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**Impacts of projected sea level rise and storm intensification on storm surge flooding within
socially vulnerable coastal communities: A Case Study of Norfolk, Virginia, USA**

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Abstract

As sea levels rise and storms intensify due to climate change, coastal communities are expected to face heightened flood risk. This study assesses how projections of future coastal flooding events align with current flood risk zone designations in Norfolk, Virginia, one of the most at-risk cities in the United States to sea level rise. The ADvanced CIRCulation (ADCIRC) model was used to simulate storm surge dynamics for three major hurricane events—Hurricanes Isabel, Sandy, and Dorian—under both observed conditions and projected future scenarios, in which sea levels were increased by 0.2 meters and wind speeds by a factor of 1.1 to represent potential changes 40 years later. Model-simulated water surface elevations were integrated into ArcGIS Pro to map flood extents. These maps were overlaid with demographic data to conduct a spatial vulnerability analysis and quantify exposure to flood risk across different communities. Results show a consistent increase in flood extent across all three storms under future conditions—ranging from a 65% increase in inundation area for Hurricane Sandy to 89% for Hurricane Dorian—and indicate that future flooding will expand beyond the Federal Emergency Management Agency’s currently designated high-risk zones. Furthermore, the social vulnerability analysis revealed that flooding is projected to increase in areas that were already identified as high flood risk and socially vulnerable. These findings highlight critical gaps in current risk assessment frameworks and underscore the need to reevaluate coastal flood zone delineations, improve risk communication, and design more equitable adaptation strategies.

Key Words ADCIRC, storm surge, flooding, social vulnerability, sea level rise

Introduction

Floods are among the most destructive and pervasive natural hazards, causing widespread physical, social, and economic disruption (Fernandez et al., 2015). Along the world’s coastlines,

coastal flooding—particularly flooding induced by storm surge—is emerging as one of the most pressing climate change-related challenges. Storm surge, the rise in sea level generated by storm-driven winds and pressure changes, can inundate vast areas of coastal land and cause severe damage to infrastructure and communities (Resio & Westerink, 2008; Gornitz, 2021). In recent decades, both the frequency and intensity of storm surge events have increased as a consequence of rising sea levels and more powerful storms (Sweet et al., 2017; Hadipour et al., 2020).

Storm surge is one of the leading causes of coastal flooding and occurs when strong winds and low atmospheric pressure during hurricanes or other intense storms push seawater towards the coast, resulting in elevated water levels that inundate normally dry land (NOAA, 2024). The height and inland reach of storm surge depend on storm size and intensity, speed of its forward motion, angle of approach to the coast, tidal and sea levels, along with the coastal and seafloor topography (NOAA, 2024). Hurricanes are a primary driver of extreme storm surge events in the US Atlantic and Gulf Coasts (Resio & Westerink, 2008; Dietrich et al., 2011). Climate projections have indicated an increasing trend in hurricane intensity, as well as an increasing likelihood in storm surges (Pörtner et al., 2019). Warmer temperatures have increased the available energy for hurricanes, leading to storms that intensify more rapidly, generate stronger winds, and produce higher and more persistent storm surges (Osler et al., 2023). These processes compound with sea-level rise to elevate baseline water levels, causing even moderate storms to produce damaging floods.

Coastal regions are uniquely exposed to these hazards due to their low elevation, proximity to major water bodies, and dense development (Reidenbach et al., 2026). These areas, often referred to as Low-Elevation Coastal Zones (LECZs), are defined as contiguous coastal land that has an elevation less than ten meters above mean sea level (Helderop & Grubestic,

2019). LECZs tend to have significantly higher population density than non-coastal areas, with rates of population growth and urbanization increasing in response to the ongoing trend of coastal migration (Neumann et al., 2015). While LECZs only make up less than 2% of the Earth's surface, they are home to more than 10% of the global population (approximately 800 million people) and 40% of the U.S. population (Helderop & Grubestic, 2019; NOAA, 2020). As coastal communities continue to grow, more people are becoming exposed to worsening coastal hazards such as sea level rise, storm surge, and coastal flooding (Allen et al., 2021).

LECZs such as Norfolk, Virginia, exemplify the intersection of high physical exposure, accelerating sea-level rise, and concentrated population and infrastructure, making them critical areas for understanding and modeling storm surge risk. Norfolk is surrounded by water on three sides, as it is located between the Chesapeake Bay and the Elizabeth River, with an average elevation of two meters above mean sea level. The low elevation of the area, coupled with its proximity to waterways, makes Norfolk highly susceptible to sea-level rise and increased exposure to flood hazards. Furthermore, Norfolk is experiencing one of the highest rates of sea-level rise on the East Coast of the United States, with sea levels rising nearly 5.6 millimeters annually and projected to be 0.47 meters above the current MSL (mean sea level rise) by 2050 (Boon et al., 2018). In addition to the physical characteristics of Norfolk, the societal importance of the area further contributes to its vulnerability to sea level rise, as it is densely populated and an important national security and economic hub, being the home of the world's largest naval base.

