NARROWING THE EXTREME WEATHER-CLIMATE GAP: QUANTIFYING THE RISKS AND DEVELOPING INTERVENTIONS TO ADDRESS THE CHANGING CLIMATE

by

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(Under the Direction of Allan D. Tate)

ABSTRACT

Natural disasters will continue to occur with greater frequency and intensity as climate change accelerates. The combined effects of these events, alongside existing structural inequalities, result in a phenomenon known as the extreme weather-climate gap. This dissertation addresses the social determinants of health and provides evidence for an effective primary prevention strategy to mitigate the effects of climate change and narrow this gap. Chapter 2 explores how the neighborhood and built environment, along with access to healthcare, interact with environmental particulate matter to influence respiratory illness hospitalizations. Chapter 3 examines whether 'like attracts like,' questioning whether evacuation intentions depend on racial and neighborhood segregation as well as income inequality. Chapter 4 investigates whether individual- and neighborhood-level technology implementations can impact disaster preparedness in diverse community contexts. This dissertation utilizes geospatial data as well as primary data derived from a pilot community trial to address these questions. The findings indicate that housing vulnerability may increase environmental risk in less urban areas, particularly with regard to exposure to particulate matter (PM2.5). Additionally, individuals residing in areas of deprivation tend to evacuate to similarly deprived areas, which, on average, are further from their residence compared to their privileged counterparts. Finally, disaster preparedness interventions are shown to be effective, particularly for individuals with high social resources. These findings aim to promote a shift from the current reactionary standard of disaster care to a more proactive approach.

INDEX WORDS: Climate Change, Structural Racism, Health Disparities, Wildfires, Evacuations, Disaster Preparedness

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

Climate Change: At a Glance

Climate change is the biggest public health threat that the world faces in the coming decades.[1–3] Populations throughout the world are already experiencing the disastrous effects of climate change. Hurricanes are occurring with greater frequency and intensity.[4–7] Droughts are leading to increased occurrences of forest fires.[8] Extreme temperatures continue to break records. From 2016 – 2022 the earth saw eight consecutive years where global temperatures were one degree Celsius above the pre-industrial levels (1850-1900).[9] The years 2016 and 2020 are tied for the hottest years in recorded history.[10,11] This increasingly extreme weather leads to an expansion of risk, affecting both critical infrastructure and resulting in adverse health outcomes. Areas in the United States (US) deemed as high risk for climate change are increasing. This emerging challenge introduces problems in areas that have little to no experience in responding to these new threats.[12] To describe the risks of climate change, it is essential to understand the science, global responses, U.S. policies, environmental racism, and the inadequacies of current disaster care standards.

Climate Change: The Science

Climate change is specifically the long-term change in temperature and weather patterns.[13] While the scientific community widely accepts that humans are driving the increase in global temperatures and extreme weather, challenges exist communicating scientific findings to broader audiences.[14] This includes the general public and policymakers. The root cause of climate change is carbon emissions which remain in the earth's atmosphere and react with ultraviolet light from the sun which produces heat. This is referred to as the greenhouse gas effect.[4] Humans release more than 37 billion tons of carbon into the atmosphere per year.[15] Which is over six times the annual emissions of 1950.[15] The primary source of carbon emissions is the burning of fossil fuel.[16] There are other gasses that contribute to global warming however carbon is the most prevalent accounting for 76% of greenhouse gas emissions. Another gas is methane, 28 times more potent than carbon and is released by agricultural activities and waste management.[16,17]

There are a multitude of ways in which the effects of climate change are tracked. These include measurements of carbon dioxide in the atmosphere as parts per million (ppm), global average temperature, and the extent of sea level rise. Carbon dioxide ppm in the atmosphere has increased 150% since 1750. Since 2002, carbon dioxide ppm has risen from 365 ppm to 400 ppm.[18] Average global temperatures are 0.9 degrees Celsius higher than the 1950-1981 reference period. Lastly, sea level rise, caused by melting ice sheets and glaciers as well as rising temperatures expanding seawater, has gone up 3.88 inches since 1993. Each of these metrics are predicted to worsen in the coming years with carbon dioxide ppm expected to rise to 550 ppm by 2050. Sea level rise is projected to increase an additional 12 inches between 2022 and 2050. Global temperatures are expected to increase an additional 0.6 degrees Celsius by 2050 on top of the 0.9-degree Celsius increase from 1950-1981.[18]

Climate Change: The World's Response

The shared solution for addressing climate change is to curtail global carbon emissions.[19] The Intergovernmental Panel on Climate Change (IPCC) indicates that the world needs to cut carbon emissions by 50% by 2030 and by 100% by 2050 to prevent catastrophic global temperature rise.[1] The Paris Agreement, a climate conference held in 2015, resulted in an international treaty that was signed by 195 countries with the goal of keeping the rise of global temperatures below 2 degrees Celsius by 2100.[20] Despite the overwhelming scientific evidence supporting climate change, approximately 109 representatives and 30 senators from the 117th US Congress do not acknowledge the evidence of climate change.[21] This has direct policy implications as these individuals hold immense power. Additionally, the position of the US in the Paris Agreement is tenuous, with a withdrawal from the agreement in 2017 and then subsequent rejoining in 2021.[22] The current presidential administration rejoined the Paris Agreement and devoted a chapter of 2023 Economic Report of the President (ERP) to addressing climate change. While global efforts to reduce carbon emissions are crucial, the report emphasizes the need to prioritize adaptation to the worsening effects of climate change, which are expected to intensify in the coming years due to ongoing energy production practices that accelerate climate change.

Economic Report of the President – 2023

Released in January of 2023, the ERP highlights the challenges that the US faces due to the changing climate and ways to better manage risk. Extreme weather caused by climate change will put a serious strain on our existing infrastructure. In the US, infrastructure construction is based on historical weather conditions which are now outdated. This means that the existing infrastructure is vulnerable to extreme weather. Additionally, accurately predicting weather is becoming increasingly difficult, and the lead time in which predictions can be reliably made is shortening.

The report further highlights how current policies in place encourage people to take more risks in the face of climate change. A cited example is the National Flood Insurance Program (NFIP). There are a total of 5 million policies under NFIP covering property worth $1.3 trillion. Currently, the program is $20.77 billion dollars in debt due to multiple destructive hurricanes.[23] A benefit of this program is that individuals that do not have the resources to relocate to an area of less vulnerability get access to an affordable insurance plan backed by the federal government. A negative of the program is the rebuilding of destroyed structures in vulnerable areas. Additionally, the flood maps used are outdated and do not reflect the true risk across the 56 states and territories where NFIP operates.[24]

The ERP emphasizes how emissions will continue until the world becomes carbon neutral. Developing strategies to adapt to climate change is equally as important as reducing emissions because the extreme weather has already arrived. However, the federal government is partly limited. State and local governments remain on the frontline of feeling the effects of climate change and are where adaptation efforts need to occur.[19] Further research is needed to examine what successful adaptation looks like. Due to the variety of ways in which climate change will affect populations, there likely is not one adaptation strategy that fits all. The ERP distills next steps into four key areas: producing and disseminating knowledge about climate risk, long-term planning for the changing climate, ensuring accurate pricing of climate risk, and protecting the vulnerable.

Climate change will disproportionately affect those that are racially minoritized as well as of low socioeconomic status (SES).[25–27] This is entrenched in how individuals of low SES do not have the resources in place to handle the challenges created by climate change. These disparities are also tied to structural racism. Structural racism being the manifestation of racism through laws, institutional practices, and public policy. Structural racism operates independently from SES on health outcomes and prevents groups from attaining what is referred to as health-enhancing resources.[28–30] These vulnerable groups will experience worse health outcomes from climate change. The linkage between environmental exposures and health among racially minoritized and low SES groups has been previously established in the field of environmental racism. Disparities as a result of climate change should be included as a form of environmental racism.[31]

Environmental Racism: History and Relevance

Environmental racism is a concept in which exposure to pollutants disproportionately affects racially minoritized and low SES groups. The term environmental racism was created by civil rights leader Benjamin Chavis in 1982.[32] The concept is rooted in the affordability of land, unequal political power, residential mobility, and poverty.[33] Additionally, past redlining of cities contributed to the geographic location of communities of color into areas that lack resources.[34–36] Disadvantaged people are unable to afford land free of potential health hazards, they lack resources to advocate for the implementation of regulations to curtail pollution from both government and private sources and they are unable to manage existing hazardous waste sites.[37,38] Another contributing factor is the notion that place is sticky. The longer individuals live in areas of concentrated poverty, the more likely they are to remain and become stuck in those conditions.[39,40] These low resource communities are unable to change their situation and move away from the areas that are affecting their health.[37,38] It is important to note that existing systems of inequality are why low-resourced individuals are not able to affect change beyond their individual circumstances.

Lastly, the direct connection between poverty and health contributes to the mechanism of environmental racism.[41] The water crisis in Flint, Michigan and the subsequent research provides an example of the wide range of studies covering environmental racism..[42,43] The city of Flint historically experienced racial discrimination and exclusionary practices which ultimately led to declines in tax revenue which prevented Flint from providing essential services for residents. When the source of water for the city was changed, to save money, the new water was corrosive to the existing lead-pipe infrastructure leading to a dangerous level of lead leaching into the drinking water. Studies examining the lead exposure found that it particularly affected low SES neighborhoods. Prior to the water switch, the prevalence of elevated blood lead levels (EBLLs) among children in Flint was 2.4%. Following the switch, the prevalence of EBLLs was 4.9%. Whereas outside of Flint the change in EBLL prevalence was 0.7% to 1.2% pre versus post respectively.[44]

Decades of exclusionary practices by the city of Flint created a budget shortfall which contributed to the water source switch and the leaching of lead into the drinking water. This disproportionately affected racially minoritized individuals. Climate change must be framed as an emerging area of environmental racism because the mechanisms that cause environmental racism are comparable to the mechanisms by which climate change will cause disproportionate health outcomes for racially minoritized and low SES groups. Importantly, climate change will likely be the worst environmental injustice in history.[31,45] There is a significant need to develop targeted strategies for vulnerable populations to mitigate the harmful effects of climate change and address the current way we respond to disasters. Disaster epidemiology is a budding field that aims to understand the negative health effects of disasters and is perfectly positioned to take on investigating injustices of climate change and predicting future consequences.

Status of Disaster Standard of Care is Inadequate

The current model for responding to natural disasters is reactionary and not sustainable. To discuss natural disasters a few definitions must be established. The International Federation of Red Cross and Red Crescent Societies (IFRC) defines a disaster as, "a sudden calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community's or society's ability to cope using its own resources."[46] The way in which the US currently deals with disasters and disaster response is no longer adequate and not tenable moving forward.

The standard of care for disasters can be best described using the cliff analogy. Developed by Jones et al., the cliff represents the figurative fall to a diseased state. A fence at the top of the cliff prevents people from falling off which is an example of primary prevention. A safety net halfway down the cliff that prevents people that do fall from hitting the ground represents secondary prevention. Lastly, an ambulance at the bottom of the cliff is there to take people who do fall and hit the ground to the hospital, which represents tertiary prevention. How close people progress to the cliff and their risk of falling off represents the social determinants of health (SDoH). The SDoH defined by the CDC as the non-medical factors that influence health outcomes.[47] How the current system responds to natural disasters is through secondary and tertiary methods. There needs to be a significant focus and investment on primary prevention methods and the SDoH. The cliff in this analogy represents experiencing a health-related outcome due to climate change. Secondary and tertiary prevention methods will not address the root causes of the problem. As climate change accelerates the number and intensity of extreme weather events, a reactionary model will not be sustainable.

The federal government's main instrument to respond to natural disasters is through the Federal Emergency Management Agency (FEMA). The Stafford Act of 1988 allows FEMA to distribute disaster aid following an event through an established fund known as the Disaster Relief Fund (DRF).[48] The money is provisioned for repairing or rebuilding damaged infrastructure or homes, providing critical services, and clearing debris. From 1992 to 2021 FEMA has spent a total of $469 billion (in 2022 dollars) on disaster responses.

This current system in place is reactionary and is not an acceptable way to handle natural disasters in the coming years. Additionally, experts call into question whether the aid distributed through the DRF is done equitably. The New York Times (NYT) has published several articles covering stories related to how racially minoritized individuals receive less money following a disaster compared to White individuals.[49] In 2022, the US Commission on Civil Rights conducted an assessment on the implications of FEMA's disaster response to hurricanes Harvey and Maria.[50] Two devastating hurricanes that occurred during 2017 and made landfall in Texas and Puerto Rico respectively. This was the first time the commission examined this topic in the 65 years of its existence. The commission's findings highlight the need for a change in the ways FEMA distributes aid. Examples that the commission provides include language barriers between those seeking assistance and the systems by which they apply for aid. In Texas, there are reports that resources providing valuable information on shelter locations after hurricane Harvey made landfall were only provided in English. Texas being a state where the US Census estimates >3.5 million people speak English less than “very well”.[51] The commission also reported disaster survivors were unable to access FEMA systems due to lack of internet access or electricity.

In addition to these key deficiencies in how FEMA distributes resources, another key finding is that there is a correlation between receiving FEMA aid and preexisting racial disparities and wealth inequality. Following hurricane Harvey, the commission examined two Texas cities, Port Arthur and Taylor Landing. The city of Port Arthur, where 70% of its population identifies as non-White and 22% identify as non-Hispanic White, saw 95% of its homes experience flooding. The city of Taylor Landing where 87% of the city identifies as non-Hispanic White received an average of $60,000 per resident whereas Port Arthur received just $84.93 per resident. This suggests that the current response model may be accelerating disparities caused by climate change. Lawmakers are attempting to address these issues. A bill, titled the FEMA Equity Act, has been introduced into the 117th US Congress. This bill is aimed at addressing the issues the Civil Rights Commission identified in their report and to center equity around how FEMA handles responding to disasters. However, this does not address the reactionary nature of the DRF.

In 2020, FEMA established the Building Resilient Infrastructure and Communities Grant Program (BRICS). This was established to provide state and local stakeholders with the funds to reduce risks faced from natural disasters. This program is a great step towards improving disaster preparedness. However, the funds from this program go mostly towards brick-and-mortar infrastructure. For example, in FY 2022 the top five project types were flood control, utility/infrastructure protection, stabilization and restoration, wildfire management, and constructing safe rooms/shelters. While these are necessary components of building resilient communities in the face of the changing climate, they should be done in tandem with programs that improve individual and household-level disaster preparedness. This dissertation aims to demonstrate how climate change will exacerbate inequalities that are a result of our existing social structures and that significant investments must be made in improving both individual and household-level resilience and disaster readiness.

A framework that should be reestablished is Prevention Preparedness Response and Recovery (PPRR). This framework is not new to the field of disaster management. Developed by the National Governors Association in 1979, PPRR is considered the gold standard, in theory, for responding to disasters.[52] The goals of this framework are to prevent disasters and mitigate harm both before, during and after a disaster occurs. A strength of PPRR is how it contains the entire spectrum of when and how to address natural disasters instead of just reacting to them. While the reactionary model is not sustainable as disasters become more frequent it is important to mention that it is a necessary component of disaster preparedness. The secondary and tertiary prevention methods widely seen in the field now fall into a category of disaster response referred to as the humanitarian aid phase. Prevention and preparedness are part of what is referred to as the developmental stage.[53] The best model forward is one in which there is an emphasis on providing resources for the developmental stage.

The Extreme Weather-Climate Gap

There is a need to specifically name the environmental injustice that climate change is causing.[54] The distinction must be made that the disparities seen because of exposure to climate change result from racism not race.[54] This is highlighted in Dr. Camara Jones' work titled, Confronting Institutionalized Racism.[55] The extreme weather-climate gap is the intersection of structural racism and climate change. The term, developed by Dr. Marshall Shepherd, refers to the collision of climate change, how we respond to climate change, and social inequalities caused by structural racism.[56] This gap exists between the wealthy versus the poor, the racially minoritized versus the not and will expand in the coming years.

There are three key components of the extreme weather-climate gap. The first being that place matters. Not all places are equal and where you live plays a large role in your health. The heat and precipitation that we experience now are more intense than previous generations experienced and this acceleration of extreme weather will continue to tax aging infrastructure in the US.[57,58] The second component is that low-income communities are at a higher risk of health outcomes related to climate change. The economic report of the president raised this point and that low-income communities lack the necessary resources to move to areas with less risk and invest in adaptation strategies. The third component is that displacement causes further marginalization. Forced movement by climate change causes marginalized populations to experience greater economic and social distress.[59] The ERP, while not specifically naming the extreme weather-climate gap, does recognize disparities in relation to climate change. These three components of the extreme weather-climate gap are supported by the underlying theories behind the SDoH.

Guiding Theory – SDoH

There are five components of the SDoH. The relevant sections that support the mechanisms behind the extreme weather-climate gap are healthcare access and quality, neighborhood and built environment, social and community context, and economic stability.[60]

These are key areas of the SDoH essential to the extreme weather-climate gap and must be further understood to make progress addressing the injustices of climate change.

Healthcare access and quality refers to how individuals get timely and quality healthcare services.[61–64] It is also defined as the fit between the characteristics and expectations of the providers and the client.[65–68] Accessibility is one of the key components of access and it is geographic, meaning it is how easily a person can get to where healthcare is located.[65] Individuals that are not able to readily access healthcare because of their location have worse health outcomes.[69–71] The geographic distribution of healthcare services has been connected to structural racism.[62,72] Historically, studies have shown the correlation between the number of African American residents and hospital closures at the neighborhood level.[73–77] Identifying areas that are lacking healthcare infrastructure is needed as climate change affects more populations. These areas without adequate access to healthcare are areas of high vulnerability and targets for interventions.

The neighborhoods and built environments in which people live greatly affect their health.[78] There is a robust literature on how neighborhood affects health.[79–83] There are several theories that support this linkage. The first theory is place stratification. This theory states that there is a literal physical and social separation between societal groups that are in power and groups that are deemed undesirable.[84,85] These powerful groups utilize discriminatory practices such as redlining to achieve this physical and social divide.[86,87] The second theory is referred to as spatial assimilation. This theory posits that there is a connection between social and economic status and geographic mobility.[88] When social and economic status improve, this theory states that people then try to improve their spatial position. However, in the US, spatial position is often controlled by the White majority.[85,40]

Disparities arise when climate change interacts with neighborhoods and the built environment that exist within a system of inequality. Hurricane Katrina is a prime historical example of this occurrence. Katrina was a natural disaster that affected an entire city and yet different outcomes occurred based on a person's neighborhood of residence. The people that were slower to return to New Orleans following Hurricane Katrina were predominantly non-White.[89,90] This was due to the majority of homes in the most flood-prone areas being inhabited by African Americans. This was a result of historical decisions to build minority communities in low-land areas that were highly vulnerable to flooding.[90] These homes were the most devastated by flooding which led to longer displacement. Further examination of New Orleans's flood maps showed approximately 50% of the White population experienced serious flooding compared to 75% of the African American population.[91] Hurricane Katrina illustrates the collision of historically discriminatory housing practices and climate change. More recently, one year after the destruction of Hurricane Harvey in Houston, Texas, 27% of Hispanic Texans reported their homes were unsafe to return to compared to 20% of Black Texans and just 11% of White Texans.[92]

There are further examples shown in the literature examining the effects of extreme heat and urban heat islands. Redlined neighborhoods compared to non-redlined neighborhoods were found to have a land surface temperatures 7 degrees Celsius higher.[93] These redlined areas experienced a lack of investment over time which led to little to no protective environmental factors in these neighborhoods.[94] These include urban greenspaces as well as urban tree canopies which alleviate surface heat and air pollution.[95,96] It is also worth noting that an increase in impervious surfaces which trap heat absorbed from the sun also do not absorb water which can contribute to flooding.[97,98]

The social component of SDoH theory relates to how social support plays a role in health outcomes.[99–102] The concepts that support this domain of the SDoH are social stress, life course theory, and social cohesion. Social stress theory postulates that individuals with disadvantaged social status are more likely to be exposed to stressors.[103–106] Life course theory states that each stage of life influences the next. In other words, the social, economic, and physical environments of the different stages of life have a significant impact on health.[107–109] If individuals are exposed to stressors during childhood, they are more likely to experience stressors later in life and those stressors are more likely to contribute to negative health outcomes.[107] Social cohesion states that the sense of solidarity that one has in their community and the strength of their interpersonal relationships improves their overall health.[110] A key indicator of social cohesion is social capital which is defined as the networks of relationships between people that allow society to function effectively.[110] Social capital is an integral part of resilience which has been widely studied as a protective factor against natural disasters.[111,112] Resilience being the process through which adaptive capacities are linked to adaptation after experiencing a disaster.[111]

Social and community context is an important component of understanding the effects of climate change. Individuals with a more robust social network will be able to come through negative experiences, like extreme weather, better than individuals who lack those social connections.[113–121] This is important for developing interventions to reduce the number of negative health outcomes that are caused by experiencing said extreme weather. Interventions that build social capital and thereby resilience can be deployed before a disaster arrives which will address the SDoH and serve as a form of primary prevention. If a disaster never arrives, improving social capital will still improve public health.

Economic stability has been widely connected to health status. Individuals that live in poverty have been shown to have worse health outcomes compared to their wealthier counterparts.[122–126] This is further explained by the income inequality hypothesis which states that health is influenced by both the level of income and the level of inequality where people live.[127] Income inequality is particularly relevant at the present time due its exacerbation by the COVID-19 pandemic. From 2020-2021, the United States saw an increase in income inequality by 1.2% marking the first time the Gini index showed an increase in income inequality since 2011.[128] The Gini index being a measure of wealth inequality.[129] The connection between economic stability and climate change being that individuals of low SES are more vulnerable to the effects of climate change for several reasons.[130–133] First, people of low SES are more likely to live in low-cost housing which increases the risk of hazards from extreme weather.[25] This is a linkage between two components of SDoH, economic stability and neighborhood and built environment. Second, people of low SES are less likely to evacuate when faced with a natural disaster.[134] This is theorized to be related to disparate access to transportation and varying levels of preparedness and risk perception.[134] Lastly, people of low SES lack the ability to minimize their exposure to environmental pollutants such as particulate matter (PM) 2.5 and extreme heat. People of higher SES are more able to alter their behavior to avoid harmful exposures as well has have equipment in their home to monitor air quality.[135] Additionally, people of higher SES are more likely to work in indoor environments compared to outdoor.[136] Lower SES people are also more energy insecure, meaning their energy bills constitute a large proportion of their income. This affects their ability to mitigate the harmful effects of extreme heat and air pollution using air conditioning.[135,137]

It is important to recognize that economic stability and neighborhood and built environment are closely linked. Economic stability often determines the neighborhood and type of house in which people reside. This provides support for examining geospatial measures of social polarization as well as social vulnerability to identify specific areas to target for intervention. Identifying the problem areas can help policymakers target specific communities with aid to mitigate the effects of climate change.

To address the extreme weather-climate gap, each chapter of this dissertation focuses on a specific theme. In Chapter 2, the theme is: How do neighborhood and built environment factors, along with access to healthcare, interact with environmental particulate matter in relation to respiratory hospitalizations? This chapter examines the relationship between climate change and social inequalities. In Chapter 3, the theme is: Does 'like attract like'? Do evacuation intentions depend on racial neighborhood segregation and income inequality? This chapter assesses the relationship between social inequalities and our responses to climate change. In Chapter 4, the theme is: Can individual and neighborhood-level technology implementation improve disaster preparedness? This chapter evaluates the relationship between climate change and our adaptive responses. The following sections provide background information on the content area for each chapter.

Background on Wildfires, PM 2.5, and Health Outcomes

The convergence of extreme droughts and human activities may have significant implications for respiratory health, even in communities that are geographically distant from the affected areas. Geographic areas experiencing droughts are expanding, along with the populations exposed to their harmful effects, such as particulate matter (PM) 2.5 from the combustion of dry vegetation during wildfires.[138] [139] Exposure to PM 2.5 has been established to vary by race/ethnicity and SES.[140–142] Structural racism likely contributes to these disparities.[143] This is supported by several theories and highlights that place matters, a key component of the extreme weather-climate gap.[84–88] Where people live is connected to the theories of place stratification, place assimilation, and the concept of access. These theories support the healthcare access and quality as well as neighborhood and built environment components of the SDoH. CDC's Social Vulnerability Index (SVI) provides, in part, a way to quantify these components.

The mechanism by which wildfires affect both proximal and distal communities involves PM 2.5 being carried and dispersed by the wind. This results in PM 2.5 contaminating the breathing air of places nowhere near the physical fire. There have been reports of wildfire-produced PM 2.5 traveling hundreds to thousands of miles.[144,145] In the U.S., the jet stream can carry PM 2.5 3,000 miles.[146] In 2023, massive wildfires in Canada caused poor air quality alerts across the Eastern US.[147–149] It was during this time that New York City recorded the worst air quality in the world.[150] This occurrence is dangerous to population health because PM 2.5 exposure has been linked to many adverse health outcomes including respiratory illnesses.[151–153] The human cost of exposure to PM 2.5 in the US is approximately 50,000 premature deaths per year.[140,154] Air pollution resulting from wildfires creates a unique situation where a natural disaster can spread pollutants extreme distances into areas that have not been historically considered high risk. This process will exacerbate long standing health disparities which contributes to the widening of the extreme weather-climate gap.

