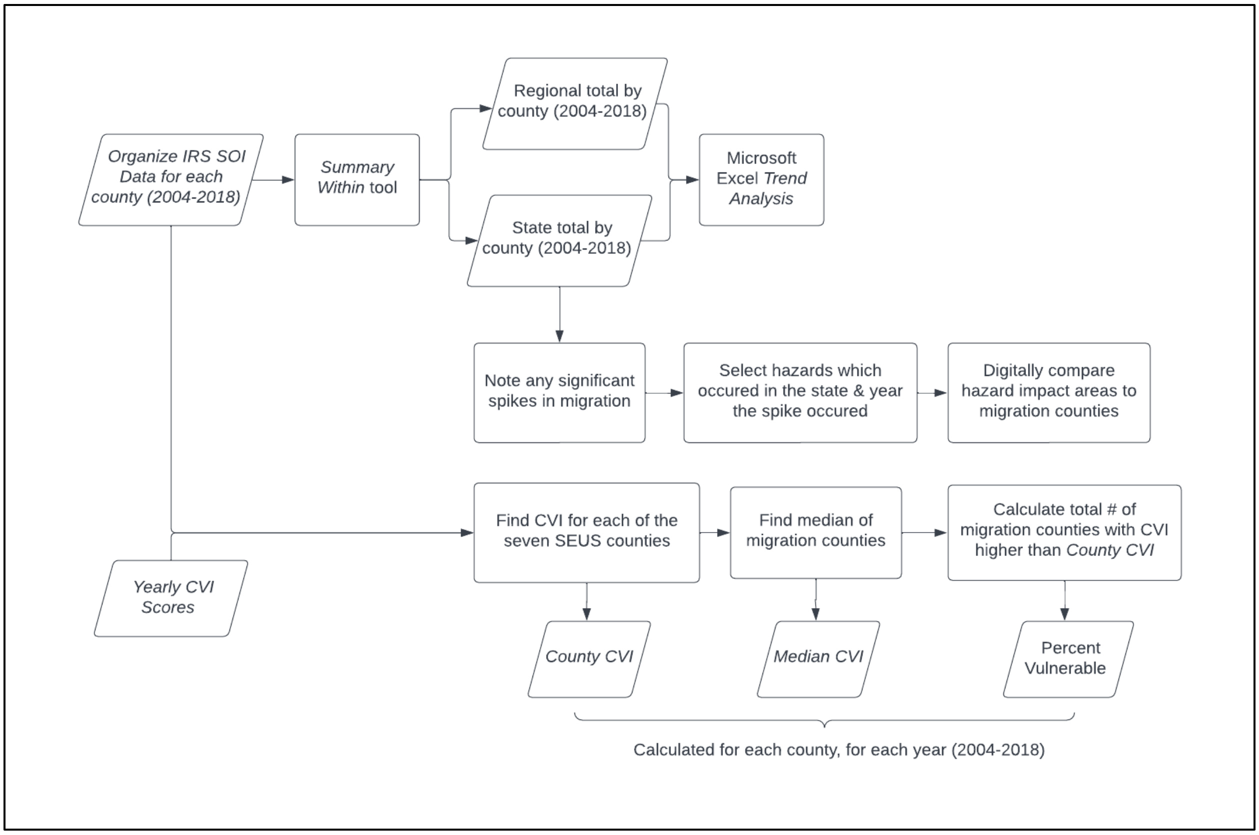


Figure 3.1. Flow Chart of methods employed in Chapter 2 to relate vulnerability to migration.

3.2.2.1 Determining Movement from Hazardous Events

It is understood that individuals will migrate in response to natural hazards. It is important to understand where these displaced individuals are coming from since destinations will need to begin preparing for more potential migrants in the future. This portion of the study is novel in the sense that there is no direct methodological basis for this work. Directly correlating migration to a hazardous event is almost impossible, especially with the granularity of the IRS migration data. Since it is at the county level, spatially the migration is very generalized, and demographically, we cannot determine if known vulnerable populations are moving. However, we can posit that a hazardous event influenced migration for a given year if we see a relative spike in that year, from a region impacted by a hazard.

To do this the IRS data is organized by county and then summed to the state and regional level, for each of the seven counties between 2003-2018 (Figure 3.1). The state totals will be analyzed for any spike in migration, then hazard events for that year and that state were chosen. Lastly, we digitally compare which counties saw out-migration for the selected years and the hazard impact area. Here is a clearer example, say Fulton County received 2,000 migrants from Louisiana in 2004; 5,000 in 2005; and 3,000 in 2006. The relative spike in migration indicates the potential for, not always, a hazard influencing migration. Seeing that the spike occurred in 2005 from Louisiana we would choose hazards which impacted the state for that year, such as Hurricane Katrina. To posit that Katrina likely influenced migration, in this case, county year-to-year migration rates and physical location are compared with one another and the hazard event. Let us say in 2004 all the migration occurred from northern Louisiana, 2005 from coastal counties, and in 2006 transitioned back to northern counties. Overlaying the tract for Katrina may highlight that Fulton County only received migrants from impacted counties in 2005. Therefore, we can posit that this spike was influenced by the event, but all the migration which took place cannot be directly attributed to it.

Although this is by no means a perfect methodology, it pushes the research closer towards understanding hazardous event impacts on migration. Furthermore, it can inform stakeholders of the seven SEUS counties which events seem to spur migration into their cities and from what regions. This way, in the future, urban counties can have policies or plans in place to deal with migration due to similar hazardous events.

3.2.2.2 Relating Migration and Vulnerability

This section, like the previous, is an introduction to new methodology, instead, attempting to relate migration and vulnerability to one another. It is important to understand where potentially vulnerable populations reside, but also where they are moving to. We are assuming that any migrant from a county is attributed the vulnerability of that county. The IRS SOI Migration Data is not broken up demographically and just provides estimated individual totals from each county. Although the individuals within the total themselves may not be deemed vulnerable to climate change due to socioeconomic, demographic, age, or sex characteristics; if the county they reside in is vulnerable, although it is generalized, they would be considered more vulnerable than someone in a less vulnerable county for a given year.

Many migrants will also experience new, potentially, unforeseen vulnerabilities at their destination. Suppose that an individual has migrated from a hurricane and flooding-prone region of Florida to Atlanta, Georgia. The individual may consider themselves less vulnerable now since they are away from their previous hazards. However, they likely do not consider that Atlanta, and other urban centers, are vulnerable in unique ways to phenomena such as the Urban Heat Island, urban flooding, and poor air quality (Brookshire 2021). Since the individual has not experienced these events prior, they may not have the capacity to adapt or become resilient in their new homes.

Results from Chapter 2 CVI and yearly IRS SOI data will be used to relate migration and vulnerability. First, the CVI score for each of the seven counties, for each year, were found and tabulated. This variable will be known as county CVI (Figure 3.1). Then a median CVI was found by determining the median of all the counties which saw migration into our counties of interest, for a given year. This concept can be difficult to explain, so as an example, Fulton

County received migrants from 339 unique counties in 2004. To get the median, only these 339 counties were selected, a layer was created, and statistics were run on that year's CVI. The result would be the median CVI of the 339 counties which had people migrate to Fulton County in 2003. The median CVI in 2005 would likely be different since the CVI scores, and the number migration counties change from year to year. This is a tedious process since it must be done independently, for each year and for each county. In turn, it allows us to understand the general vulnerability of incoming migrants for each county of interest. Median was selected over mean under the advice of Dr. Nedret Billor, due to the dataset containing a few large outliers. Median does a better job at capturing the "typical" value in a given dataset and is not heavily influenced by outliers as the average is (Zach 2021). It also represents the literal middle of the dataset, which means that half the values are larger than the median value and half are smaller.

To further relate the two ideas, the percentage of vulnerable counties was also calculated. For example, Fulton County in 2004 had a county CVI of 0.33 which is the baseline used for Fulton County. Thus, of the 339 unique counties, only those with a CVI greater than 0.33 were selected. We assume 25 counties were found to have a higher CVI and using Equation 1 the result would be 7%. We then compare the county CVI, median CVI, and percent vulnerable counties to determine if people are moving from more, or less vulnerable counties into a more, equally, or less vulnerable destination.

$$\%\,Vulnerable = \frac{Selected\ Counties}{Total\ \#\ of\ Counties} * 100 \tag{1}$$

3.3 Results

3.3.1 Migration Inflow Trends for Seven SEUS Counties

3.3.1.1 Regional Trends

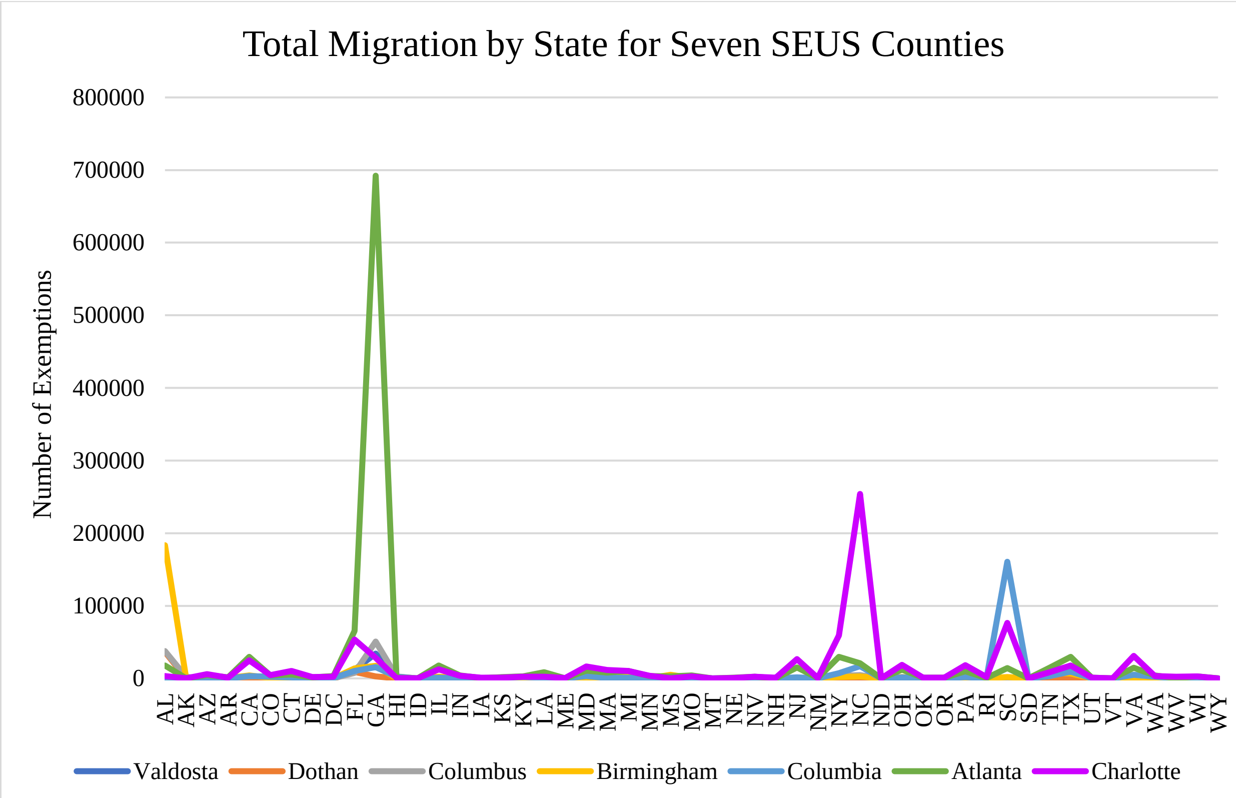
Table 3.1. Table of Regional Migration trends into the seven SEUS Counties

Region	Lowndes	Houston	Muscogee	Jefferson	Richland	Fulton	Mecklenburg
West	3,227	226	15,462	7,047	13,086	48,609	43,785
Midwest	198	0	4,035	7,985	6,275	57,135	56,778
Northeast	57	0	4,094	3,150	12,616	69,197	130,516
South	49,111	48,801	122,629	246,428	229,813	901,655	502,947

For each of the seven SEUS counties, migration rates from the South were highest compared to any other region in the United States (Table 3.1). The second highest migration rates occurred from the Northeast for Fulton and Mecklenburg, whereas the West was second highest for all other counties, aside from Jefferson which was the Midwest. The third largest rates were from the Midwest for Fulton, Mecklenburg and Lowndes, the Northeast for Richland and Muscogee, and the West for Jefferson. Most of the migration occurring from Southern states is no surprise, since all of the counties are within states classified as being southern United States. Fulton and Mecklenburg had the largest amounts of at 901,655 and 502,947, respectively. This may speak on the continued southward movement we are seeing in the United States, along with city-size maybe impacting individuals' decisions-making. Counties with larger cities do supply more opportunities for people, more access to health care, as well as provide cultural havens for marginalized communities. Therefore, people may feel more inclined to move to these larger cities, compared to SMSCs in the SEUS. Interestingly the second highest migration rates into Richland, Muscogee, Houston and Lowndes County occurred from states in the western United States. This may indicate a strong southwestward trend in migration in the United States, potentially catalyzed by drought and wildfires out west.

