The Impact of Severe Coastal Flooding on Economic Recovery Disparities:
A Study of New Jersey Communities Following Hurricane Sandy

by

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To Sam and my loved ones

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Abbreviations

ACS	American Community Survey
CV	Coefficient of Variation
DEM	Digital Elevation Model
FEMA	Federal Emergency Management Agency
GIS	Geographic information system
GISci	Geographic information science
GPS	Global Positioning System
HMA	Hazard Mitigation Assistance
IPCC	Intergovernmental Panel on Climate Change
LiDAR	Light Detection and Ranging
MOE	Margin of Error
MIZ	Minor Impact Zone
MOTF	Modeling Task Force
NASA	The National Aeronautics and Space Administration
NDRF	National Disaster Recovery Framework
NHRAP	Natural Hazards Risk Assessment Program
NJ	New Jersey
NJDEP	New Jersey Department of Environmental Protection
NIZ	None Impact Zone
SLR	Sea-level rise
SrIZ	Serious Impact Zone
SvIZ	Severe Impact Zone

SVI	Social Vulnerability Index
SSI	Spatial Sciences Institute
USC	University of Southern California
USGS	The United States Geological Survey

Abstract

Recent severe flooding caused by storms, such as Hurricane Sandy in 2012, has damaged vulnerable coastal communities across the United States at an increasing occurrence and severity. Not only do floods threaten lives and property, but they also alter the shape of a community through imbalanced recovery among socially and economically vulnerable populations. This concern begs the research question: what, if any, are the differences in recovery between communities of different economic standing concerning flood inundation levels after a severe coastal flooding event? Economic recovery disparity was investigated by analyzing New Jersey's socio-economic structure before and after Hurricane Sandy according to inundation depths categorized as impact zones: None (NIZ), Minor (MIZ), Serious (SrIZ), and Severe (SvIZ). The research design was developed to (1) examine the physical exposure of Hurricane Sandy across New Jersey; (2) investigate the socio-economic characteristics of New Jersey communities before and after Hurricane Sandy; and (3) determine whether, or not, proximity to severe flooding resulted in notable changes to citizen's economic standing. The analysis compared tabular data from 2010 and 2018 American Community Survey (ACS) 5-Year Estimates using three evaluations: population, income, and housing. Results displayed variable levels of impact throughout the entire study area from 2010 to 2018 regarding population, income, and housing; however, results did not show statistically significant relationships between economic recovery and flood inundation levels.

Chapter 1 Introduction

Affluent areas of a community historically recover more quickly from a natural disaster, while their less privileged neighbors often struggle to regain their previous lifestyle. Recovery of a community pivots on the residents' ability to return to the previously affected area without financial impediment (Howell and Elliott 2018). After a disaster, wealthier citizens can withstand the reconstruction costs and increased cost of insurance compared to others forced to relocate. The displacement of residents, particularly those who are most vulnerable, can transform the structure of a community and increase existing inequalities (van Holm 2019). Maintaining a socially and economically diverse community enables innovation and productive opportunities for all members (CityObservatory 2018).

Although New Jersey is socio-economically diverse overall, income inequality is distinct in pockets, particularly along the coast. From nuisance to severe flooding, the residents in these communities have experienced increased instability due to the ongoing devastation to one of their most important investments—their home. The growing presence of tropical storms and rising sea levels in New Jersey intensifies the need to protect those most at risk of adverse change in exposed coastal regions (Stocker et al. 2013). The most destructive natural disaster in New Jersey's history was Hurricane Sandy in 2012, where flood depths reached about 19 feet. This study reviewed New Jersey's recovery after Hurricane Sandy to better understand the relationship between a community's economic recovery and physical exposure from a severe flood event. Flood exposure and inundation depths from observed Hurricane Sandy storm surge levels determined impact zones used to track notable changes before and after the storm. Comparing 2010 and 2018 data helped illustrate recovery differences throughout New Jersey and investigate the connection between recovery and vulnerability.

1.1. New Jersey and Flooding

In the Northeastern region of the United States, New Jersey is surrounded by New York, Pennsylvania, and the Atlantic Ocean. The state's northwest region intersects with the foothills of the Appalachian Mountains, providing a dramatic landscape change to the otherwise flat topography (Figure 1). Surrounded by water bodies on three sides, New Jersey is a coastal state with the Atlantic Ocean to the east, the Delaware Bay to the south, and the Delaware River to the West. The flat topography and proximity to water bodies increase the state's risk of encountering flood-related issues.

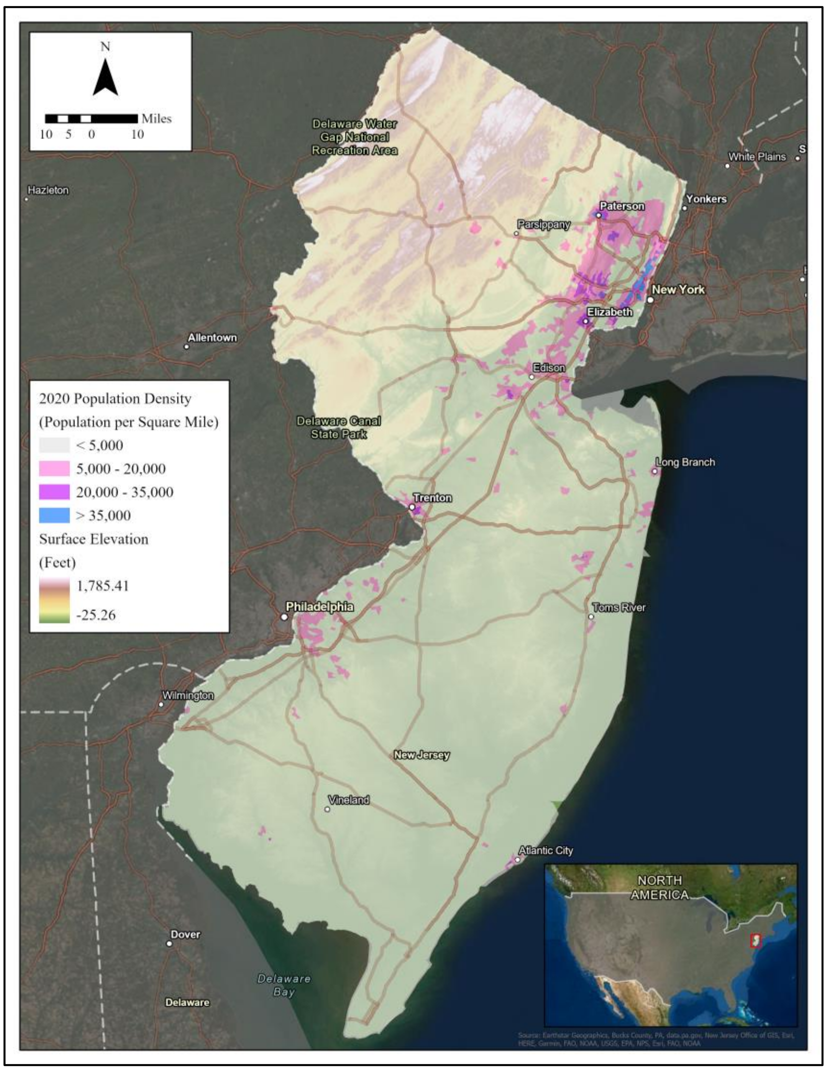

Figure 1. Study Area of New Jersey, United States.

Another factor that increases flooding is the impervious surface area due to the increased amount of real estate along the coastline. Although barrier islands do not exhibit the highest population density of the state, they are neighborhoods of dense single-family properties. Nuisance flooding, or tidal flooding, is expected on barrier islands due to high levels of impervious surfaces and high tide in low elevation areas. Naturally intended to protect the mainland shores with dunes, the current barrier island complex in New Jersey is not sustainable for annual hurricane seasons. Like Hoboken and Jersey City, other coastal cities flood due to heavy precipitation and runoff that intensify with high tides and storm surges (Athanasopoulou 2017).

In addition, New Jersey is home to two large metropolitan areas along the rivers: New York City and Philadelphia. The bordering cities of New York City and Philadelphia also influence New Jersey's economy and population, with population tending to be the densest in these regions (Figure 1). In 2020, New Jersey was deemed the most densely populated state in the United States, with about 1,263 people per square mile (US Census n.d.). As part of the Tri-State area, New Jersey has experienced a consistent rise in population due to public transport accessibility for commuters working in the nearby major cities (Figure 2). Studies show that New Jersey's exposure and population size, compared to other states, place them at an above-average threat of coastal flooding, right behind Florida and Louisiana. As of 2000, New Jersey had about 4% of the population, more than 350,000 people, at risk of a 100-year coastal flood, making them the fourth most vulnerable state to coastal flooding (States at Risk 2015). According to First Street Foundation (2020), almost 400,000 properties in New Jersey are at risk of substantial flooding, which is determined as the inundation of one centimeter or more to a structure in the 100-year storm zone and rounded to the nearest 100.

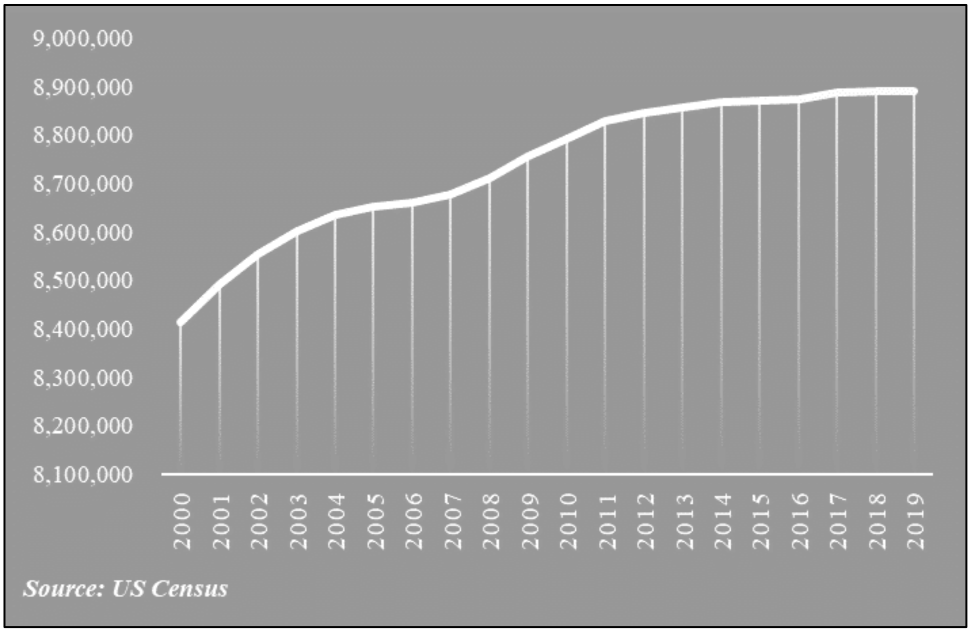

Figure 2. New Jersey's Population 2000-2019.

Compared to Florida and Louisiana, New Jersey had little experience with profound coastal damage until October 29, 2012, when Hurricane Sandy landed on Brigantine, New Jersey. In New Jersey alone, Hurricane Sandy damaged 346,000 homes, submerged 1,400 sea vessels, affected 70 drinking water systems, impacted 80 wastewater treatment plants, and eroded 194 miles of coastline (NJDEP 2015). The catastrophic damage to the once vibrant Jersey Shore was a realization among lawmakers and planners to better prepare for future storms and more frequent nuisance flooding (Bryner, Garcia-Lozano, and Bruch 2017). Observed water levels were highest along the northern section of the Jersey Shore, from Long Branch to Toms River (Figure 1). New Jersey’s barrier islands were inundated entirely or breached in some areas due to storm surge and large waves (NJDEP 2015). The International Displacement Monitoring Centre estimated that Hurricane Sandy displaced about 53,500 people three years after the disaster (Bryner, Garcia-Lozano, and Bruch 2017).

Hurricanes are less impactful in the northeast than in the southern region of the United States due to the storm losing strength while traveling away from its source. In New Jersey, most hurricane damage derives from flood inundation rather than other aspects such as wind, heavy rain, and storm surge; therefore, this study only examined flood inundation caused by Hurricane Sandy. This project aims to review flood exposure and inundation depths from Hurricane Sandy storm surge inundation levels to spot communities' most vulnerable socio-economic change concerning coastal residents.

1.2. Motivation

According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), global climate change severely affects tropical storm activity by rising sea levels, increasing hurricane rainfall, and amplifying intensity. The most vulnerable locations of coastal communities are at an increased risk due to sea-level rise (SLR) and coastal development (Stocker et al. 2013). Prominent on the United States Eastern Coastline, SLR may exacerbate in areas where land is "sinking" due to vertical motions of the Earth's crust. The region from North Carolina to New Jersey is especially undergoing strong coastal subsidence from the last deglaciation (Piecuch et al. 2018). Growing threats such as nuisance flooding and relative SLR will be of more significant concern in this zone; therefore, mitigation will be essential (Jacobs et al. 2018).

Post-disaster recovery is often the most telling way to analyze the severity of a storm. Displacing a large portion of the population may destroy a community's socio-economic structure. About 7% of the population was still displaced three years after Hurricane Sandy, primarily due to economic hardships (Bryner, Garcia-Lozano, and Bruch 2017). Retroactively identifying the areas at risk of displacement helps preserve or encourage economic diversity before a major disaster occurs. Income equality and socio-economic diversity benefit the population in need and the entire community. The current model of pushing people out of neighborhoods with economic and educational opportunities will, in turn, hinder the overall economic growth of an area (Howell and Elliott 2018). If this pattern continues, coastal communities will slowly transform into second homes for the wealthy; simultaneously, the citizens with less income will be hit harder by financial setbacks, thus increasing wealth inequality (van Holm 2019).

1.2.1. Global Climate Change and SLR

The growing risk of flood damage to coastal communities is becoming more apparent the more commonplace they become. Experts predict that global climate change will increase the frequency and severity of future tropical storm events resulting in more property damage and loss of life. The most vulnerable locations of coastal communities are at an increased risk due to SLR and impervious surfaces caused by coastal development (Stocker et al. 2013). The National Aeronautics and Space Administration (NASA) Administrator, Bill Nelson, stated that increased flooding poses an increased danger to low-lying areas near sea level due to the compounding factors of the Moon's gravitational pull, SLR, and climate change. Low elevation coastal communities have already seen the risks of high tide flooding events and expect to face worse conditions with rising sea levels, and lunar amplify tides in the mid-2030s (Rasmussen 2021).

With the rate of SLR, constant and severe flood events will become a significant issue in already sensitive areas. Also, Earth's crust plays a role in SLR, and it may affect how rising tides damage different coastal zones throughout the world—taking into consideration the relative SLR on the US East Coast will change how to manage New Jersey's coastal communities (Piecuch et al. 2018). A report conducted by Rutgers University for the New Jersey (NJ) Climate Adaptation Alliance gave projected estimates of the growing threat of SLR for the state of New Jersey. The report estimated that the likely range of SLR by the year 2030 will be 0.6 – 1.0 ft with a 67% probability (Kopp et al. 2016).

Climate change plays a significant role in defining how to reduce vulnerability and increase resiliency to disaster risk. Five points of sustainable planning and proper design improvement and integration help create a broader and deeper understanding of resilience to reduce disaster risk. Those five points on vulnerability and resilience being (1) the acknowledgment of non-qualitative characteristics of how a community avoids, reacts, and recovers from a disaster; (2) the change in perspective to view hazards as resources or opportunities to emphasize resilience; (3) the use of both absolute and proportional metrics providing different impact results; (4) the focus on contextuality or localization of the area affected; and (5) the need to examine long-term progress of recovery (Kelman, Gaillard, and Mercer 2015).

1.2.2. Maintaining Wealth Distribution in Coastal Communities

Socio-economically diverse neighborhoods stimulate the economy by providing a variety of needs, perspectives, and career opportunities and offer more robust social networks. Also, affordable housing in areas with quality resources can break the trend of intergenerational poverty and increase the likelihood of children from low-come backgrounds earning higher wages than their parents. A study of the nation's most diverse, mixed-income neighborhoods found that the communities remain diverse once established (CityObservatory 2018).

A community's existing bonds and stability help unite its residents and become more resilient when facing hardships. If neglected in the wake of a disaster, wealth gaps are emphasized, increasing inequality in susceptible areas (Howell and Elliott 2018). The dramatic increase of a community's socio-economic status, otherwise known as gentrification, is a sensitive matter to control when an area is recovering from a natural disaster. A hypothesis dubbed the "recovery machine" suggests that social status before a disaster predetermines access to resources and recovery (van Holm 2019). By this standard, less wealthy communities will, by nature, struggle in recovering. In theory, this will result in a shift where lower-income residents will endure financial troubles and leave the community creating an opportunity for developers to buy properties to sell to wealthier individuals. In the case of a disaster, high populations of low-income residents may not have the option of relocating, so they will stay in pockets of increasing poverty—lowering the community's socio-economic status overall. Vulnerable coastal regions, such as the New Jersey shore, have experienced the growing threat of severe flooding projected to affect less wealthy residents the most.

Identifying hazards and how they pose a threat to the communities is one of the many responsibilities of local governments before a disaster strikes. In attempts to assist in a community's recovery, the Federal Emergency Management Agency (FEMA) established four valuable phases called the Disaster Life Cycle for a successful and sustainable emergency management plan—mitigation, preparedness, response, and recovery (FEMA 2017) (Figure 3). Mitigation and resilience are the most important to minimize the other phases of the four steps.

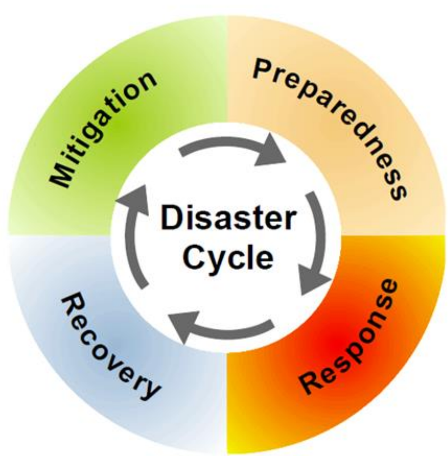

Figure 3. The Disaster Life Cycle (Flanagan et al. 2011)

Frequently lower-income areas tend to be the communities with less protection and preparedness. A study conducted in 2012 compared the recovery experience of the residents in Houston, Texas, for pre- and post-hurricane Ike preparedness and questioned whether citizens with first-hand experience of natural disasters are more prepared than those merely educated before a disaster. Their findings show that preparedness was not uniform across the population of Houston, TX, before hurricane Ike and minority populations reported poorer access to information on preparedness and evacuation (Chen, Banerjee, and Lui 2012). Due to the devastation, a lack of mitigation and preparedness leads to fewer citizens returning to their communities. Five common factors – habitability of homes, affordability of housing, financial burdens, sense of place and identity, and slow restoration of public services and facilities – have been shown to influence displaced individuals' decision to return home after the disasters (Bryner, Garcia-Lozano, and Bruch 2017).