There is ample evidence showing how social vulnerability modifies the relationship between exposure to natural disasters, such as flooding and extreme heat, and health outcomes.[155–157] However, the work examining how social vulnerability modifies exposure to PM 2.5 and respiratory health outcomes is limited.[156] Clarke et al. in 2022 applied an SVI, modeled after the CDC version, to sub counties within Uganda and assessed the relationship with PM 2.5. The main finding being that sub counties classified as highly vulnerable were exposed to greater levels of PM 2.5.[156] This is also seen in other studies that indicate vulnerable housing (one component of CDC's SVI) increases the risk of exposure to environmental hazards, and racially minoritized populations experience greater levels of SVI.[158,159] More specifically, individuals that reside in highly vulnerable housing conditions have shown an increased risk of exposure to both indoor and outdoor air pollutants.[156,160]

Varying levels of access to healthcare in the US is a major contributor to health disparities.[161] Many studies have examined how exposure to PM 2.5 is correlated with emergency department visits (EDVs).[162–164] However, research is limited in examining how physical access to healthcare modifies the association between exposure to PM 2.5 and EDVs. This is despite there being a correlation between racially minoritized groups and physical distance from emergency services.[72] This further highlights the process by which populations that live far from health services and in vulnerable housing are at an increased risk of adverse health outcomes when exposed to PM 2.5.

There are multiple challenges associated with analyzing air pollution. First, there are limitations of traditional inferential methods when analyzing spatial data. Analytic methods referred to as geographic weighted regression (GWR) account for this and are well suited to analyze air pollution data. Second, with any spatial data analysis comes the statistical bias known as the modifiable areal unit problem (MAUP).[165] The MAUP arises when different associations are seen depending on the geographic scale used in an analysis and remains a key limitation of spatial analyses.

Analytic Methods to Analyze Air Pollution

Geographically weighted regression (GWR) is a superior method to traditional inferential methods for analyzing PM 2.5 data due to its ability to account for variations over both time and space. GWR is a valuable method because it provides detailed results with respect to local variations that are of particular importance for environmental justice work.[166] This method also addresses the high variability in ambient outdoor air pollution data. The distribution, specifically of PM 2.5, varies spatially across geographies and is highly influenced by wind speed, precipitation, as well as humidity levels.[167] However, a main limitation of traditional GWR with PM 2.5 data is that it does not take into account the temporal variation of PM 2.5 concentrations.[168] This spurred the development of geographic and temporally weighted regression (GTWR). GTWR was proposed by Huang et al. in 2010 and addresses the temporal and spatial sources of variability in PM 2.5 data.[169]

Additional studies have also concluded that GTWR is the superior model compared to more traditional methods for analyzing PM 2.5 data and provides the most informative results for developing ways to mitigate exposure.[170,171] Despite being a superior method of analysis for PM 2.5 data, the use of GTWR as it applies to examining disparate exposure to PM 2.5 in the US is limited. There are numerous studies that have examined PM 2.5 utilizing GTWR in China.[171] The standard methodology for using GTWR is that it involves comparing results between traditional ordinary least squares (OLS) methods and GWR and evaluating which model performed the best. Bai et al. in 2015 found that the GTWR performed the best out of all models which included OLS, GWR, and temporally weighted regression (TWR). Bai et al. studied ground PM 2.5 concentration in central China from November 2014 through February 2015. This study qualified model performance using the coefficient of determination (R^2), mean absolute difference (MAD), root mean square error (RMSE), and mean absolute percentage error (MAPE).[172] This study also concluded that GTWR accurately estimates ground PM 2.5 levels.

Chu et al. in 2015 also examined air pollution using several different models including GTWR. This study found that GTWR provided the highest amount of detail as to the spatio-temporal variation of PM 2.5 data. GTWR has high goodness of fit and unlike GWR or TWR indicates the combination of place and time variations of PM 2.5. This information is more valuable for policymakers and for developing interventions that aim to reduce air pollution exposure.[173] Guo et al. in 2017 also evaluated GTWR performance in China and showed similar findings. The GTWR model performed better than more traditional methods such as multiple linear regression (MLR), GWR, and TWR based on R^2 values. Guo et al. also found that PM 2.5 concentrations were highly varied spatially. This study recommends utilizing GTWR to analyze PM 2.5 data.[174]

Geospatial methods have also been used to assess outcomes outside of air pollution. Several studies have examined how EDVs vary spatially. The benefit of analyzing EDVs spatially is that it addresses how access to healthcare is not equal as previously cited. Douglas et al. in 2019 examined the correlation between diesel particulate matter and EDVs. The findings of this study indicated that diesel particulate matter, produced by emissions from diesel engines, was positively associated with asthma EDVs.[175] The strength of using this method is that it allows for identification of specific geographic areas that have elevated EDVs and suggests that spatial differences in EDVs result from healthcare access disparities. This provides a road map for where to focus interventions. In this study, interventions included reappropriating land for green space in census tracts with high particulate matter levels. Douglas et al. also noted that poverty and being African American/Black, or American Indian and Alaska Native, or Native Hawaiian and Pacific Islander was also positively associated with EDVs. Other studies have utilized geospatial methods to examine EDVs. DeMass et al. in 2023 utilized a Bayesian zero-inflated negative binomial model to examine how emergency department utilization varied across census block groups. This study also looked at how responses to an SDoH survey were correlated with EDVs. The findings were that unhealthy home environments (e.g., poor air quality, lack of air conditioning) were positively correlated with EDVs.[176] Guolo et al. in 2022 assessed the relationship between heat exposure and EDVs by census tracts in Italy. This study also examined whether a census tract level measure of social vulnerability modified the relationship between heat and EDVs. The results did show that social vulnerability modified the relationship and that those living in deprived areas were at higher likelihood of an EDV due to heat exposure.[177] While the exposure in this study was not air pollution it is a similar mechanism where climate change is disproportionately causing EDVs.

This analysis aims to apply cutting-edge GTWR methods to address the association between exposure to PM 2.5 and respiratory hospital admittances and how healthcare access and social vulnerability modify this relationship. The goal of this analysis is to answer the following questions.

I. How does exposure to environmental particulate matter vary spatially from year to year in North Carolina at the zip code tabulation area (ZCTA) level?
   a. Hypothesis: PM 2.5 concentrations will be higher among more urban ZCTAs in North Carolina.

II. Does housing type and transportation social vulnerability index score and distance from the hospital modify the relationship between exposure to environmental particulate matter and respiratory hospitalizations?
   a. Hypothesis: Greater housing vulnerability and less accessible healthcare will magnify the environmental particulate matter and respiratory hospitalizations association.

Data sources for this analysis are the Atmospheric Composition Analysis Group's Satellite-derived PM 2.5 data, Healthcare Utilization Project State Inpatient Data for hospital admittances, CDC for social vulnerability data, and North Carolina geospatial data on hospital locations. The combination of these robust data sources and application of GTWR provide novel analysis of air pollution, structural factors, and respiratory health outcomes.

Background on Racial and Economic Predictors of Evacuation Behavior

Population displacement as a result of evacuations caused by natural disasters is likely to increase with the acceleration of climate change.[178] This displacement will be both short and long-term. The science of evacuations is complex as these events must occur rapidly with limited information. Delays in this process or mistakes can cost lives.[179] Social inequalities affecting evacuation behavior due to climate change is a key piece of the extreme weather-climate gap. Evacuations that occur within systems of inequalities lead to disparities and displacement causes further marginalization. The existing literature on evacuation behavior in response to disasters is extensive.[180] The specific themes that the relevant literature covers are the following: the importance of how authorities publicize evacuation orders and messaging, the decision-making process that goes into evacuations, how social connections affect evacuation behavior, and individual-level characteristics that influence evacuation behavior.

There have been several studies done examining the importance of messaging from local, state, and federal officials on evacuation behavior. There is a strong correlation between proactive and frequent messaging surrounding evacuations and the number of people who evacuate when an order is made.[181,182] In fact, messaging from public officials is the strongest influence on whether people evacuate.[182–184] The tone of the evacuation messaging also matters. Increased evacuation compliance is seen when evacuations are forced as opposed to suggested.[181]

The second key theme of the evacuation literature states that messaging from authorities, while important, is not enough to prompt individuals to make the decision to evacuate. People must perceive that they are at risk.[185] This process involves individuals understanding whether they live in an area that has been ordered or suggested to evacuate.[186] There have been several examples of individual risk perception influencing decisions to evacuate almost as much as messaging from public officials.[187–189]

Another theme that has been explored in the literature is the influence that social connections have on evacuation behavior. Studies have shown that increased social cohesion within a community contributes to an increased probability of evacuation.[190,191] Social networks act as a mechanism for passing information about threats such as natural disasters.

The actual number of social ties that someone has is shown to be correlated with whether they will evacuate.[192] This indicates that those who are socially isolated may be at greater risk of harm from natural disasters due to a lesser likelihood of evacuating. This is supported by the social and community context of the SDoH as well as social stress theory. It is of particular importance when dealing with an evacuation situation where one may depend on their community for information or help leaving the area.

The last key theme seen in the evacuation literature is that there are several individual and household characteristics associated with the decision to evacuate. Female sex as well as White race were associated with increased likelihood of evacuation.[193–195] Age was inversely correlated with likelihood of evacuation. Older populations have shown that they are less likely to evacuate.[196,197] There are conflicting findings around the correlation between education and income as well as homeownership.[195,198] Several studies have shown that those with higher incomes are more likely to evacuate.[134,199] This is supported by the economic stability component of the SDoH as well as the income inequality hypothesis and the concept of residential mobility. Household characteristics such as size, specifically the number of children residing in the household, was correlated with increased evacuation.[200,201] Members of the household being disabled was correlated with decreased evacuation likelihood as well as households with pets.[202,203]

The expansion of smartphone uses over the past several decades has allowed for more granular geo-spatial data collection. Two key studies have examined evacuation patterns utilizing anonymized GPS data collected from smartphones. The first conducted by Yabe et al. in 2020 analyzed movement patterns both before, during, and after Hurricane Irma, which made landfall in Florida and was especially devastating. In the US alone, Irma is estimated to have caused just over $77 billion dollars in damage and approximately 134 deaths. It is one of three devastating hurricanes from the 2017 US hurricane season. Yabe et al. specifically analyzed how income inequality affected evacuation patterns as well as reentry behavior after Hurricane Irma. This study estimated income for the study participants by matching the estimated census tract of residence to the median income for that respective census tract using American Community Survey (ACS) data. Approximately 6 million people were ordered to evacuate in Florida as Hurricane Irma approached. The findings from this study showed higher income was associated with a greater probability of evacuating in areas with and without an evacuation order. The study also found that those with higher income were able to evacuate to areas deemed safer which was defined as having a stable power grid and less housing damage.[199]

The second study conducted by Deng et al. in 2021 analyzed similar movement patterns as the previous study but for Hurricane Harvey. Hurricane Harvey brought an unprecedented 50 inches of rain to Houston, Texas which caused widespread flooding and damage. Unlike in Florida for Hurricane Irma, Texas did not mandate an evacuation for Hurricane Harvey. Deng et al. analyzed differences in movement patterns by race/ethnicity and SES. This study estimated the census block where people lived based on their movement patterns. Participant resident census blocks were then classified into six different groups: non-poor Black, non-poor Hispanic, non-poor White, poor Black, poor Hispanic, and poor White. Census blocks that were classified as poor were areas with ≥ 25% of the residents living below the federal poverty level. The race/ethnicity of the census block was classified using a ≥ 50% level. For example, if more than 50% of a census block was White then it was categorized as a White census tract. The study found that higher SES White populations were more likely to evacuate and had longer displacement. This is hypothesized to be related to higher SES people having more resources to remain at their evacuation site rather than return to their home in the evacuated area. Additional findings showed that approximately 6.7% of the population of the Houston Metropolitan Statistical Area (MSA) evacuated with 95% of the evacuations occurring after Hurricane Harvey made landfall. This is not surprising since there was no mandated evacuation.[134] These results are supportive of the findings from the Yabe et al. study. Higher SES people are more likely to evacuate, more likely to evacuate to a safer area, and more likely to be evacuated longer.

Understanding the mechanism of evacuations prompted by natural disasters is a key part of addressing the extreme weather-climate gap. The existing literature on the topic has only just begun to utilize geospatial methods to examine evacuation patterns. Yabe et al. in 2020 and Deng et al. in 2021 are at the cutting edge of studying this area in the evacuation behavior space. However, there are several limitations of these studies. The first being that neither examined social ties which was a result of using anonymized data. Second, the ways in which the race/ethnic groups were divided in the Deng et al. study excluded race/ethnic groups outside of the White, Black, and Latinx communities. Third, neither study examined social polarization in the context of evacuation behavior.

This study aims to evaluate how social polarization is correlated with evacuation behavior. When disasters cause evacuations in systems with existing social inequalities, it is hypothesized that individuals residing in areas of high racialized segregation will have to travel further to get to their evacuation site. Research on this topic is limited. This study seeks to address this gap in the evacuation literature by answering the following questions.

I. Is residential social polarization correlated with evacuation site social polarization?

   a. Hypothesis: The locations people listed as their evacuation site will be at a similar level of social polarization as their primary residence.

II. What role does racial neighborhood segregation and local social ties play in how far people travel to evacuate?

   a. Hypothesis: Local social ties will act as a protective factor, moderating the relationship between neighborhood racial segregation and distance to evacuation site.

Analysis of data from the Neighborhood Connectivity Survey (NCS) as well as the ACS was used to answer these research questions. NCS is a mail-based survey conducted in Pennsylvania and Ohio from 2017-2019. A component of the survey asked participants for the exact address they would evacuate if they had to leave their home for one week, two months, and indefinitely. Each evacuation location was geocoded and the distance from their home was calculated. Participant home address was used along with ACS data to calculate index of concentration at the extremes (ICE) which is a measure of social polarization.

Background on Disaster Preparedness Exercises

Identifying the mechanisms through which the extreme weather-climate gap operates is not sufficient. The need for research on specific interventions that can address this gap is essential. There are several key traits that these interventions must possess to be effective at narrowing the extreme weather-climate gap. These interventions must be a form of primary prevention or address the SDoH, they must be deployable in the absence of a disaster, and they must consider populations with diverse needs.

Several studies have been identified that utilize community-based participatory methods to build disaster preparedness. These methods are well suited to link the preparedness knowledge of professional organizations to community stakeholders especially when utilizing methods such as active learning.[204,205] Jamshidi et al. in 2016 evaluated the effectiveness of a three-day workshop that aimed to improve earthquake preparedness in Iran. The findings of this study showed that participants involved in the workshop showed improved earthquake preparedness in knowledge, attitude, and practice when compared to the control group who did not attend the workshop.[206] McNeill et al. in 2016 studied how exposure to educational material from Texas' "Ready or Not" program influenced self-reported household preparedness. This material was developed by the Texas Department of State Health Services to prepare Texans for natural disasters. The findings showed that post-intervention preparedness scores were significantly higher than pre-scores on a preparedness assessment developed by the researchers.[207] These findings are similar to James et al. in 2020 which evaluated another three-day intervention aimed and building disaster preparedness to both earthquakes and flooding in Haiti. Participants randomly assigned to receive the intervention showed a significant increase in their disaster preparedness when compared to controls. The intervention resulted in individuals engaging in an additional four disaster preparedness activities compared to before the intervention. These behaviors include making a disaster supply kit, storing important documents in a secure place, and discussing an evacuation plan with a family member.[208] These intervention studies highlight how a community-based approach is capable of improving disaster preparedness. Additional literature further suggests that community engagement is one of the best methods to improve disaster preparedness.[209]

Social capital, a key construct of social and community context, has been linked to improved disaster preparedness within the context of experiencing a disaster. Reininger et al. in 2016 examined the correlation between social capital and disaster preparedness among a sample of low-income Mexican Americans that lived in coastal communities in Texas. In this study, social capital was measured by perceived reciprocity, fairness, civic trust, and membership in various public groups. The results showed that those with high perceived fairness and civic trust were more likely to be prepared for a disaster.[210] Roque et al. in 2020 found that social capital was key to communities in Puerto Rico enhancing their resiliency following the 2017 Atlantic hurricane season. Roque et al. also noted the effectiveness of community-based participatory interventions at building social capital.[211] Additional studies support that social capital aids in all phases of disasters which includes preparation, response, and recovery.[212,213] Structural racism has been linked to inhibiting the process by which minoritized individuals aggregate social capital.[214] Additionally, lack of economic and cultural capital creates barriers for minoritized groups to use and acquire social capital.[215,216] This is the pathway by which structural racism is suggested to affect disaster preparedness. A lack of social capital among racially minoritized groups may reduce the effectiveness of a disaster exercise aimed at building preparedness. This is important to identify through methods such as needs assessments and understand because it influences the effectiveness of the intervention. It also threatens the ability to scale up interventions that build disaster preparedness if they will not benefit certain groups. This also identifies other targets for interventions, such as social capital, before engaging in community-based disaster preparedness work. These described relationships are supported by the concepts of social cohesion as well as social stress theory which have been described earlier in this chapter.

Many studies have examined the role that social capital plays in disaster resilience and disaster recovery.[120,211,217] However, no studies have been identified that examine the role that social capital plays in the effectiveness of a community-based participatory exercise aimed at improving disaster preparedness. This is a significant gap in the literature. Understanding the differences between those who attend disaster interventions and those who do not, as well as how social and community factors influence disaster preparedness, is key to the success of future interventions.

Several analytic methods were used to evaluate the effectiveness of the disaster intervention. The first was a logistic regression model that examined differences in preparedness behaviors between those who attended the exercise compared to those that did not. Second, structural equation modeling was used to examine how social capital and social resources modify the association between exercise attendance and change in disaster preparedness. Several studies have utilized structural regression to examine disaster preparedness and disaster adaptation. No studies have been identified that utilize structural regression to evaluate both social capital and social resources relationship with improved disaster preparedness following an intervention. Dang et al. in 2014 developed a structural equation model (SEM) to understand the psychological correlates with climate adaptation among farmers in Vietnam. The study found that the factors correlated with disaster adaptation were perceived risk of climate change and belief in the effectiveness of adaptation actions. Factors that were negatively correlated with disaster adaptation were rejection of climate change science and fatalism.[218] Patel et al. in 2023 applied SEM framework to understanding disaster preparedness among college students. Patel et al. found that government and university officials taking responsibility for student’s wellbeing as well as disaster risk reduction curriculum, including topics such as first-aid training and disaster medicine, were correlated with disaster preparedness and disaster awareness. Establishment of university emergency procedures as well as communication systems were also correlated with disaster preparedness. This study also found that each of these factors mediated the relationship between race, gender, ethnicity, education, and place of residence (on or off-campus) with disaster preparedness and awareness.[219]

The goals of this analysis are to evaluate the effectiveness of a community-based disaster preparedness intervention. This analysis also will evaluate how social capital and social resources are related to disaster preparedness. The specific research questions the analysis aims to answer are the following:

I. Was exposure to a disaster exercise correlated with improved participant disaster preparedness?
   a. Hypothesis: The educational intervention will bolster attitudes and knowledge about disaster preparedness at the individual and household level.

II. Do participants with higher social resources benefit from the intervention more than participants with low social resources?
   a. Hypothesis: Individuals with lower social resources will benefit less from the preparedness exercise compared to those with higher social resources

Data used to answer these research questions were collected as a part of the Athens-Clarke County Climate Resilience study (ACCCR). This study was approved by the University of Georgia Institutional Review Board (PROJECT00006621) and all participants provided informed consent in accordance with the Declaration of Helsinki. Data collection began in May of 2023 and continued through the end of January 2024. Participants took a pre-survey and then had the option to attend an in-person disaster exercise conducted by a faculty member from the Institute for Disaster Management. The exercise lasted approximately 1.5 to 2 hours and involved lectures on building emergency kits, available community resources, and a participatory mapping exercise. A post-survey was distributed to participants that attended the exercise as well as those who did not. The key items captured on the survey include social resources, social capital, physical resources, disaster preparedness, and perceived susceptibility. In accordance with the diffusion of innovation theory, the exercise is designed to highlight advantages to participating versus not as well as the simplicity of having a basic level of disaster preparation. The effectiveness of the exercise is also testable and observable through analysis of survey data. Lastly, the exercise is consistent with the values and experiences of the participants given FEMA's findings from the 2020 National Household Survey which indicates a rise in disaster preparedness behaviors.[220] This meets the standard factors that are involved in adoption of an innovation.[221–223]

Summary

The guiding research theme of this dissertation is the study of the neighborhood and built environment, multi-level social polarization, and social causes of the extreme weather climate gap. The specific themes of each chapter are the following:

I. <u>Theme 1:</u> How does neighborhood and built environment and access to health care interact with environmental particulate matter on respiratory hospitalizations? (Chapter 2)

II. <u>Theme 2:</u> Does like attract like? Do evacuation intentions depend on racial neighborhood segregation and income inequality? (Chapter 3)

III. <u>Theme 3:</u> Can an individual and neighborhood-level technology implementation improve individual risk perception in a diverse community context? (Chapter 4)

The results from this dissertation will examine and present on the mechanisms by which the extreme weather-climate gap operates, employ advanced methods, and present results on an innovative intervention to promote disaster preparedness as well as identify additional areas to intervene. The extreme weather-climate gap will widen in the coming years if reactionary methods continue to be the standard. There is great need for further quantification of the risks of climate change and development of targeted interventions to enact lasting change to narrow the gap.

CHAPTER 2

HOW DOES NEIGHBORHOOD AND BUILT ENVIRONMENT AND ACCESS TO HEALTHCARE INTERACT WITH ENVIRONMENTAL PARTICULATE MATTER ON RESPIRATORY HOSPITALIZATIONS?

Introduction

A key consequence of climate change is the expansion of risk related to the resulting extreme weather. Geographic areas that typically do not experience extreme weather events, such as wildfires, may face such events in the coming years.[12] Due to their inexperience in handling such events, these areas will face significant challenges, as they lack the resources available to regions that encounter these situations more frequently.[224] Wildfires are a notable example because a key byproduct, particulate matter 2.5 (PM 2.5), can be spread across thousands of miles affecting both proximal and distal sites.[144,145]

The distance with which PM 2.5 can be carried by the wind puts essentially every area of the U.S. at risk. As this literal PM 2.5 cloud spreads to areas on the East Coast, the intersection of climate change and social inequalities occurs. This is due to the pervasive nature of structural racism throughout the U.S. where racist policies and practices are deeply entrenched.[225,226] The theoretical support from this statement is derived from place stratification and place assimilation theories.[84–88] Racial/ethnic majorities control the geographic landscape claiming more desirable space and preventing racially/ethnically minoritized populations from improving their position.[84,85] With this intersection comes further exacerbation of longstanding health disparities and further widening of the extreme weather-climate gap.

Multiple forms of PM exist which include 1.0, 2.5, and 10. However, PM 1.0 is difficult to accurately measure in the environment and PM 10 does not penetrate as deeply into human lung tissue as PM 2.5.[227] Thus, the link between PM 2.5 exposure and respiratory illness hospitalizations has been widely established.[151–153] Exposure to PM 2.5 is linked to approximately 50,000 premature deaths per year.[140,154] A significant gap in the literature is how social vulnerability and access to health care modifies the association between PM 2.5 and respiratory illness hospitalizations. Social vulnerability is classified by the CDC as consisting of four key themes which include socioeconomic status, household composition and disability, minority status and language, and housing type and transportation.[228] The theme that this analysis focuses on is housing type and transportation. Previous studies have examined the link between housing vulnerability and exposure to environmental pollutants indicating that housing type matters.[156,160] Connections between overcrowded housing and poor indoor air quality have been established.[229] In addition to this, building type has been shown to modify exposure to air pollution.[230,231] This positions CDC's social vulnerability index (SVI) housing type metric as a way to measure vulnerable housing and assess how it modifies PM 2.5 exposure and respiratory illness hospitalizations.

A key component of health care access is physical distance to services.[61,63] Increased distance from health services has been shown to be a significant burden to accessing care.[232] This analysis uses the number of hospitals within a buffer of the geographic centroid of each zip code tabulation area (ZCTA) as a way to estimate physical access to care. To our knowledge, no studies have utilized these methods to examine social vulnerability and health care access as modifiers of the association between PM 2.5 and respiratory illness hospitalizations. Both physical distance to care and the SVI housing type evaluates healthcare access, quality, and the neighborhood and built environment components of the Social Determinants of Health (SDoH).

Healthcare Utilization Project State Inpatient Data (HCUP SID) was available from North Carolina from 2017-2019. The goal of this analysis is to understand the spatial variation of PM 2.5 across North Carolina and to examine potential modifiers of the relationship between PM 2.5 and respiratory hospitalizations. This is a unique analysis that quantifies the risk of PM 2.5 exposure within the context of climate change in a potentially underprepared geographic region. The questions this study seeks to answer are (1) do PM 2.5 concentrations cluster in urban areas in North Carolina (2) does housing type vulnerability and access to health care modify the relationship between PM 2.5 and respiratory hospitalizations. This study utilizes geographically weighted regressions to examine local relationships at the ZCTA level within North Carolina. We hypothesize that PM 2.5 will be higher among more urban areas. Additionally, we hypothesize that greater vulnerability and lack of access to health care will synergize with PM 2.5 exposure to further exacerbate respiratory hospitalizations.

