

THESIS

FLOOD INTERVENTIONS FOR SOCIALLY EQUITABLE COMMUNITY RESILIENCE

Submitted by

Catherine Hood

Department of Civil and Environmental Engineering

In partial fulfillment of the requirements

For Degree of Master of Science

Colorado State University

Fort Collins, Colorado

Fall 2024

Master's Committee:

Advisor: John W. van de Lindt

Rebecca Atadero

Anita Pena

Copyright by Catherine Hood 2024

All Rights Reserved

ABSTRACT

FLOOD INTERVENTIONS FOR SOCIALLY EQUITABLE COMMUNITY RESILIENCE

Flood hazard intensity and frequency are increasing due to climate change and diminish the resiliency of the built environment. Although funds for hazard interventions are available through programs such as the National Flood Insurance Program, Hazard Mitigation Assistance, and the US Department of Housing and Urban Development, these resources are often limited to specific flood zones and agencies have yet to fully consider social equity in their allocation. This study utilizes a community model and performs an analysis to evaluate community resilience through a social equity lens for flood intervention practices. As a case study, the computational platform IN-CORE was utilized to perform a hazard-damage-consequence model for Lumberton, NC, a community damaged by two consecutive flood events (Hurricanes Matthew and Florence). A numerical model for Lumberton was developed using an existing suite of 15 building archetypes to populate the building inventory, which consists of 20,000 structures, and then households are synthetically populated from the census block level to representatively replicate the Lumberton community. An analysis quantifies the social equity of property acquisitions. To assess the distributional equity of property acquisition scenarios, population dislocation projections and resilience metrics are employed.

ACKNOWLEDGEMENTS

To my advisor, Dr. John van de Lindt, I would like to express my sincere gratitude for the opportunity to participate in this research project, the consistent guidance, and the chance to share my research. To my committee members, Dr. Rebecca Atadero and Dr. Anita Pena, I am grateful for your willingness to serve on my committee and your valuable expertise. Dr. Dan Cox, Oregon State University, Dr. Lisa Wang, Old Dominion University, and Dr. Omar Nofal, Florida International University, I would like to convey my appreciation for your mastery and support throughout this project. I am particularly grateful to Dr. Miyuki Hino and Dr. Todd BenDor from the University of North Carolina (UNC) at Chapel Hill for their instruction and counsel. To my family and friends, I deeply appreciate the consistent support throughout this process. Your endless reassurances and encouragements have been invaluable. This study was generously funded by the UNC-Chapel Hill Coastal Resilience Center (CRC), with the Department of Homeland Security (DHS) as the primary source. This support is gratefully acknowledged, and the authors' views are presented herein, and not those of the CRC or DHS.

TABLE OF CONTENTS

ABSTRACT.....	ii
ACKNOWLEDGEMENTS	iii
LIST OF TABLES	vi
LIST OF FIGURES	vii
Chapter 1: Introduction	1
1.1: Purpose and Objectives	2
1.2: Community Resilience Literature Review	3
1.3: Property Acquisition Literature Review	5
1.4: Equity Literature Review	9
2.1: Hazard Modeling.....	13
2.2: Community Modeling	14
2.2.1: Exposure Modeling	15
2.2.2: Vulnerability Modeling	16
2.3: Building Damage and Risk Analysis	18
2.4: Synthetic Allocation.....	19
2.4.1: Population Dislocation	24
2.5: Acquisition Analysis	25
Chapter 3: Illustrative Application for Lumberton, North Carolina	35
3.1: Hazard Modeling.....	40
3.2: Community Modeling	41
3.2.1: Exposure Modeling	42
3.2.2: Vulnerability Modeling	44
3.3: Risk Analysis	45
3.4: Synthetic Allocation.....	46
3.4.1: Exposed Population	47
3.4.2: Population Dislocation	54
3.5: Acquisition Analysis	63
3.5.1: Acquisition Analysis - Exposed Buildings.....	64
3.5.2: Acquisition Analysis - Dislocated Buildings	68
3.5.3: Acquisition Analysis Conclusions.....	72
Chapter 4: Conclusions, Contributions, and Recommendations	73

4.1 Conclusions	73
4.2: Contributions.....	75
4.3: Recommendations	76
Appendix A.....	98

LIST OF TABLES

Table 1: Performance criteria describing flood damage to buildings in terms of four DS ranging from insignificant damage (DS 0) to complete damage (DS 34). Recreated from Nofal and van de Lindt, (2020).	17
Table 2: Annual household income validation.	23
Table 3: Acquisition Analysis Terms and Definitions.....	26
Table 4: Exposed buildings and people in terms of damage state.	45
Table 5: Dislocated buildings and people in terms of damage state.....	46
Table 6: Exposed buildings and people in terms of race (not including NA vacant or group quarters).	47
Table 7: Exposed buildings and people in terms of annual household income.	49
Table 8: Estimated Dislocation Rate by Damage State.	55
Table 9: Dislocated buildings and people in terms of annual household income.....	57
Table 10: Dislocated buildings and people in terms of race (not including NA vacant or group quarters).	57
Table 11: Acquisition analysis base scenarios for further calculation.....	64

LIST OF FIGURES

Figure 1: Interdependent Networked Community Resilience Modeling Environment (IN-CORE, 2023).	4
Figure 2: Framework of Methodology and Analyses	12
Figure 3: Archetype description and building visuals (Nofal and van de Lindt, 2020).....	16
Figure 4: Example of three fragility functions associated with each building archetype (Nofal and van de Lindt, 2020).	18
Figure 5: Community-level flood fragility and loss analysis framework (L_j = replacement/repair cost of each DS, P_{DS} = the exceedance probability of a DS, P_{in_DS} = the probability of being in a DS). Recreated from Nofal and van de Lindt, (2020).	19
Figure 6: Flow chart for housing unit allocation (Rosenheim et al., 2021).	20
Figure 7: Heat map depicting population density.	21
Figure 8: Acquisition Methodology for Exposed Households	27
Figure 9: Acquisition Methodology for Dislocated Households.	31
Figure 10: Lumberton in relation to Robeson County and North Carolina (Nofal and van de Lindt, 2020).	36
Figure 11: Hurricane Matthew's path and timeline created from NCH GIS Archive (2016).	37
Figure 12: Flooding in Lumberton caused by Hurricane Matthew (Wheeler, 2016).	38
Figure 13: Hurricane Florence's path and timeline created from NHC GIS Archive (2018).	39
Figure 14: Hurricane Matthew and Hurricane Florence hit North Carolina as Category 1 Hurricanes.	39
Figure 15: Hurricane Matthew flood inundation depth: (a) Flood inundation depth developed by Nofal and van de Lindt (2019); (b) Flood inundation depth developed by FEMA (2019). See Nofal and van de Lindt (2020) for more details.....	41
Figure 16: Visualization of the Lumberton building inventory overlaying the Hurricane Matthew flood inundation map.	43
Figure 17: (a) Buildings exposed and (b) buildings dislocated from flooding from Hurricane Matthew in terms of damage state.	44
Figure 18: Race and Ethnicity Percentage by Damage State.....	48
Figure 19: Exposed Buildings by Race Compared to Annual Household Income.....	51
Figure 20: Exposed Buildings by Household Income versus Damage States.	52
Figure 21: Exposed Buildings by Race versus Damage State.	54
Figure 22: Dislocated Buildings Ownership by Damage State.	56

Figure 23: Dislocated Buildings by Race Compared to Annual Household Income.	59
Figure 24: Dislocated Buildings by Annual Household Income versus Damage States.	60
Figure 25: Dislocated Buildings by Race versus Damage State.....	62
Figure 26: Buyouts Selected from Exposed Buildings: Comparison of Median and Average Incomes.	65
Figure 27: Buyouts Selected from Exposed Buildings: Comparison of Race.....	67
Figure 28: Buyouts Selected from Dislocated Buildings: Comparison of Median and Average Incomes.	69
Figure 29: Buyouts Selected from Dislocated Buildings: Comparison of Race.....	71

Chapter 1: Introduction

Increased exposure, vulnerability, and climate change drive the escalating prevalence and severity of natural hazards, posing a critical challenge for all communities (NCEI, n.d.). Significant development in vulnerable areas and floodplains and insufficient building codes are exacerbating inequalities in these areas (NCEI, n.d.). With respect to physical damage, economic losses, and social disruption, hurricanes are among the most devastating hazard events. In the aftermath of hurricanes, flooding compromises the resiliency of the built environment. Since 1980, in the United States, there have been 42 flooding events with losses exceeding \$1 billion (NCEI, 2023).

Insurance and funding opportunities are available through the National Flood Insurance Program (NFIP), the Federal Emergency Management Agency (FEMA), the US Department of Housing and Urban Development (HUD), and individual state and local government programs. However, limitations exist in addressing social equity concerns in current funding mechanisms. For example, this oversight has notable implications for communities between the 100-year and 500-year flood zones. Despite facing significant vulnerabilities, these communities often lack funding opportunities due to their heightened risk status.

In the United States, the most prevalent form of mitigation are voluntary property acquisitions (Hino et al., 2021). Property acquisitions, in the context of flood mitigation strategies, are the purchase, relocation, or demolition of a property by a government agency, in which the land remains as open space (Horn, 2024). Voluntary buyouts must present no threat or use of eminent domain (U.S. Department of Housing and Urban Development, 2024). Nearly 44,000 voluntary acquisitions in flood-prone areas have been financed by federal funding programs (Field et al., 2019). White, single-family households predominantly accept these property acquisitions,

highlighting the importance of assessing the needs and vulnerabilities of the community (Elliott et al., 2020; Mach et al., 2019).

Coastal storms and flood hazards have repeatedly impacted Lumberton, an inland city in Robeson County, North Carolina. The city has a racially, ethnically, and financially diverse population. In 2016 and 2018, Category 1 Hurricanes Matthew and Florence hit Lumberton, causing inland flooding due to torrential rains. Following these two events, property acquisitions in and around Lumberton were encouraged by FEMA. Leveraging historical demographic data and the ongoing longitudinal field study (van de Lindt et al., 2018; van de Lindt et al., 2020), this project investigates the impacts of flooding events on infrastructure in inland settings. Considering social equity, this study demonstrates the feasibility of property acquisitions in Lumberton by analyzing population dislocation and recovery modeling. The Lumberton case study is part of a large ongoing research project which will contribute to further collaborative research. This case study utilizes open-source data, developed by Nofal and van de Lindt (2020a; 2020b; 2020c), Rosenheim et al. (2019), Rosenheim (2021), IN-CORE (2021), and van de Lindt et al. (2023).

1.1: Purpose and Objectives

Concentrated in higher-income and densely populated urban areas, property acquisitions raise social equity concerns. This research aims to quantitatively measure the social equitability of property acquisitions to inform community resilience. Detailed comparative analyses of building damage, population density, racial demographics, and annual household income provide an insight into the intersection between flood hazard impacts and socio-economic vulnerabilities. A comprehensive case study is provided by applying this methodology and flood risk assessments to determine the social equitability of property acquisitions in Lumberton.

1.2: Community Resilience Literature Review

Community resilience, the ability to combat and recover from disruptions, is increasingly studied across disciplines, including social science, economics, and engineering. By developing effective strategies to enhance community resilience, these interdisciplinary efforts are crucial (Gupta et al., 2022). Essential for understanding and mitigating flood impacts, four primary components are addressed in flood risk assessments: flood hazard, exposure, vulnerability, and building performance (*Tying Flood Insurance to Flood Risk for Low-Lying Structures in the Floodplain*, 2015). Mitigating flood risk protects properties against flood damage and can lower insurance costs. Elevating utilities, installing flood openings, filling basements, and elevating and relocating properties are common flood mitigation techniques (FloodSmart.gov, n.d.). HAZUS, a software program developed by FEMA, estimates potential losses from natural hazards. Standard risk modeling methods like HAZUS can provide community-level risk assessment yet may lack building-level analysis and fragility functions. The Interdependent Networked Community Resilience Modeling Environment (IN-CORE) (van de Lindt et al., 2023), offers advanced hazard modeling, and integrates physical damage with social and economic data, to inform policy and resource allocation to address this gap and enhance community resilience. See Figure 1 for the cloud services offered by IN-CORE. Utilizing Python frameworks, projects, and modules, pyIncore allows the visualization, application, and assessment of numerous hazard simulations. IN-CORE Web Services and IN-CORE Web Tools enable user creation and retrieval of datasets, hazards, and fragilities. IN-CORE Lab is a custom Jupyter Lab that allows users to create scientific models utilizing pyIncore analyses (IN-CORE, 2021).

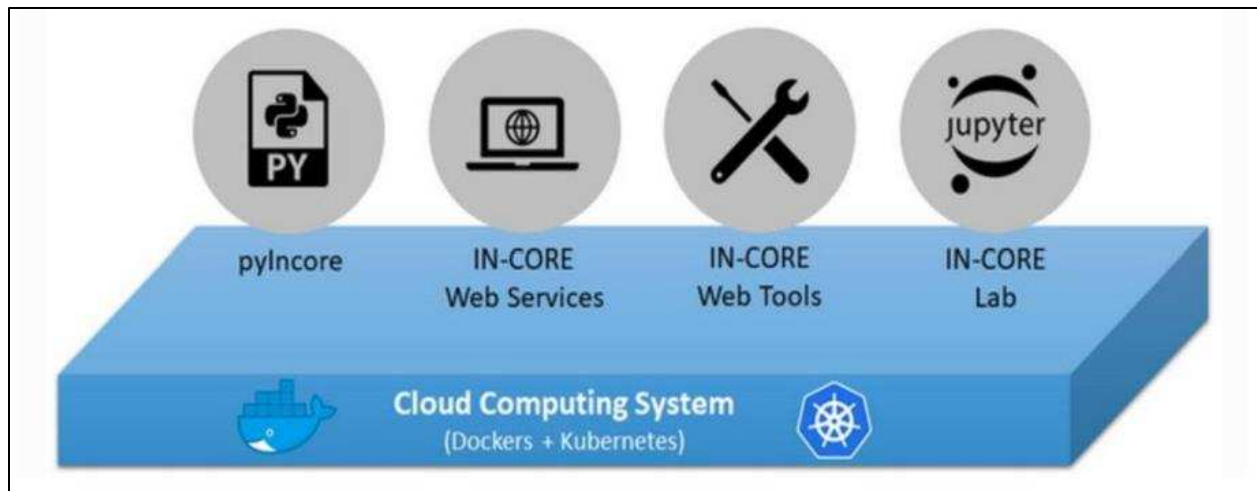


Figure 1: Interdependent Networked Community Resilience Modeling Environment (IN-CORE, 2023).

Colorado State University leads the development of IN-CORE, in a cooperative agreement with The National Institute of Standards and Technology (NIST). IN-CORE measures the resilience of communities through computational resilience analyses, enabling natural hazard impact modeling. Incorporating risk analysis with decision-making processes, IN-CORE quantitatively compares resilience strategies, i.e., “what if” scenarios. IN-CORE links physical damage with socioeconomic information to estimate impacts of population dislocations and determine the best policies for a community. Probabilistic modeling, optimization techniques, and other advancements in computational tools improve natural hazard resilience assessments (Melendez et al., 2022). Employing these tools, researchers model complex scenarios and optimize resilient community designs (Magis et al., 2010). Aimed at modeling community resilience, a study by Gupta et al. (2022) illustrates the capabilities of minimizing the social and economic losses caused by natural hazards. Researchers including Sen et al. (2021;2022) utilize Bayesian belief networks and machine learning to enhance infrastructure resilience. Innovations in hazard preparedness and response emphasize the vital roles of these advancements.

Flood damage and loss assessment methods are crucial for understanding the impacts of floods on communities. Deterministic stage-damage functions and probabilistic fragility functions enable the development of targeted mitigation strategies to reduce vulnerability (Gupta et al., 2022). As discussed by Nofal and van de Lindt (2021), probabilistic assessment of flood vulnerability across different building types can be determined using detailed building archetypes and Monte Carlo simulations. Utilizing census-block level data for building-level analysis, Rosenheim et al. (2021) aligns detailed household and housing unit characteristics to individual buildings. In practice, economic losses due to flood damage can be significantly minimized by optimizing mitigation strategies at the building level. A multi-objective optimization framework, proposed by Almoghathawi et al. (2021), highlights potential to achieve cost-effective resilience. Devising these methodologies has proven essential for implementing mitigation measures at the building and community levels.

1.3: Property Acquisition Literature Review

Across the US, extensive flooding, caused by increases in and changes in patterns of extreme weather events, results in devastating impacts to the built environment (NCEI, 2013). Therefore, natural hazard mitigation strategies and their physical and economic impacts have become increasingly important research topics.

Structural solutions, including dams, floodwalls, and levees, were the primary US flood control strategies throughout the twentieth century (Conrad et al., 1998; Wright, 2000). However, federal policy shifted towards nonstructural measures following the record-breaking floods in the Midwest in 1993, prioritizing land-use planning, acquisition of flood-damaged buildings, and regulations to limit development in hazard-prone areas (Godschalk et al., 1999).

Dominating the market, the NFIP provides over 95% of residential flood insurance policies (Hino and Burke, 2021). Created in 1968, the NFIP aims to offer federal flood insurance to residents and businesses in communities that adopt floodplain management regulations, therefore reducing flood risk to individuals and limiting reliance on federal hazard relief (*Tying Flood Insurance to Flood Risk for Low-Lying Structures in the Floodplain*, 2015). Private insurance companies and specialized state programs also offer floodplain insurance. For instance, the North Carolina Beach Plan and Strengthen Your Roof North Carolina programs supplement federal programs by providing North Carolina residents customized solutions that manage flood risks. Considering a structure's elevation and the likelihood of inundation and damage, insurance rates reflect risk of flooding. An estimated 30% of households in floodplains carry flood insurance, and many are underinsured (Almoghathawi et al., 2021; Hino and Burke, 2021).

FEMA's Flood Insurance Rate Maps (FIRMs) are the primary source of flood risk information and inform land use regulations (Hino and Burke, 2021). Estimating 13 million Americans live within a 1% annual chance floodplain, NFIP floodplain maps are highly granular, often splitting houses on the same block. Interestingly, Wing et al. (2018) estimated that 41 million Americans live within a 100-year floodplain, using high-resolution spatial data. Highlighting potential limitations in FEMA's flood mapping, this discrepancy stresses the importance of advanced flood risk assessment methods (Mach et al., 2019).

Beyond insurance coverage, agencies including FEMA and HUD provide federal funding opportunities, alongside state and local programs. Implemented when other mitigation strategies are impractical, property acquisitions hinge on factors such as a property's flood risk assessment, market value, anticipated economic loss, and the homeowner's consent to relocate (FEMA, 2016). Aimed at reducing flood vulnerabilities, property acquisition programs are utilized for properties

located within floodplains, but outside protected zones. Ensuring that funding is directed towards properties most in need of flood risk reduction, these programs' structured approach aims to maximize the effectiveness of mitigation efforts. In the US since 1993, federal programs have sponsored the acquisitions of over 44,000 properties. Funding over 70% of federally acquired buyouts, FEMA has been instrumental in financing hazard recovery efforts (Mach et al., 2019). FEMA's Hazard Mitigation Assistance program (HMA) reduces hazard losses by funding mitigation projects through the Hazard Mitigation Grant Program (HMGP), the Building Resilient Infrastructure and Communities program (BRIC), which replaced the Pre-Disaster Mitigation Grant Program in 2020, and the Flood Mitigation Grant program (FMA) (FEMA, 2020). Although typically requiring a 25% nonfederal cost match from state or local governments, or individuals, HMA programs fund up to 75% of total project costs after a Presidential major disaster declaration. Individual home and business owners are unable to directly apply for HMA funds (FEMA, 2020). The National Institute of Building Sciences (NIBS) resolved that federal mitigation grants, including those for property acquisitions, resulted in avoided losses of \$6.00 for every \$1.00 invested (Multihazard Mitigation Council, 2017; BenDor et al., 2020). While economically efficient, these programs exhibit limitations. For example, FMA grants are limited to NFIP insured properties, and structural improvements to properties acquired with HMGP funds are deed-restricted (Conrad et al., 1998). Also, HMGP funds can be used to acquire properties outside the 100-year flood boundary only if FEMA's benefit-cost analysis (BCA) requirements are met (Tate et al., 2016).

HUD programs help with recovery from large scale hazards after Presidential major disaster declarations by offering funding opportunities through the Community Development Block Grants for Disaster Recovery program (CDBG-DR). CDBG-DR programs can provide the HMA required

nonfederal cost match (25%) or directly fund property acquisitions (HUD, 2020). Mitigation efforts undertaken with CDBG-DR funds must benefit low or moderate-income (LMI) populations, reduce community vulnerabilities, or improve public safety by addressing community development (HUD, 2020).

CDBG-DR, the most flexible funding source for hazard recovery, allows states discretion in program funds' design, allocation, and management (Tate et al., 2016). Despite property ineligibility for HMGP funding due to deed restrictions and potentially encouraging redevelopment in previously flooded zones, nearly half of CDBG-DR property acquisitions were properties within the 100-year floodplain (Siders et al., 2019).

Struggling to meet cost-match requirements, state and local governments are proactively utilizing traditional and innovative financial mechanisms as tools to fund property acquisitions and minimize hazard risk, including municipal and green bonds, revolving loan funds, and stormwater utility fees (Peterson et al., 2020). Alternative funding mechanisms help maximize resource allocation for property acquisitions, aiding more homeowners (Peterson et al., 2020). Leveraging multiple funding sources, state and local governments commonly combine CDBG-DR and FEMA funding to implement property acquisitions, purchasing approximately 9,600 flood-prone properties, representing over 20% of properties acquired through federal grants (Peterson et al., 2020). Although, often inefficiently managing homeowner participation, lacking necessary data needed to accurately estimate property acquisition costs, and having conflicting requirements, state and local government programs can further grantee burdens (BenDor et al., 2020; Gao, 2021; Martin et al., 2019).

FEMA's cost benefit analysis targets homes costing less than \$323,000 (FEMA, 2022a). Typically, 80% or less of project costs are allocated to purchasing costs, although transaction costs are not

separated in federal program data (Curran-Groome et al., 2021). Other than purchasing costs, all costs are nearly \$23,000 per property (Curran-Groome et al., 2022).

In the US, between 1989 and 1998, on average 19 properties were acquired through buyout projects (median of six), yet between 2009 to 2017, the average reduced to seven properties (median of two), with many counties using buyouts only once (Mach et al., 2019; FEMA, 2020). Although constrained by funding, property acquisitions as a flood mitigation technique are increasing due to consistent development in floodplains, urbanization, and more extreme flooding events (National Climate Assessment, 2014; Kihslinger and Moraga, 2017).

1.4: Equity Literature Review

Although economically efficient at reducing future flood losses (FEMA, 2016), property acquisition programs often lack evidence of social equity. For the purposes of this project, social equity is defined as the even allocation of resources, aiming for equal distribution (horizontal equity) unless justified reasons support different distributions (vertical equity) that may affect more vulnerable populations (Martens et al., 2012; Jones and Armanios, 2020). At a programmatic level, property acquisitions are underexamined, raising concerns about exacerbating wealth disparities in minority and low-income communities (Mach et al., 2019).

Broader societal goals such as social, cultural, psychological, or long-term economic consequences are often neglected in property acquisitions (Siders et al., 2019). Criticisms arise regarding bureaucratic inefficiencies and exacerbated wealth and racial disparities. Further complicating the effectiveness of buyouts, poor communication, insufficient funding, and unequal distribution of benefits cause delays in implementation (Curran-Groome et al., 2022; De Vries, 2017; Elliott et al., 2020; Loughran and Elliott, 2019; Siders, 2019; Weber and Moore, 2019; Kraan et al., 2021;

Hino et al., 2017; Howell and Elliott, 2018; Mach et al., 2019; Peterson et al., 2020; Elliott et al., 2021). Economic factors often overshadow the growing considerations of social equity in property acquisitions (Bishop, 2017). Various dimensions of buyouts have been explored in the literature, including social equity and cost-effectiveness (Tate et al., 2016), land-use impacts (Zavar and Hagelman, 2016), and homeowner decisions (Bukvic and Owen, 2017; Binder et al., 2015). However, literature concerning transportation and infrastructure systems (Jones and Armanios, 2020; Bishop, 2017), service outages (Beck et al., 2023), and extreme heat adaptation (Turek-Hankins et al., 2020) identifies significant gaps remaining in understanding equity. Flood risk management studies regarding social equity are difficult to generalize due to contextual nuances (Hino and Nance, 2021).

Although lower income households in neighborhoods with high social vulnerabilities are often targeted (Elliott et al., 2020; Mach et al., 2019), white residents are more likely to accept property acquisitions (Robinson et al., 2018; Loughran et al., 2019; Martin et al., 2019). Single-family households, in wealthy, densely populated urban counties with greater local government capacity are often favored by federal funding programs (Bukvic and Borate, 2021; Seong et al., 2022). While mitigating property loss and human suffering in flood prone areas, buyouts perpetuate funding inequalities affecting disadvantaged groups (Freudenberg et al., 2016; Hino and Nance, 2021). Inadequate and delayed compensation often exacerbate social, economic, and spatial inequalities for low to moderate-income households (Bullard and Wright, 2009; Smiley, 2020; Tate et al., 2021; Tate et al., 2016).

Households residing in high-risk areas with limited access to safer land often lack political power and bear disproportionate hazard impacts (Willett et al., 2020). Exacerbating racial and class divisions, property acquisitions hinder post-hazard recovery efforts (Gotham, 2014; Green et al.,

2007; Green and Olshansky, 2012; Hino and Nance, 2021). To identify at-risk populations, inform policies, and optimize resource allocation, social vulnerability metrics are vital (Hinkel, 2011), although hazard type, geographic location, economic condition, and historical norms are typically overlooked (Tate et al., 2016).

To enhance community resilience, social equity must be considered (Martin et al., 2018), yet explicit equity goals and comprehensive vulnerability metrics are missing from current funding programs (Shi et al., 2022). Flood impacts beyond economic losses include the social costs of buyout programs, displacement impacts, healthcare access, employment, and physical and mental health are limited in the literature, yet typically influence a community's attitude. (Blaze & Shwalb, 2009; Hori & Schafer, 2009; Mortensen et al., 2009; Binder & Greer, 2016; Hino and Nance, 2021; Hino et al., 2017). Data limitations hinder advancements in assessing mitigation strategies and their equitability (Tate et al., 2016; Wisner et al., 2004; Cutter et al., 2003; Phillips et al., 2010). Without qualitative analyses, standardized vulnerability metrics may inadequately inform adaptation decisions. (Sanders et al., 2003; Weber & Peek, 2012; Riad & Norris, 1996). Vulnerability metrics, which have limitations at the census-tract level, are examined by Turek-Hankins et al. (2020) and highlight significant household-level differences. Capturing household-level vulnerabilities in nuanced research methodologies are required to develop inclusive and effective policies (Turek-Hankins et al., 2020).

To support vulnerable communities and mitigate unintended inequalities, advancing research on equity implications in federal funding programs is critical. This research is intended to quantify social equitability in terms of income levels, through census data, synthetic household allocation, and the IN-CORE Platform to contribute to hazard resilience efforts amidst climate change impacts.

The remaining chapters of this thesis are organized as follows and illustrated in Figure 2: Chapter 2 presents the existing methodology for evaluating hurricane risk, detailing hazard and community modeling, as well as damage and risk analyses. Chapter 3 applies these modeling techniques to Lumberton, North Carolina, an ethnically and financially diverse community, and analyzes the results to quantify the social equitability of property acquisitions. Finally, Chapter 4 provides conclusions, contributions, and recommendations to further social equity research.