To support the recovery phase of a disaster cycle, FEMA employs the National Disaster Recovery Framework (NDRF) to support disaster-impacted areas throughout restoration and redevelopment by providing Hazard Mitigation Assistance (HMA) grants and otherwise. The goal of the NDRF is to administer services for economic recovery, health, social services, housing, and natural and cultural resources after the disaster (Department of Homeland Security 2016). Conversely, the wealth gap evaluation caused by natural hazard damage has attributed to unequal distribution of government assistance (Howell and Elliott 2018). Grants and government funding greatly assist in recovery; however, the budget may not cover all the residents' losses. Establishing an in-depth planning strategy helps protect the most vulnerable in a more dynamic approach. The United Nations Development Programme created new ways to address coastal resilience using innovative financing mechanisms that fund natural infrastructure projects (Deutz

2018). These mechanisms help build economic growth before a disaster and could be valuable to fund projects for less privileged areas in coastal communities.

1.3. Research Goals

The overarching purpose of this study was to examine the socio-economic characteristics of existing coastal communities by developing an evaluation to understand the relationship between recovery and physical exposure from a severe flood event. Previous research shows that natural disaster recovery often results in changes in the community's economic characteristics. The three research goals of this thesis are to:

- examine the physical exposure of Hurricane Sandy across New Jersey;
- investigate the socio-economic characteristics of New Jersey communities before and after Hurricane Sandy; and
- determine whether proximity to severe flooding resulted in notable changes in population, income, or housing.

1.4. Study Organization

The remaining study contains four additional chapters. Chapter Two provides background on previous studies related to disaster recovery and the importance of Geographic Information Systems (GIS) modeling. Using some of the proven methods, Chapter Three details the techniques employed for testing the relationship between recovery and severe flooding, with results documented in Chapter Four. In conclusion, Chapter Five reviews the results and explores future studies.

Chapter 2 Background

This section examines assessment practices used to measure the vulnerability and recovery of communities' disasters, along with the value of using flood modeling and spatial statistics. Related literature about disaster recovery helps explain how the study expands upon existing knowledge of the socio-economic transformation of a coastal community.

2.1. Disaster Recovery Research

Natural disasters do not target certain socio-economic groups; however, there is disproportional recovery across more impoverished populations. Current literature and research fail to answer why some communities recover rather than others (Yabe et al. 2020) and the enduring socio-economic effect on a community. Instead, existing literature examines measurable costs such as property loss and migration of a population. These methods help create a connection between immediate cause and effect, yet past recovery studies minimally examined the long-term transformation of a community.

Yabe et al. (2020) examined human displacement for various study areas to understand when and why communities recover. They used mobile phone data to better understand a population's short-term and long-term migration patterns after a storm, as shown in a study for Bangladesh after a cyclone. The authors pursued the connection between the recovery of infrastructure systems and population movement after a major disaster by examining mobility trajectories across three countries' mobile phone Global Positioning System (GPS) datasets before, during, and after five significant disasters. The macro-scale of this study took another step to downscale the analysis to counties and cities after modeling displacement rates to understand the relationship between distance and duration of displacement after the disasters. Results showed that most residents returned soon after the disaster, while some remained displaced for extended periods. Factors such as population, median income, housing damage rates, and length of infrastructure recovery time contributed to heterogeneity in short-term and long-term displacement rates.

Although Yabe et al. (2020) provided essential clarity to the subject of recovery, the question still stands about who is disproportionately affected by disasters according to recovery rates. They suggested using household-level surveys to understand the demographic of people unable to return to their previous residence. Examining recovery on a large scale helps visualize the universal issues, but it does generalize the problem by comparing events with similar effects. Yabe et al.'s (2020) work did not consider or present the effects of various disasters and populations' backgrounds. Instead, the study defined demographics according to a single disaster and used this measure to understand the relationship between the length of displacement and existing socio-economic factors.

Another approach taken by researchers is to track neighborhood transformation influenced by government and philanthropic-funded assistance. Although this is not the focus of the study at large, touching upon post-disaster programs highlights the issues with current forms of recovery by showing they may not be as effective as previously thought. Previous literature reviews the effect of programs on residents' unstable financial situation.

In reviewing current disaster relief programs, a 2019 study from the University of Colorado outlined the effect of the hurricane-caused flooding to Houston, TX, that resulted in about $125 billion in damages to private and public property. Results show that averages mask an essential assortment of experiences after disasters, challenging existing narratives of federal disaster programs' effectiveness. They suggest that the current method of providing Small Business Administration disaster loans and Federal Emergency Management Agency (FEMA) grants can cause an adverse reaction to the communities they seek to support. In the methods, the researchers compared the credit outcomes of Houston residents according to the amount of flooding per Census block to track declining debt after flooding (Billings, Gallagher, and Ricketts 2019). Tracking credit rather than income can be an effective way to examine the success of recovery due to the financial setbacks to an unprepared population resulting from a major disaster. Calculating the bankruptcy rate can be adopted for determining the change of wealth in other coastal communities.

An analysis of the post-disaster assistance program, New York Rising Buyout, evaluated willing participants and their property within vulnerable zones after Hurricane Sandy to test the effectiveness of the state-run home buyout program. Literature shows that buyout programs impact relocated residents and those who live in and around buyout areas. A GIS-based overlay analysis compared the vulnerability of households with and without the buyout program. Change in vulnerability calculated a Social Vulnerability Index (SVI) and the exposure rate to flooding when participants moved from affected to unaffected neighborhoods. The study computed relocation trends from the 323 participating households. Results showed that most participants stayed near their original address. (McGhee, Binder, and Albright 2020). Creating similar study groups is an effective way to monitor and compare movement while disaster recovery is happening in real-time.

2.2. Modeling Flood Vulnerability

The previous literature presents the importance of incorporating socio-economic factors when reviewing a community's recovery. Socio-economic and demographic factors likely affect a community's recovery after a disaster due to the inability to effectively protect themselves and their property before the flooding and a lack of capital for rebuilding in the recovery phase.

Exploring the factors that make a community vulnerable, such as average income, housing equity values, disabilities, and age groups, will give a more accurate distribution of an area to predict recovery.

Understanding previous literature that recovery is related to a community's wellbeing, existing social and economic risks define such an index. Lichter and Felsenstein (2014) assessed the socio-economic consequences of extreme coastal flooding events for Tel Aviv and a collection of different-sized coastal communities in Israel. The study areas were all parts of the low-elevation coastal zone, defined as the entire area below 10-m elevation and hydrologically connected to the sea. Evaluating average income, disabilities, age groups, and the number of vehicles per household determined social vulnerability; correlating house values with flood plain elevations and gradients defined economic exposure. Also, the Gini coefficient calculated the preflood income distribution of the vulnerable areas. This article used strategies of comparing communities' vulnerability with various flood level scenarios using SLR calculations (Lichter and Felsenstein 2014). Although Lichter and Felsenstein successfully demonstrated the link between social exposure and physical susceptibility due to flooding, the Israeli-based study called for data specific to the region. When reviewing the socio-economic vulnerability in the United States, race, ethnicity, and gender are more connected due to disparity trends shown throughout history (Howell and Elliott 2018).

In a review of socio-economic vulnerably after severe flooding within the United States, the states bordering the Gulf of Mexico provide a more in-depth perspective of the population in this area. Due to the common occurrence of hurricanes in the Gulf of Mexico and the southern United States, there have been more opportunities to research socio-economic vulnerabilities in this region. An article published assessing the US Gulf used GIS methods to analyze coastal communities' vulnerability to hurricanes and flooding along the coast to highlight growing risks to the economic health of the people in these communities. Flood exposure and an SVI were analyzed and depicted overall community vulnerability. Population density and thirty social vulnerabilities categorized and calculated the vulnerability of these communities. The results showed that hurricanes and flooding could execrate vulnerability, and every component of the comprehensive index plays a vital role in exposure (Shao et al. 2020). The study presented here will compile several previous methods to construct a site-specific socio-economic vulnerability index. The process of obtaining social vulnerability data sources on a census tract level calculated the socio-economic risk of New Jersey's coastal communities. Applying the SVI equations for a simplified matrix of factors census tract level will be helpful when defining regions of coastal communities to compare later.

Presenting a community’s vulnerability using spatial thinking enhances the quality and scope of a study by providing a deeper level of understanding to the data. A study by the Universitas Negeri Malang assessed students’ knowledge of Indonesia’s and Iran’s disaster-influenced impacts through GIS. They found that spatial patterns, linkage, and relationships provide more decisive conclusions when analyzing vulnerability (Wahyuningtyas, Febrianti, and Andini 2020). Visualizing the relationship between vulnerability and physical flood exposure in New Jersey's coastal communities helps explain data otherwise absent from tabular data.

2.3. Recovery Metrics and Spatial Statistics

The recovery rate reflects how resilient a community is in the wake of a natural disaster. Many articles look to relocation data to define recovery; however, there are various ways to collect this type of data, e.g., postal service active delivery or population estimates. Additionally, the community's location increases its inherent recovery shortcomings, which calculates socio-economic and physical vulnerability.

Differences in a community’s vulnerability directly relate to an area's ability to recover. A study of the 2004 tsunami in Thailand analyzed the relationship between factors of vulnerability and developing adaptive strategies. The components of sensitivity and resilience in testing exposure were used to test recovery. A community can achieve effective recovery with proper adaptation strategies (Willroth et al. 2012). Due to the close relationship between vulnerability and recovery, the study reapplied metrics used in exposure to the recovery metrics in the review of New Jersey’s coastal communities.

Hurricane Katrina is arguably the most well-known flood disaster in US history. In a 2010 article by Finch, Emrich, and Cutter, they examined New Orleans' existing social vulnerabilities and the level of flood exposure to understand inequities in recovery. Their study used flood water levels of Hurricane Katrina to classify flood inundation at a census tract level, then combined the results with social vulnerability. Dominant components of the SVI in this study included race and class, young families, public housing, elderly, Hispanic immigrants, special needs, and natural resources employment. Average flood depth recorded during the 2005 levee breach was assigned to each census tract, and level of damage was used to classify each depth range as depth: None (0 ft), Low (<2 ft), Medium (2–4 ft), and High (>4 ft). The method of determining residential relocation was to collect data from the US Postal Service of active delivery locations and compare results before the hurricane in 2005 and after the hurricane in 2008. The study results showed that the SVI for New Orleans is significantly correlated with the percentage of returned households by using Pearson's r as the correlation statistic (Finch, Emrich, and Cutter 2010). Unlike New Jersey, New Orleans is recognized for its high risk of flooding and socio-economic disparity compared to the nation. The methods of combining social vulnerability and flood inundation shown in the study by Finch, Emrich, and Cutter give guidance on how to spatially match regions in New Jersey's coastal communities if subregions are identified.

Two articles were examined to understand the practice of comparing similar regions and how spatial matching with difference-in-differences measures could be used to understand the recovery process in New Jersey's coastal communities. Holzer's 2017 study displayed the effectiveness of the Minneapolis Neighborhood Revitalization Program by using census data for neighborhood income, home value, rent, and vacancy rate. Neighborhood quality was analyzed using difference-in-differences and hot spot analysis to compare similar neighborhoods. The core of this methodology was that two control groups were designed to share standard propensity scores. Minneapolis and St. Paul shared similar populations, racial and ethnic composition, size, and urban form, vital components to his analysis (Holzer 2017). A similar article utilized the spatial matching difference-in-differences estimator to test its effects on a 1998 flood event in Laval, Québec, Canada. The method was used to isolate the impact of a change before and after an exogenous difference between treatment and control areas (Dubé, AbdelHalim, and Devaux 2021). When matching regions in New Jersey's coastal communities, the control and treatment groups examined previously will be determined by paring vulnerability rates and flood inundation. Once the groups are defined, the relationship between vulnerability and relocation will be examined, commonly done through statistical analysis.

By examining the relationship between vulnerability and rate of relocation after a significant flood event, such as Hurricanes Katrina and Rita, researchers from Myers, Slack, and Singelmann’s 2008 study gained an understanding of the community’s recovery in the US Gulf region. They suggest that migration occurs because of social, economic, and geographic triggers.

The analysis used a dependent variable to calculate the percent of migration over one year after the hurricanes by using county population percentage. A county-level SVI was calculated and applied to macro levels of migration patterns. Another approach taken by researchers studying recovery was to understand how location factors affect a community's recovery. Spatial statistics, such as regression analyses, show significant incidences of migration along the hurricanes' path, and results showed disadvantaged populations were most likely to relocate (Myers, Slack, and Singelmann 2008). Statistical analysis such as Pearson's r and regression analyses help to assess social vulnerability, percent housing damage, and percent migration in the New Jersey's study areas. To gain a complete understanding of socio-economic characteristics and recovery, a study's site-specific vulnerability factors must be evaluated, and reliability tested.

Chapter 3 Data and Methodology

This study used a combination of tabular and spatial data to understand the correlation between New Jersey communities' economic recovery and inundation levels after Hurricane Sandy's coastal flooding event. Census tract polygons were consolidated to ensure only inhabited areas were included in the study. A state-level classification of impact zones was linked to these areas by estimating average inundation depth per census tract using the Sandy Surge boundary and assigning zones from no impact to severe impact. Next, a physical evaluation was conducted to incorporate elevation, slope, and affected census tracts to each impact zone. Finally, an analysis of economic conditions before and after Hurricane Sandy in 2012 was performed using 2010 as the baseline year and 2018 ACS 5-Year Estimates to calculate percent change.

Additionally, the reliability of the ACS was calculated using the coefficient of variation (CV). In conclusion, spatial statistic tools were employed to understand the clustering patterns and data relationships through Hot Spot Analysis. This chapter used the data and methodology to define the inundation zones, data reliability, and data connections.

3.1. Data

The inputs for this analysis consisted of public data on population, financial, and housing paired with a polygon feature class and two raster datasets (Table 1). The Hurricane Sandy surge boundary raster used observed flood inundation levels to estimate average depths per census tract. Impact zones were classified based on depth ranges (Flanagan et al. 2011) and grouped with average ground elevation heights from the digital elevation model (DEM) for a physical evaluation (Figure 5). These datasets were merged with the tabular data during analysis to determine the impact zones' population, financial, and housing characteristics before and after Hurricane Sandy.

Table 1: Data dictionary of input spatial and tabular datasets for the study analysis.

Dataset	**Type**	**Description**	**Source**
ACS 5-Year Estimates	Table	New Jersey's population, financial, and housing characteristics from 2006 – 2010 and 2014 – 2018 were compared to economic changes before and after Hurricane Sandy.	US Census Bureau
Census Tracts	Polygon Feature Class	Throughout the study, TIGER/Line census tract 2010 boundaries were used primarily for joining 2010 and 2018 ACS tables.	US Census Bureau
Hurricane Sandy 3-meter Surge Boundary in New Jersey	Raster	Storm surge extent and depth grid for Hurricane Sandy layer was used to calculate average flood inundation per census tract to classify impact zones.	US FEMA Modeling Task Force (MOTF)
New Jersey 10-foot DEM	Raster	Statewide 10-foot resolution DEM developed from Light Detection and Ranging (LiDAR) surveys. It was used to calculate average elevation and slope for different zones of impact collection for New Jersey.	New Jersey Department of Environmental Protection (NJDEP)

3.1.1. Hurricane Sandy Surge Boundary

As part of FEMA's Natural Hazards Risk Assessment Program (NHRAP), the FEMA Modeling Task Force (MOTF) generated a storm surge extent with flood depth grid from Hurricane Sandy data. They created clipped 3-meter DEMs for the state affected: Connecticut, New Jersey, New York state, and Rhode Island. The United States Geological Survey (USGS) recorded that Hurricane Sandy hit the Northeast Coast region on October 22, 2012, and did not dissipate until November 2, 2012. Surge inundation extent was created using the USGS's High-Water Marks and Storm Surge Sensor data through February 14, 2013. Next, the interpolated water surface elevation was subtracted from the most recent DEM. For the case of New Jersey, there was a LiDAR data gap for the state's southwest region, which led to missing data in the final DEM. Figure 4 shows the boundary extent for New Jersey with the missing data in Salem

County, which was considered when estimating census tracts of that region. The figure also indicates inundation levels from about 0 to 19 feet.