Methods

PM 2.5 Measure

The monthly average PM 2.5 for each ZCTA was derived from the Atmospheric Composition Analysis Group at Washington University in St. Louis. These PM 2.5 values are ug/m^3 and are computed from a combination of satellite-, simulation-, and monitor-based mechanisms. These methods provide granular data points down to the 1km x 1km resolution across North America. More detailed methods for how the raw PM 2.5 values are computed are described elsewhere.[233] Monthly mean PM 2.5 values are available from 1998 – 2022. These monthly fine resolution data points were merged with a shapefile, which is a geospatial data vector, of all ZCTAs for the entire U.S. After overlaying North Carolina's ZCTA's on the fine resolution PM 2.5 data, average ZCTA values were computed for each North Carolina ZCTA polygon. Areas of the 1km x 1km grid that were not fully inside of a ZCYA were weighted based on the amount of coverage within each respective ZCTA. The fine resolution PM 2.5 data points were weighted based on the coverage fraction of each ZCTA polygon and a mean calculation for each ZCTA was calculated per month from 2017-2019. This dataset was built using RStudio (version 4.4.1 (2024-06-14)).

Respiratory Illness Hospitalizations

Respiratory hospitalizations were derived from Healthcare Utilization Project State Inpatient Data (HCUP SID) from 2017-2019 in North Carolina. These data cover 97% of all community hospital discharges.[234] Data were available monthly at the patient-level from 2017-2019. These data contained up to 25 ICD-10-CM (diagnosis) codes for each patient. Within the STATA 18.0 environment, the ICD10 function was used to clean and classify the reported ICD-10-CM codes. The ICD10 function allows for scanning of all 25 ICD-10-CM variables for the respiratory illness ICD-10 codes J00-J99.[235] A count outcome was computed from these data for this analysis which was the total number of respiratory illness hospitalizations. If the patient had a corresponding code present in any of the 25 variables, they were classified as having the outcome. Data were then collapsed to the ZCTA level for merging with PM 2.5 data. Utilizing STATA's American Community Survey 5-year (ACS) application programming interface (API), total populations for each ZCTA were imported and merged with the ZCTA-collapsed HCUP data. This was used to compute the respiratory illness hospitalization rate per 10,000 for each ZCTA. ACS data on ZCTA population totals for each respective year from 2017-2019 were used to compute the respiratory illness hospitalization rate.

Social Vulnerability Index

Four of the five sub-scores from CDC's SVI housing and transportation score were used in this analysis. This component of SVI was selected because it is a metric of housing vulnerability which has been linked to increased exposure to PM 2.5.[141,236,237] SVI scores are released in two-year increments in even years. Higher scores indicate increased vulnerability. SVI values used in this analysis were obtained from the 2016 release as they predated the period of interest (2017-2019). The five sub-scores include the prevalence of housing structures with ten or more units (multi-unit structures), the percentage of mobile homes (mobile homes) within the ZCTA, the percentage of occupied housing with more people than rooms (overcrowding), the percentage of individuals living in group quarters (group quarters), and the percentage of individuals with no vehicle (no vehicle). To focus on housing-specific vulnerabilities, no vehicle was not included in this analysis. The four housing SVI sub-scores were included in the models separately and obtained from using RStudio (version 4.4.1 (2024-06-14)) at the ZCTA level.

Health Care Access

A map of all community hospitals within North Carolina was obtained from the state's geospatial data repository.[238] This geospatial dataset was only available in 2023. As a result, each hospital within this dataset was manually reviewed to determine whether the hospital was operational during the period of interest. A total of 163 hospitals were identified as being operational. HCUP provides guidance on methods to calculate physical distance from hospitals. This analysis utilized an adapted method which plots a geographic buffer around the centroid of every ZCTA in North Carolina and counts the number of hospitals within said buffer. The distance of the geographic buffer was determined from HCUP's 2018 analysis of driving distance from hospitals which used 48 states worth of data.[239] This analysis found that 6.60 miles represented the median travel distance to a hospital among their sample (n = 30.27 million). Approximately 15 miles represented the 75th percentile of their dataset in terms of driving distance to a hospital. Based on this, the geographic buffer for this analysis was set at 15 miles. The resulting calculated variable used in this analysis is a continuous variable representing the number of hospitals within a 15-mile circular buffer of the geographic centroid of the ZCTA. All calculations for this metric were computed in RStudio (version 4.4.1 (2024-06-14)).

Additional Covariates:

Mean age of the HCUP patients at the ZCTA level was computed when the HCUP datasets were collapsed. The percentage of the population with income in the past 12 months below the poverty level was computed for each ZCTA utilizing STATA's ACS 2016 5-year API.[240] The rural/urban commuting area code (RUCA) of each ZCTA was also derived based on the 2010 census and were also merged into the final dataset.[241] RUCA codes range from 1 to 10 and can be collapsed down into smaller categories. For this analysis, codes 1-3 were classified as metropolitan, 4-6 as micropolitan, 7-9 as small town, and 10 as rural.[242] This provides a control for potential rural/urban differences.

Statistical Analysis of Research Question 1

Evaluation of the PM 2.5 and hospitalization data was conducted using a base index to discern if monthly patterns at the ZCTA level follow similar patterns each year. The base index was calculated at the ZCTA level and was done by taking the monthly ZCTA PM 2.5 average and dividing it by the PM 2.5 average across the corresponding year. For example, the average PM 2.5 concentration for 2017 was calculated. This was used as the denominator for the base index calculation of each ZCTA monthly value for the first 12 months of the period of interest. A similar base index was calculated for the respiratory illness hospitalization rates.

Two separate generalized estimating equations (GEE) were fit with each base index as the outcome. GEE models were selected because they can account for the repeated measures of the PM 2.5 data.[243,244] The predictors included in the model were an observation year variable as well as a four-level categorical month variable (0 – January to March; 1 – April to June; 2 – July to September; 3 October to December). The interaction between observation year and the month category was evaluated. These results indicated that PM 2.5 significantly varied over the period. Figures 2.4 and 2.5 show the distribution of the base index for each ZCTA across the study period. A component of this analysis was to evaluate significant elevation in PM 2.5 levels. Examining the spread of the PM 2.5 data across ZCTAs for the three-year period showed no events that caused the PM 2.5 ug/m^3 measurements to go above 12 ug/m^3. For reference, when New York City was affected by Canadian wildfire smoke, PM 2.5 measurements reached 117 ug/m^3. The interaction of observation year and month category with the base index for respiratory hospitalizations as the outcome was not significant. Given that this is the primary outcome for RQ2 in addition to a lack of an event that meaningfully raised PM 2.5 levels a GWR was selected over a GTWR. The dataset was collapsed across the three-year period of interest.

Spatial analysis of the PM 2.5 data and respiratory illness hospitalization rates were conducted by calculating a univariate Moran's I statistic. Moran's I is utilized to determine if a variable varies spatially and if there is clustering.[245] The underlying process involves comparing the variable of interest at one location, in this analysis ZCTA, to other neighboring locations (i.e., other neighboring ZCTAs). The first step in calculating a Moran's I statistic is to create a spatial weights matrix. The construction of this spatial weight's matrix can be done via Rook's contiguity or Queen's contiguity. Queen's contiguity was selected as it is more inclusive.[246] Utilizing this method classifies ZCTA's in this dataset as neighbors if their respective boundary touches at one point. After creating the spatial weights matrix a univariate Moran's I can be calculated. All Moran's I analyses were conducted in GeoDa software package. A total of 999 permutations were done for each Moran's I calculation to ensure a robust estimate of the statistic for each variable.

Statistical Analysis of Research Question 2

Given the findings of the longitudinal and spatial analyses a geographically weighted regression (GWR) was selected to conduct the analyses for RQ2 on the collapsed dataset. When conducting GWR, results from traditional linear regression models are presented first. A Poisson model was selected to initially evaluate RQ2 given that the outcome was respiratory hospitalization rate per 10,000. Predictors in the model included mean PM 2.5 at the ZCTA from 2017-2019, SVI score for multi-unit structures, mobile homes, overcrowding, group quarters, rural/urban commuting area code (RUCA), average age of the patients in each respective ZCTA, mean poverty rate in each ZCTA, and number of hospitals within a 15-mile radius of each ZCTA. Huber-White robust standard errors were computed for all models.[247–249] There are a total of 808 ZCTAs in North Carolina. The final models were conducted using 766 ZCTAs. The 42 ZCTAs were dropped from analyses because of a lack of data for those areas. The dropped ZCTAs account for 5% of the ZCTAs in North Carolina and 4% (n = 432,989) of the total population of North Carolina. General linear model (GLM) analyses were conducted in STATA 18.0 MP (College Station, TX).

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$$

The above equation describes traditional GLM. Y_i is the dependent variable, X_i is the independent variable with β_0 being the intercept, β_1 being the slope, and ϵ_i being the error term.

$$Y_i = \beta_0(u_i,v_i) + \beta_1(u_i,v_i)X_i + \epsilon_i$$

The equation above describes GWR. Similarly to GLM, Y_i is the dependent variable, X_i is the independent variable and ϵ_i is the error term. The key difference here is that β_0 and β_1 are estimated locally at location v_i, u_i. In this analysis, the location corresponds to each ZCTA in North Carolina. This method allows for examination of local trends which is not an option in traditional GLM.[250–252] A key component of GWR is selection of a bandwidth which is the distance at which observations are considered. The selected bandwidth serves to weight the observations included in the GWR. In this case that is ZCTAs. Bandwidth selection for this analysis was done using adaptive kernel. This method allows the bandwidth to vary based on the spatial distribution of the ZCTAs.[253] As a result of the distribution of ZCTAs across North Carolina, which vary in size and include both rural and urban areas, the adaptive kernel bandwidth was selected over fixed bandwidth. This allows for the bandwidth to change (i.e. adapt) when there are more or less observations over a given space.[254] All GWR analyses were conducted in RStudio (version 4.4.1 (2024-06-14)).

Results

Table 2.1 shows the descriptive statistics for the analytic sample. A total of 766 (95%) of ZCTAs from North Carolina were included in this study. Overall, mean PM 2.5 was 6.27 ug/m^3. No ZCTAs had a three-year average PM 2.5 concentration greater than the 9.0 ug/m^3 which EPA has set as the harmful level. The average respiratory hospitalization rate was 105.79 per 10,000. The rural/urban commuting area code classification of the ZCTAs was 56% metropolitan, 21% micropolitan, 11% rural, and 10% small town. The average age of those hospitalized for respiratory illness at the ZCTA-level was 52.3 years old. The average SVI across the four key measures were 0.42, 0.49, 0.47, and 0.43 for multi-unit homes, mobile homes, crowding, and group quarters respectively. Values closer to one indicating increased vulnerability and are relative to all ZCTAs in the U.S. The average number of hospitals within a 15-mile radius of the geographic centroid of each ZCTA was 1.92. The average poverty rate across all ZCTAs was 0.12. Figure 2.1 shows a map of North Carolina ZCTAs as well as key cities and the distribution of the hospitals located throughout the state.

Spatial Analysis

Figure 2.2 shows the results from the spatial analysis of PM 2.5 across North Carolina. The figure shows the mean PM 2.5 values for each ZCTA. The values displayed are in ug/m^3. From this figure the clustering of the PM 2.5 values can be seen. The resulting Moran's I was 0.602 with a p-value of 0.001. This indicates that PM 2.5 in this sample shows statistically significant positive spatial autocorrelation. Figure 2.3 shows the distribution of respiratory illness hospitalizations across North Carolina. The Moran's I for the respiratory illness hospitalization rate was 0.088 with a p-value of 0.005 also indicating significantly positive spatial autocorrelation although not as strong at PM 2.5.

Base Index Distribution

Figures 2.4 and 2.5 show the base index calculations for each ZCTA across the study period. Figure 2.4 details the lack of a significant event that caused elevated PM 2.5 levels. Figure 2.5 also shows the relatively stable hospitalization rates across the period.

General Linear Models

The results from the Poisson regression to address RQ2 showed a significant interaction of four of the five domains of social vulnerability on the association between PM 2.5 exposure and respiratory hospitalization, sometimes weakening and sometimes strengthening the association as spatial vulnerability increased. A simple slopes analysis (estimated relationship at the mean value of the effect modifier and 1 standard deviation above and below the mean) is presented in Figures 2.6-2.10. Multi-unit housing, group quarters, and crowding were each found to weaken the relationship between PM 2.5 and respiratory hospitalizations. In Figure 2.6 for example, 1 SD less multi-unit housing than the mean strengthened the relationship between PM 2.5 and respiratory hospitalizations to 11.6 per 10,000 residents as compared with 6.5 per 10,000 people at average levels of multi-unit housing.

The interaction term between PM 2.5 and multi-unit housing SVI score was significant ($p = .002$). Figure 2.6 shows the relationship between PM 2.5 and excess respiratory hospitalizations was weaker as multi-unit housing vulnerability increased (0.1 to 0.8). Figure 2.7 shows the interaction between PM 2.5 and mobile homes SVI score was significant ($p = .018$). The relationship between PM 2.5 and excess respiratory hospitalizations was stronger as mobile homes vulnerability increased (0.2 to 0.8). Figures 2.8-2.10 show additional interactions between PM 2.5 and SVI on excess respiratory hospitalizations.

Each model accounted for the subcomponents of the Social Vulnerability Index (SVI). For example, in the model examining the interaction between SVI crowding and PM 2.5, the variables for SVI mobile homes, group quarters, multi-unit housing, and the 15-mile radius hospital variables were controlled for. Additional covariates included the average age of the hospitalized patients, the poverty level of the ZCTA, and the rural/urban commuting area code. All these additional covariates were at the ZCTA-level.

Geographically Weighted Regression

The results of the GWR are presented in Figure 2.11 with 6 maps of North Carolina ZCTAs. Each of the maps shows the local GWR coefficient for the association between PM 2.5 and respiratory illness hospitalizations. Areas that are white are ZCTAs where this coefficient was not statistically significant at $p = .05$. The map in the top left of Figure 2.11 shows the relationship between PM 2.5 and respiratory illness hospitalizations without interaction. Areas that are shaded gold are ZCTAs where PM 2.5 ug/m^3 is significantly positively correlated with respiratory illness hospitalizations. Areas that are shaded blue indicate that PM 2.5 ug/m^3 is negatively associated with respiratory illness hospitalizations. In other words, as PM 2.5 and SVI increase in these areas, respiratory illnesses decrease. The map shows that areas of positive correlation (gold) are towards the East of North Carolina as well as the Central West region. The next map to the right shows the interaction between PM 2.5 and SVI multi-unit housing. This shows an area of significant positive correlation (gold) as well as negative correlation (blue) on the East side of North Carolina. The next map showing the interaction between PM 2.5 and SVI mobile homes indicates there are pockets of positive correlation in areas spread throughout North Carolina. The interaction map between PM 2.5 and SVI crowding shows areas of positive correlation in the Central and West areas of North Carolina. The next map showing the interaction between PM 2.5 and group quarters shows pockets of significant positive and negative correlation on the East side of North Carolina. The last map shows moderate negative correlation between PM 2.5 and the number of hospitals within a 15-mile radius of the geographic centroid of the ZCTA on the East side of North Carolina.

Table 2.2 displays the root mean square error (RMSE) for comparing the Poisson model performance to that of the GWR models. RMSE is a measure of model fit comparing the predicted values of a given model to the observed values (model residuals).[250] RMSE is displayed in the units of the dependent variable which in this case is respiratory illness hospitalizations per 10,000. The GWR models overall reduced RMSE compared to the Poisson models. This reduction ranges from 35-37%. This suggests that the GWR models provided a better overall performance when compared to the more traditional GLM.

Discussion

This analysis applied a GWR model to assess statewide correlations between PM 2.5 exposure and respiratory illness hospitalizations in North Carolina. Modification of this relationship by SVI and health care access was also examined. The aims of the analysis were to better understand how consequences of climate change interact with systems of inequality across a large geographic area. A combination of multiple sources of data including HCUP SID and fine resolution PM 2.5 data allowed for an almost statewide assessment of the unique research questions. Utilizing a GWR and comparing this with traditional GLM illustrates the benefits of the former method over the latter.

Place Assimilation and Place Stratification Theories

Interpretation of the findings from the GLM regression models and the GWR models showcase the differences between the two methodologies and their connection with the theories of place assimilation and place stratification. The GLM regression results showed that PM 2.5 was positively correlated with respiratory illness hospitalizations although not significantly. The interaction results showed that for three of the four models, the relationship between PM 2.5 and excess respiratory hospitalizations was weaker as vulnerability increased. This could be due to unmeasured factors that cause respiratory hospitalizations to be higher in less vulnerable areas unrelated to ambient PM 2.5. This is also potentially indicative of marginalized populations avoiding emergency room care. However, this finding does not cohere with other studies that have looked at how lower SES people and racial/ethnic minorities are more likely to utilize emergency departments because of a lack of access to primary care providers.[255,256] Potential reasons for why the results do not align with other studies could be due to incompleteness related to the recorded ICD-10 codes.[257] Additionally, PM 2.5 exposure can cause many different health problems and people may not present at the emergency room with a respiratory illness and would therefore not be counted in this analysis. Even though exposure to air pollutants is the underlying cause. Another potential reason is that people living in more vulnerable ZCTAs may utilize an urgent care facility, which is also not included in this analysis. In support of the findings, studies done examining emergency room use during the COVID-19 pandemic found racially minoritized populations sought care at a lower rate than racial majorities as a result of a lack of trust.[258–261] However, it is worth noting the dynamics of a global pandemic and the challenges surrounding guidance about COVID-19 during the early parts of the outbreak likely heavily contributed to this lack of trust.

The spatial analyses and GWR findings are more complex. The figures that these methods produce visually represent the theories of place assimilation and place stratification. Both PM 2.5 and respiratory illness hospitalizations showed significant positive spatial correlation. In other words, similar values of both PM 2.5 and respiratory illness hospitalizations rates are clustered which can be seen in Figures 2.2 and 2.3. For PM 2.5, these areas correspond to Charlotte, Greensboro, and Raleigh which aligns with previous research that these levels are typically higher in more urban areas.[262] However, the respiratory illness hospitalizations do not follow that same pattern of clustering. This suggests that other factors than urbanicity could be driving respiratory illness hospitalizations. The figures produced from the GWR clearly show vulnerable areas of North Carolina. This is where GWR takes a step further than traditional GLM. The areas of higher vulnerability would go unnoticed using these more traditional methods. GWR allows for the teasing out of where SVI acts as a buffer or a risk factor by including local variations. The areas that appear in gold in Figure 2.11 are key target areas for intervention. In addition to this, areas that appear blue are potential learning opportunities. These are areas where as PM 2.5 increases and vulnerabilities increase respiratory illness hospitalizations decrease. There could be factors within these regions that are protective. For example, these could be areas with multi-unit housing that get routine preventive maintenance, such as air conditioning filter replacement, which could sustain high indoor air quality. Identifying these areas could also provide support for receiving funds from programs like FEMA's Building Resilient Infrastructure and Communities. Additionally, in June of 2024 the U.S. Department of Housing and Urban Development received a $469 million grant to protect families from home health and safety hazards.[263] These programs could provide financial backing to improve the housing quality in these vulnerable areas. This would both improve health immediately and better prepare these areas for future events like wildfires by mitigating housing vulnerabilities that have been proven to affect indoor air quality and health.[142,160,264]

Health Care Access

The results from the GLM looking at how access to health care modifies the association between PM 2.5 exposure and respiratory illness hospitalizations showed that increased access to care was protective. As health care access increased, respiratory illness hospitalizations decreased even as PM 2.5 levels increased. This finding connects with the concept of accessibility which is a key component of health care access. This finding is also supported in the literature that has examined physical distance to hospitals and improved health outcomes because of closer access to preventive services.[232,265–267] The results from the GWR map in Figure 2.11 showed similar findings that the interaction coefficient between PM 2.5 and healthcare access was largely protective across North Carolina.

Overall Summary

The overall findings of the clustering of PM 2.5 support the hypothesis for RQ1 and the literature related to this topic. This suggests that exposure to PM 2.5 also varies by spatial location. This led to the hypothesis for RQ2 that those living in more vulnerable housing conditions will have increased exposure to PM 2.5. Therefore, regions with high vulnerability would experience more respiratory illness hospitalizations because of increased exposure to PM 2.5. Areas where this is occurring can be seen on the maps produced by the GWR. This analysis highlights the benefits of GWR over traditional GLM. The GWR models performed better than the Poisson as measured by RMSE. Additionally, the results of the GWR provide more nuanced information that can be valuable for state and local government as well as federal agencies. Specific areas of risk have been identified and although a significant wildfire event did not occur during the period of analysis, these areas would be expected to be at an increased risk when a wildfire event takes place.

Strengths

The strengths of this analysis include a novel approach to analyzing respiratory illness hospitalizations as a result of PM 2.5 exposure. No other similar studies that combine the same datasets have been identified. The comparison of model performances provides information for future studies looking to leverage GWR to examine PM 2.5 exposure. The results of this analysis can also serve a potential roadmap for where to apply interventions such as investment in improving infrastructure.

Limitations

There are several limitations to this analysis. The first being that the HCUP SID does not cover all hospitals. Facilities that are not included and therefore not in this analysis are military hospitals or Veterans Affairs hospitals and private or non-community hospitals. Also, people who did not seek care at all would not be included in this analysis. Additionally, people close to the border of North Carolina and other states may cross the border to seek care elsewhere and would not be included in this analysis. Another limitation of this analysis is the modifiable areal unit problem (MAUP).[165] This has been described in the introductory chapter as the problem where results can change based on the geographic unit of analysis. One way to address the MAUP is to provide justification for the selected geographic unit of analysis.[268] ZCTAs can provide a granular view of spatial assimilation and can be used to examine structural racism.[40] Nonetheless, the geographic unit selected for analyses is often determined by available data. HCUP SID data is only available at the ZCTA level. Future studies should consider utilizing census tracts as they are a more accurate approximation of neighborhoods.[225] Lastly, because this analysis was done at the ZCTA level, individual-level characteristics may not match. This could potentially misclassify individuals as being vulnerable when they are not or vice versa.

Conclusion

The findings of this analysis showcase the ability to combine multiple datasets to answer unique questions related to the extreme weather-climate gap. The results produced from the GWR models provide a detailed view of areas of North Carolina that are potentially disproportionately susceptible to PM 2.5 exposure. This analysis also provided an examination of two key areas of the SDoH which are health care access and neighborhood and built environment. This is valuable information for local, state, and federal authorities as the areas affected by wildfire produced PM 2.5 exposure expand. The specific areas that were identified can be targets for multiple kinds of interventions.

