PROJECTING VULNERABILITY:

A COMBINED ANALYSIS OF SEA-LEVEL RISE, HURRICANE INUNDATION, AND SOCIAL VULNERABILITY IN HOUSTON-GALVESTON, TEXAS

by

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To my mom

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Abbreviations

3DEP	3D Elevation Program
ACS	American community survey
AHP	Analytic hierarchical process
ARA	Adjusted residential area
ARIMA	Autoregressive integrated moving average
CAT	Category
CEDS	Cadastral-based expert dasymetric system
ESL	Extreme sea level
ETS	Exponential smoothing
EWMA	Exponentially weighted moving average
FEMA	Federal Emergency Management Agency
GIS	Geographic information science
IDW	Inverse distance weighted
IPCC	Intergovernmental Panel on Climate Change
MEOW	Maximum envelope of high water
MHHW	Mean higher high water
MOM	Maximum of maximum
NTDE	National Tidal Datum Epoch
NOAA	National Oceanic and Atmospheric Administration
RA	Residential area
RCP	Representative concentration pathway
RU	Residential units

SLOSH	Sea, lake, and overland surges from hurricanes
SLR	Sea-level rise
TIN	Triangulated irregular network
TNRIS	Texas Natural Resources Information System
USC	University of Southern California
USGS	United States Geological Survey
WSE/I	Water surface elevations/inundations

Abstract

Communities in the Houston-Galveston area of Texas are consistently at risk of hurricane devastation. With warming climates and increasing greenhouse gases, sea-level rise (SLR) has become a significant consideration. Many studies have shown the correlation between SLR and vulnerability, however, little has been found on the implications of SLR with the influence of storm surge on the community. This study established the current population and projected future population at risk in 2050 and 2100 from SLR and storm surge inundation in Houston and Galveston County. The National Oceanic and Atmospheric Administration's (NOAA) projections of SLR of two-, three-, four-, and five-feet are combined with NOAA's Sea, Lake, and Overland Surges (SLOSH) predictions to produce water surface elevations as sea level rises. A social vulnerability index was created, and weights were determined, using an analytic hierarchical process to reveal the socioeconomic vulnerable population within each water surface elevation produced. A cadastral-based expert dasymetric system method was employed to improve upon census data alone for spatial data of the population at 2020. An exponential smoothing algorithm was then used to predict future populations utilizing census data from Brown University and the American Community Survey from 1960 through 2020. The final assessment establishes inhabitants who were at risk in 2020 and the projected population in 2050 and 2100 within rising sea-levels. The results identifies the neighborhoods within Harris and Galveston County that are vulnerable to sea-level rise and storm surge inundation currently and in the future. This provides these two counties, and other government agencies, a geospatial assessment of vulnerable demographics within their locality and future estimates to assist in planning, preparation, and emergency response.

Chapter 1 Introduction

The Texas Gulf Coast, specifically the Houston-Galveston area, has been impacted by climate change and has repeatedly suffered immense storm surge inundations and flooding. Between 2015 and 2017, this area saw three 500-year flood events: the Memorial Day Floods, the Tax Day Floods, and Hurricane Harvey (Boyer and Vardy 2010). The effects of sea-level rise (SLR) will accentuate this risk since this is a coastal, low-lying area. As climate change has accelerated over the last 20 years, the global mean sea level has risen exponentially ((National Oceanic and Atmospheric Administration (NOAA) 2021). With these rising sea levels, this low-lying area will observe persistent increases in flooding that will advance further inland. With the Intergovernmental Panel on Climate Change (IPCC) projections of SLR increasing within the next 30 to 70 years, future hurricanes and storm surge will likely devastate this coastal community. (Oppenheimer et al. 2019)

Hurricanes Harvey, Ike, and Rita brought record breaking rainfall and significant storm surge and they caused catastrophic flooding and billions of dollars in damage (NOAA National Hurricane Center (NHC) 2021). Hurricanes such as these are projected to become more common, devastating the surrounding areas and displacing millions of people (Carlson, Goldman, and Dahl 2016). Socioeconomic hardship will accompany this flooding and the population will become even more vulnerable. To identify the vulnerable people in this scenario, it is important to recognize the correlation between geophysical and social systems. (Chakraborty, Collins, and Grineski 2019). Both physical and demographic vulnerabilities are essential in projecting the population at risk. With the combination of SLR, hurricane inundation, and socioeconomic data, future storm surge inundation elevations and the vulnerable population within these areas are measured in this project.

The analysis in this project used spatial and tabular data with Geographic Information Science (GIS) tools to estimate future impacts of SLR on Houston and Galveston County. It combined estimates of future SLR and hurricane storm surge to estimate the future areas subject to high risk of flooding. The estimated current population and their socioeconomic status were established using 2020 data. This demographic data was intersected with water surface inundations to obtain the vulnerable population. Finally, the population within these projected vulnerable locations was estimated for 2050 and 2100, for an overall assessment of the future population at risk.

1.1 Motivation

The purpose of the project is to project the future populations that will be vulnerable to SLR and storm-surge inundation in the Houston-Galveston area. Every year, between June and November, hurricanes striking the gulf coast create a major issue and the associated risks are of significant concern. The Galveston Hurricane of 1900, Hurricane Rita, Hurricane Ike, and more recently, Hurricane Harvey, have devastated these communities. With warming global temperatures and SLR, hurricanes are becoming more frequent. According to the IPCC, many low-lying areas will experience rare Extreme Sea Level (ESL) events annually by 2050, like today's 100-year storm (Oppenheimer et al. 2019). By the end of the century, these storms will be commonplace. Only a few studies about SLR are available beyond 2100, but it is likely that it will continue to rise for thousands of years (Oppenheimer et al. 2019). The rate of loss of the Antarctic Ice Sheet and the Greenland Ice Sheet renders uncertainty beyond 2100 (Oppenheimer et al. 2019). As the ice sheets melt, sea levels rise, and hurricanes strengthen, storm surge will increase and place more people in danger. Storm surge occurs when water rises above its typical level, or astronomical tides, and spreads across land. As sea level rises, storm surge will intrude even further inland. To mitigate the casualties and losses from SLR, it is imperative to be proactive and to recognize what hazards exist and what actions can be taken.

Hurricane Harvey hit the Texas Coast in August of 2017 and was accompanied by record-breaking rainfall and catastrophic flooding (Blake 2018). The damage and lives lost from this were seen firsthand and the devastation left many in life-threatening conditions. Projecting storm surge inundation with rising sea levels and defining the susceptible population will help communities plan and prepare for the future and is a step towards social well-being.

1.2 Project Study Area

The study area for this assessment is the Houston-Galveston area of Texas located in Harris and Galveston Counties as shown in Figure 1. Galveston is an island on the Gulf of Mexico with a population slightly over 50,000 and is the main beach town for most of eastern Texas. It sits between the Gulf of Mexico, West Bay, and Galveston Bay. It is separated by a channel that leads to the Trinity Bay and the Houston Ship Canal, also known as Buffalo Bayou. Houston lies northwest of Galveston and is the fourth largest city in the United States with a population of approximately 2.4 million, and 4.7 million in the county (Population USA 2022). The Houston-Galveston port district is the second largest port for the import and export of oil in the country (US Energy Information Administration 2021). It also incorporates NASA's Johnson Space Center, is the second largest area for Fortune 1000 companies, and has the number one cancer treatment center in the country (Visit Houston Texas 2021). Aside from economics and infrastructure, the city has a very diverse demography with more than 145 languages spoken (Visit Houston Texas 2021). The bustling economy and coastal amenities draw a diverse population to the area.

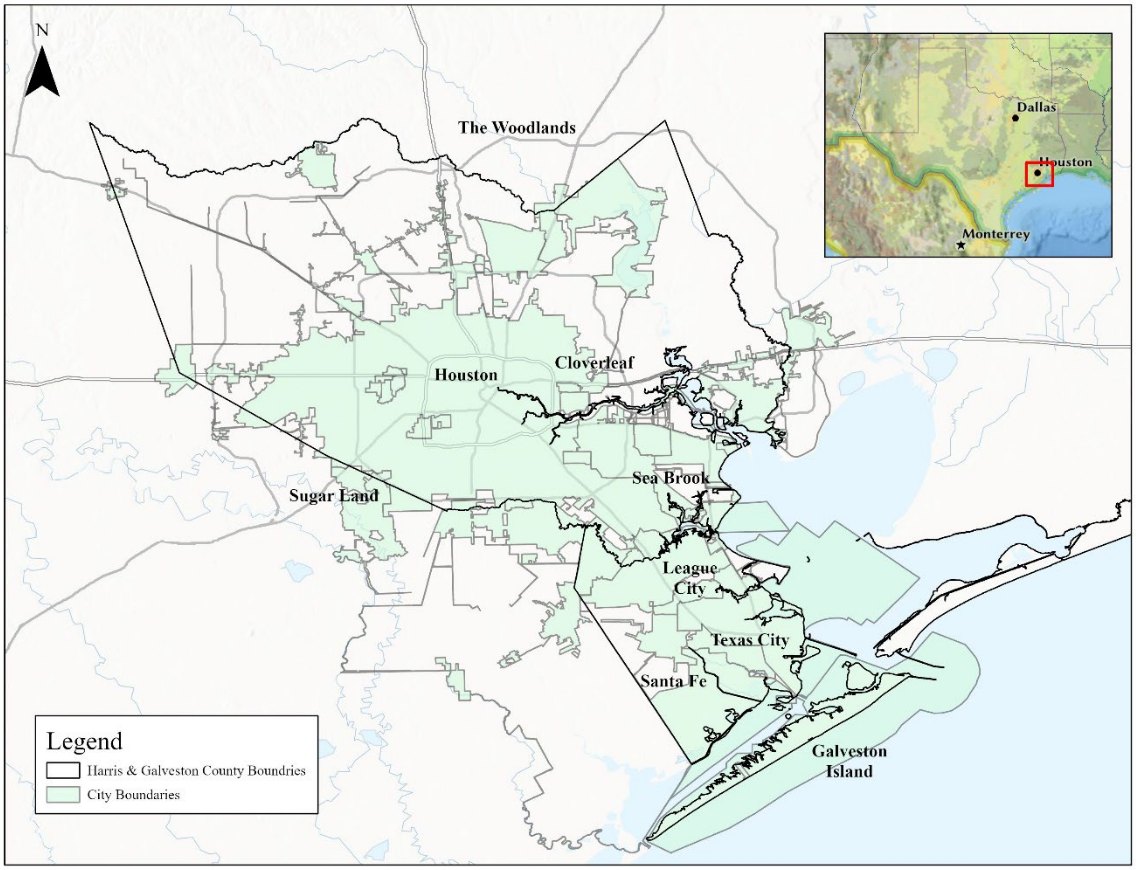

Figure 1. The City of Houston, Harris County, and Galveston County

1.2.1 Demographics

When a hurricane strikes, the damages affect the inhabitants on an extensive scale by destroying their economy, livelihoods and displacing countless families. Vulnerability, specifically social vulnerability, is founded on the concept of resiliency and the capability to deal with and recover from disasters and usually lies within impoverished communities that lack the resources to prepare and respond appropriately. Rising sea levels, larger and more frequent hurricanes, and the geophysical attributes of the locality, puts many in harm's way.

Texas has seen a steady growth in population over many centuries and has a high influx of immigrants which leads to diverse demographics. Yet, diverse demographics does not imply lack of ability to prepare and recover from disasters. Harris County's poverty rate is 8.6% and their persons with disabilities and person 65 years and older are well below the national average at 6.8% and 11.4%. The national average for persons with disabilities is 13.7% and 65 years and older is 16% (US Census 2020). Galveston County has a similar demographic with the poverty rate, persons with disabilities, and persons 65 years and older below the national average at 19.5%, 8.6%, and 15.2% (US Census 2020). With the above-mentioned demographics below the national average, these communities seem capable of coping with flooding; however, this a broad generalization of the study area. Neighborhoods in the east of Houston, like Port Houston, East Houston, Downtown, and Fifth Ward are particularly vulnerable as referenced on Disproportionately Impacted Communities – Houston Harris County Winter Storm Relief Fund. These areas are where nonprofits state they would target services and is used to increase outreach to areas in need (Houston Harris County Winter Storm Relief Fund 2023). According to data from Brown University, described in more detail in Chapter 3 herein, large minority groups and the elderly reside within comminutes in east, south, and southeast Houston.

Unlike Houston, Galveston's diversity is more scattered throughout the county and not constrained to specific neighborhoods, with a few exceptions. Low-income households are right next door to early 1900's remodeled estates. Section 8 apartments are being built within a mile or two from the beach. According to a study from the Greater Houston Community Foundation in partnership with Rice-Kinder Institute for Urban Research, Harris and Galveston County have an SVI score of 0.72 and 0.58 (0 indicating the lowest vulnerability to 1 indicating the highest vulnerability) (Understanding Houston 2023). This suggests that even though the statistics seem to support resiliency, this area has a high degree of socioeconomic vulnerability.

1.2.2 Geophysical Attributes

Houston-Galveston is a low-lying coastal area with an average elevation of forty-nine feet above sea level in Houston and seven in Galveston (US Climate Data 2021). It includes numerous water bodies and expansive coastal marshes. Galveston Bay is the largest estuarine system in Texas. It also receives runoff from the Trinity and San Jacinto Rivers (The Nature Conservatory 2013). This leaves this area extremely susceptible to flooding and storm surge. After the Galveston Hurricane of 1900, where more than 8,000 people died from storm inundation, the City of Galveston constructed a 17-foot seawall to protect inhabitants from future hurricanes (NOAA NHC 2021; Davis Jr. 1951).

Today there is a Corps of Engineers levee and two reservoirs, Addicks and Barker, to aid in flooding and storm surge protection. Still, flooding has exceeded the expected floodplain elevations numerous times. Due to heavy rainfall, Hurricane Harvey's flooding went well beyond Federal Emergency Management Agency's (FEMA) depicted flood zones and encompassed most of Harris and Galveston County as shown in Figure 2. According to Watson (2018), Hurricane Harvey, a category (CAT) 4, produced the "largest rainfall recorded in history" and hit the 500-year floodplain in some areas. The Saffir-Simpson Hurricane Wind Scale rating for hurricane categories range between categories 1-5 depending on the strength of the wind and the damage it can cause. At a CAT 4, a hurricane's sustained wind speed is between 130-156 miles per hour and will cause catastrophic damage (NOAA NWS). Hurricane Ike, a CAT 2 that struck in 2008, caused 100-year storm surge levels and Hurricane Rita, a CAT 3 at landfall that struck in 2005, caused flooding of 10 to 15 ft above normal tide (Harris County Flood Control 2021; NOAA NHC 2021). The low elevation of this area means even mild hurricanes can wreak havoc.

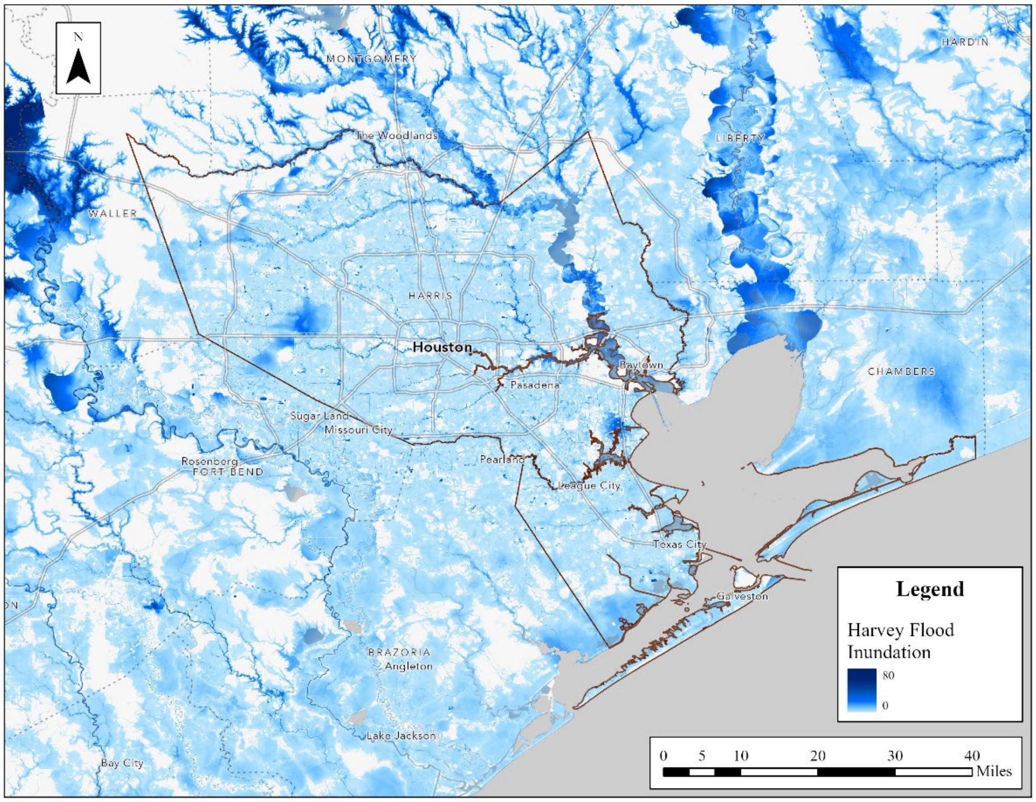

Figure 2. Harris and Galveston County, Texas flooding from Hurricane Harvey. Federal Emergency Management Administration

As a consequence of devastating floods that plague this coastal environment, land subsidence has caused the coast to shift as much as ten feet in some areas (Galloway, Jones, and Ingebritsen 1999). This region is also abundant with impervious surfaces and low infiltration rates that makes flooding evident (Blessing, Sebastian, and Brody 2017). With rising sea levels exceeding one inch per year, this area will continually be submerged. (Galloway, Jones, and Ingebritsen 1999).

1.3 Project Overview

The analysis in this project uses spatial and tabular data with GIS tools and integrates SLR, storm surge, and demographic variables to project future populations vulnerable to rising sea levels in Houston and Galveston County, Texas. NOAA's Sea, Lake, and Overland Surges from Hurricanes (SLOSH) Maximum Envelope of High Water (MEOW) Maximum of MEOW (MOM) Category 5 (CAT 5) high tide storm surge inundations model represents coastal storm surge. NOAA's SLR projected elevations of potential coastal inundation are combined with SLOSH storm surge inundations to form overall projected water surface inundations. Different SLR estimates were joined with SLOSH inundation to show impacted areas along the coast. The water surface inundations were then intersected with block groups with accuracy improved using the cadastral-based expert dasymetric system (CEDS) method. CEDS uses census blocks and tax parcels to disaggregate data to the tax parcel level and reaggregate it back to the census block. This process extracts residential lots and combines the census data to find a more accurate representation of the population and their demographics. It is used herein to estimate the total population within each SLOSH/SLR inundation for the year 2020. From that total population, the communities most vulnerable to hurricane damage were estimated using a social vulnerability index (SoVI). The SoVI factored in socioeconomic variables using data from the US Census, American Community Survey (ACS), and Brown University. An analytic hierarchical process (AHP) was applied to assess the relative importance of these variables. The weights derived from the AHP were applied using a weighted overlay to find the most vulnerable areas within the water surface elevation boundaries. An exponential smoothing algorithm (ETS) was then applied to project the population within these boundaries for the years 2050 and 2100. The collective elements examine the socioeconomic status of the total population within the inundated areas at the current sea level and in rising levels for the years 2050 and 2100.

1.4 Thesis Overview

This thesis is divided into five chapters. Chapter 1 provided a description of the motivation and background information for this project, the study area, and the attributes of the Houston-Galveston area. Chapter 2 describes the related work and relevant details of SLR and at-risk inhabitants. Additionally, it discusses previous works and the application of GIS and other tools to obtain demographic data for projecting future vulnerable populations. Chapter 3 provides the methodology of combining SLR and storm surge boundaries and estimating the socioeconomically vulnerable peoples within these inundations. It provides the data used in the analysis and the procedures for determining an accurate assessment of the current population and the future population within these water surface elevations as sea level rises. Chapter 4 illustrates the results for each of these scenarios. Chapter 5 discusses the overall results, limitations, and other considerations. The final section compares the findings of this study with other studies relevant to population vulnerability and flooding hazards within Houston and Galveston County.