3.3.1.2 State Trends

Figure 3.2. Graph of State Migration trends into the seven SEUS Counties



The largest amount of migration for the SEUS counties, primarily, occurred from counties in Alabama, California, Florida, Georgia, New Jersey, New York, South Carolina, and Virginia (Figure 3.2). For each of the seven SEUS counties intrastate, movement within the same state, migration was the highest. Each county has experienced a positive trend in intrastate migration over the 15-year period, with larger cities having the highest rates of migration. Places like Houston and Lowndes County have generally seen the same rates of interstate migration over the 15 years. High rates of migration from California may also highlight an eastward movement, away from wildfire and drought-prone regions of the United States.

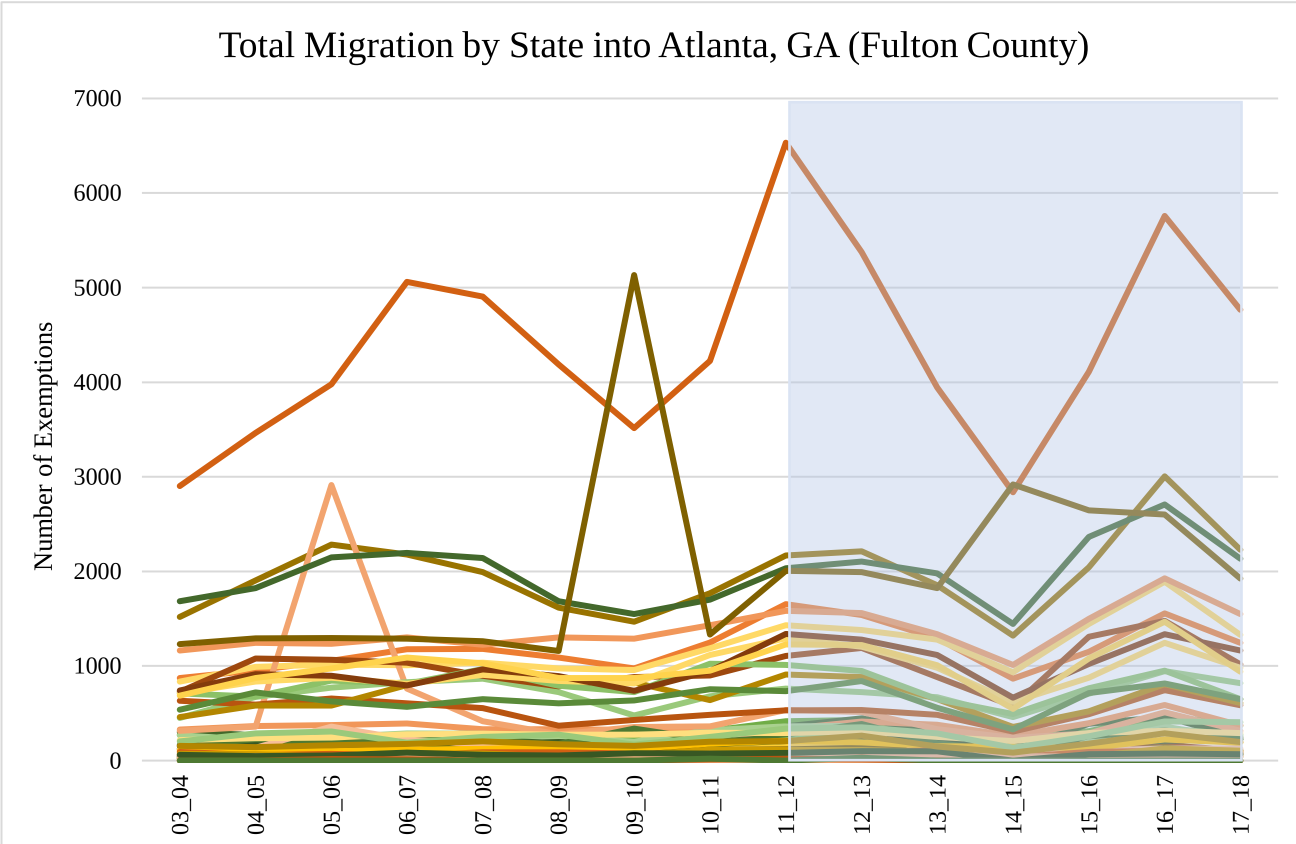


Figure 3.3. Visualization of anomaly mentioned in DeWaard et al. (2022).

Two interesting anomalies emerged in this analysis. This first issue reiterates what was said in DeWaard et al. (2022) and can be seen in Figure 3.3. State names were not included in the graph since they are not important to the error. The light blue box highlights all the data after 2011, which is when the IRS took over the organization of migration data from the U.S. Census. While there are rises and falls in some states, many oddly follow similar trends post-2011. Again, it is not known why this issue persists, not only for these counties, but the entire dataset. Another interesting anomaly can be seen in Tables 3.3-9. For each of the seven counties, the total number of counties that saw migration into each county dropped significantly in 2013. Columbia, South Carolina (Table 3.6) received migrants from 148 unique counties in 2012, and that figure dropped to 63 in 2013 and did not return to the usual number of counties through

2018. This data can be accessed at: https://brandonryanau.weebly.com/ if one would like to analyze these trends or anomalies further or analyze a more specific county.

3.3.2 Migration Influenced by Hazardous Events

3.3.2.1 Hurricane Katrina Case Study

Background

Hurricane Katrina was a Category 5 storm, which made landfall outside Buras, Louisiana on August 29, 2005, with sustained winds of 160 mph (Rafferty 2021). Roughly 1,200 fatalities were directly or indirectly related to the storm, and it remains one of the costliest natural disasters in the United States to date causing an estimated $106 billion in damage to the Gulf Coast (Rafferty 2021). It is estimated that roughly 400,000 residents were displaced for some time due to the storm and inundation (Bliss 2015). Some residents, and those with access to transportation, were able to choose their destinations, while others were shipped to random places. According to Michelle Witten, VP of Enterprise Community Partners, Inc, "FEMA loaded residents onto busses bound for Memphis, Tennessee or Salt Lake City, Utah and found out only when they got there" (Bliss 2015). Most evacuees fled towards Houston, Texas (approximately 250,000) many of whom were put into FEMA-funded apartments in high crime, high poverty neighborhoods." Moreover, basic needs, like transportation, affordable housing, schools, and Medicaid, within the city became strained leading to the Texas government seeking $2 billion in additional federal assistance (Bliss 2015).

Houston County, Alabama (Dothan)

Atlanta, and other major cities, were not the only recipients of migrants. Many SMSCs received displaced individuals from impacted areas. One such place was Houston County, Alabama (Dothan). Changes in the spatial location of migrants who moved into Houston County can be seen in Figure 3.4. Green dots indicate counties that saw movement into Houston County for a given year. It can be seen in the image that in 2004 and 2006 Houston County had no migrants from Louisiana or Mississippi, however, in 2005, indicated by the pink dots, three new counties emerged in those states. This marks the only time between 2003-2018 that Houston County had any migrants from Louisiana, 61 individuals, and Mississippi, 31 individuals. The pink points all fell within counties which declared a disaster in response to Hurricane Katrina and occur along the storm track. Therefore, we can posit, not definitively say, that the migration that occurred was strongly influenced by Hurricane Katrina.

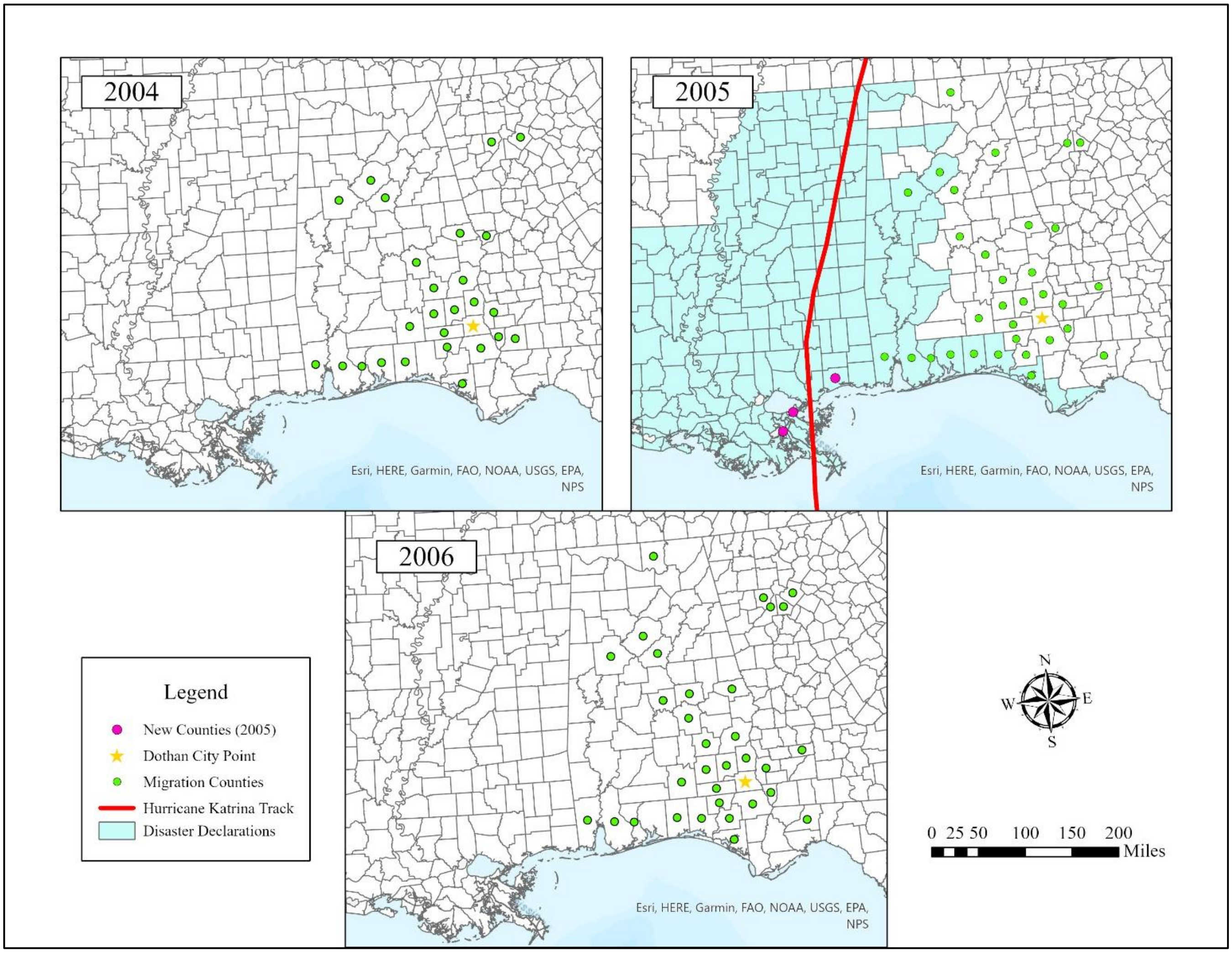


Figure 3.4. Maps of inflow, migration into, Houston County, Alabama (Dothan) from southern U.S. states for 2003-2006. Green dots indicate any county that had migration into Dothan, the pink dots represent counties which had no migration in 2004 or 2006, the red line is the track of Hurricane Katrina, and all light-blue filled counties are ones which declared a disaster in response to Katrina.

Houston County was not the only urban county to likely receive migrants as a result of the storm. Jefferson County, Alabama (Birmingham), for instance, only received 37 migrants from Orleans Parish (New Orleans, Louisiana) in 2004, but that number drastically increased to 265 in 2005, then back to 57 in 2006. From Louisiana alone, Jefferson County went from receiving 188 migrants in 2004 to 1,300 in 2005. Fulton County saw a 520% increase in migrants from Louisiana and Mississippi between 2004-2005 (Figure 3.5). All other counties, except Lowndes, Georgia, follow a similar trend of seeing exponential growth in migrants between 2004-2005, from impacted counties. This may shed light on distance or ease of transport to destination cities being a determinant for migrants.