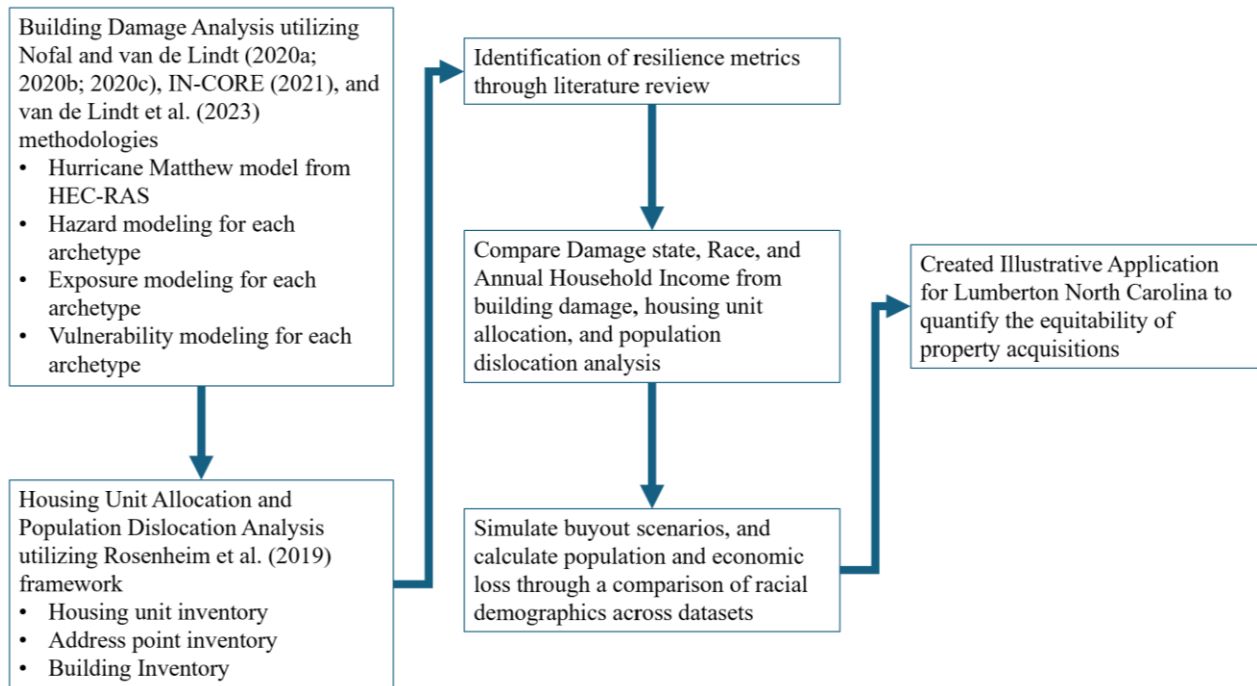


Figure 2: Framework of Methodology and Analyses

Chapter 2: Methodology for Evaluating Hurricane Risk

Assessing natural hazard risk involves evaluating community hazard, infrastructure, exposure and vulnerability models (NOAA National Centers for Environmental Information, 2023). Risk mitigation strategies are needed to reduce one or all hazard components and improve the resiliency of communities pre-and post-hazard. Requiring detailed information at various levels to evaluate community risk post-hazard, high-resolution models combine hazard, exposure, and vulnerability components.

Utilizing the IN-CORE Platform for advanced risk and resilience assessments, community infrastructure-socio-economic models focus on measuring socially equitable community resilience (IN-CORE, 2021). To synthetically populate each household to replicate the community, a numerical model was performed using structure archetypes to create the building inventory (Nofal and van de Lindt, 2020). Initially, using the Hydraulic Engineering Center's River Analysis System (HEC-RAS), Nofal modeled a community and hazard. To address damage and prepare risk and mitigation analyses at the community level, hazard, exposure, and vulnerability models were developed. Based on the work of Rosenheim et al. (2021), housing unit, building, and address point inventories were utilized in housing unit allocation and population dislocation analyses. Using the synthetic population allocation model, individual residential households were synthetically populated. When aggregated, the synthetic household reproduces census block-level information. Then, an analysis incorporates this data to quantify the social and distributional equitability of a suite of acquisition scenarios.

2.1: Hazard Modeling

Hydrologic and hydrodynamic analyses, utilizing HEC-RAS software to develop hurricane flood paths, are required for inland community hazard modeling (Nofal and van de Lindt, 2020). Using a hydrograph to depict rainfall and streamflow over time, hydrologic analyses predict water discharge in ungauged streams. Hydraulic principles are applied to hydrodynamic analysis, determining flood characteristics such as depth, extent, velocity, and duration. To assess hazard intensity for each exposed building, these flood characteristics are mapped and overlaid with the community model.

2.2: Community Modeling

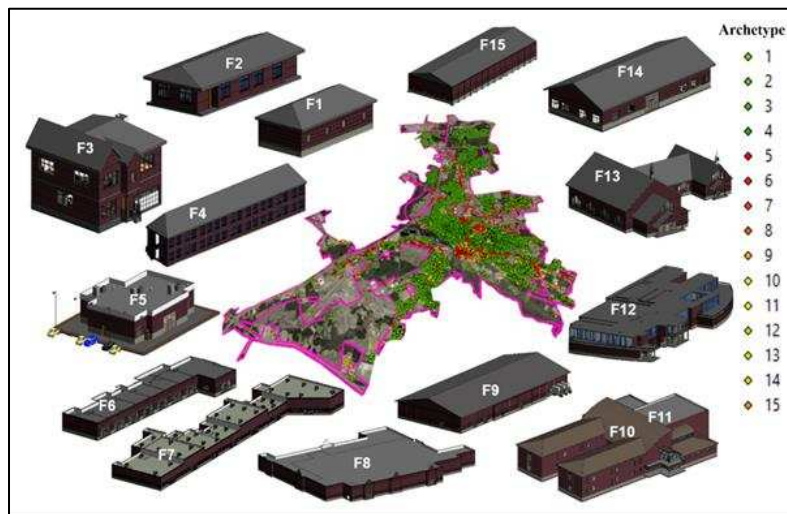
Community modeling incorporates understanding and representations of various physical social, and economic characteristics of a community (Nofal et al., 2021). Community risk profiles provide a comprehensive picture of exposure and vulnerability models. Affecting hazard recovery, a community model considers the repair of physical damage to the impacted buildings and infrastructure, and many socio-economic factors that could cause delays to the repair process. To account for the interdependent relationships between households, buildings, and networks, a comprehensive community recovery model is necessary.

Risk information decisions are dependent on the number of archetypes representing the different building typologies in the community. Characteristics such as crawl space and first-floor elevation (FFE), determine the archetypes assigned to buildings. Relationships between specific flood characteristics and their corresponding exceedance probability of a predefined damage state are represented by fragility functions, fitting a log-normal distribution. Damage states describe the probability of a building being in, or exceeding, a prescribed level of damage as a function of flood depth with respect to FFE.

2.2.1: Exposure Modeling

Essential for reliable predictions and accurately assessing flood risk, building information details exposure data. Obtained from parcel data, basic building inventory information including location, market value, occupancy, flood zone, and year built is often insufficient for flood risk assessments. To accurately capture flood damage at the community level, more detailed building characteristics are required such as building type, house dimensions, construction materials, number of stories, foundation type, first-floor elevation, and maintenance condition (Nofal et al., 2021).

Fifteen building archetypes, developed by Nofal and van de Lindt (2020), were used to comprehensively model the building inventory within the community. Figure 3 displays a brief description and visual representation of the archetypes (Nofal and van de Lindt, 2020).



Building Archetype	Building Description
F1	One-story single-family residential building on a crawlspace foundation
F2	One-story multi-family residential building on a slab-on-grade foundation
F3	Two-story single-family residential building on a crawlspace foundation
F4	Two-story multi-family residential building on a slab-on-grade foundation
F5	Small grocery store/Gas station with a convenience store
F6	Multi-unit retail building (strip mall)
F7	Small multi-unit commercial building
F8	Super retail center
F9	Industrial building
F10	One-story school
F11	Two-story school
F12	Hospital/Clinic
F13	Community center (place of worship)
F14	Office building
F15	Warehouse (small/large box)

Figure 3: Archetype description and building visuals (Nofal and van de Lindt, 2020).

Alternatively, GIS model layers hold crucial building information including location, FFE, market value, occupancy, foundation type, and number of stories. Based on building characteristics, a mapping algorithm was developed by Nofal and van de Lindt (2020) to match each building archetype within the building portfolio to real buildings in the community. Assessing hazard intensity at each building location, the mapping algorithm is applied, and the modeled community is overlaid with the hazard layer.

2.2.2: Vulnerability Modeling

To model flood vulnerability Nofal and van de Lindt (2020) developed advanced 2-D and 3-D flood fragility and loss functions. Designed to account for the probability of exceeding predefined damage states (DS) and estimate direct monetary flood losses, these functions integrate uncertainties throughout the damage model, including flood depth and duration, and replacement/repair costs. The 2D fragilities are applied in this study and shown in Table 1.

Table 1: Performance criteria describing flood damage to buildings in terms of four DS ranging from insignificant damage (DS 0) to complete damage (DS 34). Recreated from Nofal and van de Lindt, (2020).

DS	Description
DS 0	Insignificant damage to components below first-floor elevation. Water enters crawlspace/basement and touches foundation (crawlspace or slab on grade). Damage to components within the crawlspace/basement including base insulation and stores inventory. Minor damage to garage interiors including drywall, cabinets, electrical outlets, and wall insulation. (Garage is below the first-floor elevation (FFE)). No sewer backup into the living area.
DS 1	Water touches floor joints up to minor water entering the building. Damage to carpets, pads, baseboards, and flooring. Damage to the external AC unit (if the AC unit is not elevated) and the attached ductworks (if ductworks are in the crawlspace). Complete damage to the garage interior (if the garage is below FFE). Could have a sewer backup and/or mold issues. Partial damage to drywalls along with damage to electrical components (base-outlets), water heater, and furnace. Complete damage to major equipment, appliances, and furniture on the first floor. Damage to the lower bathroom and kitchen cabinets. Doors and windows may need replacement.
DS 2	Damage to the non-structural components and interiors within the whole building including (but not limited to) drywall damage to upper stories for multi-story buildings (e.g., attic, second story, etc.). Electrical switches and mid-outlets are destroyed with potential damage to ceiling lighting fixtures. Studs' reusable, some may be damaged. Major sewer backup will happen along with major mold issues. Equipment, appliances, and furniture on the upper floors are also damaged (e.g., attic, second floor, etc.).
DS 3	Significant structural damage present (e.g., studs, trusses, joints, etc.). Non-structural components and interiors are destroyed including drywall, appliances, cabinets, furniture, etc. Damage to rooftop units/components including roof insulation, sheathing, and electro-mechanical systems (rooftop AC units, electrical systems, cable railing, sound system, etc.). Foundation could be floated off. The building must be demolished or potentially replaced.

Nofal's approach accurately accounts for the combined impact of flood depth and duration by including flood duration in the vulnerability function. A mapping algorithm using hazard intensities at each location as input, assigns flood vulnerability curves or surfaces (fragility or loss functions) to each building archetype. Examples of fragility functions are shown in Figure 4. Ensuring flood risk assessments capture the varied characteristics and vulnerabilities of different building types within a community, more reliable and actionable predictions of flood damage and associated losses are possible with this comprehensive approach.



Figure 4: Example of three fragility functions associated with each building archetype (Nofal and van de Lindt, 2020).

2.3: Building Damage and Risk Analysis

Flood risk components, fragility models, and damage state probabilities are combined to compute structural damage. Flood hazard maps (containing spatial data on flood depths and extents), community models (including building data), and vulnerability models (describing the probability of a building reaching different damage states at given flood depths) are utilized in the framework. According to the characteristics of each inundated building from the community model, an archetype is assigned. Damage state probabilities are computed as the difference between the exceedance probabilities of adjacent damage states, calculating the expected loss for each building. Building's damage states are determined as the damage state with the highest probability. Seen in Figure 5, this methodology assesses overall community resilience.

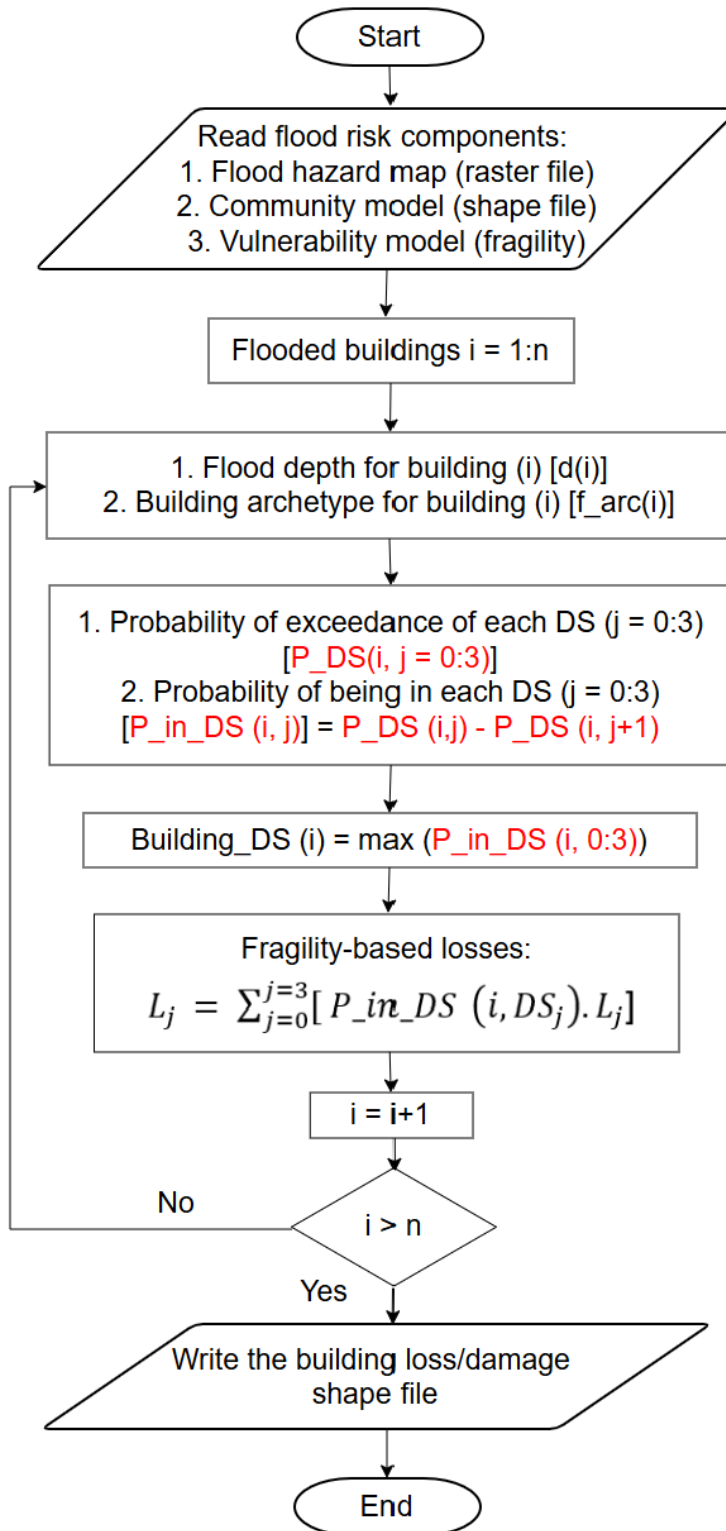


Figure 5: Community-level flood fragility and loss analysis framework (L_j = replacement/repair cost of each DS, P_{DS} = the exceedance probability of a DS, P_{in_DS} = the probability of being in a DS). Recreated from Nofal and van de Lindt, (2020).

2.4: Synthetic Allocation

Analysis data is aggregated using census blocks and tracts. Cross-referencing population counts with data collected during the 2010 Decennial Census validates the housing unit allocation results. Disparities may stem from political boundary and building inventory differences, as detailed by Rosenheim et al. (2021) in Figure 6.

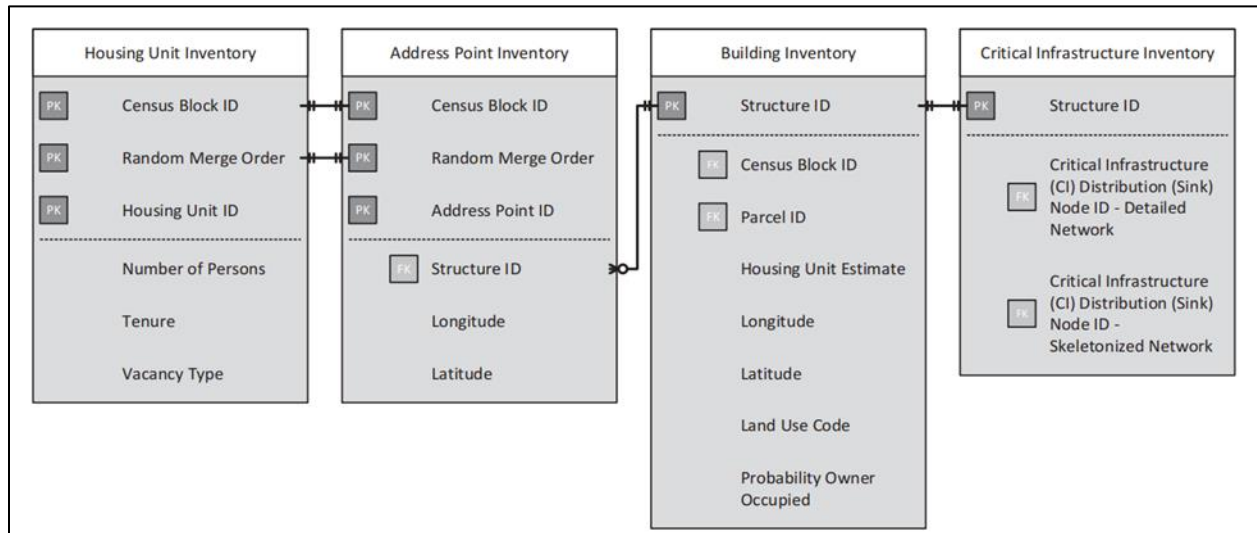


Figure 6: Flow chart for housing unit allocation (Rosenheim et al., 2021).

Establishing a comprehensive critical infrastructure inventory, this analysis aligns housing unit characteristics with physical systems such as building inventories and water networks. Hazard impact statistical analysis accounts for uncertainty in allocating housing units to buildings. Resilience-informed decision-making in natural hazards requires detailed household and housing unit characteristics.

Rosenheim et al.'s (2021) methodology follows a systematic approach: data and information availability, community model development, spatial hazard analysis, physical damage and functionality analysis, and socio-economic impact analysis (Roohi et al., 2020). Housing unit allocations provide detailed housing unit demographics including the number of people in each household, race, ethnicity, tenure, and vacancy assigned to individual housing units. Important to

note, this method is a synthetic allocation, providing accurate results at the census block and community levels, but not for individual households. Figure 7 depicts a heat map for population density resulting from the housing unit allocation validation process for Robeson County.

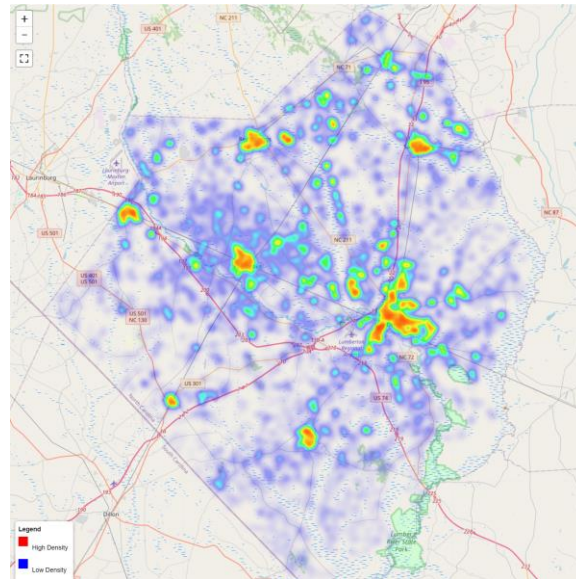


Figure 7: Heat map depicting population density.

From 2016 to 2023, a multidisciplinary team of engineers, social scientists, and economists evaluated Lumberton’s recovery process after Hurricane Matthew (van de Lindt et al., 2020). Lumberton is only a small area of Robeson County, and specific buildings were chosen for the building damage analysis, therefore validation of the housing unit allocation process was necessary. Calculated for each census tract, median and average household income were each compared to the median and average income collected by US Census data, seen in Table 2. 60% of census tracts for median household income are within 5% of census data, and 75% of the census tracts are within 10%. 50% of the census tracts for average household income are within 5% of the census data, and 70% are within 10%. Remaining census tracts, not within 10% of the census data, are geographically justified. To be geographically justified, selected buildings are not accurately represented in the census tracts. For example, if the Lumberton housing unit inventory only has

10% of the buildings that are in the census tract, they are geographically justified because the data cannot be accurately predicted. Errors occurred due to specifically analyzing select buildings in Lumberton rather than the entire County of Robeson, see Appendix Figure A1. Other household characteristics defined by the housing unit allocation process were compared to 2010 US Census data including population, tenure, race, ethnicity, family status, vacancy, group housing, and poverty, although there were no noticeable differences.

Table 2: Annual household income validation.

Census Tract	Median Population	Median Income Group	Median Household Income	Median Assigned Income	Average Assigned Income	Census Median Income	Census Average Income	Median Percent Error	Average Percent Error	Geographically Justified
37155960102	3	10	3	58316.00	58316.00	28636	42210	104%	38%	Yes
37155960402	4	15	5	171263.50	152768.25	33933	46901	405%	226%	Yes
37155960503	3	9	3	47065.50	54815.23	45154	60297	4%	9%	Yes
37155960600	2	5	3	32533.50	41624.13	32500	41691	0%	0%	No
37155960701	2	6	3	32071.00	44975.53	31615	43781	1%	3%	Yes
37155960702	2	5	3	30321.00	45895.07	31064	48927	2%	6%	No
37155960801	2	2	1	15916.00	27291.15	15503	27691	3%	1%	No
37155960802	2	5	3	29263.00	34233.67	30625	34653	4%	1%	No
37155960900	2	8	3	47644.00	63144.83	47128	71202	1%	11%	No
37155961000	2	5	3	30401.00	42853.17	32206	43207	6%	1%	No
37155961100	2	3	2	21112.00	33442.76	20987	31644	1%	6%	No
37155961200	2	5	3	27508.50	36461.56	26609	35258	3%	3%	No
37155961301	2	8	3	52623.00	71010.99	57316	75752	8%	6%	No
37155961302	2	5	3	36390.50	54752.91	38553	68103	6%	20%	No
37155961400	2	6	3	36483.00	45283.54	36182	47244	1%	4%	Yes
37155961500	2	6	3	36402.00	42290.05	38486	42380	5%	0%	Yes
37155961601	2	5	3	31054.00	39652.25	35490	45021	12%	12%	Yes
37155961602	2	6	3	41494.00	52188.73	35920	50791	16%	3%	Yes
37155961700	2	4	2	25570.50	46666.07	21500	33836	19%	38%	Yes
37155961802	2	6	3	31217.00	36643.96	31309	35980	0%	2%	Yes
							Within 5%	60%	50%	
							Within 10%	75%	70%	

2.4.1: Population Dislocation

Population dislocation is defined as households that are either forced, or choose, to leave their residence due to hazard-related damages (IN-CORE, 2021). Generally, households with higher levels of damage will be forced to relocate for safety and comfort. Depending on structure value loss, neighborhood characteristics, and structure type, the population dislocation algorithm allocates detailed housing unit and household characteristic data to each residential building. Households that will dislocate immediately following the hazard event are predicted in this model. For a detailed summary of the dislocation model, see Rosenheim et al., (2019), Peacock et al., (2008), and Peacock et al., (1997).

Results from housing unit allocation and building analyses serve as inputs for the dislocation model to predict population dislocation based on a specific hazard event (Rosenheim et al, 2021). Using the housing unit allocation analyses, housing units characterized by tenure, household size, and occupancy status, are allocated to address points (buildings). Once allocated, the value loss of each structure is determined by the hazard event, defined through fragility and hazard services, and is then used in the dislocation calculations.

Population dislocation model results contain data from the housing unit allocation (HUA) analyses, including estimates of damage states at the parcel level, with 2010 Decennial Census as primary source. Based on household surveys, the model predicts dislocation probability using a logistic regression model (Bai et al., 2009; Rosenheim et al., 2019; Peacock et al., 1997; Peacock et al., 2008; US Census Bureau, 2010). To determine dislocation probability, the logistic regression equation factors in value loss, block group characteristics, and other variables. The household is

set to dislocate if a uniformly sampled random value between 0 and 1 is less than the dislocation probability.

2.5: Acquisition Analysis

This research aims to quantify the social equitability of property acquisitions. Evaluating how input variations influence outputs under specific conditions is essential for assessing model reliability and guiding decision-making processes in risk assessment and optimization. Ensuring robust indicators, these analyses enhance assessment credibility by identifying influential factors that disproportionately affect outcomes (Kienberger and Hagenlocher, 2014; Tate, 2012).

Data analyses are divided into three datasets: the total dataset covering all housing units; the exposed dataset comprising flood-exposed buildings, and the dislocated dataset consisting of buildings selected for dislocation (a subset of the exposed dataset). Baseline metrics are derived from these datasets including total building and population counts, and income statistics. Calculations are determined for the total building count (N_{B-T}), the total population count (N_{P-T}), and the annual household incomes (AHI_{B-T}) for the total dataset. Similarly, the exposed building count (N_{B-E}), the exposed population count (N_{P-E}), and the annual household incomes (AHI_{B-E}) are calculated for the exposed dataset. The dislocated building count (N_{B-D}), the dislocated population count (N_{P-D}), and the annual household incomes (AHI_{B-D}) are determined for the dislocated dataset. Acquisition analyses metrics and definitions are listed in Table 3.

Table 3: Acquisition Analysis Terms and Definitions.

Terms	Definition
N_{BB-E}	Bought-out building count in exposed data
N_{BP-E}	Bought-out population count in exposed data
AHI_{BB-E}	Bought-out building annual household income in exposed data
N_{BB-D}	Bought-out building count in dislocated data
N_{BP-D}	Bought-out population count in dislocated data
AHI_{BB-D}	Bought-out building annual household income in dislocated data
N_{B-T}	Total building count
N_{P-T}	Total population count
AHI_{B-T}	Total building annual household income
N_{B-E}	Exposed building count
N_{P-E}	Exposed population count
AHI_{B-E}	Exposed building annual household income
N_{B-D}	Dislocated building count
N_{P-D}	Dislocated population count
AHI_{B-D}	Dislocated building annual household income
$PL-T$	Total population loss
$MEL-T$	Total economic loss in terms of median income
$AEL-T$	Total economic loss in terms of average income
$PL-E$	Exposed population loss
$MEL-E$	Exposed economic loss in terms of median income
$AEL-E$	Exposed economic loss in terms of average income
$PL-D$	Dislocated population loss
$MEL-D$	Dislocated economic loss in terms of median income
$AEL-D$	Dislocated economic loss in terms of average income

In 2021, FEMA awarded a grant of \$7.2 million to the City of Lumberton for the acquisition of 50 properties that have repeatedly flooded (Bright, 2021). Initially focusing on the exposed dataset, 11,946 buyout scenarios are simulated in this study, where 50 acquisitions are randomly distributed across four damage states: DS 0, DS 1, DS 2, and DS 3. Error handling and reproducibility of the 50 buildings random selection ensures sufficient availability of buildings for acquisitions in each

damage state. Each scenario is analyzed for metrics including the bought-out building count (N_{BB-E}), bought-out population count (N_{BP-E}), and the bought-out building annual household income (AHI_{BB-E}). Figure 8 visually represents this methodology, with terms defined in Table 3.

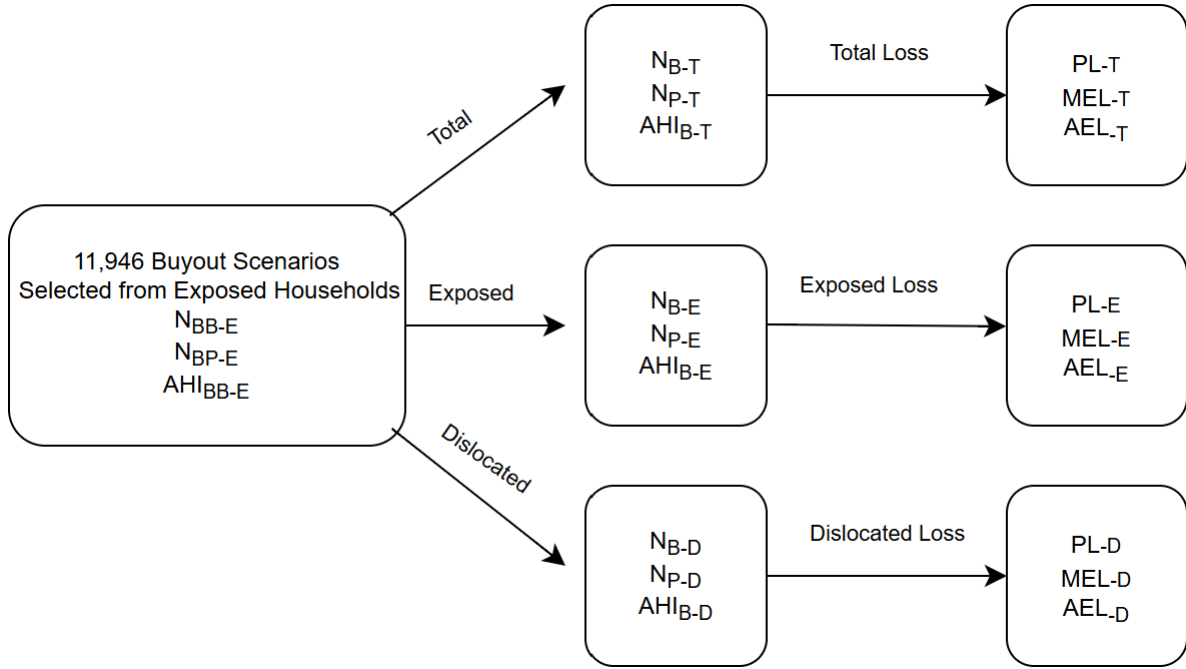


Figure 8: Acquisition Methodology for Exposed Households

Population loss of different buyout scenarios in the exposed dataset is assessed across the total population, exposed population, and dislocated population, and several metrics are computed.

$$PL_{-T} = N_{P-T} - N_{BP-E}$$

Where:

PL_{-T} is the total population loss

N_{P-T} is the total population count

N_{BP-E} is the bought-out population count in the exposed dataset

$$PL_{-E} = N_{P-E} - N_{BP-E}$$

Where:

PL_{-E} is the exposed population loss

N_{P-E} is the exposed population count

N_{BP-E} is the bought-out population count in the exposed dataset

$$PL_{-D} = N_{P-D} - N_{BP-E}$$

Where:

PL_{-D} is the dislocated population loss

N_{P-D} is the dislocated population count

N_{BP-E} is the bought-out population count in the exposed dataset.