Chapter 2 Literature Review

The Houston-Galveston area has struggled from the effects of hurricanes for centuries. This coastal region has been studied extensively for flood risks, inundations, hurricane storm surge, and SLR. Excessive damage from Hurricane Harvey in 2017 sparked investigations concerning the effects of hurricane storm surge and flooding on local industry, natural environment, wildlife, as well as social vulnerability and economic losses. Other studies focus on coastal vulnerability from SLR and the imminent devastation from the superstorms it will produce. However, these preceding studies have not combined SLR and storm surge inundation. SLR alone is a considerable factor; however, storm surge plays an integral role in flooding and damages to the local community. This literature review addresses topics including SLR, storm surge, social vulnerability factors, the CEDS method, population growth, and estimating the future inhabitants at risk within the water surface elevations.

2.1 Sea-Level Rise Projection

Sea-level rise (SLR) is a global phenomenon and a concern for all coastal communities. According to the United Nations, as of 2017, over 2.4 billion people, or 40% of the world's population live within 60 miles of coastal area. (United Nations 2017). In the US alone, eighty-seven million people or 29 percent, live in these areas. (US Census 2020) SLR is destroying natural barriers, such as salt marshes, which not only protect the coast from natural disasters but also sequester large amounts of atmospheric carbon dioxide (Conrad 2021). Changes in the carbon cycle, along with methane and other gasses, is what many scientists claim is the major cause of SLR. The effects, however, lead to severe storms, storm surges, flooding, and erosion. This creates havoc not only on the environment but on the inhabitants of the coastal community.

According to the IPCC global mean sea-level rise (GMSL) is caused by the expansion of ocean water and ocean mass gain. The major factors influencing this are seawater expansion from temperature rise, known as thermal expansion, melting glaciers, and changing ocean basin depths from Earth's movement. (NASA 2021; NOAA 2021; Rahmstorf 2012). To project GMSL rise, the IPCC assessment uses climate models with a variety of future scenarios for future greenhouse gas emission rates, called representative concentration pathway (RCPs). It calculates GMSL using different ranges of RCP's; RCP 2.6 - RCP 8.5, RCP 2.6 being the lower rate of greenhouse gas and the RCP 8.5 being the upper. The current projections estimate that sea-level will likely rise between 0.24 m (0.79 ft.) and 0.32 m (1.05 ft.) by 2050 and 0.43 m (1.41 ft.) and 0.84 m (2.76 ft.) by 2100 (Oppenheimer et al. 2019). Horton (2020) claims, in a survey conducted within the scientific community, the belief is that GMSL will likely rise higher than the IPCC projects to between 0.63 (2.07 ft.) and 1.32m (4.33 ft.) by 2100. This project will use the higher estimation of SLR utilizing two- and three-feet for the year 2050, and four- and five-feet for 2100 with the National Oceanic and Atmospheric Administration's SLR layers to conduct its study.

2.2 Mapping Inundation

Many analyses rely on FEMA's floodplain maps to depict flood extent and potential risk. However, according to many studies these maps are inaccurate. The 100-year floodplain is an inadequate predictor, and a great deal of flooding happens outside the FEMA zones (Blessing, Sebastian, and Brody 2017). FEMA's flood maps indicate that approximately 15 million people live within the 100-year flood zone. However, Smiley (2020) states that he believes this is inaccurate and that other studies found this number to be around 1.7-3.1 times higher. New models are being developed and indicate that twice as many properties are damaged from flood inundation and approximately 47% of claims made to FEMA were outside the zone (Smiley 2020). Other studies have incorporated the Hydrologic Modeling System (HEC-HMS) and the River Analysis System (HEC-RAS) developed by the US Army Corps of Engineers (HEC) to include factors not considered in FEMA's assessment (Blessing, Sebastian, and Brody 2017; Bass and Bedient 2018). Each model provides different approaches to account for flood and storm surge hazards; however, to apply localized data specific to the Gulf Coast, NOAA's SLOSH MOM High Tide Cat 5 for the Texas Basin was used.

SLOSH models are simulations of hurricane surges developed by the National Weather Service using a multitude of factors developed for specific areas. These models include elements, such as, tide levels, forward speed, storm categories, atmospheric pressure, and more localized data, like levees, rivers, bridges, etc. (NOAA SLOSH). Maloney and Preston (2014) used NOAA's SLOSH data to estimate storm surge and SLR vulnerability along the Atlantic and the Gulf Coasts following NOAA's guideline, Mapping Coastal Inundation Primer (NOAA 2012). NOAA's guideline examines different approaches in creating inundations using their simulated SLOSH data. NOAA's approach for modeling water surfaces was used in this study with the additional steps of incorporating SLR into the SLOSH layer. SLOSH High Tide Cat 5 was used to show the worst-case scenario for the region.

2.3 Cadastral-Based Expert Dasymetric System (CEDS)

The CEDS method disaggregates data to a smaller unit of measure to obtain a more precise understanding of population and US Census Bureau data. According to Maantay, Maroko, and Herrmann (2007) this method differs from other dasymetric mapping techniques in that it is more detailed and is particularly useful in "estimating population distribution in hyper-heterogeneous urban areas" (Maantay, Maroko, and Herrmann, 2007, 85). Their study on mapping population distribution in the urban environment shows how the CEDS method is more beneficial than other methods in estimating population because it uses detailed cadastral data. The CEDS uses tax lot data and residential units (RU) to analyze population. Including RU in the analysis ensures the full population is accounted for in each tax lot by incorporating the inhabitants and not simply the distribution within US Census Bureau blocks or tracts. The Maantay, Maroko, and Herrmann (2007) study incorporated a buffer around high air pollution areas and compared the methodological differences between Aerial Weighting, Filtered Aerial Weighting and CEDS. Figure 3 shows their results and the benefits of using the CEDS method.

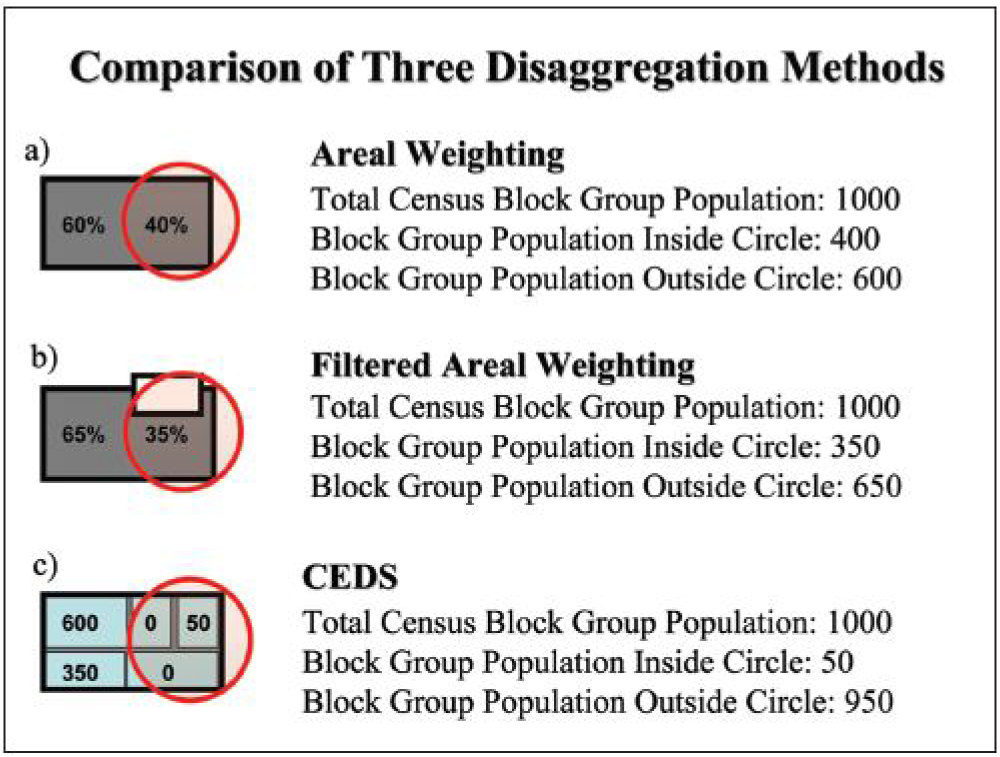

Figure 3. Comparison of disaggregation methods. Maantay, Maroko, and Herrmann

Miyake et al. (2010) uses the CEDS method in multiple studies to analyze the demographic composition of populations within specific areas. The one disadvantage of this method is that by estimating the population using residential tax lots within the same US Census

Bureau block group does not make the sub-populations independent from one another (Miyake et al. 2010). Therefore, the data needs to be reaggregated back to the level it began at. Another issue when assessing population and demographics is that not all populations are represented. Typically, the poor, homeless, undocumented immigrants, and other marginalized peoples are unaccounted for (Miyake et al. 2010).

Maantay, Maroko, and Herrmann's (2007) study compared Filtered Areal Weighting (Binary Method), adjusted residential area (ARA), RU and dasymetric mapping and found CEDS to be the most accurate and best method for population distribution. Zoning, land use, lot size, and RU were used in their study. This study uses the CEDS method starting with the US Census Bureau blocks and parcels from both Harris and Galveston County. It does not use zoning since Harris County does not have zoning regulations.

2.4 Socioeconomic and Locational Vulnerability

Coastal communities, like the Houston-Galveston area, are prone to hurricane flooding and storm surge. This suggests susceptibility based on physical location, or what Logan and Xu (2015) refer to as locational vulnerability. Vulnerability comprises many factors, and according to most scientists it is defined as conditions or exposure to hazards and the sensitivity and the resilience to it. (Turner 2003; Kasperson, Kasperson, and Turner 1995; Cutter, Mitchell, and Scott 2000; Yuan, Guo, and Zhao 2017) To accurately determine the extent of loss, both locational and socioeconomic vulnerability need to be considered.

The geophysical and socioeconomic environment are interdependent. Social vulnerability depends on the capability of the community or individuals to adapt to the environment. According to White and Hass (1975), population shifts, increased mobility, industrialization, economic factors, and housing increases and needs, are the basis of the nation's vulnerability to hazards (as cited in Cutter, Mitchell, and Scott 2000, 714). Shifts in evolution forces society to make changes that may not be desirable to accommodate ones' needs. For example, moving to a hazardous coastal community for employment and economic purposes. These socioeconomic aspects are intertwined with locational vulnerability, or geographic vulnerability, to create what Cutter, Mitchell, and Scott (2000) calls the overall place vulnerability. This project assesses the overall place vulnerability of the communities within Harris and Galveston County. It signifies which inhabitants are currently exposed and susceptible to storm surge and flooding and their socioeconomic status. The population in 2020 is represented and the estimated population in 2050 and 2100 to illustrate continued SLR and determine overall place vulnerability.

2.4.1 Modeling Social Vulnerability

Social vulnerability modeling is a difficult task as there is not one set of indicators to assess this. The Houston-Galveston area and its susceptibility and resilience to hurricanes defines the social conditions of this community. In other words, the socioeconomic influences affect the populations' ability to cope with or recover from these disasters. This can include financial hardship, disabilities, or education. Chakraborty, Collins, and Grineski (2019) assessed the environmental justice implications of Hurricane Harvey flooding and find that Black and Hispanic populations and socioeconomically deprived neighborhoods were the most vulnerable and received the most flooding, where the more affluent have the means to move away from these hazardous environments. (Chakraborty, Collins, and Grineski, 2019) However, Cutter, Mitchell, and Scott (2000) state that in South Carolina the mean housing value is highest near the coast where predominantly White populations are found. The socioeconomic determinants in each of these instances are showing different outcomes for different areas. How these factors are decided are influenced by the various attributes being measured.

In the scientific community, social vulnerability is most often determined using a SoVI. Cutter, Boruff, and Shirley (2003) adapted a SoVI to consider other vulnerabilities besides biophysical in a study on environmental hazards in the US Others have followed suit and both Burton (2010) and Flanagan et al. (2011) used a SoVI to study the impacts on the community from Hurricane Katrina in 2005 along the Mississippi's coast to help aid governments agencies and emergency management. To identify the location of socially vulnerable peoples in Harris and Galveston County a SoVI was designed to measure demographic characteristics and explore the population within water surface inundations with rising sea levels.

2.4.2 Socioeconomic Variables and Vulnerability Indices

To determine which socioeconomic variables are significant within the Houston-Galveston area, the four stages of the disaster cycle used by emergency management personnel to establish risk, are considered. These are Mitigation, Preparedness, Recovery, and Response. A community that can withstand the consequences of a disaster in all four categories are more resilient, while the inhabitants that lack these abilities are more susceptible to devastation. A SoVI helps determine the population that is more susceptible. According to Flanagan et al. (2011), a SoVI consists of four categories or domains that portray the major subcomponents of establishing risk for disaster management. They are socioeconomic status, household composition and disability, minority status and language, and housing and transportation. Socioeconomic status includes factors like income, poverty, age, education, disability, and employment. Low-income households may not have transportation or the ability to evacuate. Poverty limits resources and can create homelessness, food shortages, health issues, and the inability to seek aid (Flanagan et al. 2011). The elderly, young, and disabled are at a disadvantage and may need support during disasters, such as medical care or transportation. These disadvantages lead to the inability to prepare and recover from disasters.

The four domains listed above are the basis for constructing a SoVI and generating explanatory variables within this project as shown in Table 1. A study conducted by Chakraborty, Collins, and Grineski (2019) on the implications of Hurricane Harvey flooding on the Greater Houston Area used five explanatory variables to create an index of significant socioeconomic factors, no high school education, limited English language proficiency, income below poverty level, no vehicles, and unemployment. They found these variables to be significantly associated with their flood extent and comprised a majority of the population within these neighborhoods. Flanagan et al. (2011) used 15 explanatory variables to create a SoVI for disaster management with a case study on the impact of Hurricane Katrina. This study focused on deaths related to drownings and found that the elderly was the most impacted. Most residents were in nursing homes which correlates with the inability to evacuate without support. Table 2 references each vulnerability variable chosen and the study to which it relates. In each instance, once the explanatory variables are decided, an index was created, weights were assigned to vulnerability indicators, and a percentile rank was established.

Table 1. Explanatory variables

Groups	Variables	REFID
Socioeconomic status		
	below poverty level/low income	1, 2, 3, 5, 6
	unemployed	1, 3, 4, 5
	no high school	1, 2, 3, 4, 5
Household composition and disability		
	elderly (65 and over)	1, 2, 3, 5, 6
	younger than 5	2, 3, 5, 6
	disabled	1, 2, 5
	single parents	1, 5
	renting	3, 5, 6
	persons in group quarters	1
Minority status and language		
	Black/African American	1, 2, 3, 4, 5
	Asian	1, 2, 3, 4, 5
	Hispanic	1, 2, 3, 4, 5
	do not speak English well/at all	1, 2, 4, 5
	female	3, 5, 6
Housing and transportation		
	no vehicle	1, 3, 4, 6
	proximity to pub transportation/number of bus stops	

Table 2. Explanatory variables reference table

REFID	**Source**	**Article**
1	Flanagan, et. al.	A Social Vulnerability Index for Disaster Management
2	Bodenreider, et. al	Assessment of Social, Economic, and Geographic Vulnerability Pre- and Post-Hurricane Harvey in Houston, Texas
3	Fucile-Sanche, Davlasheridze	Adjustments of Socially Vulnerable Populations in Galveston County, Texas USA Following Hurricane Ike
4	Chakroborty, et. al.	Exploring the Environmental Justice Implications of Hurricane Harvey Flooding in Greater Houston, Texas
5	Cutter, et.al.	Social Vulnerability to Environmental Hazards Index
6	Li and Lam	A spatial dynamic model of population change in a vulnerable coastal environment

2.4.3 Social Vulnerability Indexing and Weights

The three most common approaches when creating an index are deductive, hierarchical, and inductive (Tate 2012). The deductive approach was typically applied in earlier SoVI indexes and usually contains ten or less indicators (Cutter, Mitchell, and Scott 2000; Montz and Evans 2001; Wu et al. 2002; Dwyer et al. 2004; Collins et al. 2009; Lein and Abel 2010, as cited in Tate 2012). This approach uses variables from accepted universal knowledge. The hierarchical method typically consists of ten to twenty indicators and can contain sub-indices within the index. The inductive approach consists of twenty or more indicators and is the basis for Cutter's SoVI index that has been used in numerous studies. The hierarchical method has proved to be an effective method for decision making and prioritizing by pairing indicators. This was the method used in this study.

In a multicriteria analysis, such as this one, the AHP is a technique to quantify the weights of each indicator against each other and determine the relative importance of the relationship. It correlates each indicator and the weight assignments through a comparative matrix. The resulting weights of the AHP are based on a pairwise comparison of the criteria and a principal eigenvector value of greater than one to indicate independent indicators.

Applying weights to explanatory variables helps determine the importance of each indicator. The more important the variable, the heavier the assigned weight. There is no recognized methodology on how to construct an index; however, past studies have introduced some criteria for ranking each variable (Tate, 2012; Cutter, 2000; Yuan, 2017). Using judgment to assign relative importance is subjective; however, according to Tate (2013) it is comparable to assigning equal weights to each indicator. Gathongo and Tran (2020) used the AHP method in a study to assess social vulnerability in Kenya by assigning weights to the exposure, sensitivity, and adaptive capacity of villages. They followed Saaty's (2008) weighting method (1-9) to assign weights by level of hierarchy; the hierarchical method. By obtaining a consistency ratio under 10%, Gathongo and Tran (2020) surmised their judgment of selected indicators to be satisfactory. The benefit of weighting using an AHP is that it quantifies subjective data using a statistical process to recognize the relative importance of each indicator. The output of the AHP assigns each weight a percentile rank to create an index ranking indicator set, i.e. a SoVI.

2.5 Population Growth and Exponential Smoothing Algorithm (ETS)

Population growth fluctuates and is dependent on many factors, birth rate, death rate, rate of immigration, ecological systems, environment, economy, food supply. Different formulas have been used to project future population; Percent Change, Linear Growth, Arithmetical Increase or Arithmetical Mean Method, but the most common methods area the Autoregressive Integrated Moving Average (ARIMA) and the ETS. According to Winters (1960), the exponential smoothing forecasting model or ETS has advantages over conventional models. It has better results, requires less information, and responds faster to shifts in the time series. It is also non-stationary as compared to the stationary ARIMA model.

The ETS method originated with a US Navy analyst Robert G. Brown during World War II (Bayak 2022; Gass and Harris 2000; as cited in Gardner 2006). He developed a method to incorporate trends and seasonality into the ETS equation. Holt continued work on the ETS method and developed his own version for dealing with seasonal data. Winters tested Holt's work and this method became known as the Holt-Winters forecasting system (Gardner 2006). This model forecasts time series by utilizing three attributes: "a typical value (average), a slope (trend) over time, and a cyclical repeating pattern (seasonality)," known as the Triple Exponential Smoothing Formula (SolarWinds 2019). An Exponentially Weighted Moving Average (EWMA) applies weights to values or attributes to smooth a time series. It weighs recent data more heavily than older data. The Triple Exponential Smoothing Formula applies the EWMA for each of the three attributes, average, trend, and seasonality (SolarWinds 2019).

Since the origination of ETS, it has become the prominent method in doctoral programs, business forecasting, planning and budgeting, traffic-flow forecasting and many other time series-based approaches. It has been incorporated into numerous programs and software and Microsoft Excel has a function which runs an ETS (FORESCASTS.ETS). Baykal, Colak, and Kılınc (2022) used this technique to forecast climate boundary maps from 2021-2060 as it accounts for the alpha, beta, and gamma, or triple AAA values, and minimizes the mean global error. Excel uses the target date (value to predict, date/time or numeric), value (historical values), timeline (range of numeric values), seasonality (length of the season), data completion (accounts for missing data values), and aggregation (aggregates multiple points with the same time stamp) to calculate the forecast (Microsoft 2021). Utilizing the ETS in this study accounts for the projected population distribution within each SLR rise elevation for the year 2050 and 2100.

Chapter 3 Methods

The goal of this project is to identify localities of people vulnerable to hurricane storm surge and SLR in Harris and Galveston County. Water surface elevations were identified for five SLR scenarios. The current at-risk population was ascertained for 2020 and the future population within these inundations were determined. The methodologies for each process are described in this chapter beginning with an overview of the project and the data used. The project analysis section describes the four analyses applied to obtain the final results; the generation of the water surface elevations, the CEDS method, the creation of the SoVI, the future population growth determined by an ETS.

3.1 Methods Overview

This analysis began with the creation of water surfaces from hurricane storm surge and SLR in Harris and Galveston County. It uses NOAA's SLOSH MOM Cat 5 High Tide storm surge inundations as a baseline, subsequently referred to as SLOSH. Current sea level is represented as SLR zero feet, while two- and three-feet SLR layers are used for 2050 and four- and five-feet for 2100. Each SLR layer is combined with SLOSH storm surge showing the respective scenarios of inundations. Current SLR at zero feet is combined with SLOSH inundations and are compared to two- and three-feet SLR layers for 2050 and four- and five-feet for 2100.