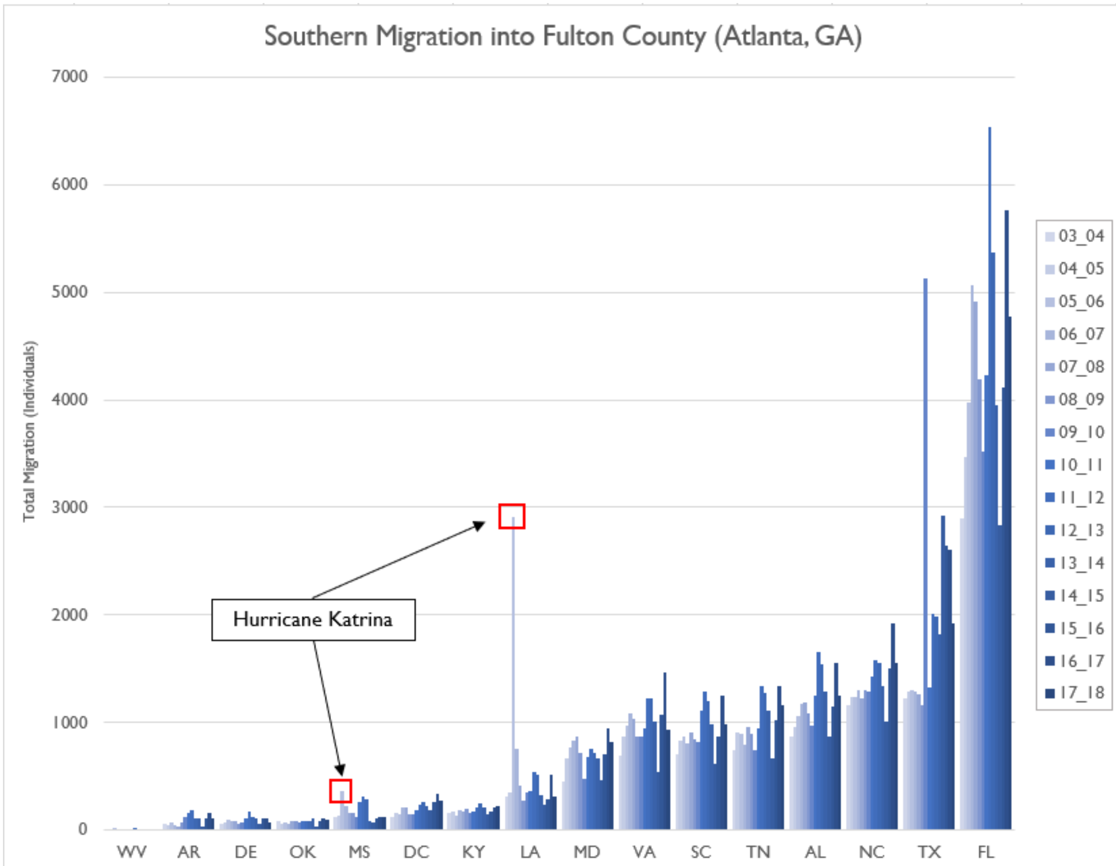


Figure 3.5. Graph of southern state migration rates into Fulton County (Atlanta, Georgia) for 2003-2018. Lighter blue indicates earlier in the time series, and dark blue indicates later. States are organized in ascending order, left to right, by total population.

While Houston County may have not received many migrants (90 migrants) in 2005, compared to other larger cities, this information is still crucial. Houston County had not received, except in 2005, any migration from Louisiana or Mississippi between 2003-2018. This could inform local governments that they could expect some amount of migration from the Gulf Coast region given a similar event.

3.3.2.2 Hurricane Sandy Case Study

Background

When Hurricane Sandy made landfall on October 29, 2012, it was rated a category 3 storm, with 80 mph sustained winds (Rafferty 2021). It is estimated that over 8.5 million people lost power because of the storm, with roughly $71.4 billion in estimated damages. Roughly a year after the storm over 30,000 residents of New York and New Jersey were still displaced by the storm. Many displaced barely received any compensation from Federal assistance, with the largest payout being $36,000, and the government instructed individuals to file claims with their insurance. Most received less than it would cost to rebuild their homes, while others had their claims denied because it was deemed the destruction was due to “earth movement,” not inundation (McGeehan and Palmer 2013).

Fulton County, Georgia (Atlanta)

Unlike Hurricane Katrina, Hurricane Sandy has not been as heavily studied to analyze where those displaced by the storm had relocated. Figure 3.6 illustrates migration into Fulton County from the northeast in 2011-2013. Again, the pink dots indicate counties which had migration only in the year 2012, and not in 2011 or 2013. All the pink dots contain some amount of null data for the years between 2003-2018. This means that these counties did not frequently see migration into Fulton County, on a yearly basis. Each pink dot (county) Hurricane Sandy’s track passes over had no migration into Fulton County for 2011 or 2013. While there is not a large shift in the total amount of migrants from New York and New Jersey between the three years, there is still the potential that Hurricane Sandy may have forced some 182 people to relocate to Fulton County, Georgia.

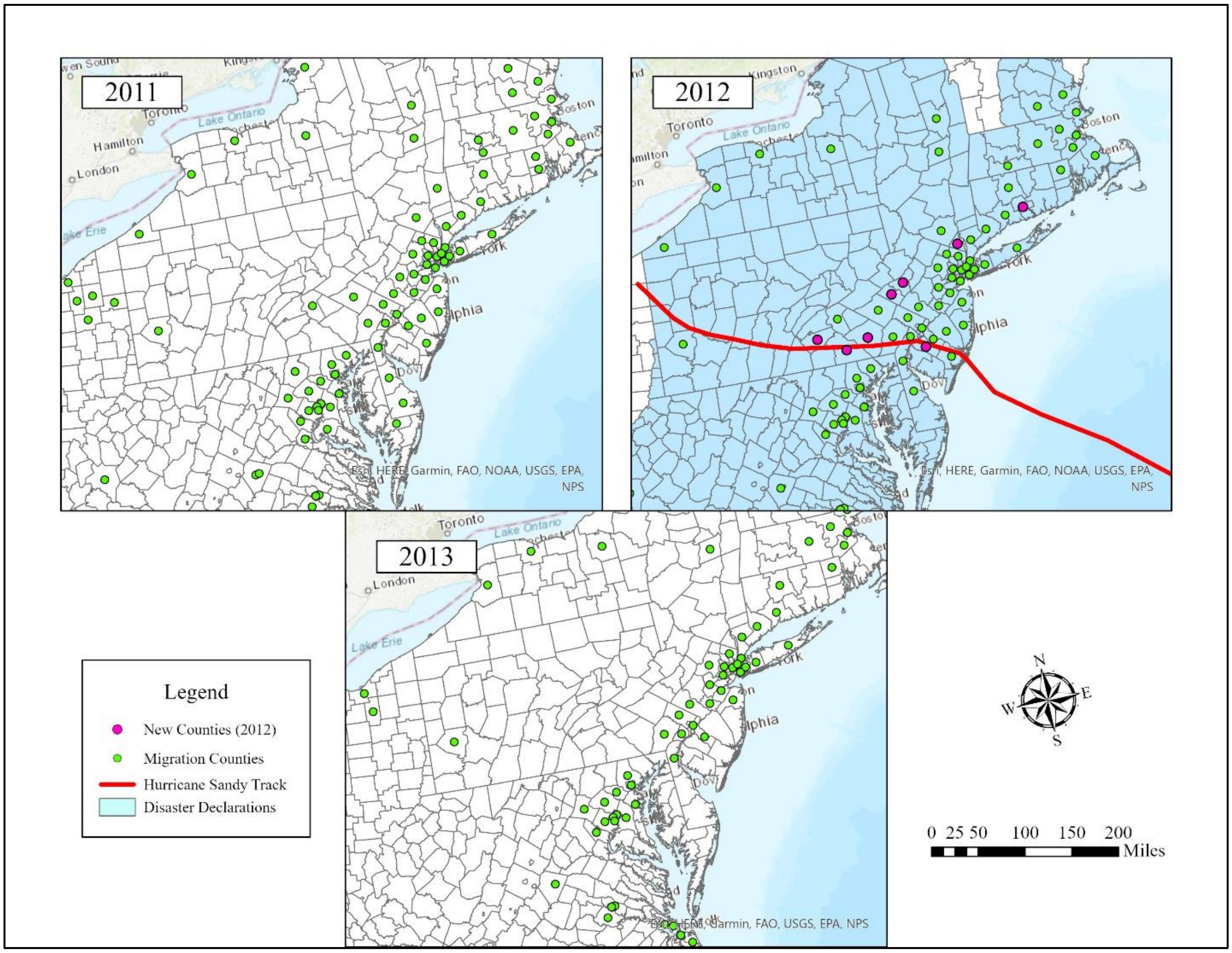


Figure 3.6. Maps of migration into, Fulton County, Georgia (Atlanta) from northeastern U.S. states for 2011-2013. Green dots indicate any county that had migration into Atlanta, the pink dots represent counties which had no migration in 2011 or 2013, the red line is the track of Hurricane Sandy, and all light-blue filled counties are ones which declared a disaster in response to Sandy.

Muscogee County, Georgia (Columbus)

Another potential destination for residents may have been Muscogee County, Georgia, (Figure 3.4) which received 359 migrants from impacted regions of New York and New Jersey in 2012. Of those 359 migrants, 92 were from counties in which it was the first time Muscogee

County received migration from that particular county, or no migration occurred from the affected county in 2011 and 2013 but saw migration in 2012. Bergen County, New York, which is the most northern pink dot in Figure 3.7, only had individuals move to Muscogee County in 2012. 2012 also marked the last time any of the pink dot counties saw any migration into Muscogee County through 2013-2018.

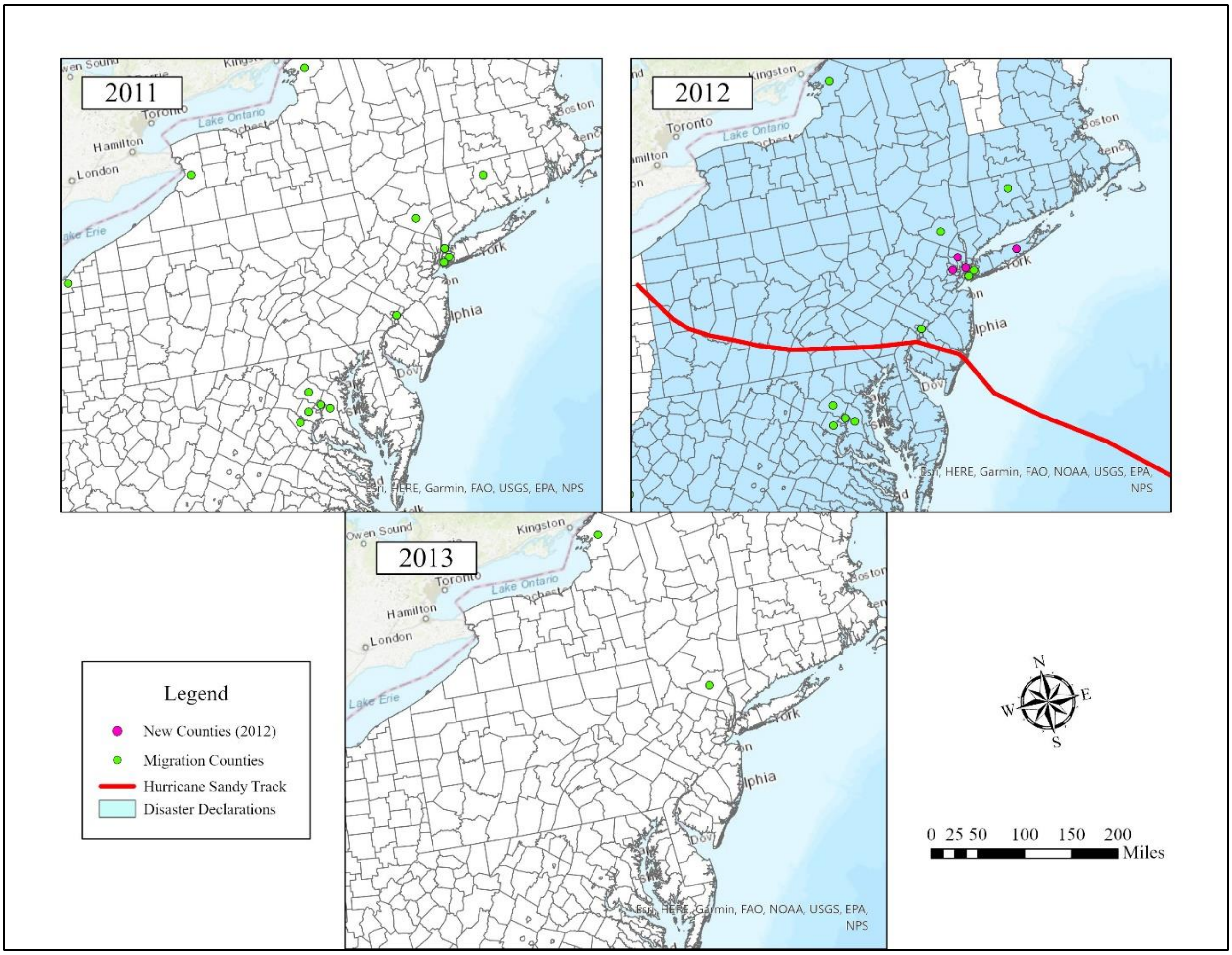


Figure 3.7. Maps of inflow, migration into, Muscogee County, Georgia (Columbus) from northeastern U.S. states for 2011-2013. Green dots indicate any county that had migration into Columbus, the pink dots represent counties which had no migration in 2011 or 2013, the red line is the track of Hurricane Sandy, and all light-blue filled counties are ones which declared a disaster in response to Sandy.