Many communities, such as Norfolk, rely on floodplain maps to identify, manage, and mitigate flooding events and the associated risks. The Federal Emergency Management Agency (FEMA) produces Flood Insurance Risk Maps (FIRMs) that delineate floodplains, displaying

88 flood zones and areas designated as Special Flood Hazard Areas. FEMA defines high-risk areas
89 to have a 1% chance or higher of experiencing a flood each year (FEMA, 2005). FEMA defines
90 a flood as “a general and temporary condition of partial or complete inundation of 2 or more
91 acres of normally dry land area or of 2 or more properties (at least 1 of which is the
92 policyholder's property)” that occurs from multiple flooding scenarios, including, in the context
93 of this paper, an overflow of tidal waters (FEMA, 2020). FIRMs provide an integral public
94 service, as they are used by communities to help determine flood insurance rates for the National
95 Flood Insurance Program (NFIP), guide floodplain management regulations, and promote
96 community awareness by providing the public with information about current flood hazards in
97 their community. FIRMs are created using a variety of data including historic meteorological and
98 hydrologic data, open-space conditions, flood control works, information on development and
99 land use, and topographic data (FEMA, 2005).

100 FEMA is required to update flood maps every five years as flood risks are not static and
101 change over time due to a variety of factors, including changes in land use patterns and climate
102 change impacts. The FIRM for Norfolk was most recently updated in 2017. Currently, FEMA
103 does not incorporate future climate projections, such as sea level rise or increasing storm
104 intensities, in the creation of its flood maps, making it likely that current FIRMs underestimate
105 future coastal flood exposure in vulnerable LECZs like Norfolk (Lehmann, 2020). Updating
106 these maps to reflect projected climate conditions and surge dynamics is critical for effective risk
107 communication and resilience planning.

108 To address these limitations, physically based hydrodynamic models such as the
109 ADvanced CIRCulation (ADCIRC) model can simulate storm surge under both historical and
110 future climate scenarios. ADCIRC is a powerful computational tool widely used for simulating

storm surges, tides, and coastal circulation, making it valuable for floodplain and flood hazard mapping (Luettich et al., 1992). By calibrating model input parameters, such as wind speed, atmospheric pressure, precipitation patterns, and sea level rise, ADCIRC can quantify how coastal and riverine systems may respond to varying climate conditions, allowing for the prediction of the potential impacts of more frequent and/or severe storms and long-term sea level rise on flood risk and coastal dynamics (Hill et al., 2009).

Hydrodynamic models are essential tools for predicting and understanding coastal flooding, particularly in the context of increasing storm intensity and sea level rise. Models such as ADCIRC are widely used in flood mapping because they simulate coastal hydrodynamics over complex landscapes, providing spatially explicit outputs such as flood extent, water depth, and flow velocity (Dietrich et al. 2011; Yin et al. 2016). These outputs are crucial for quantifying flood hazards and informing risk assessments. FEMA relies on several hydrodynamic and wave models, including HEC-RAS (Hydrologic Engineering Center's River Analysis System), ADCIRC, and SWAN (Simulating Waves Nearshore), to develop FIRMs and other flood hazard mapping products (FEMA, 2017).

Previous studies have demonstrated the effectiveness of these models in capturing the multifaceted nature of coastal flooding. For example, Castrucci and Tahvildari (2018) used Delft3D to assess the vulnerability of flood-prone localities in the Hampton Roads region, including the city of Norfolk, under several sea level rise projections. Although Delft3D was used in this case, the study highlights the broader utility of hydrodynamic modeling suites, such as ADCIRC, in simulating storm surge and coastal processes. Given that storm surges are among the primary hazards associated with hurricanes, hurricane events are commonly used to simulate the impacts of storm surge flooding. Irish et al. (2014) used ADCIRC's hindcasting capabilities

to simulate Hurricane Katrina under sea level and climate conditions from 1900 to provide insight regarding future coastal inundation trends in the greater New Orleans area in Louisiana. Kim et al. (2021) advanced this approach by integrating inland and coastal models to simulate hurricane-induced flooding in the Southeast Texas region, offering a more comprehensive view of inundation patterns and enhancing predictive capabilities for emergency planning and resilience efforts.