Annual household income was used to determine the economic loss of the different buyout scenarios of the exposed data across the total population, exposed population, and dislocated population, in which several metrics are calculated.

$$MEL_{-T} = \text{median}(AHI_{B-T} - AHI_{BB-E})$$

Where:

MEL_{-T} is the total economic loss in terms of median income

AHI_{B-T} is the total building annual household income

AHI_{BB-E} is the bought-out building annual household income in the exposed dataset

$$MEL_{-E} = median(AHI_{B-E} - AHI_{BB-E})$$

Where:

MEL_{-E} is the exposed economic loss in terms of median income

AHI_{B-E} is the exposed building annual household income

AHI_{BB-E} is the bought-out building annual household income in the exposed dataset

$$MEL_{-D} = median(AHI_{B-D} - AHI_{BB-E})$$

Where:

MEL_{-D} is the dislocated economic loss in terms of median income

AHI_{B-D} is the dislocated building annual household income

AHI_{BB-E} is the bought-out building annual household income in the exposed dataset

$$AEL_{-T} = average(AHI_{B-T} - AHI_{BB-E})$$

Where:

AEL_{-T} is the total economic loss in terms of average income

AHI_{B-T} is the total building annual household income

AHI_{BB-E} is bought-out building annual household income in the exposed dataset

$$AEL_{-E} = average(AHI_{B-E} - AHI_{BB-E})$$

Where:

AEL_{-E} is the exposed economic loss in terms of average income

AHI_{B-E} is the exposed building annual household income

AHI_{BB-E} is bought-out building annual household income in the exposed dataset

$$AEL_{-D} = average(AHI_{B-D} - AHI_{BB-E})$$

Where:

AEL_{-D} is the dislocated economic loss in terms of average income

AHI_{B-D} is the dislocated building annual household income

AHI_{BB-E} is bought-out building annual household income in the exposed dataset

Depicted in Figure 9, the dislocated dataset utilizes the same methodology, with metrics described in Table 3. Dislocated building datasets simulate 7,211 scenarios and calculated the total number of buildings bought-out (N_{BB-D}), the population count of the bought-out buildings (N_{BP-D}), and the annual household income of the bought-out buildings (AHI_{BB-D}).

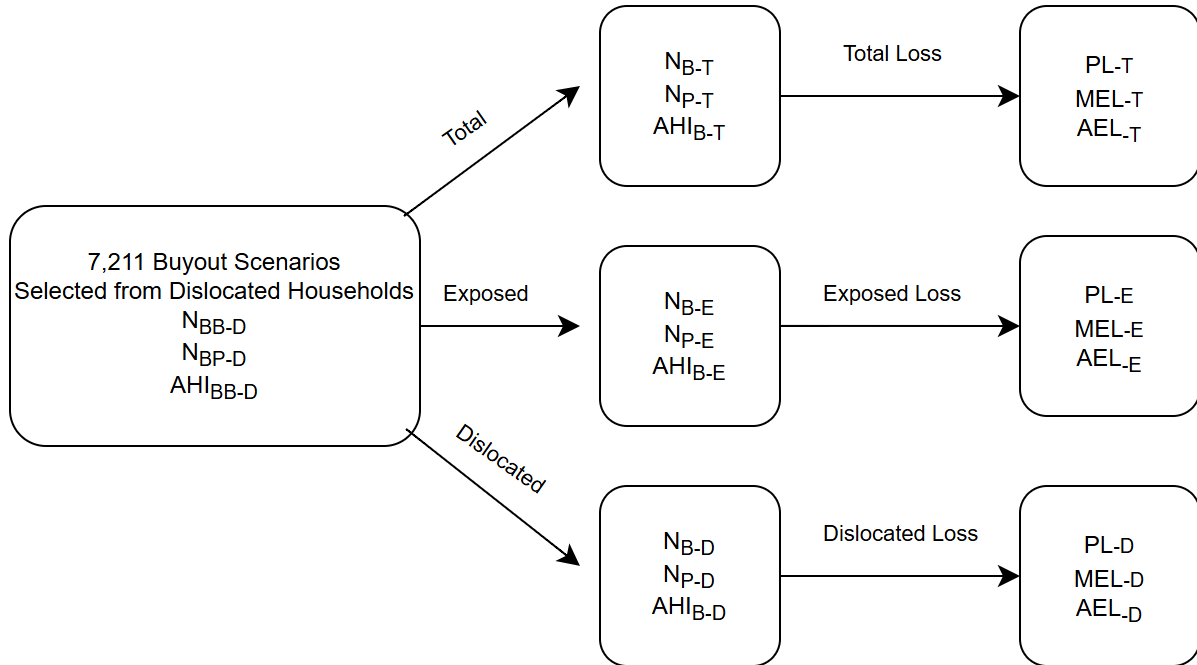


Figure 9: Acquisition Methodology for Dislocated Households.

Population loss of the different buyout scenarios of the dislocated data is assessed across the total population, exposed population, and dislocated population, and several metrics are estimated.

$$PL_{-T} = N_{P-T} - N_{BP-D}$$

Where:

PL_{-T} is the total population loss

N_{P-T} is the total population count

N_{BP-D} is the bought-out population count in the dislocated dataset

$$PL_{-E} = N_{P-E} - N_{BP-D}$$

Where:

PL_{-E} is the exposed population loss

N_{P-E} is the exposed population count

N_{BP-D} is the bought-out population count in the dislocated dataset

$$PL_{-D} = N_{P-D} - N_{BP-D}$$

Where:

PL_{-D} is the dislocated population loss

N_{P-D} is the dislocated population count

N_{BP-D} is the bought-out population count in the dislocated dataset

Several metrics are computed in which annual household income determines the economic loss of the different buyout scenarios of the dislocated data across the total population, exposed population, and dislocated population.

$$MEL_{-T} = median(AHI_{B-T} - AHI_{BB-D})$$

Where:

MEL_{-T} is the total economic loss in terms of median income

AHI_{B-T} is the total building annual household income

AHI_{BB-D} is the bought-out building annual household income in the dislocated dataset

$$MEL_{-E} = \text{median}(AHI_{B-E} - AHI_{BB-D})$$

Where:

MEL_{-E} is the exposed economic loss in terms of median income

AHI_{B-E} is the exposed building annual household income

AHI_{BB-D} is the bought-out building annual household income in the dislocated dataset

$$MEL_{-D} = \text{median}(AHI_{B-D} - AHI_{BB-D})$$

Where:

MEL_{-D} is the dislocated economic loss in terms of median income

AHI_{B-D} is the dislocated building annual household income

AHI_{BB-D} is the bought-out building annual household income in the dislocated dataset

$$AEL_{-T} = \text{average}(AHI_{B-T} - AHI_{BB-D})$$

Where:

AEL_{-T} is the total economic loss in terms of average income

AHI_{B-T} is the total building annual household income

AHI_{BB-D} is the bought-out building annual household income in the dislocated dataset

$$AEL_{-E} = average(AHI_{B-E} - AHI_{BB-D})$$

Where:

AEL_{-E} is the exposed economic loss in terms of average income

AHI_{B-E} is the exposed building annual household income

AHI_{BB-D} is the bought-out building annual household income in the dislocated dataset

$$AEL_{-D} = average(AHI_{B-D} - AHI_{BB-D})$$

Where:

AEL_{-D} is the dislocated economic loss in terms of average income

AHI_{B-D} is the dislocated building annual household income

AHI_{BB-D} is the bought-out building annual household income in the dislocated dataset

Identifying metrics from the literature (see Table A1), this study aims to quantify the reliability of property acquisition strategies and identify critical variables influencing outcomes such as population dynamics, socioeconomic factors, and community resilience. Integrating these analyses ensures reasonable assessments, supporting informed decision-making in urban planning and hazard management. Enhancing the understanding of flood mitigation, this approach provides guidance toward more equitable solutions for community property acquisitions.

Chapter 3: Illustrative Application for Lumberton, North Carolina

Situated along the Lumber River in Robeson County, North Carolina, Lumberton, an ethnically and financially diverse community, seen in Figure 10, is a clear representation of economic fragility exacerbated by climate change-induced natural hazards. According to the 2010 Census data, Lumberton had a total population of 21,000 people, with an approximate employment rate of 50%, significantly lower than the US average of 64% (U.S. Census Bureau, n.d.). Additionally, 30% of the population was living below the poverty level, double the US average of 15%. Compared to the US average of \$50,000, Lumberton's median household income was \$32,000 and the median property value was \$112,000, contrasting the US average of \$120,000. Lumberton has tri-racial demographics and a minority-majority population (American Community Survey, 2015). Approximately 7% of the population is Hispanic or Latino, and Lumberton's racial composition is 41% White alone, 37% Black or African American alone, 13% American Indian and Alaska Native alone, 2% Asian alone, >1% Native Hawaiian and Other Pacific Islander alone, 4% some other race alone, and 3% two races or more. On average, Lumberton individuals and households have lower economic resources compared to different areas across the state of North Carolina (van de Lindt et al., 2018). Highlighting the economic challenges faced by Lumberton residents, these statistics establish the vulnerabilities this community faces in terms of impacts from natural hazards.

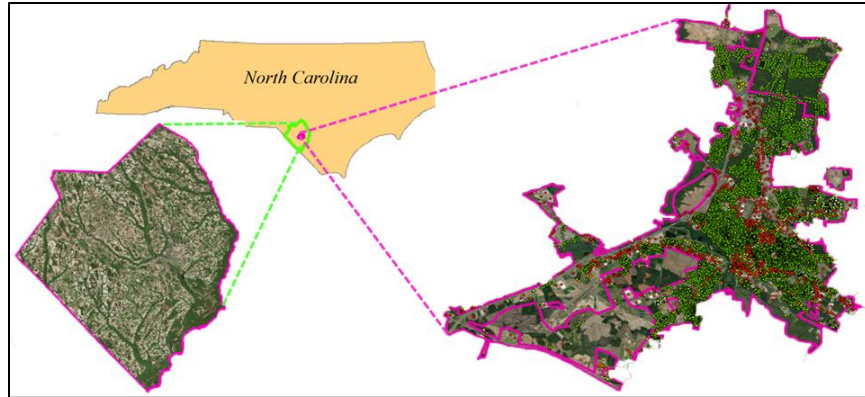


Figure 10: Lumberton in relation to Robeson County and North Carolina (Nofal and van de Lindt, 2020).

Lumberton has implemented various mitigation measures aimed at reducing flood risks. Protecting low-lying communities south of the Lumber River, the U.S. Department of Agriculture built a levee, completed in September 1974 and managed by the City of Lumberton (van de Lindt et al., 2018). However, challenges arise when levees and other structural protective measures are implemented including high maintenance costs, environmental impacts, and increased development in hazardous areas (Hino et al., 2017). Following Hurricane Fran in 1996, Lumberton initiated buyouts acquiring 21 properties, reflecting typical outcomes among similar case studies, the lots remain vacant (BenDor et al., 2020). Constraining the accuracy of current analyses, challenges in data quality and detail highlight the need for improved data collection to fully understand the implications of property acquisition programs (BenDor et al., 2020).

Hurricane Matthew began as a Category 1 storm in the Caribbean Sea on September 29, 2016, and rapidly intensified to a Category 4 storm on October 1, making landfall in Florida as a Category 2 storm, and Category 1 storm in North Carolina bringing significant rainfall. Figure 11 depicts Hurricane Matthew's path and when it made landfall as a Category 1 Hurricane. Resulting in 49 casualties, Hurricane Matthew caused severe damage (National Centers for Environmental Information, 2023).

Lumberton flood management plans are designed for recurrence intervals (100-year events). According to NOAA Atlas 14, the average expected precipitation for a 500-year event in Lumberton is 11.8 inches (National Weather Service, n.d.). However, Hurricane Matthew was categorized between a 200- and 500-year event due to Lumberton experiencing 12 inches of rain in 48 hours.



Figure 11: Hurricane Matthew's path and timeline created from NCH GIS Archive (2016).

Increased precipitation from Hurricane Matthew resulted in swelling of the Lumber River, which runs through the center of Lumberton, and its tributaries. Rising to record heights the river caused widespread flooding. Due to the Lumber River's history of timber transportation, beaver-built dams and buildup of sediment and debris elicited ineffective drainage, exacerbating the flooding (NC State Parks, 2017). Designed to protect the city from flooding by acting as a levy-sand wall

barrier, the I-95 embankment failed at the underpass, allowing water to flood the city. Lumberton was without electrical power for five days and without water for three weeks. Figure 12 depicts the flooding in Lumberton after Hurricane Matthew. Previously considered outside the 100-year floodplain due to the levee, many households were unprepared and uninsured for such an event, complicating recovery efforts when Hurricane Florence hit Lumberton in September 2018.



Figure 12: Flooding in Lumberton caused by Hurricane Matthew (Wheeler, 2016).

In the Atlantic Ocean on September 1, 2018, Hurricane Florence began as a Category 1 storm and rapidly intensified to a Category 3 storm on September 9, and Category 4 on September 10. On September 12, Florence weakened to a Category 2 storm and on September 14 made landfall in North Carolina as a Category 1 storm, as shown in Figure 13. Lingering for several days, North Carolina was devastated by catastrophic flooding. Florence's slow movement and heavy rainfall, 15 to 18 inches of rain on saturated soil, led to record-breaking floods. Resulting in damages of approximately \$29.3 billion and claiming 53 lives, Florence was one of the costliest hurricanes in U.S. history. Due to unprecedented levels of rainfall and subsequent flooding, Florence's impact surpassed that of previous hurricanes, including Hurricane Matthew in 2016 and Hurricane Floyd in 1999 (National Centers for Environmental Information, 2023). Hurricane Matthew's and

Florence’s paths are depicted together in Figure 14, as well as the location at which they hit North Carolina as Category 1 storms.

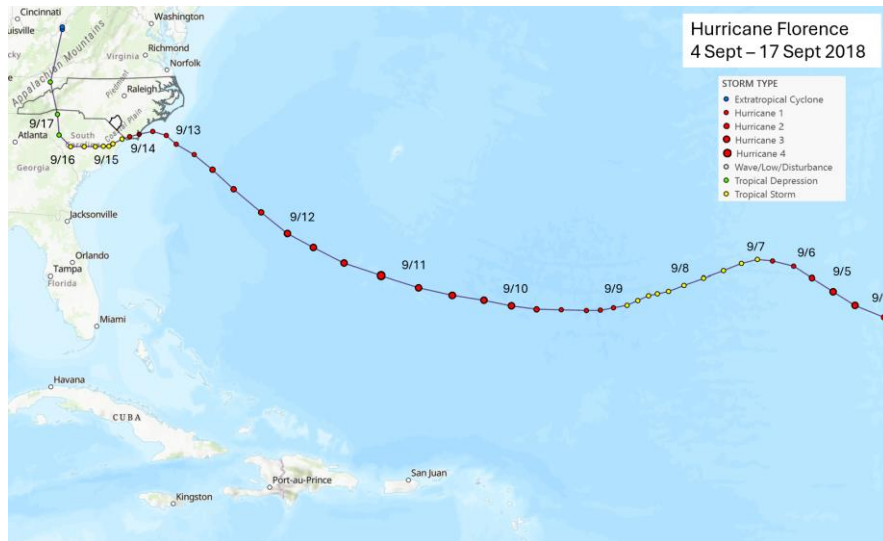


Figure 13: Hurricane Florence's path and timeline created from NHC GIS Archive (2018).

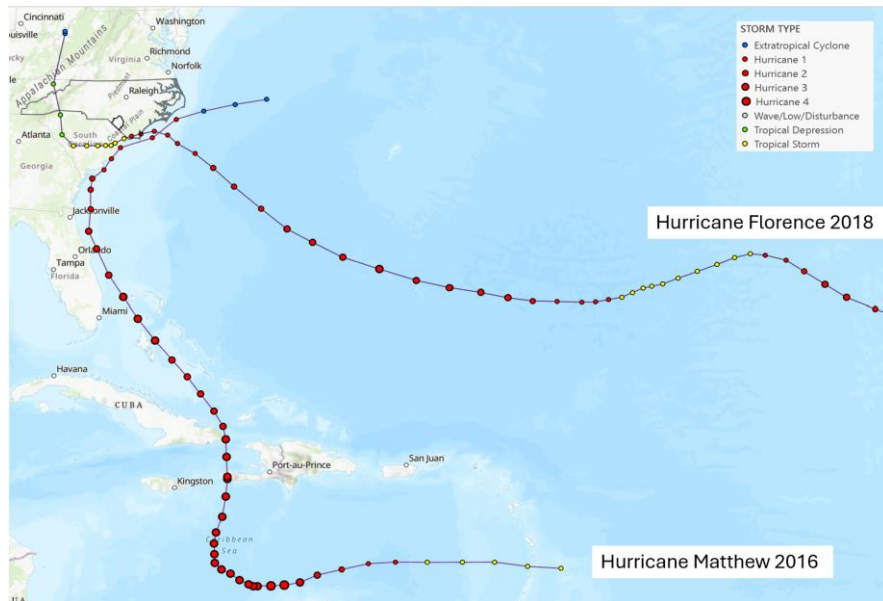


Figure 14: Hurricane Matthew and Hurricane Florence hit North Carolina as Category 1 Hurricanes.

Lumberton was devastated by the impact of the two events two years apart. After Hurricane Matthew, FEMA received 18,372 applications for assistance from Robeson County and granted

\$23.4 million as of January 2017 (Hunter, 2017). Reducing the severity of the event, the City of Lumberton implemented temporary berms and pumps to reduce the water swelling from riversides. However, critical weaknesses in Lumberton's flood protection infrastructure and the socio-economic consequences were unveiled by the damage caused by these hurricanes. Hazard-damage-consequence models highlight Lumberton's vulnerability to climate change-induced natural hazards and emphasize the need for resilient infrastructure development to enhance the community's ability to withstand future floods.

Utilizing the methodology presented in Chapter 2, a hazard-damage-consequence model was developed for Lumberton after Hurricane Matthew. Hazard, exposure, and vulnerability models were utilized in the development of a hazard approach to account for the total damage/loss of each exposed building.

3.1: Hazard Modeling

To determine the extent of damage a specific hazard causes to a community, hazard modeling is necessary. Using hydrologic and hydrodynamic models, flood hazards are characterized by their frequency, intensity, and spatial distribution. By analyzing river characteristics, soil, and land use, hydrologic modeling uses precipitation to estimate water flow and discharge. The Lumber River and smaller streams like Red Springs Creek contribute to flooding in Lumberton. Changes in water movement over time and factors affecting infiltration and runoff can be estimated using flow hydrographs and boundary conditions in hydrologic analyses. Flow data estimates from hydrographs are used in hydrodynamic modeling to predict flood depths and extents, while considering topographic features. HEC-RAS and other advanced models simulate complex surface

and groundwater interactions. Hazard modeling helps to identify vulnerable areas, inform floodplain management, and design mitigation techniques.

Digital Elevation Models (DEM) provide ground elevations used to determine flood depths. Water Surface Elevations (WSE) incorporate DEMs to plan and respond to natural hazards. Comprehensive hazard maps visualize flood risks and guide mitigation efforts using DEMs and flow hydrographs. Utilizing pre-existing models and maps, this study performs hazard modeling analyses. Nofal et al. (2020) published Hurricane Matthew flood inundation maps to IN-CORE and compared them to FEMA flood inundation maps, as shown in Figure 15.

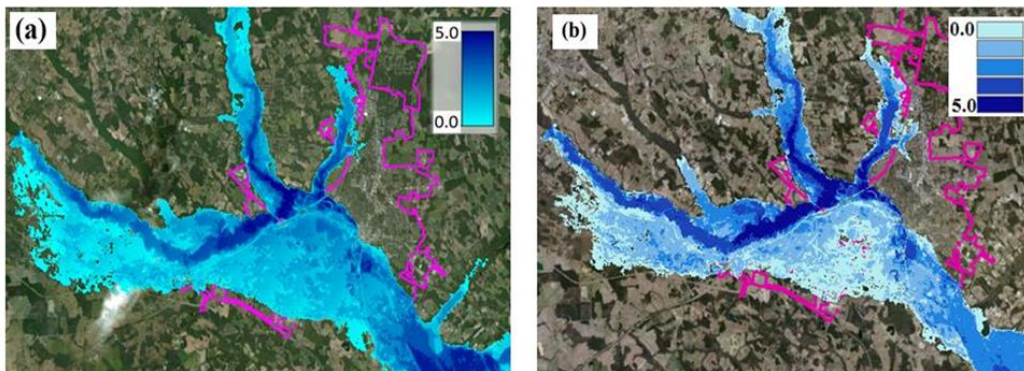


Figure 15: Hurricane Matthew flood inundation depth: (a) Flood inundation depth developed by Nofal and van de Lindt (2019); (b) Flood inundation depth developed by FEMA (2019). See Nofal and van de Lindt (2020) for more details.

3.2: Community Modeling

Community modeling uses detailed building information, collected after Hurricanes Matthew and Florence, to identify exposed assets in and around Lumberton. From 2016 to 2023, a multidisciplinary team of engineers, social scientists, and economists visited Lumberton to evaluate the recovery process and collect community data (van de Lindt et al., 2018; van de Lindt et al., 2020; Sutley et al., 2021; van de Lindt et al., 2021; Helgeson et al., 2021; Watson et al., 2022). Gathering evidence of recovery efforts, teams engaged with city officials and conducted

citizen surveys. Google Street View and Google My Maps, supplemented by Google Earth, NC OneMap, and National Structure Inventory (NSI) were used to verify first floor elevation and other building characteristics in and around Lumberton. GIS was used to conduct spatial analysis of the collected building data. This data was utilized to create a comprehensive building inventory for Lumberton.

Employing a portfolio of 15 building archetypes, 20,000 buildings in the Lumberton building inventory were populated using a numerical model (Nofal and van de Lindt, 2020). Describing buildings in terms of building occupancies, the 15 archetypes also consider various characteristics such as footprint area, roof structure, and number of stories. Additionally, for each archetype building components were developed. Interior components include appliances, furniture, and cabinetry, while non-structural components comprise windows, and heating and cooling units, and structural components constitute roofing, flooring, and walls (Nofal and van de Lindt, 2020). To represent a community with acceptable accuracy, these archetypes are minimized. Total functionality of each building is accounted for within a community by considering buildings as a system of systems. Providing valuable insights for future planning and mitigation efforts, this modeling enables detailed assessment of Lumberton's built environment vulnerabilities.

3.2.1: Exposure Modeling

Elements at risk in a selected area are identified and quantified using exposure models, including physical assets such as buildings, infrastructure, and population data. Exposure models detail parts of communities that could be impacted by hazards. 20,000 buildings, their locations, archetype, and other characteristics including first-floor elevation, and roof and foundation category are

represented in Lumberton exposure models (Nofal and van de Lindt, 2020). Figure 16 displays the Lumberton building inventory.

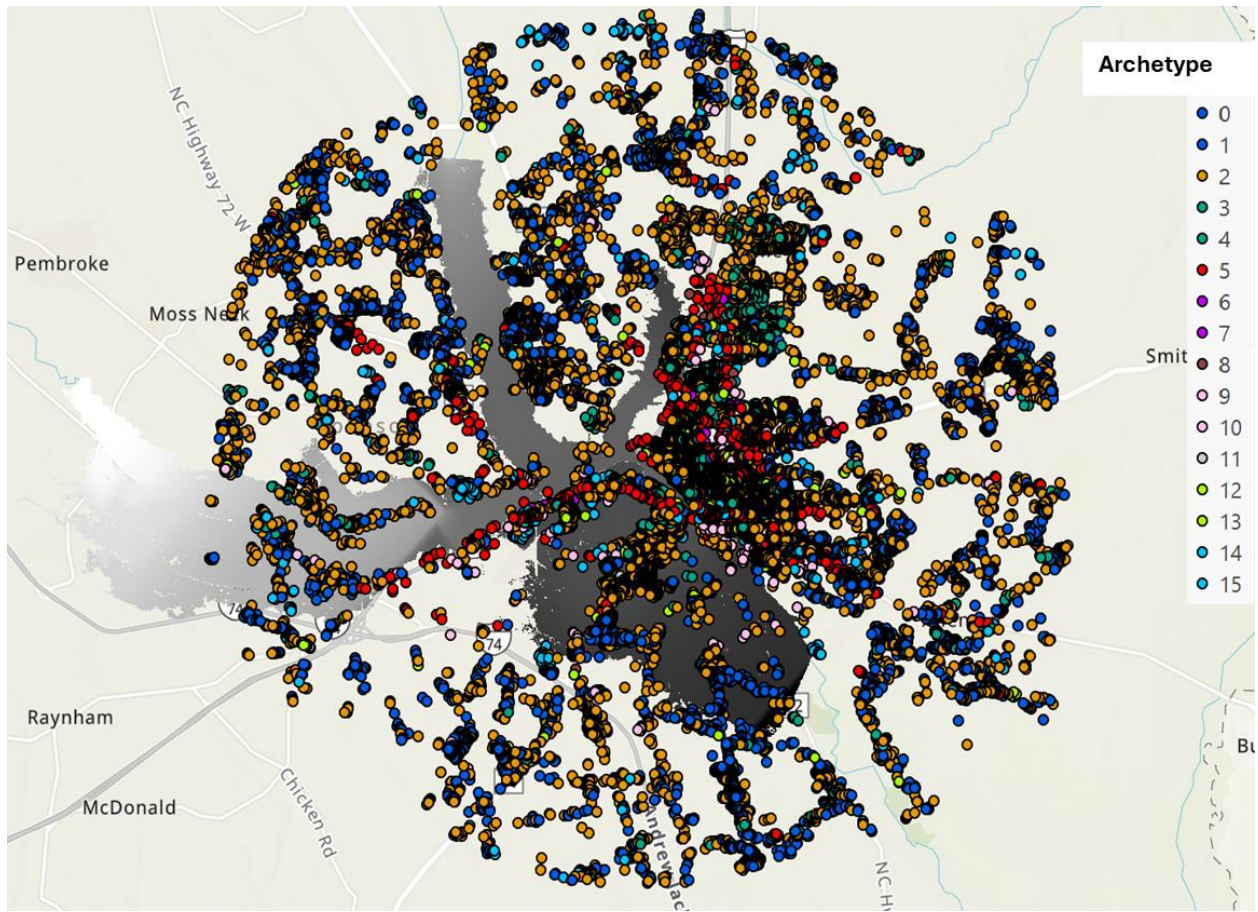


Figure 16: Visualization of the Lumberton building inventory overlaying the Hurricane Matthew flood inundation map.

High-resolution community models combine building exposure and hazard characteristics, including flood depths and inundation maps to describe exposure levels. Exposure models were developed by overlaying hazard maps with Lumberton’s housing unit inventory to predict flood exposure for each building within the community.

3.2.2: Vulnerability Modeling

Vulnerability models assess exposed assets damage when subjected to a hazard. Fragility curves describe the probability of reaching or exceeding damage or loss levels given hazard intensity. For flood-prone areas like Lumberton, fragility curves quantify building vulnerabilities and guide risk management and mitigation strategies.

Damage analyses were conducted using IN-CORE to assess the impacts of Hurricane Matthew on Lumberton. In terms of four damage states, a set of performance criteria was developed describing flood damage to buildings. Informing damage and occupancy levels, damage states describe both building functionality and serviceability. Damage states, in this study, are sequential, DS 0 must be exceeded before reaching DS 1. Without notable velocity, damage from flooding in Lumberton was mostly non-structural including building content and equipment. Vulnerabilities of homes in floodplains are highlighted by Hurricane Matthew flooding events. Figure 17 displays exposed and dislocated buildings in terms of damage states.