A CEDS method was employed for a more accurate estimate of total population in 2020 by disaggregating the data to the tax lot level and reaggregating it back to the census block group. This intersection of this data with the WSE represents the current inhabitants affected. To further ascertain the populaces at risk, a SoVI was created. This established the demographic indicators and the AHP method was then employed to determine percentile ranks for each. Sixteen variables are explored, and their importance weighted, and a weighted overlay illustrates the most vulnerable areas within each inundation level. This data describes the populace, and their social standing, which resides within the potential risk area.

Brown University data, containing ACS data from the years 1960 through 2010, and US Census data for 2020 was used to project future populations utilizing an ETS. The ETS leverages past population data to project the future population. The final assessment represents the current vulnerable populace in 2020 and the projected vulnerable population in 2050 and 2100 within the estimated sea level rise elevations.

3.2 Data

The data for this project consisted of tabular and spatial data in both vector and raster format. The data names, types, scale, coordinate system and source are listed in Table 1. The spatial data comprised of sea level and elevation data, census block boundaries, tax and land use parcels, and bus stop locations that were included in the SoVI. The tabular data used was US Census, ACS, and Brown University Data census data.

Table 3. Spatial and Tabular Data

Data	Type	Scale	Original Coordinate System	Source	Date
SLOSH MOM High Tide Cat 5	Raster	Atlantic & Gulf Coast	NAD 1983	NOAA	2012
SLR	Raster	Multiple	NAD 1983	NOAA	2016
DEM	Raster	Northeast Texas	NAD 1983	USGS	2018
Census	Tabular	Block Group & Tract	-	US Census Bureau	2020
ACS	Tabular	Block Group & Tract	-	ACS	2020
Brown University (1950-2010)	Tabular	Tract level	-	NHGIS	1950-2010
Tiger/line shapefiles	Vector	Block Group & Tract	NAD 1983	US Census Bureau	2020
Brown University Tracts (1950-2010)	Vector	Tract level	NAD 1983	NHGIS	1950-2010
Harris and Galveston County Boundaries	Vector	County	WGS 1984	Harris Central Appraisal District	2020
Harris County tax lots	Vector	Parcel	NAD 1983 StatePlane Texas S Central FIPS 4204 (US Feet)	TNRIS	2020
Galveston County tax lots	Vector	Parcel	NAD 1983 StatePlane Texas S Central FIPS 4204 (US Feet)	Galveston Central Appraisal District	2020

3.2.1 SLR and SLOSH

SLR inundations from NOAA are in one-foot increments from 1-10 feet of rise inundation extent. NOAA's SLR depth grid raster shows inundation extents at the current mean higher high water (MHHW) level, or the mean of the higher tidal water heights over the National Tidal Datum Epoch (NTDE) in a tidal day (NOAA Tides and Currents). NOAA creates the tidal model, using their VDATUM transformation software, to represent the MHHW in orthometric values or North American Vertical Datum of 1988 (NOAA Tides and Currents). This data illustrates the potential flooding within certain coastal areas. The SLR layers for Brazoria, Chambers, Galveston, Harris, and Liberty Counties were downloaded from NOAA's Office for Coastal Management Sea Level Rise Data 1-10 ft Sea Level Rise Inundation Extent, located on their InPort website hosted by NOAA Fisheries. (NOAA Office for Coastal Management). The SLR elevations of zero, two-, three-, four- and five-feet were chosen to reflect the IPCC and other estimates within the scientific community's assessment of projected SLR in 2050 and 2100.

NOAA's SLOSH MOM data represents hypothetical storm surge extents using a computerized model to analyze elements like atmospheric pressure, forward speed, and historical track data (NOAA SLOSH). The SLOSH layer depicts the worst-case scenario from high water values to show flooding at certain locations. The available basins coverage from NOAA is shown in Figure 45. The SLOSH MOM Category 5 High Tide is used in this study to depict worst-case scenario inundation levels.

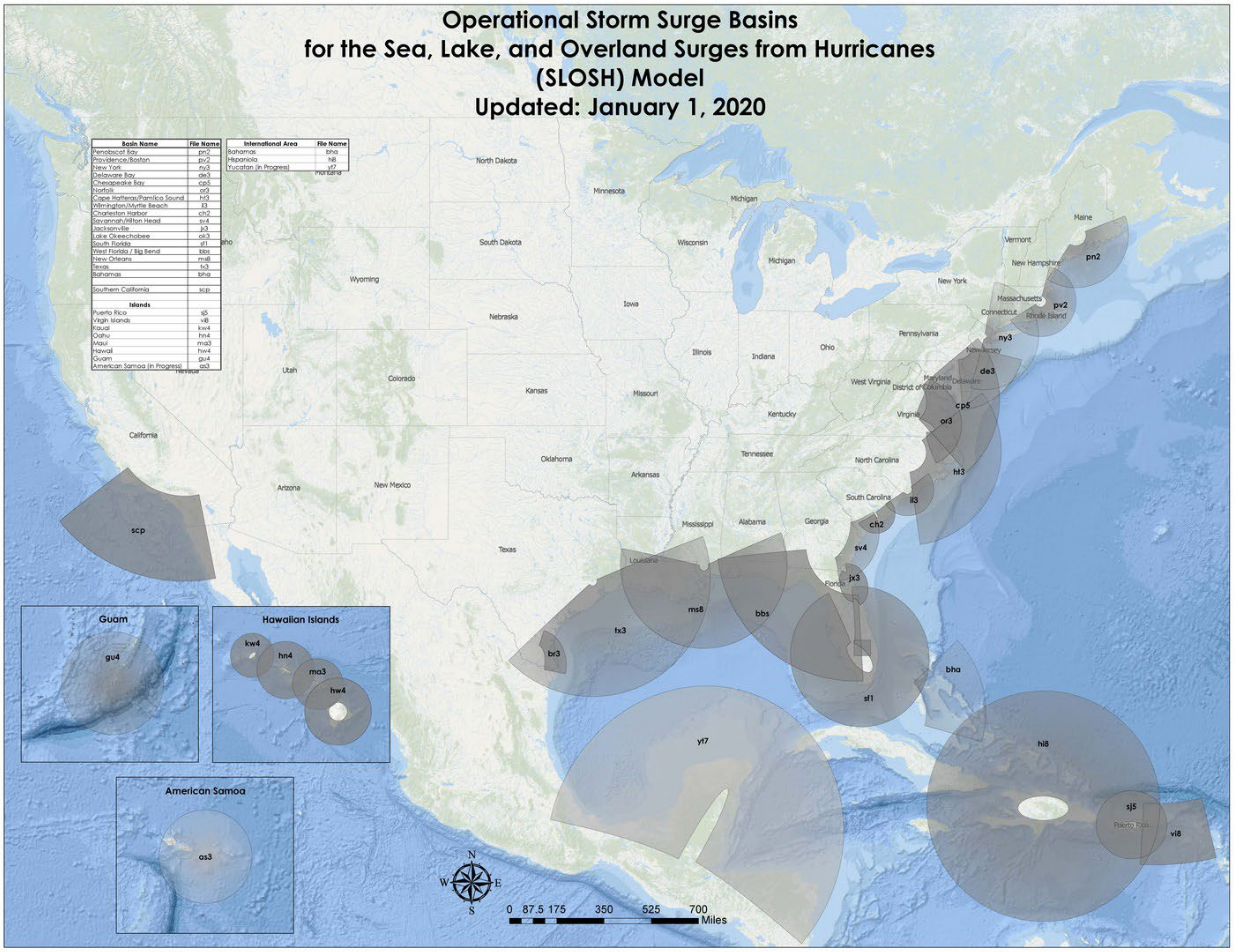

Figure 4. NOAA's operational storm surge basins. Source: NHC

3.2.2 Digital Elevation Model

A United States Geological Survey (USGS) 1/3 arcsec (10m) DEM was downloaded from the USGS National Map website. The DEM is a product of the 3D Elevation Program (3DEP) managed by the USGS providing high-quality lidar elevation products nationwide. The 10m DEM has the most coverage and is the highest resolution seamless DEM provided by the 3DEP service (USGS 3DEP). This DEM was used in the inundation analysis process to subtract land values from the SLR and SLOSH combined layers to produce a final water surface elevation.

3.2.3 Tax Parcel Data

Tax parcel data was obtained for the CEDS method, and the residential lots extracted to represent the population. The parcel data for Harris County was obtained through Harris Central Appraisal District and supplemented with Texas Natural Resources Information System (TNRIS) data. The TNRIS data contained the land use codes and was needed to determine residential lots. Harris county classifies residential lots into six categories as shown in Table 2. All the residential categories were used in this study to fully represent the population within the county regardless of single or multifamily units for a total of 721,253.

Table 4. Harris County residential classification codes

A1	Single-Family
A2	Mobile Homes
B1	Multi-Family
B2	Two-Family
B3	Three-Family
B4	Four- or More-Family

Galveston County data was obtained through the Galveston Central Appraisal District. Their land use categories for residential classifications only consist of one, RL for residential lot. Galveston County had a total of 121,531 residential lots.

3.2.4 Census and Brown University Data

Census data was from the US Census Bureau, the ACS, and Brown University (credited to the National Historical GIS). The census data provided demographic data in 2020 for use in the CEDS method. To follow the CEDS method the data is disaggregated from the block group level to the tax lot or parcel level and was therefore downloaded as block groups.

The ACS, established by the US Census, provided data in five-year estimates and was used for supplemental data when needed. These data were also obtained at the block group level. The Tiger/Line shapefiles, also a subset of the US Census, was downloaded and joined to that tabular data to provide a geographical reference to the demographic data.

The Brown University demographic data was obtained from a MapUSA project on diversity and disparity (IPUMS USA). This dataset is credited to the US Census Bureau. The project, called A Human Mapping Project (1940-2010) entailed demographic data, to include Harris and Galveston County, from 1940-2010. The census data for these years are maintained by the National Archives and Records Administration but have limited accessibility and demographic data (Census History). The Human Mapping Project contained the demographic data needed for this project along with the geospatial data for the coinciding year. Information about this project can be found through Brown University and MapUSA. Figure 5. shows a section of Harris County, Texas depicting the percent in poverty in 1960 created from the Brown University data.

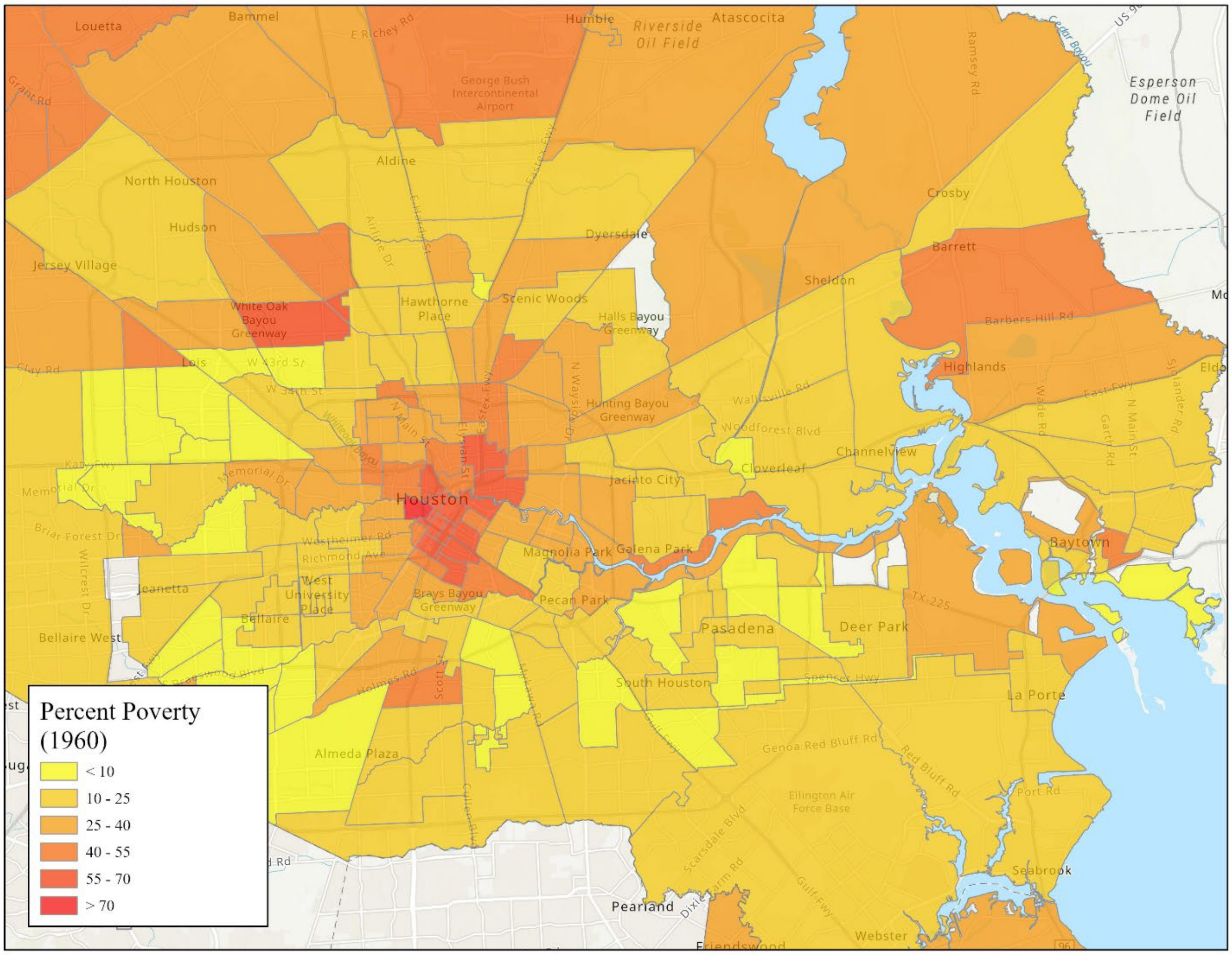

Figure 5. Percent poverty in Harris County, Texas in 1960. Sources: Brown University and MapUSA

3.3 Project Analysis

This section describes the tabular and GIS data integrated to create the water surface elevations from SLR and SLOSH data. It then discusses the CEDS method employed to obtain a more accurate assessment of the current population. Additionally, the SoVI, AHP, and weighted overlay analysis portrayed the at-risk population and finally, the ETS and population growth is explored.

3.3.1 Projecting Water Surface Elevations

This analysis combines NOAA's zero-feet SLR for current conditions, two- and three-feet for the year 2050, and four- and five-feet for 2100, with SLOSH data to conduct its study. The flow chart in Figure 5 shows the methodology used to create water surface inundations for each sea level rise instance. The SLR layers are prepared using ArcGIS's *SetNull* tool[1] to remove invalid or no data values. The same tool is also run on the USGS DEM to remove null values. Both rasters are reprojected into NAD1983 State Plane Texas South Central FIPS 4204 Feet to match the Harris and Galveston County data. The *Times* tool is then used to convert elevations from meters to feet by multiplying by 3.28083333.

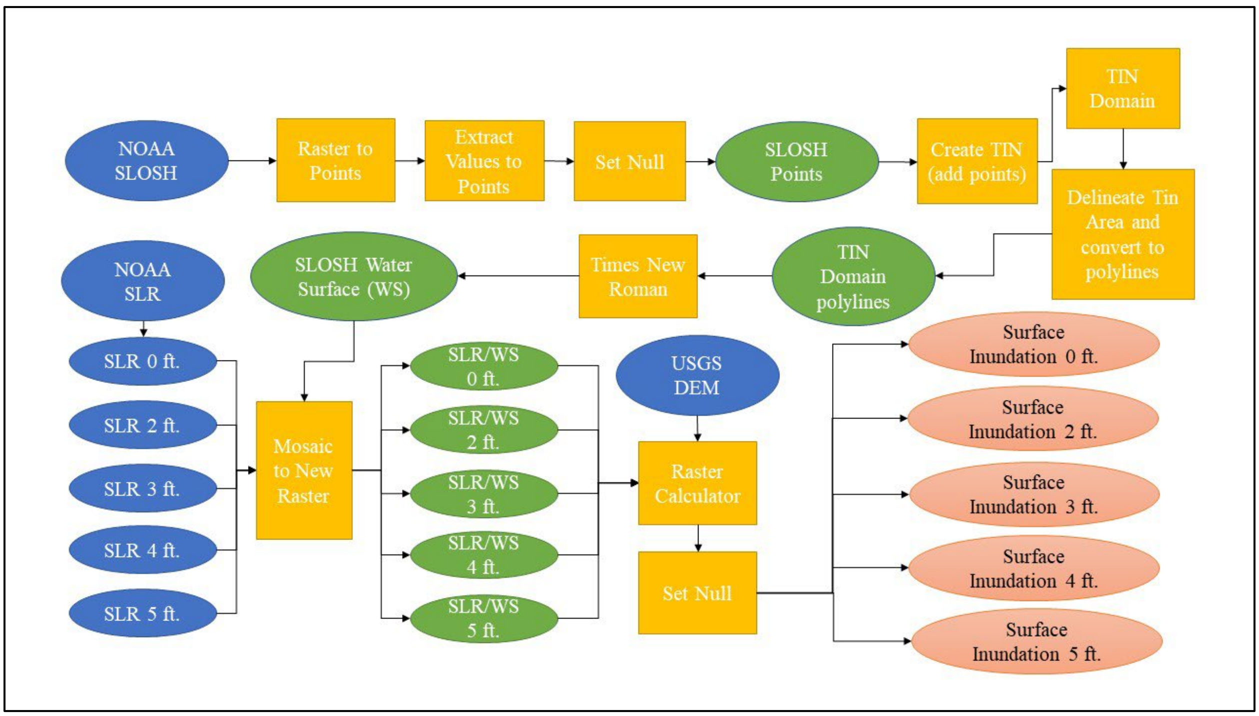

Figure 6. Workflow for projecting SLR and SLOSH inundation boundaries

[1] All tools refered to hereafter are ArcGIS tools.

The SLOSH data preparation consisted of converting the hightide SLOSH MOM grids to points. Elevations were obtained from the original SLOSH MOM grid. The point layer was then reprojected into NAD1983 State Plane Texas South Central FIPS 4204 Feet and a new field is added to multiply the values by 3.28083333, from meters to feet. To create a smooth raster surface by interpolating the extracted points, a second order inverse-distance weighted (IDW) was applied. Given the density of the points and known z values, this method is the most appropriate to interpolate this data. Prior to running the IDW a triangulated irregular network (TIN) dataset was created by importing the points. A TIN domain was then generated to create a polygon that represents the interpolation area. The *DelineateTinArea* tool was used to create a polygon around the perimeter of the TIN or interpolated point area. This allows the IDW to interpolate the area appropriately and not connect unrelated points. The polygon was then converted to polylines. Before running the *IDW* tool, random points were selected and removed from the point layer to use as checkpoints to evaluate the final IDW layer elevations. A second order IDW was run with the TIN domain polyline as the input barrier. The output created a smooth water surface elevation from the original SLOSH grid that indicates hurricane storm surge from a CAT 5 at high tide. This is then merged with each SLR elevation and demonstrates how storm surge is intensified with the inclusion of SLR.

The SLOSH and SLR data were combined with the *Mosaic to New Raster* tool, using a mosaic operator of sum and a processing extent of *Union of Inputs*. This created one raster with the sum of elevations and extent of both the SLOSH and SLR layers. The *Raster Calculator* was used to subtract the DEM from the new combined raster resulting in a surface inundation (NOAA 2012). The *SetNull* tool was applied to remove values that did not represent water inundations and the final output is an interpolated water surface. This process is repeated for each SLR increase producing a total of five interpolated water surfaces. Figure 6 demonstrates SLR at an elevation of two feet, Figure 7 is the SLOSH MOM layer Cat 5 High Tide, and Figure 8 represents the interpolated water surface, water surface elevation, of the combined SLR at two feet and SLOSH layer.