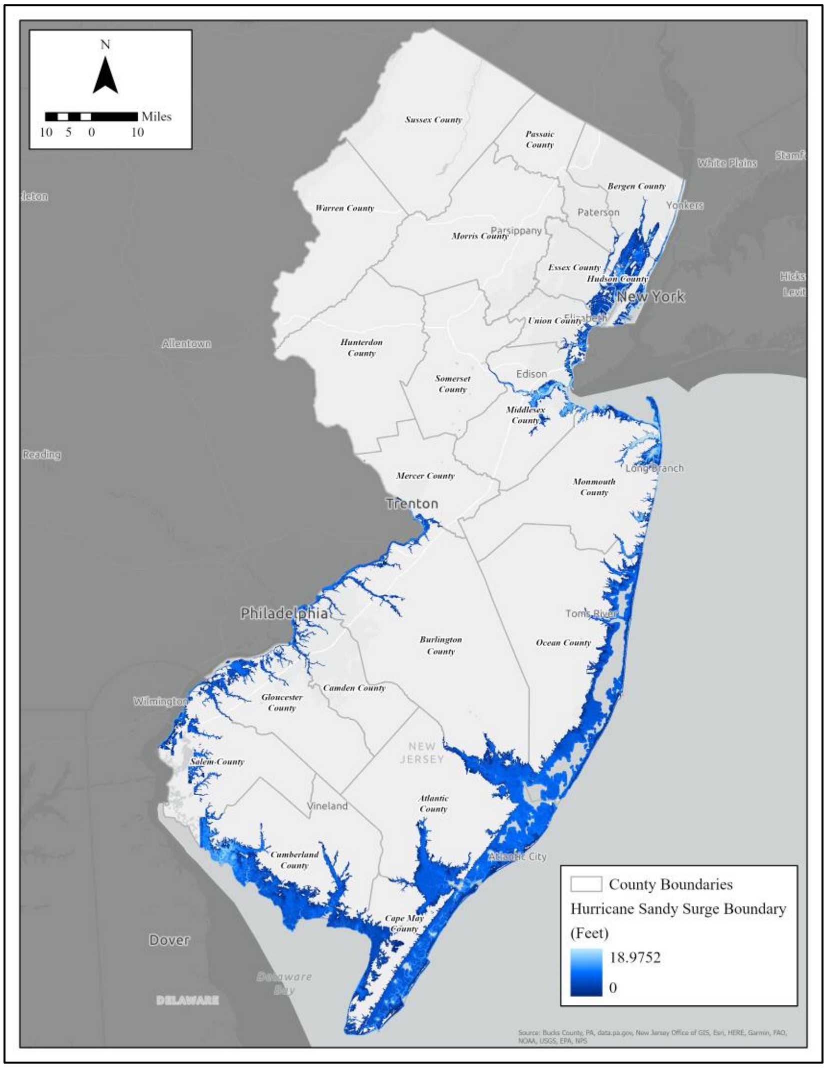

Figure 4. New Jersey's Hurricane Sandy Surge Boundary.

3.1.2. ACS 5-Year Estimates and Accuracy

The US Census Bureau conducts an annual survey known as ACS, in which household data, such as social, economic, housing, and demographic information, is recorded from a sample and estimated for a community (Fuller 2018). The survey poses more detailed questions than the Decennial Census of Population and Housing to give communities current information to plan investments and services (Parmenter and Lau 2013). For this study, 5-year estimates were analyzed due to the data's availability in low to high population sizes, which can be seen in census tracts for New Jersey. Consecutively, this can increase the accuracy of the data in question. Due to the nature of the survey's sampling methodology, each estimate has an associated Margin of Error (MOE) that equates to the possible variation of the estimated value (Fuller 2018).

For this study, each of the 16 variables from the ACS Estimates was gathered for New Jersey at the census tract level and applied to the study's population, income, and housing evaluations (Appendix A). According to the impact group, the evaluations compared ACS surveys 2010 and 2018. Due to the aggregation of estimates, the MOE data was also aggregated using an equation that is the square root of the sum of each MOE estimate multiplied by itself (Equation 1).

Equation 1. Aggregated Margin of Error Equation.

$$MOE_{Sum} = \sqrt{{MOE_{est1}}^2 + {MOE_{est2}}^2 \ldots}$$

The MOE uses the Census Bureau Standard of 90% confidence level, where the lower the number, the more reliable the data is. To further test the level of reliability of an estimate, each impact zone’s variable had an associated CV calculated. Aggregated CV used an equation of dividing the aggregated MOE by 1.645 and dividing that result by the estimate, expressed as a percentage (Equation 2) (Parmenter and Lau 2013).

Equation 2. Coefficient of Variation for Aggregated Margin of Error Equation.

$$CV = \frac{(MOE_{Sum}/1.645)}{Estimate} * 100$$

Like MOE, the higher the number, the less reliable the data. When reviewing CV for this study, reliability will be considered following Parmenter and Lau (2013): less than 15% is high reliability, between 15-30% is moderate reliability, and over 30% is low reliability. ACS Census Tracts with no population were excluded from the study to maintain the most accurate data. Also, the final estimations did not include estimates or MOEs with asterisks or dashes due to these symbolizing too few observations in the source data.

3.2. Research Design

Disaster-induced economic change was assessed using three primary evaluations: population, income, and housing. The process employed spatial and tabular data that compared ACS variables before and after Hurricane Sandy. Also, patterns in the value differences were explored to test clustering and relationships throughout the study area using *Hot Spot Analysis (Getis-Ord Gi*)* and *Spatial Autocorrelation (Global Moran's I)*. Before evaluations took place, the study area was first consolidated to only review New Jersey census tracts with a population from the 2010 ACS 5-Year Estimate Total Population data table. The tracts with no population were eliminated from the analysis tables and feature class polygon. The scrubbed census tract polygon was applied to the impact zone classification using Hurricane Sandy depth grids to calculate average flood inundation per census tract.

3.2.1. Impact Zone Classification

New Jersey census tracts were allocated according to Hurricane Sandy's surge boundary using raster and vector data to spatial estimate mean flood inundation depths per census tract. The analysis utilized ArcGIS Pro's *Zonal Statistics as Table* tool to calculate the mean depth of Hurricane Sandy surge raster within each census tract given. The output table from this analysis was joined to the original 2010 feature class polygon for all future evaluations.

Impact zones were defined by four inundation depths and approximate levels of damage: None (NIZ) (0 ft), Minor (MIZ) (0-2 ft), Serious (SrIZ) (2-4 ft), and Severe (SvIZ) (>4 ft)

(McCarthy et al. 2006). Census tracts with a mean inundation depth evaluated each impact zone within these ranges. For instance, when average mean land elevation was calculated for the severely impacted zones, only census tracts with a mean inundation depth above 4-feet were included in the analysis.

3.2.2. Physical Evaluation

Like the impact zone classification, the census tracts were first allocated according to mean land elevation and slope for the physical evaluation. First, ArcGIS Pro's *Zonal Statistics as Table* tool calculated average elevation grids per census tract using the New Jersey 10-foot DEM (Figure 5). ArcGIS Pro's Slope tool utilized New Jersey 10-foot DEM to estimate percent raise with the output of a new raster to calculate slope inclination. Mean, minimum, and maximum percent slope per census tract was computed using the *Zonal Statistics as Table* tool. Elevation and slope estimations were assigned to each census tract, and the output tables were joined to the 2010 census tract polygon containing impact zone classifications. The completed feature class and joined tables were then exported using ArcGIS Pro's Table to Excel.

The remainder of the physical evaluation was conducted in Microsoft Excel by sorting and grouping census tract estimations by impact zone. The census tracts in each impact zone were calculated using the COUNT function in a separate calculations tab. Average mean elevation, average mean slope, average minimum slope, and average maximum slope were also calculated for each impact zone. Each category used the AVERAGE function in the calculations tab to calculate the average result for the census tracts within the given impact zone.

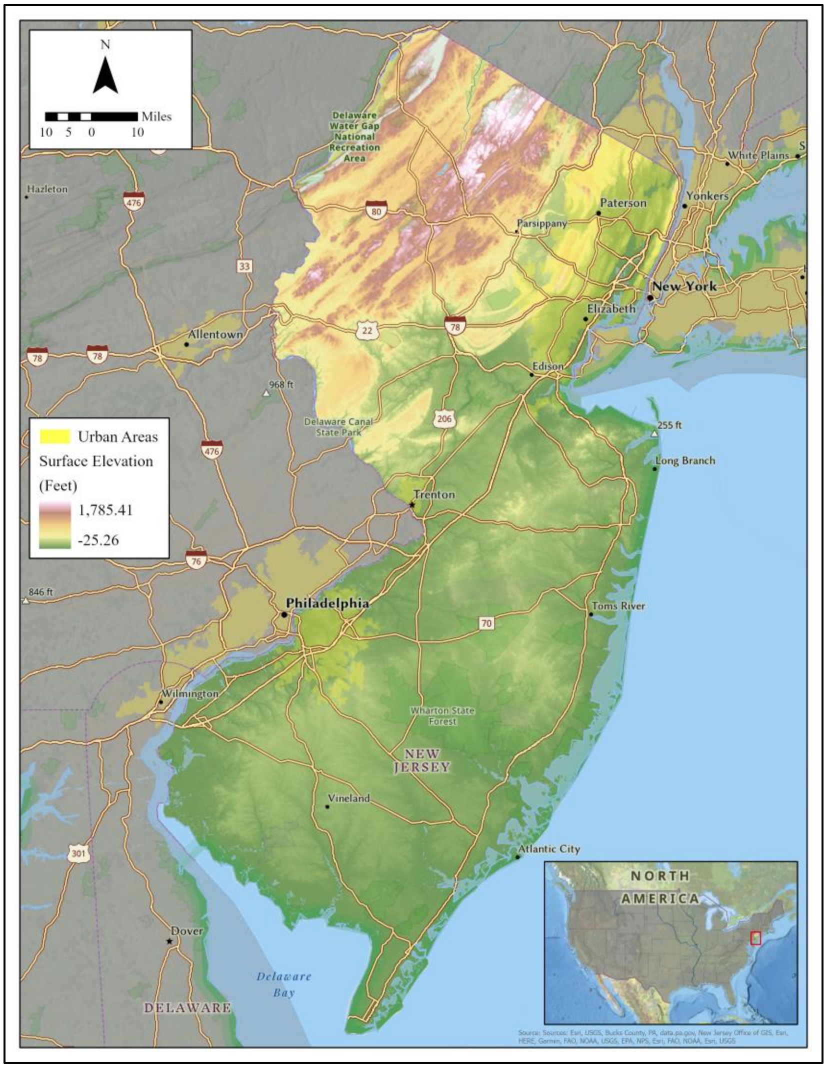

Figure 5. Surface Elevation of New Jersey.

3.2.3. Comparison of Years Before and After Disaster

2010 and 2018 data profiles from ACS 5-Year Estimates were used to compare recovery disparities among Hurricane Sandy impact zones. According to the year range, each evaluation used associated data profiles (Appendix A) applied to two copies of classified census tracts in ArcGIS Pro. The 2006 – 2010 ACS data were analyzed first, followed by the 2014 – 2018 ACS data. Each updated feature class was exported as an Excel spreadsheet and added as a new tab in the Excel file created in the physical evaluation, where sorting and grouping were used to calculate the impact zones' results. Calculations from before and after Hurricane Sandy were compared using percent change (Equation 3) by subtracting the 2018 result from the 2010 result and dividing that outcome by the 2010 result.

Equation 3. Percent Change Equation.

$$c = \frac{x_2 - x_1}{x_1} * 100$$

CV was calculated for every ACS variable to ensure transparent reliability by aggregating each census tracts' MOE by impact zone to estimate the final CV (Fuller 2018). Also, spatial statistics, such as clustering and regression, were performed to test the relationship of the outcomes on a census tract level.

3.2.3.1. Population Evaluation

In ArcGIS Pro, the census tract size was calculated by adding a field named "Area_sqmil" and using *Calculate Geometry* to estimate the area in square miles of each polygon. The 2010 and 2018 ACS "Total Population" data profiles were joined to two separate copies of the updated and classified census tract feature class using Census Tract ID. Each feature class copy was exported using *Table to Excel* and added to the master Excel file as new tabs.

Total population, total population percentage, and population density were added to the calculation tab of the spreadsheet for each year range. The total population was calculated using the SUM function of the people in all census tracts in each impact zone. Total population percentage was calculated using the total population result and dividing that by the sum of all the census tract population and multiplying by 100 for percentage. Population Density was calculated using the total population result and dividing that by the sum of the zone's square mile area. The Total Population variable from each year's data profile had a calculated CV using the final CV equation. Each zonal result from 2010 was compared to 2018 to calculate the percent change.

3.2.3.2. Income Evaluation

In ArcGIS Pro, the 2010 and 2018 ACS "Median Income in The Past 12 Months" and "Poverty Status in The Past 12 Months by Sex by Age" data profiles were joined to two separate copies of the classified census tract feature class using Census Tract ID. Each feature class copy was exported using *Table to Excel* and added to the master Excel file as new tabs. When comparing dollar value data from 2010 to 2018, the data were not normalized across data profiles. Therefore, the income evaluation compared data horizontally at its inflation-adjusted dollar amount for the year presented.

Average median household income, lowest median household income, highest median household income, and persons below poverty percentage were added to the calculation tab of the spreadsheet for each year range. Average median household income was calculated using the AVERAGE function on the Median Household Income variable across each impact zone. The lowest median household income was calculated using the MIN function on the Median Household Income variable across each impact zone. The highest median household income was calculated using the MAX function on the Median Household Income variable across each impact zone. The Median Household Income and Persons Below Poverty Estimate variables from each year's data profile had a calculated CV using the final CV equation. Each zonal result from 2010 was compared to 2018 to calculate the percent change.

Household income classes were estimated using the Pew Research Center standards and the 2010 and 2018 ACS "Income in The Past 12 Months" data profiles. According to a 2016 report, the national middle-class household income range was between $45,200 and $135,600

(Kochhar 2018). With best efforts to meet this range, this study categorized the middle-class between $50,000 and $149,999. Values below that range were considered lower-class, and those above that range were considered upper-class. The 2010 and 2018 ACS "Income in The Past 12 Months" data profiles were first edited in Excel to create a total percentage of households per income class per census tract. Each variable within the range of the income class was added to a column labeled low, middle, or upper class. Using Census Tract ID, this edited table joined two separate copies of the classified census tract feature class in ArcGIS Pro. Each feature class copy was exported using *Table to Excel* and added to the master Excel file as new tabs.

Lower-income households, middle-income households, and upper-income households were added to the calculation tab of the spreadsheet for each year range. Lower-income households were calculated by adding the total number of households with less than $50,000 annual income by impact zone and dividing it by the total number of households by impact zone. Middle-income households were calculated by adding the total number of households between $50,000 and $150,000 annual income by impact zone and dividing it by the total number of households by impact zone. Upper-income households were calculated by adding the total number of households with more than $150,000 annual income by impact zone and dividing it by the total number of households by impact zone. The Estimated Household Income variables from each year's data profile had a calculated CV using the final CV equation. Each zonal result from 2010 was compared to 2018 to calculate the percent change.

3.2.3.3. Housing Evaluation

In ArcGIS Pro, the 2010 and 2018 ACS "Households and Families" and "Vacancy Status" data profiles were joined to two separate copies of the classified census tract feature class using Census Tract ID. Each feature class copy was exported using *Table to Excel* and added to the master Excel file as new tabs.

Owner-occupied housing units, renter-occupied housing units, and vacant housing units were added to the calculation tab of the spreadsheet for each year range. Owner-occupied housing units were calculated as a percentage by adding the total number of owned housing units in the impact zones and dividing it by the total number of all housing units by impact zone. Renter-occupied housing units were calculated as a percentage by adding the total number of rented housing units in the impact zones and dividing it by the total number of all housing units by impact zone. Vacant housing units were calculated as a percentage by adding the total number of vacant housing units in the impact zones and dividing it by the total number of housing units by impact zone. The Owner-Occupied, Renter-Occupied, and Vacant Housing Unit variables from each year's data profile had a calculated CV using the final CV equation. Each zonal result from 2010 was compared to 2018 to calculate the percent change.

3.2.3.4. Spatial Statistics

Before statistics were applied, the value difference of each variable was calculated to estimate socio-economic change by census tract from 2010 to 2018. The value differences were calculated in a new CSV file by subtracting 2010 data from 2018 data for population, population density, median household income, Persons below poverty, lower-income households, middle-income households, upper-income households, owner-occupied housing, renter-occupied housing, and vacant housing units. In ArcGIS Pro, the table was joined to a copy of the updated and classified 2010 census tract feature class using Census Tract ID. To estimate the occurrence of clustering in the study area, *Incremental Spatial Autocorrelation* was first implemented to determine the peak distance of statistically significant clustering. Using the optimal distance in the fixed distance band option, the *Hot Spot Analysis (Getis-Ord Gi*)* tool was deployed for each variable difference. Clustering of high and low values was further analyzed with a final spatial statistic to test the distribution and reliability of the data. The *Spatial Autocorrelation (Global Moran's I)* tool was used to indicate whether the features were spatially correlated, while randomly distributed components favored the null hypotheses. A positive Moran's I value rejects the null hypothesis by expressing a tendency toward clustering. Spatial significance was rated according to the z-score value, where the higher the number was, the more statistically significant the spatial relationships were.

Chapter 4 Results

The study aimed to examine the socio-economic characteristics of existing coastal communities by developing an evaluation to understand the relationship between recovery and physical exposure from a severe flood event. The impact zone classification indicated that, for the 1,999 census tracts analyzed, more than half of the population resided in NIZ. The physical evaluation revealed that New Jersey's elevation and slope were relatively uniform except for the dramatic elevation increase in the northwestern NIZ, accounting for four times the average mean height of the other zones. Overall, the community's transformation from before to after Hurricane Sandy was not overtly apparent; across all the zones, the population increased, the average median household income increased, persons below poverty increased, and owner-occupied housing decreased. Some distinct findings were that the tract with the lowest median household income in the SrIZ saw an increase of 66% in median household income, and the tracts with the highest median household income in the NIZ and SvIZ increased almost 100%. The MIZ had the softest increase in median household income and the highest increase in renter-occupied housing compared to the other impact zones. The CV for all the aggregated ACS data proved reliable, with the highest unreliability being 9%. However, the non-aggregated ACS data for the lowest and highest median household income proved to be exceptionally high. The complete results of New Jersey's population, financial, and housing data change are outlined in this chapter.

4.1.1. Impact Zone Classification

Data scrubbing eliminated five of the 2010 census tract polygons with nominal population size and margin of error, leaving a total of 1,999 census tracts used in the study. The ArcGIS Spatial Analyst Tool Zonal Statistics as Table calculated mean flood inundation of the Hurricane Sandy Surge Boundary depth grids across the census tract polygons. Figure 6 shows the impact zones were classified according to impact zones of None (NIZ) (0 ft), Minor (MIZ) (0-2 ft), Serious (SrIZ) (2-4 ft), and Severe (SvIZ) (>4 ft) (McCarthy et al. 2006). The totals for the study area include the NIZ with 1,329 tracts, followed by SvIZ with 363, SrIZ with 194, and MIZ with 83 census tracts.