Conversely, Bronx County, New York, had individuals move to Muscogee County each year between 2008-2011. Then, in 2012 Muscogee County no longer received any migrants from Bronx County from 2013-2018. This may point to Hurricane Sandy inhibiting, or halting, migration which may have otherwise continued if Hurricane Sandy did not occur. While there is a potential that the other seven cities still received migrants from Sandy, Fulton and Muscogee County paint a clear example of how storms may influence human movement.

3.3.3 Climatic Vulnerability and its Relationship to Migration

Overall

Table 3.2. Table of climate vulnerability scores for each of the seven SEUS counties, for 2003-2018.

Year	Lowndes	Houston	Muscogee	Jefferson	Richland	Fulton	Mecklenburg
2003	0.22	0.24	0.23	0.32	0.22	0.26	0.26
2004	0.24	0.26	0.28	0.25	0.21	0.33	0.26
2005	0.26	0.25	0.27	0.28	0.27	0.30	0.28
2006	0.24	0.21	0.23	0.27	0.26	0.30	0.32
2007	0.23	0.21	0.25	0.29	0.26	0.29	0.32
2008	0.22	0.23	0.22	0.26	0.26	0.32	0.32
2009	0.21	0.21	0.19	0.22	0.25	0.32	0.32
2010	0.23	0.24	0.25	0.26	0.27	0.32	0.33
2011	0.23	0.25	0.24	0.27	0.27	0.33	0.33
2012	0.23	0.22	0.24	0.29	0.27	0.33	0.34
2013	0.23	0.21	0.21	0.23	0.27	0.31	0.33
2014	0.22	0.24	0.22	0.27	0.26	0.32	0.33
2015	0.23	0.20	0.23	0.25	0.27	0.31	0.33
2016	0.17	0.19	0.22	0.20	0.23	0.24	0.24
2017	0.28	0.24	0.26	0.27	0.32	0.35	0.33
2018	0.22	0.22	0.21	0.26	0.31	0.31	0.36
Average	0.23	0.23	0.23	0.26	0.26	0.31	0.31
Rank	386	341	290	105	104	36	29
Trend	-	-	-	-	+	+	+

Out of the seven counties of interest, Mecklenburg and Fulton County tied for the highest average CVI, 0.31, followed by Richland and Jefferson County, 0.26, and Muscogee, Houston, and Lowndes County, 0.23 (Table 3.2). While these counties are not ranked as the most vulnerable in the United States, five of the seven are in the 10th percentile of vulnerability. This means, in comparison to the entire dataset, the selected counties are more vulnerable than many of the counties in the United States. Mecklenburg, Fulton, and Richland County all had a positive, increasing, trend in vulnerability over time, whereas Jefferson, Muscogee, Houston, and Lowndes County saw a negative, decreasing, trend over time.

Fulton County, Georgia (Atlanta)

Table 3.3. Table of the relationship between migration and vulnerability for Fulton County, Georgia (Atlanta).

Year	County CVI	Median CVI	Number of Counties above County CVI	Total Number of Counties	Percent Vulnerable
2003	0.26	0.22	94	324	29.01%
2004	0.33	0.22	25	339	7.37%
2005	0.30	0.24	33	354	9.32%
2006	0.30	0.23	44	353	12.46%
2007	0.29	0.23	50	373	13.40%
2008	0.32	0.23	32	345	9.28%
2009	0.32	0.22	23	335	6.87%
2010	0.32	0.24	37	395	9.37%
2011	0.33	0.23	27	446	6.05%
2012	0.33	0.25	34	396	8.59%
2013	0.31	0.25	36	240	15.00%
2014	0.32	0.25	27	196	13.78%
2015	0.31	0.24	32	239	13.39%
2016	0.24	0.18	35	271	12.92%
2017	0.35	0.27	27	246	10.98%
2018	0.31	-	-	-	-

The highest county and median CVI occurred in 2017 at 0.35, and 0.27, respectively (Table 3.3). For each year in the time series, Fulton County, Georgia had a higher county CVI score than the median CVI. This means that, in general, people are moving from less vulnerable counties into the more vulnerable Fulton County. This is further highlighted by the number of counties which had a higher CVI than Fulton County. In many of the years no more than 15% of the counties, which had individuals migrate to Fulton County, were more vulnerable than Fulton. This means that Fulton County receives a sizable portion of its migrants from areas deemed less vulnerable, meaning that many individuals are becoming more vulnerable by moving into the county.

Jefferson County, Alabama (Birmingham)

Table 3.4. Table of the relationship between migration and vulnerability for Jefferson County, Alabama (Birmingham).

Year	County CVI	Median CVI	Number of Counties above County CVI	Total Number of Counties	Percent Vulnerable
2003	0.32	0.24	24	172	13.95%
2004	0.25	0.24	76	185	41.08%
2005	0.28	0.27	65	174	37.36%
2006	0.27	0.24	52	176	29.55%
2007	0.29	0.24	42	185	22.70%
2008	0.26	0.24	71	181	39.23%
2009	0.22	0.23	99	159	62.26%
2010	0.26	0.25	69	160	43.13%
2011	0.27	0.25	66	187	35.29%
2012	0.29	0.26	62	192	32.29%
2013	0.23	0.25	51	81	62.96%
2014	0.27	0.24	24	66	36.36%
2015	0.25	0.25	39	83	46.99%
2016	0.20	0.18	45	115	39.13%
2017	0.27	0.27	46	89	51.69%
2018	0.26	-	-	-	-

For Jefferson County, Alabama, the highest county CVI occurred in 2007 and 2012 at 0.29 and the highest median CVI of 0.27 occurred in 2005 and 2017 (Table 3.4). Jefferson Countyhad a higher CVI than the median for each year except 2009 and 2013. 2009 and 2013 were also the years in which 60% of the counties, which had people emigrate to Jefferson County, were more vulnerable than Jefferson County. On average, Jefferson Countyreceives migrants from more vulnerable counties 40% of the time. This means Jefferson County, receives migrants from extremely vulnerable areas whilst also being extremely vulnerable itself. Meaning, that individuals may potentially get caught in a cycle of vulnerability even though they are moving to a new destination, away from the vulnerabilities they previously faced.

Mecklenburg, North Carolina (Charlotte)

Table 3.5. Table of the relationship between migration and vulnerability for Mecklenburg, North Carolina (Charlotte).

Year	County CVI	Median CVI	Number of Counties above County CVI	Total Number of Counties	Percent Vulnerable
2003	0.26	0.22	91	366	24.86%
2004	0.26	0.22	93	401	23.19%
2005	0.28	0.23	84	433	19.40%
2006	0.32	0.22	28	440	6.36%
2007	0.32	0.22	27	443	6.09%
2008	0.32	0.21	32	393	8.14%
2009	0.32	0.21	23	371	6.20%
2010	0.33	0.23	26	390	6.67%
2011	0.33	0.23	27	421	6.41%
2012	0.34	0.24	35	423	8.27%
2013	0.33	0.24	25	269	9.29%
2014	0.33	0.24	21	217	9.68%
2015	0.33	0.23	21	287	7.32%
2016	0.24	0.17	35	346	10.12%
2017	0.33	0.26	21	286	7.34%
2018	0.36	-	-	-	-

Mecklenburg County had the highest county CVI in 2018, 0.36, and the highest median CVI in 2017, 0.26 (Table 3.5). For every year Mecklenburg County had a higher county CVI than the median CVI and had low percentages of individuals moving from more vulnerable counties. 2004 and 2005 marked the highest percentage of vulnerable counties at 24.86%, 23.19%, and 19.40%, respectively. This means that individuals are migrating from less vulnerable counties into the more vulnerable Mecklenburg County.

Richland, South Carolina (Columbia)

Table 3.6. Table of the relationship between migration and vulnerability for Richland, South Carolina (Columbia).

Year	County CVI	Median CVI	Number of Counties above County CVI	Total Number of Counties	Percent Vulnerable
2003	0.22	0.24	86	154	55.84%
2004	0.21	0.24	130	185	70.27%
2005	0.27	0.26	74	185	40.00%
2006	0.26	0.24	73	182	40.11%
2007	0.26	0.24	69	197	35.03%
2008	0.26	0.23	62	187	33.16%
2009	0.25	0.23	55	172	31.98%
2010	0.27	0.25	63	177	35.59%
2011	0.27	0.25	62	189	32.80%
2012	0.27	0.25	76	190	40.00%
2013	0.27	0.24	31	95	32.63%
2014	0.26	0.23	24	73	32.88%
2015	0.27	0.23	33	112	29.46%
2016	0.23	0.2	30	131	22.90%
2017	0.32	0.28	30	106	28.30%
2018	0.31	-	-	-	-

Richland County had the highest county CVI in 2017, 0.32 with 2018 having an almost identical score of 0.31 (Table 3.6). The highest median CVI occurred in 2017, 0.28. The median CVI exceeded the county CVI only in 2004. For both these years, Richland County received migrants from 55.84% and 70.27%, respectively, more vulnerable counties. These early spikes, or spikes similar to it, may indicate a potential event that may have influenced migration into Richland County. On average it is less vulnerable than 37.40% of counties which had individuals emigrate to it. This means that Richland County may receive migrants from vulnerable areas, whilst also being vulnerable itself.

Muscogee County, Georgia (Columbus)

Table 3.7. Table of the relationship between migration and vulnerability for Muscogee County, Georgia (Columbus)

Year	County CVI	Median CVI	Number of Counties above County CVI	Total Number of Counties	Percent Vulnerable
2003	0.23	0.24	69	115	60.00%
2004	0.28	0.24	51	101	50.50%
2005	0.27	0.26	46	105	43.81%
2006	0.23	0.25	65	100	65.00%
2007	0.25	0.24	42	101	41.58%
2008	0.22	0.25	83	120	69.17%
2009	0.19	0.23	90	116	77.59%
2010	0.25	0.24	79	140	56.43%
2011	0.24	0.25	91	151	60.26%
2012	0.24	0.26	103	148	69.59%
2013	0.21	0.24	44	63	69.84%
2014	0.22	0.24	28	42	66.67%
2015	0.23	0.23	27	54	50.00%
2016	0.22	0.17	20	65	30.77%
2017	0.26	0.27	30	51	58.82%
2018	0.21	-	-	-	-

Muscogee County had the highest county CVI in 2004, 0.28 and the highest median CVI in 2017, 0.27 (Table 3.7). The median CVI exceeded the county CVI in 2006, 2008, 2009, 2011-2014, and 2017. On average Muscogee County receives migrants from 58% more vulnerable counties. The highest rate was 77.59% in 2009. While Muscogee County is vulnerable in its unique ways, compared to the counties it receives migrants from, it is generally less vulnerable. Such a large percentage of vulnerable counties indicates that Muscogee County will likely continue to receive potentially vulnerable populations, or it may be a potential destination for climate migrants in the future.

Houston County, Alabama (Dothan)

Table 3.8. Table of the relationship between migration and vulnerability for Houston County, Alabama (Dothan).