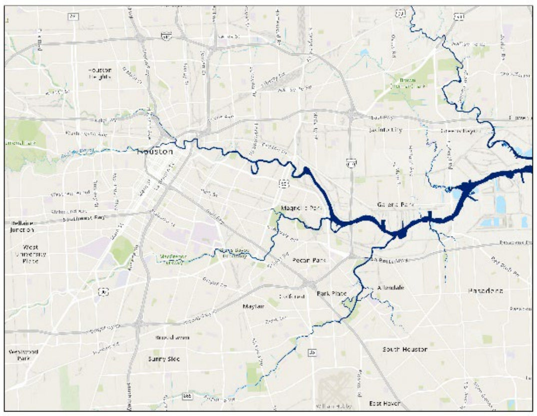

Figure 7. NOAA's SLR 2 feet

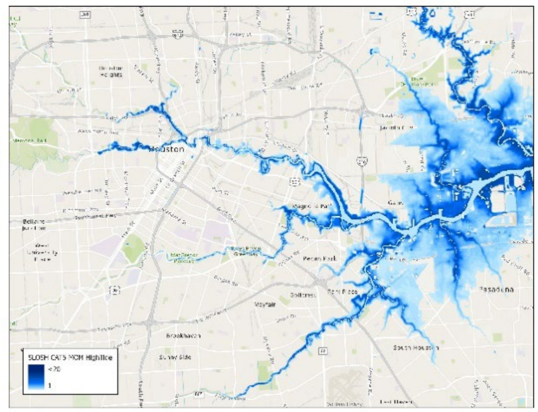

Figure 8. SLOSH MOM Cat 5 High Tide

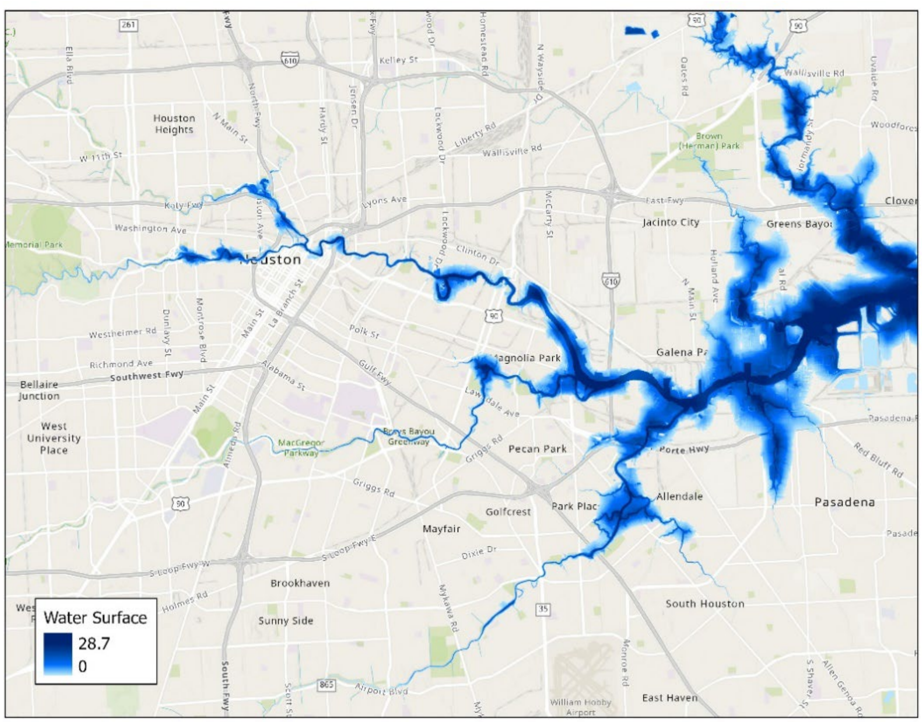

Figure 9. Interpolated Water Surface Inundation - SLOSH and SLR two-feet

The process of creating an interpolated surface using IDW, combining the SLOSH and SLR data, subtracting the DEM, and setting null to non-water surface values was done using ArcGIS Pro Python 3 (Arcpy) as shown in Appendix A.

3.3.2 Mapping the Cadastral-based Expert Dasymetric System (CEDS)

The CEDS methods uses 2020 census data and disaggregates the data to the tax lot level for a more accurate assessment of population and its attributes. Data preparation for census data consisted of joining the geospatial block groups with the tabular data using the "GEOID" Codes. The Harris County parcel data is joined with the TNRIS parcel data to add the land use codes to determine residential lots. The land use code field for Harris County is the "state_land" and Galveston is the "landuse." The population census data is then spatially joined with the parcel data using the *Intersect* tool and clipped to the county boundary. This combined data creates a new layer for each county, one for Harris and one for Galveston. Residential lots are extracted from each county to account for only residential land use. These new layers are intersected again with the interpolated water surface inundations for each rate of emissions, creating ten new layers, five for each county. Figure 10 is a diagram of the process taken to prepare and combine census and parcel data and then the intersection of the results with the water surface inundations.

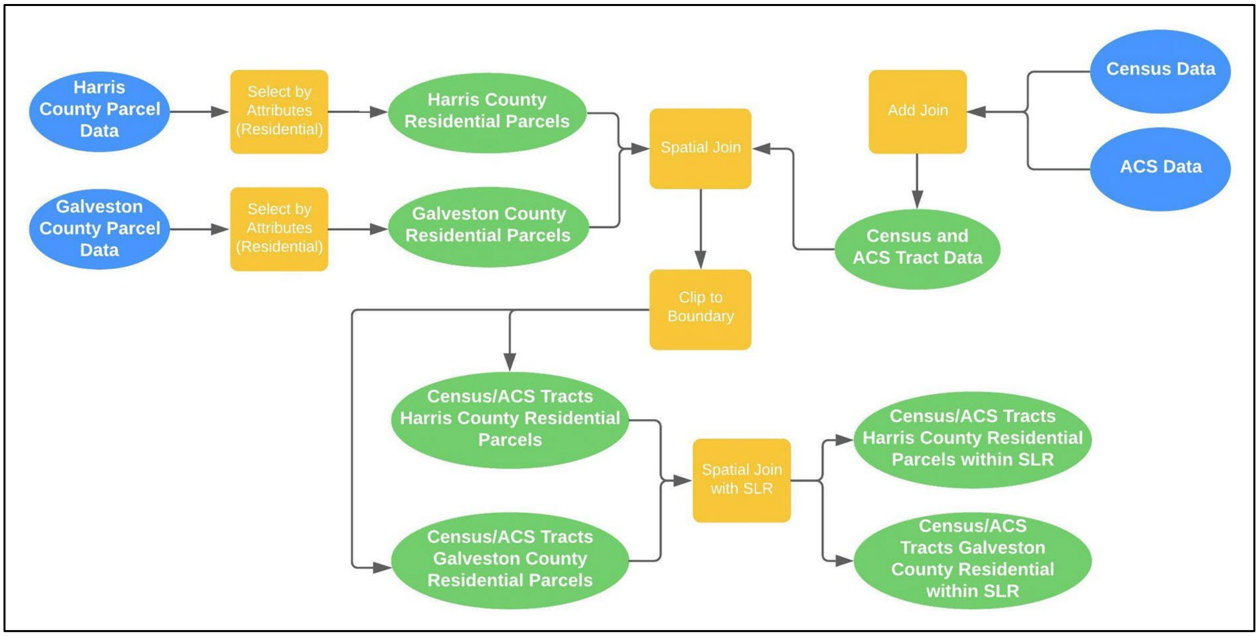

Figure 10. Census and parcel data preparation intersected with WSE flow chart

Once the residential parcels are intersected with the water surface inundations, statistics are calculated for the RU and residential area (RA), using summary statistics, and a sum value is returned for the RU and RA fields. If the parcel RA value is null or zero but census data is showing RU, then an ARA is necessary to account for missing data. The equation for calculating the ARA is:

$$ARA = M * (BA * RU / TU) + RA$$

$$\text{IF } RA = 0 \text{ and } RU <> 0, \text{ THEN } M = 1, \text{ ELSE } M = 0$$

where BA is the building area, TU is the total number of units, and M is binary value designation ancillary data for ARA. (Maantay, Maroko, and Herrmann 2007). If the calculated difference between each estimated population is less than or equal to the ARA, then the RU population is used. Otherwise, the ARA value is used as the “superior proxy unit” (Maantay, Maroko, and

Herrmann 2007, 88). Once it is established if the RU or ARA will be used the derived population needs to be calculated. This project uses the RU to determine population as there were no missing or null values within the residential data.

To find the RUs, the *Dissolve* tool is used. This tool obtains the U_I and Uc values for each of the ten new layers, five in Harris County and Five in Galveston County, to find the sum of the housing units (HU) impacted by surface inundations. What this data finds are the sum of the tax lot HU's within the water surface ($U_{I)}$ and the total HU's in each block group (Uc). The parameters used in the dissolve tool are the census blocks for the dissolve field and the housing units of the tax lots for the statistics field. The total population from the census data was also added as a statistic field since it is needed later in the equation (POPc).

To determine the percentage of impacted HU's in each block group U_I /Uc, a field was added to each of the layers for Harris and Galveston County at each inundation level called "Percent_HU." The *Calculate Field* tool was used, using Python 3 as the expression type, and the sum of HU's in each water surface inundation was divided by the sum of total HU's in each county census block group. The next step is to solve for the POP_d or the total population in each block group. A new field is created, "POP_Derived," and the *Field Calculator* tool was used to multiply the percent of HU's, "Percent_HU", by the total population in each block group. This generates the total dasymetric derived population or the POP_I in each block group. The formula for calculating this is:

$$POP_I – POP_C * U_I / U_C$$

where U_I is the number of proxy units at the tax lot level (RU or ARA), U_C is the number of proxy units at the block level (RU or ARA), and POP_I is the census population. (Maantay, Maroko, and Herrmann 2007)

The CEDS method disaggregated the data at the tax lot level and then re-aggregated it back to the block group level. These steps are done with five iterations for each county, one modeling current sea-level and one for each of the four projected water surface inundation extents for each county. The final product of the CEDS method are ten layers with a derived impacted population within water surface inundation extents based on census and parcel level data.

3.3.3 Modeling Vulnerability

A SoVI was created to define social vulnerabilities within each water surface elevation for Harris and Galveston, County Texas. The deciding indicators selected are shown in Table 2 for a total of sixteen. They encompass each of the four categories of vulnerability that are significantly associated with the population most susceptible to storm surge and flooding. The appropriate census data was joined with each block group and was then intersected with water surface elevations of zero-, two-, three-, four, and five-feet.

Table 5. Vulnerability factors and indicator selection

Vulnerability Domains	Vulnerability Factors	Description
Socioeconomic status	Below poverty level/low income	The past 12 months below poverty
	Unemployed	Total Unemployed
	No high school education	Total education up to 12th grade with no diploma
Household composition and disability	Elderly	65 and over
	Young	5 and under
	Disabled	Disabled Veterans and non-Veterans
	Single parents	No spouse present with children under 18
Social identity and language	Do not speak English well	Combined do not speak English well/not at all
	Female	Total Female
	Black/African American	Total Black/African American
	Asian	Total Asian
	Hispanic	Total Hispanic
Housing and transportation	Persons in group quarters	Total in group quarters
	Renting	Total renters
	No vehicle	Total no vehicle
	Proximity to Public Transportation	Bus Stops

Based on Saaty's (2008) weighting method, each vulnerability indicator was reclassified to create a scale factor between 1-5 using census data for each specific vulnerability factor. This was done using the field calculator and each scale factor reclassification is shown in Appendix B. A scale factor of 5 signifies it is more favorable and of higher importance. To create a scale factor for the proximity to public transportation, or bus stops, a buffer was created around each block group of a quarter mile. The bus stops were scaled 1-5 as well; however, a higher weight was given to areas with minimal or no bus stops. Each vulnerability indicator table was intersected with each water surface elevation generating five new layers. Next, these five layers were converted to raster layers using the *Polygon to Raster* tool with the scale factor as the value. This creates new raster layers for each of the water surfaces and each of the sixteen vulnerabilities with values ranging from 1-5 for a total of 80 layers.

An AHP was run to calculate the percentage or weights of each indicator. The AHP uses a pairwise comparison of the sixteen variables to compare to each other and ranks them on a scale of 1-9 as shown in Figure 9. A rank of 1 means the two variables are equal and 2 through 9 indicates how much weight the two variables should hold. The output of the AHP assigns each weight a percentile rank to create an index ranking indicator set. The final index score was then used in a weighted overlay.

5	below poverty level/low income	Disabled	1	2 3 4 5 6 7 8 9
6	below poverty level/low income	single parents	1	2 3 4 5 6 7 8 9
7	below poverty level/low income	renting	1	2 3 4 5 6 7 8 9
8	below poverty level/low income	persons in group quarters	1	2 3 4 5 6 7 8 9

Figure 11. AHP indicator ranking scale example

The weighted overlay tool was used to overlay the raster layers by measuring the weights of each according to their importance. The sixteen rasters created in the previous step for the water surfaces were added as the input rasters. The output percentile rank derived from the AHP was used for the percent of influence of each indicator. The field value range of the indicators were 1-5 based on the original scale factor. This process was repeated for each water surface elevation. The final product results in five weighted overlay rasters indicating the areas containing the most susceptible population.

3.3.4 Population Growth and Exponential Smoothing Algorithm (ETS)

The ETS algorithm is computed using Microsoft Excel with the CEDS data for 2020 and the Brown University data from 1960 through 2010 to calculate the future population. In the previous step, the CEDS data was intersected with the water surface elevations to show the population within inundations. To prepare the Brown University data, each year was also intersected with the water surface elevations to account for the same geographic population as the CEDS method. The ETS is then performed with this historical data to project the future population for 2050 and 2100.

The ETS computes a forecast using three required variables, Target Date, Values, and Timeline, and three optional variables, Seasonality, Data Completion and Aggregation. The target date is the value to be projected. For the purpose of this study, two ETS forecasts are run to project the population using target dates of 2050 and 2100. The Values are the numeric data that is being forecasted or the historical population from each year from 1960-2020. The Timeline is the step between each data set. For this project the timeline is ten years because the census data is decennial. The ETS forecast optional parameters are for Seasonality, Data Completion and Aggregation. The Seasonality is a number that informs the algorithm whether it should use seasonality, anything above a value of one, or if it is linear, a value of 0. The pattern of seasonality should follow the Timeline; however, by using a value of one the formula will auto detect the Seasonality variable (Microsoft 2021). A value of one is used to allow auto detection as the data is straightforward and has an interval of exactly ten years. The Data Completion value is used when Values are missing, in this case it is referring to the data from 1960-2020. A value of one interpolates that data and fills in the missing values and a value of zero replaces the value with zero. Since there are no missing values in this dataset, this option is not used. The last variable is Aggregation. This variable is numeric and is used if there is duplicate data for the same Timeline. As an example, if the census data for 2020 and the CEDS method data for 2020 are both used then Aggregation needs to be established. The options for this variable are AVERAGE, SUM, COUNT, COUNTA, MIN, MAX, and MEDIAN. The default value uses AVERAGE. For this study the CEDS data is used, as this is the more accurate representation of the population, and the default value of one or AVERAGE. The final output shows the projected values, or population, for the years 2050 and 2100. These values depict an estimate of who will be impacted by water surface inundations for projected SLR in 2050 and 2100 compared to the current population established for 2020.

Chapter 4 Results

This study accomplished its goal of identifying the vulnerable population within SLOSH inundations for a SLR of zero-, two-, three-, four, and five-feet to show current conditions and SLR elevations for 2050 and 2100. The results consist of four subsections; water surface elevations, CEDS method, vulnerability index, and projected future population. Each section considers both Harris and Galveston County results.

4.1 Water Surface Elevations

The purpose of determining storm surge at different SLR elevations is to discover who is within those inundations, their socioeconomic status, and vulnerable population. One important vulnerability is being within storm surge inundation boundaries, and this is the first step in understanding the communities in Harris and Galveston County. This was accomplished by combining SLOSH with differing SLR elevations to create a water surface elevation. The final water surfaces created from the merged SLR elevations and SLOSH show where MOM storm surge with a CAT 5 hurricane at high tide will extend. The different water surfaces indicate storm surge at current sea-level elevation, SLR zero feet, and what is likely to occur in the years 2050, SLR two- and three-feet., and 2100, SLR four- and five-feet. Figure 13 portrays a water surface at SLR of zero feet with residential lots for Harris and Galveston County to illustrate how storm surge affects the current population. The water surface almost entirely encompasses Galveston Island and a part of Galveston County. If a CAT 5 storm at high tide were to strike this area Galveston Island would be almost completely inundated. Harris County fared better with most of the residential areas to the north and northwest. However, the areas near Galveston

Bay and the Houston Ship Channel are already within the water surface inundations at current conditions.

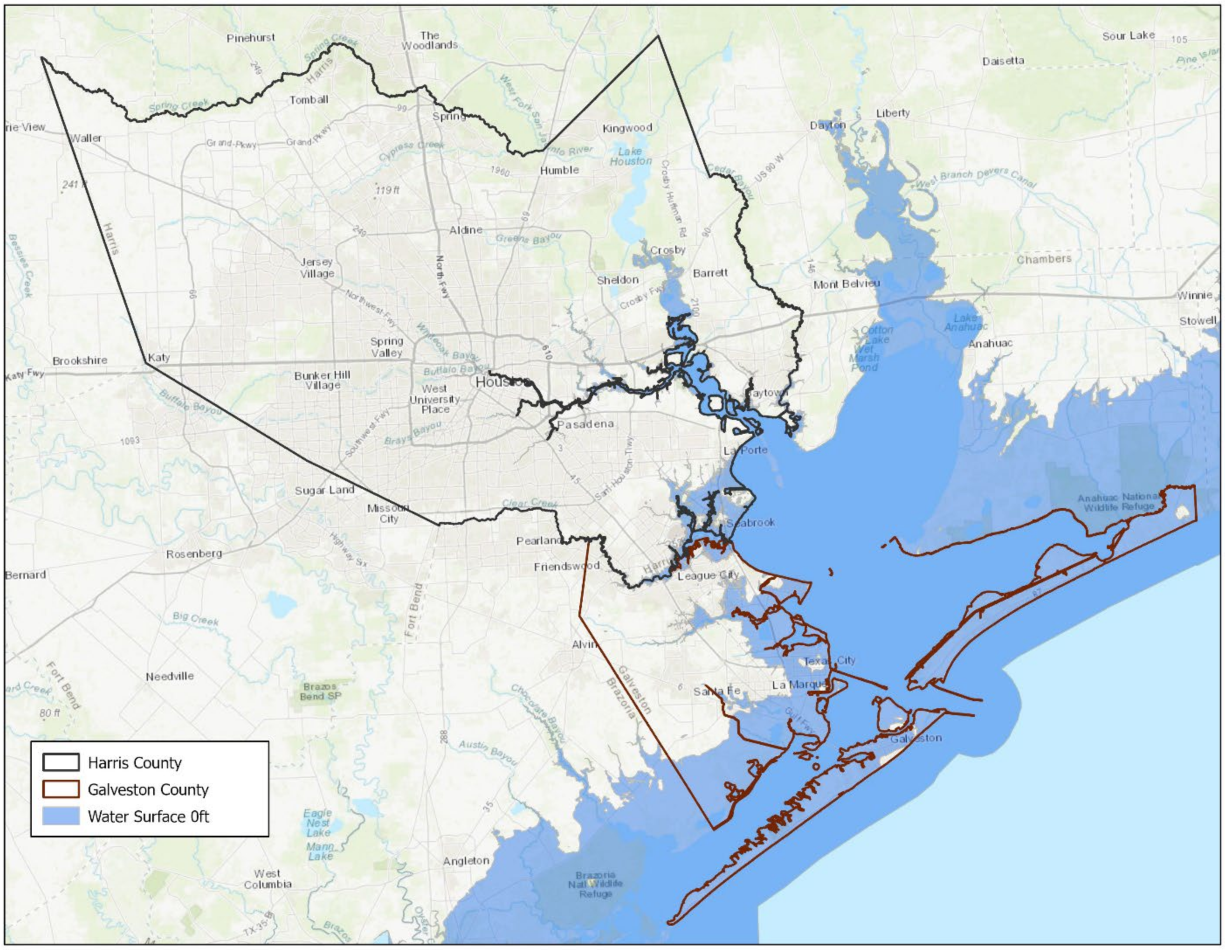

Figure 12. Water Surface Inundations at SLR zero feet for 2020, Harris and Galveston Counties

As sea-level continues to rise, a greater population will fall within water surface inundations. The following figures illustrate the progression of inundation as sea level rises and the additional residential parcels affected. Each county is shown separately. Since Harris County is very large and inundations are only near Galveston Bay and the Houston Ship Channel, Figure 1516 only shows the section of the county that is within inundations. Figure 1617 depicts Galveston County from current conditions to SLR of five feet.