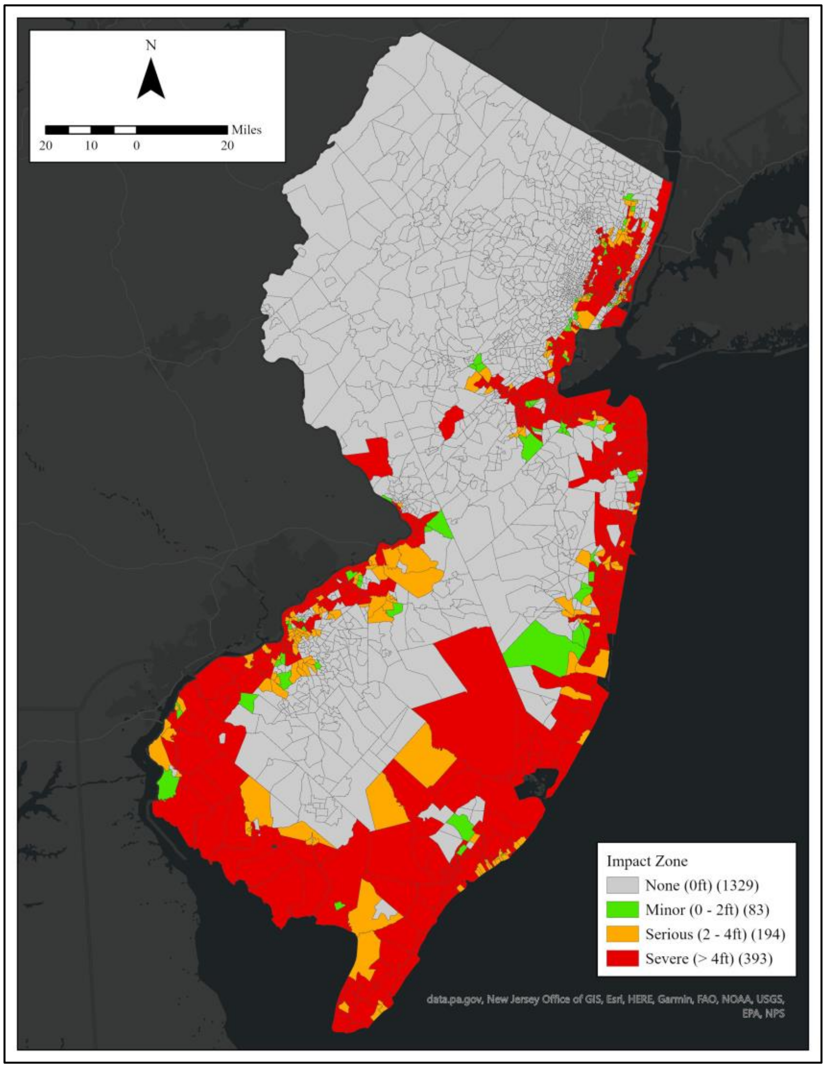

Figure 6. Hurricane Sandy Surge Impact Zones of New Jersey.

4.1.2. Physical Evaluation

Before comparing 2010 and 2018 ACS data, the study area's land elevation and slope were examined using the New Jersey 10-foot DEM concerning 2010 census tracts. The analysis showed that around two-thirds of the census tracts examined remained in the NIZ, with the smallest sample size residing in the MIZ (Table 2). The NIZ exhibited the highest average mean elevation of 194 feet, average mean slope of 2.9 percent rise, and average maximum slope of 11.1 percent rise. Impact zones Minor, Serious, and Severe had similar results for average mean elevation, average mean slope, and average minimum slope. SvIZ did show the second highest average maximum slope; however, it was closer to the MIZ and SrIZ than NIZ.

Table 2. Physical Evaluation of Elevation and Slope per Impact Zone.

Impact Zone	**Census Tracts**	**Average Mean Elevation (Feet)**	**Average Mean Slope (Percent Rise)**	**Average Minimum Slope (Percent Rise)**	**Average Maximum Slope (Percent Rise)**
None (0 ft)*	1329*	194*	2.9*	0.2*	11.1*
Minor (0-2 ft)	83	41	1.8	0.2*	5.5
Serious (2-4 ft)	194	33	1.5	0.1	5.2
Severe (>4 ft)	393	30	1.6	0.0	7.2

**** Result(s) with the highest value in the dataset.***
***** Impact Zone(s) in the dataset with the largest difference in results from the evaluation.***

The zonal statistics spatial analyst estimated the highest mean elevation and slope in the state's northwestern region, coinciding with most NIZ (Figure 7 and 8). The distribution of mean elevation throughout the census tracts was displayed in Figure 7, highlighting the difference in incline from 0.98 to 1,200 feet. While Figure 8 showed a slightly more distributed mean slope with the highest percentage rise in the northwest and some in the central-eastern region of the state. Overall, the physical evaluation showed that New Jersey's elevation and the slope were relatively uniform throughout most of the study area, with the highest in the northwestern region.

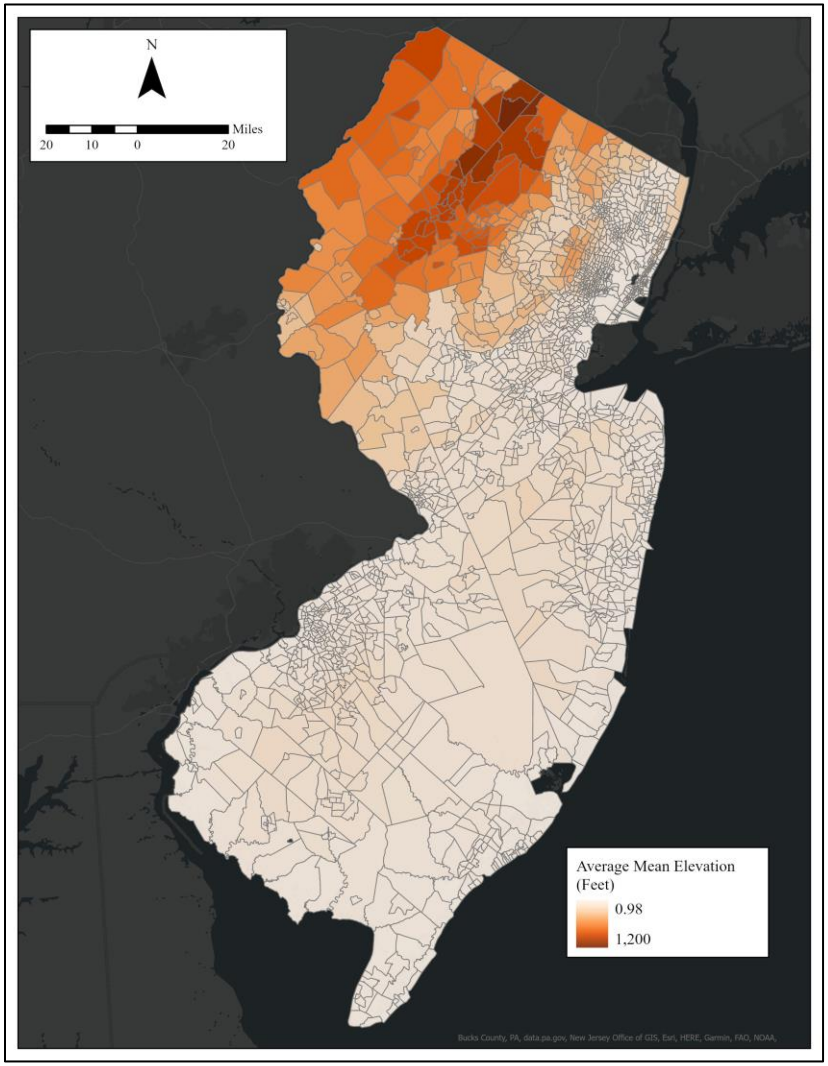

Figure 7. Average Mean Elevation per Census Tract in New Jersey.

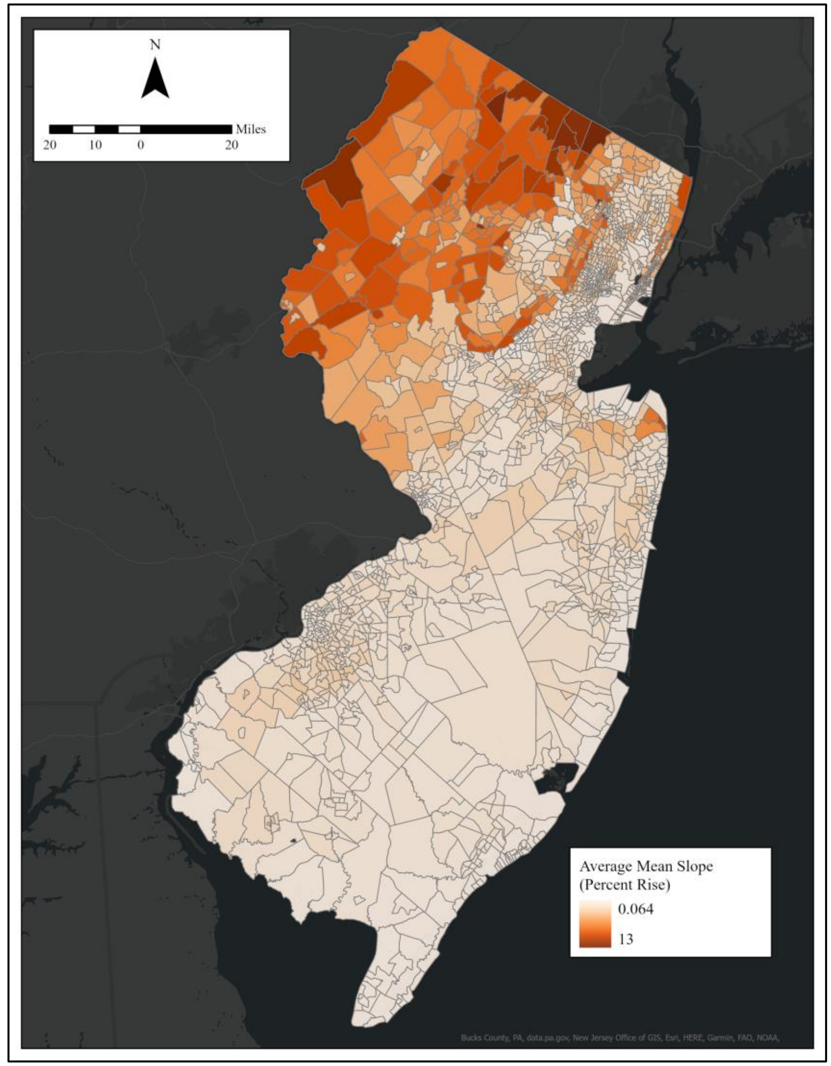

Figure 8. Average Mean Slope per Census Tract in New Jersey.

4.1.3. Comparison of Years Before and After Disaster

In comparing 2010 and 2018 data profiles from ACS 5-Year Estimates, the tabular data was linked to impact zone classified 2010 census tract data to evaluate population, income, and housing. In addition, the reliability of the data was tested according to MOE aggregation and the CV of each variable in the impact zones. The ACS data used in the study proved to be highly reliable, with an average of 1.67% and the least reliable variable being 9% from 2018 Median Household Income in the MIZ (Table 4). According to the CV results, the most reliable ACS data examined was total population, and the least reliable was median household income.

4.1.3.1. Population Evaluation

The population evaluation analyzed the total population, population percentage, and population density of census tracts by impact zone using 2010 and 2018 ACS data profiles. The highest total population resided in the NIZ, with more than 6 million residents with the lowest total population in the MIZ (Table 3). In comparing data years 2010 and 2018, population distribution remained about the same, with more than half of the total population in the NIZ followed by 18% in SvIZ.

Table 3. Population Evaluation per Impact Zone for ACS Years 2006 – 2010 and 2014 – 2018.

ACS 5-year Dataset	**Impact Zone**	**Population**	**Total Population Percentage**	**Population Density (Population per square mile)**	**CV for Population Estimate**
2006-2010	None (0 ft)**	6,031,482*	69%*	1,250	0%
	Minor (0-2 ft)	333,117	4%	1,729*	1%
	Serious (2-4 ft)	769,335	9%	1,551	0%
	Severe (>4 ft)**	1,587,489	18%	687	0%
2014-2018	None (0 ft)**	6,119,636*	69%*	1,268	0%
	Minor (0-2 ft)	345,973	4%	1,797*	1%
	Serious (2-4 ft)	779,045	9%	1,566	0%
	Severe (>4 ft)**	1,636,028	18%	708	0%

** Result(s) with the highest value in the dataset.*
*** Impact Zone(s) in the dataset with the largest difference in results from the evaluation.*

The population steadily increased across all impact zones, with the most percent increase in the MIZ of 4% due to its already low population, although growth rates were roughly the same across all zones (Figure 9). The SvIZ also showed a population of over 1.5 million with a percent change of 3%. The total population across the census tracts from 2010 and 2018 ACS data profile estimates only increased by 159,259 individuals.

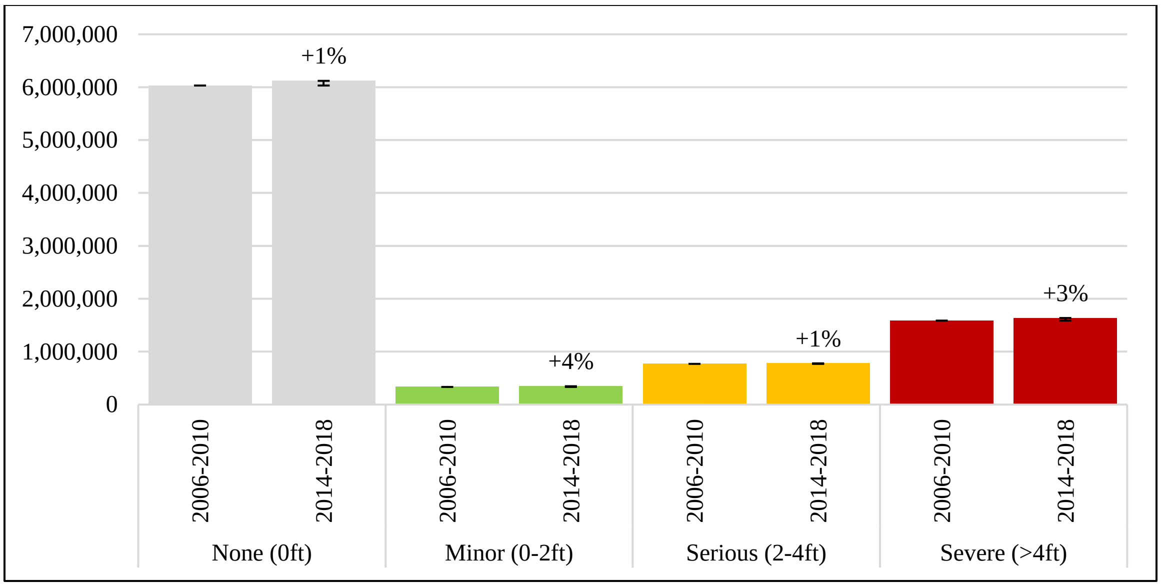

Figure 9. Population Change Graph, 2006 – 2010 and 2014 – 2018.

At a glance, most of the highest density areas were in the northeastern and south to the central-western region of the state, which intersects the Hurricane Sandy Surge boundary (Figure 10). In 2010, the remainder of the state, although still dense, had a population density below 5,000 people per square mile. Table 3 examination by impact zone displayed a similar population density in 2010 between 1,250 and 1,729 people per square mile in impact zones None, Minor, and Serious. Although the densest census tracts in the state were in the SvIZs, the overall population density for this zone was the lowest, with only 687 people per square mile. Most of this zone had lower population density with more extensive census tracts; therefore, the low population regions overpowered the pockets of high density. Population density did not increase substantially in 2018 due to the steady overall increase in population across all impact zones.

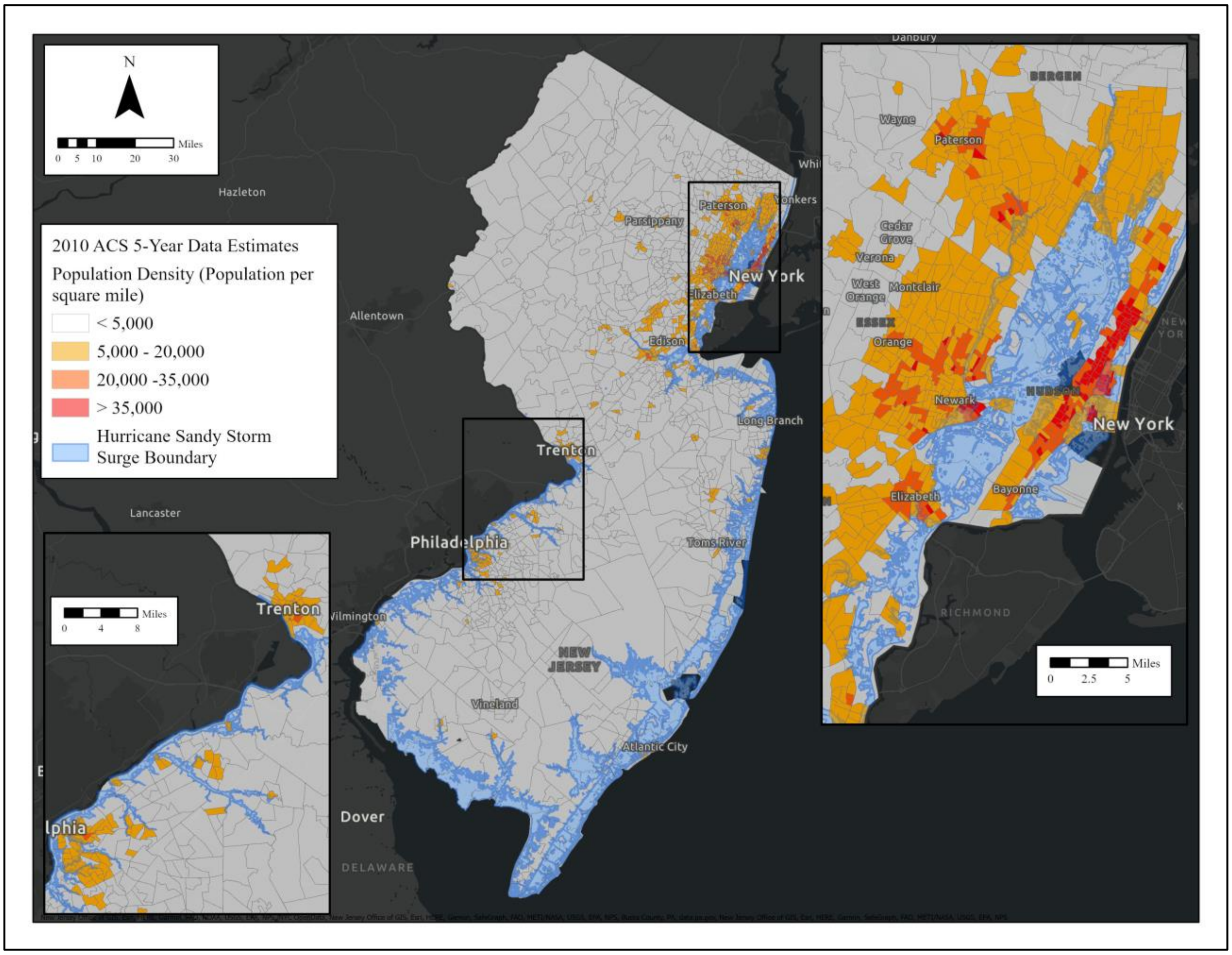

Figure 10. 2010 Population Density per Census Tract in Hurricane Sandy Surge Boundary.