Table 2.1 – Descriptive Statistics of North Carolina ZCTA Analytic Sample 2017-2019

Descriptives	**(n = 766)**
PM 2.5 ug/m^3	6.27 ± 0.94
Respiratory Hospitalization Rate per 10,000	105.79 ± 92.03
Rural/Urban Commuting Area Code	
Metropolitan	430 (56%)
Micropolitan	164 (21%)
Rural	88 (11%)
Small Town	84 (10%)
Average Age of Hospitalized	52.3 ± 5.75
SVI Multi-Unit	0.42 ± 0.36
SVI Mobile Homes	0.49 ± 0.29
SVI Crowding	0.47 ± 0.32
SVI Group Quarters	0.43 ± 0.35
Hospital 15-mile Radius	1.92 ± 2.76
Poverty Rate	0.12 ± 0.09

Table 2.2 - Root Mean Square Error (RMSE) of Respiratory Illness Hospitalization Rate per 10,000 for Poisson and GWR Models

	GWR	**Poisson**	**Difference - GWR vs. Poisson**
Model 1 - Resp_Rate = PM 2.5	53.7308	83.7663	-36%
Model 2 - Resp_Rate = PM 2.5 * M-Unit	52.3408	83.4165	-37%
Model 3 - Resp_Rate = PM 2.5 * Mobile	53.1113	83.5829	-36%
Model 4 - Resp_Rate = PM 2.5 * GroupQ	52.0873	83.3835	-38%
Model 5 - Resp_Rate = PM 2.5 * Crowd	52.6578	83.6370	-37%
Model 6 - Resp_Rate = PM 2.5 * Radius	53.1633	83.5565	-36%

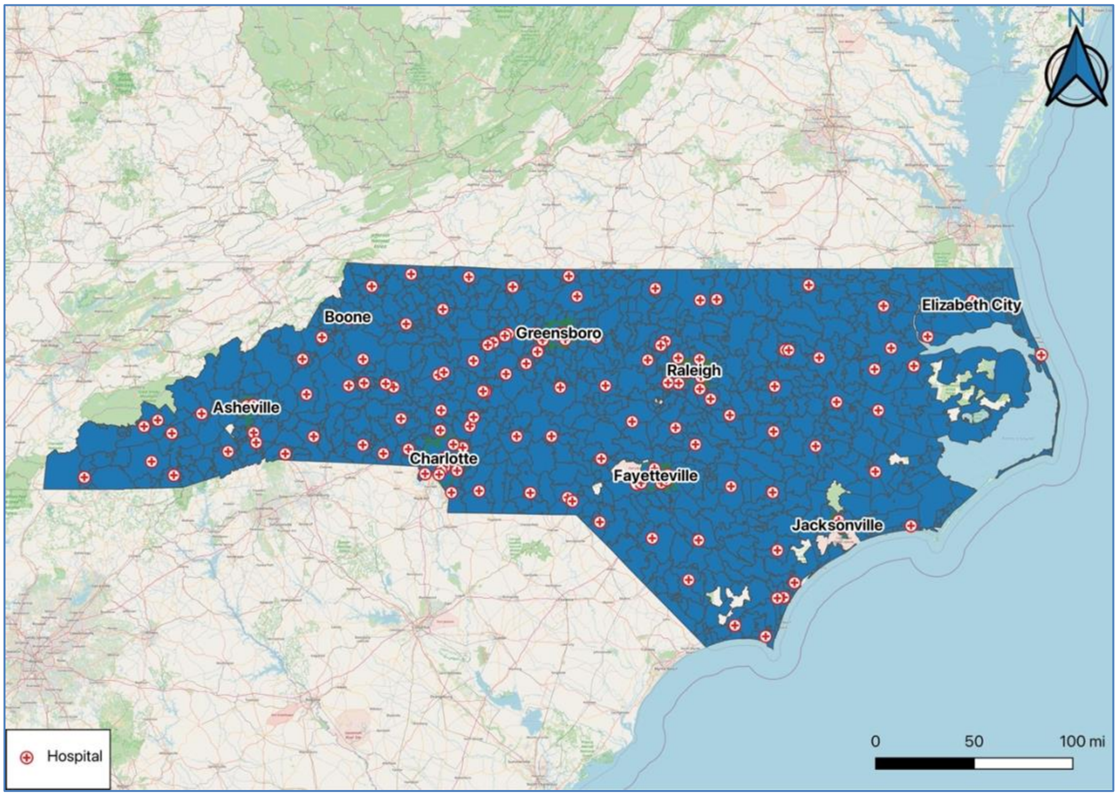

Figure 2.1 – North Carolina ZCTAs, Cities, and Hospitals

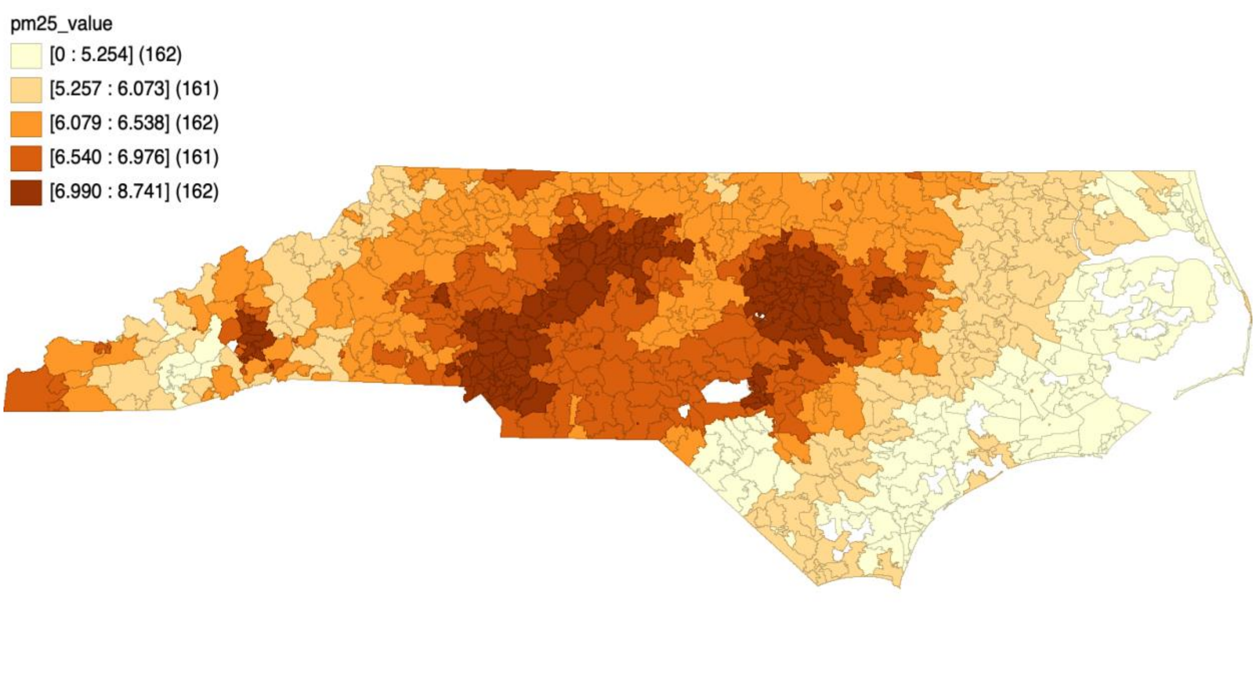

Figure 2.2 – Spatial Analysis of PM 2.5

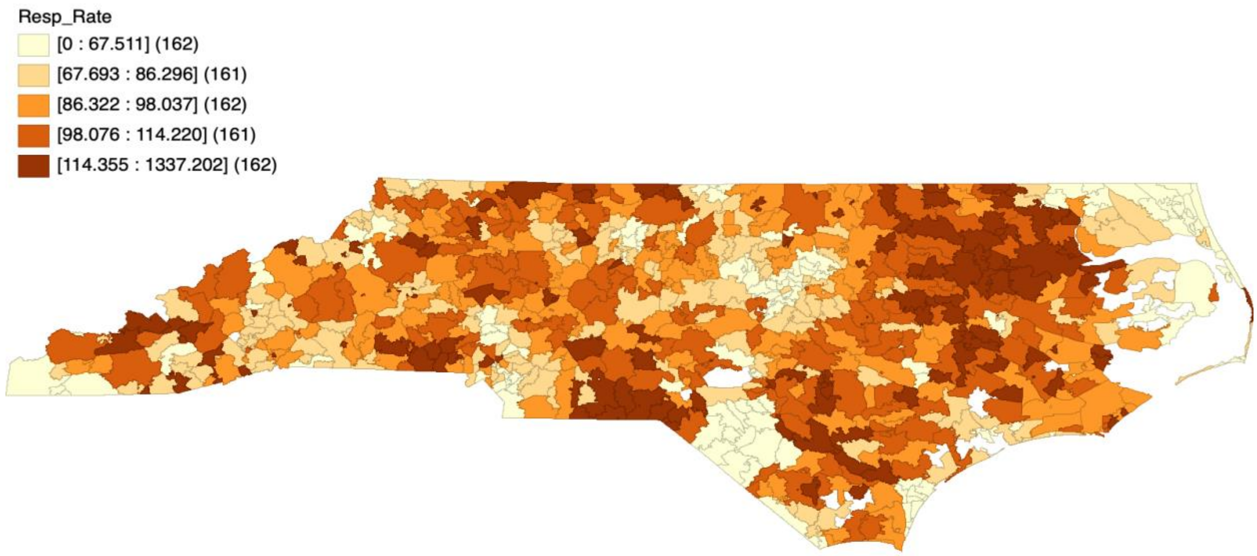

Figure 2.3 – Spatial Analysis of Respiratory Hospitalizations per 10,000

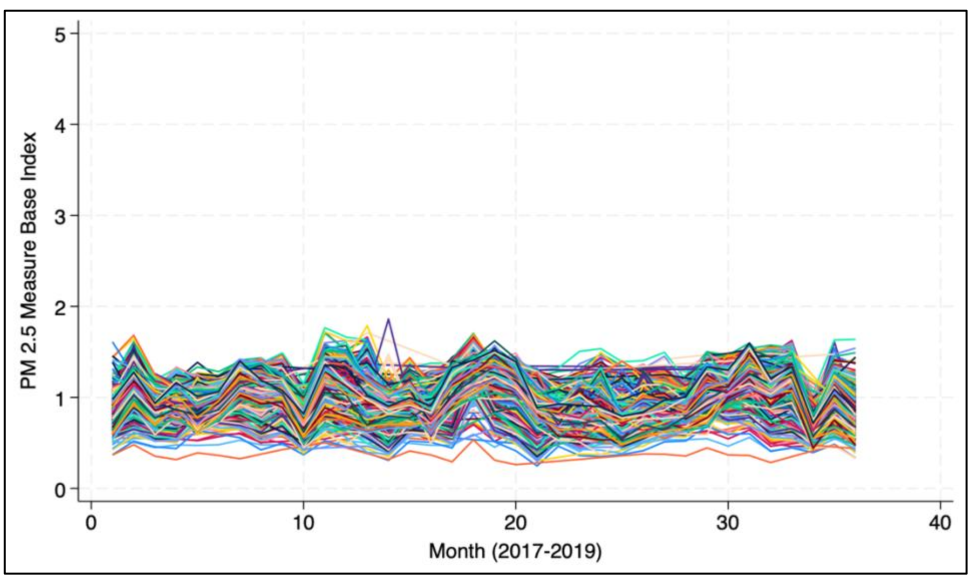

Figure 2.4 – PM 2.5 Base Index by ZCTA from 2017-2019 by Month

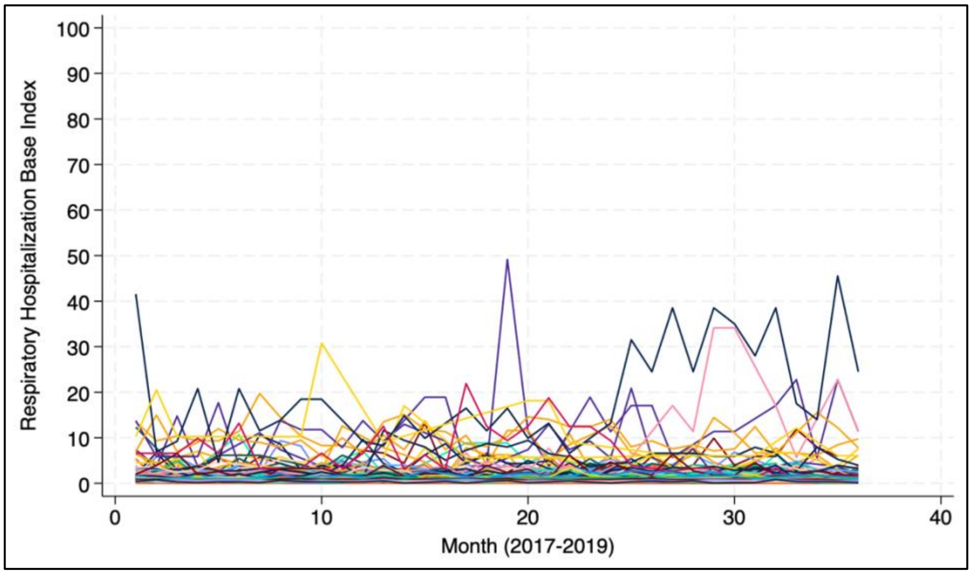

Figure 2.5 – Respiratory Hospitalization Rate Base Index by ZCTA from 2017-2019 by Month

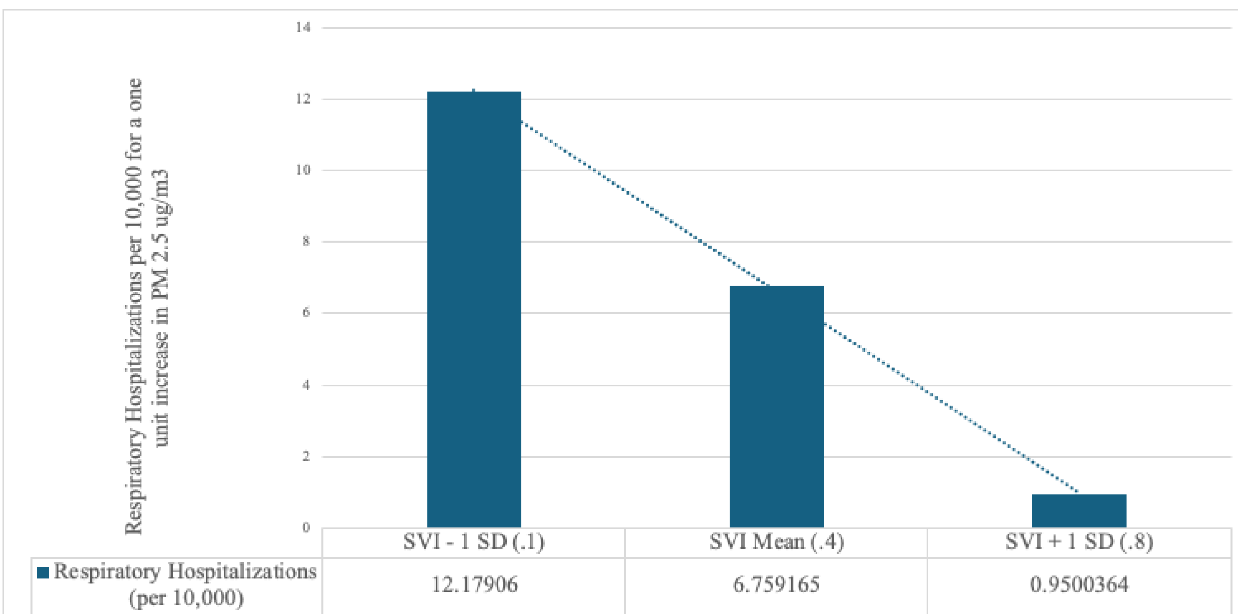

Figure 2.6 - Interaction of SVI Multi-Unit Housing (M-Unit) on PM 2.5 – Respiratory Illness Hospitalization Relationship: M-Unit Housing Marginal Effects at SVI (+/- 1 SD M-Unit

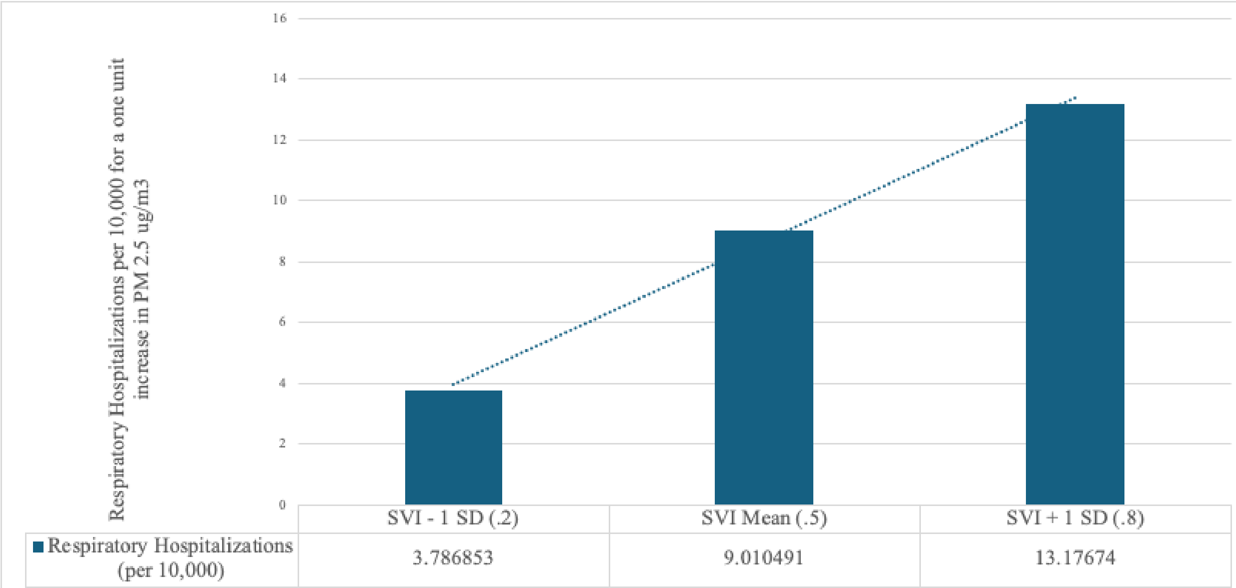

Figure 2.7 - Interaction of SVI Mobile Homes (Mobile) on PM 2.5 – Respiratory Illness Hospitalization Relationship: Mobile Marginal Effects at SVI (+/- 1 SD Mobile)

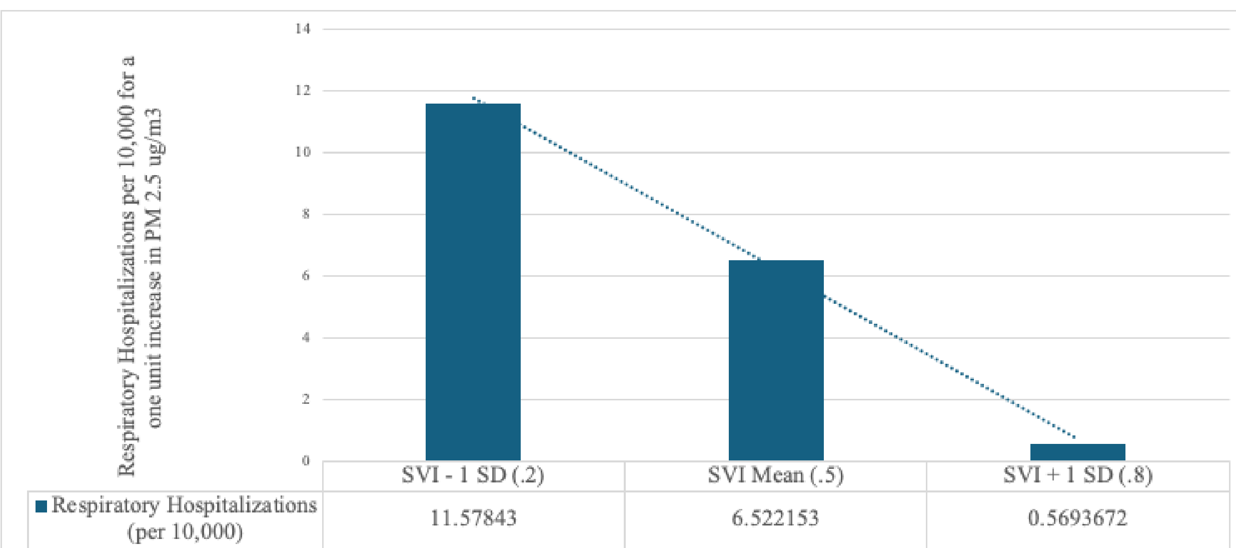

Figure 2.8 - Interaction of SVI Group Quarters (GroupQ) on PM 2.5 – Respiratory Illness Hospitalization Relationship: GroupQ Marginal Effects at SVI (+/- 1 SD GroupQ)

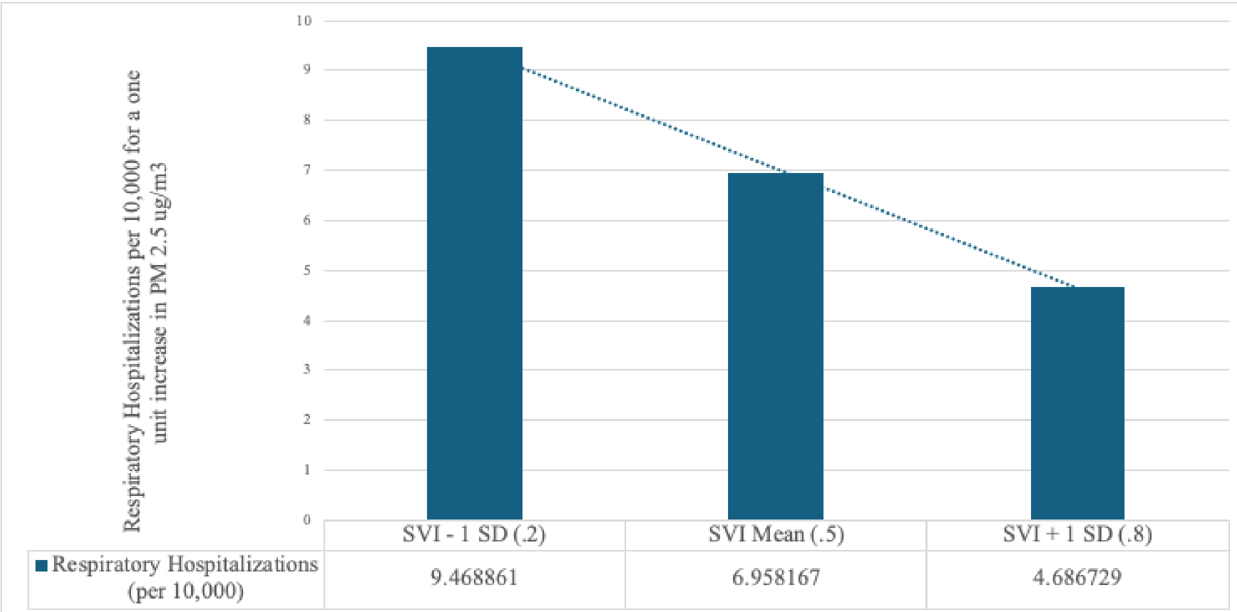

Figure 2.9 - Interaction of SVI Crowding (Crowd) on PM 2.5 – Respiratory Illness Hospitalization Relationship: Crowd Marginal Effects at SVI (+/- 1 SD Crowd)

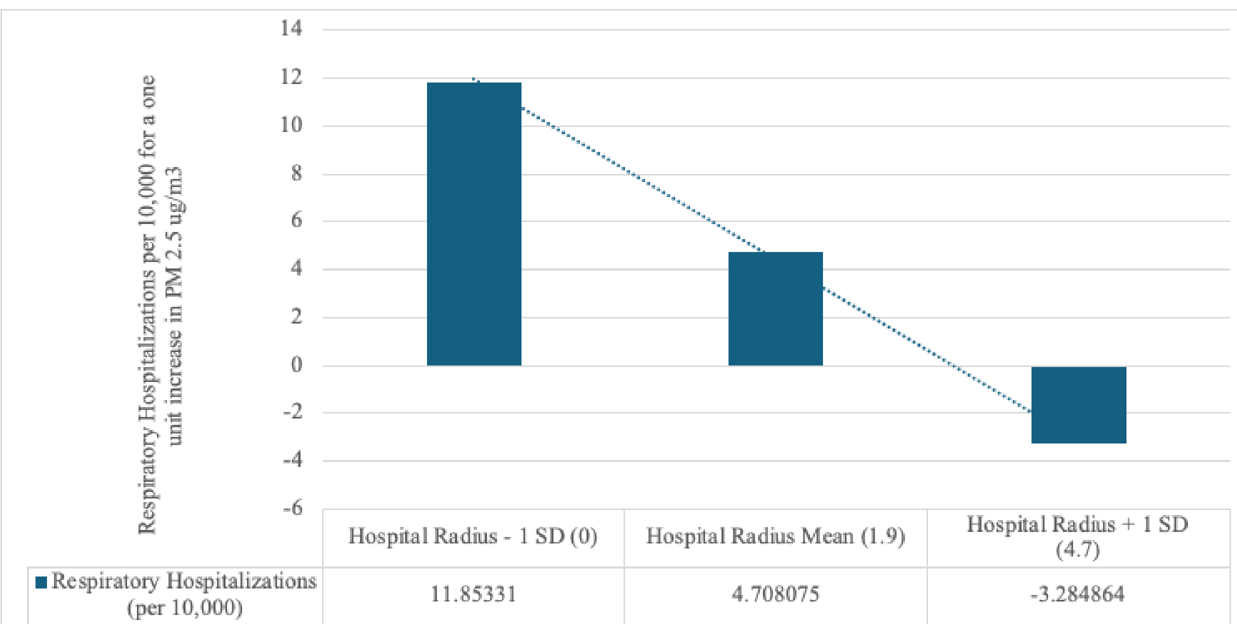

Figure 2.10 - Interaction of Hospital Radius (Radius) on PM 2.5 – Respiratory Illness Hospitalization Relationship: Radius Marginal Effects at Radius (+/- 1 SD Radius)

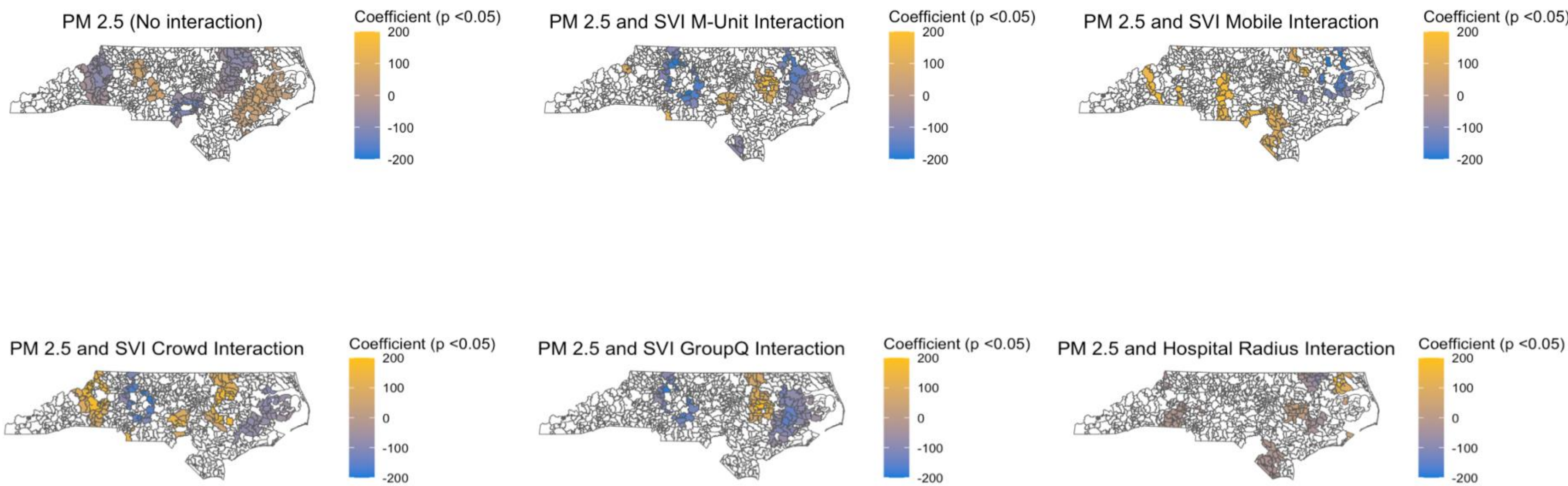

Figure 2.11 - GWR Coefficients Showing the Correlation Between PM 2.5 ug/m^3 and Respiratory Illness Hospitalizations Along with SVI and Hospital Radius Interaction Across North Carolina ZCTAs

CHAPTER 3

DOES LIKE ATTRACT LIKE? DO EVACUATION INTENTIONS DEPEND ON NEIGHBORHOOD RACIAL SEGREGATION?