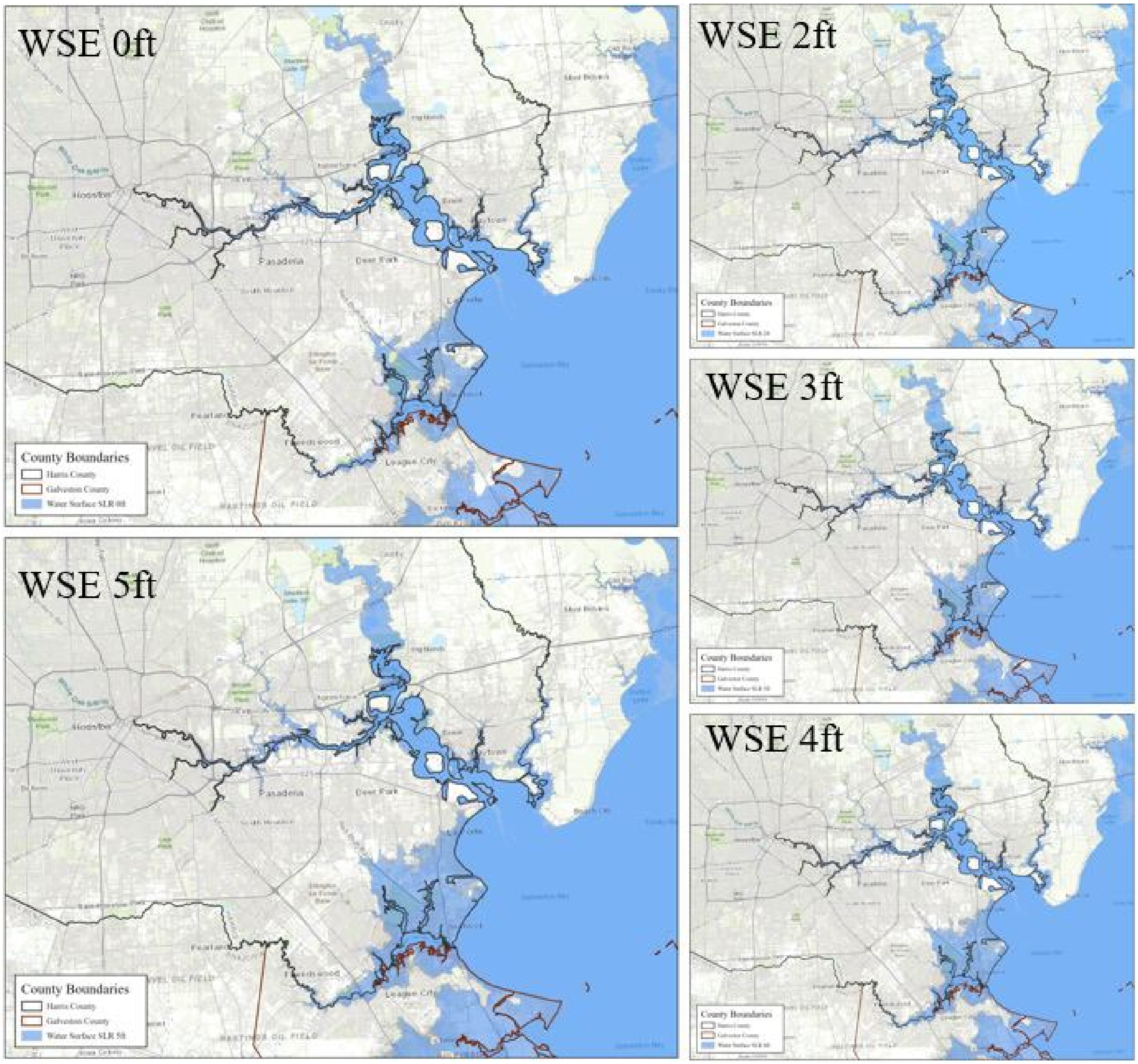

Figure 13. Harris County WSE at SLR zero-, two-, three-, four, and five-feet

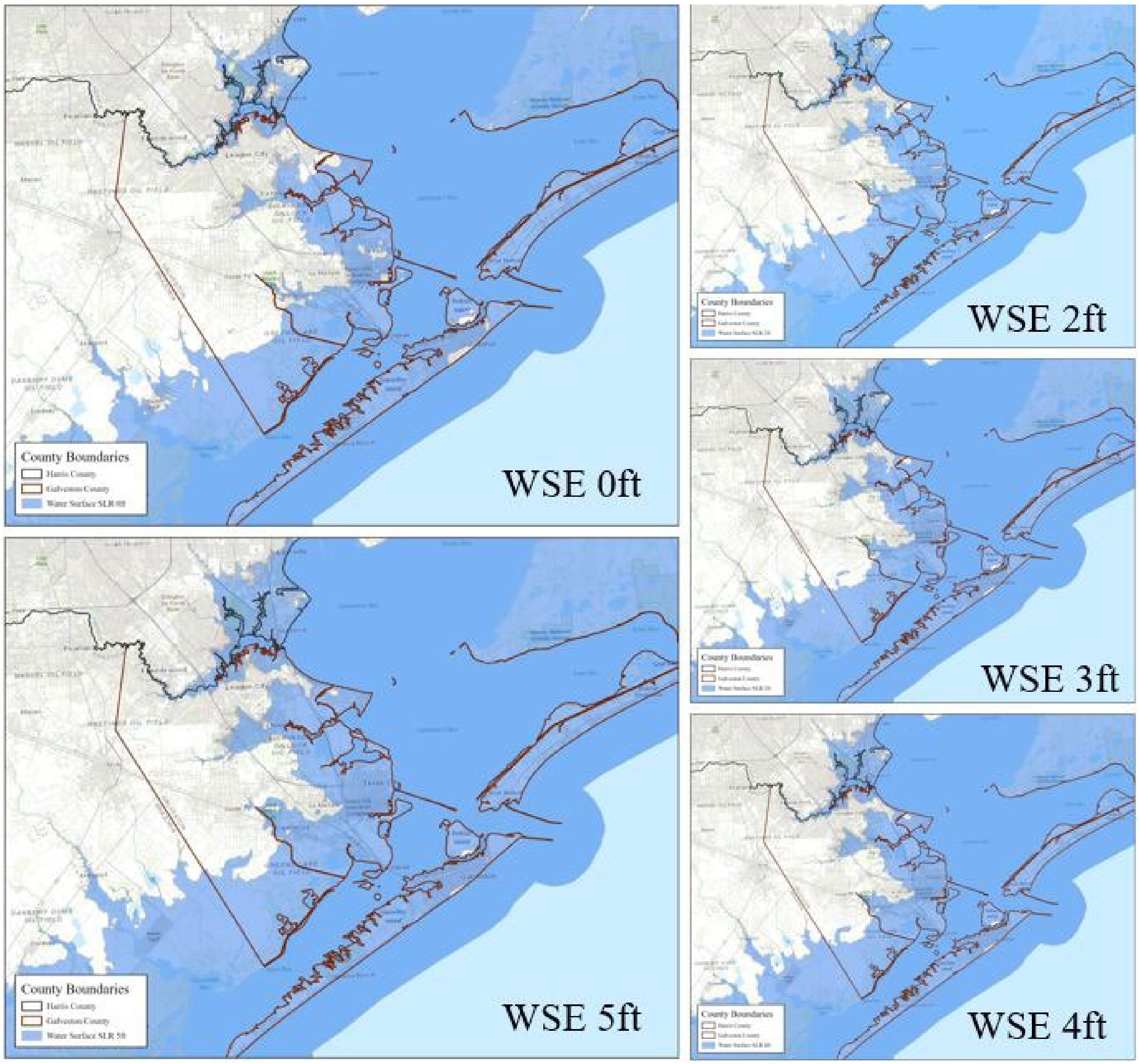

Figure 14. Galveston County WSE at SLR zero-, two-, three-, four, and five-feet

As sea level rises in Harris County, the most notable rise in water surface elevations is east of Galveston Bay and the northeast near the Houston Ship Canal, San Jacinto River, and Buffalo Bayou. Galveston county was mostly inundated at SLR of zero, but as inundations rise to five feet, the southeastern section near Avenue R ½ becomes submerged.

Defining the water surface elevations and intersecting the residential parcels is the first step in discovering the at-risk population. The next step is establishing a SoVI to determine the socioeconomic status of the inhabitants within these inundations.

4.2 Cadastral-based Expert Dasymetric System

Through the CEDS method of data disaggregation and reaggregation, this analysis shows the population density for Harris and Galveston County within each water surface elevation. The sum of the at-risk population was calculated at the tax lot level, reaggregated back to the block level, and intersected with each water surface layer. The water surface of zero feet represents the current conditions of the population impacted in 2020. As sea level rises the projected impacts are shown using two- and three feet for 2050 and four- and five feet for 2100. This estimated impact on the population is categorized by density per square mile. The density is shown by block group within each water surface elevation.

4.2.1 CEDS Method Galveston County

Through generating a population density map for Galveston County, the areas of vulnerability are analyzed at each SLR projection. Figure 16 shows the differences in population density for each water surface elevation with the population density ranges. It's noticeable that as sea level rises and the water surface encroaches further inland, the population density increases.

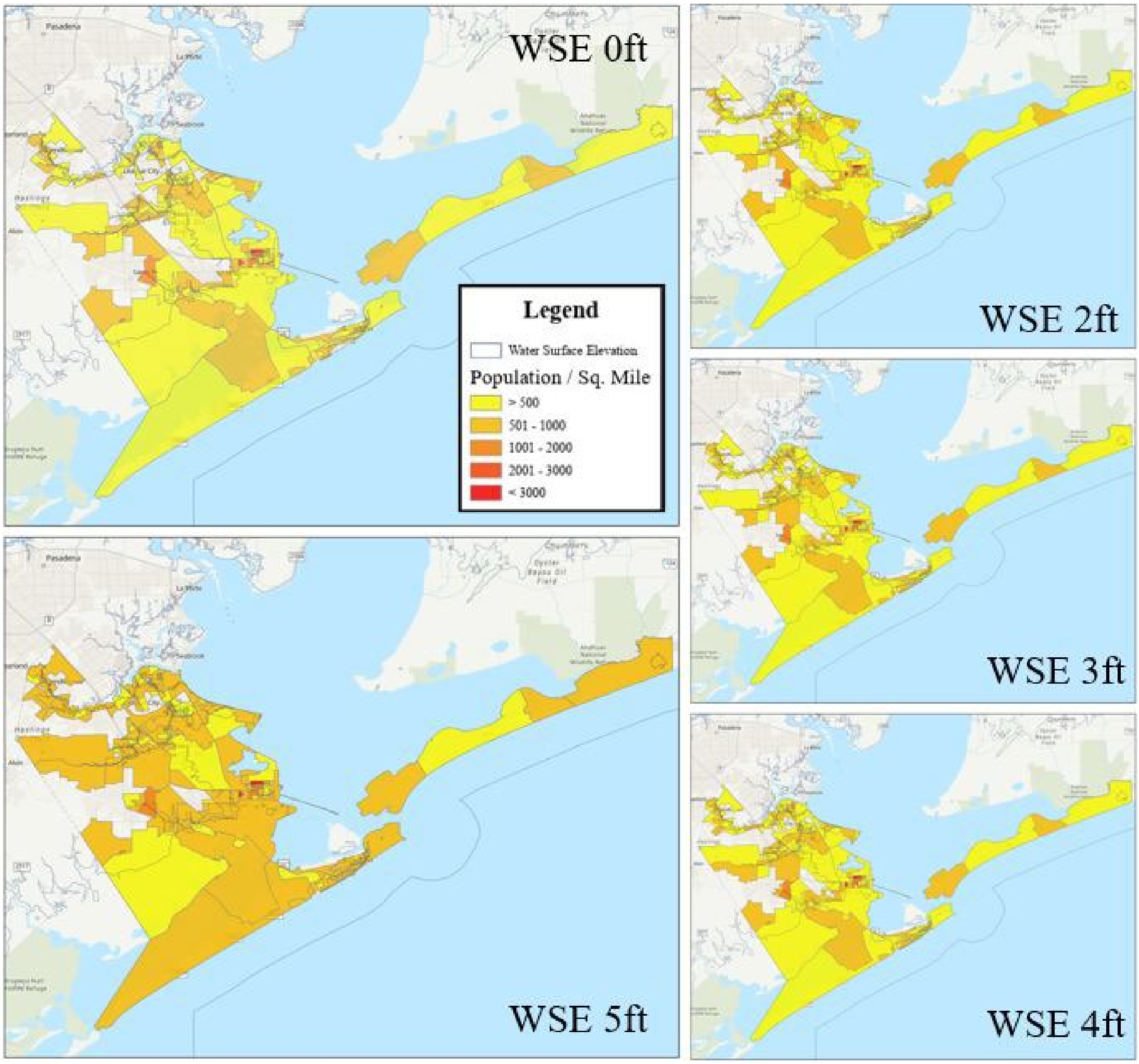

Figure 15. Galveston County water surface population density map

Most of Galveston County is affected by inundations regardless of sea-level rise with a few exceptions. The northeast area, the central-east area, and the northwest, become further impacted as sea level rises to five feet. The northeast area lies on the Galveston Bay and touches Moses Bay, Dollar Bay, and Clear Lake. This area, along with other blocks that adjoin water bodies and rivers, are primarily affected with heightened sea-levels. The northeast area with the highest densification falls within Texas City with a few blocks indicating more than 2,000 and/or 3,000 persons per square mile. Another high densification area is the central part of Galveston County, near Santa Fe with over 2,000 persons per square mile. Galveston Island is similar where most of the island is inundated at current conditions; however, there is a small section that is not impacted until sea level rises to four feet as shown in Figure 18.

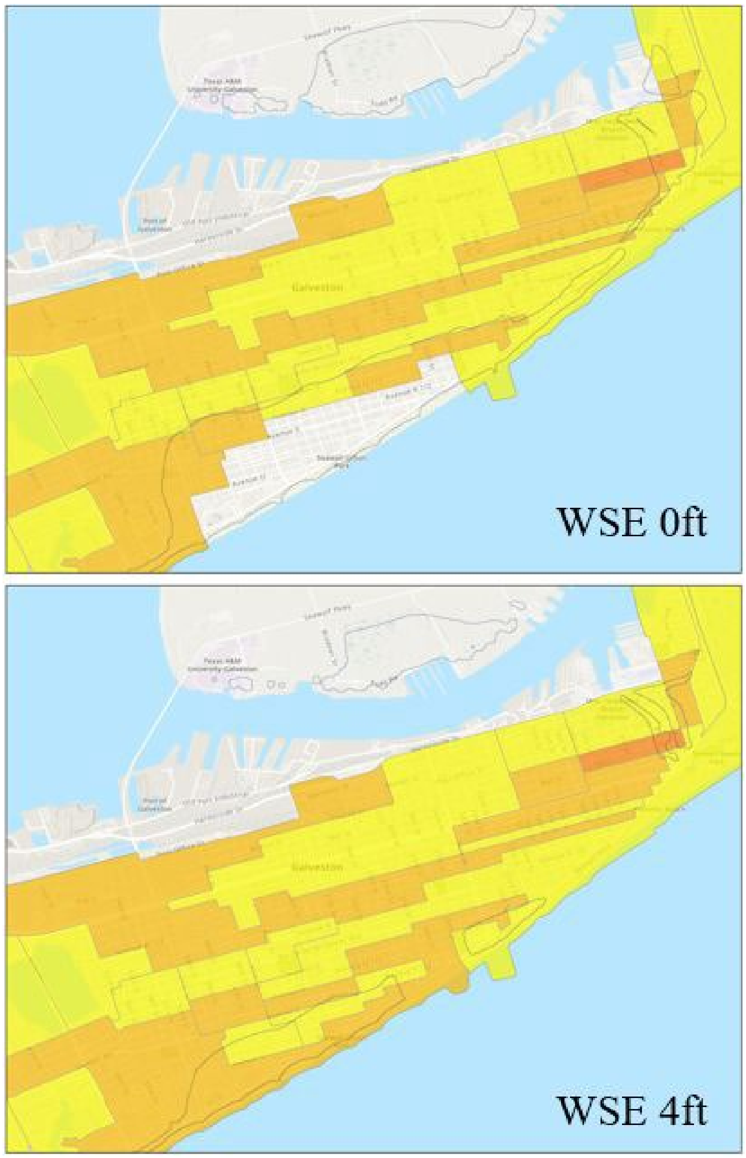

Figure 16. Galveston Island water surface population density maps at zero- and four-feet

Although the southern part of the island sits directly on the Gulf of Mexico, it is protected by a 5-foot-wide, 17-foot-high seawall. This alleviates some inundation on the southeastern end of the island. Although at a water surface of four feet, this area is still flooded. The northern area of Galveston Island consists mostly of shipyards for oil and mining and cruise line docks. Since only residential lots were considered, this area is not included in this study.

4.2.2 CEDS Method Harris County

The population density map for Harris County shows slightly different results from Galveston County. The population density is shown in Figure 19 with the density ranges for each water surface elevation. For Harris County the population density appears to become less once the water surface reaches five feet. However, this does not necessarily indicate a decline in the population within those block groups, but a larger area in square miles. For instance, the northeastern section near Mont Belvieu (the large yellow area to the northeast) is only inundated at five feet and covers an area of over 40 sq. mi., but only a few residential parcels are within the water surface inundations; therefore, decreasing the population density.

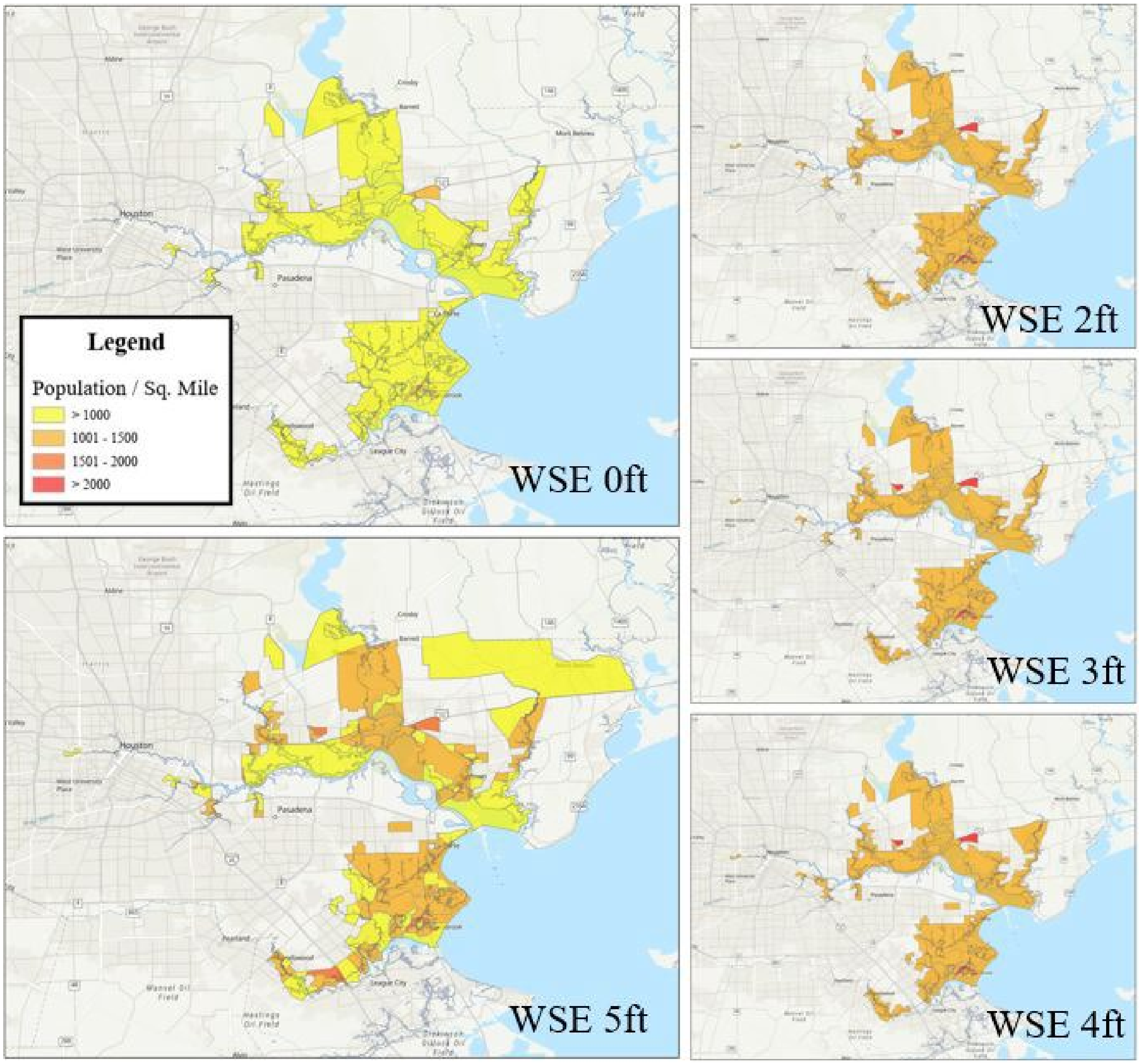

Figure 17. Harris County water surface population density

Most of the areas inundated are adjacent to the Houston shipping Canal, Buffalo Bayou, which extends west into downtown Houston, and the San Jacinto River, which runs to the north. There are four main areas of concern with a population density of over 1,500. The southwest area, west of I-45 near Friendswood north of Clear Creek River, the southeast area near Seabrook and El Lago north of Clear Lake, the northeast area near Lynchburg, and the north central area near Cloverleaf. Both Lynchburg and Cloverleaf are surrounded by numerous streams and canals.