4.1.3.2. Income Evaluation

The income evaluation analyzed the median household income, persons below poverty, and income classes of census tracts by impact zone using 2010 and 2018 ACS data profiles. In 2010, the average median household income throughout the impact zones ranged between $62,817 and $77,906 (Table 4). However, in 2018 the average median household income broadened its range to $67,838 and $89,752. Comparing the two data profile years across impact zones, the results showed that average median household income experienced a 15% change increase in NIZ, MIZ, and SrIZ, with a 16% change in the SvIZ (Figure 11).

In 2010, the lowest median household income for all impact zones ranged from $9,393 to $13,624, with the lowest in the SrIZ and the highest in the NIZ. Conversely, in 2018, the lowest median household income range became more rigid, ranging between $12,443 to $15,579 (Table 4). The lowest impact zone switched to the MIZ, while the SrIZ changed from the lowest in 2010 to the highest in 2018. Comparing the two data profile years, the results showed that the lowest median household income increased overall but at different levels of percent change (Figure 12). The SrIZ grew at 66%, followed by MIZ at 29% and SvIZ at 25%. The NIZ experienced a minor change with an increase of 8%, showing that this zone's lowest median household income remained comparatively constant from 2010 to 2018. When reviewing the reliability of the individual census tract where median income originated, all the 2018 ACS data had a standard deviation greater than the mean. The highest CV in the 2010 ACS data was 21%, making this census tract less reliable than the rest of the impact zones but still purposeful. The other CV values for the 2018 ACS data were too high to be considered reliable.

The highest median household income in 2010 ranged from $131,298 in the SrIZ to $238,162 in the NIZ. While the highest median household income in 2018 ranged from $171,635 to $441,283 in the same impact zones as 2010 (Table 4). The highest median household income distribution remained the same in 2010 and 2018; however, impact zones None and Severe considerably increased. The NIZ displayed an increase of 85%, and the SvIZ revealed a 90% increase, while MIZ increased 15% and SrIZ experienced a 31% increase (Figure 13). The impact zones with the original highest median household income, None and Severe, increased significantly while the other zones, Minor and Serious, increased marginally by comparison.

When reviewing the reliability of the individual census tract where median income originated, most of the ACS data was unfavorable. The CV values for the 2010 ACS data ranged from 7% to 71%, and 2018 ACS data ranged from 61% to 71%. The U.S. Census case studies consider above 30% CV to be low reliability; therefore, all the 2018 ACS data in this evaluation cannot be considered trustworthy. However, most of the impact zones from the 2010 ACS data were reliable except for MIZ.

In 2010, the population percentage considered below the poverty level in each impact zone ranged from 8% to 12%. The persons below poverty percentage from 2018 resulted in a range more uniform, with impact zones None and Severe at 10% and Minor and Serious at 13% (Table 4). Poverty increased overall, with the most remarkable percent change of 17% in the MIZ (Figure 14). Considering the 2019 ACS 5-Year Estimates revealed the national poverty level to be 13.4%, New Jersey's general poverty level remains low (US Census Bureau).

Table 4. Median Household Income Evaluation per Impact Zone for ACS Years 2006 – 2010 and 2014 – 2018.

ACS 5-year Dataset	**Impact Zone**	**Average Median Household Income**	**CV for Median Household Income**	**Lowest Median Household Income**	**CV for Lowest Median Household Income**	**Highest Median Household Income**	**CV for Highest Median Household Income**	**Persons Below Poverty (Percentage of Population)**	**CV for Persons Below Poverty**
2006-2010	None (0 ft)**	$77,906*	0%	$13,624*	13%	$238,162*	11%	8%	1%
	Minor (0-2 ft)	$62,817	3%	$9,631	13%	$162,500	71%*	11%	4%
	Serious (2-4ft)**	$59,160	1%	$9,393	15%	$131,298	7%	12%*	3%
	Severe (>4 ft)	$70,212	1%	$12,210	21%*	$214,323	8%	9%	2%
2014-2018	None (0 ft)	$89,752*	2%	$14,729	125%*	$441,283*	61%	10%	1%
	Minor (0-2 ft)	$72,430	9%	$12,443	111%	$187,121	71%*	13%*	3%
	Serious (2-4ft)**	$67,838	6%	$15,579*	107%	$171,635	68%	13%*	2%
	Severe (>4 ft)	$81,163	4%	$15,243	112%	$407,346	61%	10%	2%

** Result(s) with the highest value in the dataset.*

*** Impact Zone(s) in the dataset with the largest difference in results from the evaluation.*

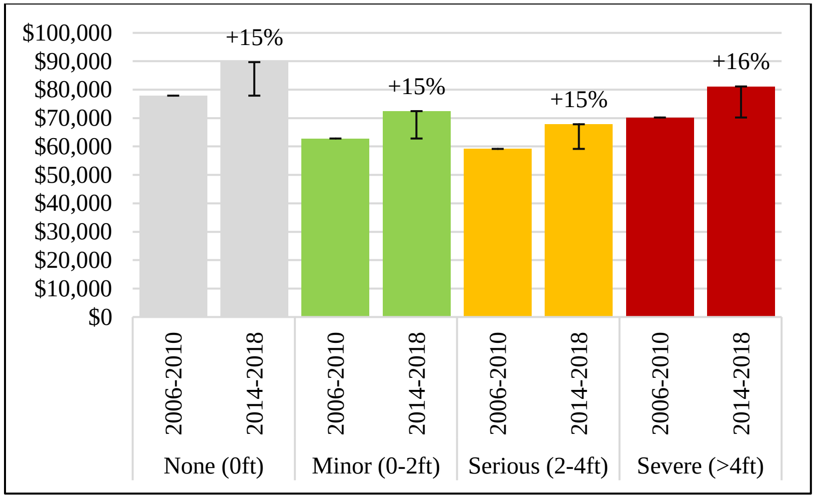

Figure 11. Average Median Household Income Graph, 2006-2010 and 2014-2018.

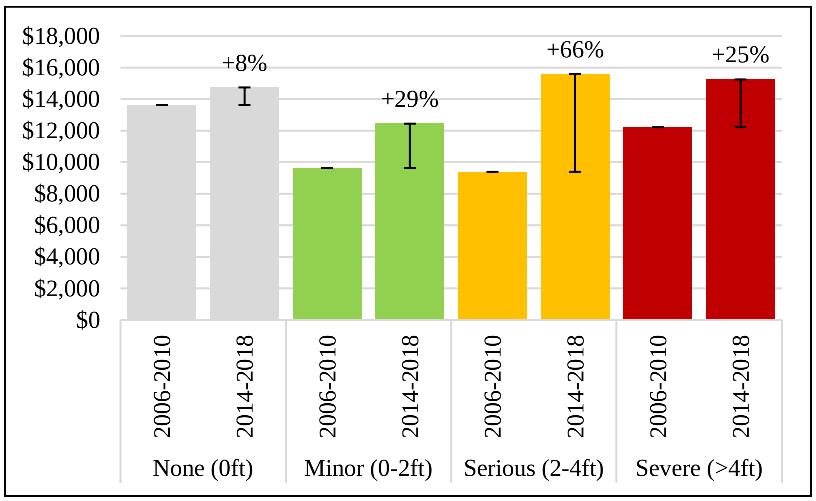

Figure 12. Lowest Median Household Income Graph, 2006-2010 and 2014-2018.

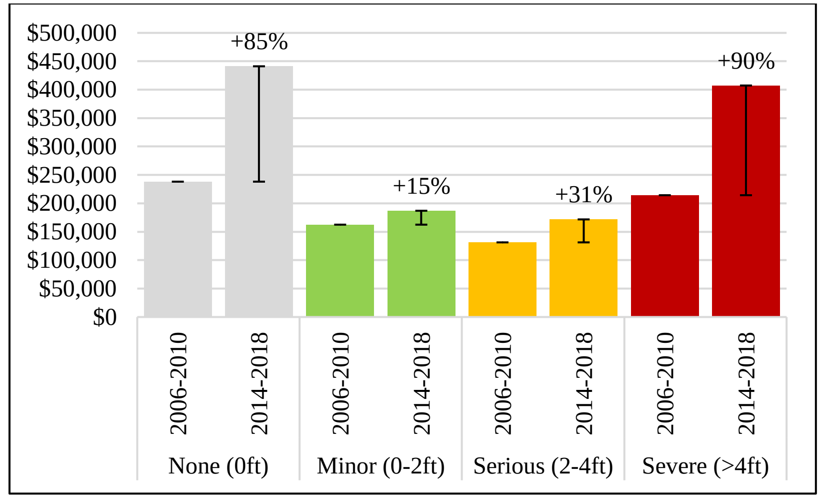

Figure 13. Highest Median Household Income Graph, 2006-2010 and 2014-2018.

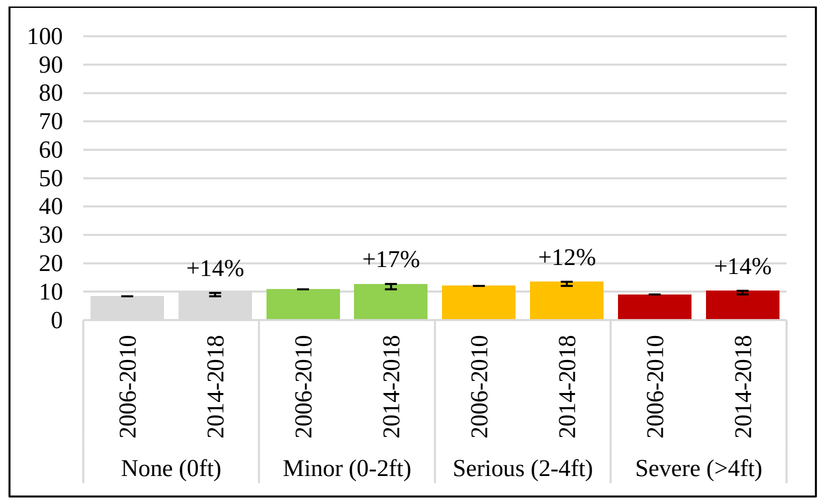

Figure 14. Persons Below Poverty Percentage Graph, 2006-2010 and 2014-2018.

Household income classes in this study are defined as lower (less than $50,000 annual income), middle ($50,000 - $150,000 annual income), and upper (more than $150,000 annual income). The distribution of household income classes in 2010 and 2018 proved to be similar throughout the impact zones, with most of the households in the middle-income class (Table 5). In 2010, the highest percentage of upper-income households and the lowest percentage of lower-income households resided in the NIZ. Also, the SrIZ was the lowest percentage of upper-income households and the highest percentage of lower-income households in 2010. This distribution remained true for the 2018 results.

When comparing 2010 and 2018, there was a percent change decrease of 9% throughout the impact zones for lower-income households; however, the SvIZ showed a considerable reduction of 12% (Figure 15). Middle-income households also showed a consistent decrease among impact zones, with a decline of 7% in the NIZ (Figure 16). Upper-income households showed the most variation in percent change with increased values up to 64% in the SrIZ and an increased 34% in the NIZ (Figure 17). The inundated zones have a higher percent change compared to NIZ, but there is not a consistent increase towards deeper flood depth.

Table 5. Income Classes Evaluation per Impact Zone for ACS Years 2006 – 2010 and 2014 – 2018.

ACS 5-year Dataset	Impact Zone	Lower-Income Households Percentage (Less than $50,000 Annual Income)	CV for Lower-Income Households	Middle-Income Households Percentage ($50,000 - $150,000 Annual Income)	CV for Middle-Income Households	Upper-Income Households Percentage (More than $150,000 Annual Income)	CV for Upper-Income Households
2006-2010	None (0 ft)	34%	1%	48%*	0%	18%*	1%
	Minor (0-2 ft)	43%	4%	46%	3%	11%	8%
	Serious (2-4 ft)**	44%*	1%	47%	1%	9%	3%
	Severe (>4 ft)	37%	1%	48%*	1%	14%	2%
2014-2018	None (0 ft)**	31%	1%	44%	0%	24%*	1%
	Minor (0-2 ft)	39%	4%	44%	3%	17%	4%
	Serious (2-4 ft)	40%*	1%	45%	1%	15%	2%
	Severe (>4 ft)**	33%	1%	46%*	1%	21%	1%

** Result(s) with the highest value in the dataset.*
*** Impact Zone(s) in the dataset with the largest difference in results from the evaluation.*

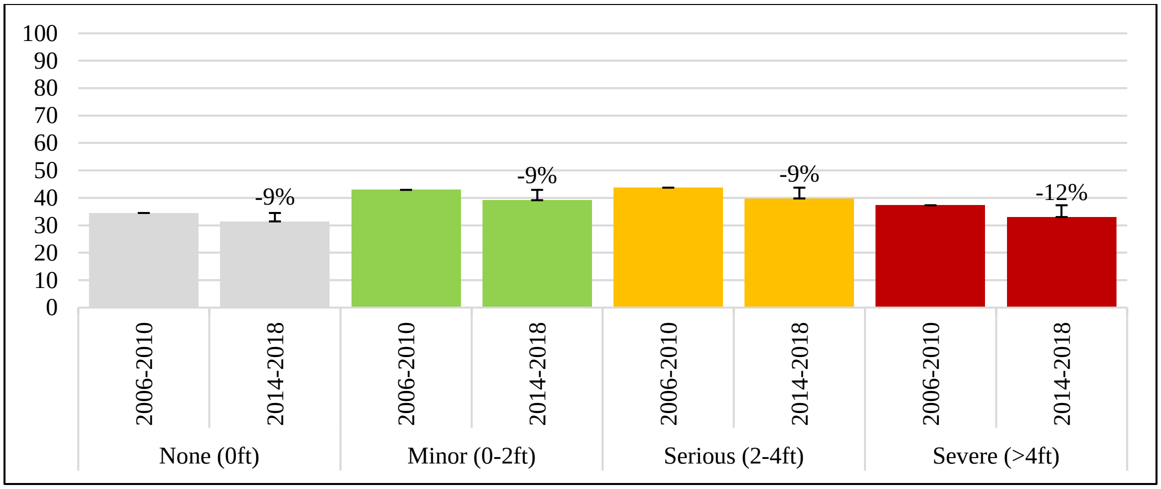

Figure 15. Lower-Income Households Percentage Graph, 2006 – 2010 and 2014 – 2018.

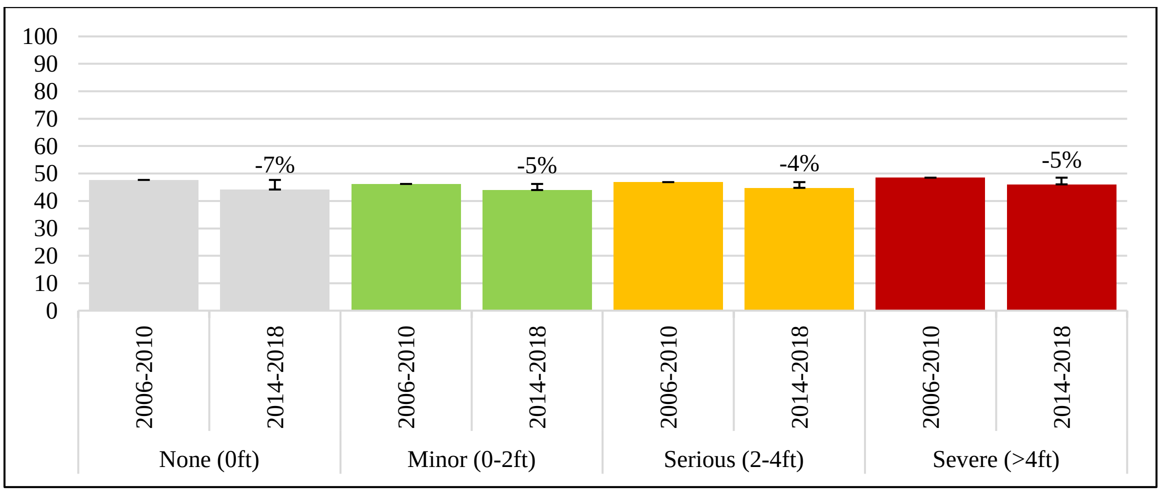

Figure 16. Middle-Income Households Percentage Graph, 2006 – 2010 and 2014 – 2018.

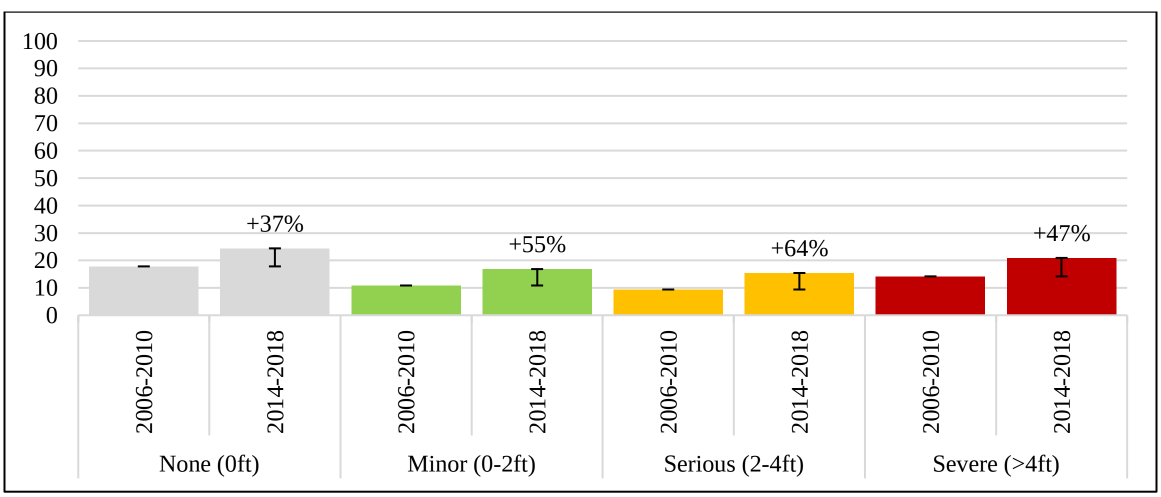

Figure 17. Upper-Income Households Percentage Graph, 2006 – 2010 and 2014 – 2018.