Year	County CVI	Median CVI	Number of Counties above County CVI	Total Number of Counties	Percent Vulnerable
2003	0.24	0.23	11	31	35.48%
2004	0.26	0.25	9	34	26.47%
2005	0.25	0.27	36	48	75.00%
2006	0.21	0.24	38	45	84.44%
2007	0.22	0.24	23	40	57.50%
2008	0.23	0.25	25	40	62.50%
2009	0.21	0.22	27	35	77.14%
2010	0.24	0.25	27	43	62.79%
2011	0.25	0.25	29	51	56.86%
2012	0.22	0.26	41	44	93.18%
2013	0.21	0.23	13	17	76.47%
2014	0.24	0.23	6	14	42.86%
2015	0.20	0.23	17	19	89.47%
2016	0.19	0.18	3	22	13.64%
2017	0.24	0.26	16	20	80.00%
2018	0.22	-	-	-	-

The highest county CVI occurred in 2004, 0.26, and the highest median CVI occurred in 2005, 0.27 (Table 3.8). The median CVI exceeded the county CVI in 2005-2010, 2012, 2013, 2015, and 2017; the county CVI either tied or exceeded the median CVI in all other years. On average 62.25% of counties are more vulnerable than Houston County, with the highest occurring at 93.18%. This means that individuals have been, generally, moving into a less vulnerable county over time. It also may indicate vulnerable populations moving into the area and may indicate a potential first stop for climate migrants in the future.

Lowndes County, Georgia (Valdosta)

Table 3.9. Table of the relationship between migration and vulnerability for Lowndes County, Georgia (Valdosta).

Year	County CVI	Median CVI	Number of Counties above County CVI	Total Number of Counties	Percent Vulnerable
2003	0.22	0.22	29	61	47.54%
2004	0.24	0.25	33	61	54.10%
2005	0.26	0.26	28	61	45.90%
2006	0.24	0.24	34	66	51.52%
2007	0.23	0.24	40	65	61.54%
2008	0.22	0.24	44	65	67.69%
2009	0.21	0.24	47	62	75.81%
2010	0.23	0.24	54	71	76.06%
2011	0.23	0.25	50	75	66.67%
2012	0.23	0.26	55	62	88.71%
2013	0.23	0.24	15	25	60.00%
2014	0.22	0.25	16	20	80.00%
2015	0.23	0.25	20	30	66.67%
2016	0.17	0.19	23	39	58.97%
2017	0.28	0.31	24	34	70.59%
2018	0.22	-	-	-	-

The highest county and median CVI in Lowndes County occurred in 2017, at 0.28 and 0.31, respectively (Table 3.9). In 2005, and 2006, Lowndes County had the same county and median CVI, whereas, for all other years the median CVI exceeded the county CVI. On average 64.78% of counties are more vulnerable than Lowndes County, with the highest percentage occurring in 2021 at 88.71%. This means that Lowndes County may be a hot spot destination for potentially vulnerable populations, and a future destination for climate-displaced migrants particularly those in Florida.

3.4 Discussion

Although we cannot say, with full confidence, that any spike or anomalous migration was fully caused by a natural hazard for a given year; we can say that these surges were at least influenced by the hazards. Houston County is a clear example of an extremely likely, and known, case where individuals likely relocated due to the damage of Hurricane Katrina. Again, the only time Houston County has received any migration from Louisiana was in 2005, specifically from impacted areas. There are few articles that talk about evacuees who moved into Houston County, most being from the local Dothan newspaper. This is important because larger cities tend to dominate the news when it comes to natural hazards.

Larger cities have more capacity to deal with sudden influxes, as illustrated by Houston, Texas, even though they have struggled to support displaced individuals financially and equitably. In 2005, there were potentially 90 vulnerable individuals who moved into Houston County and needed local assistance for recovery. More importantly, larger urban counties [cities] have largely dominated risk analysis since they are places where people, assets, and political power concentrate (Birkmann et al. 2016). Yet, SMSCs are presently the fastest growing city type, and populations within these cities are expected to increase by 32% by 2050, compared to the anticipated growth rate of 26% for large cities and megacities. It is easy to see how this growth, compounded by external migration, will likely further exacerbate the vulnerabilities of SMSCs (Birkmann et al. 2016).

Each county, aside from Lowndes County, likely received displaced individuals from Hurricane Katrina. This speaks to the idea that there is likely a threshold of reasonable distance for migrants displaced by hazards. Now, this is not for every case, as familial connections, social networks, or occupations can influence how far an individual travels. However, it seems that if another large-scale event were to occur in the region the counties, and many counties in the south, can anticipate receiving some migrants. This could also be why we do not see many spikes in-migration from New York and New Jersey in 2012 in the seven SEUS counties. Locations this far south are unlikely to be the migrant's first choice for relocation. Many want to move inland temporarily, rebuild, and move back into their homes. Fulton County saw the clearest and definitive spike in migration from affected counties, which may point to city size being a considerable factor. A study by Robinson, Dilkina, and Moreno-Cruz (2020) found that those displaced by future sea-level rise scenarios' primary destinations were counties just inland of their origin, but climate migrants also move farther toward large cities which offer more opportunities. This may shed light as to why equally as far counties like Richland and Mecklenburg received migrants from Katrina over Lowndes.

So, how does this all relate to vulnerability? Let us use Hurricane Katrina and Houston County, Alabama (Dothan) as an example. In 2004, 2005, 2006 Dothan had a county CVI of 0.26, 0.25, and 0.21 and median CVI of 0.25, 0.27, and 0.24, respectively. The county CVI decreases over this time, where we see a sudden increase and then sudden decrease in the median CVI. In 2005, 75% of the counties Houston County received migrants from were more vulnerable and on average, 62.25% of counties are more vulnerable than Houston County. Knowing that Houston County likely received migrants from Katrina we can begin to understand how destination cities' vulnerability should be considered. Although Houston County is considered less vulnerable, it is receiving more vulnerable populations, not only during hazard years but during other years as well. This points to Houston County needing to ensure action is taken so there are enough resources (housing, transportation, healthcare) for vulnerable populations which may call Houston County their home in the future.

Compare this to the larger cities in the study, like Jefferson County, Alabama. The highest median CVI occurred in 2005, 0.27, but did not beat the county CVI of 0.28 for that year. On average, only 40% of counties are more vulnerable than Jefferson County. This points to migrants, especially in 2005, moving into an area which is more vulnerable than where they previously resided. Again, many residents move to larger urban areas to experience a higher quality of living and may not anticipate facing more vulnerabilities within these city classes. Jefferson County has recently seen an increase in urban flooding and flash flooding events. An event on March 16, 2022, resulted in over 50 water rescues being conducted by local fire departments, and one death (Garrison 2022). Jefferson County has also been ranked as the city with the 14^{th} highest levels of particulate air pollution, and the 46^{th} worst city in terms of ozone pollution (Pillion 2019). Again, these are likely hazards and factors recently displaced migrants may not consider when choosing a destination city.

Urban counties and local governments are the ones which will have to face the brunt of the climate migration crisis. With the results of this study, we can better inform cities in the southeast where individuals are coming from if they are displaced by hazards. Moreover, these cities can get an understanding of how vulnerable they are to climate change, and start putting adaptation plans, policies, and critical infrastructure development into action.

3.4.1 Limitations

One major limitation to this study is the IRS SOI Tax Migration data. This data is only available at the county level, which makes relating migration to hazards much more difficult. A much larger spatial unit generalizes where the migration occurred from and where vulnerable populations are. We know that all the migration did not occur from the same area within the county, nor does every place within the county experience the same vulnerability. Moreover, data before 2011 are not full-year estimates of migration, but only until late September of the filing year. This means that the data likely has an underestimation of the actual amount of migration which took place for hazards before this time, like Hurricane Katrina.

Another limitation of this study is the methodology. Since there have been no studies which attempt to analyze and relate hazards, vulnerabilities, and migration, there is no peer-reviewed methodological basis for this study. We believe, although not perfect, this is a strength, rather, since it opens the discussion to have studies move in a new, interdisciplinary direction.

3.4.2 Future Research

There is a myriad of potential studies which can springboard or be developed from the results and methodology produced in this study. Some potential topics of study are:

1. Conduct a similar study with newer IRS data in the American West. Particularly to analyze the impacts of wildfires on migration.
2. Conduct this study at a smaller spatial scale, for a single city.
3. Branch outside of the U.S., given there is available data, to understand how cities are being impacted by climate migrants in Latin America, sub-Saharan Africa, and Southeast Asia.
4. Look at smaller scale hazards (like tornadoes and mesoscale convective systems) and their impact on rural migration.

The climate migrant crisis, at this point, is almost unavoidable. However, steps can be taken, and measures can be put in place to make vulnerable, or recipient cities more resilient to the effects of climate change and induced migration.

3.4.3 Concluding Remarks

While this study has many limitations, and those should be acknowledged, it is believed that the results and methodology presented in this study can be and should be used to further our understanding of vulnerable populations and displaced peoples in the United States. While many believe the United States may be immune to the effects and consequences of climate change, we could not be further from the truth (Figure 3.8). According to the Internal Displacement Monitoring Centre more than 10.5 million people have been displaced in the United States, due to natural hazards, since 2008. Actions and plans must be put into place to better prepare United States cities to deal with influxes of people from the coast, due to sea level rise, from the west coast, due to drought, lack of water, and wildfires, and those from marginalized communities.

Figure 3.8. Managed Retreat in the United States. The Federal Emergency Management Agency and the Department of Housing and Urban Development have funded managed retreat across the United States (small dots). Large circles note communities who have relocated together or are considering relocation, and stars indicate academic studies and reports. From Siders (2019).

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Appendix A

Extending Beyond the Ivory Tower: Communicating Science within Graduate Studies

A.1 Introduction

Since 2017, the National Science Foundation (NSF) has been building a foundation for the 10 Big Ideas through pioneering research and pilot activities. These ten ideas are Future of Work at the Human-Technology Frontier, Growing Convergence Research, Harnessing the Data Revolution, Mid-scale Research Infrastructure, Navigating the New Arctic, NSF 2026, NSF Includes, Quantum Leap, Understanding the Rules of Life, and Windows on the Universe. Of the ten ideas, Growing Convergence Research is one that many universities, like Auburn University, have decided to tackle. Convergence is, as NSF Director France Córdova states, "A deeper, more intentional approach to the integration of knowledge, techniques, and expertise from multiple disciplines to address the most compelling scientific and societal challenges" (NSF 2017). In 2019, NSF invested $30 million into pioneering research and pilot activities surrounding each Big Idea (NSF 2022). One of these projects, attempting to address convergence research, is the National Science Foundation Research Traineeship (NRT) Program.

A.1.1 Auburn NRT Program

The NRT program aims to, "train the next generation of interdisciplinary researchers to use state-of-the-art theory and modeling tools to pursue action-based science aimed at increasing resilience to climate-related hazards and disasters" (Auburn University 2022). Trainees within the program will conduct research while collaborating with stakeholders, learn effective science communication strategies, and aim to improve inclusion, equity, and diversity within the NRT program and STEM. In this chapter, I will discuss some of the experiences and opportunities I have received being an NRT Trainee. I will also highlight areas of limitation and improvement for data scientists and several ways a graduate student may be able to bridge the gap between scientists and the public. This chapter will take a less formal tone since I am speaking on my NRT experiences and providing my opinions and suggestions for fellow graduate students.

A.2 Interdisciplinary Engagement

A.2.1 Non-degree Coursework

One requirement of the NRT program, for master's students, is to take two required courses, Natural Hazard Risk and Disaster Resilience and Science Communication, and one required elective outside of your undergraduate discipline. Since my undergraduate degree was in GIS, data, and Atmospheric Science, I was required to take a social science elective. My atmospheric science department was half in physics and half in geography, so I was fortunate enough to see the upside of interdisciplinary coursework early on. A major benefit to taking courses outside the realm of Geography is that it allows me to become a better, well-rounded, versatile scientist. Dr. Bryan Collisson, professor of psychology at Azusa Pacific University says, "certain subjects, like psychology, are hub disciplines that inform and provide meaningful implications for countless other fields, including nursing, biology, and business" (Cayot 2020). Although I had taken alternative courses in my undergraduate studies, such as a non-technical scientific writing course, public speaking, and groundwater resources management; they were not required by the department, and I still wanted to do research within the confines of my own field at the end of the day.

Coming to Auburn University I had planned to continue my undergraduate research focusing on Urban Heat Island development throughout the United States. One of the first NRT courses I took was the Natural Hazard Risk and Disaster Resilience taught by Dr. Christopher Burton. In this course, we were introduced to the concept of social vulnerability and what goes into disaster management planning. To say this course changed me would be an understatement. This course, rather, foundationally changed my direction of study and research. I had finally found a topic that was an intersection of weather, GIS, and social sciences, and one I would have not likely found if I were not forced outside of my comfort zone. Through this course, I was introduced to new methodology, new ways of thinking, and a new, burgeoning field of study to pursue.