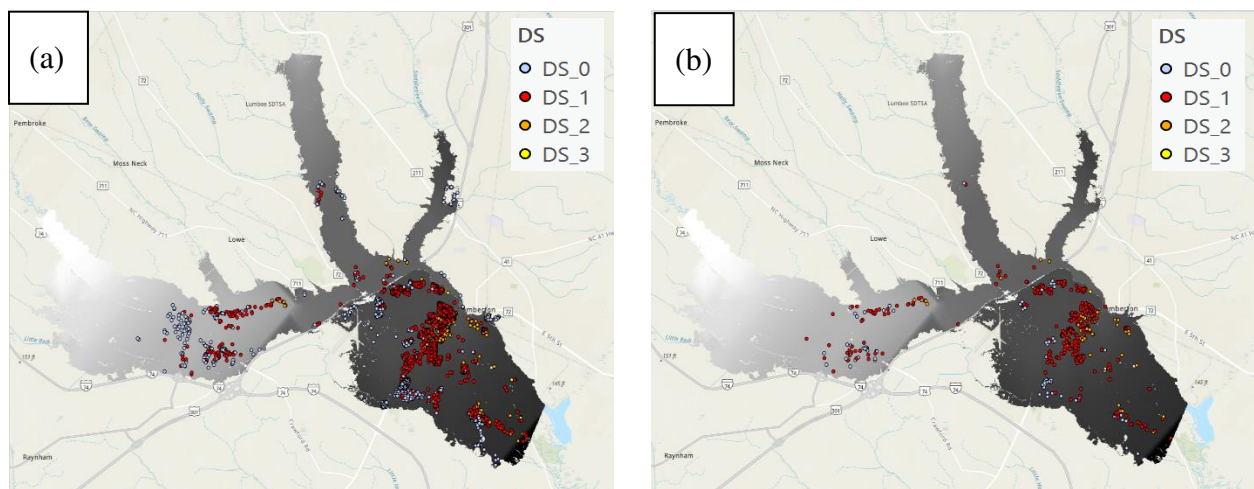


Figure 17: (a) Buildings exposed and (b) buildings dislocated from flooding from Hurricane Matthew in terms of damage state.

3.3: Risk Analysis

Described in section 2.3, the community-level loss/damage analyses framework determines flood damage for each building by matching each building's hazard intensity with the building's archetype and associated vulnerability functions.

To calculate flood risk for community resilience analyses, the exceedance probability of each damage state is used. Hurricane Matthew building damage is described by four damage states, with the majority of damaged homes in DS 0 and DS 1, indicating minor damage to the structure. It should be noted that DS 0 does not necessarily mean that the building had no damage but could have minor damage to components below the first-floor elevation. Higher damage states are identified in areas south of the Lumber River impacted by the levee breach. In total, 2,874 buildings were exposed, affecting 6,635 people, as depicted in Table 4. Approximately 29% of exposed buildings experienced damage in DS 0, 62% in DS 1, 8% in DS 2, and less than 1% in DS 3. Dislocated buildings are defined as buildings that are exposed, and the homeowner relocated for a period of time. 564 buildings were dislocated, affecting 1,293 people, as shown in Table 5. Nearly 14% of dislocated buildings encountered damage in DS 0, 73% in DS 1, 13% in DS 2, and less than 1% in DS 3.

Table 4: Exposed buildings and people in terms of damage state.

DS	Exposed Building Count	Percentage	Exposed People Count	Percentage
DS 0	843	29.33%	2063	31.09%
DS 1	1789	62.25%	4078	61.46%
DS 2	232	8.07%	472	7.11%
DS 3	10	0.35%	22	0.33%
Total	2874	100%	6635	100%

Table 5: Dislocated buildings and people in terms of damage state.

DS	Dislocated Building Count	Percentage	Dislocated People Count	Percentage
DS 0	77	13.65%	197	15.24%
DS 1	411	72.87%	935	72.31%
DS 2	71	12.59%	150	11.60%
DS 3	5	0.89%	11	0.85%
Total	564	100%	1293	100%

3.4: Synthetic Allocation

Using building analyses, population allocation and dislocation enhance the understanding of a community’s socio-economic and demographic status in the aftermath of natural hazards. Established algorithms and diverse data sources, that synthetically allocate households to housing units, reveal the distribution and characteristics of the population.

High-resolution spatial data of households and housing unit characteristics in Robeson County are linked to residential buildings by applying Rosenheim’s synthetic allocation approach (Rosenheim et al., 2021). Combining socio-economic data within IN-CORE provides detailed demographic characteristics for the community allocated to each structure.

Population allocation algorithms synthetically assign households to housing units and labor to businesses. Housing unit demographics are known at the census block level yet estimated at the housing level. To build the social model of the community, each household is synthetically populated to replicate the Lumberton community with household information including size, race, ethnicity, tenure, and income. Demographic definitions from the U.S. Census are listed in Appendix Table A2.

3.4.1: Exposed Population

Lumberton is considered tri-racial, with the majority of exposed households Black or African American alone (62% of exposed buildings and 61% of people). American Indian and Alaska Native alone populations are the second-highest affected group (23% of exposed buildings and 24% of people). White alone populations represent 14% of buildings and 13% of people. Other racial groups make up a small percentage of the exposed households, depicted in Table 6.

Table 6: Exposed buildings and people in terms of race (not including NA vacant or group quarters).

Race	Total Buildings	Percentage	Total People	Percentage
1. White alone	355	13.61%	873	13.16%
2. Black or African American alone	1606	61.58%	4032	60.77%
3. American Indian and Alaska Native alone	593	22.74%	1584	23.87%
4. Asian alone	2	0.08%	7	0.11%
5. Native Hawaiian and Other Pacific Islander alone	2	0.08%	5	0.08%
6. Some Other Race alone	10	0.38%	26	0.39%
7. Two or More Races	40	1.53%	108	1.63%
Total	2608	100%	6635	100%

Lumberton’s racial/ethnic damage state distribution is illustrated in Figure 18. Across all three plots, DS 1 contained the largest number of households with 190 Non-Hispanic White alone households (54%), 1,088 Non-Hispanic Black or African American alone households (68%), and 299 American Indian and Alaska Native alone households (51%). DS 0 has the second largest share of households with 132 Non-Hispanic White alone households (38%), 351 Non-Hispanic Black or African American alone households (22%), and 267 American Indian and Alaska Native alone households (45%). In terms of economic and damage impacts, flooding from Hurricane Matthew was not an “equal opportunity” event.

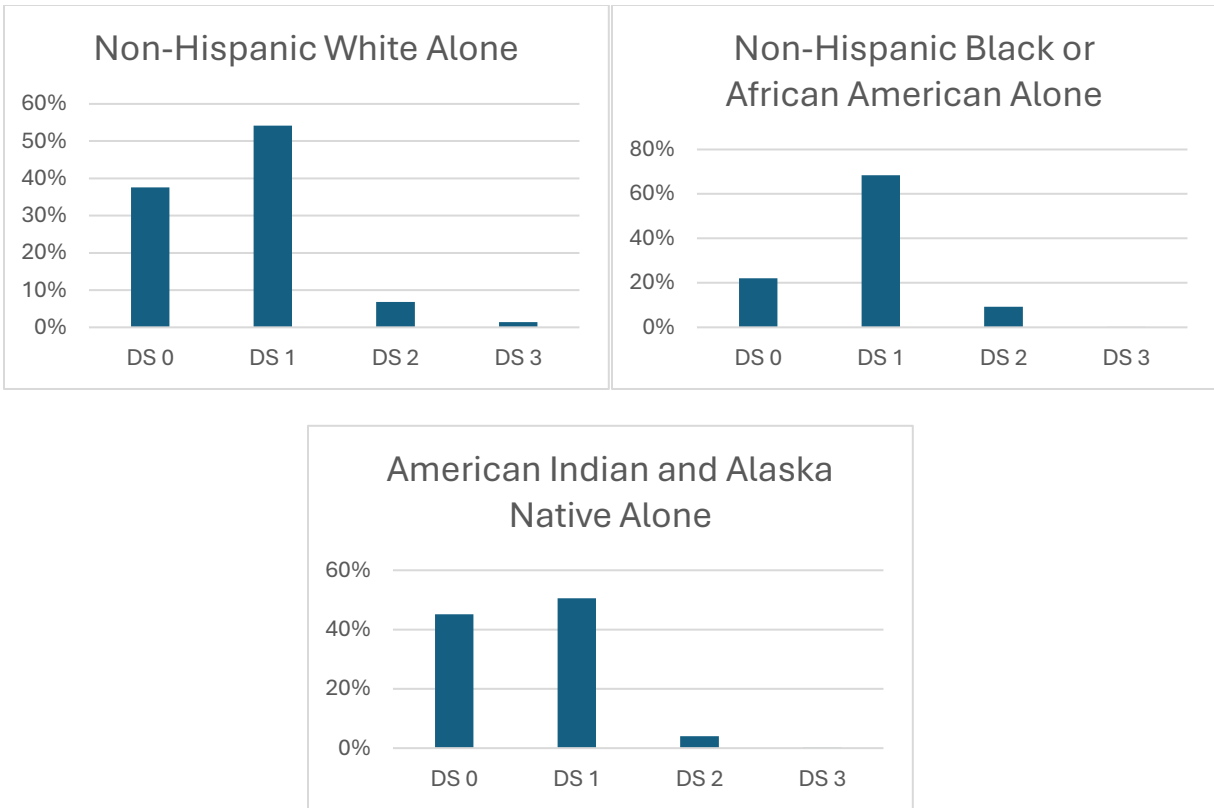


Figure 18: Race and Ethnicity Percentage by Damage State.

Annual household income (HHinc) versus race is analyzed to understand the income distribution of households affected. Household income was categorized by six groups:

0. not applicable because it is either vacant or group quarters
1. Less than \$15,000
2. \$15,000 to \$25,999
3. \$25,000 to \$74,999
4. \$75,000 to \$99,999
5. \$100,000 or more.

Income group 3, annual household income between \$25,000 and \$74,999, has the largest group of exposed people and buildings (37% of exposed buildings, 44% of people). A significant portion of exposed buildings fall into income group 1, an annual household income of less than \$15,000 (33% of exposed buildings and people). Income group 2, annual household income between \$15,000 and \$24,999, represents 13% of exposed buildings and 14% of people. Higher income groups (group 4, annual household income between \$75,000 and \$99,999, and group 5, annual household income of \$100,000 or more) represent a smaller percentage of affected buildings and people, as seen in Table 7.

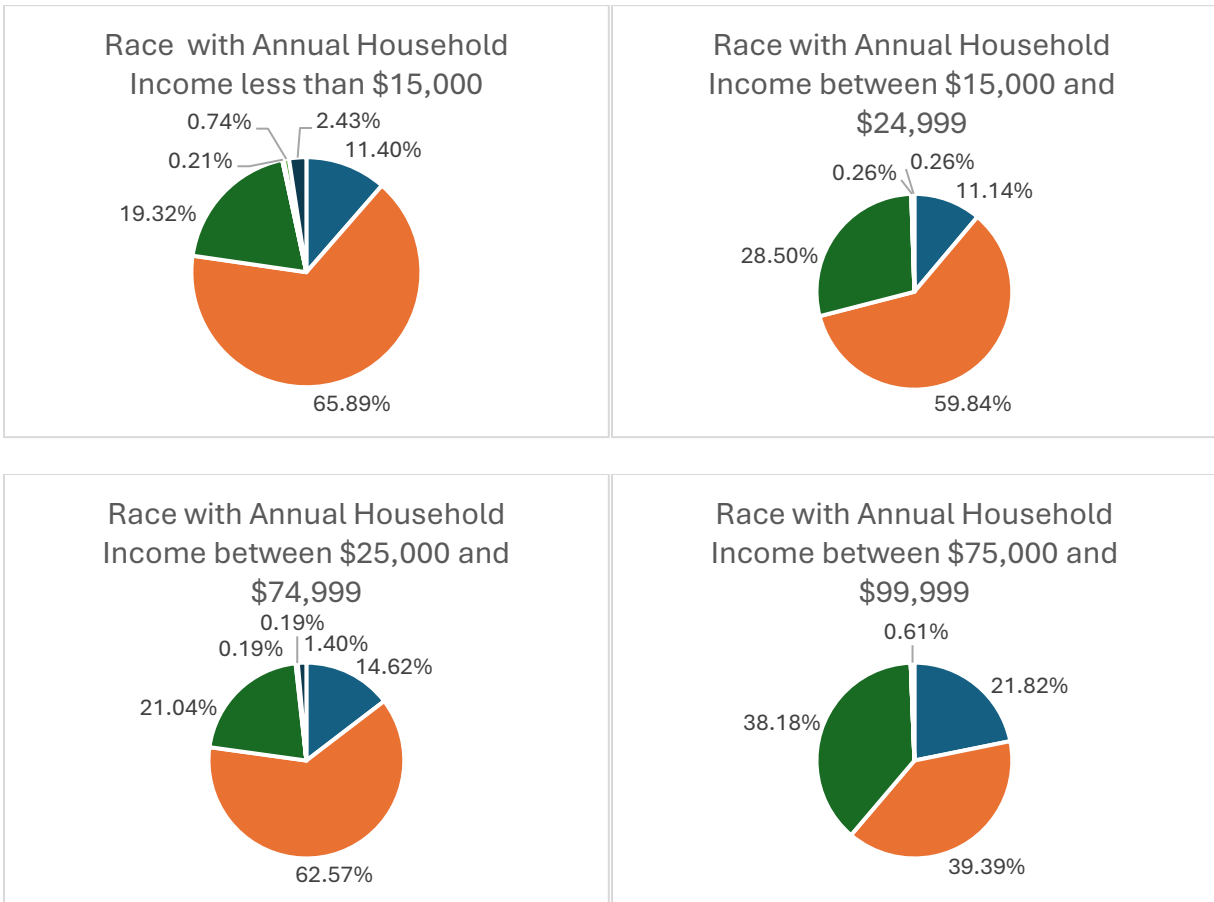
Table 7: Exposed buildings and people in terms of annual household income.

Household Income	Total Buildings	Percentage	Total People	Percentage
0.NA vacant or group quarters	266	9.26%	0	0.00%
1.Less than \$15,000	947	32.95%	2165	32.63%
2.\$15,000 to \$24,999	386	13.43%	914	13.78%
3. \$25,000 to \$74,999	1074	37.37%	2940	44.31%
4.\$75,000 to \$99,999	165	5.74%	519	7.82%
5.\$100,000 or more	36	1.25%	97	1.46%
Total	2874	100%	6635	100%

Lower income households are disproportionately affected by flooding. A significant number of exposed households fall into the income brackets of less than \$15,000. Middle-income households, income between \$25,000 and \$74,999, are also unequally affected, highlighting economic vulnerability.

Affected disparately by flooding, Black or African American alone residents comprise the majority of the exposed population and buildings. American Indian and Alaska Native alone populations are also significantly influenced, suggesting a need for targeted community support.

As shown in Figure 19, Black or African American alone households have the highest representation in households earning less than \$15,000 (66%), between \$15,000 to \$24,999 (60%), and between \$25,000 to \$74,999 (63%). Black or African American alone households (39%) and American Indian and Alaska Native alone (38%) have similar percentages of households with incomes between \$75,000 and \$99,999. The highest percentage of households earning \$100,000 or more are Black or African American alone (39%), closely followed White alone and American Indian and Alaska Native alone household (31%).



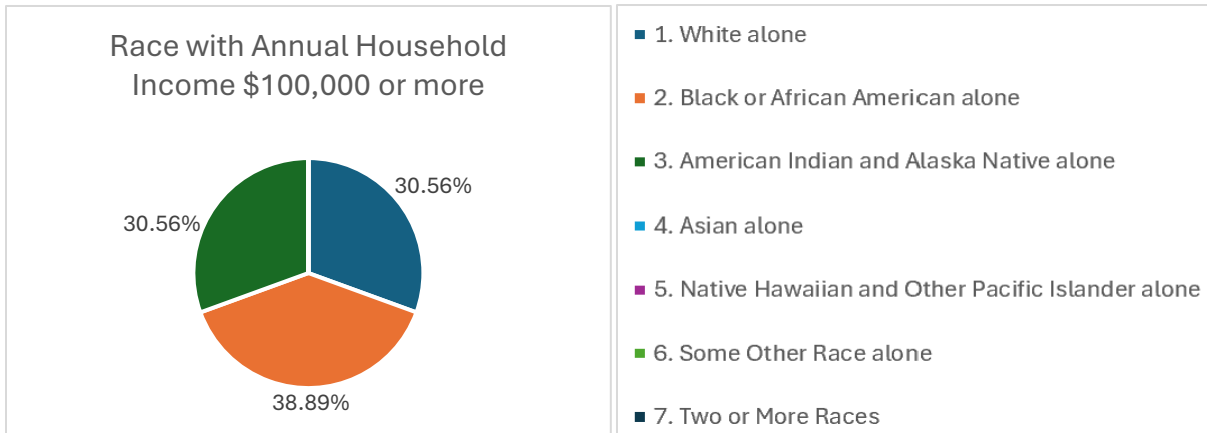
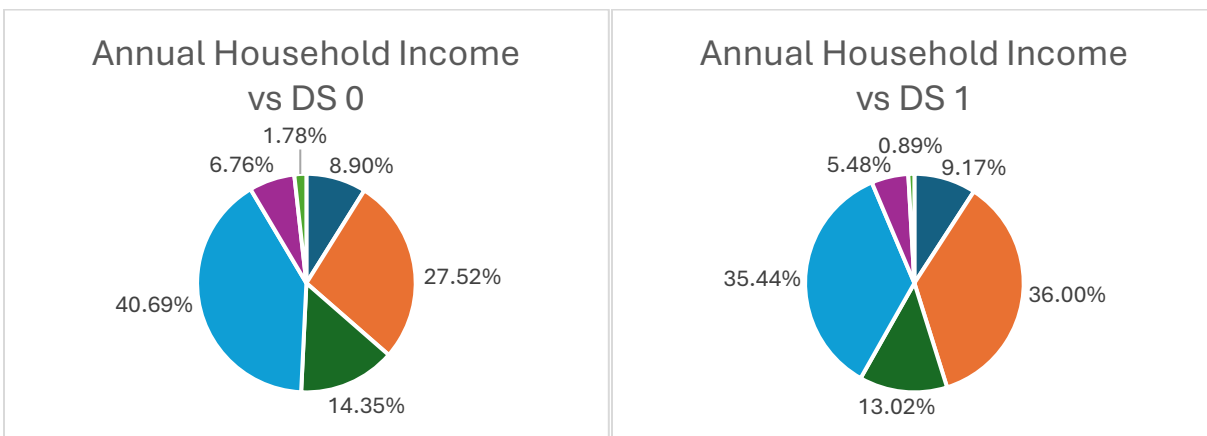


Figure 19: Exposed Buildings by Race Compared to Annual Household Income.

White alone households have larger representation in higher income brackets, indicating better economic conditions. Black or African American alone households are predominantly in the lowest income bracket, suggesting higher economic vulnerability. American Indian and Alaska Native alone households have a substantial presence in lower income brackets, demonstrating economic diversity. Income disparities are evident between racial groups; compared to other racial groups, White alone households generally fare better economically.

Emphasizing lower- and middle-income prevalence, Figure 20 provides insights into household income distribution patterns. Underscoring the complexity of economic challenges, this comparison highlights opportunities to address income disparities and promote economic equity.



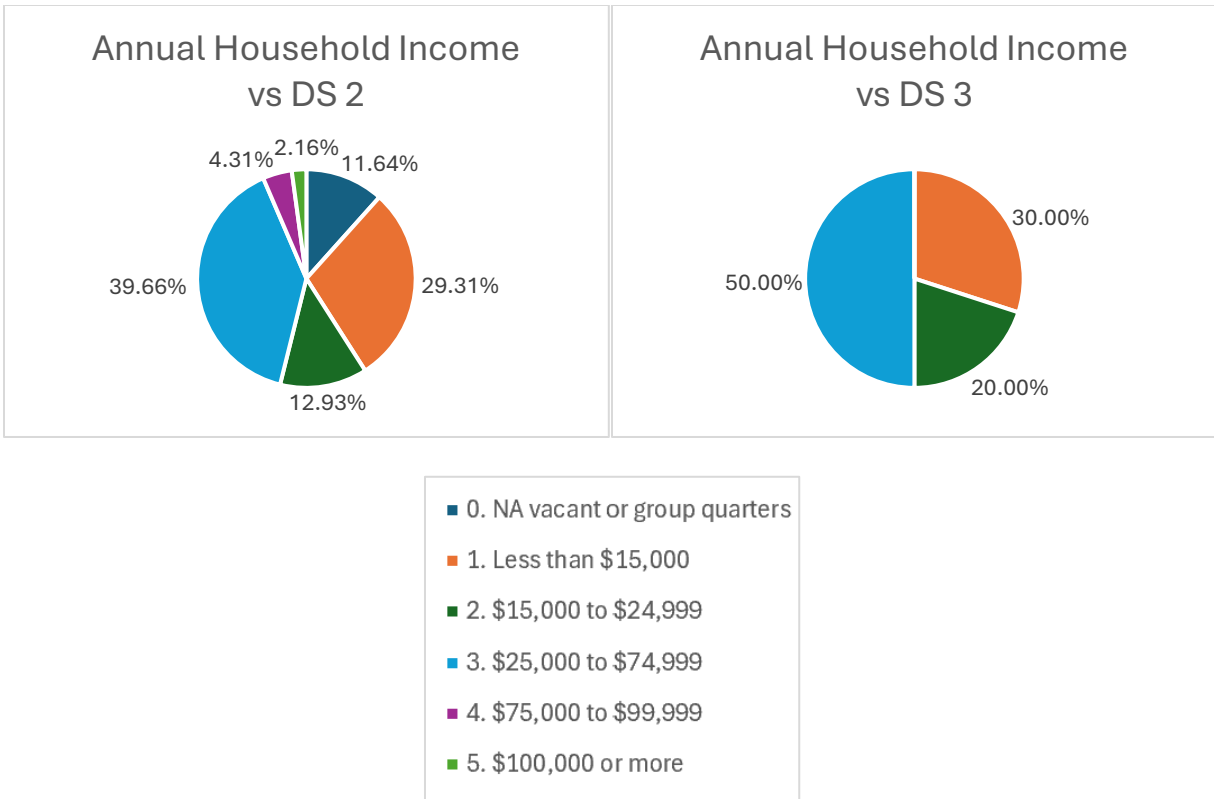
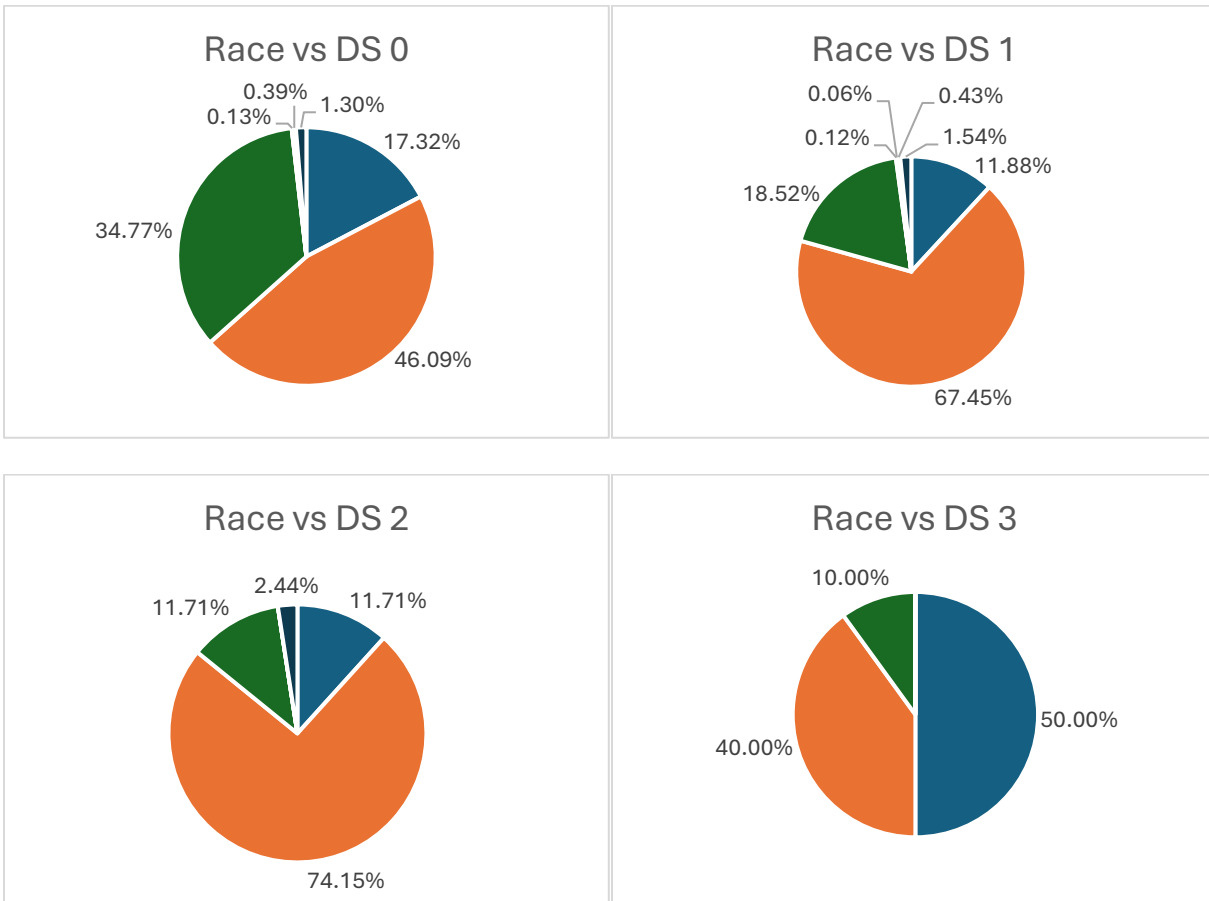


Figure 20: Exposed Buildings by Household Income versus Damage States.

Income bracket 1 (< \$15,000) is particularly prominent across all damage states, with DS 1 containing the highest percentage of households (36%) and people (1,454), suggesting economic vulnerability. Over 40% of households in each damage state have an annual household income less than \$25,000, where households in DS 2 and DS 3 could result in the household relocating for a period of time. Across all damage states, the largest income bracket is \$25,000 to \$74,999, indicating a broad base of middle-income households. Higher income brackets (especially > \$75,000) have lower percentages across all damage states, indicating challenges in achieving higher economic status. Varying distributions across income brackets and damage states highlight Lumberton's economic profile.

Figure 21 illustrates the distribution of exposed buildings across different racial groups and damage states. Black or African American alone households show the highest percentages in

DS 0, DS 1, and DS 2, with a considerable presence in DS 3, indicating minority races are disproportionately affected by natural hazards. American Indian and Alaska Native alone households have significant percentages in DS 0, with lower percentages in DS 1, DS 2, and DS 3. White alone households represent smaller percentages in DS 1 and DS 2 compared to DS 0, with a higher representation in DS 3 (50%). According to these results, Black or African American alone residents are disproportionately affected by flooding in Lumberton, with their representation increasing in higher damage states. See appendix Figures A2 through A6 for exposed buildings damage states versus other demographics.



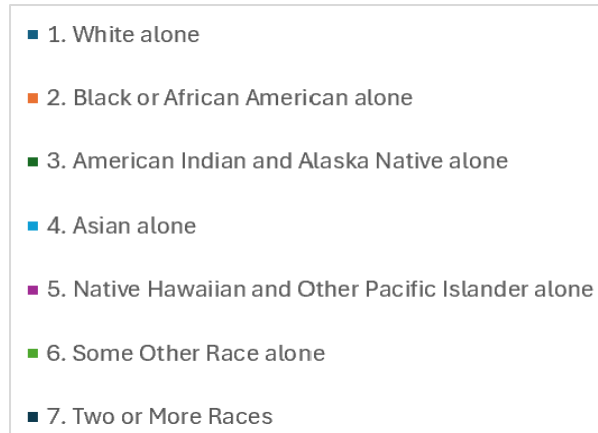


Figure 21: Exposed Buildings by Race versus Damage State.

Across damage states, economic and racial disparities contribute to varying levels of social vulnerability, with lower income groups and minority racial groups facing greater challenges in assessing resources, and other essential services. Particularly in hazard recovery contexts, targeted mitigation and support programs are needed to address the specific economic challenges faced by Black or African American alone and American Indian and Alaska Native alone communities. Highlighted in the data, certifying equitable access to resources and counsel is crucial to mitigating disparities.

3.4.2: Population Dislocation

Population dislocation refers to households forced, or that choose, to leave their residences due to hazard-related damages. Described in Section 2.4.1, the population dislocation model predicts immediate post-hazard event dislocations by allocating detailed housing unit and household characteristic data to each residential building. Refer to Rosenheim et al. (2019) and Peacock et al. (1997) for a comprehensive explanation of the dislocation model.

Housing unit allocation and building results serve as inputs for dislocation models, characterizing housing units by tenure, household size, and occupancy status, and determining structure value loss through fragility and hazard services. Distributional equity of buyout scenarios is determined through population dislocation projections and resilience metrics.

According to the Lumberton field study survey and interviews, the average days of dislocation was $34.4 \text{ d} \pm 2.4 \text{ d}$, with a median of 61 d, and $26.8 \text{ d} \pm 2.7 \text{ d}$, with a median of 9 d, respectively (van de Lindt et al., 2018). From the study data, Table 8 details the estimated dislocation rate by damage state. Households in higher damage states are more likely to relocate for a period of time.

Table 8: Estimated Dislocation Rate by Damage State.

	Buildings	Population
DS 0	9.13%	9.55%
DS 1	22.97%	22.93%
DS 2	30.60%	31.78%
DS 3	50%	50%

Natural hazard literature regarding population dislocation suggests that low-income and minority populations occupy the highest hazard areas (FEMA, 2018). In addition, compared to homeowners, renters tend to experience higher levels and longer periods of dislocation (Peacock and Girard, 1997; Lin et al., 2008; Comerio, 1998; Zhang and Peacock, 2008; Peacock et al., 2014). Figure 22 illustrates the tenure of dislocated households by damage state. Dislocated rental housing percentages increased as damage to a structure worsened. In most cases, even with elevated damaged properties, low-income homeowners tend to stay in their homes. Especially when

insurance covers short-term accommodation expenses, higher-income homeowners are more motivated to temporarily relocate.