Introduction

The extreme weather-climate gap results from the collision of climate change, how society responds to climate change, and the social inequalities caused by structural racism. This analysis investigates how structural factors influence individual responses to three evacuation scenarios: evacuating for one-week, two-months, and indefinitely. The existing literature on this topic is limited. Studies have examined the characteristics of individuals that are more likely to leave their home when faced with a situation that warrants an evacuation. Being White, female, having a higher income, owning you own home, and a having a greater number of people living in your home were all associated with an increased likelihood of evacuating.[193–195] The associated literature that utilizes geographic information systems (GIS) to analyze geospatial data during natural disasters has found that higher income and residence in predominantly White census tracts were associated with an increased likelihood of evacuating.[134,199] These findings from previous studies suggest differences in evacuation behaviors between racial/ethnic and income groups are the manifestation of inequities as a result of structural racism. To understand and ultimately address what is driving these differences we must examine the SDoH.

The relevant components of the SDoH related to this topic are neighborhood and built environment, economic stability, and social and community context. The theories of place stratification and spatial assimilation support the neighborhood and built and environment component. These theories suggest that the neighborhoods and environments where we live have been shaped over decades using discriminatory practices. Those classified as the racial/ethnic majorities claiming the more desirable space from racially/ethnically minoritized groups. Consequently, when these neighborhoods and environments are exposed to natural disasters, disparate outcomes will continue to result. Social cohesion and social stress theory support the social and community context component. Individuals with low social support are lacking a key stress-buffer that is also linked to improved health.[270–272] Additionally, lack of social cohesion could result in a smaller support network to be leveraged during a disaster situation. Lastly, the income inequality hypothesis supports the economic stability component. People will have worse outcomes if they do not have the resources to prepare for a natural disaster.

This study aims to understand the mechanism through which structural factors are associated with evacuation intentions and how social ties buffer this association. This is a novel topic that looks at relationships between structural factors and the behavior people would engage in if faced with an evacuation. The questions this study seeks to answer are (1) is residential social polarization correlated with evacuation site social polarization and (2) what role does racial neighborhood segregation, and local social ties play in how far people travel to evacuate? This study utilizes an index of concentration at the extremes (ICE) measure to quantify neighborhood-level structural inequalities which, to our knowledge, have not been used by another study in relation to evacuation intentions. We hypothesize that those residing in census tracts with concentrated deprivation will have evacuation sites in areas of similar deprivation. Additionally, people in deprived census tracts will have further distance to travel when faced with an evacuation but having stronger local social ties may reduce evacuation distance.

Methods

The main source of data for this analysis is the Neighborhood Connectivity Survey (NCS). NCS was a mail-based survey conducted from 2017 to 2018 in three geographic locations (Akron, Ohio; State College, Pennsylvania; Philadelphia, Pennsylvania). Mailing addresses where the survey was sent were determined by dropping random points in ArcGIS and reverse geo-coding to obtain the participant's physical address. A total of 20,000 surveys were sent out with 1,023 surveys returned of which 966 (4.8%) were sufficiently completed for inclusion in this analysis. This success rate is in line with previously published work comparing random digit dialing (RDD) to address-based mailing (ABS) which found RDD had a 2-8% success rate while ABS had a 1.9-11.7% success rate.[273]

A total of 52 (5%) records were excluded for insufficient completion of the survey. The items measured in the survey included migration (e.g., where participants lived over time), social ties (e.g., friends/families, relationship with neighbors), affiliated institutions (e.g., professional, religious, school organizations) access to news (e.g., subscriptions to news sites), travel (e.g., where have the respondents visited), key demographics (e.g., age, race, employment status, education history), and the specific addresses where participants would evacuate to if they had to leave their city for one-week, two-months, and indefinitely.

NCS residence location data as well as evacuation site location were plotted in Quantum Geographic Information Software (QGIS) 3.32 (Lima) over U.S. Census Bureau 2016 census tract shapefiles as this year preceded data collection. This allowed for identification of the specific census tracts where study participants lived as well as where they would evacuate. After identifying specific census tracts, the Census Application Programming Interface (Census API) function in STATA was used to download 2016 American Community Survey (ACS) 5-year data at the census tract level. This U.S. Census data was then merged with the NCS dataset.

Census tract-level social polarization

Merging of NCS data with ACS 5-year data was used to calculate the index of concentration at the extremes variable which is a measure of social polarization.[274–276] The operationalization of an ICE variable using the ACS data was chosen over similar measures like the Gini coefficient or index of dissimilarity because ICE captures extreme social polarization. The Gini coefficient and index of dissimilarity do not assign different values for areas of homogeneity.[277,278]

$$ICE_i = (A_i - P_i)/T_i$$

A_i = Number of individuals in the privileged extreme

P_i = Number of individuals in the group of deprivation

T_i = Total population in the census tract

There is one operationalization of ICE included in this analysis which is non-Hispanic White alone versus non-White non-Hispanic and Hispanic. This ICE variable was calculated for the census tract of residence as well as each of the census tracts the participants reported as where they would evacuate. The use of non-Hispanic White alone versus non-White non-Hispanic and Hispanic allowed for inclusion of all racial and ethnic groups whereas more traditional ICE variables typically exclude racial/ethnic groups. All ICE variables were divided into tertiles.[274,277]

Social Ties

The mail-based survey asked participants to self-report their local social ties. The local social ties questions were adapted from the Medical Outcomes Study short-form health survey.[279] Participants reported frequency on a five-point Likert scale (1-Never; 2-Daily; 3-Weekly; 4-Monthly; 5-Yearly) that they ate lunch with coworkers, socialized in-person with friends, ate lunch with friends, have people over to their home to socialize, and go to others' homes to socialize. This grouping of five variables will be referred to as frequency of socialization. Participants also reported the extent to which they agreed on a five-point Likert scale (1-Strongly disagree; 2-Disagree; 3-Neither disagree nor agree; 4-Agree; 5-Strongly agree) that they have a good social network in their place of residence (e.g., friends, family, etc.), that they borrow items from neighbors/local friends, that they request house or pet sitting from neighbors/local friends, that they discuss political candidates with neighbors/local friends, and that they ask their neighbors/local friends for restaurant recommendations. This grouping of five variables will be referred to as agreement with socialization.

A principal component analysis (PCA) was conducted on each of the two groups of variables to reduce collinearity, minimize overfitting of the regression models, and maximize construct validity. Correlation between the sub-variables of frequency of socialization and agreement with socialization was conducted. Moderate positive correlation was detected between variables in each of the two groups. Conducting the Kaiser-Meyer-Olkin test showed overall that the frequency of socialization and agreement with socialization indicate (0.76 and 0.78 respectively) that PCA is useful with these data.[280,281] The PCA for frequency of socialization showed one component had an eigenvalue of 2.42 that explained 67% of the item level variability. The scree plot also indicated selection of one component was sufficient (eigenvalue >= 1). This component was mostly defined by getting lunch with friends (0.49), going to other people's homes to socialize (0.49), and socializing in person with friends (0.48) and was named, "socialize with friends."

Conducting the PCA for agreement with socialization found that one component had an eigenvalue of 2.66. This component explained 48% of the variability. Examination of scree plots also suggested that selecting one component was appropriate.[282,283] The component was most defined by the loadings of asking neighbors and local friends for restaurant recommendations (0.49), borrowing items from neighbors/friends (0.49), and requesting house or pet sitting from neighbors/friends (0.46). This component was named, "reliance on neighbors."

Distance to Evacuation Site

Evacuation location was geocoded and the physical distance from the residence of the participants was calculated for each scenario. Euclidean distance was calculated between the residence and evacuation sites. Euclidean distance is the straight-line distance between two points on a map. It is generally accepted that Euclidean distance is equivalent to driving distance.[284] A total of 11 (1%) records were excluded from the analysis for having evacuation sites outside of the U.S.

Individual Sociodemographics

The mail-based survey asked for participants to self-report the highest level of education completed (Less than high school; High school or equivalent; Vocational or technical training; Associate's degree; Bachelor's degree; Master's degree; Professional degree; or Doctoral degree), their gender (Male; Female; Undisclosed), age (18-24; 25-34; 35-44; 45-54; 55-64; 65-74; 75-84; or 85+), race (Asian; Black or African American; Hispanic or Latino; White or Caucasian; Middle Eastern/North African; Bi-racial; Undisclosed), employment status (Employed full time; Employed part time; Student full-time; Student part-time; Unemployed; Retired; Unable to work), and number of people including themselves residing in their home (1; 2; 3; 4; 5; 6; 7; 8+).

Census Tract Sociodemographics.

A census tract level control used in the analyses is percent of the census tract living below the poverty level. This variable was merged from U.S. Census Bureau ACS 5-year data.

Statistical Analysis of Research Question 1

The analytic method used for this research question is a beta regression. A beta regression was selected after the dependent variable (evacuation site ICE score) was converted to a percentile. Evacuation site ICE score was a percentile ranging from >0 to <1 (e.g., 0.01, 0.2, etc.). This transformation was done due to the original dependent variable's non-normal distribution, non-constant error variance, and to improve interpretability of the results.[285] A total of three beta regressions were fit with each residence ICE score as the independent variable and each evacuation site ICE score as the dependent variable. The independent variable, residence ICE score, was treated as a categorical variable split into tertiles. A separate model was run for each evacuation scenario (one-week, two-months, and indefinitely). Controls included categorical race and gender as well as continuous age, education, and percent of census tract living below the poverty level.

Statistical Analysis of Research Question 2

The analytic method used for this research question is a generalized linear model (GLM) with Poisson distribution and identity link after assessing the assumptions of ordinary least squares regression. The independent variable is the residence ICE score with the dependent variable being the distance in miles to the participant's listed evacuation site. Residence ICE score was treated as a categorical variable split into tertiles. Evacuation site distance was treated as a continuous variable. Controls were again categorical race and gender as well as continuous age, education, and percent of census tract living below the poverty level. A separate GLM was run for each evacuation site destination for a total of three models. Additionally, effect modification was assessed via the Wald test for the two components from the PCA with the residence ICE score and the three evacuation scenarios. The two components from the PCA were treated as continuous in the models.

Huber-White robust standard errors were computed for all models as well as two-tailed statistical significance at the .05 level.[247,249,286,287] All data merges and analyses were conducted in STATA 18.0 MP (College Station, TX). Listwise deletion was use for participants who did not list an evacuation site. These missing values were addressed using a marginal structural model.

Sensitivity Analysis

A total of 494 (51%) participants did not report any evacuation location for all three scenarios. Conducting Little's Missing Completely at Random (MCAR) test in STATA gives a χ^2 distance of 30.33 with degrees of freedom of 9 and p = <.001. This test indicates that the three evacuation location variables of interest are not MCAR at the significance of level of .05.[288] This raised the question of whether this missing data was missing at random (MAR) or missing not at random (MNAR). The survey did not have an option for respondents to indicate they did not have an evacuation site location. The theoretical constructs that are the basis for the research questions in this chapter lend support to both options. Participants in the survey either did not have a place to evacuate to and left the answer blank or did have a place to evacuate but skipped those questions. In support of MAR, the data that was collected on the participants that are not missing, such as number of people residing at the home, race/ethnicity, gender, and education could explain why those individuals did not indicate where they would evacuate. This aligns with the theories previously mentioned and the existing literature on evacuation science. Racially minoritized low-income groups are less likely to evacuate. Those with larger families or children are more likely to evacuate. It is also plausible that this is an example of MNAR. Participants that did not list an evacuation site may in fact not have an evacuation site to go to. In this case, the missingness of this variable is related to the actual response being missing.

A propensity score was calculated to create balance among covariates between those who have an evacuation location and those that do not. First, a dichotomous variable was created that indicated whether the participant had an evacuation site or did not. A propensity score was calculated for this variable. This was done by fitting a logistic model that included age, race, gender, highest education, having a child under the age of 18, employment status, reliance on neighbors, and socializing with friends. The propensity score had a mean value of 0.49 with a minimum of 0.21 and a max of 0.73. The propensity score for each study participant was calculated by using the predict procedure in STATA. Evaluation of the propensity score was done by utilizing the two-way histogram function within STATA. This histogram showed good overlap between those with an evacuation site vs. those without an evacuation site. A stabilized weight using this propensity score was then calculated by dividing the probability of having an evacuation site by the propensity score for those who had the evacuation site and then dividing one minus the probability of having an evacuation site by one minus the propensity score. This stabilized weight was then applied to the generalized linear models in this analysis using STATA's PWEIGHT function (sampling weights). The stabilized weight was selected over the non-stabilized weight to reduce the variance of the effect estimate.[289]

Results

Sample characteristics are shown in Table 3.1. A total of 966 participants provided adequate responses on the survey for inclusion in this analysis. The overall sample is 68% female. Approximately 5% of the sample was 18-24 years old, 18% was 25-34 years old, 15% was 35-44 years old, 15% was 45-54 years old, 20% was 55-64 years old, 17% was 65-74 years old, 8% was 75-84 years old, and 2% was 85+ years old. The breakdown of race/ethnicity was 81% White, 13% Black or African American, 2% Hispanic or Latino, 2% Bi-racial, 2% Asian, 0.2% Native American, and 0.2% Middle Easter/North African. Approximately 31% of participants reported their highest level of education as high school or equivalent, 27% reported an associate's degree, 18% a bachelor's degree, 10% vocational or technical training, 8% a master's degree, and 6% less than high school. Approximately 10% of the sample reported that they had a vacation home that they used. Table 3.2 shows key differences in the concentrated privilege tertile and the concentrated deprivation tertile within the residence ICE race score. Comparing the non-White non-Hispanic and Hispanic (concentrated deprivation) group to the non-Hispanic White (concentrated privilege) group shows that the concentrated deprivation group has a $26,682.31 lower median annual income, 4.67% higher unemployment, $46,862.03 lower median property value, 19% higher poverty rate, and $244.03 lower monthly mortgage. These differences characterize the meaning behind the terminology of concentrated deprivation and concentrated privilege.

Beta Regression

Participants were asked to list the location of where they would evacuate to for one-week, two-months, and indefinitely. The response rate for each evacuation question was 423 for (44%) for the one-week scenario, 397 (41%) for the two-week scenario, and 353 (37%) for the indefinite scenario. Sociodemographics between each subsample were approximately the same. The results in Table 3.3 show the marginal contrasts between the middle and concentrated privilege groups compared to the concentrated deprivation group of the ICE evacuation site score percentile. The results show that the concentrated privilege group's evacuation site ICE score for the one-week evacuation scenario is 14 percent points (pp) higher than those of the people living in census tracts of concentrated deprivation (95% CI – 0.06; 0.23, $p = .001$). The results also show that for the two-month scenario the concentrated privilege group's evacuation site ICE score is 8pp higher than the concentrated deprivation group (95% CI – 0.004; 0.17, $p = .038$).

General Linear Models

The second research question evaluates the relationship between residence ICE score and distance to evacuation site. A total of three models were fit and the results are shown in Table 3.4. Overall, the results consistently show that the most privileged tertile had a shorter distance to travel to their evacuation sites when compared to the most deprived. These results were significant among the indefinite evacuation scenario. The concentrated privilege group had to travel 169.21 miles less than the concentrated deprivation group (95% CI: -337.96; -0.47, p = .049) to reach their evacuation site.

The second part of research question two is evaluating the effect modification of the relationship between residence ICE score and distance required to travel to get to an evacuation site by the principal components socialize with friends and reliance on neighbors. Effect modification was assessed for each principal component (2), for the ICE race residence score, and evacuation scenario (3) for a total of six models. Table 3.5 shows the results from all the fitted models. Effect modification was not found among the fitted models. Table 3.5 shows the marginal values for each ICE tertile in terms of distance to the evacuation site for interpretability. One of the six models did not converge. Although not significant, the socializing with friends models did show a consistent pattern between the evacuation site scenarios. As socializing with friends increased among those living in concentrated deprivation, the evacuation site distance decreased. However, the opposite was seen among those in concentrated privilege where evacuation site distance increased as socializing with friends increased.

Sensitivity Analysis

Applying the stabilized weights to the models yielded slightly different results compared to the models without the weights. Tables 3.6, 3.7, and 3.8 show the results from Tables 3.3, 3.4, and 3.5 after applying the stabilized weights. Table 3.6 shows the contrasts between the concentrated privilege group and the concentrated deprivation group for evacuation site ICE score. Those among the concentrated privilege group had evacuation sites with 15 pp higher ICE score than those living in concentrated deprivation (95% CI: 0.06; 0.23, p = .001). Table 3.7 shows the results of the relationship between residence ICE score and distance to evacuation site. Overall, the weighted results show a similar relationship between ICE score and distance to evacuation site with a significant difference seen between the concentrated privilege group and the concentrated deprivation group for both the one-week and indefinite scenarios (One-week = -104.21, 95% CI: -198.03; -10.38, p = .029; Indefinite = -224.61, 95% CI: -410.92; -38.30, p = .018). The results in Table 3.8 show the weighted interaction results. These results also follow the trends seen in the unweighted results. The results showed that as socialization with friends among the concentrated deprivation group increased, distance to the evacuation site decreased (-59.11, 95% CI: -140.56; 22.35, p = .155).

Discussion

This study examined the relationship between residential racial segregation and evacuation intentions. To study the extreme weather climate gap necessitates understanding the relationship between measures of structural racism and the confluence of how individuals plan to respond to the dangers of climate change within existing social structures. This study utilized a measure of racial segregation to understand the different mechanisms that drive the extreme weather-climate gap. The significant results in this study demonstrate the need for multi-level interventions in the evacuation science space. These interventions include community-based participatory exercises aimed and educating individuals on their susceptibility to the dangers of climate change as well as how to build an effective preparedness plan.

Theories of Spatial Assimilation and Residential Mobility

The results support the hypothesis that people will evacuate to areas of similar privilege as their residence. This is reinforced by the theories of residential mobility and spatial assimilation. Participants living in privileged census tracts are anticipating that they will evacuate to areas of greater privilege than those living in areas of deprivation. This could partly be explained by participants residing in deprived census tracts lacking the resources to move to areas of privilege even when an emergency event is forcing them to relocate. This coheres with studies that examined differences in evacuation patterns by SES status which found that those from higher SES standing were more likely evacuate to areas deemed safer and more stable.[134,199] This is important in the context of evacuations because more privileged census tracts will likely be more resourced to handle influxes of displaced people. This was seen during the COVID-19 pandemic where patients from rural areas without intensive care units had to be transported hundreds of miles and often to other states to receive treatment.[290] The differences seen in the results between evacuation scenarios could be due to participants changing their evacuation site based on the scenario. This suggests that the location people evacuate to depends on the length of time they will be away from their home indicating that these participants are thinking about how their evacuation site may serve their perceived needs. These findings suggest that the theories of residential mobility and spatial assimilation may not be restricted to just where people live but could also apply to where they would relocate because of a disaster.

Income Inequality Hypothesis

The findings also showed a consistent pattern across all evacuation scenarios that the concentrated privilege group would have to travel fewer miles than the concentrated deprivation group to get to their evacuation site. This is supported by the income inequality hypothesis. Those with less resources may face more challenges related to evacuating because they are further from their places of refuge. Additionally, the perception of how burdensome an evacuation may be could inhibit prompt relocation in the face of danger. These findings demonstrate a specific burden that is prevalent among study participants residing in the census tracts of concentrated deprivation who likely already have limited resources. The demographic differences between the privileged and deprived census tracts highlighted in Table 3.2 show only a snapshot of what having limited resources looks like. The differences seen in distance to evacuation sites also pose a challenge for those that do not own their own vehicle and cannot leverage public transportation to get to a potentially unique location. This also creates obstacles for individuals or families that are evacuating with personal belongings or pets. It is even more challenging considering that public transportation systems are typically suspended during natural disasters. These findings describe key components of the process of how displacement can lead to further marginalization and how the perceived economic marginalizations may perpetuate delayed evacuations.

Interaction of Local Social Support

No effect modification was seen in the unweighted models conducted in this study. Reliance on neighbors and socializing with friends, which both quantified local social ties, did not statistically modify the relationship between residence ICE score and distance to evacuation site. However, when looking at the ICE stratum marginal effect in Table 3.5 to examine trends, the results showed that as socializing with friends increased among the concentrated deprived census tracts, the distance to the evacuation site decreased. This could indicate that improved local social ties decrease the distance needed to travel to an evacuation site but only for those living in census tracts of concentrated deprivation. This suggests that an intervention aiming to improve social ties would need to be tailored to specific regions. If applied to census tracts of concentrated privilege it may not reduce the distance needed to travel to an evacuation site.

Findings from Weighted Models

The results from the weighted GLMs showed similar findings for the analysis looking at how residence ICE score was correlated with evacuation site distance. The findings in Table 3.7 showed that the concentrated deprivation group would have to travel less to reach their evacuation site when compared to the deprived group. The weighted GLM results assessing the interaction between reliance on neighbors and socializing with friends in Table 3.8 showed similar results from the unweighted models. Five of the six models showed that as reliance on neighbors or socialization with friends increased, the distance to the evacuation site decreased for the concentrated deprivation group. However, the opposite was seen among the concentrated privilege groups. The interaction term was also significant among the two-week scenario for socialization with friends. These results support the findings from the unweighted regression that an intervention aimed at improving social connections cannot be applied to an entire city and would have to be tailored to specific areas or in the case of this analysis, census tracts.

Strengths

This analysis was able to evaluate how participants may change their evacuation site based on the scenario that they are faced with. This is an important strength because participants may rely on different family or friends depending on the type of evacuation required, which this analysis was able to explore. The nuances of evacuation science and the unpredictable nature of the events that cause evacuations make it a difficult topic to study. The use of a dataset that captures evacuation intentions provides a unique observation into the actions people would take if an event were to happen. The benefit being that harm did not befall the participants of this study, but we can still learn from the results in the absence of a natural disaster. This means that we can intervene and enact change before an event occurs that causes the types of evacuation scenarios brought up in this study. Additionally, this study was conducted in Pennsylvania and Ohio. These areas are not typically considered at risk for climate change related events such as hurricanes and wildfires. However, we feel that these areas are vulnerable to extreme weather (e.g., cold snaps, heatwaves, etc.). Getting a snapshot of evacuation intentions among a group that may not normally think about needing to evacuate, potentially because of extreme weather, serves as a valuable risk assessment as at-risk areas expand.

Limitations

There are several limitations of this study. First, approximately half of the sample did not list a location where they would evacuate. We are unable to determine if these people did not have an evacuation site or skipped the survey question. We attempted to address this using propensity score and applying the stabilized weights to the models and providing both weighted and unweighted results. Second, it is important to note that evacuations can be caused by events not related to climate change. There was no specification about the type of natural disaster on the survey which could change where people decide to evacuate. Lastly, the ICE measure is a census-tract level measure and may not match the privilege status of individuals enrolled in the study.

Conclusion

The results of this study highlight key associations between a structural measure of social polarization and evacuation intentions. Racial segregation is associated with more burdensome evacuation plans. The findings suggest that disasters that cause evacuations may activate spatial assimilation processes which can lead to furthering privilege division. More analyses are needed to explore how social support buffers burdensome evacuation plans. More disaster studies need to examine the SDoH and utilize measures of structural racism to further understand the extreme weather-climate gap. Evaluation of community-level interventions aimed at improving disaster preparedness are also needed.