A.2.2 Students & Faculty

Being a part of the NRT also allowed me to interact with students and faculty within a variety of different disciplines, which is another added benefit to taking courses outside your degree. Taking a class outside of your major means that your classmates will likely have different academic experiences than you and can lead to collaboration or new ways of thinking (Harbrecht 2016). The NRT has students and faculty across earth system science, engineering, geosciences, forestry and wildlife sciences, climate since, data science, sociology, agriculture, and social science disciplines (Auburn University 2022). The exciting thing about this is that the number of faculty, students, variety of disciplines, and offered coursework has increased each year of the NRT program. Taking classes outside of your discipline likely means that most of your classmates have had different academic experiences from your own. These differing experiences can lead to opportunities for students to learn from one another, interact with new ways of thinking, and opens potential for collaboration and more (Harbrecht 2016). Likewise, branching out allows you to meet faculty outside of your major, which for a graduate student, can act as a great resource to be on your committee, aid with research, networking, acting as a mentor, etc.

In Spring 2022, the NRT at Auburn University held the university's first "Climate Event, which brought in non-profits, NGOs, and roughly 100 students and faculty, across a variety of disciplines, from Auburn University, University of South Alabama, University of Alabama Huntsville, Auburn University Montgomery, University of Alabama, and the University of Alabama at Birmingham. It was at this event where I met many faculty at the university, and surrounding universities, conducting climate science research. These interactions have led to new future collaborations for my Ph.D. research, and I was even asked to give a talk for a course within the School of Forestry. Although this is a specific event tailored for networking with stakeholders and academics, it highlights the benefits of interacting and engaging outside one's academic bubble.

A.3 Outreach & Communication with Non-Scientific Audiences

Outreach and interacting with non-scientific audiences are difficult and is why many choose not to pursue it within their research. The idea of "pushing beyond the ivory tower" is a challenge for many scientists, including myself. This concept is not a recent development; however, former NOAA chief administrator Jane Lubchenco proposed a similar idea back in 1998. Her paper titled *Entering the Century of the Environment: A New Social Contract for*

Science, argued that scientists need to be more forthcoming and share their research to benefit society at large (Baron 2010).

As Randy Olson, a Doctor of Biology turned filmmaker, says, "Science, from the beginning of time, has always consisted of two parts. Doing science: collecting data, testing hypothesis, running experiments is the first part, whilst communicating that science is the second" (Olson 2018). Gregor Mendel is an example of what poor science communication looks like. Today, known as the Father of Genetics, Mendel kept his work a secret predominately publishing in obscure journals whilst he was alive. It was not until many decades later that other researchers would find Mendel's work, which would ultimately fill in the missing pieces of Darwin's Theory of Evolution. So, how do scientists go about being less like a scientist?

Another anecdote from Olson details the frustrations that a German nuclear engineer faced when interacting with the public. The engineer argued that they had all the data, numbers, and facts to show the public that nuclear power was completely safe. However, the Green Party, an environmentalist political party, had run such an effective fear-mongering campaign that the public would not listen to scientists' reasoning. The German engineer was, as Olson terms it, communicating to "the head." "The head" is characterized by logic and analysis and is where many academics spend their lives (Olson 2018). The further you move away from the head, the broader an audience you reach because you start connecting on different levels. "The heart" is characterized by emotions and passion, whereas "the gut" is home to humor and instinct.

The Green Party communicated to people's "hearts," focusing on the fear people had of nuclear energy after the Chornobyl nuclear accident. Research shows that people's values and political views have a greater influence on individuals' perceptions of climate change than their scientific understanding (Climate Outreach 2018). So, rather than just throwing out facts and figures and expecting the public to do a complete 180, communicate to people's "hearts" and "guts", such as their values, cognitive barriers, or preconceptions, instead.

A.4 Access to Data & Information

A.4.1 GIS Data

One major limitation to this study, and a potential issue plaguing most geospatial studies, is the availability, access, and organization of geospatial data. Issues with data organization mostly arose with the United States Census data. Older data tables are saved in .csv format, which leads to, what I like to call, the "leading zero" issue. This issue stems from the .csv format, which does not save any formatting, or equations within the sheet. In turn, excel automatically removes the leading zeros of FIPS codes, rendering them useless unless modified by the user. It becomes extremely tedious and time-consuming to resolve this issue, especially, like in this study's case, when you are working with multiple variables, over multiple years. This issue can be easily solved, from the source of the data, by saving in .xls or .xlsx format.

Availability and access to data tend to go hand in hand. A portion of this study takes place prior to 2010, which marks when finding reliable, yearly, socioeconomic, and demographic variable data becomes increasingly difficult. A quick Google search for county-level Female-Headed Household (FHH) statistics, for instance, yields a link to 1990 Census poverty statistics for FHH; which is not useful for this study. Moving to the U.S. Census website, finding the data of interest can become even more difficult, even for someone who has worked with this type of data a lot. Attempting to figure out which table contains the information you need can be tedious and next to impossible. While the interface has improved drastically since the 2020 Census, the usability of the website can prove to be an obstacle for stakeholders, non-profits, or other academics, which can lead to research taking longer or for a project to be given up all together.

Other issues arose when attempting to find variables for the EVI and the HVI. Finding county-level temperature and precipitation data, for instance, proved challenging. Average temperature and precipitation are available on a myriad of websites; however, the data is generally saved in raster format and not joined to any census boundary. In turn, I had to get assistance from a member of my lab to create the county-level temperature and precipitation datasets. Similarly, I was unable to find a county-level impervious surface dataset. Which, I in turn had to spend three days creating, considering download and processing time.

A.4.2 News

Another roadblock that presented itself was the availability of and access to non-technical news sources. As a data scientist, I do not have the opportunity to engage and work with the communities I am doing research on. So, I turn to news sources to add firsthand accounts, personal statements, infographics, or statistics to my research. When researching stories on natural hazards and climate change I look towards Bloomberg City Lab, National Geographic, Cheddar, VICE, VOX, the New York Times, the Washington Post, and The Wall Street Journal. Sources like VOX and VICE are great because they tend to cover a wide variety of topics, do a fantastic job at communicating complex subject matter in lay terms, they have a robust social media presence, and they largely seek donations meaning there is no paywall. Comparatively, the larger news sources like the New York Times, Washington Post, and Wall Street Journal all have some form of a paywall or a limit on the number of articles you are allowed to read per week. For example, *The Great Climate Migration* by Abraham Lustgarten was a major catalyst in propelling me to analyze climate migration in the United States. This article provides a plethora of interviews, photographs, and information about climate migrants presently on the move in

Central America. All this information can function as a great addition to my research, so long as I am not out of free articles for the week.

A.5 Discussion

So, as a graduate student, what can I do? For starters, one's department or school does not need to have an NRT to become more interdisciplinary. Discuss with your department or your advisor about some alternative classes you could add to your curriculum. Classes like public speaking or basic coding are always useful academically and professionally. The NSF and American Association for the Advancement of Science have been continuously pushing for scientists to be better trained in communicating with non-technical audiences. Exposing oneself to new classes and disciplines will also likely breed new friendships and potential collaboration with faculty.

Next, make your data and publications open-source or free to view. Understandably, there are many instances where one would want to keep their data private. Either it is groundbreaking research, the publication may not be out yet, or the data will be used in further research. That does not mean, though, that all your data should be kept on your office desktop. The county-level NLCD dataset I created, for instance, is a dataset a lot of researchers could potentially benefit from and making it publicly available would save others a lot of computing time. Moreover, having data publicly available allows you to reach those non-technical audiences, and allows communities, NGOs, and non-profits to interact with and use the data themselves. Websites, like GitHub which uses Zenodo, can archive your data and attach a DOI to the archive, which makes it easier to reference the data in the literature and protects one's ownership of the data.

Another avenue for a student to pursue is utilizing different social platforms to communicate their research. The 2000s have given rise to multiple social media platforms, such as Facebook, Twitter, Instagram, and TikTok. Cate Larsen, also known as '*groovygeologist'*, is a geology science communicator who uses TikTok, Instagram, and her podcast, Rocks & Hops and The Schist of It, to inform lay individuals about geology. She has even given TED Talks on how she uses social media to communicate her science at universities around the United States. Now, this is not to say that social media or giving talks is the only way that one can communicate one's science; find your niche instead. Professor Allison Grant, from the University of Alabama, uses photography to show the interplay between social systems and climate change. Craig Laing, from the University of Tennessee at Chattanooga, uses his passion for miniature and model train building to visualize individuals' sense of place. Find something you are passionate about or exceed at and use that as your communication medium.

As graduate students, academics, and scientists, we are long past the archaic model of simply teaching, conducting research, and publishing papers. We need to train and be trained on how to better communicate our science and how to conduct more robust interdisciplinary research. As Dr. Marshall Shepherd puts it, "We increasingly need end-to-end scientists. Use your geosciences [science] background to do sound science but develop a broader skill set to engage beyond the ivory tower" (MIT-WHOI 2022).

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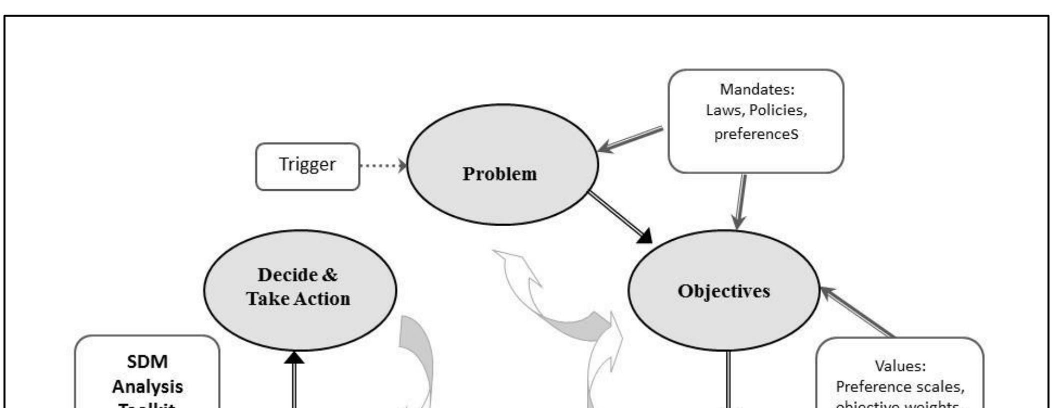
Appendix B

Utilizing Structured Decision Making & Co-production for Data-Driven Solutions

B.1 What is Structured Decision Making & Co-production?

Structured Decision Making, or SDM, is defined as, “the collaborative and facilitated application of multiple objective decision making and group deliberation methods to environmental and public policy problems” (Gregory 2012). The primary purpose of an SDM process is to aid and inform decision-makers, rather than to prescribe a preferred solution (Gregory 2012). While SDM might seem difficult to implement and complex, it is rather a simple set of concepts and helpful steps based on seven key concepts. These seven concepts are the problem, objectives, alternatives, consequences, tradeoffs, uncertainty, and a decision. A helpful visualization of the SDM process is outlined in Figure B.1, below.



The problem is the first step of the SDM process. Here one may be approached by a group of stakeholders with a problem, or one may seek a problem to find a solution. At this stage, it is important to answer three questions: 1.) What is the decision (or series of decisions) to be made, by whom, and when? 2.) What is the range of alternatives and objectives that can be considered? 3.) What kind of decision is it and how could it usefully be structured (Gregory 2012)?

Objectives attempt to specifically define “what matters” in one’s decision and can be kept as simple as, “Maximize the elk population within the 25 sq. km. area.” Good objectives are <u>complete</u>, no essential objectives are missing; <u>concise</u>, they are straight to the point with no ambiguity; <u>sensitive</u>, influenced by alternatives; <u>understandable</u>, stated so they make sense to all parties; and <u>independent</u>, or that you do not need one objective to understand the importance of another (Gregory 2012).

Alternatives are complete solutions to a given problem that can be directly compared by decision-makers (Gregory 2012). A fitting example of alternatives is when you are choosing a flight. Say, a ticket on Flight A is $200 but must make one stop with a two-hour layover. Flight

B, on the other hand, is $350 with no layover, but two stops. The two alternatives you are given will impact your decision. Prior, money may have been your primary concern, but seeing the two-hour layover of Flight A may lead you to choose Flight B. Good alternatives are mutually exclusive – one and only one of the proposed alternatives can be selected – and directly comparable (Gregory 2012).