4.1.3.3. Housing Evaluation

The housing evaluation analyzed the owner-occupied, renter-occupied, and vacant housing units of census tracts by impact zone using 2010 and 2018 ACS data profiles. In 2010, owner-occupied housing units were similar among all the impact zones ranging from 58% to 69%. The corresponding renter-occupied housing units were similar across impact zones and ranged from 31% to 42% (Table 6). The peak percentage of owner-occupied units was in the NIZ, and the lowest rate was the MIZ. In 2018, housing units exhibited slightly more variation among impact zones with 53% and 66% of owner-occupied ranges, respectively, and renter-occupied ranges between 34% and 47%. The highest and lowest percentage for the impact zone remained the same for 2018.

Throughout the comparison of 2010 and 2018 data, overall owner-occupied housing units decreased, and renter-occupied housing units increased (Figure 18 and 19). Impact zones None, Serious, and Severe decreased by 4% and 5%, while Minor decreased 9% (Figure 18). The corresponding renter-occupied housing units increased by 9% in impact zones None and Severe. The SrIZ had the lowest increase at 6%, and MIZs had the highest at 12% (Figure 19). The data shows that the most occupied housing change occurred in the MIZ.

In 2010, vacant housing units were predominately in the SvIZ, with 22% of housing units vacant in this zone. A similar distribution of vacant housing units was seen in 2018, with 24% vacancies in the SvIZ (Table 6). Housing vacancy trended towards the most impacted zones. Vacancies increased in all impact zones from 2010 to 2018, with the highest percent change of 12% in the SrIZ and the lowest percentage change of 7% in the SvIZ (Figure 20).

Table 6. Housing Evaluation per Impact Zone for ACS Years 2006 – 2010 and 2014 – 2018.

ACS 5-year Dataset	**Impact Zone**	**Owner-Occupied Housing Units**	**CV for Owner-Occupied Housing Units**	**Renter-Occupied Housing Units**	**CV for Renter-Occupied Housing Units**	**Vacant Housing Units**	**CV for Vacant Housing Units**
2006-2010	None (0 ft)	69%*	0%	31%	0%	7%	1%
	Minor (0-2 ft)	58%	2%	42%*	2%	8%	4%
	Serious (2-4 ft)	60%	1%	40%	1%	17%	2%
	Severe (>4 ft)**	66%	0%	34%	1%	22%*	1%
2014-2018	None (0 ft)	66%*	0%	34%	0%	8%	1%
	Minor (0-2 ft)	53%	1%	47%*	2%	9%	4%
	Serious (2-4 ft)	57%	1%	43%	1%	19%	1%
	Severe (>4 ft)**	63%	0%	37%	1%	24%*	1%

** Result(s) with the highest value in the dataset.*

*** Impact Zone(s) in the dataset with the largest difference in results from the evaluation.*

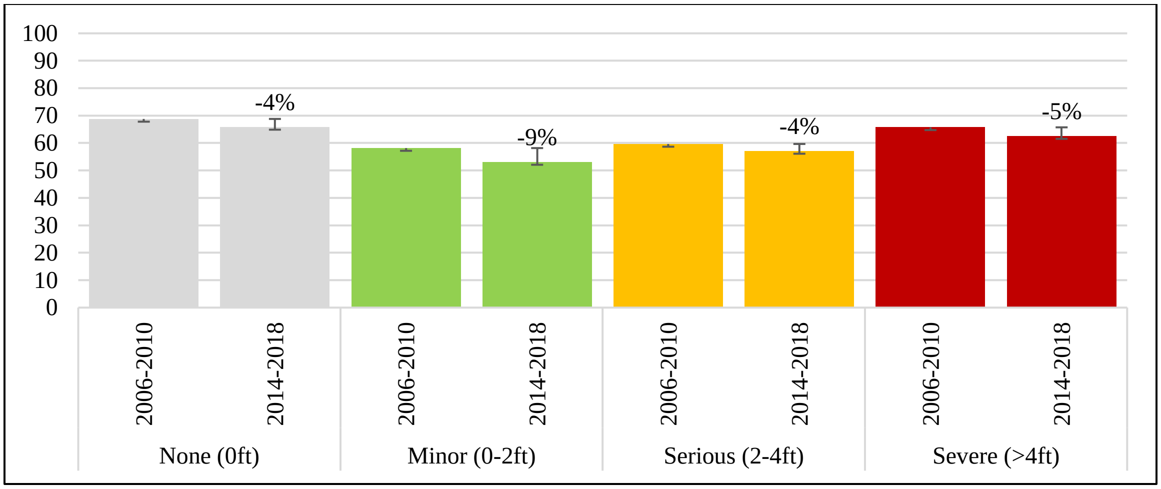

Figure 18. Percentage of Owner-Occupied Housing Units Graph, 2006-2010 and 2014-2018.

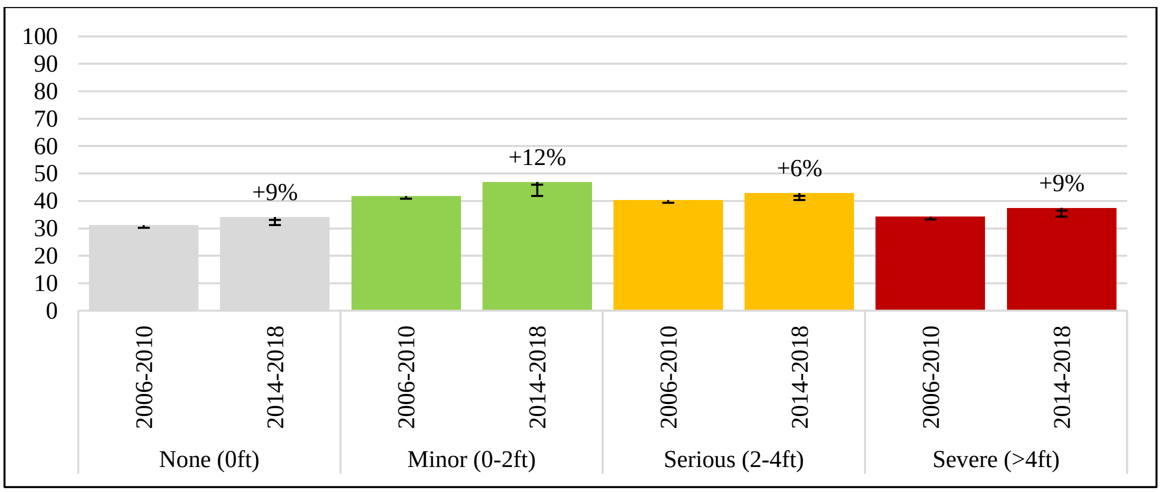

Figure 19. Percentage of Renter-Occupied Housing Units Graph, 2006-2010 and 2014-2018.

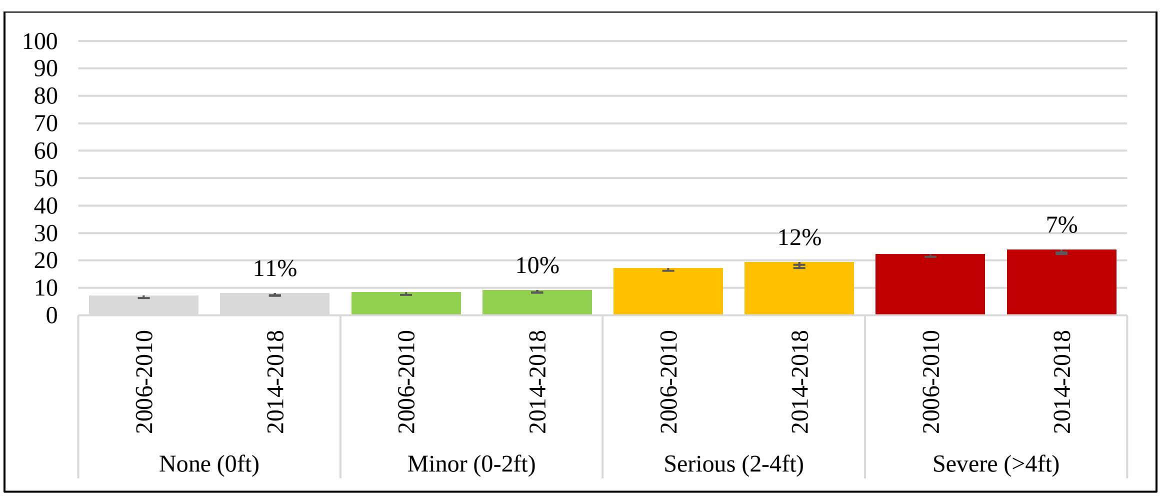

Figure 20. Percentage of Vacant Housing Units Graph, 2006-2010 and 2014-2018.

4.1.3.4. Spatial Statistics

The statistical analysis evaluated the value changes from 2010 to 2018 for population, population density, median household income, people below poverty, lower-income households, middle-income households, upper-income households, owner-occupied housing, renter-occupied housing, and vacant housing units. The *Incremental Spatial Autocorrelation* tool calculated statistically significant z-score peaks at 20,542 meters and 25,701 meters to indicate distances where clustering of census tracts is most pronounced. Using an estimated distance of statistically significant clustering, 21,000-meter fixed distance band was used in the Hot Spot Analyses.

The *Hot Spot Analysis (Getis-Ord Gi*)* tool estimated the clustering census tracts of highest and lowest values for the variables' value change. Clustering of population change from 2010 to 2018 was documented in Figure 21. The northeastern region to the state's central region experienced high to moderate clustering of high values. While clustering of low values was less concentrated, expressing high to low clustering in the northwest, south, and central east regions. Population Density was a much more concentrated value change, with high clustering of high values in the northeastern region and high clustering of low values in the central west area (Figure 22). The highest number of census tracts for both population cluster analyses were insignificant.

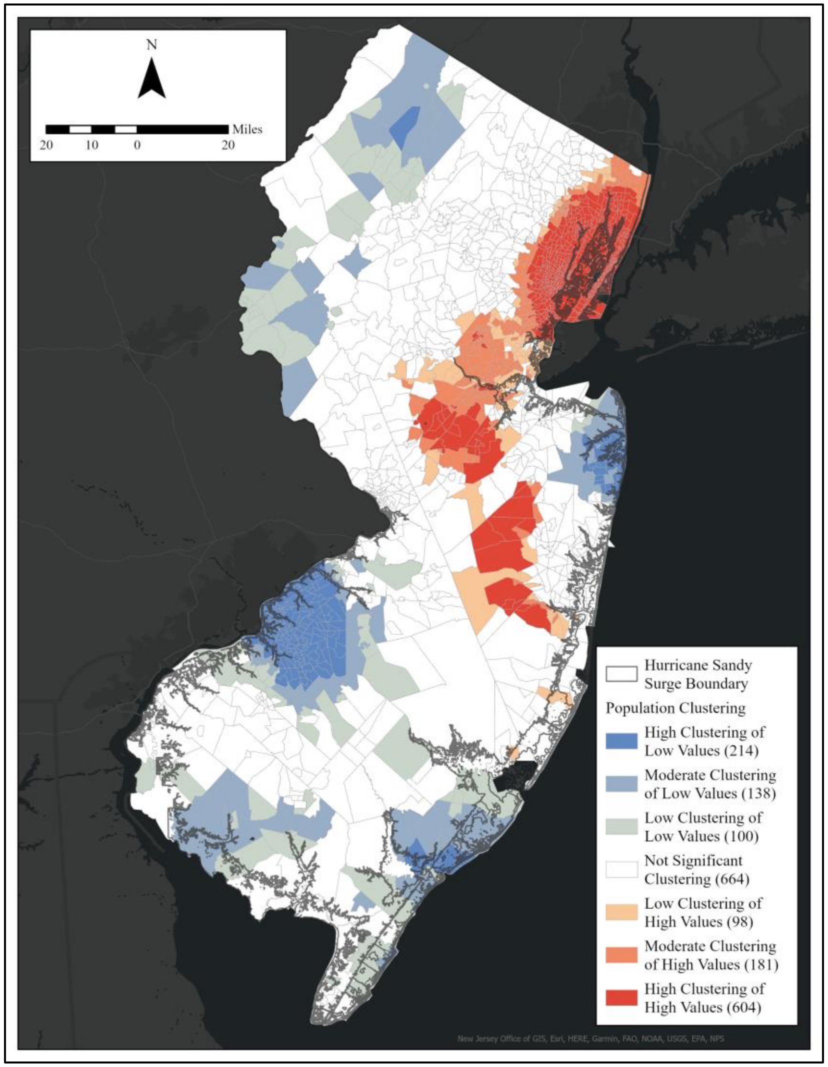

Figure 21. Hot Spot Analysis of Population Difference from 2010 – 2018.

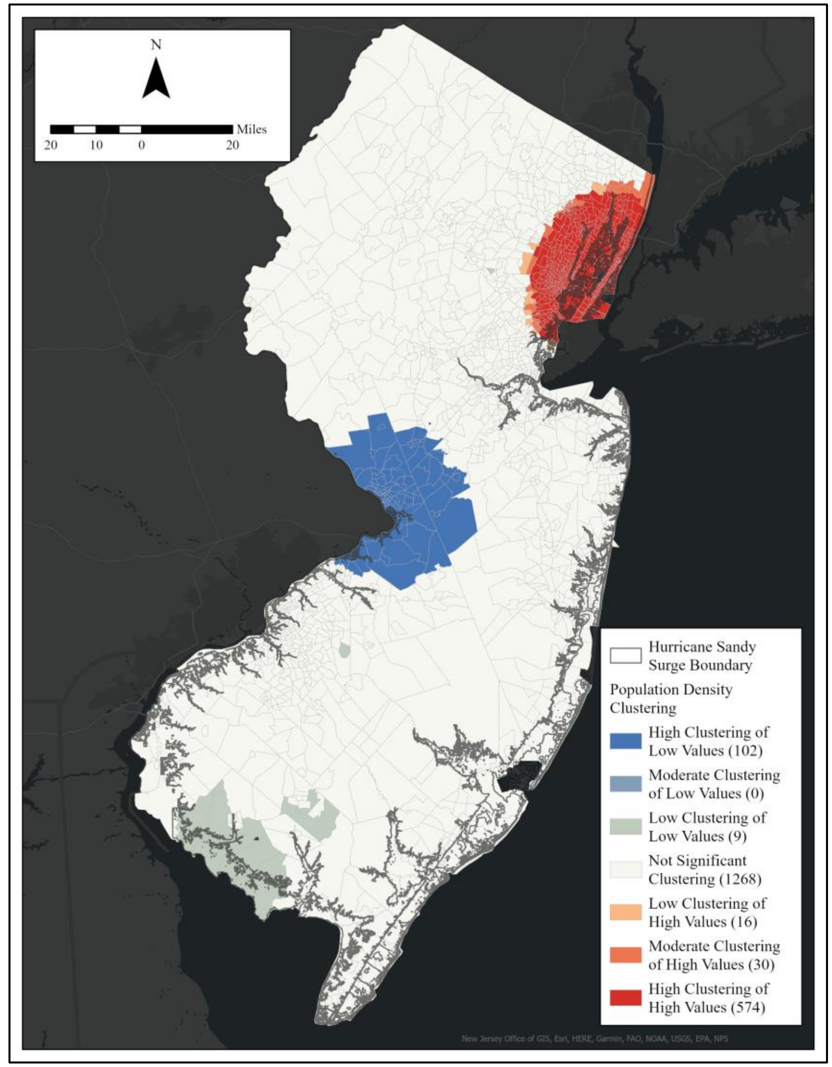

Figure 22. Hot Spot Analysis of Population Density Difference from 2010 – 2018.

Clustering of median household income change from 2010 to 2018 was documented in Figure 23. The crescent-shaped high to moderate clustering of high values were in New Jersey's northeast region and did not interact much with the Hurricane Sandy storm surge boundary. However, most of the high to low clustering of low values were along the storm surge boundary from the northeast to the southwest regions. The gap of insignificant clustering in the northeastern part of median household income was also expressed as a moderate to low clustering of high values of persons below poverty in Figure 24. Low-value clustering is not well displayed in the Hot Spot Analysis due to the overall increase in poverty levels from 2010 to 2018. Most of the persons below poverty clusters of change were along the coastline; however, it is not as significant as median household income change. The highest number of census tracts for median household income and persons below poverty cluster analyses were insignificant.

Clustering of lower-income household change from 2010 to 2018 was documented in Figure 25. High to low clustering of high values were observed in the state's central region, with a few outliers in the north and southeast. The increased number of lower-income households in these sections did not interact much with the Hurricane Sandy storm surge boundary. However, the central region appears to branch off from the boundary with decreased clustering. While high to moderate clustering of low values were expressed solely on the coastline, interacting with the storm surge boundary. Concentrations of reducing lower-income households were observed in the northeastern area, central-eastern region, and southern peninsula of the state. The patterns of lower-income households did not reflect the same patterns shown in the middle- and the upper-income household trends. The highest number of census tracts for the lower-income households cluster analysis were insignificant, with most of the tracts in the state's southern section.