Table 3.1 - Neighborhood Connectivity Survey Participant Characteristics

	Total (n = 966)	One-Week (n = 423)	Two-Months (n = 397)	Indefinitely (n = 353)
Female	653 (68%)	301 (71%)	285 (72%)	256 (73%)
Age				
18-24 years old	45 (5%)	23 (5%)	23 (6%)	22 (6%)
25-34 years old	174 (18%)	67 (16%)	65 (16%)	63 (18%)
35-44 years old	147 (15%)	55 (13%)	49 (12%)	55 (16%)
45-54 years old	149 (15%)	69 (16%)	62 (16%)	53 (15%)
55-64 years old	191 (20%)	89 (21%)	82 (21%)	61 (17%)
65-74 years old	162 (17%)	82 (19%)	75 (19%)	65 (18%)
75-84 years old	78 (8%)	36 (8%)	36 (9%)	29 (8%)
85+	20 (2%)	6 (1%)	5 (1%)	5 (1%)
Race/Ethnicity				
White	778 (81%)	354 (84%)	339 (86%)	295 (84%)
Black or African American	127 (13%)	43 (10%)	38 (10%)	37 (10%)
Hispanic or Latino	19 (2%)	7 (2%)	4 (1%)	5 (1%)
Asian	19 (2%)	8 (2%)	9 (2%)	8 (2%)
Native American	2 (0.2%)	1 (0.2%)	0	1 (0.3%)
Middle Eastern/North African	2 (0.2%)	2 (0.5%)	2 (0.5%)	2 (0.6%)
Bi-racial	21 (2%)	8 (2%)	5 (1%)	5 (1%)
Education				
Less than high school	61 (6%)	21 (5%)	19 (5%)	17 (5%)
High school or equivalent	297 (31%)	125 (30%)	119 (30%)	102 (29%)
Vocational or technical training	99 (10%)	44 (10%)	45 (11%)	37 (11%)
Associate's degree	257 (27%)	116 (27%)	109 (27%)	101 (29%)
Bachelor's degree	172 (18%)	82 (19%)	74 (19%)	67 (19%)
Master's degree	80 (8%)	35 (8%)	31 (8%)	29 (8%)
Professional degree	0	0	0	0
Doctoral degree	0	0	0	0

Table 3.2 - Census Tract Contrasts

Outcome Variable	Contrast (non-Hispanic Non-White and Hispanic vs. White)
Annual Median Family Income	-$26,682.31
Percent Unemployed	+4.67
Median Property Value	-$46,862.03
Poverty Rate	+19%
Monthly Mortgage	-$244.03

Table 3.3 - Comparison of Residence ICE Score with Evacuation Site ICE Score

Predictor		Tertile Contrast	Standard error	p-value	95% CI LB	95% CI UB
	Outcome: ICE Race Score for One-Week Evacuation Site					
ICE Race Residence	Concentrated Deprivation	*ref.*				
	Middle vs. Concentrated Deprivation	0.08	0.04	0.050	-0.00004	0.15
	Concentrated Privilege vs. Concentrated Deprivation	0.14	0.04	0.001**	0.06	0.23
	Outcome: ICE Race Score for Two-Month Evacuation Site					
	Concentrated Deprivation	*ref.*				
	Middle vs. Concentrated Deprivation	0.02	0.04	0.644	-0.06	0.09
	Concentrated Privilege vs. Concentrated Deprivation	0.08	0.04	0.038*	0.004	0.17
	Outcome: ICE Race Score for Indefinite Evacuation Site					
	Concentrated Deprivation	*ref.*				
	Middle vs. Concentrated Deprivation	0.02	0.05	0.603	-0.07	0.11
	Concentrated Privilege vs. Concentrated Deprivation	0.08	0.05	0.110	-0.02	0.18

* = <0.05, ** = 0.001

Table 3.4 - Residential ICE Score Correlation with Evacuation Site Distance

		Tertile Contrast	Standard error	p-value	95% CI LB	95% CI UB
	Outcome: Distance to One-Week Evacuation Site					
ICE Race Residence	Concentrated Deprivation	*ref.*				
	Middle vs. Concentrated Deprivation	-10.13	48.34	0.834	-104.88	84.62
	Concentrated Privilege vs. Concentrated Deprivation	-86.79	46.99	0.064	-178.88	5.31
	Outcome: Distance to Two-Month Evacuation Site					
	Concentrated Deprivation	*ref.*				
	Middle vs. Concentrated Deprivation	78.77	69.72	0.259	-57.88	215.41
	Concentrated Privilege vs. Concentrated Deprivation	-32.83	65.29	0.6151	-160.78	95.13
	Outcome: Distance to Indefinite Evacuation Site					
	Concentrated Deprivation	*ref.*				
	Middle vs. Concentrated Deprivation	-21.89	79.3	0.783	-177.31	-133.64
	Concentrated Privilege vs. Concentrated Deprivation	-169.21	86.1	0.049*	-337.96	-0.47

* = <0.05, ** = <0.001

Table 3.5 – Effect Modification by Local Social Ties on Residence ICE Score and Evacuation Site Distance

		ICE Stratum Marginal Effect	SE	p-value	95% C.I. LB	95% C.I. UB
ICE Race Residence	**Outcome: Distance to One-Week Evacuation Site**					
	Concentrated Deprivation x Rely on Neighbors	4.76	23.90	0.842	-42.08	51.60
	Middle x Rely on Neighbors	14.40	19.86	0.468	-24.52	53.34
	Concentrated Privilege x Rely on Neighbors	4.94	11.07	0.655	-15.76	26.64
	Outcome: Distance to Two-Month Evacuation Site					
	Concentrated Deprivation x Rely on Neighbors	-	-	-	-	-
	Middle x Rely on Neighbors	-	-	-	-	-
	Concentrated Privilege x Rely on Neighbors	-	-	-	-	-
	Outcome: Distance to Indefinite Evacuation Site					
	Concentrated Deprivation x Rely on Neighbors	24.65	46.33	0.595	-66.15	115.45
	Middle x Rely on Neighbors	25.69	38.09	0.500	-48.97	100.34
	Concentrated Privilege x Rely on Neighbors	4.78	26.22	0.855	-46.60	56.16
ICE Race Residence	**Outcome: Distance to One-Week Evacuation Site**					
	Concentrated Deprivation x Socialize with Friends	-18.81	30.16	0.533	-77.93	40.31
	Middle x Socialize with Friends	4.59	22.90	0.841	-40.29	49.48
	Concentrated Privilege x Socialize with Friends	11.22	15.46	0.468	-19.08	41.52
	Outcome: Distance to Two-Month Evacuation Site					
	Concentrated Deprivation x Socialize with Friends	-36.94	31.62	0.243	-98.90	25.03
	Middle x Socialize with Friends	3.55	43.65	0.935	-82.02	89.11
	Concentrated Privilege x Socialize with Friends	30.68	28.47	0.281	-25.12	86.49
	Outcome: Distance to Indefinite Evacuation Site					
	Concentrated Deprivation x Socialize with Friends	-45.57	40.83	0.264	-125.6	-34.45
	Middle x Socialize with Friends	15.51	35.34	0.661	-53.76	84.78
	Concentrated Privilege x Socialize with Friends	42.22	24.84	0.089	-6.46	90.90
* = <0.05, ** = <0.001						

Table 3.6 – Weighted Comparison of Residence ICE Score with Evacuation Site ICE Score

Predictor		Tertile Contrast	Standard error	p-value	95% CI LB	95% CI UB
	Outcome: ICE Race Score for One-Week Evacuation Site					
ICE Race Residence	Concentrated Deprivation			*ref.*		
	Middle vs. Concentrated Deprivation	0.08	0.04	0.054	-0.001	0.15
	Concentrated Privilege vs. Concentrated Deprivation	0.15	0.04	0.001**	0.06	0.23
	Outcome: ICE Race Score for Two-Month Evacuation Site					
	Concentrated Deprivation			*ref.*		
	Middle vs. Concentrated Deprivation	0.03	0.04	0.432	-0.05	0.11
	Concentrated Privilege vs. Concentrated Deprivation	0.09	0.04	0.038*	0.01	0.17
	Outcome: ICE Race Score for Indefinite Evacuation Site					
	Concentrated Deprivation			*ref.*		
	Middle vs. Concentrated Deprivation	0.03	0.05	0.604	-0.07	0.12
	Concentrated Privilege vs. Concentrated Deprivation	0.08	0.05	0.136	-0.03	0.19
* = <0.05, ** = 0.001						

Table 3.7 – Weighted Residential ICE Score Correlation with Evacuation Site Distance

		Tertile Contrast	Standard error	p-value	95% CI LB	95% CI UB
	Outcome: Distance to One-Week Evacuation Site					
ICE Race Residence	Concentrated Deprivation	*ref.*				
	Middle vs. Concentrated Deprivation	-26.1	49.46	0.598	-123.03	70.86
	Concentrated Privilege vs. Concentrated Deprivation	-104.21	47.87	0.029*	-198.03	-10.38
	Outcome: Distance to Two-Month Evacuation Site					
	Concentrated Deprivation	*ref.*				
	Middle vs. Concentrated Deprivation	34.36	67.23	0.609	-97.42	166.14
	Concentrated Privilege vs. Concentrated Deprivation	-47.6	67.37	0.48	-179.64	84.45
	Outcome: Distance to Indefinite Evacuation Site					
	Concentrated Deprivation	*ref.*				
	Middle vs. Concentrated Deprivation	-58.32	90.33	0.519	-235.37	118.73
	Concentrated Privilege vs. Concentrated Deprivation	-224.61	95.06	0.018*	-410.92	-38.3
* = <0.05, ** = <0.001						

Table 3.8 – Weighted Effect Modification by Local Social Ties on Residence ICE Score and Evacuation Site Distance

		ICE Stratum Marginal Effect	SE	P-value	95% C.I. LB	95% C.I. UB
ICE Race Residence	**Outcome: Distance to One-Week Evacuation Site**					
	Concentrated Deprivation x Rely on Neighbors	4.98	24.77	0.841	-43.56	53.53
	Middle x Rely on Neighbors	1.69	23.36	0.942	-44.10	47.46
	Concentrated Privilege x Rely on Neighbors	6.86	7.79	0.378	-8.39	22.10
	Outcome: Distance to Two-Month Evacuation Site					
	Concentrated Deprivation x Rely on Neighbors	-	-	-	-	-
	Middle x Rely on Neighbors	-	-	-	-	-
	Concentrated Privilege x Rely on Neighbors	-	-	-	-	-
	Outcome: Distance to Indefinite Evacuation Site					
	Concentrated Deprivation x Rely on Neighbors	11.59	51.02	0.820	-88.41	111.58
	Middle x Rely on Neighbors	9.84	47.90	0.837	-84.04	103.71
	Concentrated Privilege x Rely on Neighbors	11.32	26.03	0.664	-39.70	62.34
ICE Race Residence	**Outcome: Distance to One-Week Evacuation Site**					
	Concentrated Deprivation x Socialize with Friends	-15.29	27.78	0.582	-69.74	39.16
	Middle x Socialize with Friends	17.49	23.52	0.457	-28.61	63.59
	Concentrated Privilege x Socialize with Friends	16.83	23.52	0.226	-10.42	44.08
	Outcome: Distance to Two-Month Evacuation Site*					
	Concentrated Deprivation x Socialize with Friends	-42.27	30.88	0.171	-102.79	18.25
	Middle x Socialize with Friends	51.27	29.87	0.086	-7.28	109.81
	Concentrated Privilege x Socialize with Friends	38.56	28.32	0.173	-16.93	94.05
	Outcome: Distance to Indefinite Evacuation Site					
	Concentrated Deprivation x Socialize with Friends	-59.11	41.56	0.155	-140.56	22.35
	Middle x Socialize with Friends	46.49	34.17	0.174	-20.49	113.47
	Concentrated Privilege x Socialize with Friends	49.51	18.55	0.008*	13.14	85.87
* = <0.05, ** = <0.001						

CHAPTER 4

CAN AN INDIVIDUAL AND NEIGHBORHOOD-LEVEL TECHNOLOGY IMPLEMENTATION IMPROVE INDIVIDUAL DISASTER PREPAREDNESS IN A DIVERSE COMMUNITY CONTEXT?

Introduction

Previous chapters have explored the mechanisms underlying the extreme weather-climate gap. This chapter takes a step further, offering an analysis of a two-arm community-based exercise pilot trial aimed at enhancing disaster preparedness. Prior studies have shown the effectiveness of similar exercises.[206–208] These preparedness exercises ranged from distributing educational materials to multi-day in-person sessions. The findings from these studies indicate that allocating resources to programs aimed at enhancing disaster preparedness fosters readiness among participants, potentially resulting in life-saving outcomes.[206–208] Additionally, these exercises are valuable because they can be deployed in the absence of a disaster to improve public health resilience.

Prior studies have also shown the positive correlation between the quantification of social and community context via social capital and social resources with disaster preparedness.[210,291] This is a current area of interest because no studies were identified from inception to August 2024 that examined the relationship between social and community context and disaster preparedness within the framework of a community-based intervention. Examining this knowledge gap addresses the extreme weather-climate gap, as the literature indicates that social capital is not equitably distributed, and structural factors can inhibit an individual's ability to build and retain social capital and social resources.[292,293] Social capital being the networks of relationships between people that allow society to function effectively.[110]

The theoretical support for the social and community context of the SDoH is rooted in social cohesion and social stress theory which have been previously described.[103–105,110,268] Additionally, this implementation is supported by the diffusion of innovation theory. The exercise meets all five of the adopter categories which include relative advantage, compatibility, complexity, trialability, and observability.[221–223] These theories are relevant because they provide a basis for understanding how constructs like social capital and social resources impact overall health and motivate understanding how the intervention affects disaster preparedness among the study sample which then may diffuse into the community. Understanding the relationship between exposure to the intervention and disaster preparedness and how high or low social resources modify this relationship is critical for scaling up disaster preparedness work.

This study examined the effectiveness of a community-based exercise at improving disaster preparedness. The positive deviance approach to tracking the behavior change potentially caused by the exercise was taken. This approach places participants into groups referred to as positive deviants and negative deviants. It is a way to better understand both the characteristics of those who improved their behavior compared to those who did not and acceptable points of community intervention.[294] The research questions this study seeks to answer are (1) was exposure to a disaster exercise correlated with improved participant disaster preparedness compared to those who selected not to participate and (2) do participants with higher social resources benefit from the intervention more than participants with low social resources? We hypothesize that the educational exercise will bolster attitudes and knowledge about disaster preparedness at the individual level. We also hypothesize that individuals with lower social resources will benefit less from the preparedness exercise compared to those with higher social resources.

Methods

Design

The Athens-Clarke County Climate Resilience Study (ACCCRS) was a two-time point cohort study with a voluntary in-person exercise. The study was designed to improve disaster preparedness within Athens-Clarke County (ACC) and evaluate factors that are correlated with disaster preparedness that range from sociodemographic characteristics to measures of social capital and social resources. At the first time point of the study, participants completed a 62-item questionnaire. From this survey, participants could elect to attend an optional in-person exercise. This exercise was held at the Institute of Disaster Management at University of Georgia's Health Sciences Campus. The exercise was designed to last 1 to 1.5 hours and aimed at improving participants disaster preparedness. Specific components of the exercise were presentations on disaster readiness as well as a participatory mapping exercise that aimed to educate participants on their susceptibility to natural disasters. To reduce participant burden, 11 repeat sociodemographic questions from the pre-survey were dropped from the post-survey. Directly following the exercise, participants were sent a reduced 51-item follow up questionnaire via email. Participants that elected not to participate in the exercise were sent the same 51-item questionnaire approximately one week after completing the pre-survey. The surveys were created and administered electronically through Qualtrics. If participants did not complete the survey, study staff sent up to three reminders via email. This study was approved as human subjects research by the University of Georgia Institutional Review Board (PROJECT00006621).

Recruitment

ACCCRS recruited participants from May 2023 to January 2024. Inclusion criteria for the study included residents of ACC and adults 18+ years old. Convenience sampling was employed to recruit study subjects. Recruitment methods included handing out flyers, posting in ACC Facebook groups, having neighborhood leaders as well ACC district commissioners share information in their newsletters, posting on ACC Unified Government's official social media accounts (e.g., Twitter, Instagram, etc.), disseminating study information through official University of Georgia listservs, and setting up a table at the Athens-Clarke County Library. The materials that were distributed contained information on how to complete an eligibility questionnaire on Qualtrics which asked for the potential subject's home address, age, and email. Study staff contacted those who met the inclusion criteria. All participants provided informed consent and completed our UGA IRB approved written consent form. Study materials were only available in English. Once participants completed the consent form, they were enrolled in the study and sent the first survey. After the initial survey, participants who expressed interest in attending an in-person exercise were scheduled to participate. Study subjects were offered $10 for each completed survey (up to $20) and $20 for participating in the in-person exercise. All incentives were offered as Amazon e-gift cards and were distributed via email.

Data Collection

The eligibility form received 2,965 responses. Qualtrics screened approximately 1,714 responses that were classified as potential bots and another 809 did not meet the inclusion criteria. Approximately 442 records met the inclusion criteria and were contacted. A total of 117 participants completed the consent process and were enrolled in the study over a 9-month period. Both the pre- and post-surveys were designed to take approximately 15-30 minutes to complete. A record was kept of which participants attended the in-person exercise via a sign-in sheet. A total of 110 (94%) pre-surveys were completed. A total of 108 (92%) post-surveys were sent out, of which 106 (91%) were completed. Two pre-survey records were dropped after study staff determined the participants were not residents of ACC. The final number of study participants is 106 (91%). Post-surveys for non-exercise participants were sent approximately 2 weeks after completing the pre-survey.

Measures

The online survey collected demographics from participants which were adapted from the Athens Wellbeing Project and included the following: street address, zip code, birth city, birth state, years lived in ACC, email address, sex, age, race/ethnicity, highest level of education, monthly household income, work status, federal benefits received (e.g., Supplemental Nutrition Assistance Program, Social Security Disability, etc.), health insurance status, children enrolled in ACC schools, and mode of transportation routinely used.[295]

The online survey also collected information on physical resources which included a binary variable (0-No; 1-Yes) on whether the participants had a disaster plan and if they had insurance to cover disaster related damages. Participants reported on a 5-point Likert scale (1-

Not true at all; 2-Rarely true; 3-Sometimes true; 4-Often true; 5-True nearly all of the time) if they had a week supply of food at home, if they had stable or permanent housing, and if their utilities were working (e.g., electricity, gas). These questions were adapted from the Disaster Adaptation and Resilience Scale (DARS) physical resources section. Next participants reported on a 5-point Likert scale (1-Not true at all; 2-Rarely true; 3-Sometimes true; 4-Often true; 5-True nearly all of the time) their social resources which included whether they feel like they belong in their community, they get the support they need from friends and family, they have people to turn to and ask for help, and if their family is there for them during difficult times. These questions were adapted from the DARS social resources section.[296] Higher values indicated more social resources. This scale showed good internal consistency with a Cronbach's alpha of 0.85.

Social capital was measured on a 4-point Likert Scale by asking participants if they think most people would try to take advantage of them if they got the chance (1-People take advantage of me all of the time; 2-People take advantage of me most of the time; 3-People are fair to me most of the time; 4-People are fair to me all of the time), if most people can be trusted (1-People can never be trusted; 2-People usually cannot be trusted; 3-People can usually be trusted; 4-People always can be trusted), and if most people are just looking out for themselves (1-People are always looking out for themselves; 2-People are usually looking out for themselves; 3-People are usually helpful ; 4-People are always helpful). Social capital questions were adapted from the General Social Survey.[210,293] Higher values indicated higher social capital. This scale showed acceptable internal consistency with a Cronbach's alpha of 0.70. Participants were also asked to self-report their perceived susceptibility to disasters on a 5-point Likert scale (1-Strongly disagree; 2-Disagree; 3-Neither agree nor disagree; 4-Agree; 5-Strongly agree) via the following questions: I may experience a disaster in the next couple of years, I feel safe in my home if a disaster occurred, it is important for me to always have an emergency kit on hand, I have a list or have memorized emergency contact numbers to handle emergency situations and disasters, and I have thought about a safe place to go in the event of a disaster other than my home. These questions were adapted from the General Disaster Preparedness Belief Scale (GDPBS).[297] Higher values indicated more belief in susceptibility to disasters. This scale showed poor internal consistency with a Cronbach's alpha of 0.50.

Participants also self-reported their resilience which was measured on a 5-point Likert scale (1-Not at all true; 2-Rarely true; 3-Sometimes true; 4-Often true; 5-True nearly all of the time) via the following questions: when I feel upset, I pay attention to my feelings, I am able to manage sad feelings, and I give myself time to recover from difficult situations. These questions were adapted from the Brief Resilience Scale.[298] Participants were asked to self-report their level of self-efficacy on a 4-point Likert scale (1-Not at all true; 2-Rarely true; 3-Often true; 4-True nearly all of the time) via the following questions: I am confident I can deal with unexpected events, I can solve difficult problems when I put my mind to it, it is typically easy for me to accomplish my goals, if I am in trouble, I can usually think of a solution on my own. These questions were adapted from the Generalized Self-Efficacy Scale (GSES).[299] Participants were asked to rate their perceived stress level on a 5-point Likert scale (1-Never; 2-Almost never; 3-Sometimes; 4-Fairly often; 5-Very often) via the following questions: in the last month have you felt nervous and stressed, in the last month, how often did you experience serious unexpected change in plans or events that bothered you, in the last month, how often have you felt that you were unable to control the important things in your life, and in the last month, how often have you been upset because of things that were outside of your control. These questions were adapted from the Perceived Stress Scale (PSS).[300]

Participants were then asked the location (i.e. city and state) they would go if they had to evacuate their home for one week, two months, and indefinitely. These questions were adapted from the Neighborhood Connectivity Survey (NCS).[301] Participants were asked if they or a member of their household had special medical needs (Daily medication; Home health aide/Home health nurse; Wheelchair/Cane/Walker; Dialysis; Oxygen supply; Electrically dependent; Other; None), whether they or a member of their house had disabilities (Impaired hearing; Impaired vision; Developmental/Cognitive disability; Difficulty understanding English; Difficulty understanding written material; None). These questions were adapted from the Center for Disease Control's Community Assessment for Public Health Emergency Response survey (CASPER).[302] Participants were then asked if they had pets at home they were responsible for (0-No; 1-Yes), if they know where to find resources to better prepare themselves for an emergency or a disaster (0-No; 1-Yes), what is the best way to receive emergency notifications and alerts (Email; Phone call; Siren; Text message; Television broadcast), if they receive emergency alerts on their smartphone (Yes, via the UGA SAFE app; Yes, via another emergency alert system; No, I do not receive emergency alerts; No, I do not have a smartphone), and if they had an emergency bag that would help them survive on their own for at least 72 hours (0-No; 1-Yes). Lastly, participants were asked if they had ever experienced a disaster while living in ACC (Extreme temperature; Flood; Wildfire; Drought; Tropical storm; Other) and if they had emergency preparedness items in their car (Jumper cables; Flares or reflective triangle; Ice scraper; Car cell phone charger; Blanket; Paper map). These questions were adapted from a classroom survey distributed by the Institute of Disaster Management at The University of Georgia.

Research Question 1 Predictors

The primary predictor for this analysis was a dichotomous variable that indicated whether the participant attended an in-person disaster exercise.

Research Question 1 Outcomes

Participants were grouped into two groups for each outcome to evaluate the effectiveness of the in-person exercise. A total of four positive deviant (PD) and negative deviant (ND) outcomes were created using the four main preparedness outcomes. These were whether the participant had a plan for disasters, if they received emergency alerts on their smartphone, if they had an emergency bag, and if they knew where to find resources to be better prepared for disasters. PDs were those that answered no on the pre-survey to the four outcomes but yes on the post-survey. Participants that answered yes on the pre-survey and yes on the post-survey were also classified as PDs. Those that answered yes to the preparedness outcomes on the pre-survey and then no on the post-survey were classified as NDs. Those that answered no on both the pre- and post-survey were also categorized as NDs. The grouping of participants as PDs or NDs was done to further understand how disaster preparedness behaviors changed between the pre- and post-survey. Participants that remained prepared or improved their preparedness may have different characteristics than those who did not improve or their preparedness worsened. Examining these characteristics may help improve the exercise in future studies.

Research Question 1 Logistic Regression and Bivariate Analyses

Logistic regression was used to evaluate the likelihood of being in the PD or ND group. Tables 4.7-4.10 detail the bivariate analyses using the ttest and chi-square (x2) test to evaluate differences between the ND and PD groups across key demographics and baseline social capital, social resources, perceived susceptibility, perceived stress, distress regulation, and self-efficacy. Covariates that were significantly different between the PDs and the NDs were controlled for in the respective logistic models. A total of four logistic models were fitted and the results are shown in Tables 4.3 and 4.4.

Research Question 2 Predictors

The primary predictor for this analysis was a binary variable indicating if the participants attended the in-person exercise. The effect modifiers included in the models were social capital and social resources. Two latent class analyses were conducted, and posterior probabilities were generated to determine the likelihood of each participant belonging to a high social capital or low social capital group as well as a high or low social resources group. The final latent class model for social capital yielded an entropy value of 0.97. Entropy ranges from 0 to 1 and higher values indicate greater accuracy of the classification.[303] The final latent class model for social resources yielded an entropy of 0.95. Both entropy values for social capital and social resources indicate that participants were appropriately assigned to their respective classes. A mediating pathway through change in perceived susceptibility was evaluated in the path models. The change in perceived susceptibility was calculated by subtracting the post-survey score from the pre-survey score. The question, "I feel safe in my home," was reverse scored. Higher values on this perceived susceptibility scale indicated that participants felt they were more susceptible to disasters (e.g., I strongly disagree that I feel safe in my home if a disaster occurred).

Research Question 2 Outcomes

A total of four path models were fit for each of the key outcomes that were taken from the post-survey. The four outcomes were the same as research question 1 with whether the participant was PD or ND for the four main preparedness outcomes.

Research Question 2 Analysis

Generalized structural equation modeling (GSEM) was selected to evaluate the relationship between social resources and disaster preparation. The path analysis was selected to model how a system of social resources, social capital, and perceived susceptibility related to the target susceptibility mediating pathway on disaster preparedness. Additionally, the path analysis was selected based on previously observed relationships between social capital and social resources and their influence on disaster preparedness.[210,291] A measurement model was used after evaluating the latent constructs and determining that the variable loadings did support constructing a latent variable for both social capital and social resources, which are detailed in Tables 4.5 and 4.6. Additionally, GSEM was selected over traditional SEM to appropriately represent the variance family of the binary primary outcome. Model invariance testing was conducted to explore implementation effects that may depend on existing high or low social capital and social resources. Statistical significance testing was done using GSEM procedures which allow for manual specification of variable distribution. A binomial distribution with a logit link was specified for the binary outcomes in each model. To assist with interpretation, the path coefficients shown in the figures were produced using the SEM function which allows for standardization of path coefficients for interpretability. In addition to the four binary outcome models, one path analysis was fitted using the traditional SEM function within STATA. A continuous outcome was constructed which was a count of the number of the four main disaster preparedness outcomes and ranged from 0 to 4. All data analysis was conducted in STATA 18.0 MP (College Station, TX).[304]

Results

Sample Demographics

The study characteristics are detailed in Tables 4.1 and 4.2 which shows overall demographics and by those who attended the in-person exercise and those who did not. Overall, the study sample was on average 38 years old and predominantly not male (78%) and White (72%). The sample was educated with 92% having an associate's degree or higher. Thirty three percent of the sample reported a household income between $2,001 - $5,000 per month, 20% reported between $5,000 - $8,000 per month, and 36% reported household monthly income greater than $8,000. Most of the sample reported their work status as working part- or full-time (83%). Across these demographics, the only significant difference between those who attended the exercise compared to those who did not was age. Other differences may exist, but we may lack sufficient power to detect them. Those who attended the exercise were on average 8.6 years older than those who did not attend.