4.3 Vulnerability Index

The SoVI and AHP calculated the at-risk population by weighing the vulnerability indicators within the block groups intersected with the water surface elevations. These values were interpreted using a weighted overlay to indicate the areas of most susceptibility to hurricane storm surge and flooding. The indicators used in the SoVI are listed in Table 2. An AHP was calculated using an online calculator supplied by Business Performance Management Singapore that can be found at the following URL, https://bpmsg.com/ahp/ahp-calc.php. The AHP was given sixteen indicators for a total of 120 pairwise comparisons.

The Eigenvalue of the AHP, which indicates variance between the selected factors and should be above 1, was 18.18%. The consistency ratio of the pairwise comparison was 9.1% which should be below 0.1 (10%) to indicate an acceptable measure of reliability (Saatay 1990). The final output of the AHP was within satisfactory tolerances for both eigenvalue and the consistency ratio. The resulting AHP matrix with the final indicators is shown in Figure 21.

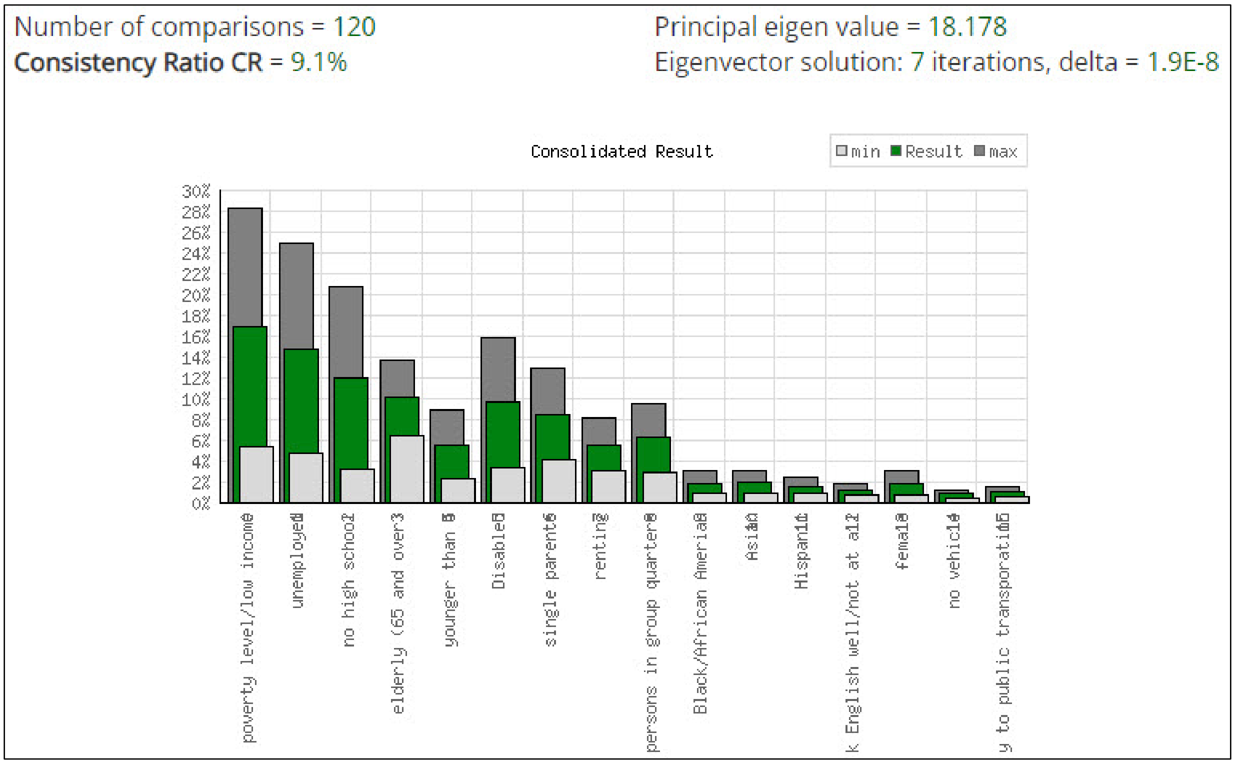

Figure 18. Analytic Hierarchical Process matrix results

The resulting percentages from the AHP were applied to a weighted overlay for each water surface elevation. Figure 22 shows the areas with the highest vulnerability for each along with a legend. Areas in red designate the highest vulnerable populations or a scale factor of 5 followed by the areas in orange with a scale factor of 4.

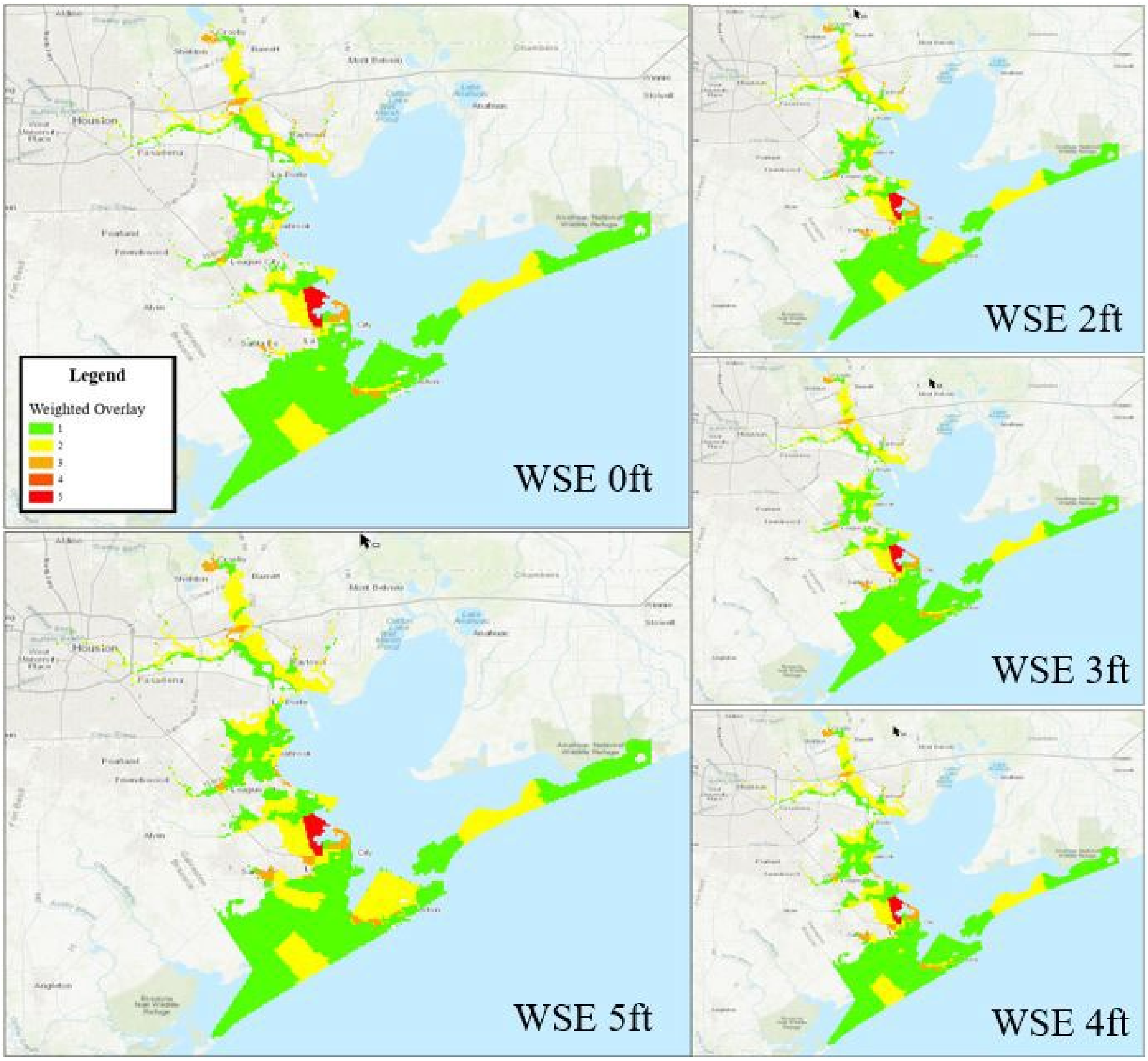

Figure 19. Weighted overlay vulnerability indicator results

The highest vulnerable area within the water surface elevations is northwestern Texas City. Located in Galveston County, Texas City resides along the coast of Galveston Bay. The northeastern section of the city, shown in orange, indicates the next highest area of vulnerability. Other areas of interest in Galveston County are to the south near the causeway entrance to Galveston Island, near Broadway Street and Harborside Drive, to the west of Texas City near Hitchcock and Santa Fe, and to the northwest near League City which extends into Harris

County near Webster. There are no extremely vulnerable areas of interest in Harris County; however, to the north there are two noticeable orange areas. One area is near Lynchburg, on the coast of Burnet Bay and Buffalo Bayou near the Lynchburg Reservoir. Further north, near Magnolia Gardens is another area of concern. This area lies east of the San Jacinto River, south of Lake Houston, and has numerous surrounding lakes.

4.4 Population Growth and Exponential Smoothing Algorithm (ETS)

The population ETS was derived for each block group within each water surface elevation for the projected population in 2050 and 2100 using Microsoft Excel Forecast.ETS calculation. The Brown University data along with the CEDS method data from 1960 through 2020 was used as the historical or past data of which the forecasted values were generated. The data shows a steady rise in population until 2010 and then a slight decline in 2020 in both counties with a few exceptions. Table 3 reflects the population from 1960 through 2100 for Harris County and Table 4 shows Galveston County. The data covers the population within the water surface elevations only and not the entire counties. Harris County shows an incline in population in 2050 and 2100 for all water surface elevations leaving even more people vulnerable. Galveston County shows a steady incline as well, except in block three in each water surface elevation. Block three had a noticeable decline in population starting in 2020 and the ETS shows a continual decline into 2050 and 2100.

Table 6. Harris County Exponential Smoothing Algorithm, existing and forecast results

Harris	1960	1970	1980	1990	2000	2010	2020	2050	2100
WSE 0 - Block 1	56,749	59,864	63,548	64,267	69,698	85,061	74,679	92,165	110,576
WSE 0 - Block 2	57,680	59,177	60,571	61,028	62,975	66,868	68,391	73,745	83,086
WSE 0 - Block 3	27,076	28,001	28,469	30,145	31,290	31,789	33,958	36,816	42,610
WSE 0 - Block 4	2,050	2,235	2,415	2,648	2,719	3,218	3,008	3,900	4,785
WSE 2 - Block 1	58,737	62,378	64,257	65,120	67,896	86,215	80,959	96,547	117,864
WSE 2 - Block 2	60,019	61,494	62,467	64,927	66,006	68,164	72,565	76,953	87,218
WSE 2 - Block 3	28,062	28,846	29,423	30,648	31,141	32,469	33,958	36,504	41,447
WSE 2 - Block 4	2,147	2,394	2,761	3,085	3,373	4,621	5,525	7,110	10,116
WSE 3 - Block 1	65,488	68,722	72,852	74,649	77,369	86,574	83,221	95,519	111,025
WSE 3 - Block 2	61,095	62,890	64,561	66,318	68,642	71,346	74,170	82,593	96,633
WSE 3 - Block 3	28,770	29,569	30,154	31,284	32,231	33,149	34,900	37,673	42,850
WSE 3 - Block 4	2,289	2,427	2,986	3,214	3,618	4,826	5,684	7,321	10,373
WSE 4 - Block 1	68,340	72,656	76,485	78,033	84,541	92,614	90,716	105,326	125,100
WSE 4 - Block 2	61,797	64,865	66,567	69,287	75,307	76,168	80,155	89,550	105,276
WSE 4 - Block 3	29,357	30,369	31,025	31,836	35,602	36,259	37,911	42,312	49,957
WSE 4 - Block 4	2,401	2,648	3,287	3,537	3,948	5,148	5,863	7,562	10,619
WSE 5- Block 1	72,638	77,053	81,071	85,253	94,127	98,165	102,823	118,705	144,767
WSE 5- Block 2	63,281	66,693	68,792	71,952	75,287	77,952	80,155	88,989	103,018
WSE 5- Block 3	30,186	31,153	31,869	32,404	35,604	36,846	37,911	42,018	48,943
WSE 5- Block 4	2,563	2,862	3,573	3,822	4,325	6,084	7,214	9,433	13,575

Table 7. Galveston County Exponential Smoothing Algorithm, existing and forecast results

Galveston	1960	1970	1980	1990	2000	2010	2020	2050	2100
WSE 0 - Block 1	63,557	66,212	68,176	68,860	71,724	78,497	73,031	81,753	89,957
WSE 0 - Block 2	40,514	44,989	48,559	54,005	56,361	59,566	76,557	86,236	115,546
WSE 0 - Block 3	33,961	35,737	36,543	38,113	43,105	42,666	27,474	35,745	31,494
WSE 0 - Block 4	15,278	15,981	16,373	17,187	17,281	17,479	17,074	18,069	19,350
WSE 0 - Block 5	2,291	2,479	3,228	3,795	4,213	4,479	3,723	5,284	6,716
WSE 0 - Block 6	2,267	2,329	2,484	2,603	2,780	2,805	2,494	2,921	3,201
WSE 2 - Block 1	72,082	74,409	75,736	76,509	79,430	85,274	78,848	86,805	92,737
WSE 2 - Block 2	53,465	54,173	54,862	56,854	58,315	61,236	84,103	85,063	108,441
WSE 2 - Block 3	36,812	37,679	38,527	39,084	41,151	44,819	29,416	35,223	29,975
WSE 2 - Block 4	16,532	17,235	17,247	17,432	17,526	18,380	17,642	18,645	19,502
WSE 2 - Block 5	2,378	2,516	3,358	3,624	4,367	4,602	3,912	5,529	6,928
WSE 2 - Block 6	2,403	2,541	2,674	2,814	2,964	3,215	2,648	3,216	3,456
WSE 3 - Block 1	71,889	74,202	77,364	78,267	80,216	87,301	80,338	89,418	97,009
WSE 3 - Block 2	53,979	57,642	58,964	59,315	61,745	78,686	90,128	105,855	138,047
WSE 3 - Block 3	37,264	38,862	39,527	40,126	43,630	47,497	32,253	39,410	36,215
WSE 3 - Block 4	17,023	17,278	17,385	17,526	17,824	18,620	17,962	18,932	19,834
WSE 3 - Block 5	2,842	3,167	3,408	4,136	4,430	4,724	4,023	5,319	6,392
WSE 3 - Block6	2,407	2,566	2,713	2,898	3,047	3,346	2,941	3,534	4,014
WSE 4 - Block 1	78,228	79,736	82,724	83,732	80,701	92,317	84,203	96,732	103,430
WSE 4 - Block 2	55,167	59,128	61,342	62,020	62,605	86,207	93,114	110,998	145,287
WSE 4 - Block 3	38,120	39,415	40,325	41,123	46,879	49,844	33,372	42,450	42,424
WSE 4 - Block 4	17,447	17,530	18,115	17,715	16,744	19,276	17,980	18,642	19,206

WSE 4 - Block 5	3,343	3,502	3,521	4,218	3,481	4,847	3,723	5,382	5,480
WSE 4 - Block 6	2,486	2,592	2,618	3,062	3,210	3,653	2,494	3,371	3,520
WSE 5- Block 1	81,420	83,347	87,367	88,484	86,513	96,758	90,100	102,981	111,257
WSE 5- Block 2	59,147	62,707	63,451	63,678	64,129	95,635	94,773	110,376	143,748
WSE 5- Block 3	39,284	41,521	42,064	44,612	49,196	52,255	34,963	44,446	41,929
WSE 5- Block 4	17,862	18,124	18,635	17,886	18,240	19,852	17,980	18,968	19,516
WSE 5- Block 5	3,486	3,521	3,599	4,383	3,481	4,969	3,723	5,350	5,902
WSE 5 - Block 6	2,547	2,645	2,815	3,210	3,376	3,925	2,494	3,507	3,609

Chapter 5 Discussion and Conclusions

This study assessed the effects of SLR and hurricane storm surge on the community and the vulnerable population within Harris and Galveston County, Texas. The current areas of concern for 2020 were established as well as the projected population in 2050 and 2100 as sea level rises. The goal was to ascertain where storm surge would encroach with rising sea levels, the socioeconomic vulnerable peoples within that area, and the projected population within estimated sea level rise elevations.

This chapter reviews the results of the final assessment of the inundation areas and the population within. The study findings are discussed along with the limitations and considerations. The final section compares the results of this study to similar study findings for a greater understanding of the issues that Harris and Galveston County face.

5.1 Study Findings

This analysis discovered the areas of significance across Harris and Galveston County with rising-sea- levels and storm surge. Throughout the study, there was a common theme in some locations. Combining the CEDS population density maps, the weighted overlay, and the water surface elevation at five feet of SLR, these patterns become apparent. Most notably, Texas city had the highest population density, with more than 2,000 – 3,000 people per square mile, and the highest vulnerable population in both Harris and Galveston County as indicated in Figure 24. This suggests that this is a major area of concern for evacuations and emergency management personnel during hurricanes. Other areas that have recurring themes of high population density and high vulnerability are the Santa Fe/Hitchcock area in Galveston County and the Lynchburg/Channelview area in Harris County.