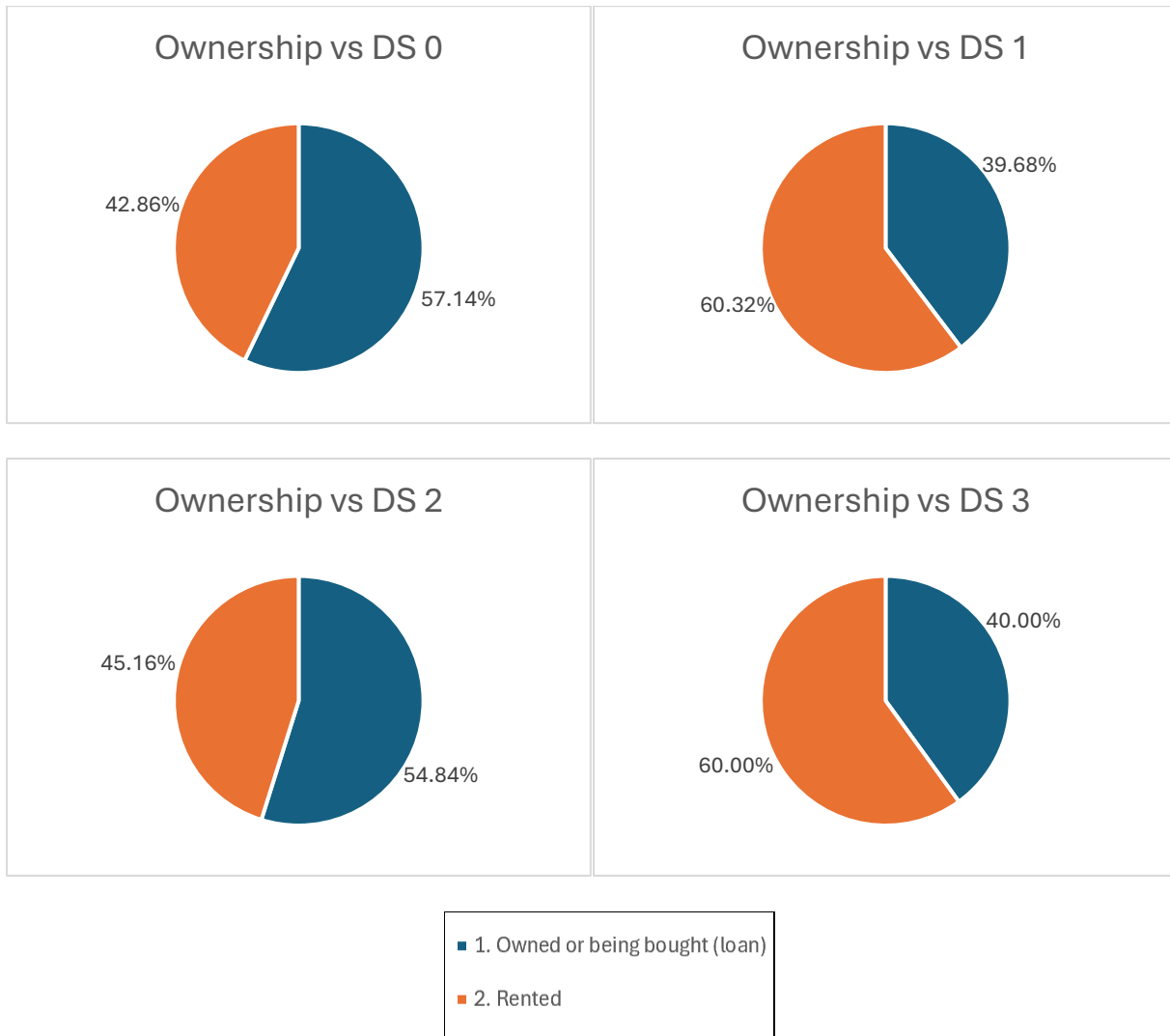


Figure 22: Dislocated Buildings Ownership by Damage State.

From this analysis, due to the simulated Hurricane Matthew flooding event, a total of 1,293 people in 564 buildings dislocated. According to Lumberton field study data, in Robeson County alone, approximately 1,400 people dislocated from their homes (van de Lindt et al., 2018). Total dislocated population differences are due to the synthetic allocation process.

Table 9 presents households allocated by annual household income. Table 10 depicts the number of buildings and people dislocated by race. As shown, households with an annual income less than \$15,000 populate a large percentage of dislocated buildings, with Black or African American alone households having the highest representation.

Table 9: Dislocated buildings and people in terms of annual household income.

Household Income	Total Buildings	Percentage	Total People	Percentage
0.NA vacant or group quarters	49	8.69%	0	0.00%
1.Less than \$15,000	202	35.82%	477	36.89%
2.\$15,000 to \$24,999	73	12.94%	170	13.15%
3.\$25,000 to \$74,999	208	36.88%	548	42.38%
4.\$75,000 to \$99,999	26	4.61%	82	6.34%
5.\$100,000 or more	6	1.06%	16	1.24%
Total	564	100%	1293	100%

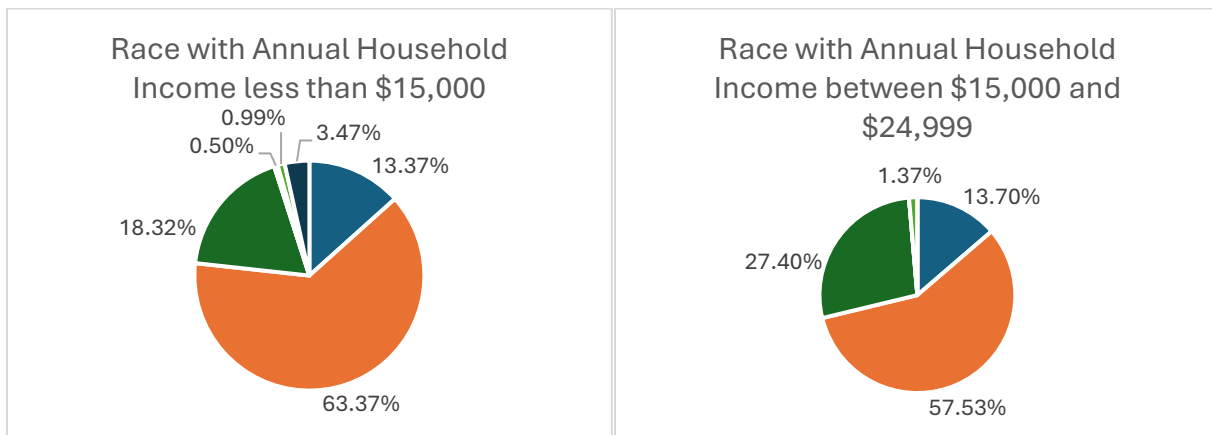
Table 10: Dislocated buildings and people in terms of race (not including NA vacant or group quarters).

Race	Total Buildings	Percentage	Total People	Percentage
1.White alone	82	15.92%	195	15.08%
2. Black or African American alone	299	58.06%	742	57.39%
3.American Indian and Alaska Native alone	117	22.72%	309	23.90%
4.Asian alone	0	0.00%	0	0.00%
5. Native Hawaiian and Other Pacific Islander alone	1	0.19%	3	0.23%
6. Some Other Race alone	4	0.78%	10	0.77%
7. Two or More Races	12	2.33%	34	2.63%
Total	515	100%	1293	100%

Dislocated buildings are 58% Black or African American alone households. While other races have much lower percentages, with American Indian and Alaska Native alone households accounting for 23%, and white alone households representing 16% of dislocated buildings. In

terms of displaced households, these results indicate Black or African American alone and Alaska Native alone communities are disproportionately impacted.

Dislocated building distribution across racial groups and annual household income are illustrated in Figure 23. 18% of White alone households fall within the middle-income brackets (\$25,000 to \$74,999), with 31% an annual income of \$75,000 to \$99,999, and no representation in the highest income bracket (\$100,000 or more). Black or African American alone households have the highest representation (63%) in the lowest income bracket (less than \$15,000), and a significant presence with an annual household income of \$15,000 to \$24,999 (58%) and \$25,000 to \$74,999 (55%). American Indian and Alaska Native alone households exhibit notable presence in the lower income brackets (less than \$15,000 at 18% and \$15,000 to \$24,999 at 27%), with 24% of household with middle-income bracket (\$25,000 to \$74,999).



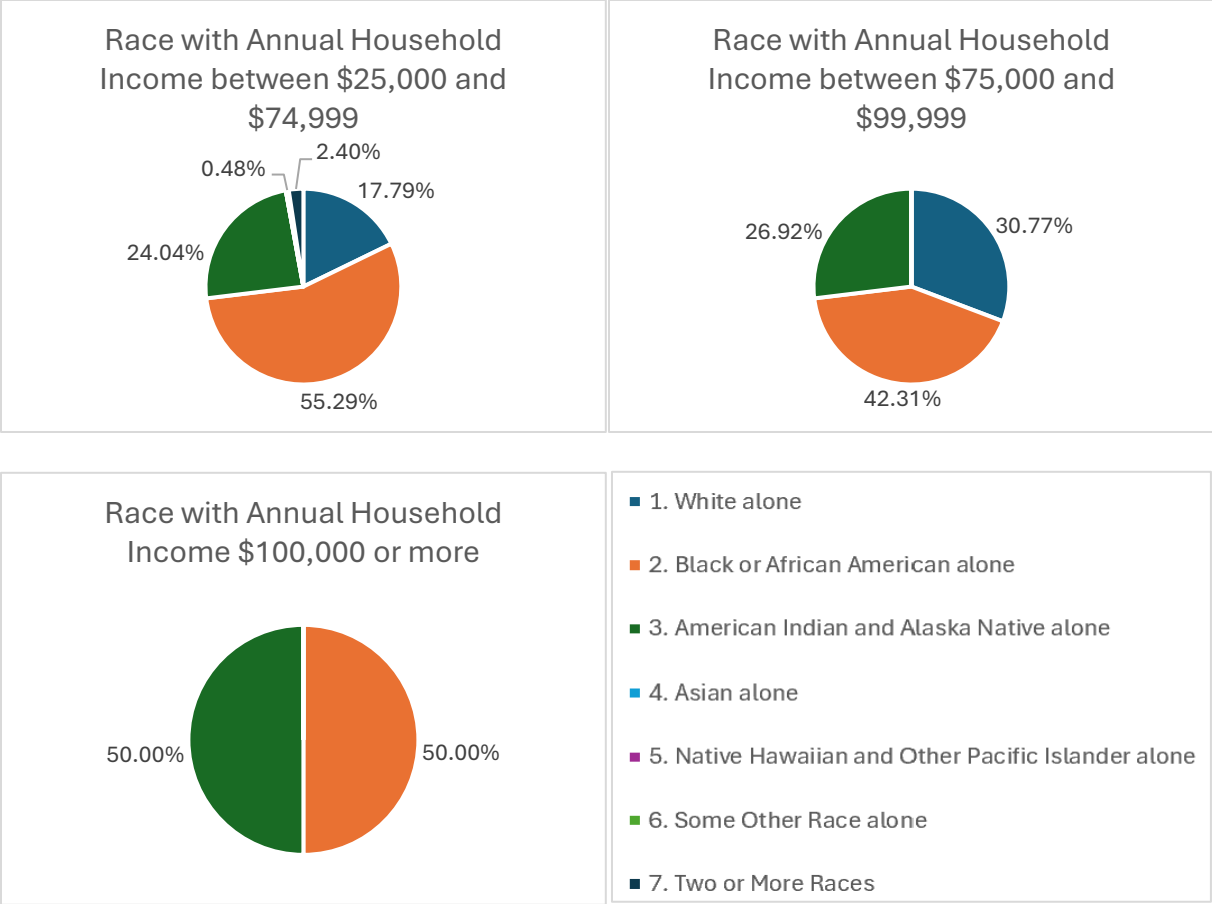


Figure 23: Dislocated Buildings by Race Compared to Annual Household Income.

Dislocated building distribution across annual household incomes and damage states are illustrated in Figure 24. Households with an annual income less than \$15,000 have the highest percentages in DS 0 (32%) and DS 1 (37%), and significant representation in DS 2 (31%) and DS 3 (40%), indicating vulnerabilities across damage states. Households with an income between \$15,000 to \$24,999 have low presence in DS 0 (19%), DS 1 (12%), and DS 2 (11%). \$25,000 to \$74,999 household income shows prominent representation in DS 0 (36%), DS 1 (36%) and DS 2 (39%), with the highest percentages in DS 3 (60%). Households with annual household income greater than \$75,000 have minimal presence across all damage states.

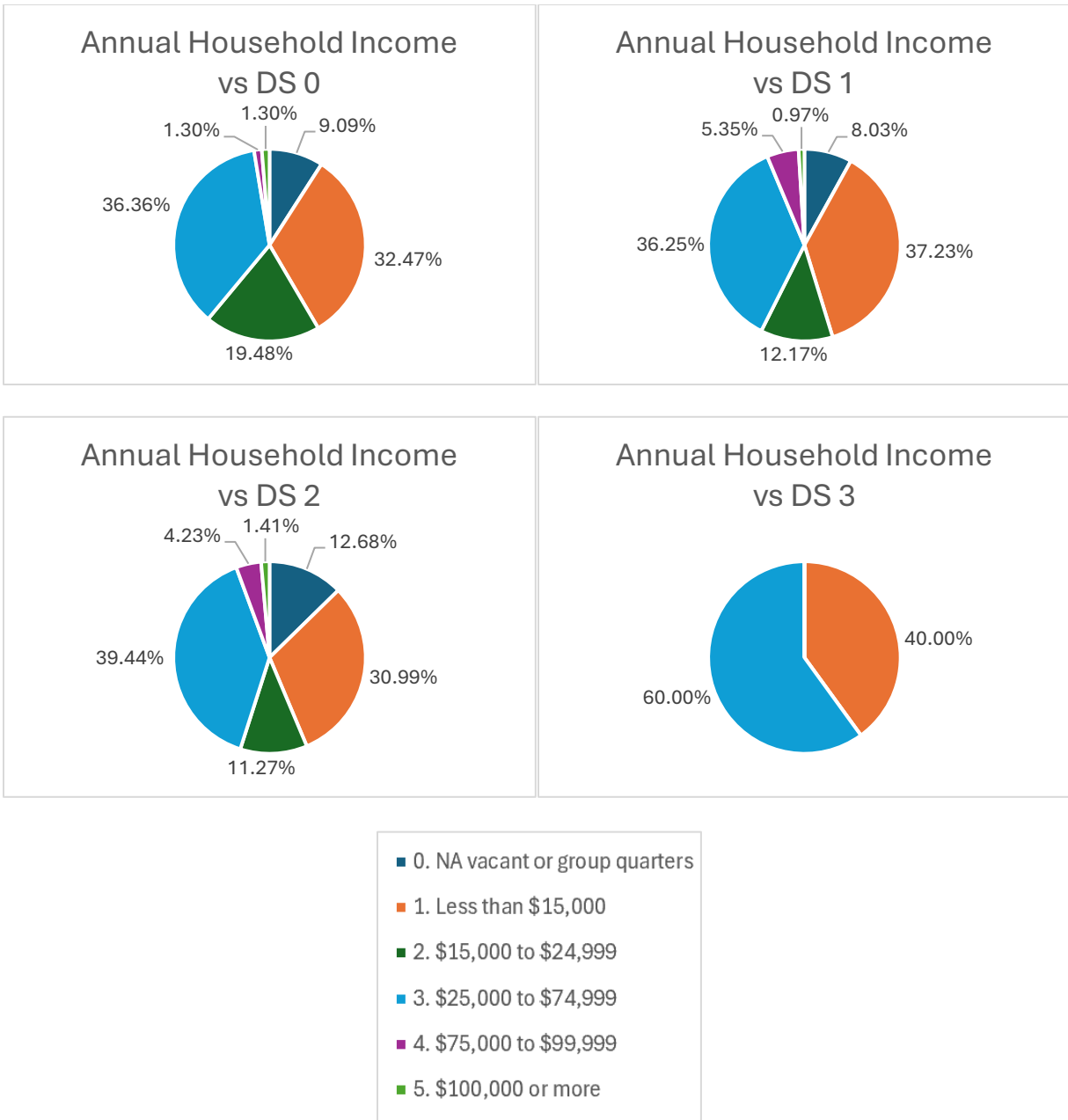


Figure 24: Dislocated Buildings by Annual Household Income versus Damage States.

Determining greatest damage and recovery benefits of property acquisitions, annual household income is a significant demographic indicator, influencing households' participation in property acquisitions. All damage states exhibit a trend where the majority of households fall into income bracket 1, less than \$15,000, and income bracket 3, \$25,000 to \$74,999.

Low-income households (less than \$25,000) exhibit high vulnerability across all damage states, with the highest representation in DS 1 and DS 0. Middle income households (\$25,000 to \$74,999) show significant representation in higher damage states (DS 2 and DS 3). Higher-income households (< \$75,000) exhibit low vulnerability across all damage states.

Mirroring exposed dataset patterns, Black or African American alone dislocated households are disproportionately impacted by natural hazards in Lumberton, representing at least 40% of each DS, with DS 2 having the highest percentage.

Dislocated building damage states in terms of race are depicted in Figure 25. Black or African American alone households exhibit significant vulnerabilities, with the highest representation in DS 1 (60%), and DS 2 (66%), and notable presence in DS 0 and DS 3 (40%). American Indian and Alaska Native alone households have high representation in DS 0 (43%) and significant presence in DS 1 (21%). White alone households have moderate presence across all damage states, with 60% of households in DS 3. Dislocated building damage states verses other demographics can be seen in appendix Figures A7 through A10.

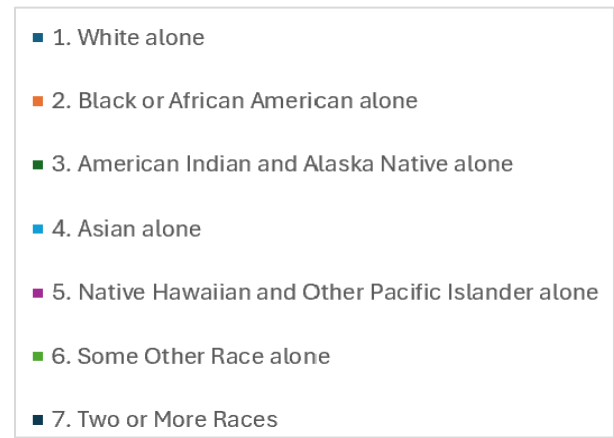
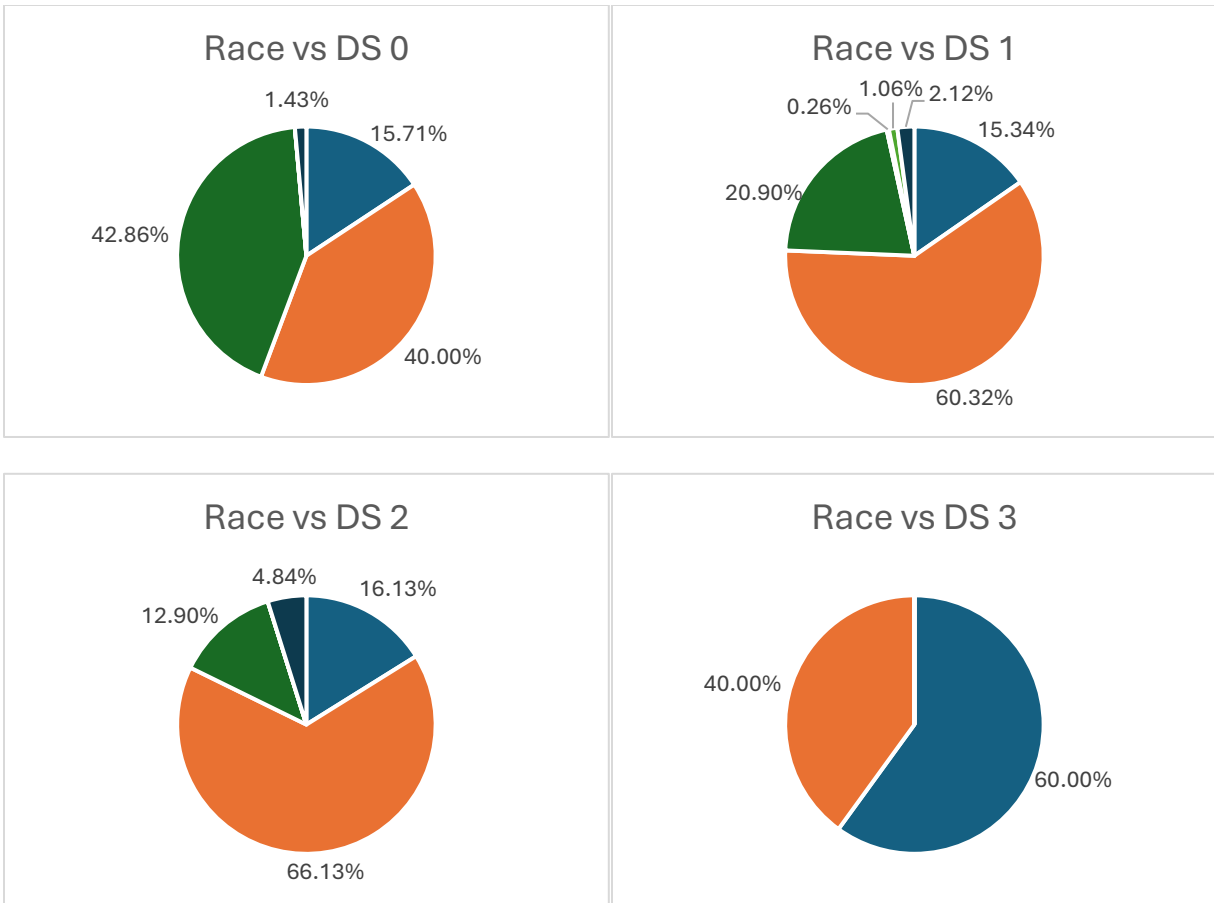


Figure 25: Dislocated Buildings by Race versus Damage State.

Inclusive hazard response and recovery efforts address the needs of the most vulnerable racial and income groups, reducing disparities and promoting resilience across all communities. Highlighting vulnerabilities among racial groups, Black or African American alone households are the most

impacted across damage states. Demographic and income information ensures policy decisions promote economic stability and equity. Emphasizing economic disparities faced the Lumberton community, this analysis provides insight into the income distribution and racial demographics across different racial groups.

3.5: Acquisition Analysis

Described in Section 2.5, to determine how different input variables influence particular outputs under a set of given assumptions, acquisition analyses were conducted. Economic and demographic impacts of hazard-related buyouts are examined in this study for households selected from the exposed and dislocated datasets. Comparing income and racial compositions across bought-out buildings, total buildings, exposed buildings, and dislocated buildings, this analysis emphasizes economic vulnerabilities and implications of hazard management strategies.

Exposed populations have lower median and average income compared to the total population, shown in Table 11, indicating at risk households have lower annual incomes. Within the exposed categories, DS 1 has the highest number of households with lower median and average incomes. Even more pronounced, dislocated populations have the lowest median and average incomes, suggesting economic vulnerability among dislocated households. Dislocated households in DS 1 exhibit lower median and average annual incomes compared to DS 2 and DS 3, quantifying that flood hazards are more likely to affect economically disadvantaged households, consistent with published research (Roohi et al., 2020; Cutter et al., 2003; Phillips et al., 2010; Shi et al., 2022).

Table 11: Acquisition analysis base scenarios for further calculation.

Scenario	Buildings	Population	Median Income	Average Income
Total	52,801	133,199	\$29,566	\$42,051
Exposed	2,874	6,635	\$24,032	\$32,231
Dislocated	564	1,293	\$20,989	\$30,546
Exposed DS 0	843	2,063	\$27,612	\$36,209
Exposed DS 1	1,789	4,078	\$21,324	\$30,167
Exposed DS 2	232	472	\$25,357	\$33,984
Exposed DS 3	10	22	\$26,335	\$26,137
Dislocated DS 0	77	197	\$20,055	\$30,238
Dislocated DS 1	411	935	\$20,435	\$30,411
Dislocated DS 2	71	150	\$26,931	\$32,443
Dislocated DS 3	5	11	\$28,660	\$21,508

3.5.1: Acquisition Analysis - Exposed Buildings

Focusing initially on the exposed dataset, this study simulates 11,946 buyout scenarios where 50 acquisitions are randomly distributed across four damage states: DS 0, DS 1, DS 2, and DS 3. Each scenario is analyzed for metrics including the bought-out building count (N_{BB-E}), bought out population count (N_{BP-E}), and the bought out building annual household income (AHI_{BB-E}). Figure 26 illustrates the comparison of median and average incomes across bought-out buildings selected from the exposed dataset, total buildings, exposed buildings, and dislocated buildings. Bought-out buildings have the lowest average annual household incomes.

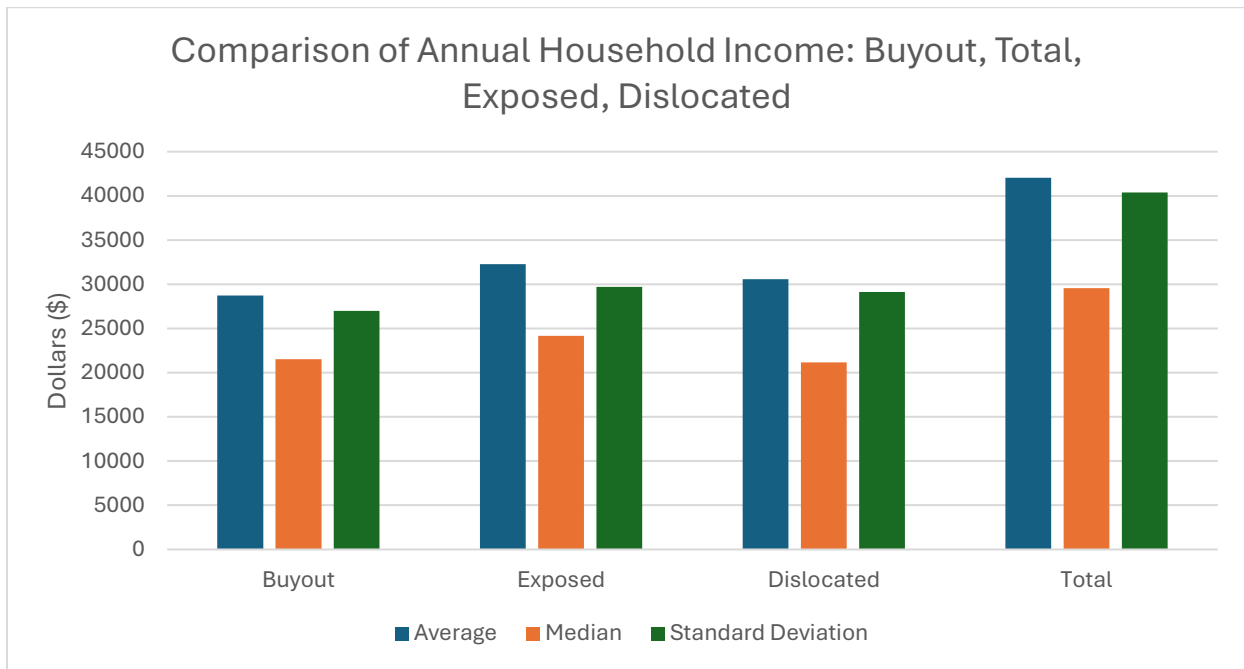


Figure 26: Buyouts Selected from Exposed Buildings: Comparison of Median and Average Incomes.

The median annual household income of the bought-out buildings is \$21,514, and the average annual household income is \$28,730, with a standard deviation of \$26,992. Standard deviation measures the dispersion around the average. The total dataset has a median household income of \$29,574 and average annual household income of \$42,063, with a standard deviation of \$40,370. For the exposed dataset, the median household income is \$24,155 and average household income is \$32,292, with a standard deviation of \$29,699. The dislocated dataset has a median household income of \$21,148 and an average household income of \$30,560, with a standard deviation of \$29,143.

Supporting earlier discussions, this data indicates higher economic vulnerability among buyout participants, suggesting that lower income households may be disproportionately affected by

buyout programs. Although lower than the total building dataset, the median and average incomes of the exposed buildings dataset are higher than those of the bought-out buildings and dislocated buildings. Highlighting economic challenges among displaced populations, dislocated buildings feature lower median and average incomes.

Figure 27 illustrates comparisons of racial demographics from the buyouts selected from the exposed buildings. The majority of bought-out buildings selected from the exposed dataset are owned or rented by Black or African American alone households (average 48%), followed by American Indian and Alaska Native alone households (average 24%), and only 16% White alone households. More diverse, the total buildings group has the highest percentage of American Indian and Alaska Native alone (average 34%), and a notable representation of White alone households (average 30%) and 22% Black or African American alone households. Most of the exposed buildings are Black or African American alone households (average 56%), followed by American Indian and Alaska Native alone (average 21%), and only 12% White alone households. 53% of the dislocated households are Black or African American alone, 21% American Indian and Alaska Native alone, and only 14% White alone.