Logistic Regression

The results from the logistic regression of the preparedness outcomes categorized as PDs or NDs are shown in Tables 4.3 and 4.4. For each of the four outcomes, the odds of being in the PD group was higher among those who attended the exercise compared to those that did not. The odds of being in the PD group for having a disaster plan are 3.38 (p = 0.037, 95% CI: 1.08, 10.61) times higher among the group that attended the exercise compared to those that did not.

The odds of being in the PD group for receiving smartphone emergency alerts was not significantly higher among the group that attended the exercise compared to those that did not. The odds of being in the PD group for having an emergency bag were 12.89 ($p = 0.017$, 95% CI: 1.59, 13.93) times higher among those who attended the exercise compared to those that did not. Lastly, the odds of being in the PD group for knowing where to find resources were 3.33 ($p = 0.014$, 95% CI: 1.27, 8.68) times higher among those who attended the exercise compared to those that did not.

Path Analysis

The univariate statistics for both social capital and social resources are included in Tables 4.5 and 4.6. The three components of social capital are people taking advantage of you (mean = 2.88; SD = 0.46), most people can be trusted (mean = 2.79; SD = 0.44), and people are just looking out for themselves (mean = 2.55; SD = 0.54). The four components of social resources are community belonging (mean = 3.91; SD = 0.92), support from friends or family (mean = 4.14; SD = 0.90), people to ask for help (mean = 4.28; SD = 0.94), and family support during difficult times (mean = 4.04; SD = 1.19). Because of low factor loadings for the components of both social capital and social resources, latent variables were not constructed.

Perceived Susceptibility Mediating Pathway of Attending an Exercise and Having a Disaster Plan Association by High and Low Social Resources

We examined one mediating pathway between exercise attendance and whether the participants were PDs or NDs for having a disaster plan (Figure 4.1). We conducted a model invariance test to compare participants who had high social resources (H) and low social resources (L). Overall, significant differences were seen between H vs. L groups ($p = .015$) indicating that the system statistically depended on social resources of participants. Exercise attendance was positively correlated with change in perceived susceptibility among both the H and L groups ($\beta = 0.16$ vs. 0.31). Perceived susceptibility was not correlated with belonging to the PD group for having a disaster plan for both the H and L groups ($\beta = 0.01$ vs. -0.01). The direct path for exercise attendance to the PD group for having a disaster plan showed positive correlation for the H and weak negative correlation for the L group ($\beta = 0.28$ vs. -0.05). Model fit statistics, such as the root mean square error (RMSEA), indicate how well the model fits the data. The comparative fit index (CFI) is also a useful metric for determining model fit, especially for smaller sample sizes.[219] RMSEA and CFI for this model were 0.11 and 0.55 respectively suggesting poor model fit likely due to inability to fully address confounding bias given the limited sample size.

Perceived Susceptibility Mediating Pathway of Attending an Exercise and Receiving Smartphone Emergency Alerts Association by High and Low Social Resources

We examined one mediating pathway between exercise attendance and whether the participants were PDs or NDs for receiving emergency smartphone alerts (Figure 4.2). The model invariance test between the H and L groups for social resources was not significant ($p = .052$). Exercise attendance was positively correlated with change in perceived susceptibility among both the H and L groups ($\beta = 0.14$ vs. 0.31). Change in perceived susceptibility was positively correlated with being a PD for receiving smartphone alerts among the H group and significantly positively correlated among the L group ($\beta = 0.18$ vs. 0.42). The direct path for exercise attendance to the PD group for receiving smartphone alerts was slightly positively correlated for both the H and L groups (β = 0.03 vs. 0.11). Model fit statistics were 0.13 and 0.75 for RMSEA and CFI respectively.

Perceived Susceptibility Mediating Pathway of Attending an Exercise and Having an Emergency Bag Association by High and Low Social Resources

We examined one mediating pathway between exercise attendance and whether the participants were PDs or NDs for having an emergency bag (Figure 4.3). The model invariance test between the H and L groups was not significant ($p = 0.092$). Exercise attendance was positively correlated with a change in perceived susceptibility among both the H and L groups (β = 0.14 vs. 0.31). Change is perceived susceptibility was weakly correlated with having an emergency bag for the H and L groups (β = 0.03 vs. 0.04). The direct path for exercise attendance on the PD group for having an emergency bag was positively correlated for the H and L groups (β = 0.34 vs. 0.14). Model fit statistics were 0.11 and 0.78 for RMSEA and CFI respectively.

Perceived Susceptibility Mediating Pathway of Attending an Exercise and Knowing Where to Find Resources Association by High and Low Social Resources

We examined one mediating pathway between exercise attendance and whether the participants were PDs or NDs for knowing where to find resources (Figure 4.4). The model invariance test was not significant between the H and the L groups ($p = .054$). Exercise attendance was positively correlated with a change in perceived susceptibility among both the H and L groups (β = 0.14 vs. 0.34). Change in perceived susceptibility was weakly positively correlated with knowing where to find resources for both the H and L groups (β = 0.11 vs.

<0.001). The direct path for exercise attendance on the PD group for knowing where to find resources was positively correlated for both the H and L groups (β = 0.36 vs. 0.24). Model fit statistics were 0.10 and 0.75 for RMSEA and CFI respectively.

SEM Model with Continuous Outcome

A traditional SEM model was fitted by combining the four binary outcomes into a single continuous variable that ranged from zero to four. This represented the number of disaster preparedness behaviors that the participants adopted on the post-survey. The standardized SEM results are shown in Figure 4.5. The model invariance tests did not indicate significant overall differences between the H and L groups ($p = .08$). Exercise attendance was positively correlated with change in perceived susceptibility for the H group and significantly positively correlated for the L group (β = 0.14 vs. 0.31). Change in perceived susceptibility was positively correlated with disaster preparedness for both the H and L groups (β = 0.11 vs. 0.18). The direct path of exercise attendance was significantly positively correlated with disaster preparedness for the H group and positively correlated for the L group (β = 0.37 vs. 0.16). Model fit statistics were 0.12 and 0.79 for RMSEA and CFI respectively.

Perceived Susceptibility Mediating Pathway of Attending an Exercise and Disaster preparedness by High and Low Social Capital

A total of four GSEM models assessing the association between exercise attendance and preparedness outcomes at high and low social capital were fully identified. This indicates the models are likely overfitted and so their output was not included in this analysis. One SEM model was fitted assessing the continuous outcome at high and low social capital was also fully identified and not included.

Discussion

Logistic Regression

Attending the disaster exercise was associated with a significantly increased likelihood of belonging to the PD group for three of the four disaster preparedness outcomes. This also supports the hypothesis of research question one that the exercise will bolster attitudes and knowledge about disaster preparedness at the individual and household level. This finding coheres with other studies that have examined disaster preparedness exercises.[206–208] The strongest association was seen for having an emergency bag (OR = 12.89, p = 0.017). This suggests that an in-person exercise is particularly helpful for preparedness behaviors that involve physically procuring materials to have in the event of a disaster. Making resources available to people about what they should have in an emergency bag may not be enough. In-person demonstrations of what a kit looks like and what the specific items are that go into a kit may be the best way to ensure people have these types of materials available at home. We did not see increased odds of having smartphone alerts for those that attended the exercise compared to those that did not. This could be due most of the sample (67%) indicating that they already received emergency alerts at baseline. The findings of the logistic regression demonstrate that preparedness exercises can be less time intensive than similar prior studies and still improve preparedness. The results are particularly important for scaling these types of preparedness exercises up by reducing both facilitator and participant burden.

Path Analysis

The findings suggest potential differences between people with high and low social resources. The model invariance test was statistically significant for one of the five models and just above the .05 threshold for an additional two models. Four of the five models showed the correlation of exercise attendance directly on preparedness was higher among the high social resources group. This aligns with the existing literature that has found that those with more social resources are more likely to be prepared for natural disasters.[210,291] A lack of social resources can contribute to social isolation, which not only reduces individual's perceived susceptibility to natural disasters but also creates barriers to disaster preparedness.[305,306] Access to information is the mechanism through which social resources operate on disaster preparedness. Higher social resource individuals are more connected with their community and receiving said information.[291,306]

Exercise attendance was associated with an increase in perceived susceptibility to disasters and was approximately twice as strong among the low social resources group compared to the high social resources group. This connects with the findings of how social resources modify the direct effect of the exercise on preparedness. The exercise was better at improving perceived susceptibility among those who attended the exercise in the low social resources group potentially because these participants had more to gain relative to the high social resources group. This is due to social resources being connected to susceptibility.[291,307] Those who are more connected to their community are more aware of their risk for events like natural disasters which could be why their change in perceived susceptibility was lower following the exercise.[291,307]

When looking at how perceived susceptibility was correlated with disaster preparedness, we see a weak positive correlation for both the high and low social resource groups in four of the five models. The exercise itself may be correlated with increased perceived susceptibility; however, this increase is not the primary mechanism for effecting disaster preparedness behaviors on the post-survey. This could be due to several factors. Other studies have shown that geography plays a significant role in perceptions of susceptibility to natural disasters.[307] People who live on the coast may have different perceptions about susceptibility to natural disaster relative to people who live in landlocked areas.[308] The exercise may have effectively communicated susceptibility to climate change, however, due to the geographic location of Athens-Clarke County the perceptions of susceptibility may not translate into preparedness action. In other words, participants may feel that the threats of climate change are real, but Athens-Clarke County is not susceptible to natural disasters. This is informative for the content development for future exercises. Change in perceived susceptibility was significantly correlated with receiving smartphone alerts among the low social resources group. This suggests that perceptions of susceptibility may be crucial to getting people to ensure they are set up to receive smartphone alerts related to disasters and that this is important for low social resource individuals as their other methods of receiving information may be limited.[305,306] Other mechanisms that are more strongly correlated with disaster preparedness like self-efficacy should be studied. Disaster exercises that focus on improving self-efficacy may see improved disaster preparedness compared to our exercise.

The findings are supported by the theories of social cohesion and social stress theory.[103,105,110,270,309] Greater social resources were correlated with disaster preparedness. This connects with social cohesion, those who were more connected to their community had increased disaster preparedness on the post-survey compared to participants with low social resources. Additionally, these findings relate to social stress theory. Those with lower social resources may experience stressors, such as poverty or discrimination, that act as barriers to the effectiveness of the exercise. This can manifest as not being able to obtain disaster preparedness equipment because of the cost. Additionally, a lack of trust in authorities could prevent people from adopting the recommended preparedness behaviors.

The findings suggest that disaster preparedness exercises can be an effective health promotion tool. These exercises may better prepare individuals for future natural disasters which can reduce negative health outcomes. Additionally, if these exercises are community-based they may build trust by connecting community members with local authorities. This could also identify gaps that exist in community-level disaster preparedness. For example, community member perceptions versus the realities of local authorities' capabilities.

The findings from this pilot study explored the relationships between the social and community context component of the SDoH. Future studies should examine other constructs that may modify the association between a disaster exercise and disaster preparedness. This is crucial as these exercises must also be scaled up and include more diverse populations. Exercises may need to be tailored to the specific region in which they are implemented.

Strengths

The longitudinal design allows for a more robust analysis of key factors associated with disaster preparedness within the structural regression framework. All measures included in this analysis were self-reported by the participants rather than observational. Additionally, previously published studies on disaster exercises involved sessions lasting three or more days, which can be quite burdensome for participants. This study assessed and demonstrated the effectiveness of a preparedness exercise that lasted approximately 1.5 hours.

Limitations

There are several limitations associated with this study. Most of the sample consisted of White participants, especially those that attended the disaster. It is possible different relationships exist for other races/ethnicities that we were not able to examine in the analyses due to low numbers of non-White participants. Replication studies will be needed with larger sample sizes to fully understand the constructed system. The use of convenience sampling could have resulted in enrolling participants that are more likely to be aware of disasters and disaster preparedness or were more willing to adopt the preparedness behaviors than the general population. Lastly, due to budgetary restrictions, the materials for this study were only offered in English. Significant challenges exist for non-English speakers in the disaster preparedness space.

Conclusion

In-person disaster exercises are an effective way to improve disaster preparedness, particularly for more intensive activities like having an emergency bag. Higher social resources were correlated with increased disaster preparedness relative to participants with low social resources. Disaster preparedness exercises that target low social resource areas should incorporate components that aim to improve community belonging as this may impact the effectiveness of the exercise. Perceived susceptibility was not significantly correlated with disaster preparedness. Future exercises should explore additional moderators between exercise attendance and disaster preparedness.

Table 4.1 – Athens-Clark County Climate Resilience Study Demographics

Respondent Characteristics	Overall n=106 (%)	Attended n=29 (%)	Non-Attended n=77 (%)	p-value
Age mean (±SD)	38.37 (±14.89)	44.6(±16.6)	36.0 (±13.6)	0.007
Gender				
Male	24 (23%)	9 (31%)	15 (19%)	
Female or Non-Binary	83 (78%)	20 (69%)	62 (81%)	0.323
Race/ Ethnicity				
White	76 (72%)	19 (66%)	57 (74%)	
Non-White	30 (34%)	10 (34%)	20 (26%)	0.386
Education				
Less than College	8 (8%)	2 (7%)	6 (8%)	
Associate or Bachelor's Degree	52 (49%)	12 (41%)	40 (52%)	
Graduate or Terminal Degree	46 (43%)	15 (52%)	31 (40%)	0.566
Household Income				
≤ $2,000	9 (8%)	1 (3%)	8 (10%)	
$2,001 -$5,000	35 (33%)	13 (45%)	22 (29%)	
$5,001-$8,000	21 (20%)	6 (21%)	15 (19%)	
>$8,000	38 (36%)	7 (24%)	31 (40%)	0.214
Working status				
Working full-time	66 (62%)	13 (45%)	53 (69%)	
Working part-time	22 (21%)	10 (9%)	12 (16%	
Currently unemployed, but actively seeking work	2 (2%)	0	2 (3%)	
Not working for pay (unable to work, retired, student, etc.)	3 (3%)	2 (7%)	1 (1%)	
Stay at home caregiver	13 (12%)	4 (14%)	9 (12%)	0.068

Table 4.2 – Athens-Clark County Climate Resilience Study Demographics Continued

	Overall	**Attended**	**Non-Attended**	**p-value**
Respondent Characteristics	**n=106 (%)**	**n=29 (%)**	**n=77 (%)**	
Baseline Social Capital Mean (±SD)	2.74 ± (0.38)	2.70 ± (0.08)	2.75 ± (0.04)	0.495
Baseline Social Resources Mean (±SD)	4.09 ± (0.82)	3.81 ± (0.18)	4.20 ± (0.08)	0.027
Perceived Susceptibility Change Score Mean (±SD)	0.20 ± (0.44)	0.32 ± (0.08)	0.15 ± (0.05)	0.068
Perceived Stress Mean (±SD)	1.91 ± (0.73)	2.10 ± (0.15)	1.84 ± (0.08)	0.096
Distress Regulation Mean (±SD)	2.84 ± (0.70)	2.87 ± (0.12)	2.83 ± (0.08)	0.751
Self-Efficacy Mean (±SD)	3.22 ± (0.48)	3.30 ± (0.08)	3.19 ± (0.08)	0.292
Having a Disaster Plan on Post-Survey (±SD)				
Yes	61 (58%)	21 (72%)	40 (52%)	
No	44 (42%)	7 (28%)	37 (48%)	0.034
Receive Smartphone Alerts on Post-Survey				
Yes	73 (69%)	23 (79%)	50 (65%)	
No	33 (31%)	6 (21%)	27 (35%)	0.154
Have an Emergency Bag on the Post-Survey				
Yes	37 (35%)	16 (55%)	21 (27%)	
No	69 (65%)	13 (45%)	56 (73%)	0.007
Knowing Where to Find Resources on the Post-Survey				
Yes	79 (75%)	28 (97%)	51 (66%)	
No	27 (25%)	1 (3%)	26 (34%)	0.001

Table 4.3 - Logistic Regression Results Examining Factors Associated with Adopting the Disaster Preparedness Behaviors

Outcome	Predictor	OR	SD	p-value	95% CI
I have a plan in the event of a disaster.	**Exercise**				
	Did not attend	ref.			
	Attended	3.38	1.97	0.037	1.08; 10.61
	Gender				
	Male	ref.			
	Not male	0.42	0.30	0.222	0.11; 1.68
	Race/Ethnicity				
	White	ref.			
	Not White	3.10	2.19	0.109	0.78; 12.37
	Social capital	0.09	0.09	0.018	0.01; 0.66
	Perceived stress	0.61	0.22	0.171	0.30; 1.23
	Distress regulation	3.52	1.90	0.020	1.22; 10.16
I receive emergency alerts on my smartphone.	**Exercise**				
	Did not attend	ref.			
	Attended	1.82	0.97	0.259	0.64; 5.18
	Education				
	Less than college	ref.			
	Associate or bachelor’s Degree	2.70	2.26	0.237	0.52; 13.93
	Graduate or terminal Degree	6.02	5.18	0.037	1.12; 32.54
	Self-Efficacy	2.16	1.09	0.128	0.80; 5.83

Table 4.4 - Logistic Regression Results Examining Factors Associated with Adopting the Disaster Preparedness Behaviors Continued

Outcome	Predictor	OR	SD	p-value	95% CI
I have an emergency bag.	**Exercise**				
	Did not attend	ref.			
	Attended	12.89	13.77	0.017	1.59; 104.66
	Race/Ethnicity				
	White	ref.			
	Not White	3.72	2.61	0.061	0.94; 14.72
	Perceived susceptibility	3.12	1.81	0.051	1.00; 9.75
I know where to find resources.	**Exercise**				
	Did not attend	ref.			
	Attended	3.33	1.63	0.014	1.27; 8.68
	Perceived susceptibility	5.42	2.48	0.000	2.21; 13.30

Table 4.5 – Standardized Latent Variable Relationships with Survey Items (Social Capital)

Latent Variable	Univariate mean ± SD	β	95% CI	p-value
Social Capital				
Do you think most people would try a take advantage of you	2.88 ± 0.46	0.53	0.34, 0.71	<0.001
Would you say most people can be trusted	2.79 ± 0.44	0.93	0.70, 1.16	<0.001
Would you say people are just looking out for themselves	2.55 ± 0.54	0.56	0.37, 0.75	<0.001

Table 4.6 – Standardized Latent Variable Relationships with Survey Items (Social Resources)

Latent Variable	Univariate mean ± SD	β	95% CI	p-value
Social Resources				
I feel like I belong in my community	3.91 ± 0.92	0.63	0.50, 0.75	<0.001
I get the support I need from my friends or family	4.14 ± 0.90	0.95	0.89, 1.00	<0.001
I have people I can turn to and ask for help	4.28 ± 0.94	0.84	0.76, 0.92	<0.001
My family is there for me during difficult times	4.04 ± 1.19	0.70	0.60, 0.81	<0.001

Table 4.7 – Bivariate Results of PDs and NDs for Having a Disaster Plan

	I have a plan in the event of a disaster.		
	Positive Deviance	Negative Deviance	
	n = 61	n = 44	p-value
Attended Exercise			
Yes	21 (66%)	7 (16%)	
No	40 (34%)	37 (84%)	0.034
Gender			
Male	18 (30%)	5 (11%)	
Female or Non-Binary	43 (70%)	39 (89%)	0.027
Race/Ethnicity			
White	39 (64%)	36 (82%)	
Not White	22 (36%)	8 (18%)	0.045
Household Income			
≤ $2,000	4 (7%)	5 (11%)	
$2,001 -$5,000	20 (34%)	15 (34%)	
$5,001-$8,000	13 (22%)	8 (18%)	
>$8,000	21 (36%)	16 (36%)	0.853
Education			
Less than college	3 (5%)	5 (11%)	
Associate or bachelor's degree	36 (59%)	16 (36%)	
Graduate or terminal degree	22 (36%)	23 (52%)	0.061
Employment			
Working full-time	36 (59%)	30 (68%)	
Working part-time	13 (21%)	8 (18%)	
Currently unemployed, but actively seeking work	2 (3%)	1 (2%)	
Not working for pay (unable to work, retired, student, etc.)	9 (15%)	4 (9%)	
Stay at home caregiver	1 (2%)	1 (2%)	0.866
Age	39.11 (SD 2.02)	36.48 (SD 1.89)	0.360
Social Capital Mean	2.66 (SD 0.05)	2.85 (SD 0.05)	0.012
Social Resources Mean	4 (SD 0.12)	4.21 (SD 0.10)	0.197
Perceived Susceptibility Mean	3.26 (SD 0.06)	2.94 (0.06)	0.000
Perceived Stress Mean	1.85 (SD 0.09)	2.03 (SD 0.11)	0.216
Distress Regulation Mean	2.94 (0.09)	2.67 (0.10)	0.044
Self-Efficacy Mean	3.29 (0.06)	3.11 (0.06)	0.050

Table 4.8 – Bivariate Results of PDs and NDs for Receiving Emergency Alerts

	I receive emergency alerts on my smartphone.		**p-value**
	Positive Deviance	**Negative Deviance**	
	n = 73	**n = 33**	
Attended Exercise			
Yes	23 (68%)	6 (18%)	
No	50 (32%)	27 (82%)	0.154
Gender			
Male	14 (19%)	10 (30%)	
Female or Non-Binary	59 (81%)	23 (70%)	0.205
Race/Ethnicity			
White	55 (75%)	21 (64%)	
Not White	18 (25%)	12 (36%)	0.215
Household Income			
≤ $2,000	6 (8%)	3 (10%)	
$2,001 -$5,000	22 (31%)	13 (42%)	
$5,001-$8,000	18 (25%)	3 (10%)	
>$8,000	26 (36%)	12 (39%)	0.333
Education			
Less than college	3 (4%)	5 (15%)	
Associate or bachelor’s degree	33 (45%)	19 (58%)	
Graduate or terminal degree	37 (51%)	9 (27%)	0.027
Employment			
Working full-time	45 (62%)	21 (64%)	
Working part-time	16 (22%)	6 (18%)	
Currently unemployed, but actively seeking work	1 (1%)	2 (6%)	
Not working for pay (unable to work, retired, student, etc.)	9 (12%)	4 (12%)	
Stay at home caregiver	2 (3%)	0	0.585
Age	39.66 (1.74)	35.51 (2.5)	0.186
Social Capital Mean	2.74 (0.04)	2.74 (0.07)	0.931
Social Resources Mean	4.14 (0.10)	3.99 (0.15)	0.383
Perceived Susceptibility Mean	3.16 (0.06)	3.10 (0.07)	0.558
Perceived Stress Mean	1.95 (0.09)	1.83 (0.11)	0.469
Distress Regulation Mean	2.87 (0.09)	2.78 (0.11)	0.553
Self-Efficacy Mean	3.28 (0.06)	3.08 (0.08)	0.044

Table 4.9 – Bivariate Results of PDs and NDs for Knowing Where to Find Resources

	I Know where to find resources.		
	Positive Deviance	**Negative Deviance**	
	n = 78	**n = 27**	**p-value**
Attended Exercise			
Yes	28 (36%)	1 (4%)	
No	50 (64%)	26 (96%)	0.001
Gender			
Male	19 (24%)	5 (19%)	
Female or Non-Binary	59 (76%)	22 (81%)	0.533
Race/Ethnicity			
White	51 (65%)	24 (89%)	
Not White	27 (35%)	3 (11%)	0.020
Household Income			
≤ $2,000	5 (7%)	4 (15%)	
$2,001 -$5,000	25 (33%)	9 (33%)	
$5,001-$8,000	16 (21%)	5 (19%)	
>$8,000	29 (39%)	9 (33%)	0.632
Education			
Less than college	4 (5%)	4 (15%)	
Associate or bachelor's degree	40 (51%)	12 (44%)	
Graduate or terminal degree	34 (44%)	11 (41%)	0.260
Employment			
Working full-time	47 (60%)	18 (67%)	
Working part-time	19 (24%)	3 (11%)	
Currently unemployed, but actively seeking work	2 (3%)	1 (4%)	
Not working for pay (unable to work, retired, student, etc.)	9 (12%)	4 (15%)	
Stay at home caregiver	1 (1%)	1 (4%)	0.610
Age	38.65 (1.73)	37.81 (2.73)	0.803
Social Capital Mean	2.71 (0.04)	2.84 (0.07)	0.112
Social Resources Mean	4.07 (0.10)	4.16 (0.15)	0.652
Perceived Susceptibility Mean	3.20 (0.06)	2.85 (0.07)	0.017
Perceived Stress Mean	1.93 (0.09)	1.89 (0.12)	0.805
Distress Regulation Mean	2.78 (0.08)	2.98 (0.12)	0.224
Self-Efficacy Mean	3.26 (0.06)	3.10 (0.08)	0.133