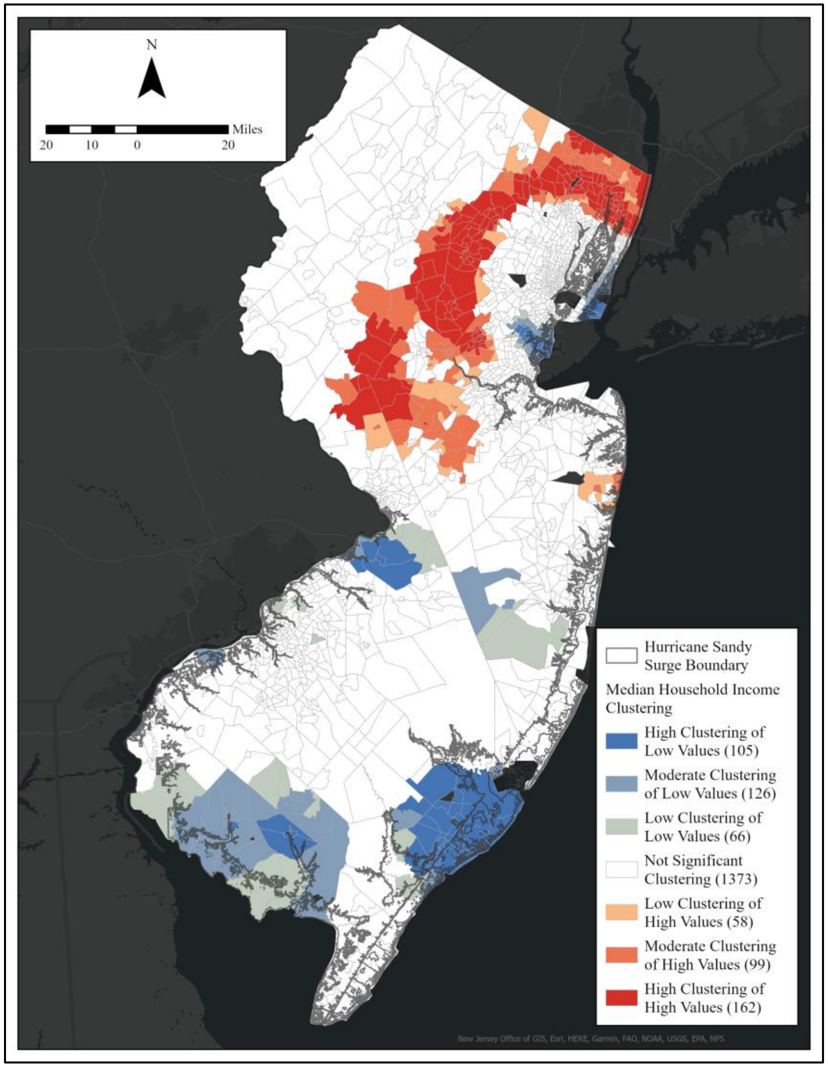

Figure 23. Hot Spot Analysis of Median Household Income Difference from 2010 – 2018.

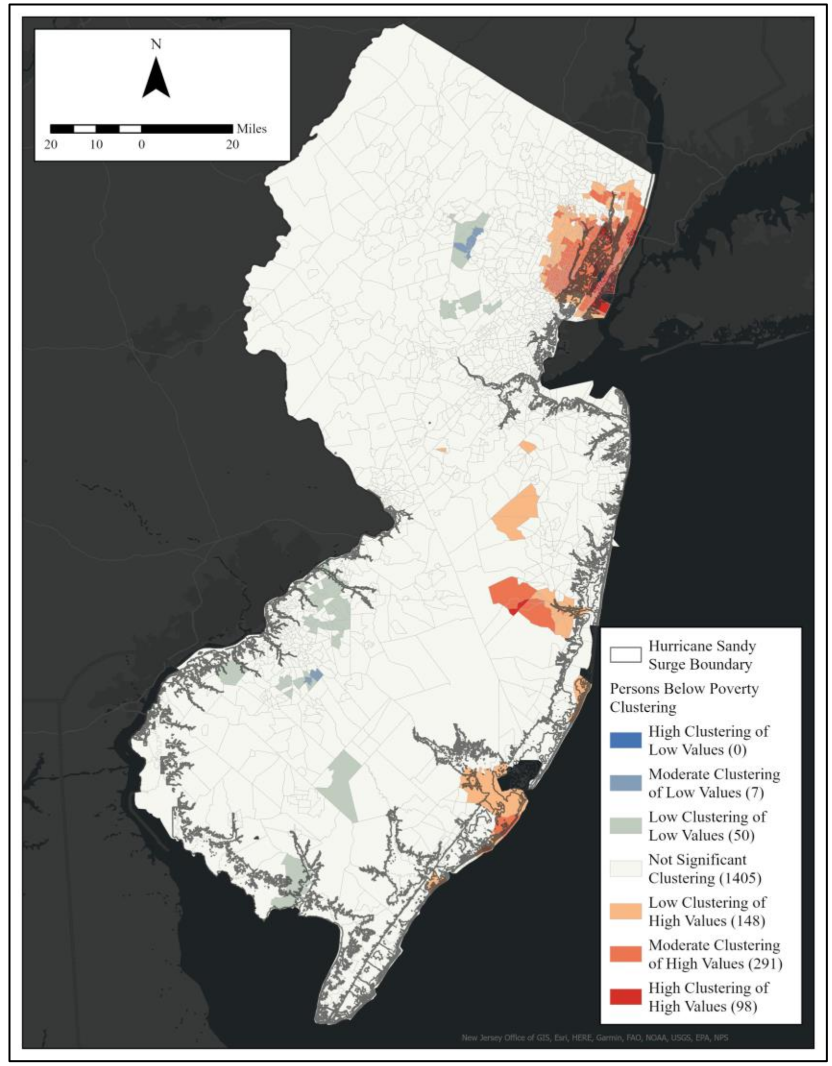

Figure 24. Hot Spot Analysis of Persons Below Poverty Difference from 2010 – 2018.

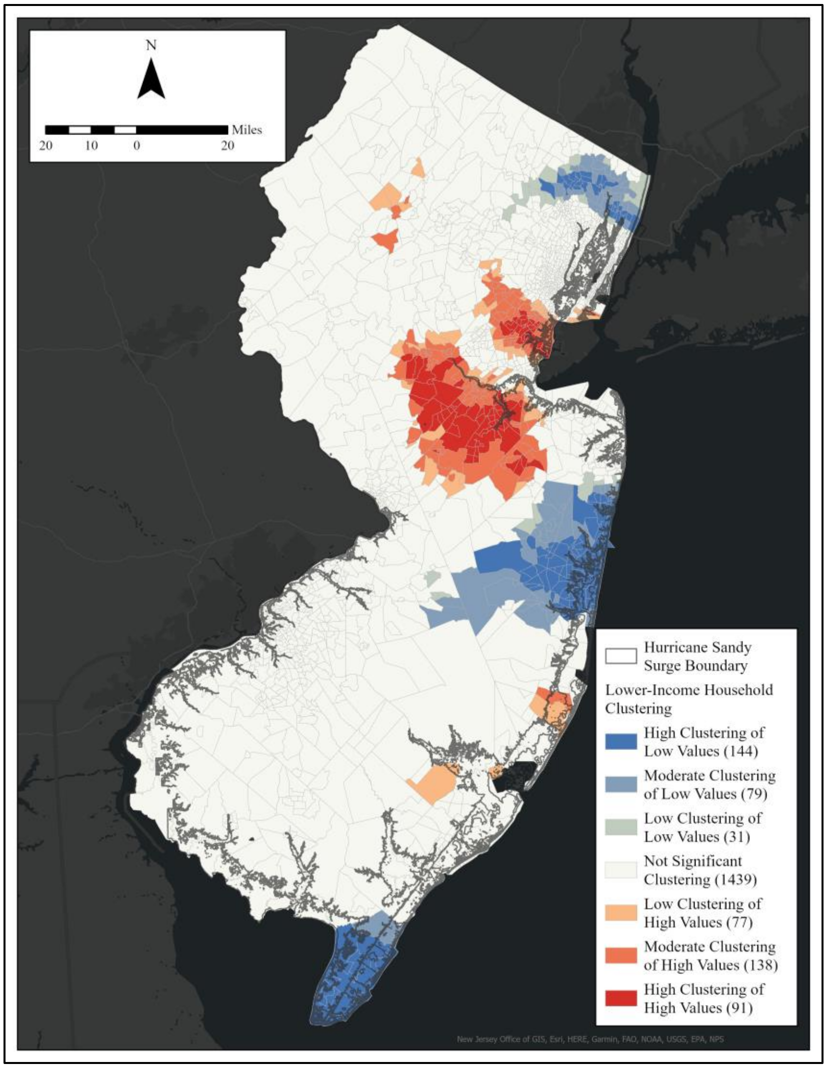

Figure 25. Hot Spot Analysis of Lower-Income Household Difference from 2010 - 2018.

The Hot Spot Analysis for middle- and upper-income household change from 2010 to 2018 shows related trends (Figure 26 and 27). High clustering of increased middle-income households in the northeastern area also showed moderate clustering of decreased upper-income households. While high to moderate clustering of middle-income households in the rest of the northern to the central region also showed high to moderate clustering of increased upper-income households. Outliers for middle-income expressed a high-value cluster in the southeast, and upper-income represented a low-value cluster in the southern coastline. Both income households showed a moderate to low clustering of low values in the southwestern region.

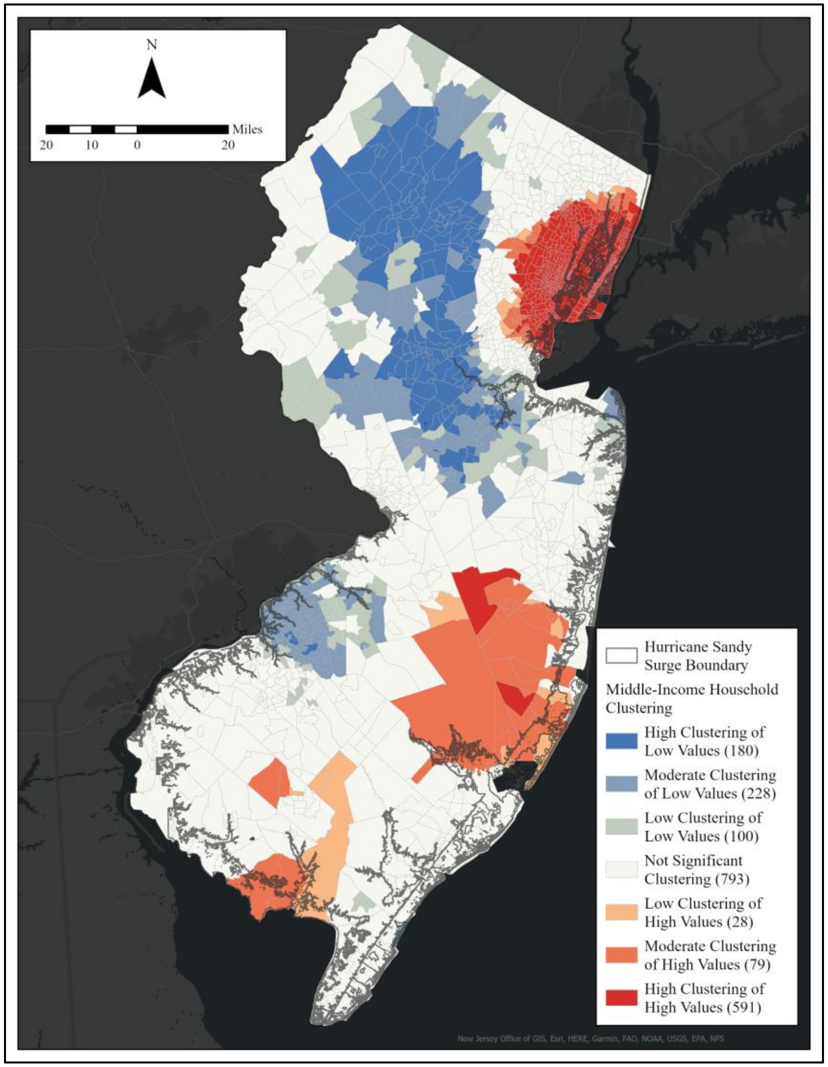

Figure 26. Hot Spot Analysis of Middle-Income Household Difference from 2010 - 2018.

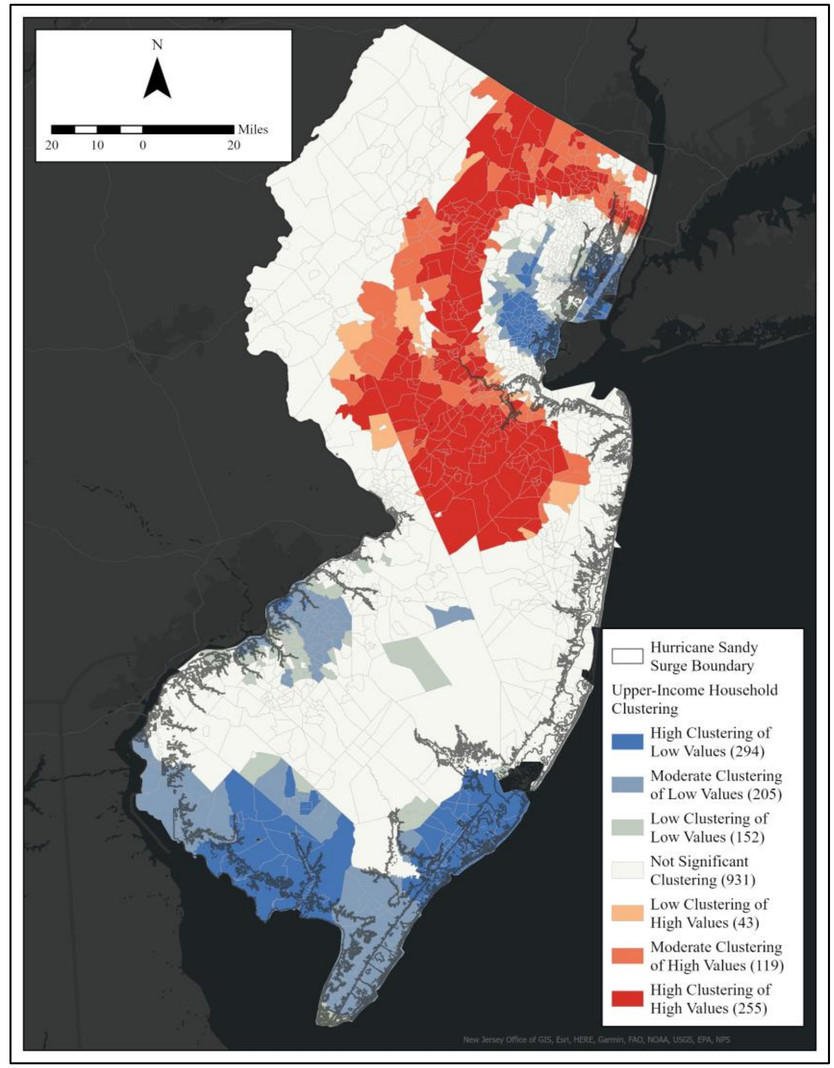

Figure 27. Hot Spot Analysis of Upper-Income Household Difference from 2010 - 2018.

The Hot Spot Analysis for owner- and renter-occupied housing unit change from 2010 to 2018 shows related trends (Figure 28 and 29). Instead of the clustering showing adverse results from owner to renter values, the clustering was comparable. Owner-occupied housing units expressed high clustering of high values in a small area to the southeastern region with scattered moderate to low clustering in the northeast, central, and southwest areas. High clustering of high values for renter-occupied housing units was more concentrated to the northeastern and the central regions, with a small moderate to low high cluster in the southeastern area.

A small cluster of decreasing owner-occupied housing units was observed in the southwestern and southeastern areas. However, the rest of the low-value clusters were moderate to low. High and low values of clusters for owner-occupied housing units were scattered throughout the study area. High clustering of low-value renter-occupied housing units was mainly in the southern peninsula. The other low value moderate to low clusters in the southwest and central east areas. There does not appear to be a relation between high clustering and proximity to the Hurricane Sandy storm surge boundary. The highest number of census tracts for the owner- and renter-occupied housing unit cluster analysis was insignificant with most of the tracts in the state's northern section.

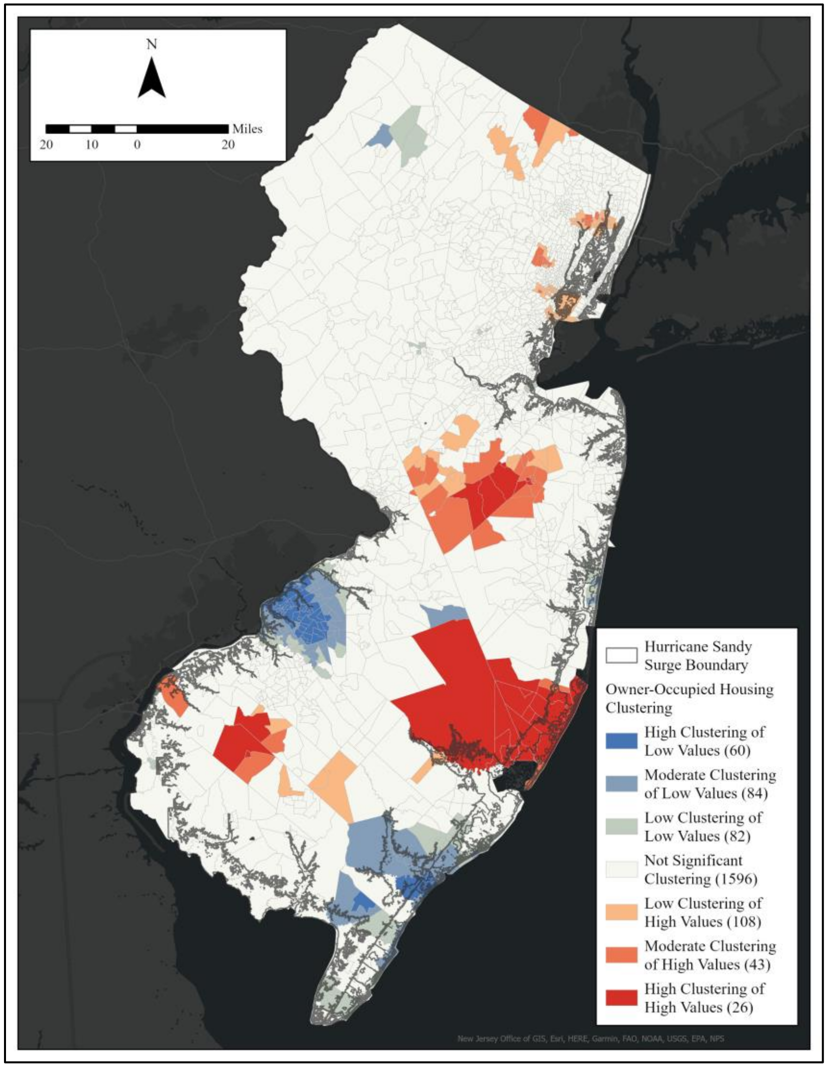

Figure 28. Hot Spot Analysis of Owner-Occupied Housing Difference from 2010 – 2018.