As coastal flooding becomes more frequent, this can lead to many implications for the communities at risk, including frequent road closures, increased erosion, saltwater intrusion, reduced stormwater drainage capacity, and deterioration and destruction of infrastructure and homes that were not built to withstand frequent inundation and exposure to saltwater (Crimmins et al., 2023). Furthermore, the inundation of coastal areas can reduce the capacity of communities to retreat or adapt to the hazard. This is especially apparent in socially disadvantaged coastal communities, which are often disproportionately affected by sea level rise and have a history of underinvestment in infrastructure (Martinich et al. 2013; Best et al., 2023). In these areas, the built environment is less resilient to the shock of natural disasters and sea level rise, and communities have a reduced capacity to prepare for, respond to, and adapt to natural hazards. Disproportionately impacted communities include racial minorities, older populations, renters, persons with disabilities, and low-income communities (Best et al., 2023).

To assess the impacts of sea level rise and increased storm intensity on storm surge flooding, this study utilizes ADCIRC simulations of three hurricane events: Isabel (2003), Sandy (2012), and Dorian (2019). Specifically, this study aims to answer the following questions: (1) How do projections of sea level rise and storm intensification affect the extent and depth of storm surge flooding in Norfolk, Virginia? (2) How do projections of future flooding intersect

with current FEMA flood risk zone designations? (3) What are the relationships between flood risk and social vulnerability, and how do flooding projections interact with these relationships?

2: Methods

2.1 Site Description

The study area encompasses the city limits of Norfolk (Fig. 1). Norfolk is a low-lying coastal city located on a peninsula in southeastern Virginia and is part of the greater Hampton Roads metropolitan region. Norfolk is the fourth most populous city in Virginia, as it is home to over 230,000. It encompasses approximately 170 square kilometers, and has 11 kilometers of beachfront along the Chesapeake Bay, with a total of 373 kilometers of shoreline along its lakes, rivers, and the Bay (The City of Norfolk, n.d.). Norfolk is naturally low-lying, with an average elevation of four meters, ranging from seven meters below sea level to 42 meters above sea level.



Fig. 1 Map of the Norfolk study area. Service layer image credits: VGIN, Esri, TomTom, Garmin, SafeGraph, GeoTechnologies, Inc, METI/NASA, USGS, EPA, NPS, USDA, USFWS

2.2 ADCIRC Description and Model Setup

To determine the future implications of sea level rise and storminess on flood risk in Norfolk, the ADCIRC hydrodynamic model was used to conduct simulations under historic and projected future climate conditions. ADCIRC solves fluid motion equations (such as the continuity equation and the momentum equations) on a rotating Earth, utilizing an unstructured finite-element mesh to represent complex coastal geometries and bathymetry (Luettich et al., 1992). The model can be run in two-dimensional or three-dimensional barotropic modes and computes water elevation and velocity (Hill et al., 2009). ADCIRC inputs include bathymetry, tidal forcing conditions, and atmospheric wind and pressure fields, while primary outputs include the change in water surface elevation over time and velocity fields that characterize coastal and estuarine circulation.

ADCIRC's ability to integrate atmospheric data with hydrodynamic processes makes it well-suited for simulating water level responses to extreme weather events such as hurricanes and severe storms (Hill et al., 2009). The high-resolution capacities of ADCIRC allow for precise modeling of water movement through complex coastal, estuarine, and riverine systems, helping to identify vulnerable areas, inform mitigation strategies, and guide infrastructure planning (Hill et al., 2009).

2.3 Model Domain, Mesh, and Forcing

Storm surge simulations were conducted using output from a well-tested ADCIRC model for the mid-Atlantic region, from which results for the Norfolk region and the Eastern Shore of Virginia were extracted to quantify flooding patterns. The model is based on the FEMA_R3_2010 ADCIRC mesh and bathymetry, which was developed for storm surge risk assessment across the mid-Atlantic region (Blanton et al., 2011). The computational grid

contains approximately 1.7 million nodes and spans the western North Atlantic Ocean, the Gulf of Mexico, and the Caribbean Sea. This large model domain allows dynamic coupling between the open ocean, continental shelf, and coastal floodplains, enabling realistic simulation of storm surge generation and propagation.

The mesh resolution is approximately 2 km in the open ocean and is progressively refined toward the coastline, reaching a finest resolution of about 30 m in coastal areas to better resolve topographic features such as tidal channels and coastal floodplains (Fig. 2a). Tidal boundary conditions along the outer eastern boundary are prescribed using the regional Atlantic Ocean Inverse Solution of TOPEX/Poseidon (TPXO) tidal model (Egbert & Erofeeva, 2002). The tidal constituents included in the simulations are M_2 , N_2 , S_2 , K_2 , K_1 , O_1 , P_1 , and Q_1 .