Within any decision-making process, there is some amount of uncertainty. Whether it be with the data you are using, which is a large problem in the climate science community, a model you are running, or even uncertainty of other stakeholders' values. It is important to address uncertainty with a non-ambiguous objective setting and expert opinions. Consequences can help alleviate some of this uncertainty. Consequences, in an environmental management context, are generally analyzed using consequence tables or decision matrices, which can be seen in Figure B.2.

These tables are an extremely helpful tool to help quantify the strengths and weaknesses of a single decision. Criteria, in this case, are the performance measures generated during the objective setting phase of SDM. Every stakeholder is going to have different sets of values and goals, which will impact how certain performance measures are weighted. Weighting determines the impact of a particular performance measure. Cost is extremely important in any decision-making process so weighting it highly makes sense. We then get to the step of determining which alternative is the best choice. In the case of Figure B.2, we are trying to determine which company an employer should higher under contract. By assigning scores we can quantitatively determine which is the best solution, in this case, the higher number will indicate the ideal decision.

Weighted Decision Matrix							
		OPTIONS					
Criteria	Weighting	Company A		Company B		Company C	
		Score	Total	Score	Total	Score	Total
Cost	5	5	25	3	15	4	20
Service Level	4	3	12	5	20	2	8

From this point, a decision is reached and, hopefully, implemented. This does not mean, however, that all parties involved may have their goals or concerns addressed. SDM is also not a rigid, linear system that follows a singular path. For instance, the addition of new stakeholders may cause the project objectives to change, or you may reach the end of the process and realize some of your alternatives are no longer viable options. Making decisions is difficult, and SDM gives stakeholders the ability to make informed, robust, and concrete decisions.

Co-production and SDM often go hand in hand. Co-production is the collaborative process that brings different knowledge systems, backgrounds, and methodologies together to address research, policy, or management decisions (NNA-CO 2022). This process is more than just collaborative problem framing and trust-building; it develops capacity, builds networks, fosters social capital, and implements actions that contribute to sustainability (Norström et al. 2020). The Navigating the New Arctic Community Office, for instance, uses co-production to support roles for Indigenous knowledge and provides training for initiating, designing, and implementing collaborative research with Arctic Indigenous communities (NNA-CO 2022).

B.2 Case Study: Fulton County, Georgia (Atlanta)

B.2.1 Overview of Atlanta

Atlanta is the capital of Georgia and is in the northeastern portion of the state. Atlanta majorly lies within Fulton County, is one of the largest cities in the southeastern United States with an approximate population of five million residents, and acts as one of the most important trades and transportation hubs in the entire United States. Atlanta also acts as a hub for many migrants and has become an ideal destination for new homeowners in the southeast. The Urban Institute determined Atlanta would grow by 2.4 percent a year, rising to 7.5 million by 2030 (Pendall 2010). With expected population growth and rapid urban expansion, the urban heat in Atlanta is expected to increase 8 degrees Celsius by 2100. The expansion will also put potential residents at risk of wildfire exposure and extreme urban flooding (States at Risk 2015). With all this in mind, it is easy to see why vulnerability and migration data may be of interest to the city of Atlanta.

B.2.2 Mock Structured Decision Making & Co-production Process

B.2.2.1 Problem

How might climate-induced migration impact urban form and development in Atlanta, Georgia?

B.2.2.2 Objectives, Measures, and Source Table

Table B.1. Objective, Measure and Source Table for a mock SDM process in Fulton County, Georgia.

Objectives	Measures	Source of information
1. Analyze the amount of migration into Atlanta due to significant natural hazards	-The amount of people	-SOI IRS Tax Migration data
2. How does this influx of people impact urban systems within the city	-Availability of transportation, housing, basic needs, etc. -Energy use -Access to basic needs	-Likely provided by the city of Atlanta

B.2.2.3 Evaluation of Potential Stakeholders

Table B.2 lists some potential stakeholders who may have a lot of influence on the problem at hand or may be groups who have been previously left out of stakeholder decisions. This is by no means a comprehensive list of stakeholders, nor should it be. A major part of the SDM and co-production process is that it is iterative, or that there is no single approach for success (Norström et al. 2020). One may find that a new stakeholder needs to be introduced halfway through the SDM process. Also, the needs of the stakeholder could change, or the data may not be useful, so they no longer need to be a part of the process.

Table B.2. List of stakeholder and stakeholder description for a mock SDM process in Fulton County, Georgia.

Name of Stakeholder	Stakeholder Description	Interest
Atlanta Department of City Planning	The mission of the Department of City Planning is to enable high-quality, sustainable, and equitable growth, and development of Atlanta by facilitating more options for travel, thriving neighborhoods, exceptional design in architecture, attentive customer service and public engagement in all our work (Department of City Planning, n.d.).	Migration Data Vulnerability Index
Atlanta Department of Public Works	The mission of the Department of Public Works is to enhance the quality of life by providing environmentally safe protections for the welfare of all citizens. DPW promotes livable, walkable, green, and sustainable communities, and to support economic development (Department of Public Works, n.d.).	Migration Data
Atlanta Department of Transportation	Atlanta continues to emerge as an international city and global business	Migration Data

	powerhouse. To remain competitive and support anticipated growth, the city requires a transportation network that reduces automobile reliance and offers convenient, affordable, and safe travel alternatives (Atlanta DoT, n.d.).	
Atlanta Housing	The Housing Authority of the City of Atlanta, Georgia (AH), is the largest housing authority in Georgia and one of the largest in the nation. AH provides and facilitates affordable housing resources for nearly 22,000 low-income households (Atlanta Housing, n.d.).	Migration Data
Georgia Emergency Management and Homeland Security Agency	Georgia's preparedness, response, and recovery agency. They work with public and private sector organizations to prevent and respond to natural and man-made emergencies (Georgia EMHSA, n.d.).	Vulnerability Index
Federal Emergency Management Agency (FEMA)	A federal agency designed to aid in disaster and hazard mitigation and response (FEMA, n.d.).	Vulnerability Index
New American Pathways	Support new Americans on their pathways from arrival through citizenship (New American Pathways, n.d.).	Migration Data
Community Foundation for Greater Atlanta (Frances Hollis Brain Foundation Fund)	Supports nonprofits that benefit vulnerable and underserved communities (Community Foundation for Greater Atlanta, n.d.).	Vulnerabilty Index

B.3. Utilization of Climate and Migration Data

Researchers tend to produce a lot of quality and usable data through their work. However, there is often a gap between researchers and stakeholders on how to properly utilize said data. This issue is further exacerbated when trying to tackle complex climate change adaptation problems. Often, when tasked with integrating climate information into their planning processes, decision-makers face two main challenges: (1) they find it difficult to know what climate information and data are best suited for a particular problem, and (2) they often perceive that climate information and data coming out of the scientific community is not usable in decisions (Briley, Brown, and Kalafatis 2015). Therefore, it is important we understand the needs and goals of our stakeholders and supply them with relevant and usable data to make an informed decision. In my research, my data will take on three forms: Raw Data, Finalized Data, and Polished Data. Below, I will outline how each data format can be useful to stakeholders and the SDM process.

B.3.1 Raw Data

Much of the data for this project are stored in Excel tables as raw data. Information such as the IRS SOI Migration and Social Vulnerability data (SOVI) comes pre-tabled, whereas the Exposure Vulnerability Index (EVI) and Hazard Vulnerability Index (HVI) will have to be processed and then tabled. Having data in this format can be extremely useful for stakeholders because the data is at its base level. By that, I mean the data has not been processed and can be altered or amended in any way to fit the needs of the stakeholder. For example, Figure B.3 is a screenshot of IRS County Inflow data for Fulton County (Atlanta, Georgia)

	A	B	C	D	E	F	G	H	I	J	K	L
1–2	Origin State Code	STATE_FIPS	Origin County Code	CNTY_FIPS	FIPS	FIPS_USE	State	County Name	Number of returns	Number of exemptions	Adjusted gross income	Date
3	13	13	089	089	13089	13089	GA	De Kalb Co	7,369	12,375	304,995	1/31/2003
4	13	13	067	067	13067	13067	GA	Cobb Coun	3,796	6,205	198,741	2/1/2003
5	13	13	135	135	13135	13135	GA	Gwinnett C	2,698	4,759	125,303	2/2/2003
6	13	13	063	063	13063	13063	GA	Clayton Co	2,191	4,701	57,132	2/3/2003
7	13	13	117	117	13117	13117	GA	Forsyth Co	544	939	36,073	2/4/2003
8	13	13	057	057	13057	13057	GA	Cherokee C	506	821	24,505	2/5/2003
9	13	13	097	097	13097	13097	GA	Douglas Co	374	735	13,798	2/6/2003
10	13	13	113	113	13113	13113	GA	Fayette Cou	360	602	14,066	2/7/2003
11	17	17	031	031	17031	17031	IL	Cook Coun	321	533	21,388	2/8/2003
12	13	13	151	151	13151	13151	GA	Henry Coun	312	562	11,218	2/9/2003
13	13	13	059	059	13059	13059	GA	Clarke Cou	253	298	6,502	2/10/2003
14	06	06	037	037	06037	06037	CA	Los Angele	248	429	14,423	2/11/2003
15	13	13	077	077	13077	13077	GA	Coweta Co	244	453	8,650	2/12/2003
16	12	12	086	086	12086	12086	FL	Miami Dade	223	354	9,304	2/13/2003
17	37	37	119	119	37119	37119	NC	Mecklenbur	221	364	17,681	2/14/2003
18	12	12	011	011	12011	12011	FL	Broward Co	205	361	9,733	2/15/2003
19	36	36	061	061	36061	36061	NY	New York C	201	261	18,033	2/16/2003
20	12	12	095	095	12095	12095	FL	Orange Co	186	294	8,953	2/17/2003
21	01	01	073	073	01073	01073	AL	Jefferson C	174	299	11,940	2/18/2003
22	48	48	201	201	48201	48201	TX	Harris Cou	172	295	11,063	2/19/2003
23	48	48	113	113	48113	48113	TX	Dallas Cou	157	252	8,546	2/20/2003
24	36	36	047	047	36047	36047	NY	Kings Coun	154	249	5,519	2/21/2003
25	13	13	247	247	13247	13247	GA	Rockdale C	148	240	5,934	2/22/2003
26	12	12	057	057	12057	12057	FL	Hillsboroug	146	241	9,130	2/23/2003
27	37	37	183	183	37183	37183	NC	Wake Coun	145	236	8,705	2/24/2003
28	12	12	099	099	12099	12099	FL	Palm Beac	141	222	7,950	2/25/2003
29	13	13	051	051	13051	13051	GA	Chatham C	136	224	8,264	2/26/2003
30	13	13	139	139	13139	13139	GA	Hall County	132	207	9,460	2/27/2003
31	12	12	031	031	12031	12031	FL	Duval Coun	131	222	6,501	2/28/2003
32	36	36	081	081	36081	36081	NY	Queens Co	126	243	4,591	3/1/2003
33	47	47	037	037	47037	47037	TN	Davidson C	126	184	7,275	3/2/2003
34	25	25	017	017	25017	25017	MA	Middlesex C	[illegible]	[illegible]	[illegible]	3/3/2003

This table indicates how much migration into Atlanta occurred from each county in the United States. The two primary columns of interest are the 'Number of returns' and 'Number of Exceptions.' 'Number of returns' filed, approximates the number of households that migrated; whereas 'Number of personal exemptions' claimed, approximates the number of individuals. This study's migration analysis is based on the 'Number of exemptions' data, which means all the findings will focus on the scale of the individual, rather than the household. While this may be useable to some stakeholders, there is the potential that it is not usable for all stakeholders. For instance, construction agencies, city planners, or real estate agencies may be more interested in approximating how many new households need to be built or anticipate how many families may be moving into a new city. Data in this raw format would allow them to easily replicate my study while utilizing the data they find to be the most useable.

The Climate Vulnerability Index (CVI) is another important example of how raw data can be usable by stakeholders. One important aspect of a vulnerability index is that it is adaptable and amendable. By that, I mean the CVI can easily be changed to fit the needs of a stakeholder allowing them to easily delete or add data they think is important. The HVI in this study primarily focuses on weather hazards; comparatively, a stakeholder may be more interested in drought or sea-level rise. In this raw format, stakeholders can easily add representative data to the index and generate an index that is tailored to their needs with minimal effort, and time wasted.

B.3.2 Finalized Data

Finalized data is data that has been assessed, and organized and is a “step-up” from raw data. Finalized data has many benefits for stakeholders, that raw and polished data may not offer. Finalized data is comprised of data layers, tables, and graphs.