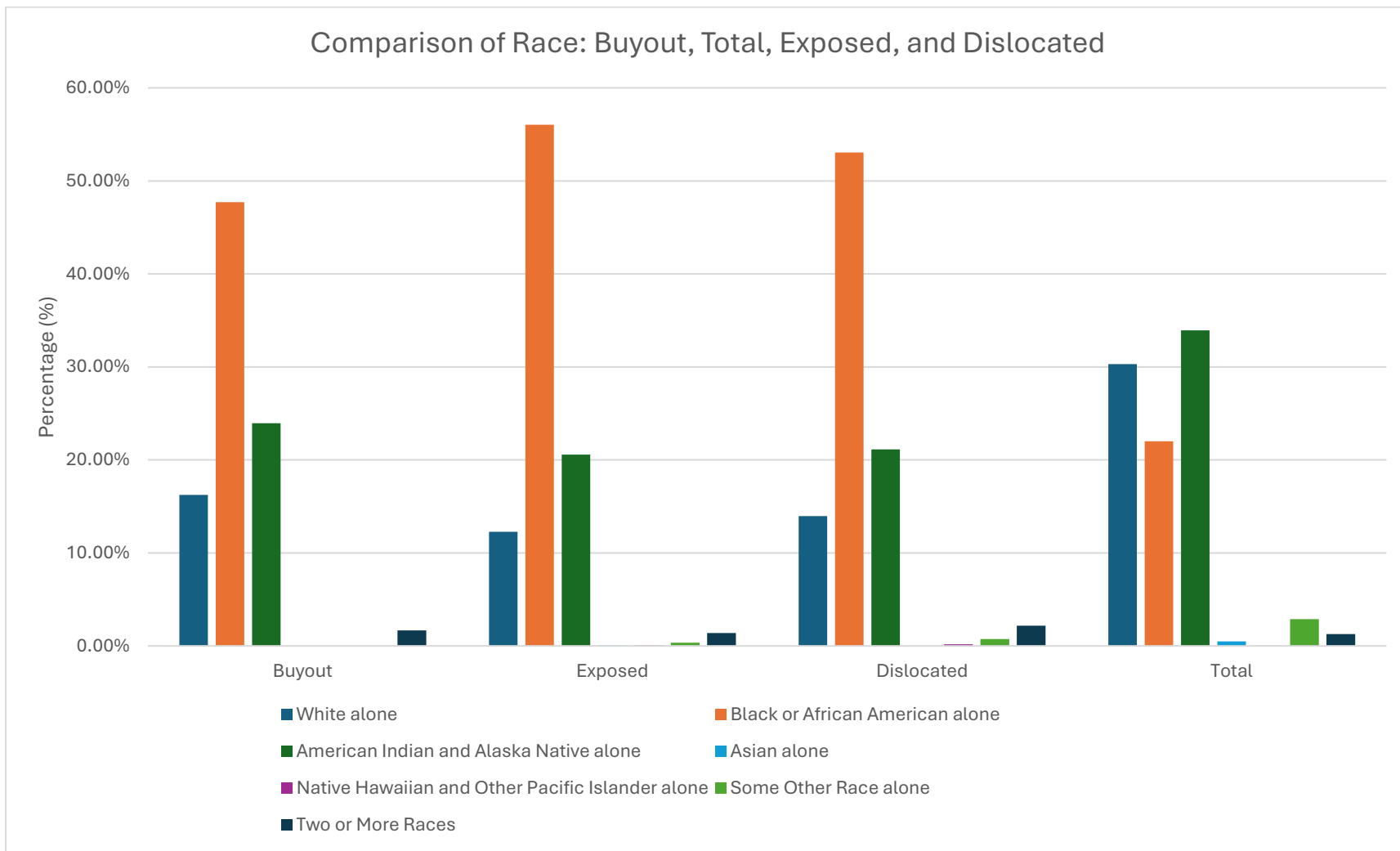


Figure 27: Buyouts Selected from Exposed Buildings: Comparison of Race.

Most consistent, the total buildings have less variation in racial composition percentages. Bought-out buildings show more variation, particularly among Black or African American alone and American Indian and Alaska Native alone households. Asian alone, Native Hawaiian and Other Pacific Islander alone, and Some Other Race alone households have negligible representation across all datasets. Higher percentages of Black or African American alone in the bought-out, exposed, and dislocated buildings suggest greater vulnerability and impact on these racial groups. Hazard management and recovery efforts need to consider the racial composition of affected populations to ensure equitable recovery and resources are provided to reduce disparities and mitigate long-term socioeconomic impacts. High percentages of Black or African American alone households in the bought-out, exposed, and dislocated groups highlight the need for targeted mitigation strategies.

3.5.2: Acquisition Analysis - Dislocated Buildings

Considering the dislocated dataset, 7,211 buyout scenarios are simulated in this study where 50 acquisitions are randomly distributed across four damage states: DS 0, DS 1, DS 2, and DS 3. Each scenario is analyzed for the following metrics: the total number of buildings bought out (N_{BB-D}), the population count of the bought-out buildings (N_{BP-D}), and the annual household income of the bought-out buildings (AHI_{BB-D}). Figure 28 depicts annual household income comparisons of the buyouts selected from the dislocated dataset. Trends seen in buyout scenarios of the exposed dataset are also seen here.

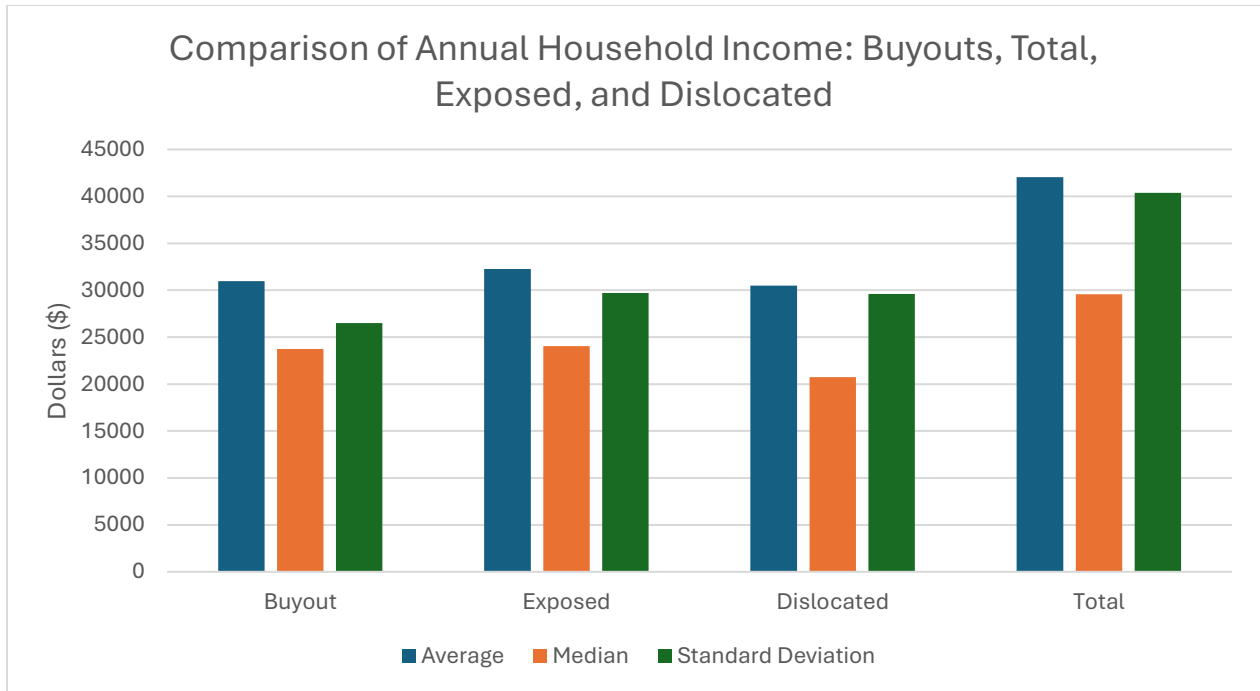


Figure 28: Buyouts Selected from Dislocated Buildings: Comparison of Median and Average Incomes.

The median annual household income of the bought-out buildings is \$23,750, and the average annual household income is \$30,970, with a standard deviation of \$26,507. The total dataset has a median annual household income of \$29,570 and average annual household income of \$42,062, with a standard deviation of \$40,371. For the exposed dataset, the median household income is \$24,055, and annual household income of \$32,254, with a standard deviation of \$29,712. The dislocated dataset has a median household income of \$20,731, and average annual household income of \$30,504, with a standard deviation of \$29,602.

Supporting earlier discussions, higher economic vulnerability is indicated among buyout participants, suggesting that acquisition programs may disproportionately affect lower-income households. Highlighting economic challenges among displaced populations, similar to bought-out buildings, the dislocated buildings have lower median and average incomes. Racial demographics of buyouts selected from the dislocated dataset are compared in Figure 29.

Predominantly, the bought-out buildings households consist of Black or African American alone (average 50%), followed by American Indian and Alaska Native alone (average 22%) and White alone (average 20%). Showing a more balanced racial distribution, the total building group includes 30% White alone households, 22% Black or African American alone households, and 34% American Indian and Alaska Native alone households. Dominating exposed buildings, there are 56% Black or African American alone households, followed by 21% American Indian and Alaska Native alone households, and 12% White alone households. Similarly, the dislocated buildings households are predominantly Black or African American alone (average 53%), followed by American Indian and Alaska Native alone (average 21%), and White alone (average 14%). Across all categories, there is virtually no representation of Asian alone and Native Hawaiian and Other Pacific Islander alone populations.

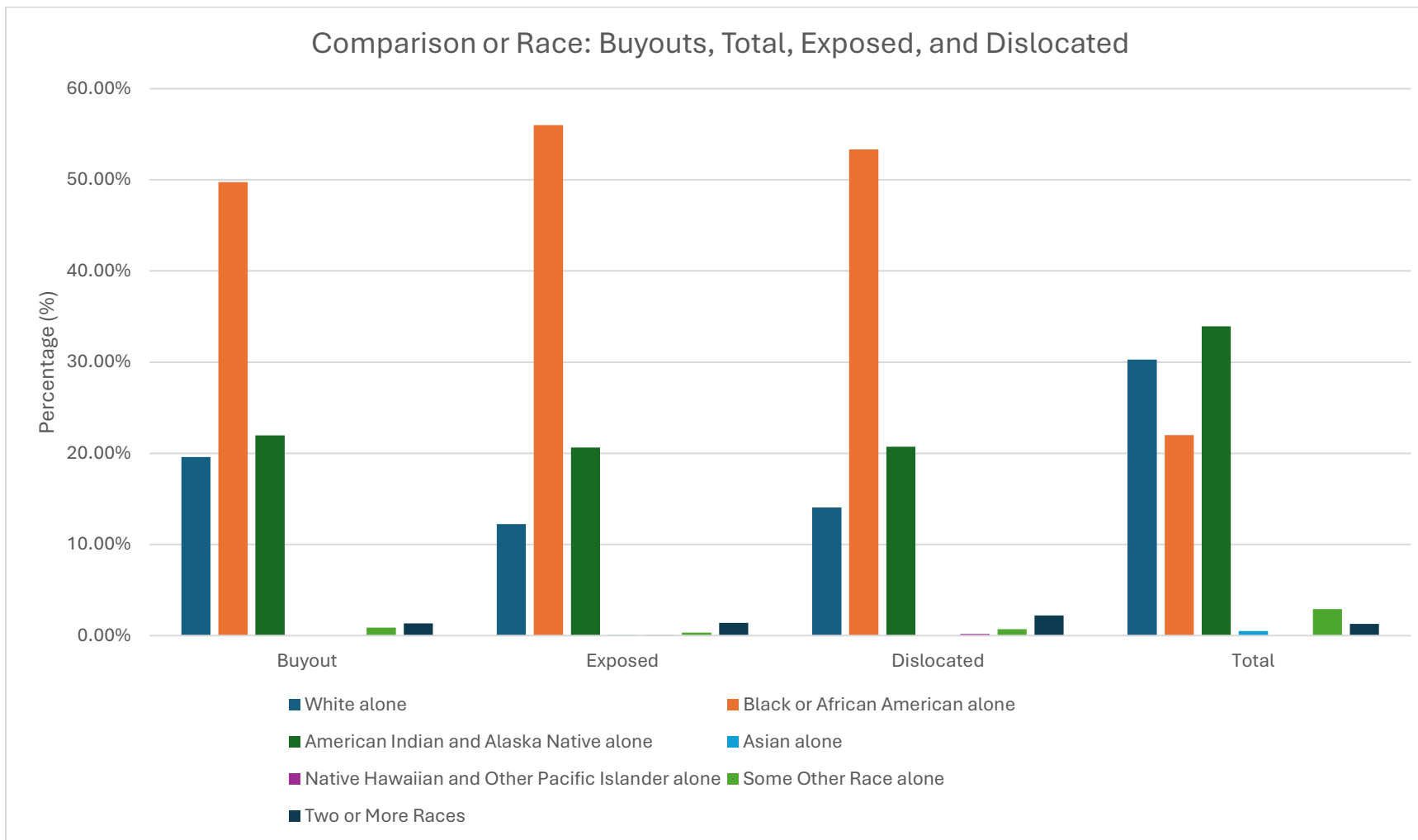


Figure 29: Buyouts Selected from Dislocated Buildings: Comparison of Race.

Particularly in the bought-out, exposed, and dislocated dataset, these results indicate Black or African American alone households are disproportionately affected and face higher risks and vulnerabilities in natural hazards. With a more balanced representation in the total dataset, White alone households are less present in bought-out, exposed, and dislocated buildings.

3.5.3: Acquisition Analysis Conclusions

To quantify the social equitability of property acquisitions, this analysis evaluates simulated buyout scenarios through examination of racial demographics and annual household income. Providing similar conclusions, the analyses of property acquisitions selected from the exposed and dislocated datasets determine lower income levels and minority households are more prevalent in the bought-out populations. Outliers in income data among the bought-out buildings suggest that neighborhoods more susceptible to flood hazards may face economic challenges and disparities post-hazard. Aligning with broader racial disparities, Black or African American alone households' higher percentage in bought-out buildings quantify that historically marginalized communities may face greater impacts and varying levels of support in hazard and recovery efforts. By prioritizing lower-income, minority households, this data indicates that property acquisitions in Lumberton would be more socially equitable. Race and income statistics in the bought-out buildings align with broader trends, promoting equitable strategies to address racial and income disparities during and after hazard events. Hazard response and recovery efforts address racial disparities and promote equity in Lumberton by concentrating on the needs of Black or African American alone communities.

Chapter 4: Conclusions, Contributions, and Recommendations

Exhibiting “discriminatory patterns,” floods disproportionately affect lower-income households in lower-lying land. Recognizing inequalities in funding opportunities and resource allocation, the City of Lumberton is exploring mitigation strategies, promoting resilient and equitable natural hazard preparedness (Sports, 2020).

Existing literature indicates wealthier, densely populated urban communities benefit from property acquisitions due to alternative housing options and accessible financial resources. Socially equitable property acquisitions in Lumberton would require vertical equity with justified reasons that support different (uneven) distributions that protect vulnerable populations. Results of this case study quantify that property acquisitions in Lumberton would address the needs of low-income minority communities and are therefore more socially equitable.

4.1 Conclusions

Leveraging existing work, historical social-science data, and the ongoing Lumberton longitudinal field study, high-resolution flood risk models and analyses are utilized to mitigate flood hazards in this research. To enhance vulnerability assessments and mitigation planning, these models integrated detailed geographic data and building characteristics. Using IN-CORE, this study assesses the social equitability of property acquisitions by evaluating hazard, infrastructure, community exposure, and vulnerability models. Combining damage assessments with socio-economic and demographic data from the neighborhood level (census block) households were synthetically allocated to understand Hurricane Matthew’s impact on Lumberton. Providing valuable statistical insights into income variations and racial distributions, the acquisition analysis compares bought-out and non-bought-out households’ post-hazard. Highlighting significant

economic disparities, particularly for lower-income groups, concerns about socio-economic inequalities exacerbated by property acquisition programs are reinforced.

Results from the damage analysis determined the majority of damaged homes were found to be in DS 0 and DS 1, indicating minor damage to the structure. Approximately 29% of exposed buildings experienced damage in DS 0, 62% in DS 1, 8% in DS 2, and less than 1% in DS 3. Due to the levee breach, higher damage states were found in households located south of the Lumber River.

The majority of households affected by the flooding event are Black or African American alone (62% of exposed buildings and 58% of dislocated buildings). American Indian and Alaska Native alone households are the second-largest affected group (23% of exposed and dislocated buildings), while White alone households represent 14% of exposed buildings and 16% of dislocated buildings.

By comparing race with annual household income, this study determined that White alone households are likely to fall into higher income brackets (>30% of exposed white alone households have an annual income of \$100,000 or more). Black or African American alone households are primarily in the lowest income bracket (\geq 57% of exposed and dislocated households have an annual income of \$24,999 or less), demonstrating economic vulnerability. American Indian and Alaska Native alone households have a substantial presence in lower income brackets (>25% of exposed and dislocated households have an annual income between \$15,000 and \$24,999).

In both the exposed and dislocated datasets, the majority of bought-out buildings were owned or rented by Black or African American households (>48%), followed by American Indian and Alaska Native alone households (>20%). Based on this study, Lumberton property acquisitions

would be socially equitable as a recovery mechanism used by more low-income minority households. Documented in literature, and now quantified with modeling, with increasing representation in higher damage state and lower income brackets, Black or African American alone households are disproportionately affected by flooding in Lumberton. Property acquisition decision making processes can be adjusted for social equity recommendations to improve economic mobility post-hazard.

In summary, this research emphasizes the intersection of annual household income and racial demographics with exposure modeling and flooding impacts. Through census data, synthetic household allocation, and the IN-CORE Platform, this study demonstrates a way to quantify how to make socially equitable property acquisitions with respect to annual household income.

4.2: Contributions

Damage State, Race, and Annual Household Income Comparison: Evaluating the reliability of property acquisitions, this research provides a detailed comparative analysis of damage states, racial demographics, and annual household income, offering quantitative understanding of the intersection between flood impacts and socioeconomic vulnerabilities. Verifying that floods exhibit “discriminatory patterns,” lower income brackets and higher damage states had a higher presence of Black or African American alone households.

Economic and Demographic Impacts of Hazard-Related Property Acquisitions Analysis: Acquisition analyses were employed to examine the social equity implications of property acquisition strategies in flood prone regions through evaluation of annual household income and racial demographics across multiple datasets. Future hazard mitigation research can apply this framework to assess socio-economic impacts of mitigation efforts.

Lumberton, NC Case Study on Socially Equitable Property Acquisitions: A comprehensive case study is provided on the social equitability of property acquisition scenarios in Lumberton, a financially and ethnically diverse community. By prioritizing low-income minority households, 50 buyouts would be more socially equitable in Lumberton. Socio-economic impacts of property acquisitions in flood-prone inland areas provides a reference for community resilience and hazard mitigation efforts.

4.3: Recommendations

Following hurricanes, this research examined inland flooding events. All elements of hurricanes should be factored into further research, including storm surge and wind damage impacts. Combining aspects of coastal and inland communities would contribute to a more thorough comprehension of hurricane hazards, enabling a comprehensive evaluation of mitigation and adaptation management.

Acquisition analyses concentrated exclusively on baseline variables of population, building count, annual household income, and racial demographics. Incorporation of additional data, including household market value and insurance coverage, is necessary to increase consideration of social equity in property acquisitions.

Promoting socio-economic equity in effective property acquisitions, qualitative and quantitative data and assessments are integral. Only quantitative data is considered in this methodology, qualitative elements of recovery efforts including land-use impacts, homeowner decisions, and long-term socio-economic outcomes must be reviewed in future analyses. Ensuring equitable recovery and effective risk mitigation, property acquisitions must comprise a holistic approach.

References

- Almoghathawi, Y., González, A.D., and Barker, K. (2021). Exploring Recovery Strategies for Optimal Interdependent Infrastructure Network Resilience. *Network. Spat. Econ.* 2021, 21, 229–260.
- Attary, N., Van De Lindt, J. W., Barbosa, A. R., Cox, D. T., & Unnikrishnan, V. U. (2019). "Performance-Based Tsunami Engineering for Risk Assessment of Structures Subjected to Multi-Hazards: Tsunami following Earthquake." *Journal of Earthquake Engineering*, 23, 1–20.
- Bai, J., Hueste, M.B.D. and Gardoni, P. (2009), Probabilistic Assessment of Structural Damage due to Earthquakes for Buildings in Mid-America *Journal of Structural Engineering* 135(10) DOI: 10.1061/(ASCE)0733-9445(2009)135:10(1155)
- Baker, C. K., Binder, S. B., Greer, A., Weir, P., & Gates, K. (2018). Integrating Community Concerns and Recommendations into Home Buyout and Relocation Policy. *Risk, Hazards & Crisis in Public Policy*, 9(4), 455–479. <https://doi.org/10.1002/rhc3.12144>
- Beck, A. L., Cha, E. J., & Peacock, W. G. (2023). Incorporation of Equity into Infrastructure Decision-Making: Development of an Equity Metric for Infrastructure Retrofitting.
- Beck, A. L., Cha, E. J., & Peacock, W. G. (n.d.). Incorporation of Equity into Infrastructure Decision-Making: Development of an Equity Metric for Infrastructure Retrofitting. *14th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP14*.
- BenDor, T. K., Salvesen, D., Kamrath, C., & Ganser, B. (2020). Floodplain Buyouts and Municipal Finance. *Natural Hazards Review*, 21(3), 04020020. [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000380](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000380)

- Binder, S. B., & Greer, A. (2016). A historical assessment of home buyout policy: Are we learning or just failing? *Housing Policy Debate*. doi:10.1080/10511482. 2016.1245209
- Binder, S. B., & Greer, A. (2016). The Devil Is in the Details: Linking Home Buyout Policy, Practice, and Experience After Hurricane Sandy. *Politics and Governance*, 4(4), 97–106. <https://doi.org/10.17645/pag.v4i4.738>
- Binder, S. B., C. K. Baker, and J. P. Barile. 2015. “Rebuild or relocate? Resilience and post disaster decision-making after Hurricane Sandy.” *Am. J. Community Psychol.* 56 (1–2): 180–196. <https://doi.org/10.1007/s10464-015-9727-x>.
- Bishop, J. (2017). *Building Sustainable Cities of the Future*. Springer.
- Blaze, J. T., & Shwalb, D. W. (2009). Resource loss and relocation: A follow-up study of adolescents two years after Hurricane Katrina. *Psychological Trauma: Theory, Research, Practice, and Policy*, 1(4), 312–322. doi:10.1037/a0017834
- Bright, D. (2021, September 19). City of Lumberton awarded \$7.2 million to buy, demolish flood-damaged properties. WBTW. <https://www.wbtw.com/news/state-regional-news/city-of-lumberton-awarded-7-2-million-to-buy-demolish-flood-damaged-properties/>
- Bukvic, A., and G. Owen. 2017. “Attitudes toward relocation following Hurricane Sandy: Should we stay or should we go?” *Disasters* 41 (1): 101–123. <https://doi.org/10.1111/disa.12186>.
- Bullard RD, Wright B (2009) Introduction. In: Bullard RD, Wright B (eds) *Race, place, and environmental justice after Hurricane Katrina: struggles to reclaim, rebuild, and revitalize New Orleans and the Gulf Coast*. Westview Press, Boulder, CO, pp 1–15
- Center for Science Education. (n.d.). Hurricane damage. University Corporation for Atmospheric Research. Retrieved June 4, 2024, from <https://scied.ucar.edu/learning-zone/storms/hurricane-damage>

- Comerio, M.C. (1998). *Disaster hits home: New policy for urban housing recovery*. Berkeley: University of California Press.
- Conrad, D.R., McNitt, B., Stout, M. (1998) *Higher ground: a report on voluntary property buyouts in the nation's floodplains*. National Wildlife Federation, Washington, DC
- Curran-Groome, W., Haygood, H., Hino, M., BenDor, T. K., & Salvesen, D. (2021). Assessing the full costs of floodplain buyouts. *Climatic Change*, 168(1–2), 3. <https://doi.org/10.1007/s10584-021-03178-x>
- Curran-Groome, W., Hino, M., BenDor, T. K., & Salvesen, D. (2022). Complexities and costs of floodplain buyout implementation. *Land Use Policy*, 118, 106128. <https://doi.org/10.1016/j.landusepol.2022.106128>
- Cutter SL, Boruff BJ, Shirley WL (2003) Social vulnerability to environmental hazards. *Soc Sci Q* 84(1):242–261
- De Vries (2017) Temporal vulnerability and the post-disaster ‘window of opportunity to woo:’ a case study of an African American floodplain neighborhood after Hurricane Floyd in North Carolina. *Humam Ecology* 45:437–448.
- Elliott JR, Brown PL, Loughran K (2020) Racial inequities in the federal buyout of flood-prone homes: a nationwide assessment of environmental adaptation. *Socius* 6:237802312090543. <https://doi.org/10.1177/2378023120905439>
- Federal Emergency Management Agency, *Hazard Mitigation Assistance Guidance* (U.S. Department of Homeland Security, 2015)
- Federal Emergency Management Agency. *Building Resilient Infrastructure and Communities (BRIC)*; Federal Emergency Management Agency: Washington, DC, USA, 2020.

Federal Emergency Management Agency. Flood Mitigation Assistance Grant Program; Federal Emergency Management Agency: Washington, DC, USA, 2020.

Federal Emergency Management Agency. Hazard Mitigation Assistance; Federal Emergency Management Agency: Washington, DC, USA, 2020

FEMA (2015) Hazard mitigation assistance guidance addendum. Federal Emergency Management Agency (FEMA), Washington, D.C. Last accessed 19 Oct 2022 from: https://www.fema.gov/sites/default/files/2020-07/fy15_hma_addendum.pdf

FEMA (2016) Hazard mitigation assistance cost share guide. Federal Emergency Management Agency (FEMA), Washington, D.C. Last accessed 19 Oct 2022 from: https://www.fema.gov/sites/default/files/2020-08/fema_hma_cost-share-guide.pdf

FEMA (2016). "Hazard mitigation assistance cost share guide." Retrieved from <https://www.fema.gov/media-librarydata/14637666649644e6dd22652cb7c8a6162904f3b1b-2022/FinalHMACostShareGuide508.pdf>.

FEMA (2021a) 3 Years Long, 3 Years Strong: New Jersey's Successful Approach to Purchasing Homes along Sandy's Flooded Path. In: FEMA Tools Pract. Case Study Library. Last accessed 21 Mar 2022 from: <https://www.fema.gov/case-study/3-years-long-3-years-strong-new-jerseys-successful-approach-purchasing-homes-along>.

FEMA (2021b) Building resilient infrastructure and communities FY 2020 Sub application Status. FEMA website. Last accessed on 19 Oct 2022 from: <https://www.fema.gov/grants/mitigation/building-resilient-infrastructure-communities/after-apply/fy-2020-subapplication-status>

FEMA (2022a) Methodology report acquisition benefit-cost analysis (BCA) efficiencies for HMA programs. Federal Emergency Management Agency (FEMA), Washington, D.C. Last

accessed 19 Oct 2022 from: https://www.fema.gov/sites/default/files/documents/fema_rlsrl-acquisition-efficiency-methodology-report.pdf

FEMA (2022b) President Biden, Vice President Harris, FEMA announce flood mitigation initiative to aid four states impacted by Hurricane Ida. Federal Emergency Management Agency (FEMA) Press Release HQ-22-03, Washington, D.C. Last accessed 19 Oct 2022 from: <https://www.fema.gov/press-release/20220321/president-biden-vice-president-harris-fema-announce-flood-mitigation>

Field, C., Hino, M., Johnston, E., Kraan, C., Mach, K., & Siders, A. R. (2019, October 9). Managed retreat through voluntary buyouts of flood-prone zones - science. *Science Advances*. <https://www.science.org/doi/10.1126/sciadv.aax8995>

FloodSmart.gov. (n.d.). Reduce risks, cut cost of flood insurance. Federal Emergency Management Agency. Retrieved June 4, 2024, from <https://www.floodsmart.gov/reduce-risks>

Freudenberg R, Calvin E, Tolkoﬀ L, Brawley D (2016) Buy-in for buyouts: the case for managed retreat from flood zones. Lincoln Institute for Land Policy, Cambridge, MA

Gao. 2021. "FEMA Should Take Additional Steps to Streamline Hazard Mitigation Grants and Assess Program Effects." Retrieved February 7, 2021 (<https://www.gao.gov/assets/720/712172.pdf>).

Godschalk, D., T. Beatley, P. Berke, D. Brower, and E. Kaiser. 1999. *Natural hazard mitigation: Recasting disaster policy and planning*. Washington, DC: Island Press.