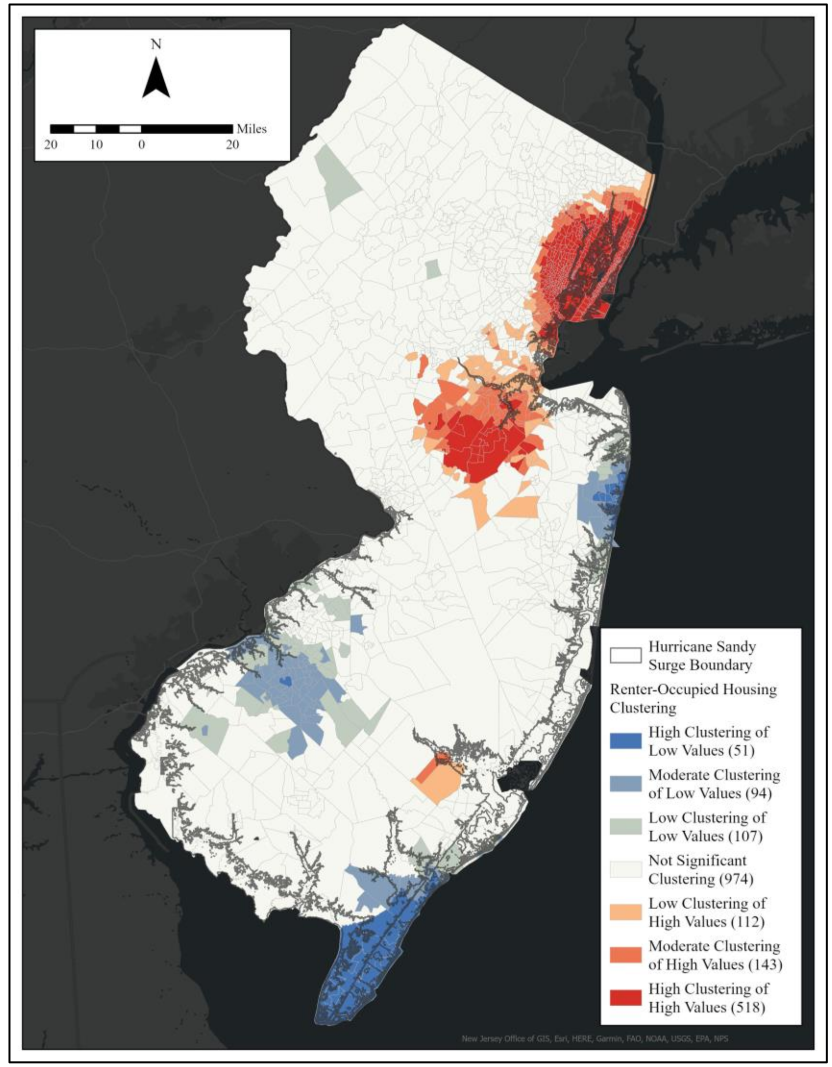

Figure 29. Hot Spot Analysis of Renter-Occupied Housing Difference from 2010 – 2018.

There was a clear difference between cluster values and regions for vacant housing unit change from 2010 to 2018 (Figure 30). High clustering of high values was displayed throughout most of the southern region and part of the northwestern area. Most of the high clustering of increased vacancies in the southern region was along the Hurricane Sandy storm boundary. High clustering of low values was exclusively in the northeastern area, with some moderate to low clustering in the central area, which all interacted with the storm surge boundary. Vacant housing unit Hot Spot Analysis was the only clustering analysis that expressed higher low-value census tracts than insignificant tracts.

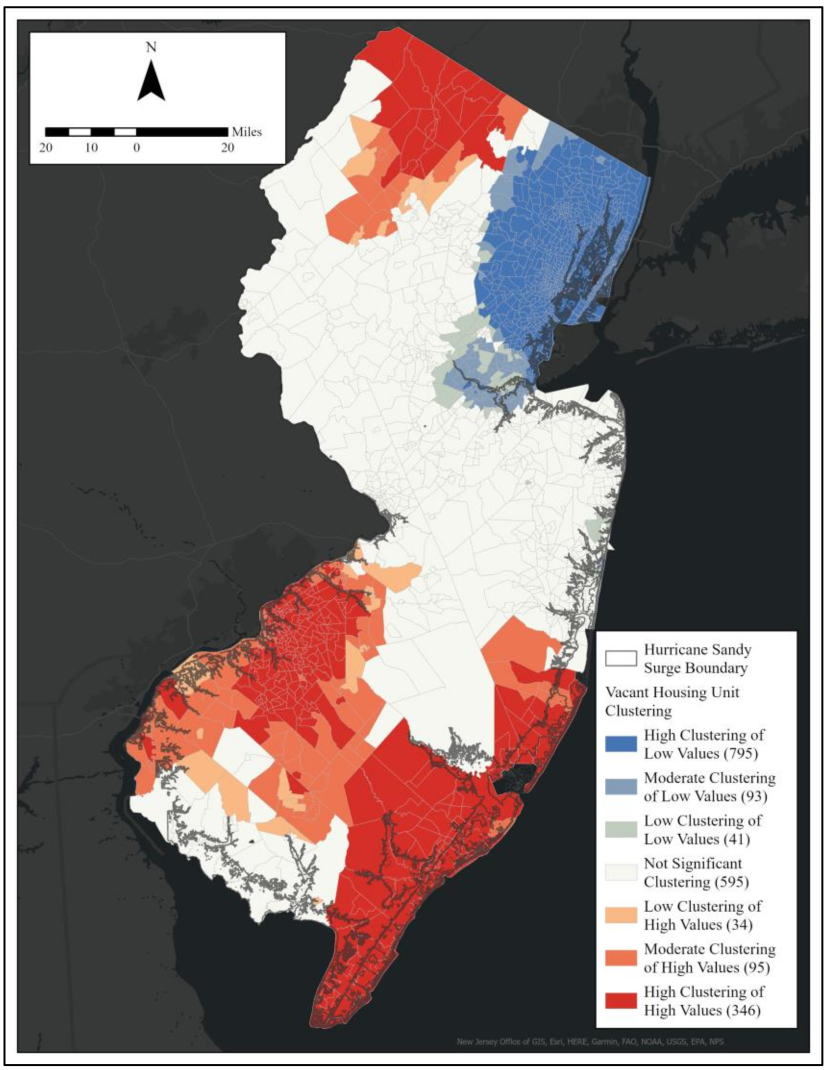

Figure 30. Hot Spot Analysis of Vacant Housing Unit Difference from 2010 – 2018.

To validate the statistical distribution and reliability of the value changes, the *Spatial Autocorrelation (Global Moran's I)* tool tested census tracts' relation to each other. All variables investigated had a clustered distribution except for persons below poverty, which had a random distribution (Table 7). The variable with the most significant clustering was vacant housing units with a z-score above 30. Variables with low z-scores and clustered distribution were owner-occupied housing units, median household income, and lower-income households. Due to their low scores, caution was used when interpolating the Hot Spot Analysis.

Table 7. Spatial Autocorrelation (Global Moran's I) of Variable Difference from 2010-2018.

Variable Difference from 2010 to 2018	**Moran's Index**	**Critical Value (z-score)**	**Distribution Type**
Population	0.024	8.897	Clustered
Population Density	0.018	6.807	Clustered
Median Household Income	0.015	5.583	Clustered
Persons Below Poverty**	-0.002	-0.402	Random
Lower-Income Households	0.015	5.615	Clustered
Middle-Income Households	0.030	10.943	Clustered
Upper-Income Households	0.032	11.622	Clustered
Owner-Occupied Housing	0.008	3.097	Clustered
Renter-Occupied Housing	0.026	9.486	Clustered
Vacant Housing Units**	0.083	30.045*	Clustered

** Result(s) with the highest value in the dataset.*
*** Variable(s) in the dataset with the largest difference in results from the analysis.*

Chapter 5 Discussion and Conclusion

This study analyzed the relationship between New Jersey communities' economic standing and level of impact after Hurricane Sandy's coastal flooding event by evaluating population, income, and housing metrics before and after the disaster. The analysis designated impact zones according to the mean flood inundation depth estimated in each census tract observed. The study aimed to understand a community's recovery in various inundation levels and whether proximity to severe flooding results in a notable change. Comprehending this association can assist in protecting the neighborhoods most likely to struggle after an extreme flood event. The impact zone classification used to organize results into approximate levels of damage—None (NIZ) (0 ft), Minor (MIZ) (0-2 ft), Serious (SrIZ) (2-4 ft), and Severe (SvIZ) (>4 ft)—by variable and year. The physical evaluation of elevation, slope, and census tract count was first introduced to examine the zones' characteristics that may influence comparative assessments. The 2010 and 2018 ACS data profile estimates were assessed for each impact zone's population, income, and housing evaluations. The following chapter discusses the significance of this study's assessment findings and limitations and suggested future research.

5.1. Limitations and Future Research

Although the evaluations successfully obtained insight into socio-economic conditions in New Jersey's census tracts and classified impact zones, there remains room for improvement in the data and analyses. Notable limitations in data quality, methodology factors, and research scale decreases the reliability of the study's results. The two data quality limitations identified were: reliably of ACS data and Hurricane Sandy storm surge data gaps. Next, the three methodology factor limitations identified were: impact zone classifications, normalization of dollar-values, and broader vulnerability focus. Finally, the only research scale limitations identified was examining a large study area rather than subregions. These limitations can produce a more accurate and desirable outcome through further research.

The core tabular data used in the study was a 2010 and 2018 ACS data profile comparison of population, income, and housing throughout the four classified impact zones. Although the variables provided adequate knowledge of the study area's conditions before and after Hurricane Sandy, further research would benefit from a deeper understanding of New Jersey's vulnerability itself. Highlighting site-specific weaknesses in socio-economic conditions help to identify valid notable changes. Some data quality drawbacks would benefit from a comprehensive analysis of the vulnerability of data collected.

In comparing household income from 2010 to 2018 ACS data, income appears to increase more than they have due to the values not using a constant dollar value. Although the data was not normalized, the results were not impacted because the compared zones would still result in the same trends. Future analysis comparing incomes from 2010 and 2018 ACS would benefit from constant dollar values.

At the census tract level, some ACS data were considered unreliable due to the estimated variables and range of error applied to each result. If there was not enough sample data collected for the surveys, the estimated findings would be less reliable. However, grouping data in classified zones help increase trustworthiness by aggregating MOE and averaging less reliable data. In this study, census tracts were grouped by impact zones where MOE was aggregated for most examined variables. Some evaluations, such as lowest and highest median household income, did not call for grouping of ordinal categories, resulting in magnified CV values. The spatial statistics assessment also compared data on an individual census tract level during hot spots analysis. Due to higher uncertainty of non-aggregated results, the hot spot analysis was considered exploratory. Although ACS provides more specialized and accessible data, it is less reliable than decennial census data. With the new 2020 decennial census reports, New Jersey's communities can evaluate population and household trends on a more reliable ten-year range.

Another primary input data used in the study was the Hurricane Sandy storm surge boundary. Due to the observed data gap in the layer, census tracts in the western region of Salem County were a limiting factor in the results. The other coastal census tracts categorized as SrIZ rather than SvIZ might have originated from the overlap of inundation boundary to the census tract. The flood depth range within a census tract could have varied greatly, especially if the census tract is large. Therefore, the mean depth would have decreased during zonal statistics if the census tract had areas with no flood depth. Limitations in the storm surge boundary could be improved by updating the DEM on which the layer was based.

For this study, the impact zone classifications followed the methodology introduced by McCarthy et al. (2006) to examine storm recovery in New Orleans post-Hurricane Katrina. Upon further evaluation, the depth intervals would have benefited from adding another impact zone due to the maximum depth reaching 19 feet. Through this more comprehensive analysis, the researcher may find more considerable recovery disparities in areas of over 10 feet. The impact zone depths may have been too limiting for estimates in a more extensive and diverse landmass, like New Jersey, rather than New Orleans.

In the hot spot analysis review, there was apparent clustering in certain regions identified as New York Metropolitan area, Central Raritan River, Philadelphia Metropolitan area, Delaware Bay region. One major limitation was the scale of the study area due to the lack of a clear connection between the impact zone and notable change. A more concentrated analysis of the trends within these clustered regions may further explain the relationship. Overall, it would be best to generate a site-specific impact zone range and clustered communities to evaluate disaster-influenced recovery disparities.

There is potential for further exploration of a natural disaster's influence on a community's economic recovery, especially in severe flooding. The likelihood of flood-related damage will continue to increase as climate change, and SLR continues to grow as a threat to coastal communities. Hurricane Sandy pressed the importance of protecting vulnerable areas resulting in government funds given to citizens to ensure fair and equal recovery. Due to rising sea levels and the risk they pose on an explaining population, FEMA flood hazard areas will need to be revised. Remapping the zones will assist in locating vulnerable areas and impact subsidy distribution such as flood insurance and floodplain buyback programs such as the NJDEP Blue Acres program. However, locating the vulnerable areas before a severe flood event supports local officials in establishing better safeguards to protect these communities preemptively.

A community can experience harm in forms other than physical destruction and economic hardship caused by a disaster. Although the concept was not explored in this study, it would be noteworthy to explore further New Jersey's recovery of Hurricane Sandy from the lens of disaster-influenced gentrification. Exploring future research in this subject would include examining housing prices and cost of living along with socio-economic evaluations. An area's shift from poor neighborhoods to wealthy, boutique lofts can often be accelerated due to a disaster. Tracking that likelihood may encourage more affordable housing developments in the areas marked at risk.

5.2. Conclusions

The study aimed to understand a community's recovery in various inundation levels and whether proximity to severe flooding results in a notable change; however, spatial relationships proved more complex than initially thought. Results did not show statistically significant differences between groups within the study area, leading to a rejection of the null hypothesis. There are broader economic factors that overwhelmed the effects of flooding from Hurricane Sandy, such as multiple sources of hurricane damage, economic dependence on nearby cities, and the impact of the Great Recession.

Concerning Hurricane Sandy, this study only examined flood inundation; nevertheless, there are more damage factors associated with hurricanes. Other aspects such as wind, heavy rain, and storm surge could have played a role in recovery disparities. However, these factors are not as impactful in the study area's region compared to the southern part of the United States. Isolating damage to only one aspect lowered the statistical analysis of spatial relationships and ignored non-coastal recovery. However, New Jersey's diversity in landscape, demographics, and economy takes most of the responsibility in the study's resulting null hypothesis.

Broader factors contributing to the conclusion can be explained as a product of the study area's proximity to cities and diverse elevation. Unlike other study areas examined, such as New Orleans, New Jersey varies greatly in economic ranges and geography. The rates of urbanization, economic growth, and socio-economic characteristics of this study area rely heavily on its distance from the metropolis of New York and Philadelphia. Impervious surfaces of the metropolitan areas provide an element of increased flooding that was not seen throughout the SvIZ in the study. Instead, the clustered urban areas showed the most change due to economic dependence on the nearby cities and lack of stormwater infiltration into the ground.

The recovery of the Great Recession influenced New Jersey's economic status in the time frame of 2010 to 2018, which collapsed the housing market and affected much of the low to the middle class. A substantial divide in income classes was created before Hurricane Sandy's damage due to the economic crisis; therefore, the results of this study may not have been as substantial during parallel recoveries. Nevertheless, the results did rely on sub-regionality rather than inundation zones due to differing socio-economic composition within clusters. Based on the hot spot analysis, trends appeared to show people moving from the state's southern region, notably the Philadelphia metropolitan area, to the New York metropolitan area. If this trend is accurate, the wealthiest residents moved to northern areas away from flood impact zones, while the less affluent moved to the more impacted north and central regions.

The evaluations within the study identified disparities in income growth among the wealthiest residents in the NIZ and SvIZ. However, Hot Spot Analysis and Spatial Autocorrelation conveyed a more complex dynamic between census tracts. Spatial relationships were most robust in the Vacant Housing Unit variable with a z-score of 30.05, where most of the vacancies increased in the south and decreased in the north of New Jersey. Subregional clustering in the state's northern, central, and southern sections suggested more dependence on regions than impact zones. Results suggest several factors at play, and the isolated variables examined in this study did not illuminate the entire narrative. Although the data exhibited variation from 2010 to 2018, the results were not significant enough to claim a correlation exclusively between economic recovery and proximity to severe flooding.

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Appendix A ACS 5-Year Estimate Attributes

Evaluation Type	Variable	Source Table (Data Profile)
Population Evaluation	Total Population Estimate	Total Population (B01003)
Income Evaluation	Estimated Household Income Less than $10,000	Income in The Past 12 Months (In 2010 and 2018 Inflation-Adjusted Dollars) (S1901)
	Estimated Household Income $10,000 to $14,999	
	Estimated Household Income $15,000 to $24,999	
	Estimated Household Income $25,000 to $34,999	
	Estimated Household Income $35,000 to $49,999	
	Estimated Household Income $50,000 to $74,999	
	Estimated Household Income $75,000 to $99,999	
	Estimated Household Income $100,000 to $149,999	
	Estimated Household Income $150,000 to $199,999	
	Estimated Household Income $200,000 or more	
	Median Household Income (Dollars)	Median Income in The Past 12 Months (In 2010 and 2018 Inflation-Adjusted Dollars) (S1903)
	Persons Below Poverty Estimate	Poverty Status in The Past 12 Months by Sex by Age (B17001)
Housing Evaluation	Owner-Occupied Housing Units	Households and Families (S1101)
	Renter-Occupied Housing Units	
	Vacant Housing Units	Vacancy Status (B25004)

Source: US Census Bureau