Figure B.4 is an example of IRS County inflow data for Atlanta, Georgia as a processed graph. This graph supplies us with information regarding how many people migrated into Atlanta for every given year broken up by the state. Some information a stakeholder can draw from this is the fact that we see a spike in migration from Louisiana and Mississippi post-Katrina. We can also see that these states see a significant drop in migration in the years prior to and following 2005-2006. Therefore, we can infer those individuals displaced from Hurricane Katrina sought Atlanta as a new destination after the storm. This can also inform stakeholders that if a similar event occurs, they may expect a similar spike in residents from these states.

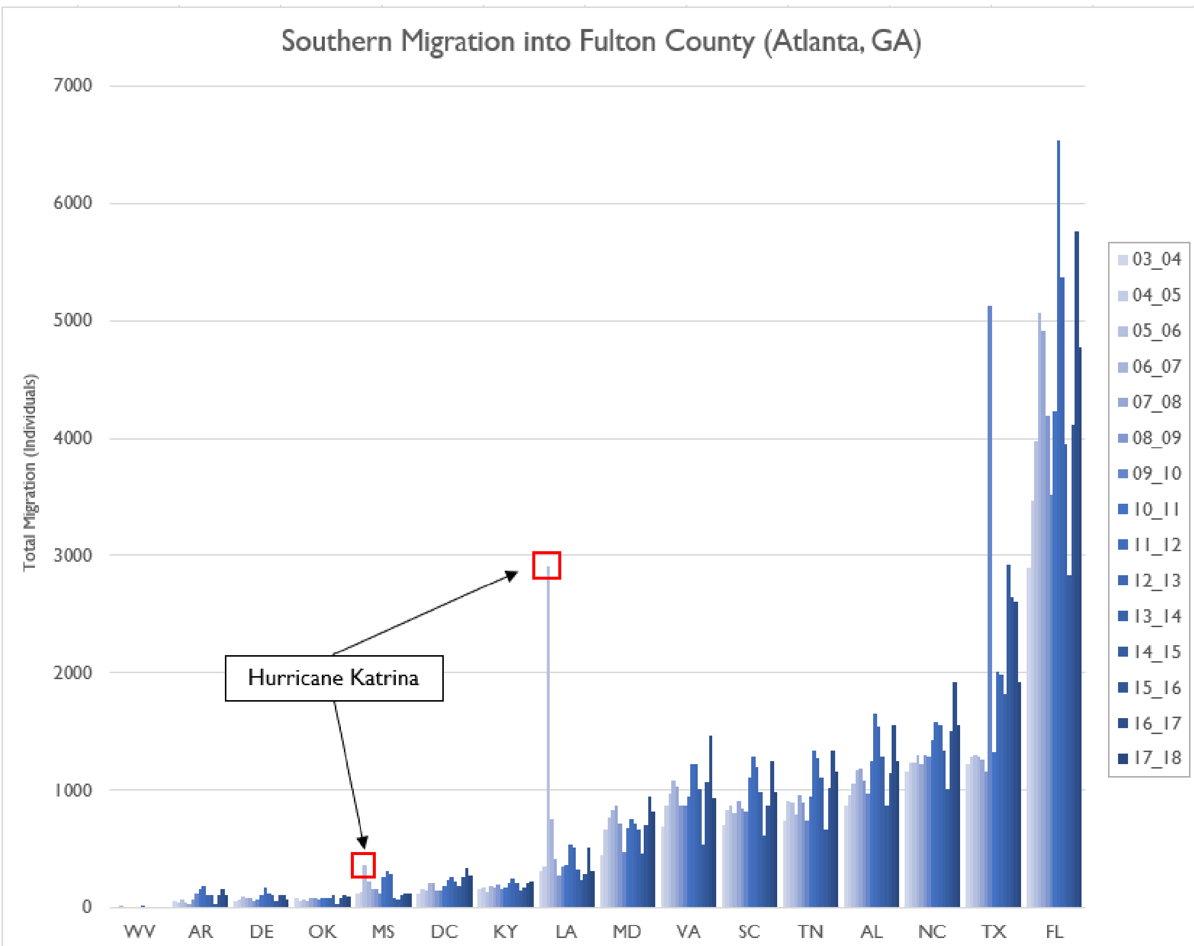
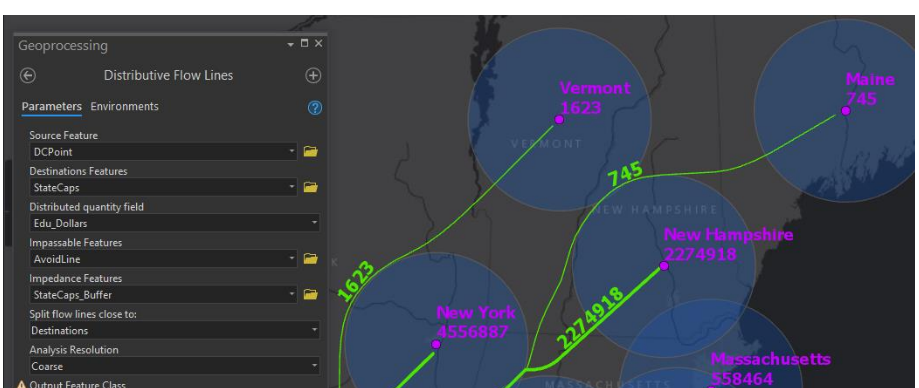


Figure B.4. Image of finalized graph of inflow IRS SOI migration data at the state level, for Fulton County (Atlanta, Georgia).

This data also includes fully generated GIS layers such as points, lines, and polygons. While these layers will already be processed, having data in ArcGIS layers can be extremely valuable to stakeholders. These layers can be used by stakeholders to make comparisons to other datasets, further other research, or even run different geoprocessing tools on the data to find alternative results. Finalized data offers stakeholders easy usability and opens more practical and timely ways to make decisions.

B.3.2.1 Distributive Flow Lines (DFLs)

This portion of the study was adapted from Berry (2019). In her blog, Lisa Berry, a Senior Product Engineer on the Living Atlas team at Esri, mapped inflow and outflow migration for the years 2015-2016 at the state and county level. The Distributive Flow Lines (DFLs) mapping tool was created by Bob Gerlt, who is a member of the Esri Applications Prototype Lab. Flow maps depict outflow, the flow of something from a single source to many destinations. They can also show inflow, stuff flowing from many destinations to a single source, which the DFL tool can be used for both cases (Gerlt 2019). The source feature does not require an integer or information fields, as it is the location where the flow lines will terminate. The destination feature, however, requires an integer field indicating the amount of “stuff” received from or flowing into the source. While this tool does not indicate the path taken by migrants to reach their destination, it provides better visualization of where migrants have moved from and makes it easier to compare migration to hazard occurrence. An example of the DFL tool can be seen in Figure B.5. This tool is a great way to visualize migratory flows and allows users to interact and interpret data more easily.



B.3.3 Polished Data

Polished Data is a “step-up” from finalized data, and is fully organized, analyzed, and publishable. Data in this format is unamendable, or there will be no need to change or alter the data. This data format gives stakeholders data layers, images, and maps that can immediately be used in presentations or reports. Figure B.6 is an example of a finalized DFL map for Fulton County (Atlanta, Georgia). At this stage, there are no changes, aside from symbolization, that the stakeholder should make to the data. Now, a stakeholder has usable data that can be utilized in the SDM process without having to spend time on data organization, processing, and symbolization.

As mentioned in Appendix A, none of this data is any good if stakeholders and policy makers are unable to access it. One way I am combatting that issue is using GitHub, ArcGIS StoryMaps, and my professional website to store my data. ArcGIS StoryMaps is a story-authoring web-based application that enables you to share your maps in the context of narrative text and other multimedia content (ESRI 2020). StoryMaps allows for a user to have a more interactive experience with the data and gives stakeholders a way to easily engage with other stakeholders or the community. Links to my StoryMap and migration data can be found here:

https://brandonryanau.weebly.com/ and

https://storymaps.arcgis.com/stories/79e227ad28e64cd086ada5a541e2ec45.

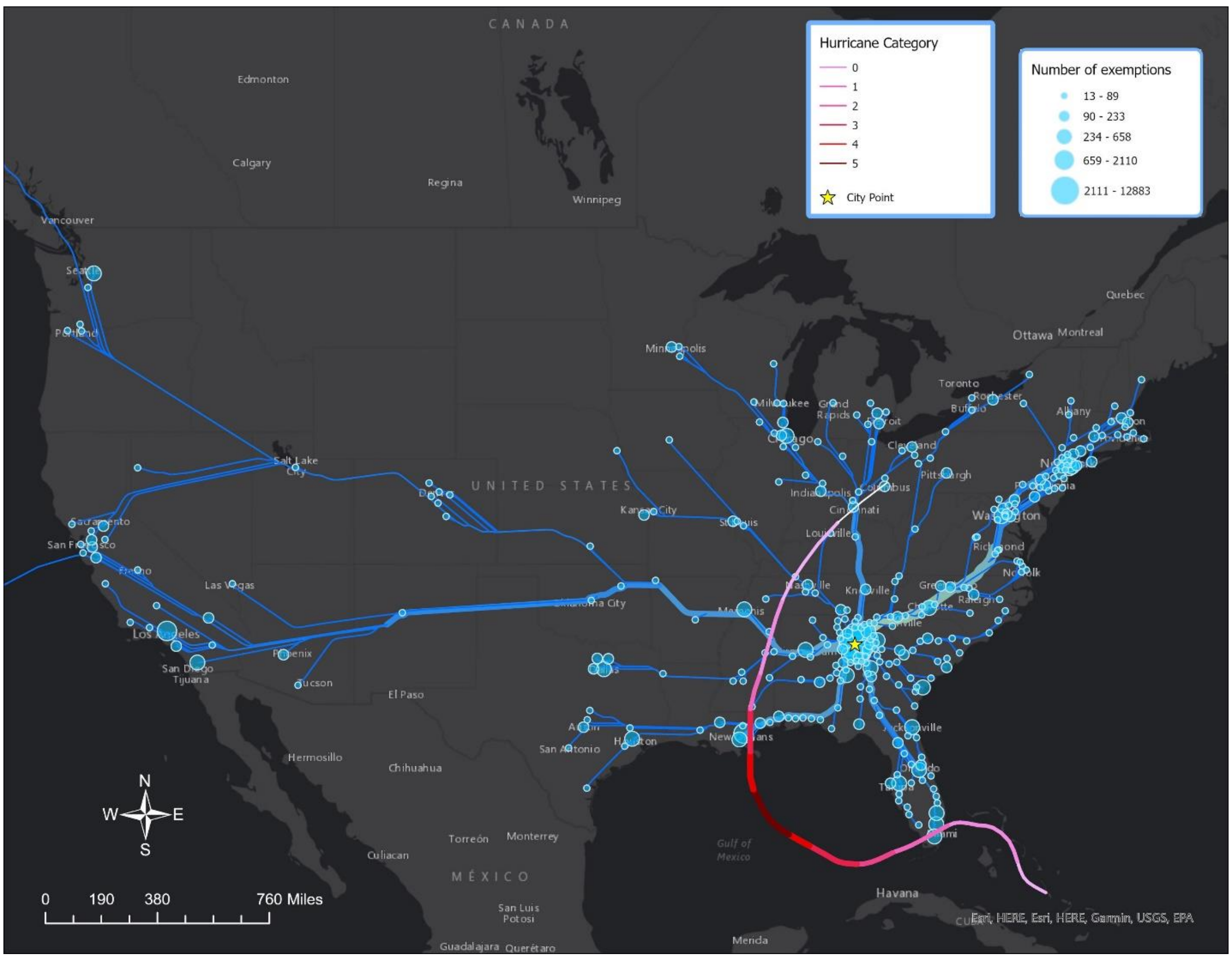


Figure B.6. Image of finalized DFL of inflow migration into Fulton County (Atlanta, Georgia). Larger proportion circles mean more people migrated from that county, the thicket and more yellow the line means more flow along that pathway, and the red line indicates the Hurricane Katrina storm track.

B.4 Discussion

SDM can be a valuable resource and tool which can be used to make climate-related decisions using data-driven science. Ultimately, the goal of my research, and the NRT project at large, is to take my science to the next level. Publications, posters, and lectures are all important, yes, but what is the use if the people who truly need to hear about your research never hear about it? SDM allows us to bridge this gap with stakeholders, community leaders, and policy makers. This chapter, again, highlights how my data may benefit stakeholders, what the steps for that process may look like, and provides access to the data used within this study.

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