Gold, A., Anarde, K., Grimley, L., Neve, R., Srebnik, E. R., Thelen, T., Whipple, A., & Hino, M. (2023). Data From the Drain: A Sensor Framework That Captures Multiple Drivers of Chronic Coastal Floods. *Water Resources Research*, 59(4), e2022WR032392. <https://doi.org/10.1029/2022WR032392>

- Gotham, K. F. (2014). Racialization and rescaling: Post Katrina rebuilding and the Louisiana Road Home Program. *International Journal of Urban and Regional Research*, 38(3), 773–790.
doi:10.1111/14682427.12141
- Green, R., Bates, L., & Smyth, A. (2007). Impediments to recovery in New Orleans' Upper and Lower Ninth Ward one year after Hurricane Katrina. *Disasters*, 31(4), 311–335
- Green, T. F., & Olshansky, R. B. (2012). Rebuilding housing in New Orleans: The Road Home Program after the Hurricane Katrina disaster. *Housing Policy Debate*, 22(1), 75–99
- Gupta, H. S., Nofal, O. M., González, A. D., Nicholson, C. D., & van de Lindt, J. W. (2022). Optimal Selection of Short- and Long-Term Mitigation Strategies for Buildings within Communities under Flooding Hazard. *Sustainability*, 14(16), 9812.
<https://doi.org/10.3390/su14169812>
- Helgeson, J., Hamideh, S., & Sutley, E. J. (2021). The Lumberton, North Carolina Flood of 2016, Wave 3: A Community Impact and Recovery-Focused Technical Investigation Following Successive Flood Events. National Institute of Standards and Technology.
<https://doi.org/10.6028/NIST.SP.1230-3>
- Hine, D., & Hall, J. W. (2010). Information gap analysis of flood model uncertainties and regional frequency analysis. *Water Resources Research*, 46(1), 2008WR007620. <https://doi.org/10.1029/2008WR007620>
- Hine, D., & Hall, J. W. (2010). Information gap analysis of flood model uncertainties and regional frequency analysis. *Water Resources Research*, 46(1), 2008WR007620. <https://doi.org/10.1029/2008WR007620>

- Hinkel J (2011) “Indicators of vulnerability and adaptive capacity’’: towards a clarification of the science policy interface. *Glob Environ Change* 21(1):198–208. doi:10.1016/j.gloenvcha.2010.08.002
- Hino, M., & Burke, M. (2020). *Does Information About Climate Risk Affect Property Values?* (w26807; p. w26807). National Bureau of Economic Research. <https://doi.org/10.3386/w26807>
- Hino, M., & Burke, M. (2021). The effect of information about climate risk on property values. *Proceedings of the National Academy of Sciences*, 118(17), e2003374118. <https://doi.org/10.1073/pnas.2003374118>
- Hino, M., & Hall, J. W. (2017). Real Options Analysis of Adaptation to Changing Flood Risk: Structural and Nonstructural Measures. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, 3(3), 04017005. <https://doi.org/10.1061/AJRUA6.0000905>
- Hino, M., & Nance, E. (2021). Five ways to ensure flood-risk research helps the most vulnerable. *Nature*, 595(7865), 27–29. <https://doi.org/10.1038/d41586-021-01750-0>
- Hino, M., BenDor, T. K., Branham, J., Kaza, N., Sebastian, A., & Sweeney, S. (2024). Growing Safely or Building Risk?: Floodplain Management in North Carolina. *Journal of the American Planning Association*, 90(1), 50–62. <https://doi.org/10.1080/01944363.2022.2141821>
- Hino, M., Field, C. B., & Mach, K. J. (2017). Managed retreat as a response to natural hazard risk. *Nature Climate Change*, 7(5), 364–370. <https://doi.org/10.1038/nclimate3252>

- Hori, M., & Schafer, M. J. (2009). Social costs of displacement in Louisiana after Hurricanes Katrina and Rita. *Population and Environment*, 31(1/3), 64–86. doi:10.1007/s11111-009-0094-0
- Horn, D. P. (2024). Floodplain buyouts: Federal funding for property acquisition. <https://crsreports.congress.gov/product/pdf/IN/IN11911>
- Howell J, Elliott J (2018) As disaster costs rise, so does inequality. *Socius Social Res Dyn World* 4:237802311881679. <https://doi.org/10.1177/2378023118816795>
- Hunter, T.C. (2017). Help Remains for Matthew Victims. *Robesonian*, January 20. Retrieved June 4, 2024 (<http://robesonian.com/news/95322/fema-to-close-office-on-monday>)
- IN-CORE (2021). "IN-CORE Manual." Retrieved from <https://incore.ncsa.illinois.edu/doc/incore/index.htm>
- Jones, S. H., & Armanios, D. E. (2020). Methodological Framework and Feasibility Study to Assess Social Equity Impacts of the Built Environment. *Journal of Construction Engineering and Management*, 146(11), 05020016. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0001914](https://doi.org/10.1061/(ASCE)CO.1943-7862.0001914)
- Kihlslinger, R.; Moraga-Lewy, N. *Financing and Incentivizing Floodplain Buyouts: A Guide*; Environmental Law Institute: Washington, DC, USA, 2017.
- Kraan, C. M., Hino, M., Niemann, J., Siders, A. R., & Mach, K. J. (2021a). Promoting equity in retreat through voluntary property buyout programs. *Journal of Environmental Studies and Sciences*, 11(3), 481–492. <https://doi.org/10.1007/s13412-021-00688-z>
- Kraan, C. M., Hino, M., Niemann, J., Siders, A. R., & Mach, K. J. (2021b). Promoting equity in retreat through voluntary property buyout programs. *Journal of Environmental Studies and Sciences*, 11(3), 481–492. <https://doi.org/10.1007/s13412-021-00688-z>

- Lin, Y.S., Peacock, W.G., Lu, J.C., and Zhang, Y. (2008). Household dislocation algorithm 3: A logistic regression approach 08-05R. Retrieved from [hrrc.arch.tamu.edu/publications/research reports/08-05R Dislocation Algorithm 3.pdf](http://hrrc.arch.tamu.edu/publications/research%20reports/08-05R%20Dislocation%20Algorithm%203.pdf)
- Loughran, K., & Elliott, J. R. (2019). Residential buyouts as environmental mobility: Examining where homeowners move to illuminate social inequities in climate adaptation. *Population and Environment*, 41(1), 52–70. <https://doi.org/10.1007/s11111-019-00324-7>
- Loughran, K., Elliott, J. R., & Kennedy, S. W. (2019). Urban Ecology in the Time of Climate Change: Houston, Flooding, and the Case of Federal Buyouts. *Social Currents*, 6(2), 121–140. <https://doi.org/10.1177/2329496518797851>
- Mach, K. J., Hino, M., Siders, A. R., Koller, S. F., Kraan, C. M., Niemann, J., & Sanders, B. F. (2022). From Flood Control to Flood Adaptation. In K. J. Mach, M. Hino, A. R. Siders, S. F. Koller, C. M. Kraan, J. Niemann, & B. F. Sanders, *Oxford Research Encyclopedia of Environmental Science*. Oxford University Press. <https://doi.org/10.1093/acrefore/9780199389414.013.819>
- Mach, K. J., Kraan, C. M., Hino, M., Siders, A. R., Johnston, E. M., & Field, C. B. (2019). Managed retreat through voluntary buyouts of flood-prone properties. *Science Advances*, 5(10), eaax8995. <https://doi.org/10.1126/sciadv.aax8995>
- Magis, K. Community Resilience: An Indicator of Social Sustainability. *Soc. Nat. Resource*. 2010, 23, 401–416.
- Martens, K., A. Golub, and G. Robinson. 2012. “A justice-theoretic approach to the distribution of transportation benefits: Implications for transportation planning practice in the United States.” *Transportation Research Part A-policy and Practice*. 46 (4): 684–695. <https://doi.org/10.1016/j.tra.2012.01.004>.

- Martin, Carlos, Brandi Gilbert, Dan Teles, Brett Theodos. 2019. Housing Recovery and CDBG-DR: A Review of the Timing and Factors Associated with Housing Activities in HUD's Community Development Block Grant for Disaster Recovery Program. HUD Office of Policy Development and Research.
- Martin, N., J. Forrester, and J. Ensor. 2018. "What is equitable resilience?" *World Dev.*, 109: 197205. <https://doi.org/10.1016/j.worlddev.2018.04.020>
- Melendez, A.; Caballero-Russi, D.; Gutierrez Soto, M.; Giraldo, L.F. Computational Models of Community Resilience. *Nat. Hazards* 2022, 111, 1121–1152.
- Memari, M., Attary, N., Masoomi, H., Mahmoud, H., van de Lindt, J. W., Pilkington, S. F., & Ameri, M. R. (2018). "Minimal building fragility portfolio for damage assessment of communities subjected to tornadoes." *Journal of Structural Engineering*, 144(7), 4018072. [https://doi.org/10.1061/\(ASCE\)ST.1943-541X.0002047](https://doi.org/10.1061/(ASCE)ST.1943-541X.0002047)
- Mortensen, K., Wilson, R. K., & Ho, V. (2009). Physical and mental health status of Hurricane Katrina evacuees in Houston in 2005 and 2006. *Journal of Health Care for the Poor and Underserved*, 20(2), 524–538. doi:10.1353/hpu.0.0130
- Multihazard Mitigation Council. 2017. Natural hazard mitigation saves 2017 interim report: An independent study. Washington, DC: National Institute of Building Sciences.
- Muñoz, C., & Tate, E. (2016). Unequal Recovery? Federal Resource Distribution after a Midwest Flood Disaster. *International Journal of Environmental Research and Public Health*, 13(5), 507. <https://doi.org/10.3390/ijerph13050507>
- National Centers for Environmental Information. (n.d.). Risk and vulnerability | Billion-dollar weather and climate disasters. National Oceanic and Atmospheric Administration.

Retrieved June 4, 2024, from <https://www.ncei.noaa.gov/access/billions/risk-and-vulnerability>

National Climate Assessment. 2014. Extreme weather. US global climate change research program. Washington, DC: National Climate Assessment.

National Weather Service. (n.d.). Precipitation Frequency Data Server: Precipitation Frequency Data Map. Retrieved from https://hdsc.nws.noaa.gov/pfds/pfds_map_cont.html

NC State Parks. (2017). Retrieved June 4, 2024 (<http://www.ncparks.gov/lumber-river-state-park/history>).

NHC GIS Archive - Tropical Cyclone Best Track. National Hurricane Center and Central Pacific Hurricane Center. (2016). https://www.nhc.noaa.gov/gis/archive_besttrack_results.php?id=al14&year=2016&name=Hurricane+MATTHEW

NHC GIS archive - tropical cyclone best track. National Hurricane Center and Central Pacific Hurricane Center. (2018). https://www.nhc.noaa.gov/gis/archive_besttrack_results.php?id=al06&year=2018&name=Hurricane+FLORENCE

NOAA National Centers for Environmental Information (NCEI). (2023). “U.S. Billion-Dollar Weather and Climate Disasters”. <https://www.ncei.noaa.gov/access/billions/>, DOI: 10.25921/stkw-7w73

NOAA National Centers for Environmental Information. (2023). U.S. billion-dollar weather and climate disasters. National Oceanic and Atmospheric Administration. <https://www.ncei.noaa.gov/access/billions/> <https://doi.org/10.25921/stkw-7w73>

Nofal, O. M. (2021). Fragility-Based Flood Risk Modeling to Quantify the Effect of Policy Change on Losses at the Community Level. *Civil Engineering Research Journal*, 11(5). <https://doi.org/10.19080/CERJ.2021.11.555822>

- Nofal, O. M., & van de Lindt, J. W. (2020a). "High-Resolution Approach to Quantify the Impact of Building-Level Flood Mitigation and Adaptation Measures on Flood Losses at the Community-Level." *International Journal of Disaster Risk Reduction*, 101903. <https://doi.org/10.1016/j.ijdr.2020.101903>
- Nofal, O. M., & van de Lindt, J. W. (2020b). "Minimal Building Flood Fragility and Loss Function Portfolio for Resilience Analysis at the Community-Level." *Water*, 12(8), 2277. <https://doi.org/10.3390/w12082277>
- Nofal, O. M., & van de Lindt, J. W. (2020c). Probabilistic Flood Loss Assessment at the Community Scale: Case Study of 2016 Flooding in Lumberton, North Carolina. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, 6(2), 05020001. <https://doi.org/10.1061/AJRUA6.0001060>
- Nofal, O. M., & van de Lindt, J. W. (2021). High-resolution flood risk approach to quantify the impact of policy change on flood losses at community-level. *International Journal of Disaster Risk Reduction*, 62, 102429. <https://doi.org/10.1016/j.ijdr.2021.102429>
- Nofal, O. M., Rosenheim, N., Patil, J., Zhou, X., Lindt, J. W. van de, Duenas-Osorio, L., & Cha, E. J. (2022). Interdependent Households-Buildings-Networks Community-Level Post-Hazard Functionality Assessment Methodology. *8th International Symposium on Reliability Engineering and Risk Management*, 579–585. https://doi.org/10.3850/978-981-18-5184-1_MS-18-034-cd
- Nofal, O. M., van de Lindt, J. W., & Do, T. Q. (2020). "Multi-variate and Single-variable Flood Fragility and Loss Approaches for Buildings." *Reliability Engineering & System Safety*, 202, 106971. <https://doi.org/10.1016/j.ress.2020.106971>

- Nofal, O. M., van de Lindt, J. W., Cutler, H., Shields, M., & Crofton, K. (2021). Modeling the Impact of Building-Level Flood Mitigation Measures Made Possible by Early Flood Warnings on Community-Level Flood Loss Reduction. *Buildings*, 11(10), 475. <https://doi.org/10.3390/buildings11100475>
- Nofal, O. M., van de Lindt, J. W., Do, T. Q., Yan, G., Hamideh, S., Cox, D. T., & Dietrich, J. C. (2021). Methodology for Regional Multihazard Hurricane Damage and Risk Assessment. *Journal of Structural Engineering*, 147(11), 04021185. [https://doi.org/10.1061/\(ASCE\)ST.1943-541X.0003144](https://doi.org/10.1061/(ASCE)ST.1943-541X.0003144)
- Nofal, O. M., van de Lindt, J. W., Yan, G., Hamideh, S., & Dietrich, C. (2021). MULTI-HAZARD HURRICANE VULNERABILITY MODEL TO ENABLE RESILIENCE-INFORMED DECISION. *Proceedings of International Structural Engineering and Construction*, 8(1). [https://doi.org/10.14455/ISEC.2021.8\(1\).RAD-01](https://doi.org/10.14455/ISEC.2021.8(1).RAD-01)
- Nofal, O.M. High-Resolution Multi-Hazard Approach to Quantify Hurricane-Induced Risk for Coastal and Inland Communities. Ph.D. Thesis, Colorado State University, Fort Collins, CO, USA, 2021
- Nofal, O.M.; van de Lindt, J.W. High-Resolution Approach to Quantify the Impact of Building-Level Flood Risk Mitigation and Adaptation Measures on Flood Losses at the Community-Level. *Int. J. Disaster Risk Reduction*. 2020, 51, 101903
- Nofal, O.M.; van de Lindt, J.W. High-Resolution Flood Risk Approach to Quantify the Impact of Policy Change on Flood Losses at Community-Level. *Int. J. Disaster Risk Reduction*. 2021, 62, 102429.
- Nofal, O.M.; van de Lindt, J.W. Minimal Building Flood Fragility and Loss Function Portfolio for Resilience Analysis at the Community Level. *Water* 2020, 12, 2277

- O. E. J. Wing, P. D. Bates, A. M. Smith, C. C. Sampson, K. A. Johnson, J. Fargione, P. Morefield, Estimates of present and future flood risk in the conterminous United States. *Environ. Res. Lett.* 13, 034023 (2018)
- O. E. J. Wing, P. D. Bates, C. C. Sampson, A. M. Smith, K. A. Johnson, T. A. Erickson, Validation of a 30 m resolution flood hazard model of the conterminous United States. *Water Resources. Res.* 53, 7968–7986 (2017)
- Peacock, W. G., & Girard, C. (1997). Ethnic and racial inequalities in hurricane damage and insurance settlements. In W. G. Peacock, B. H. Morrow, & H. Gladwin (Eds.), *Hurricane Andrew: Ethnicity, gender and the sociology of disasters* (pp. 171–190). New York and London: Routledge.
- Peacock, W. G., & Ragsdale, A. K. (1997). Social systems, ecological networks and disasters: Toward a socio-political ecology of disasters. In W. G. Peacock, B. H. Morrow, & H. Gladwin (Eds.), *Hurricane Andrew: Ethnicity, gender, and the sociology of disasters* (pp. 20–35). New York and London: Routledge.
- Peacock, W. G., Killian, C. D., & Bates, F. L. (1987). The effects of disaster damage and housing aid on household recovery following the 1976 Guatemalan earthquake. *International Journal of Mass Emergencies and Disasters*, 5(1), 63–88.
- Peacock, W. G., Lin, Y. S., Lu, J. C., & Zhang, Y. (2008). Household dislocation algorithm 2: An OLS through the origin approach 08-04R. [hrrc.arch.tamu.edu/publications/research-reports/08-04R Dislocation Algorithm 2.pdf](http://hrrc.arch.tamu.edu/publications/research-reports/08-04R%20Dislocation%20Algorithm%20.pdf)
- Peacock, W. G., Morrow, B. H., & Gladwin, H. (Eds.). (1997). *Hurricane Andrew: Ethnicity, gender, and the sociology of disasters*. New York and London: Routledge.

- Peacock, W. G., Van Zandt, S., Zhang, Y., & Highfield, W. E. (2014). Inequities in long-term housing recovery after disasters. *Journal of the American Planning Association*, 80(4), 356–371.
- Peacock, W. G., Zhang, Y., & Dash, N. (2006). Sheltering, temporary housing, and permanent housing recovery following a major natural disaster in the United States. International Workshop on Disaster Recovery and Rescue. Taiwan.
- Peek, L., Tobin, J., Lindt, J. W., & Andrews, A. (2021). Getting Interdisciplinary Teams into the Field: Institutional Review Board Preapproval and Multi-Institution Authorization Agreements for Rapid Response Disaster Research. *Risk Analysis*, 41(7), 1204–1212. <https://doi.org/10.1111/risa.13740>
- Peterson, K., Apadula, E., Salvesen, D., Hino, M., Kihslinger, R., & BenDor, T. K. (2020). A Review of Funding Mechanisms for US Floodplain Buyouts. *Sustainability*, 12(23), 10112. <https://doi.org/10.3390/su122310112>
- Phillips B, Thomas D, Fothergill A, Blinn-Pike L (2010) Social vulnerability to disasters. CRC Press, Boca Raton
- Porter, K. (2021). A Beginner’s Guide to Fragility, Vulnerability, and Risk. In M. Beer, I. A. Kougioumtzoglou, E. Patelli, & I. S.-K. Au (Eds.), *Encyclopedia of Earthquake Engineering* (pp. 1–29). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-36197-5_256-1
- Ready NC. (n.d.). Floods. North Carolina Department of Public Safety. Retrieved June 4, 2024, from https://www.readync.org/EN/Informed_NatHaz_Flood.html
- Resilience Seminar Series. (n.d.). Retrieved June 4, 2024, from <http://resilience.colostate.edu/seminar/20230221.shtml>

- Riad, J. K., & Norris, F. H. (1996). The influence of relocation on the environmental, social, and psychological stress experienced by disaster victims. *Environment and Behavior*, 28(2), 163–182.
- Robinson, C.S., Davidson, R.A., Trainor, J.E., Kruse, J.L., Nozick, L.K. (2018) Homeowner acceptance of voluntary property acquisition offers. *Int J Disaster Risk Reduction* 31:234–242. <https://doi.org/10.1016/j.ijdr.2018.05.002>
- Roohi, M., van de Lindt, J. W., Rosenheim, N., Hu, Y., & Cutler, H. (2020). Implication of building inventory accuracy on physical and socio-economic resilience metrics for informed decision-making in natural hazards. *Structure and Infrastructure Engineering*, 17(4), 534-554. <https://doi.org/10.1080/15732479.2020.1845753>
- Rosenheim, N. (2021) “Detailed Household and Housing Unit Characteristics: Data and Replication Code.” DesignSafe-CI. <https://doi.org/10.17603/ds2-jwf6-s535>
- Rosenheim, N., Guidotti, R., Gardoni, P., and Peacock, W.G. (2019). Integration of detailed household and housing unit characteristic data with critical infrastructure for post-hazard resilience modeling. *Sustainable and Resilient Infrastructure* DOI: 10.1080/23789689.2019.1681821
- Sanders, S., Bowie, S. L., & Bowie, Y. D. (2003). Chapter 2 lessons learned on forced relocation of older adults. *Journal of Gerontological Social Work*, 40(4), 23–35.
- Sen, M.K.; Dutta, S.; Kabir, G. Flood Resilience of Housing Infrastructure Modeling and Quantification Using a Bayesian Belief Network. *Sustainability* 2021, 13, 1026. [CrossRef]
13. Sen, M.K.; Dutta, S.; Kabir, G. Modelling and Quantification of Time-Varying Flood Resilience for Housing Infrastructure Using Dynamic Bayesian Network. *J. Clean. Prod.* 2022, 361, 132266.

- Seong K, Losey C, Gu D (2022) Naturally resilient to natural hazards? Urban–rural disparities in hazard mitigation grant program assistance. *House Policy Debate* 32:190–210. <https://doi.org/10.1080/10511482.2021.1938172>
- Shane Crawford, P., Mitrani-Reiser, J., Sutley, E. J., Do, T. Q., Tomiczek, T., Nofal, O. M., Weigand, J. M., Watson, M., van de Lindt, J. W., & Graettinger, A. J. (2022). Measurement Approach to Develop Flood-Based Damage Fragilities for Residential Buildings Following Repeat Inundation Events. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, 8(2), 04022019. <https://doi.org/10.1061/AJRUA6.0001219>
- Shi, L., Fisher, A., Brenner, R. M., Greiner-Safi, A., Shepard, C., & Vanucchi, J. (2022). Equitable buyouts? learning from state, county, and local floodplain management programs. *Climatic Change*, 174(3–4). <https://doi.org/10.1007/s10584-022-03453-5>
- Siders, A. R., Hino, M., & Mach, K. J. (2019a). The case for strategic and managed climate retreat. *Science*, 365(6455), 761–763. <https://doi.org/10.1126/science.aax8346>
- Siders, A. R., Hino, M., & Mach, K. J. (2019b). The case for strategic and managed climate retreat. *Science*, 365(6455), 761–763. <https://doi.org/10.1126/science.aax8346>
- Smiley KT (2020) Social inequalities in flooding inside and outside of floodplains during Hurricane Harvey. *Environ Res Lett* 15:0940b3. <https://doi.org/10.1088/1748-9326/aba0fe>
- Sports, J. B. (2020, August 5). City Council members received update on flooding-mitigation project. *Robesonian*. <https://www.robsonian.com/news/136681/city-council-members-received-update-on-flooding-mitigationproject#:~:text=Since%20after%20Hurricane%20Matthew%20hit%20Robeson%20County%20in,and%20longterm%20environmental%20function%20within%20historically%20flood-prone%20areas.>

- Stewart, S. R. (2017). *Tropical Cyclone Report: Hurricane Matthew (AL142016)*, 28 September – 9 October 2016. National Hurricane Center. Retrieved from https://www.nhc.noaa.gov/data/tcr/AL142016_Matthew.pdf
- Stewart, S. R., & Berg, R. (2019). *Tropical Cyclone Report: Hurricane Florence (AL062018)*, 31 August–17 September 2018. National Hurricane Center. Retrieved from https://www.nhc.noaa.gov/data/tcr/AL062018_Florence.pdf
- Sutley, E. J., Dillard, M. K., & van de Lindt, J. W. (2021). *Community Resilience-Focused Technical Investigation of the 2016 Lumberton, North Carolina Flood: Community Recovery One Year Later*. National Institute of Standards and Technology. <https://doi.org/10.6028/NIST.SP.1230-2>
- Tate, E., Strong, A., Kraus, T., & Xiong, H. (2016). Flood recovery and property acquisition in Cedar Rapids, Iowa. *Natural Hazards*, 80(3), 2055–2079. <https://doi.org/10.1007/s11069-015-2060-8>
- Turek-Hankins, L. L., Hino, M., & Mach, K. J. (2020). Risk screening methods for extreme heat: Implications for equity-oriented adaptation. *PLOS ONE*, 15(11), e0240841. <https://doi.org/10.1371/journal.pone.0240841>
- Tying Flood Insurance to Flood Risk for Low-Lying Structures in the Floodplain* (p. 21720). (2015). National Academies Press. <https://doi.org/10.17226/21720>
- U.S. Census Bureau. (n.d.). 2010 Robeson County Census Data. Retrieved from <https://data.census.gov/table?q=2010%20robeson%20county>
- U.S. Census Bureau. (n.d.). Glossary. U.S. Department of Commerce. Retrieved June 6, 2024, from <https://www.census.gov/glossary>

US Department of Commerce, N. (2021, August 26). Hurricane Matthew in the Carolinas: October 8, 2016. National Weather Service. <https://www.weather.gov/ilm/Matthew>

U.S. Department of Housing and Urban Development. CDBG-DR: Community Development Block Grant Disaster Recovery Program; U.S. Department of Housing and Urban Development: Washington, DC, USA, 2020.

U.S. Department of Housing and Urban Development. (2024). 1378 CHG-8 chapter 5 real property acquisition5-hud.<https://www.hud.gov/sites/dfiles/OCHCO/documents/1378c5CPDH.pdf>

van de Lindt, J., Peacock, W., Mitrani-Reiser, J. , Rosenheim, N. , Deniz, D. , Dillard, M. , Tomiczek, T. , Koliou, M. , Graettinger, A. , Crawford, P. , Harrison, K. , Barbosa, A. , Tobin, J. , Helgeson, J. , Peek, L. , Memari, M. , Sutley, E. , Hamideh, S. , Gu, D. , Cauffman, S. and Fung, J. (2018). The Lumberton, North Carolina Flood of 2016: A Community Resilience Focused Technical Investigation, Special Publication (NIST SP), National Institute of Standards and Technology, Gaithersburg, MD, [online], <https://doi.org/10.6028/NIST.SP.1230> (Accessed August 12, 2024)

Van de Lindt, J. W., Kruse, J., Cox, D. T., Gardoni, P., Lee, J. S., Padgett, J., McAllister, T. P., Barbosa, A., Cutler, H., Zandt, S. V., Rosenheim, N., Navarro, C. M., Sutley, E., & Hamideh, S. (2023, August 28). *The Interdependent Networked Community Resilience Modeling Environment (in-core)*. University of Illinois Urbana-Champaign. <https://experts.illinois.edu/en/publications/the-interdependent-networked-community-resilience-modeling-enviro>

van de Lindt, J. W., Peacock, W. G., Mitrani-Reiser, J., Rosenheim, N., Deniz, D., Dillard, M. K., Tomiczek, T., Koliou, M., Graettinger, A., Crawford, S., Harrison, K. W., Barbosa, A., Tobin, J., Helgeson, J. F., Peek, L., Memari, M., Sutley, E., Hamideh, S., Gu, D.,

- Cauffman, S. A., & Fung, J. F. (2018). *The Lumberton, North Carolina Flood of 2016: A community resilience focused technical investigation* (NIST Special Publication 1230). National Institute of Standards and Technology. <https://doi.org/10.6028/NIST.SP.1230>
- van de Lindt, J. W., Peacock, W. G., Mitrani-Reiser, J., Rosenheim, N., Deniz, D., Dillard, M., Tomiczek, T., Koliou, M., Graettinger, A., Crawford, P. S., Harrison, K., Barbosa, A., Tobin, J., Helgeson, J., Peek, L., Memari, M., Sutley, E. J., Hamideh, S., Gu, D., Fung, J. (2020). Community Resilience-Focused Technical Investigation of the 2016 Lumberton, North Carolina, Flood: An Interdisciplinary Approach. *Natural Hazards Review*, 21(3), 04020029. [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000387](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000387)
- van De Lindt, J., Peacock, W.G., Mitrani-Reiser, J., Rosenheim, N., Deniz, D., Dillard, M., Tori Tomiczek, T. (2020). “Community resilience-focused technical investigation of the 2016 Lumberton, North Carolina, flood: An interdisciplinary approach.” *Natural Hazards Review* 21, no. 3 (2020): 04020029. [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000387](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000387)
- Watson, M. , Crawford, S. , Sutley, E. and Loerzel, J. (2022), The Lumberton, North Carolina Flood of 2016, Wave 4: Occupancy and Operational Status During the COVID-19 Global Pandemic, Special Publication (NIST SP), National Institute of Standards and Technology, Gaithersburg, MD, [online], <https://doi.org/10.6028/NIST.SP.1230-4>, https://tsapps.nist.gov/publication/get_pdf.cfm?pub_id=935403 (Accessed August 12, 2024)
- Weber A, Moore R (2019) Going under: long wait times for post-flood buyouts leave homeowners underwater. Natural Resources Defense Council, Washington, DC

- Weber, A., & Moore, R. (2019). *LONG WAIT TIMES FOR POST-FLOOD BUYOUTS LEAVE HOMEOWNERS UNDERWATER*.
- Weber, L., & Peek, L. (2012). *Displaced: Life in the Katrina diaspora*. Austin, TX: University of Texas Press.
- Wheeler, A. (2016, October 11). *Aerial photos show devastating impact of Hurricane Matthew on North Carolina*. International Business Times UK. <https://www.ibtimes.co.uk/these-photos-devastating-impact-hurricane-matthew-north-carolina-1585756>
- Willett, J., Tamayo, A., & Kern, J. (2020). Understandings of environmental injustice and sustainability in marginalized communities: A qualitative inquiry in Nevada. *International Journal of Social Welfare*, 29(4), 335–345. <https://doi.org/10.1111/ijsw.12456>
- Wisner B, Blaikie P, Cannon T, Davis I (2004) *At risk: natural hazards, people's vulnerability and disasters*, 2nd edn. Routledge, New York
- Wright, J. 2000. *The nation's responses to flood disasters: A historical account*. Madison, WI: Association of State Floodplain Managers.
- Zavar E, Hagelman RRI (2016) Land use change on U.S. floodplain buyout sites, 1990-2000. *Disaster Prev Manag* 25:360–374. <https://doi.org/10.1108/DPM-01-2016-0021>

Appendix A

APPENDIX LIST OF TABLES

Table A 1: Most common metrics in property acquisition programs found in the literature.	99
Table A 2: US Census demographic terms and definitions (Census Glossary).....	101

APPENDIX LIST OF FIGURES

Figure A 1: Examples of census tracts used for synthetic allocation validation: a) census tract populating 2010 census data correctly, b) census tract geographically justified.....	102
Figure A 2: Exposed Buildings Tenure versus Damage States	103
Figure A 3: Exposed Buildings Ethnicity versus Damage States.....	104
Figure A 4: Exposed Buildings Family versus Damage State.....	105
Figure A 5: Exposed Buildings Vacancy versus Damage States.....	106
Figure A 6: Exposed Buildings Poverty versus Damage States.....	107
Figure A 7: Dislocated Buildings Ethnicity versus Damage States.....	108
Figure A 8: Dislocated Buildings Family versus Damage States.....	109
Figure A 9: Dislocated Buildings Vacancy versus Damage States.....	110
Figure A 10: Dislocated Buildings Poverty versus Damage States.....	111

Table A 1: Most common metrics in property acquisition programs found in the literature.