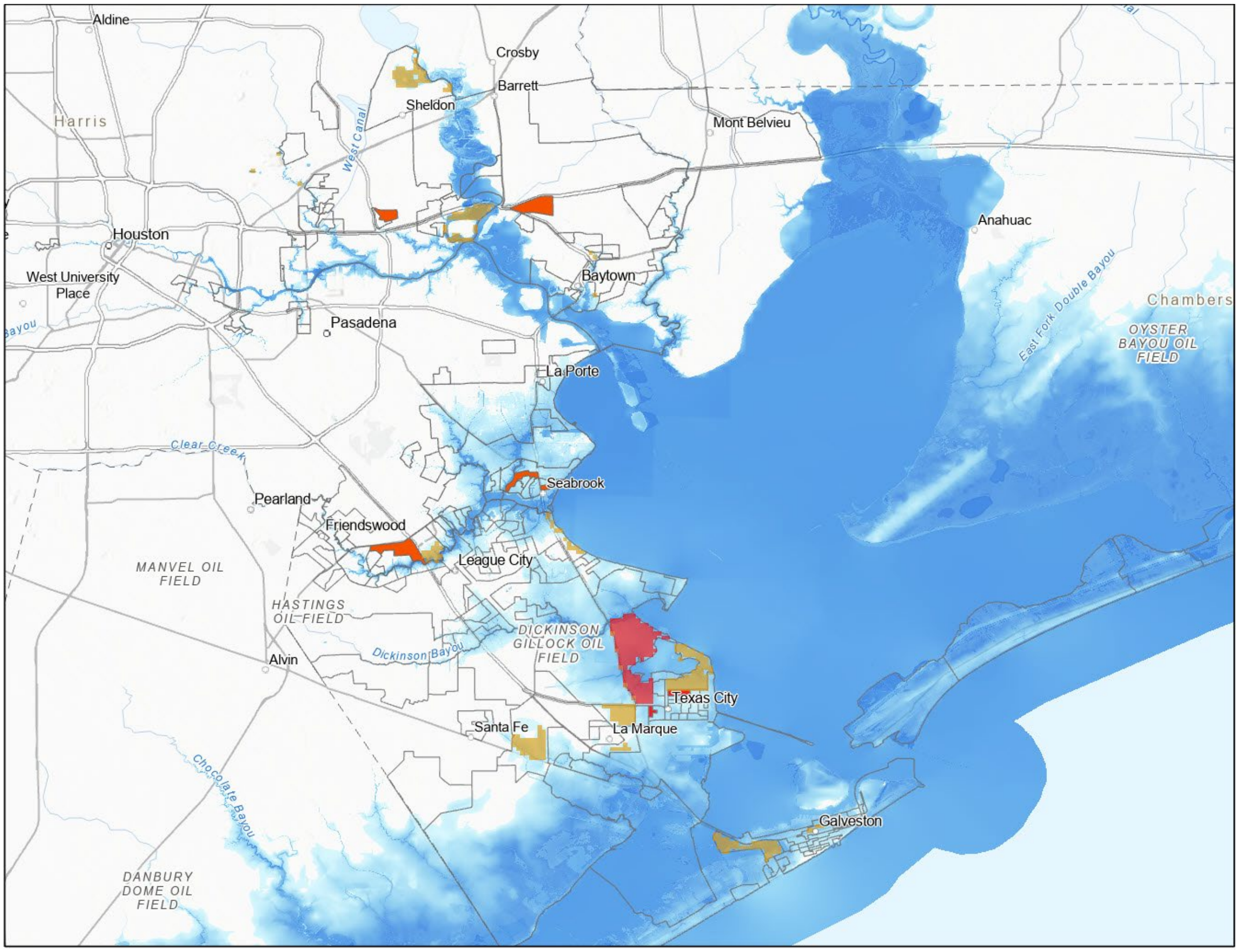

Figure 20. Density map and weighted overlay with a water surface elevation of five feet

Highly vulnerable populations that may also need assistance during hurricane flooding are located near Broadway Street and Harborside Drive and League City/Webster in Galveston County, and Magnolia Gardens, Cloverleaf, and Seabrook/El Lago in Harris County. The areas with high socioeconomic vulnerability and the least available public transportation (bus stops) are the Santa Fe/Hitchcock area with the nearest bus stop just under a mile and the League City/Webster area with the nearest bus stop over two miles away.

The past population data indicates an overall increase in population throughout most of the decades. The one anomaly was in 2020 when the population declined in most areas.

Fluctuations may be caused by population relocation and/or a decreased desire to live in coastal communities prone to flooding and storm surge. In 2017 Hurricane Harvey stagnated over the study area and dumped record amounts of rainfall over Houston and Galveston. The devastation that occurred may be the source of the decline in population.

The resulting ETS shows a population growth pattern into 2050 and 2100. The one exception to this is block three in Galveston County as mentioned in the results section. The average percent increase in population in Harris County is 119% with block one having the highest population rise. This block encompasses Magnolia Gardens, Cloverleaf, and part of Seabrook where there is high socioeconomic vulnerability. This indicates that as sea level rises and the population increases in these areas, even more people will be at risk. The average percent increase in population in Galveston County is 115% with block two having the highest population rise. This block includes the area near Broadway Street and Harborside Drive, a small part of Hitchcock, League City, and an even smaller section of Texas City. This suggests that the areas with the most growth are not a large portion of the vulnerable areas within this county.

5.2 Limitations and Considerations

This study used census data from ACS and Brown University, accredited to NHGIS. The Brown University data ultimately came from the census bureau and ACS. There are indications that this data is incomplete and does not accurately assess the current population. As Miyake et al. (2010) stated it does not always incorporate the poor, homeless, undocumented immigrants, and other marginalized peoples. The census data may exclude citizens and the final output only represents the findings of the data available. Improvements in the census data or the collection process would generate a more accurate representation of the population. As mentioned in the previous section, the census data for 2020 showed a decline in most areas within both counties.

This may also be caused from inaccurate census data. Since the ETS was developed utilizing census data, this inherently can cause inaccuracies within the estimated future population.

Socioeconomic vulnerable peoples within SLR and SLOSH MOM High Tide Cat 5 elevations were analyzed but did not incorporate the entire county. The data in this study only included residents within the water surface elevations. Although this encompassed almost all of Galveston County, a great deal of residential lots in Harris County to the north and northwest were not within the inundations. This data also does not account for situations like Hurricane Harvey where rainfall is a major concern and should be taken into consideration. The actual susceptible community may signify a different population in the event of a Cat 5 hurricane with extreme rainfall amounts; however, the data presented will give emergency management professionals and first responders an indication of the communities in need.

The study indexing, or the indicators themselves, are based on judgement. It is founded on the professional community's assessment of socioeconomic vulnerability. These indicators may exclude populations that have other incapacities and need assistance. Other geophysical attributes, such as proximity to evacuation routes, shelters, police/fire stations, may also paint a different picture. This technique can be used in additional studies incorporating these factors to discover different susceptibilities.

The python script was only used for the creation of the water surface elevations but can be extended to include the CEDS method. The script made the inundation process easier to run for repetitive analyses. It looped through each SLR elevation to create a new raster by combining NOAA's Sea Leve Rise rasters with NOAA's SLOSH MOM Cat 5 High Tide interpolated raster surface. It then subtracted the DEM and set null to remove cells that are not water surface elevations. This script can be expanded upon or modified and applied to any scenario that requires looping through data.

5.3 Comparison Analysis and Conclusion

The Houston-Galveston area has been studied throughout the years due to its low-lying coastal location, its substantial population, economics, infrastructure, and its persistent flooding. This study focused on how SLR and storm surge affects the communities in Harris and Galveston County and which areas have the most vulnerable population. Previous studies vary in location with some focusing on only Houston, others Galveston, and others incorporating the Greater Houston Area. Some indicators used in these other analyses consisted of land subsidence, air pollution, Superfund sites, home health care centers, FEMA's National Flood Hazard Layer, and how they are relative to either flooding or SLR and the vulnerable populations.

In a study from Chakraborty, Collins, and Grineski (2019) on the environmental justice implications from Hurricane Harvey flooding, portions of their choropleth map that overlap this projects study area shows the most flooding occurred in Lynchburg and Magnolia Park in Harris County and Hitchcock, near Broadway Street and Harborside Drive, and League City in Galveston County. There was also a high correlation between Harvey flooding and Black, Hispanic, and socioeconomically deprived residents within this area. This is not inclusive of all the areas reflected in their study, but the areas that show overlap in each of the studies. Another study by Fucile-Sanchez and Davlasheridze (2020) discovered the socially vulnerable population after Hurricane Ike, 2008, in Galveston County. Using similar vulnerability indicators as this study, they found that the areas with the highest susceptible peoples were Hitchcock, Texas City, and San Leon. A study in Houston by Bodenreider et al. (2019) on the social, economic, and geographic vulnerability pre- and post-Hurricane Harvey used demographic data and environmental factors, such as, Superfund sites, wastewater discharge, and ozone. This study only incorporated the metropolitan areas of Houston; however, Magnolia Park and Cloverleaf are within multiple areas of concern. Both are represented in the percent of people living in poverty and percent of people of color in relation to Superfund sites and the percent of people living in poverty relative to air pollution. In a comparison of the results of this study to other studies an obvious repetitiveness is found. The most common areas are listed in Table 5.

Table 8. Repetitive Vulnerable Areas in Harris and Galveston County

Harris County	Galveston County
Magnolia Park	Entrance to Galveston Island (near Broadway Street and Harborside Drive)
Cloverleaf/ Lynchburg	League City/Webster
Seabrook/El Lago	Hitchcock/Santa Fe

For emergency management and disaster relief purposes the above-mentioned areas should be the main focus. The highest population increase has also been seen within these locations and they also lack public transportation. Figure 25 shows the boundaries of these cities from the Houston-Galveston Area Council's Regional Data Hub (H-GAC) for a geographical perspective, except for Magnolia Park and Broadway Street and Harborside Drive into Galveston County. The boundary for these areas is sections of the weighted overlay and population density vulnerability areas. Magnolia Park is a section in Houston and the town/city boundary includes the entire metropolitan area.

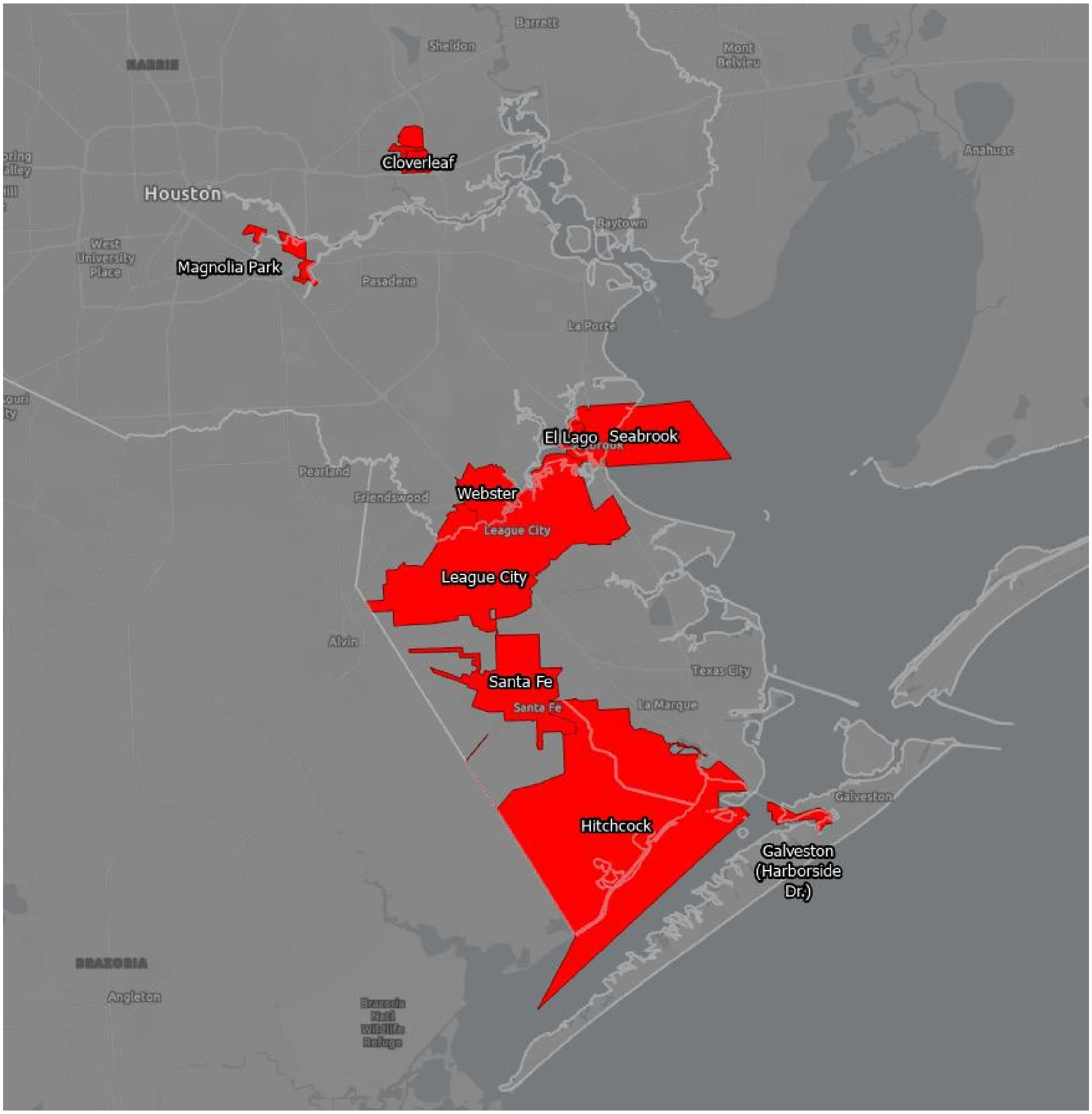

Figure 21. Geographically Significant Vulnerable Areas

This study identified the vulnerable population and provided insight into the current areas of interest and the estimated growth patterns into 2050 and 2100. Although this study only incorporated the communities within SLR and SLOSH Cat 5 MOM inundations or water surface elevations, it is indicative of the areas in need from multiple other studies. The SLOSH models accounted for tide levels, forward speed, storm categories, and atmospheric pressure; however, this study can be used as a foundation and expanded upon to account for precipitation, stream flow, subsidence, or past hurricane paths. This research gives government officials, policy makers, and emergency managers awareness of their local communities and the population at risk and allows Harris and Galveston County to better prepare for hurricanes and natural disasters.

References

Bass, B. and Bedient P. 2018. "Surrogate Modeling of Joint Flood Risk Across Coastal Watersheds." Journal of Hydrology 558: 159-173.

Baykal, T. M., Colak, H. E., and Kılınc, C. "Forecasting Future Climate Boundary Maps (2021–2060) Using Exponential Smoothing Method and GIS." The Science of the total environment 848 (2022): 157633–157633.

Blake, E. S. 2018. "The 2017 Atlantic Hurricane Season: Catastrophic Losses and Costs." Weatherwise 71, no. 3: 28-37.

Blessing, R., Sebastian, A., and Brody, S. D. 2017. "Flood Risk Delineation in the United States: How Much Loss Are We Capturing?" Natural Hazards Review 18, Issue 3.

Bodenreider, C., Wright, L., Barr, O., Xu, K. and Wilson, S.. 2019. "Assessment of Social, Economic, and Geographic Vulnerability Pre- and Post-Hurricane Harvey in Houston, Texas." Environmental justice 12, no. 4 (2019): 182–193. American Society of Civl Engineers. DOI: 10.1061/ (ASCE)NH.1527-6996.0000242

Boyer, D., and Vardy, M. "Flooded City: Affects of (Slow) Catastrophe in Post-Harvey Houston." Current anthropology 63, no. 6 (2022): 615–636.

Burton, C. G. 2010. "Social Vulnerability and Hurricane Impact Modeling." Natural hazards review 11, no. 2: 58-68.

Carlson, C., Goldman, G., Dahl, K. 2016. Stormy Seas, Rising Risks: Assessing Undisclosed Risk from Sea Level Rise and Storm Surge at Coastal US Oil Refineries. In: Drake, J., Kontar, Y., Eichelberger, J., Rupp, T., Taylor, K. (eds) Communicating Climate-Change and Natural Hazard Risk and Cultivating Resilience. Advances in Natural and Technological Hazards Research, vol 45. Springer, Cham. https://doi.org/10.1007/978-3-319-20161-0_19

Chakraborty, J., Collins, T. W., and Grineski, S. E. 2019. "Exploring the Environmental Justice Implications of Hurricane Harvey Flooding in Greater Houston, Texas." American journal of public health 109, no. 2: 244-250.

Conrad, H. "Are Coastal Marshes Drowning Faster than Expected?" Texas A&M University Engineering, June 17, 2021. https://engineering.tamu.edu/news/2021/06/ocen-are-coastal-marshes-drowning-faster-than-expected.html.

Cutter, S. L., Boruff, B. J., and Shirley, W. L. 2003. "Social Vulnerability to Environmental Hazards." Social science quarterly 84, no. 2: 242-261.

Cutter, S. L., Mitchell, J. T., and Scott, M. S. 2000. "Revealing the Vulnerability of People and Places: A Case Study of Georgetown County, South Carolina." Annals of the association of American Geographers 90, no. 4: 713-737. "Coastal Areas." The United States Census

Bureau, July 23, 2020. https://www.census.gov/topics/preparedness/about/coastal-areas.html.

Davis Jr, A. B. 1951. "History of the Galveston Sea Wall." Coastal Engineering Proceedings, no. 2: 24-24.

Federal Emergency Management Administration (FEMA) (2018). FEMA - Harvey Flood Depths Grid, HydroShare, https://doi.org/10.4211/hs.165e2c3e335d40949dbf501c97827837

Flanagan, B. E., et al. 2011. "A Social Vulnerability Index for Disaster Management." Journal of homeland security and emergency management 8, no. 1.

Fucile-Sanchez, E., and Davlasheridze, M. 2020. “Adjustments of Socially Vulnerable Populations in Galveston County, Texas USA Following Hurricane Ike.” Sustainability (Basel, Switzerland) 12, no. 17 (2020): 7097–.

Galloway, D. L., Jones, D. R., and Ingebritsen, S. E. 1999. Land Subsidence in the United States. Vol. 1182: US Geological Survey.

Gardner, E. S. 2006 “Exponential Smoothing: The State of the art—Part II.” International journal of forecasting 22, no. 4 (2006): 637–666.

Gathongo, N., and Tran L.. “Assessing Social Vulnerability of Villages in Mt. Kasigau Area, Kenya, Using the Analytical Hierarchy Process.” GeoJournal 85, no. 4 (2020): 995–1007.

“Geo Galveston - Texas.” Temperature - Precipitation - Sunshine - Snowfall, 2021. US Climate Data. Accessed September 20, 2021. https://www.usclimatedata.com/map/USTX0499.

Harris County Flood Control. 2021. Hurricane Ike 2008. Accessed September 20, 2021. https://www.hcfcd.org/About/Harris-Countys-Flooding-History/Hurricane-Ike-2008

Horton, B. P., et al. 2020. "Estimating Global Mean Sea-Level Rise and Its Uncertainties by 2100 and 2300 from an Expert Survey." npj Climate and Atmospheric Science 3, no. 1: 1-8.

Houston Harris County Winter Storm Relief Fund. 2023. “Disproportionately Impacted Communities.” Accessed January 14, 2023. https://winterstormrelieffund.org/?page_id=131

“Houston Population 2022.” Population USA. Accessed March 10, 2022. http://www.usapopulation.org/houston-population/

IPUMS USA, University of Minnesota, www.ipums.org. Accessed November 13, 2010.

Kasperson, J. X., Kasperson, R. E., and Turner, B. L. 1996. "Regions at Risk: Exploring Environmental Criticality." Environment: Science and Policy for Sustainable Development 38, no. 10: 4-29.

Logan, J. R, and Xu Z. 2015. “Vulnerability to Hurricane Damage on The US Gulf Coast Since 1950.” Geographical review vol. 105,2 (2015): 133-155. doi:10.1111/j.1931-0846.2014.12064.x

Maantay, J. A., Maroko, A. R., and Herrmann, C. 2007. "Mapping Population Distribution in the Urban Environment: The Cadastral-Based Expert Dasymetric System (Ceds)." Cartography and Geographic Information Science 34, no. 2: 77-102.

Maloney, M. C., and Preston, B.L. 2014. “A Geospatial Dataset for US Hurricane Storm Surge and Sea-Level Rise Vulnerability: Development and Case Study Applications.” Climate risk management 2, no. C (2014): 26–41.

Microsoft. 2021. FORESCASTS.ETS Function. Accessed January 7, 2023. https://support.microsoft.com/en-us/office/forecast-ets-function-15389b8b-677e-4fbd-bd95-21d464333f41

Miyake, K. K., et al. 2010. "Not Just a Walk in the Park: Methodological Improvements for Determining Environmental Justice Implications of Park Access in New York City for the Promotion of Physical Activity." Cities and the Environment 3, no. 1: 1.

NASA. April 2021. Global Climate Change. Vital Signs of the Planet. Accessed September 26, 2021. https://climate.nasa.gov/vital-signs/sea-level/

National Oceanic and Atmospheric Administration (NOAA) Climate.gov (2021) Climate Change: Global Sea Level. Accessed September 20, 2021. https://www.climate.gov/news-features/understanding-climate/climate-change-global-sea-level

National Oceanic and Atmospheric Administration (NOAA) Coastal Services Center. (2012) Mapping Coastal Inundation Primer. Accessed September 20, 2021. https://coast.noaa.gov/data/digitalcoast/pdf/coastal-inundation-guidebook.pdf.

National Oceanic and Atmospheric Administration (NOAA) National Westher Service. Saffir-Simpson Hurricane Scale. Accessed May 3, 2023. https://www.weather.gov/mfl/saffirsimpson#:~:text=The%20Saffir%2DSimpson%20Hurricane%20Wind,loss%20of%20life%20and%20damage.

National Oceanic and Atmospheric Administration (NOAA) Sea, Lake, and Overland Surges form Hurricanes (SLOSH) National Hurricane Center. Accessed September 20, 2021. https://www.nhc.noaa.gov/surge/slosh.php.

National Oceanic and Atmospheric Administration (NOAA) Office for Coastal Management. Sea Level Rise Data: 1-10 ft Sea Level Rise Inundation Extent. Accessed September 22, 2021. https://www.fisheries.noaa.gov/inport/item/48106

National Oceanic and Atmospheric Administration (NOAA) Tides and Currents. Tidal Datums. Accessed May 3, 2023.

https://tidesandcurrents.noaa.gov/datum_options.html#:~:text=MHHW*,the%20National%20Tidal%20Datum%20Epoch.