Table 4.10 – Bivariate Results of PDs and NDs Having an Emergency Bag

	I have an emergency bag.		
	Positive Deviance	**Negative Deviance**	
	n = 37	**n = 68**	**p-value**
Attended Exercise			
Yes	16 (43%)	13 (19%)	
No	21 (57%)	55 (81%)	0.008
Gender			
Male	11 (30%)	13 (19%)	
Female or Non-Binary	26 (70%)	55 (81%)	0.216
Race/Ethnicity			
White	23 (62%)	52 (76%)	
Not White	14 (38%)	16 (24%)	0.121
Household Income			
≤ $2,000	3 (8%)	6 (9%)	
$2,001 -$5,000	10 (28%)	24 (36%)	
$5,001-$8,000	9 (25%)	12 (18%)	
>$8,000	14 (39%)	24 (36%)	0.778
Education			
Less than college	3 (8%)	5 (7%)	
Associate or bachelor's degree	21 (57%)	31 (46%)	
Graduate or terminal degree	13 (35%)	32 (47%)	0.493
Employment			
Working full-time	20 (54%)	45 (66%)	
Working part-time	9 (24%)	13 (19%)	
Currently unemployed, but actively seeking work	1 (3%)	2 (3%)	
Not working for pay (unable to work, retired, student, etc.)	7 (19%)	6 (9%)	
Stay at home caregiver	0	2 (9%)	0.414
Age	38.43 (2.70)	38.44 (1.72)	0.998
Social Capital Mean	2.67 (0.07)	2.78 (0.04)	0.146
Social Resources Mean	4.05 (0.14)	4.12 (0.10)	0.663
Perceived Susceptibility Mean	3.36 (0.08)	3.02 (0.05)	0.000
Perceived Stress Mean	1.99 (0.13)	1.88 (0.08)	0.445
Distress Regulation Mean	2.68 (0.15)	2.92 (0.07)	0.097
Self-Efficacy Mean	3.27 (0.09)	3.19 (0.05)	0.444

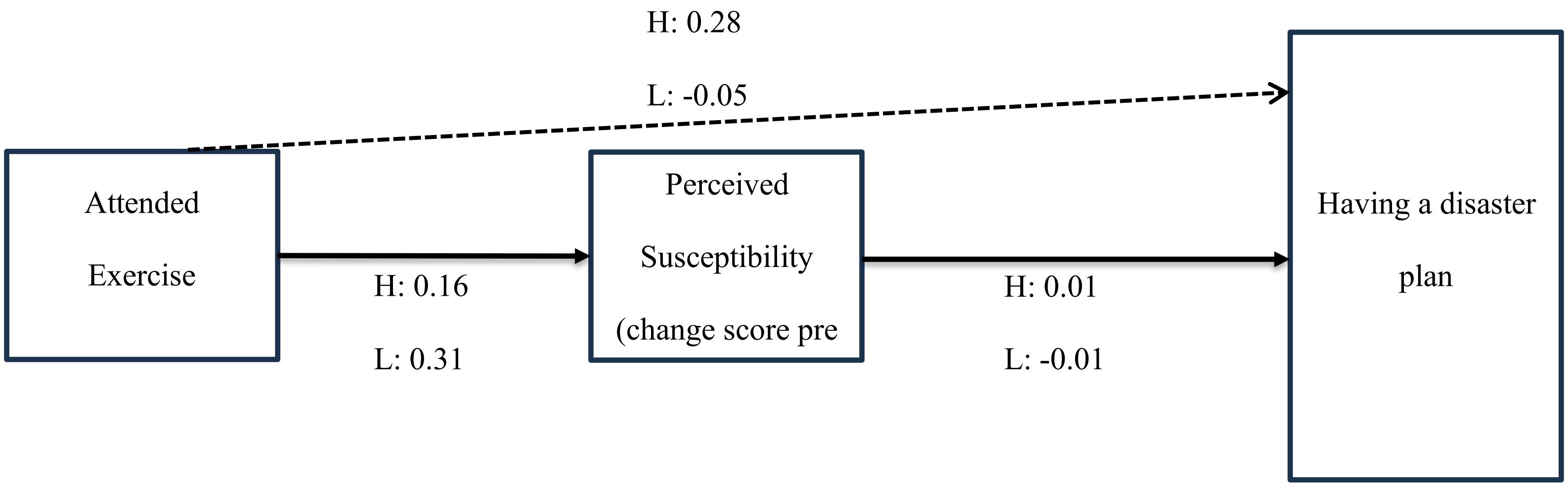

Figure 4.1: Longitudinal Path Model of Exercise Attendance on Having a Disaster Plan on the Post-Survey through Change in Perceived Susceptibility to Disasters (N = 106). Model invariance test high social resources (H) versus low social resources (L) was significant (p = 0.015). Model adjusted for age.

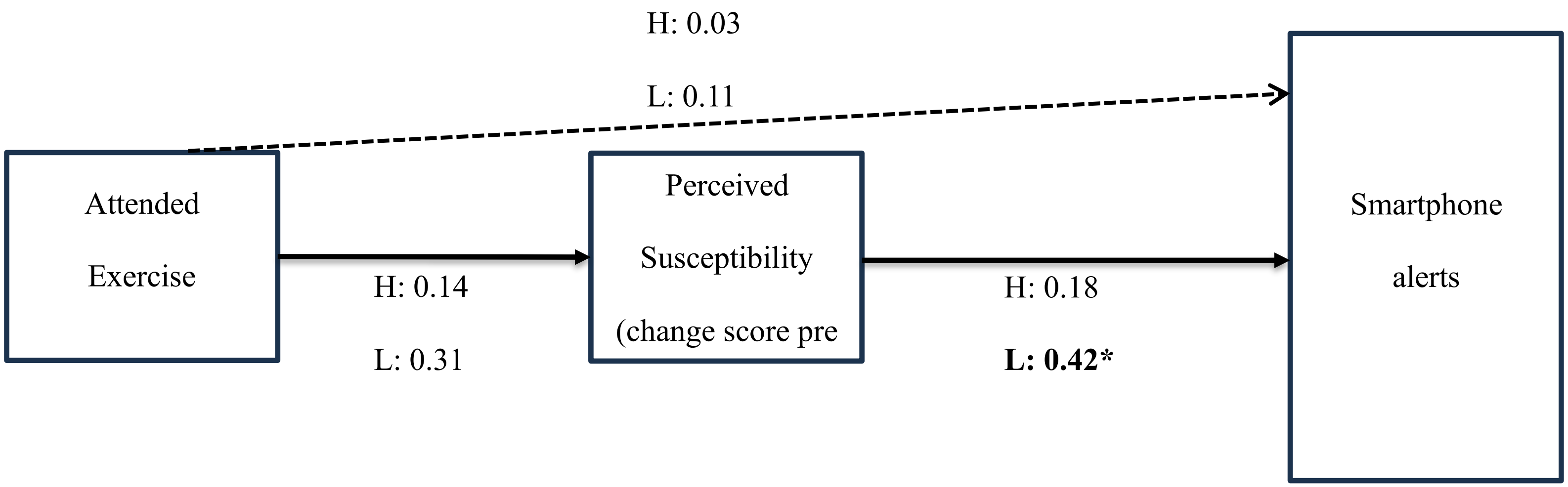

Figure 4.2: Longitudinal Path Model of Exercise Attendance on Receiving Smartphone Emergency Alerts on the Post-Survey through Change in Perceived Susceptibility to Disasters (N = 106). Model invariance test high social resources (H) versus low social resources (L) was significant (p = 0.052). Model adjusted for age.

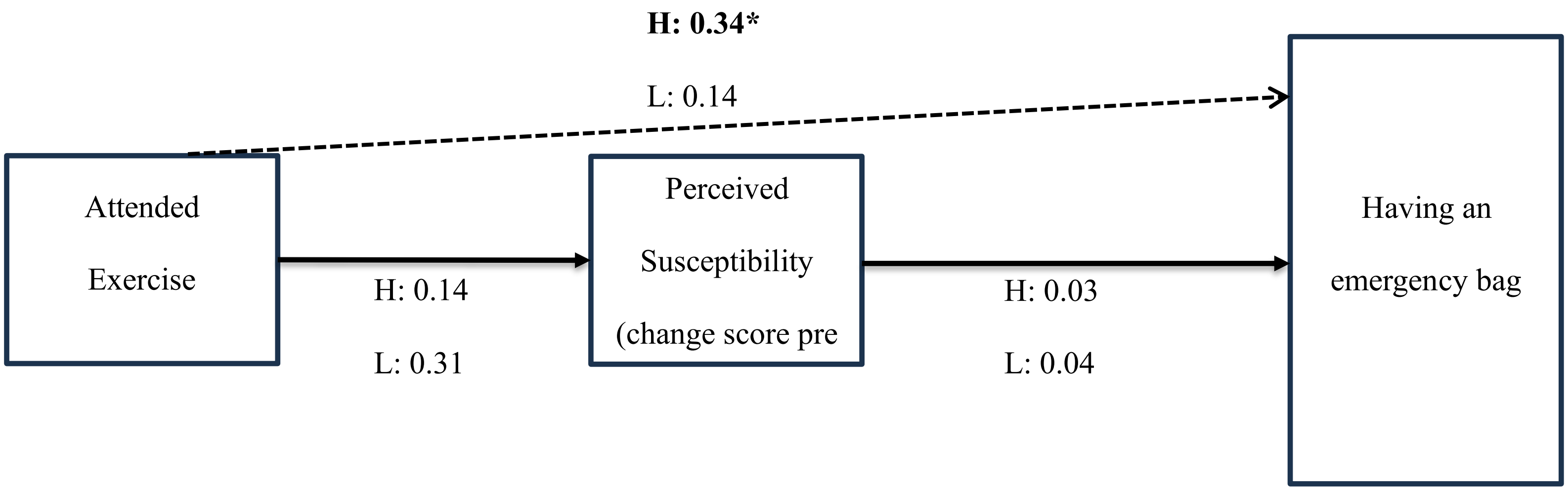

Figure 4.3: Longitudinal Path Model of Exercise Attendance on Having an Emergency Bag on the Post-Survey through Change in Perceived Susceptibility to Disasters (N = 105). Model invariance test high social resources (H) versus low social resources (L) was significant (p = 0.092). Model adjusted for age.

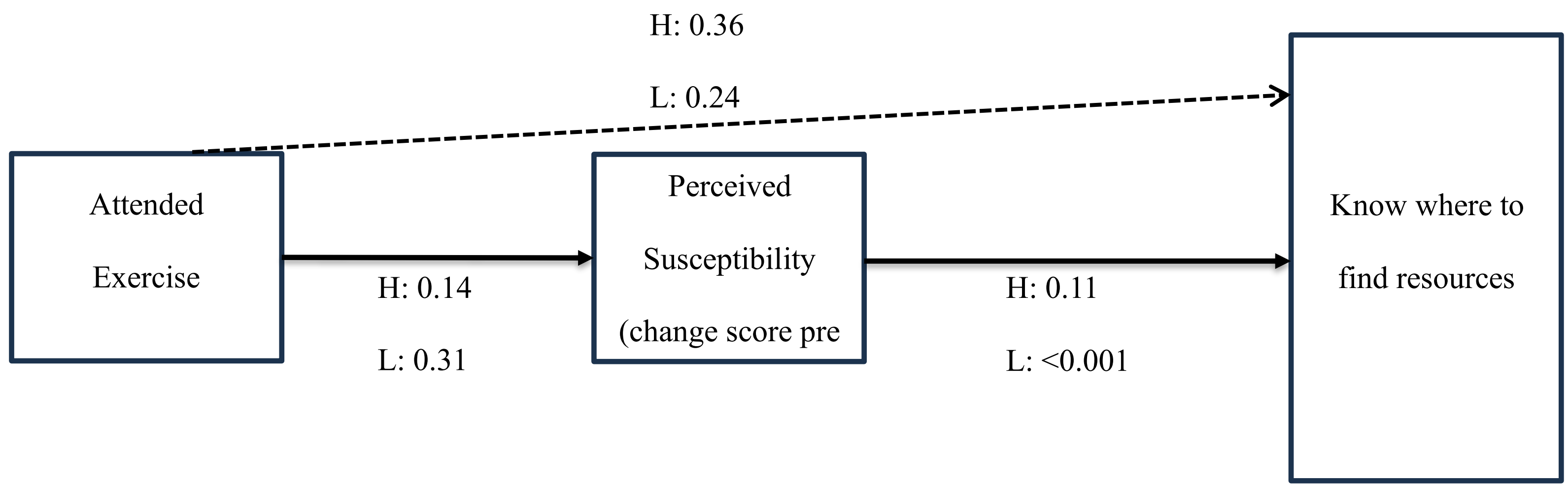

Figure 4.4: Longitudinal Path Model of Exercise Attendance on Knowing Where to Find Resources on the Post-Survey through Change in Perceived Susceptibility to Disasters (N = 106). Model invariance test high social resources (H) versus low social resources (L) was significant (p = 0.054). Model adjusted for age.

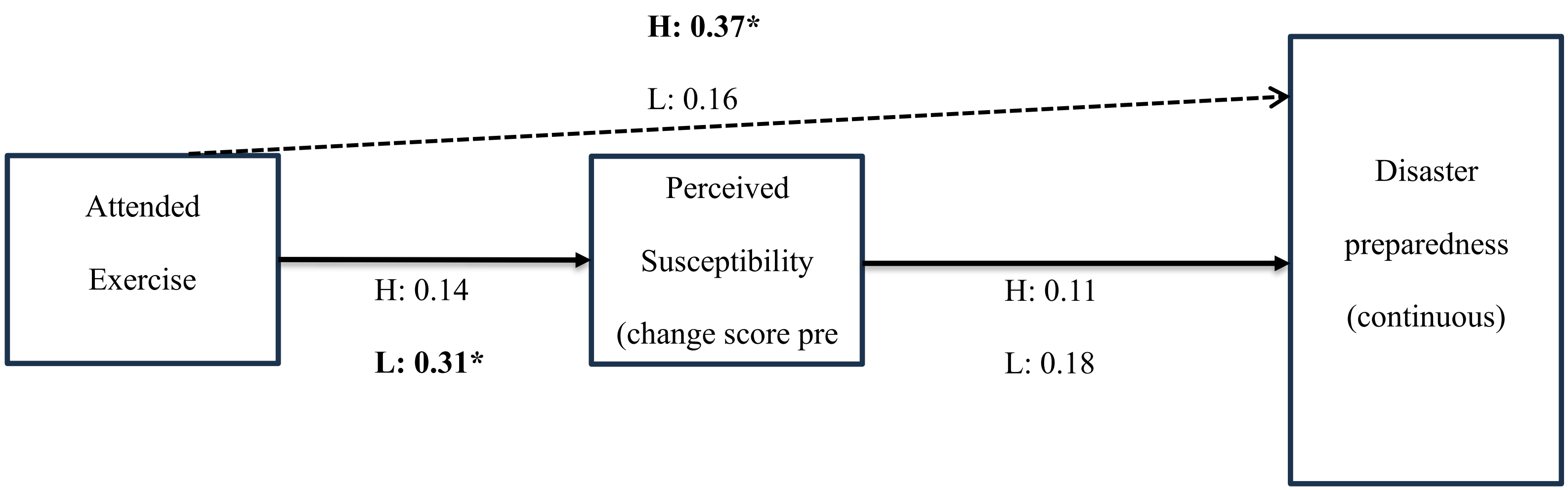

Figure 4.5: Longitudinal Path Model of Exercise Attendance on Number of Adopted Preparedness Behaviors on the Post-Survey through Change in Perceived Susceptibility to Disasters (N = 105). Model invariance test high social resources (H) versus low social resources (L) was significant (p = 0.075). Model adjusted for age.

CHAPTER 5

CONCLUSION

Background and Problem Statement

Climate change is the biggest threat to public health that we face in the coming decades.[1,2,310] The current disaster standard of care and how we handle disasters related to climate change is reactionary, which is inadequate. An emphasis must be placed upon primary prevention methods as well as addressing the social determinants of health (SDoH). Institutionalized racism affects all domains of the SDoH which results in health disparities.[28,311,312] The manifestation of health disparities related to climate change is referred to as the extreme weather-climate gap. Despite the importance of this topic, no epidemiological studies have been identified that specifically name the extreme weather-climate gap. Evidence is presented on how environmental exposures and housing vulnerability affect health outcomes, how residential deprivation affects evacuation behaviors, and the mechanisms through which a community intervention improves disaster preparedness. The goal of these analyses is to disrupt the extreme weather-climate gap and to stop its expansion as climate change accelerates.

Chapter 2

A primary contribution of this chapter was to demonstrate that environmental risk factors cluster in areas with population density. Surprisingly, respiratory illness hospitalizations were not confined to the regions with elevated PM 2.5 which may suggest that some unmeasured aspects of the environment or preventive health behaviors exert a buffering effect against environmental risk factors and population respiratory illness hospitalizations. Housing vulnerability was one specific spatial effect modifier that appeared to confer excess environmental risk in less urban areas. This finding connects with the larger research that economically and racially minoritized individuals are more likely to live in substandard housing.[142,160,264] This vulnerable housing leads to disproportionate exposure to pollutants like PM 2.5.[141,236,237] Lastly, the presence of an increased number of hospitals had a protective effect against increased respiratory illness hospitalizations. This coheres with findings that decreased physical access to care can affect overall health.[265–267] This operates through a lack of preventive services.

These findings illustrate place stratification theory and show areas of high exposure, high vulnerability, and elevated morbidity. This theory speaks to how it is more difficult for racially and economically minoritized individuals to relocate from areas that are deemed undesirable. This in turn results in continued exposure to potentially harmful areas.[84,85] The findings also connect with the geographic component of healthcare.[65,68] The greater presence of hospitals there are in a particular area the larger the protective effect. The theories of spatial assimilation and life course theory are less directly connected but add explanation to the longer-term process that these findings cause. Spatial assimilation postulates that the areas of high vulnerability found in this study are barriers to the people living in those areas from leaving to more desirable spaces.[88]

The implications from these results provide a potential roadmap for federal, state, and local authorities to vulnerable areas. These places of high risk are the intersection of high health risk and high housing vulnerability. To know where these vulnerable areas are allows for improved planning when disasters arrive. It also provides locations for where to intervene. These results could be used to advocate for these areas to take advantage of FEMA's Building Resilient Infrastructure and Communities program to improve housing structures in these areas. This would in turn improve health immediately by reducing housing vulnerabilities, which have been proven to contribute to poor health, but would also prepare vulnerable infrastructure for events like poor air quality due to wildfires. Lastly, the differences shown in the maps across the state suggest that a one-size-fits-all state-level intervention is not suitable; instead, interventions must be tailored to specific locations.

There are several key areas that are recommended for future research on this topic. First, longitudinal studies are needed to examine the long-term health effects of exposure to wildfire smoke. Second, more research is needed examining household indoor air quality for people living in public housing developments. Further understanding the mechanism through which racially and economically minoritized individuals are disproportionately exposed to environmental pollutants is needed.

A component of the extreme-weather climate gap is that place matters. This analysis produced maps that indicate that place indeed matters in the context of exposure to PM 2.5 and respiratory illness hospitalizations. By directly examining the interaction between vulnerable housing, healthcare access, and PM 2.5 exposure, this analysis addresses the social determinants of health (SDoH) and identifies key areas for implementing primary prevention strategies.

Chapter 3

The findings of this chapter contribute to knowledge about how place stratification theory operates within the context of evacuation science. Study subjects residing in deprived census tracts self-selected to evacuate to areas of similar deprivation following a disaster when compared to their neighbors residing in more privileged census tracts. This poses a problem because, in the event of a disaster, displaced individuals are likely to experience disparate recovery outcomes as they relocate to areas that align with the privilege level of their residence.[89,90,199,313] On top of this, people residing in deprived census tracts selected areas that were further away than their privileged counterparts. The effect modification of local social ties buffering evacuation site deprivation level and distance to evacuation site was not seen except for one scenario. For one model, local social ties reduced the distance needed to travel to the evacuation site but only for the deprived group and in the indefinite evacuation scenario. This could point to the effect of enclaves. While these areas would be classified in this analysis as highly segregated, they may offer some protection via social connections when faced with a disaster prompting evacuation.

The relevant theories that these findings connect with are first, the income inequality hypothesis.[199] The measure used in this chapter was that of racialized segregation. However, results presented show significant economic disparities between these areas and those of more privilege. These areas have more burdensome evacuation plans than those residing in more privileged census tracts. Residential mobility is also closely tied to the findings.[33] Even in a hypothetical situation where the study participants could have selected anywhere to evacuate, the findings showed that people who live in deprived areas may not have the social and/or economic resources to move to areas of privilege. The support for social stress theory is mixed.[103–105] There could be a protective effect of living in an area like a racial enclave where people of similar backgrounds group together. These areas may be of low social status, but a sense of connected identity may offer protection against stressors. However, participants from areas of more privilege may have more expansive social networks and therefore more options to evacuate to.

Those living in deprived census tracts may not have as many resources to leverage if local options are not available because a disaster affects their entire city. Lastly, life course theory resonates in this chapter because of the immense strain having to evacuate causes on a person's life.[108] Relocating to an area that is well resourced would greatly improve long-term outcomes. However, these findings suggest that those with fewer resources will likely relocate to areas that also lack resources.

This analysis leverages a unique dataset that captures potential evacuation behaviors and combines it with a widely studied metric of social polarization. The results of this study imply significant differences in evacuation plans by level of residential racial segregation. No studies in the evacuation literature have utilized the metrics included in this analysis, making the contributions of this chapter particularly novel. To counteract the effect of residential deprivation predicting evacuation site deprivation, work must be done on improving community inclusivity.

Future research should leverage existing geospatial technology to track individuals that are faced with an evacuation. This could be best done by conducting a longitudinal study tracking individuals that live in coastal areas that are affected by hurricanes. Tracking these individuals and how they respond to a real evacuation and collecting individual level data on these people would be an informative next step. The questions posed in this chapter informed on the type of content presented in the disaster exercise that is discussed in Chapter 4. Specifically, educating participants on having evacuation plans in place and knowing where to find supportive resources during a disaster.

This chapter highlights two additional key components of the extreme weather-climate gap: that displacement causes further marginalization, and that low-income communities are at higher risk. This analysis also directly examined components of the SDoH as well as a robust metric that quantifies social polarization.

Chapter 4

The analyses of this chapter contribute to understanding factors that enhance or inhibit the effectiveness of a disaster preparedness exercise. It further contributes that a community-based exercise can be short and can significantly improve disaster preparedness.[206–208] The exercise was particularly effective at teaching participants how to prepare an emergency bag that could last 72 hours. The results also indicate differences between the high and low social resources groups. Attending the exercise for participants in the high social resource group was more positively correlated with disaster preparedness than those belonging to the low social resources group. Exercise attendance was associated with increased change in perceived susceptibility however whether this was correlated with improved preparedness was mixed.

The findings of this analysis did cohere with the supporting theories of social cohesion and social stress theory.[100,104,110] These theories informed on the hypothesis that people who lack social resources and who are more likely to be exposed to stressors would not gain as much from an exercise as someone with high social resources and low exposure to stressors. The results showed that those with higher social resources were benefiting more from the exercise in terms of disaster preparedness than those with low social resources. Having lower social resources is potentially a barrier to the effectiveness of the intervention.

The results from this chapter suggest that community-based exercises aimed at improving disaster preparedness work. This importantly demonstrates how investing in primary prevention methods can be done in the disaster preparedness space. This emphasizes the prevention and preparedness components of the prevention-preparedness-response-recovery (PPRR) framework. Resources can effectively be spent prior to a disaster arriving and can improve outcomes when a disaster arrives *and* if one does not. The findings related to social resources and perceived susceptibility inform on future content of disaster exercises and other types of interventions. Initiatives that bolster social resources may in turn improve disaster preparedness.

Future studies should attempt to scale up the sample enrolled in the study to cover a larger geographic area. These studies should also leverage resources to produce multi-lingual materials to address certain barriers to disaster preparedness. Future studies should also emphasize enrollment of individuals that are minoritized and utilize community leaders that can help bolster enrollment from these groups. More longitudinal studies that evaluate the uptake of the information taught during the exercises are needed. Assessing whether the initially adopted behaviors are still being practiced after 6 months or a year is also crucial. The process of identifying factors that create lasting change can also inform on the structure of the exercise content. Lastly, future studies in this area should conduct cost-benefit analyses around these types of exercises. A fundamental way to change policy is to demonstrate that this is saving money and saving lives.

This chapter directly examines a way in which we can address the extreme weather-climate gap through primary prevention. In terms of the cliff analogy, the community-based participatory exercise represents the fence at the top of the cliff preventing people from falling. This intervention can be readily deployed in the absence of a disaster and will improve public health if a disaster never arrives. Investing in this type of intervention also moves away from the reactionary methods currently in use.

Impact Statement

This dissertation investigates the mechanisms through which the extreme weather-climate gap operates using advanced analyses and takes the next step in exploring how local, state, and federal stakeholders can effectively address this issue. This dissertation stands as a call for help from the public health community. It is an injustice that marginalized populations continue to bear the brunt of the destruction from climate change. There is a unique opportunity that lies ahead where continued epidemiologic research into the extreme weather-climate gap can support a paradigm shift in the prevention science space.

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