Title	Authors	Variables
Complexities and costs of floodplain buyout implementation	Curran-Groome, W., Hino, M., BenDor, T. K., & Salvesen, D. (2022).	wealth racial
Five ways to ensure flood-risk research helps the most vulnerable	Hino, M., & Nance, E. (2021).	poverty rates risk race income mental and physical health employment education
Flood recovery and property acquisition in Cedar Rapids, Iowa	Tate, A., Strong, T., Kraus, T., & Xiong, H. (2021).	poverty tenure elderly children unemployed linguistic isolation disabled low education attainment female headed household Hispanic no vehicle access
The geographic and social distribution of disaster losses in the United States.	Cutter, S. L., Burton, C. G., & Emrich, C. T. (2003).	socioeconomic status age race ethnicity gender functional needs home ownership health language proficiency
Social science research needs: Focus on vulnerability and mitigation	Phillips, B. D., Morrow, B. H., & Blinn-Pike, L. (2010)	socioeconomic status age race ethnicity gender functional needs home ownership health language proficiency
Managed retreat through voluntary buyouts of flood-prone properties.	Mach, K. J., Kraan, C. M., Hino, M., Siders, A. R., Johnston, E. M., & Field, C. B. (2019).	population density income education racial diversity population English language proficiency
Methodological framework and feasibility study to assess social	Jones, S.H., & Armanios, D.E. (2020)	wealth status race

equity impacts to the built environment		family composition education housing
Promoting equity in retreat through voluntary property buyout programs.	Kraan, C. M., Hino, M., Niemann, J., Siders, A. R., & Mach, K. J. (2021).	income level race ethnicity
Risk screening methods for extreme heat: Implications for equity-oriented adaptation	Turek-Hankins, L.L., Hino, M., & Mach, K.J. (2020).	poverty education attainment linguistic isolation population density race
Equitable buyouts? Learning from state, county, and local floodplain management programs	Shi, L., Fisher, A., Brenner, R.M., Greiner-Safi, A., Shepard, C., & Vanucchi, J. (2022).	socioeconomic racially inequitable
Understandings of environmental injustice and sustainability in marginalized communities: A qualitative inquiry in Nevada	Willett, J., Tamayo, A., & Kern, J. (2020).	race income ethnicity gender age economic class local
Integrating social equity into urban transportation planning: A critical evaluation of equity objectives and measures in transportation in North America	Manaugh, K., Badami, M.G., & El-Geneidy, A.M. (2015)	income age gender minority status location
Measuring social equity in urban energy use and interventions using fine scale data	Tong, K., Ramaswami, A., Xu, C., Feiock, R., Schmitz, P., & Ohlsen, M. (2021)	income public health race gender age education family size
Promoting equity in retreat through voluntary property buyout programs	Kraan, C.M., Hino, M., Neimann, J., Siders, A.R., & Mach, K.J. (2021)	household income race ethnicity eligibility to participate acceptance or refusal to offer reasons for refusal

Table A 2: US Census demographic terms and definitions (Census Glossary).

Household Income	“The sum of the income of all people 15 years and older living in the household A household includes related family members and all the unrelated people, if any, such as lodgers, foster children, wards, or employees who share the housing unit. A person living alone in the housing unit, or a group of unrelated people sharing a housing unit, is also counted as a household.”
Race	“The data on race were derived from answers to the question on race. The U.S. Census Bureau collects race data in accordance with guidelines provided by the U.S. Office of Management and Budget (OMB), and these data are based on self-identification. The racial categories included in the census questionnaire generally reflect a social definition of race recognized in this country and not an attempt to define race biologically, anthropologically, or genetically. In addition, it is recognized that the categories of the race question include race and national origin or sociocultural groups. OMB requires that race data be collected for a minimum of five groups: White, Black or African American, American Indian or Alaska Native, Asian, and Native Hawaiian or other Pacific Islander. OMB permits the Census Bureau to also use a sixth category - Some Other Race. Respondents may report more than one race.”
Tenure	“Refers to the distinction between owner-occupied and renter occupied housing units.”
Ethnicity	“The U.S. Census Bureau adheres to the U.S. Office of Management and Budget’s (OMB) definition of ethnicity. There are two minimum categories for ethnicity: Hispanic or Latino and Not Hispanic or Latino. OMB considers race and Hispanic origin to be two separate and distinct concepts. Hispanics and Latinos may be of any race.”
Family Household	“A family includes a householder and one or more people living in the same household who are related to the householder by birth, marriage, or adoption. All people in a household who are related to the householder are regarded as members of his or her family.”
Vacant Housing Unit	“A housing unit is vacant if no one is living in it at the time of enumeration, unless its occupants are only temporarily absent. Units temporarily occupied at the time of enumeration entirely by

	people who have a usual residence elsewhere are also classified as vacant.”
Poverty	“Following the Office of Management and Budget’s (OMB’s) Directive 14, the Census Bureau uses a set of money income thresholds that vary by family size and composition to determine who is in poverty. If the total income for a family or unrelated individual falls below the relevant poverty threshold, then the family (and every individual in it) or unrelated individual is considered in poverty.”
Nonfamily Household	“A nonfamily household consists of a householder living alone (a one-person household) or where the householder shares the home only with people to whom he/she is not related (e.g., a roommate).”
Group Quarters	“The Census Bureau classifies all people not living in housing units as living in group quarters. A group quarters is a place where people live or stay, in a group living arrangement, that is owned or managed by an entity or organization providing housing and/or services for the residents.”

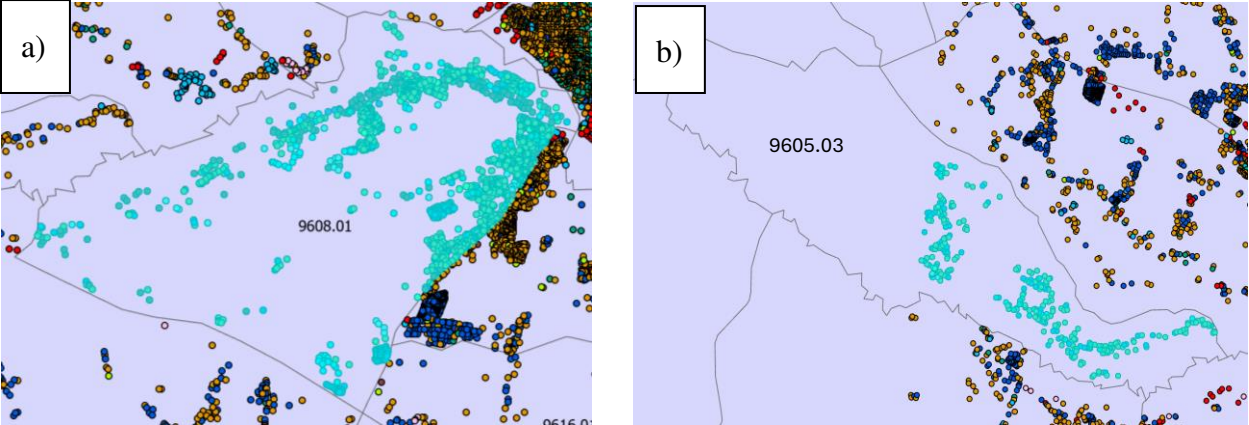


Figure A 1: Examples of census tracts used for synthetic allocation validation: a) census tract populating 2010 census data correctly, b) census tract geographically justified.



Figure A 2: Exposed Buildings Tenure versus Damage States

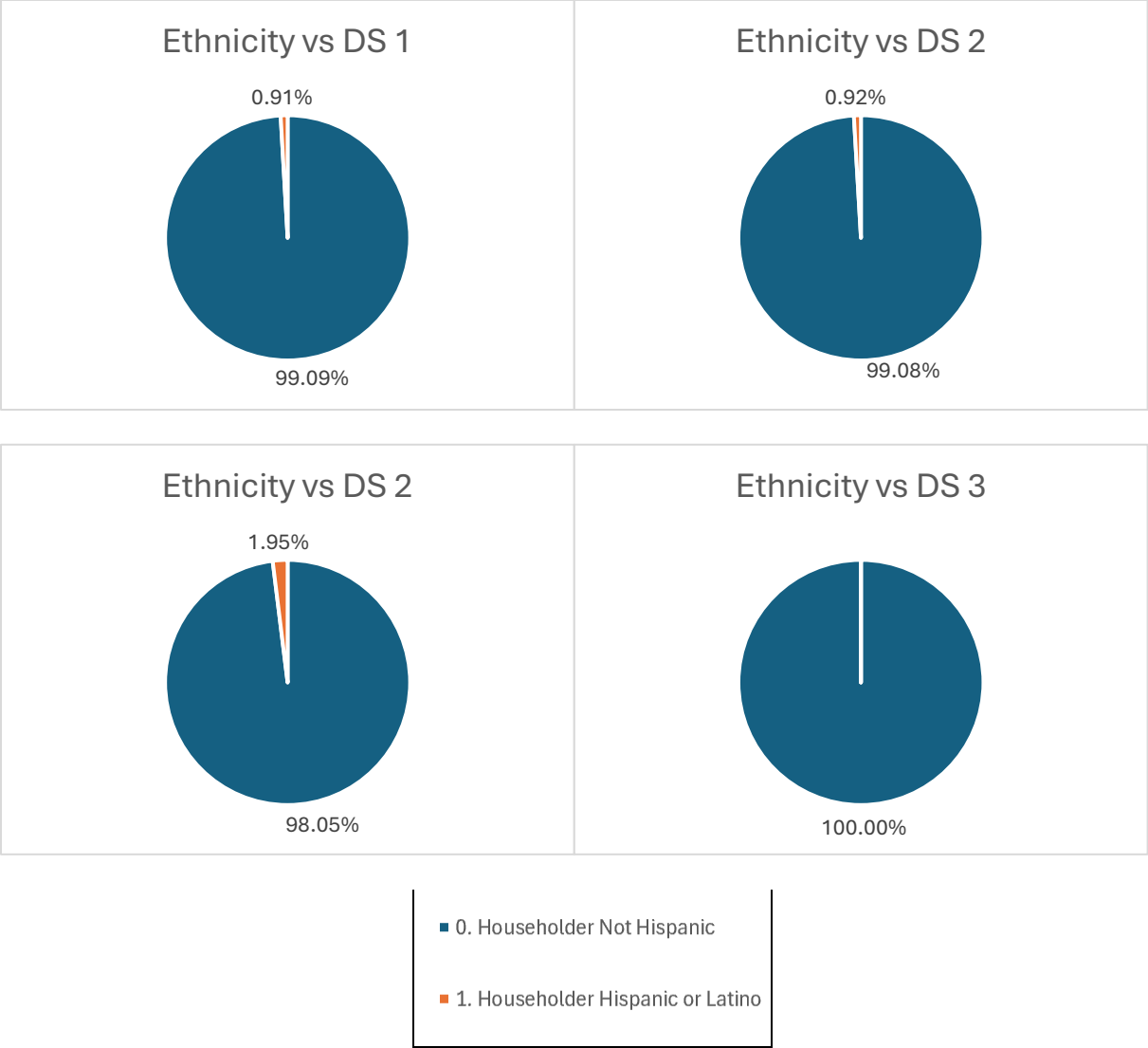


Figure A 3: Exposed Buildings Ethnicity versus Damage States.

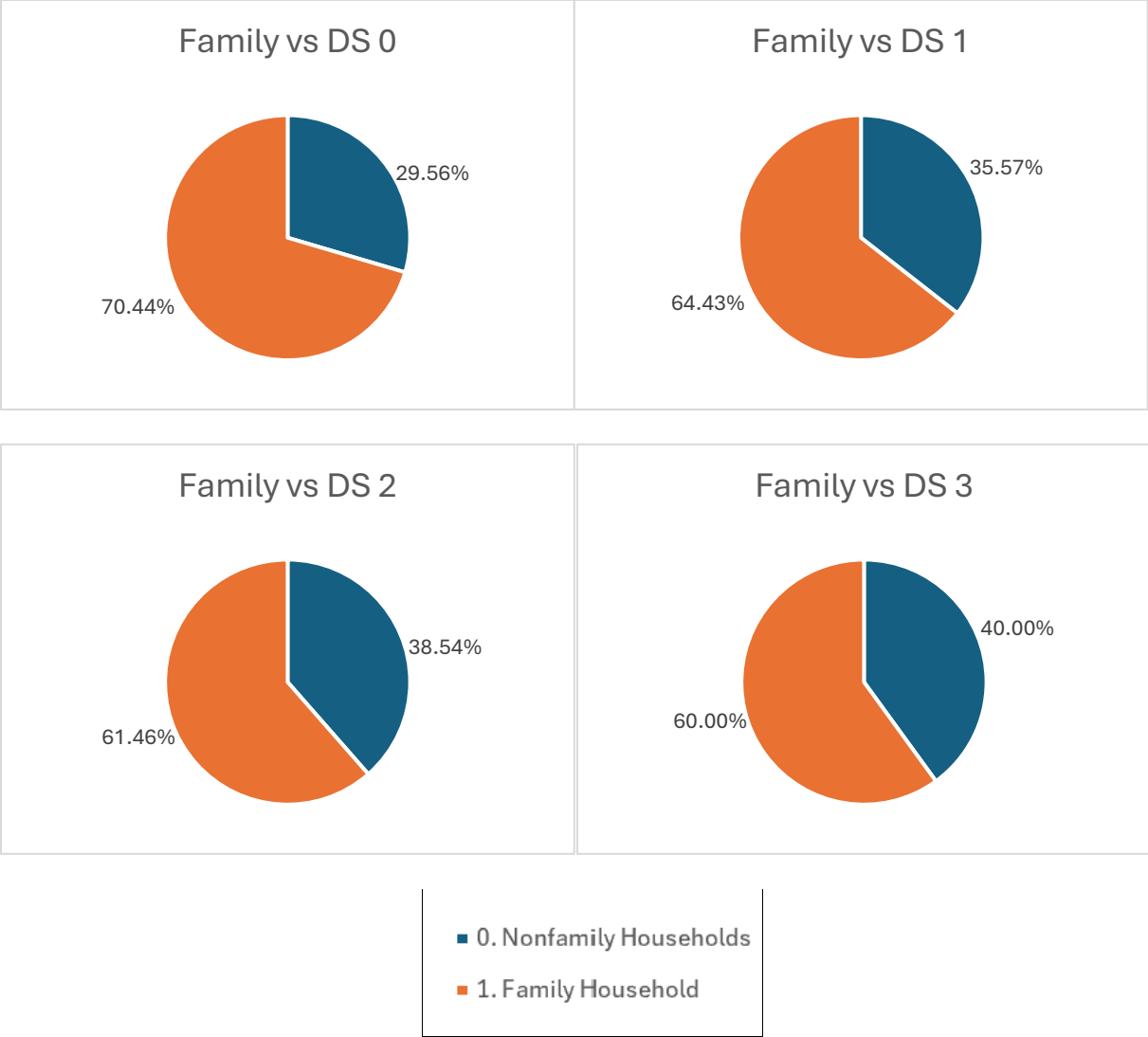
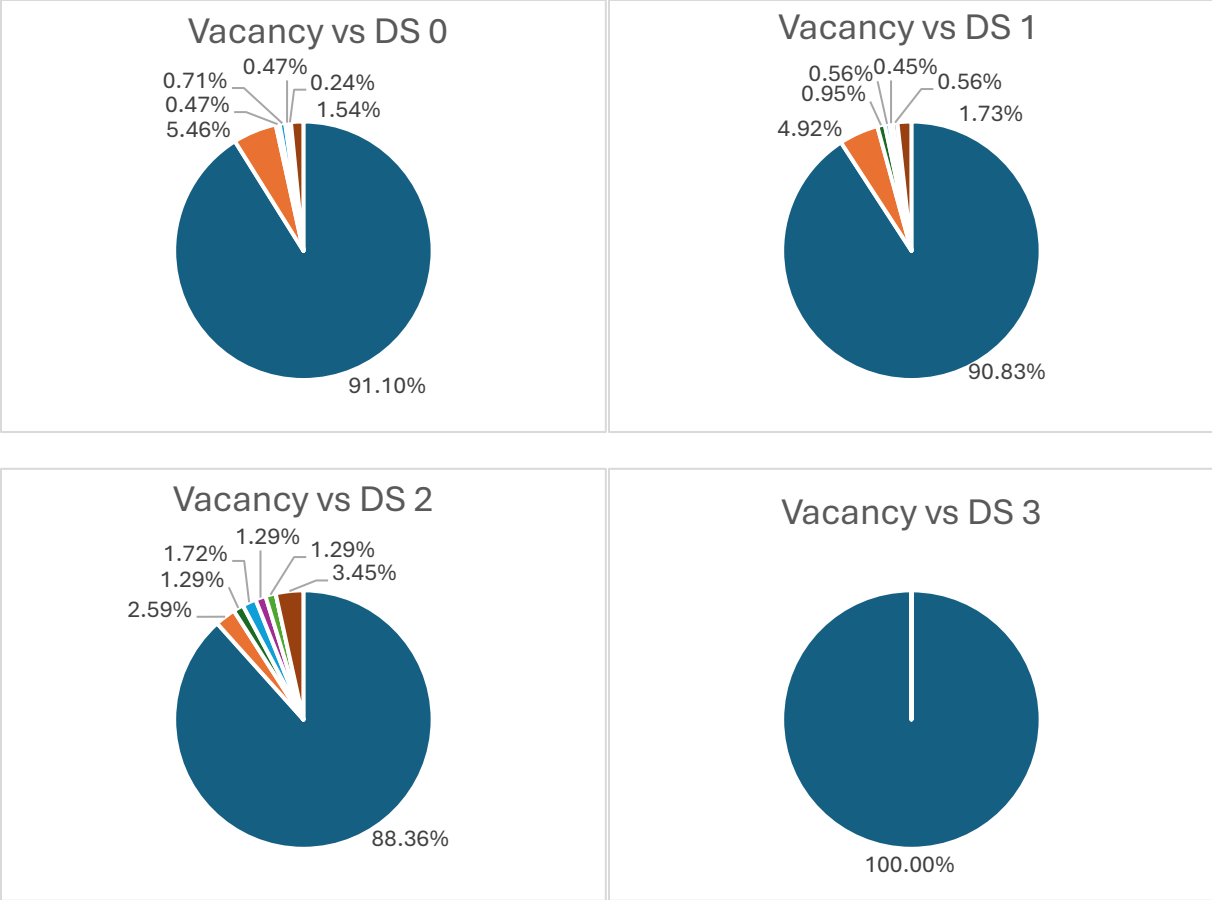


Figure A 4: Exposed Buildings Family versus Damage State.



- 0. NA Not Vacant
- 1. For rent
- 2. Rented, not occupied
- 3. For sale only
- 4. Sold, not occupied
- 5. For seasonal, recreational, or occasional use
- 6. For migrant workers
- 7. Other vacant

Figure A 5: Exposed Buildings Vacancy versus Damage States.



Figure A 6: Exposed Buildings Poverty versus Damage States.

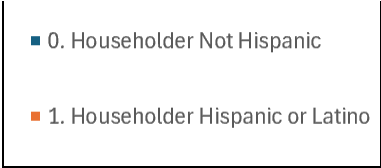


Figure A 7: Dislocated Buildings Ethnicity versus Damage States.

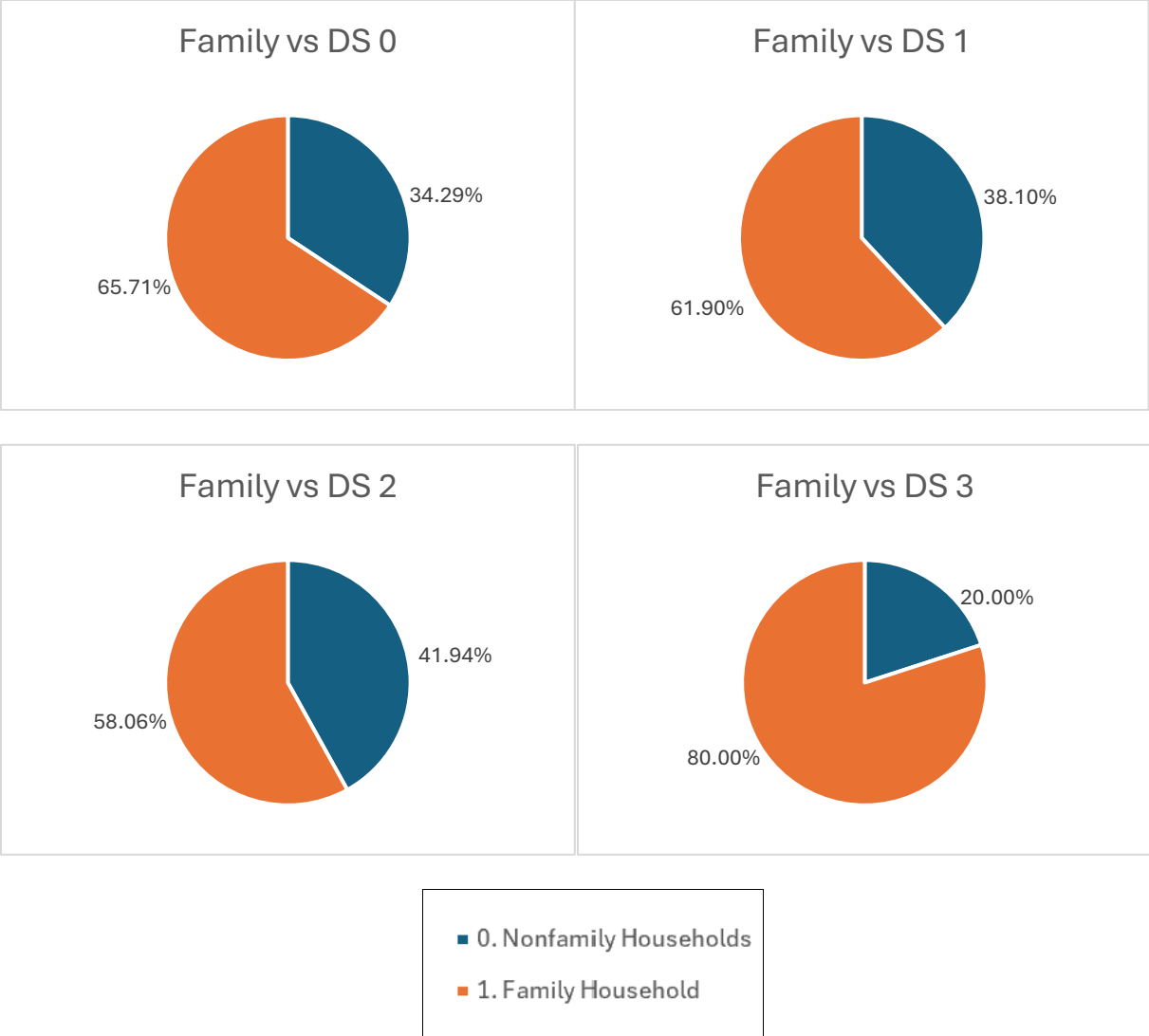
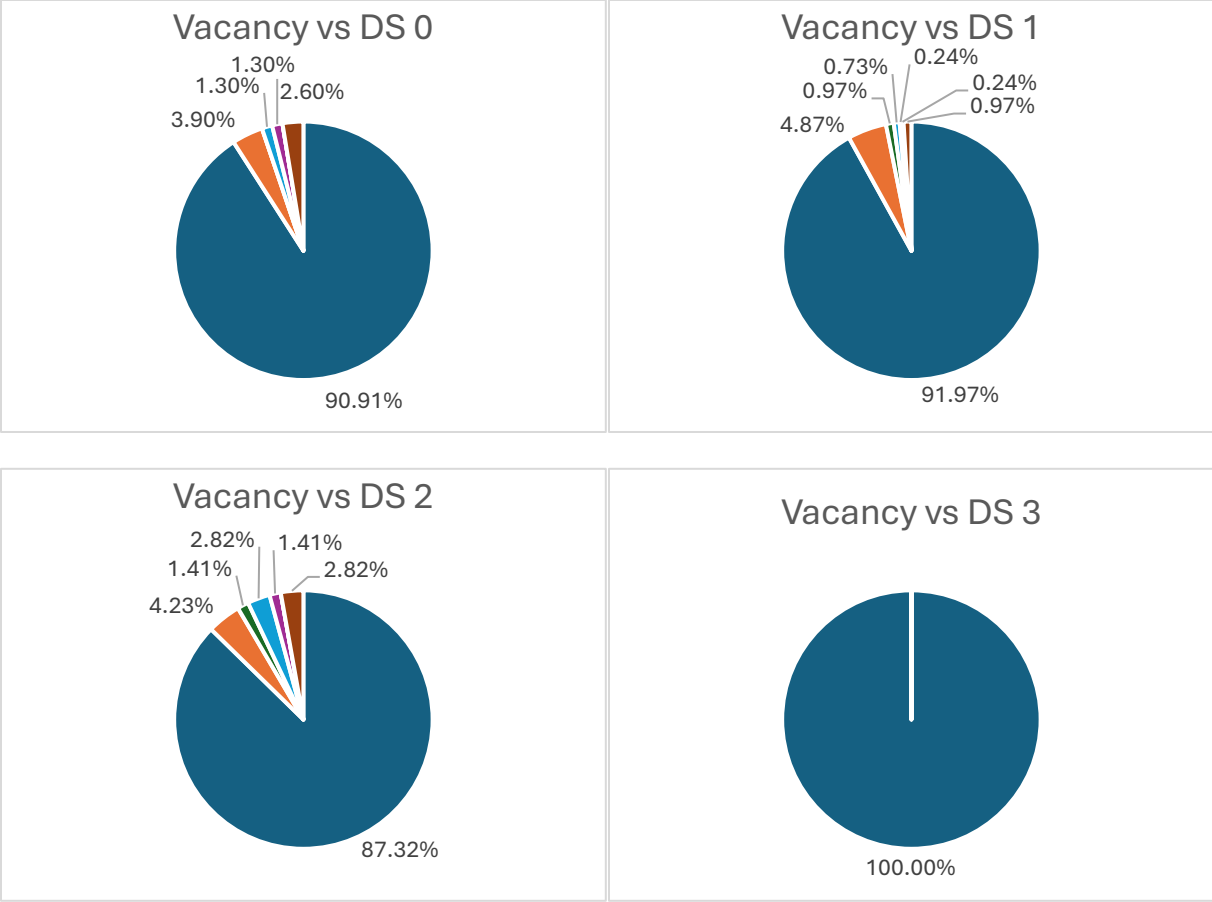


Figure A 8: Dislocated Buildings Family versus Damage States.



- 0. NA Not Vacant
- 1. For rent
- 2. Rented, not occupied
- 3. For sale only
- 4. Sold, not occupied
- 5. For seasonal, recreational, or occasional use
- 6. For migrant workers
- 7. Other vacant

Figure A 9: Dislocated Buildings Vacancy versus Damage States.



Figure A 10: Dislocated Buildings Poverty versus Damage States.