Office for Coastal Management, 2023: NOAA Office for Coastal Management Sea Level Rise Data: 1-10 ft Sea Level Rise Inundation Extent from 2010-06-15 to 2010-08-15. NOAA National Centers for Environmental Information, https://www.fisheries.noaa.gov/inport/item/48106.

Oppenheimer, M., et. al. 2019. Sea Level Rise and Implications for Low-Lying Islands, Coasts and Communities. IPCC Special Report on the Ocean and Cryosphere in a Changing Climate [H.-O. Pörtner, D.C. Roberts, V. Masson-Delmotte, P. Zhai, M. Tignor, E. Poloczanska, K. Mintenbeck, A. Alegría, M. Nicolai, A. Okem, J. Petzold, B. Rama, N.M. Weyer (eds.)]. In press.

Rahmstorf, S. (2012) Modeling Sea Level Rise. Nature Education Knowledge 3(10):4. Accessed September 6, 2021. https://www.nature.com/scitable/knowledge/library/modeling-sea-level-rise-25857988/

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. International Journal of Services Sciences, 1(1), 83–98.

Saaty, T. L. 1990. "How to Make a Decision: The Analytic Hierarchy Process." European journal of operational research 48, no. 1 (1990): 9–26.

Smiley, K. T. 2020. "Outdated and Inaccurate, FEMA Flood Maps Fail to Fully Capture Risk." Rice University, Kinder Institute for Urban Research. Accessed December 30, 2022. https://kinder.rice.edu/urbanedge/outdated-and-inaccurate-fema-flood-maps-fail-fully-capture-risk

SolarWinds. 2019. Holt-Winters Forecasting and Exponential Smoothing Simplified. Accessed January 7, 2023. https://orangematter.solarwinds.com/2019/12/15/holt-winters-forecasting-simplified/#:~:text=What%20Is%20the%20Holt%2DWinters,cyclical%20repeating%20pattern%20(seasonality).

Tate, E. 2012. "Social Vulnerability Indices: A Comparative Assessment Using Uncertainty and Sensitivity Analysis." Natural hazards (Dordrecht) 63, no. 2 (2012): 325–347.

Tate, E. 2013. "Uncertainty Analysis for a Social Vulnerability Index." Annals of the Association of American Geographers 103, no. 3 (2013): 526–43. http://www.jstor.org/stable/23485404.

The Nature Conservatory. 2013. "Sea Level Rise. Research & Scenarios for a Changing Coast." StormSmart.org. Accessed January 12, 2023. http://slr.stormsmart.org/texas/

The Ocean Conference. Factsheet: People and Oceans. New York, June 5-9, 2017. United Nations. Accessed September 8, 2021. https://www.un.org/sustainabledevelopment/wp-content/uploads/2017/05/Ocean-fact-sheet-package.pdf

Turner, B. L., et al. 2003. "A Framework for Vulnerability Analysis in Sustainability Science." Proceedings of the national academy of sciences 100, no. 14: 8074-8079.

Understanding Houston. 2023. “Vulnerability to and Impacts from Disasters. Exploring unequal effects of natural disasters on Houston communities.” Accessed January 14, 2023. https://www.understandinghouston.org/topic/disasters/vulnerability-impacts#social_vulnerability

US Census. History. Cesnus Records. Accessed May 4, 2023. https://www.census.gov/history/www/genealogy/decennial_census_records/census_records_2.html

US Department of Commerce and National Oceanic and Atmospheric Administration. "Hurricanes in History." National Hurricane Center. Accessed September 22, 2021. https://www.nhc.noaa.gov/outreach/history/

US Energy Information Administration. (EIA) 2021. “The Port District of Houston-Galveston Became a Net Exporter of Crude Oil in April.” Today in Energy. Accessed September 15, 2021. https://www.eia.gov/todayinenergy/detail.php?id=36932.

US Geological Survey. About 3DEP Products and Services. Accessed May 4, 2023. https://www.usgs.gov/3d-elevation-program/about-3dep-products-services

US Geological Survey, 2018. Characterization of Peak Streamflows and Flood Inundation of Selected Areas in Southeastern Texas and Southwestern Louisiana from the August and September 2017 Flood Resulting from Hurricane Harvey. by Watson, K. M., et al.

Visit Houston Texas. Facts and Figures. 2021. Accessed August 27, 2021. Houston Facts & Figures | Find Population, Culture & Industry Data (visithoustontexas.com)

Winters, P. R. 1960. “Forecasting Sales by Exponentially Weighted Moving Averages.” Management Science 6, no. 3 (1960): 324–42. http://www.jstor.org/stable/2627346.

Yuan, S., Guo, J., and Zhao, X. “Integrated Weighting Technique for Coastal Vulnerability to Storm Surges.” Journal of Coastal Research, 2017, 6–12. http://www.jstor.org/stable/44252799.

Appendices

Appendix A. Python Script

Creation of water surface elevations.

```
import os
import arcpy

spat_ref='PROJCS["NAD_1983_StatePlane_Texas_South_Central_FIPS_4204_Feet",GEOGCS
["GCS_North_American_1983",DATUM["D_North_American_1983",SPHEROID
["GRS_1980",6378137.0,298.257222101]],PRIMEM["Greenwich",0.0],UNIT
["Degree",0.0174532925199433]],PROJECTION["Lambert_Conformal_Conic"],PARAMETER
["False_Easting",1968500.0],PARAMETER["False_Northing",13123333.33333333],PARAMETER
["Central_Meridian",-99.0],PARAMETER["Standard_Parallel_1",28.38333333333333],PARAMETER
["Standard_Parallel_2",30.28333333333333],PARAMETER["Latitude_Of_Origin",27.83333333333333],UNIT
["Foot_US",0.3048006096012192]]'

arcpy.env.overwriteOutput=True

# This script first creates a water surface by adding together NOAA's Sea Leve Rise rasters with NOAA's
SLOSH MOM Cat5 High Tide interpolated raster surface.
# It loops through each SLR elevation and creates a new combined raster. The USGS DEM is then
subtracted from each of the five new rasters.
# The setnull tool removes invalid or no data values that do not indicate water surface.
# The study area is Harris and Galveston County, Texas.

# This creates an interpolated surface from points generated for the SLOSH layer using Inverse Distance
Wieghted (IDW) with TIN Domain delineation
def create_IDW_raster():
    with arcpy.EnvManager(outputCoordinateSystem=spat_ref, snapRaster=r"SLR_Prep
\SLR_2ft_vert_3.tif"):
        arcpy.ddd.Idw(r"D:\Education\USC\Thesis\Thesis - Semester 2\Thesis_V3\Thesis_V3.gdb
\MOM_Cat5_HT_wet_even_2", "Elevation_cor", r"D:\Education\USC\Thesis\Data\Sea Level Rise
\z_MOM_SLR_v2000\IDW_SLR_comb\MOM_CAT5_IDW.tif", 9.461624641240904, 2, "VARIABLE 12",
"MOM_Cat5_TinDomain_poly")


# This defines the loops needed to run the same process for each SLR elevation.
def loop_mosaic_new_raster():
    MOSAIC_TO_NEW_raster_IDW_AND_SLR(0)
    MOSAIC_TO_NEW_raster_IDW_AND_SLR(2)
    MOSAIC_TO_NEW_raster_IDW_AND_SLR(3)
    MOSAIC_TO_NEW_raster_IDW_AND_SLR(4)
    MOSAIC_TO_NEW_raster_IDW_AND_SLR(5)

def loop_momslrwse_minus_dem_output_depth():
    MOMSLRwse_minus_DEM_output_depth(0)
    MOMSLRwse_minus_DEM_output_depth(2)
    MOMSLRwse_minus_DEM_output_depth(3)
    MOMSLRwse_minus_DEM_output_depth(4)
    MOMSLRwse_minus_DEM_output_depth(5)

def loop_MOMSLRwse_minus_DEM_output_setnull():
    MOMSLRwse_minus_DEM_output_setnull(0)
    MOMSLRwse_minus_DEM_output_setnull(2)
    MOMSLRwse_minus_DEM_output_setnull(3)
    MOMSLRwse_minus_DEM_output_setnull(4)
    MOMSLRwse_minus_DEM_output_setnull(5)
```

```
# This process adds the IDW together with SLR at each elevation using the SUM of both rasters.
# It changes the name of the output file to match the SLR elevation being added to SLOSH

def MOSAIC_TO_NEW_raster_IDW_AND_SLR(slr_depth_INCREASE_integer=0):

    idw_wse="MOM_Cat5_IDW_Resample"
    slr_depth_rise_integer="SLR_Prep\SLR_2ft_vert_3.tif"
    slr_depth_rise_integer=   slr_depth_rise_integer.replace("2ft",str(slr_depth_INCREASE_integer) + "ft")
    inputs=idw_wse + ";" + "'" +  slr_depth_rise_integer    + "'"

    output_folder= r"D:\Education\USC\Thesis\Data\Sea Level Rise\z_MOM_SLR_v2000\IDW_SLR_comb"
    output_raster_name="MOM_SLR_2ft.tif"
    output_raster_name=output_raster_name.replace("2ft",str(slr_depth_INCREASE_integer) + "ft")

    extent_str="3304332.35927706 13886236.7893465 3338377.89880329 13899001.4851957 " + spat_ref
    with arcpy.EnvManager(compression="'LZW' 75", resamplingMethod="BILINEAR", extent=extent_str):

        arcpy.management.MosaicToNewRaster(inputs,output_folder, output_raster_name, spat_ref,
"32_BIT_FLOAT", None, 1, "SUM", "FIRST")


# Subtract the DEM from the previous step (MOSAIC_TO_NEW_raster_IDW_AND_SLR) to subtract the land
surface
def MOMSLRwse_minus_DEM_output_depth(slr_depth_INCREASE_integer=0):

    full_path_folder_slr =r"D:\Education\USC\Thesis\Data\Sea Level Rise\z_MOM_SLR_v2000\IDW_SLR_comb"
    full_path_folder_dem=r"D:\Education\USC\Thesis\Thesis_V2"

    dem_usgs="USGS_NED_13arcsec.tif"
    slr_input="MOM_SLR_2ft.tif"
    slr_input=  slr_input.replace("2ft", str(slr_depth_INCREASE_integer) + "ft")

    output_folder= r"D:\Education\USC\Thesis\Data\Sea Level Rise\z_MOM_SLR_v2000\IDW_SLR_comb"
    output_raster_name="MOMSLR_2ft_minus_DEM.tif"
    output_raster_name=output_raster_name.replace("2ft",str(slr_depth_INCREASE_integer) + "ft")
    outraster_full_path=os.path.join(output_folder,output_raster_name)

    string_inputs=slr_input   + " - " + dem_usgs


    rasters=[full_path_folder_slr + "\\" + slr_input, full_path_folder_dem + "\\" + dem_usgs]
    rasters=[slr_input,  dem_usgs]
    raster_names=[slr_input, dem_usgs]
    print(rasters[0])
    print(rasters[1])
    print(raster_names)
    print(string_inputs)
    with arcpy.EnvManager(outputCoordinateSystem=spat_ref, cellSize="MINOF"):
        output_raster = arcpy.sa.RasterCalculator(rasters,raster_names, string_inputs)
        output_raster.save(outraster_full_path)
    print("yeah, saved to ","\n",outraster_full_path)
```

```
# SetNull to remove cells that are not water surface elevations.
# This steps creates the final water surface elevation of the combined SLOSH and different SLR elevations.

def MOMSLRwse_minus_DEM_output_setnull(slr_setnull_INCREASE_integer=0):
    input_full_path = r"D:\Education\USC\Thesis\Thesis - Semester 2\Thesis_V4\z_MOM_SLR_v2100
\MOM_SLR_minus_DEM_3\MOMSLR_2ft_minus_DEM.tif"
    input_MOMSLR_DEM_setnull = "MOM_SLR_minus_DEM_3\MOMSLR_2ft_minus_DEM.tif"
    input_MOMSLR_DEM_setnull=input_full_path.replace("2ft", str(slr_setnull_INCREASE_integer) + "ft")

    output_folder= r"D:\Education\USC\Thesis\Thesis - Semester 2\Thesis_V4\z_MOM_SLR_v2100
\MOM_SLR_DEM_Setnull_4"
    output_raster_name="MOMSLR_DEM_2ft_Setnull.tif"
    output_raster_name=output_raster_name.replace("2ft",str(slr_setnull_INCREASE_integer) + "ft")

    print(input_MOMSLR_DEM_setnull)

    out_raster = arcpy.sa.SetNull(input_MOMSLR_DEM_setnull, input_MOMSLR_DEM_setnull, "VALUE < 0");
    out_raster.save(output_folder + '\\'+ output_raster_name)
```

Appendix B. Scale Factor Reclassification

Field calculator calculations for each scale factor reclassification

Below poverty level/low income:

```
reclass(!Total_Poverty!)

def reclass(Total_Poverty):
 if (Total_Poverty <= 49):
  return 1
 elif (Total_Poverty >= 50 and Total_Poverty <=99):
  return 2
 elif (Total_Poverty >= 100 and Total_Poverty <= 149):
  return 3
 elif (Total_Poverty >= 150 and Total_Poverty <= 199):
  return 4
 elif (Total_Poverty >= 200):
  return 5
```

Unemployed:

```
reclass(!Total_Unemployed_1!)

def reclass(Total_Unemployed_1):
 if (Total_Unemployed_1 <= 49):
  return 1
 elif (Total_Unemployed_1 >= 50 and Total_Unemployed_1 <=99):
  return 2
 elif (Total_Unemployed_1 >= 100 and Total_Unemployed_1 <= 149):
  return 3
 elif (Total_Unemployed_1 >= 150 and Total_Unemployed_1 <= 199):
  return 4
 elif (Total_Unemployed_1 >= 200):
  return 5
```

No high school education:

```
reclass(!Total_noDiploma!)

def reclass(Total_noDiploma):
 if (Total_noDiploma <= 199):
  return 1
```

```
 elif (Total_noDiploma >= 200 and Total_noDiploma <=299):
  return 2
 elif (Total_noDiploma >= 300 and Total_noDiploma <= 399):
  return 3
 elif (Total_noDiploma >= 400 and Total_noDiploma <= 599):
  return 4
 elif (Total_noDiploma >= 600):
  return 5
```

Elderly (65 over):

```
reclass(!Total_65!)

def reclass(Total_65):
 if (Total_65 <= 199):
  return 1
 elif (Total_65 >= 200 and Total_65 <=299):
  return 2
 elif (Total_65 >= 300 and Total_65 <= 399):
  return 3
 elif (Total_65 >= 400 and Total_65 <= 499):
  return 4
 elif (Total_65 >= 500):
  return 5
```

Young (under 5):

```
reclass(!Total_Und_5!)

def reclass(Total_Und_5):
 if (Total_Und_5 <= 99):
  return 1
 elif (Total_Und_5 >= 100 and Total_Und_5 <= 199):
  return 2
 elif (Total_Und_5 >= 200 and Total_Und_5 <= 299):
  return 3
 elif (Total_Und_5 >= 300 and Total_Und_5 <= 399):
  return 4
 elif (Total_Und_5 >= 400):
  return 5
```

Disabled:

```
reclass(!Total_Disability!)
```

```
def reclass(Total_Disability):
 if (Total_Disability <= 199):
  return 1
 elif (Total_Disability >= 200 and Total_Disability <=299):
  return 2
 elif (Total_Disability >= 300 and Total_Disability <= 399):
  return 3
 elif (Total_Disability >= 400 and Total_Disability <=499):
  return 4
 elif (Total_Disability >= 500):
  return 5
```

Single parents:

```
reclass(!Total_SingleParents!)

def reclass(Total_SingleParents):
 if (Total_SingleParents <= 49):
  return 1
 elif (Total_SingleParents >= 50 and Total_SingleParents <=99):
  return 2
 elif (Total_SingleParents >= 100 and Total_SingleParents <= 149):
  return 3
 elif (Total_SingleParents >= 150 and Total_SingleParents <=199):
  return 4
 elif (Total_SingleParents >= 200):
  return 5
```

Do not speak English well:

```
reclass(!Total_Eng!)

def reclass(Total_Eng):
 if (Total_Eng <= 199):
  return 1
 elif (Total_Eng >= 200 and Total_Eng <=299):
  return 2
 elif (Total_Eng >= 300 and Total_Eng <= 399):
  return 3
 elif (Total_Eng >= 400 and Total_Eng <=499):
  return 4
 elif (Total_Eng >= 500):
  return 5
```

Female:

```
reclass(!Total_Female!)

def reclass(Total_Female):
 if (Total_Female <= 399):
  return 1
 elif (Total_Female >= 400 and Total_Female <=699):
  return 2
 elif (Total_Female >= 700 and Total_Female <= 999):
  return 3
 elif (Total_Female >= 1000 and Total_Female <= 1499):
  return 4
 elif (Total_Female >= 1500):
  return 5
```

Black/African American:

```
reclass(!Total_Black_AfricanAmerican!)

def reclass(Total_Black_AfricanAmerican):
 if (Total_Black_AfricanAmerican<=199):
  return 1
 elif (Total_Black_AfricanAmerican>= 200 and Total_Black_AfricanAmerican<=299):
  return 2
 elif (Total_Black_AfricanAmerican>= 300 and Total_Black_AfricanAmerican<= 499):
  return 3
 elif (Total_Black_AfricanAmerican>= 500 and Total_Black_AfricanAmerican<= 699):
  return 4
 elif (Total_Black_AfricanAmerican>= 700):
  return 5
```

Asian:

```
reclass(!Total_Asian!)

def reclass(Total_Asian):
 if (Total_Asian <= 199):
  return 1
 elif (Total_Asian >= 200 and Total_Asian <=299):
  return 2
 elif (Total_Asian >= 300 and Total_Asian <= 399):
  return 3
```

```
 elif (Total_Asian >= 400 and Total_Asian <=499):
  return 4
 elif (Total_Asian >= 500):
  return 5
```

Hispanic:

```
reclass(!Total_Hispanic!)

def reclass(Total_Hispanic):
 if (Total_Hispanic <= 399):
  return 1
 elif (Total_Hispanic >= 400 and Total_Hispanic <=699):
  return 2
 elif (Total_Hispanic >= 700 and Total_Hispanic <= 999):
  return 3
 elif (Total_Hispanic >= 1000 and Total_Hispanic <= 1499):
  return 4
 elif (Total_Hispanic >= 1500):
  return 5
```

Persons in group quarters:

```
reclass(!Total_GroupQuaters_1!)

def reclass(Total_GroupQuaters_1):
 if (Total_GroupQuaters_1 <= 49):
  return 1
 elif (Total_GroupQuaters_1 >= 50 and Total_GroupQuaters_1 <=99):
  return 2
 elif (Total_GroupQuaters_1 >= 100 and Total_GroupQuaters_1 <= 149):
  return 3
 elif (Total_GroupQuaters_1 >= 150 and Total_GroupQuaters_1 <= 399):
  return 4
 elif (Total_GroupQuaters_1 >= 400):
  return 5
```

Renters:

```
reclass(!Total_Renters!)

def reclass(Total_Renters):
 if (Total_Renters <= 999):
```

```
  return 1
 elif (Total_Renters >= 1000 and Total_Renters <=1999):
  return 2
 elif (Total_Renters >= 2000 and Total_Renters <= 2999):
  return 3
 elif (Total_Renters >= 3000 and Total_Renters <=9999):
  return 4
 elif (Total_Renters >= 10000):
  return 5
```

No vehicle:

```
reclass(!Total_NoVehicles!)

def reclass(Total_NoVehicles):
 if (Total_NoVehicles <= 19):
  return 1
 elif (Total_NoVehicles >= 20 and Total_NoVehicles <=39):
  return 2
 elif (Total_NoVehicles >= 40 and Total_NoVehicles <= 79):
  return 3
 elif (Total_NoVehicles >= 80 and Total_NoVehicles <=99):
  return 4
 elif (Total_NoVehicles >= 100):
  return 5
```

Proximity to Public Transportation (Bus Stops):

```
reclass(!BusStops!)

def reclass(BusStops):
 if (BusStops ==0):
  return 5
 elif (BusStops >= 0 and BusStops <=5):
  return 4
 elif (BusStops >= 6 and BusStops <= 10):
  return 3
 elif (BusStops >= 11 and BusStops <= 20):
  return 2
 elif (BusStops >= 21):
  return 1
```