Three historic storm surge events were selected for simulation: Hurricane Isabel (2003), Hurricane Sandy (2012), and Hurricane Dorian (2019) (Fig. 2b). Each event was simulated over a 15-day period, including a 3-day model spin-up, with a model time step of 1 s. Hourly spatially varying wind and atmospheric pressure fields from the ERA5 reanalysis dataset provided by the Copernicus Climate Change Service were used to drive the model for each event. The simulations were executed in parallel mode on the Research Computing Platform at the University of Virginia.

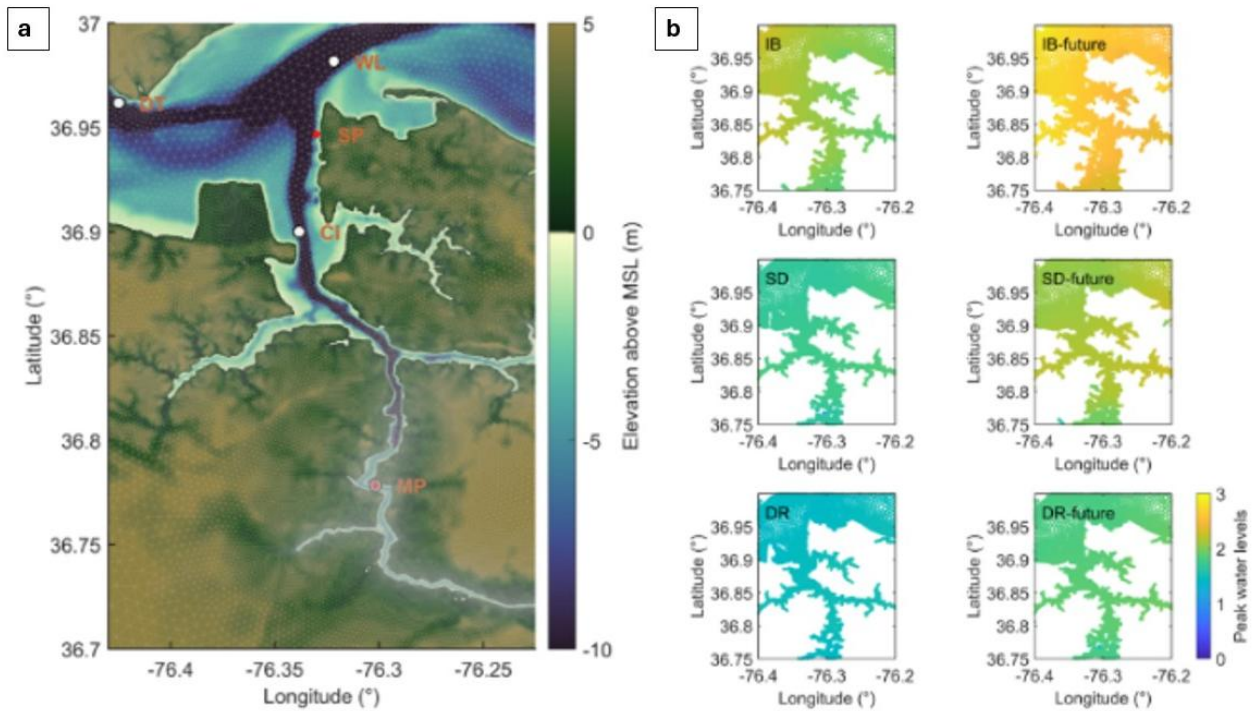


Fig. 2a ADCIRC model grid and depth for Norfolk, VA along with NOAA tide gauge stations used in the validation process (CI = Craney Island Light, MP = Money Point, SP = Sewells Point) **Fig. 2b** ADCIRC output (elevation above mean sea level, in meters) for each of the six storm simulations (IB = Hurricane Isabel, SD = Hurricane Sandy, DR = Hurricane Dorian)

2.4 Model Validation

Model performance was evaluated by comparing simulated water levels with observations from NOAA tide gauge stations including Wachapreague (ID 8631044), Kiptopeke (ID 8632200), and Sewells Point (ID 8638610), for the three simulated storm events (Zhu & Wiberg, 2023). Model skill was quantified using statistical metrics, including bias, coefficient of determination (R^2), and root mean square error (RMSE). Overall, the ADCIRC simulations show good agreement with observed water levels across all events (Fig. 3).

For Hurricane Isabel, the model produced an average bias of 0.02 m, an R^2 of 0.86, and an RMSE of 0.14 m. For Hurricane Sandy, the average bias was -0.12 m, with an R^2 of 0.85 and an RMSE of 0.17 m. For Hurricane Dorian, the model yielded an average bias of -0.13 m, an R^2 of 0.76, and an RMSE of 0.18 m across the three validation stations.

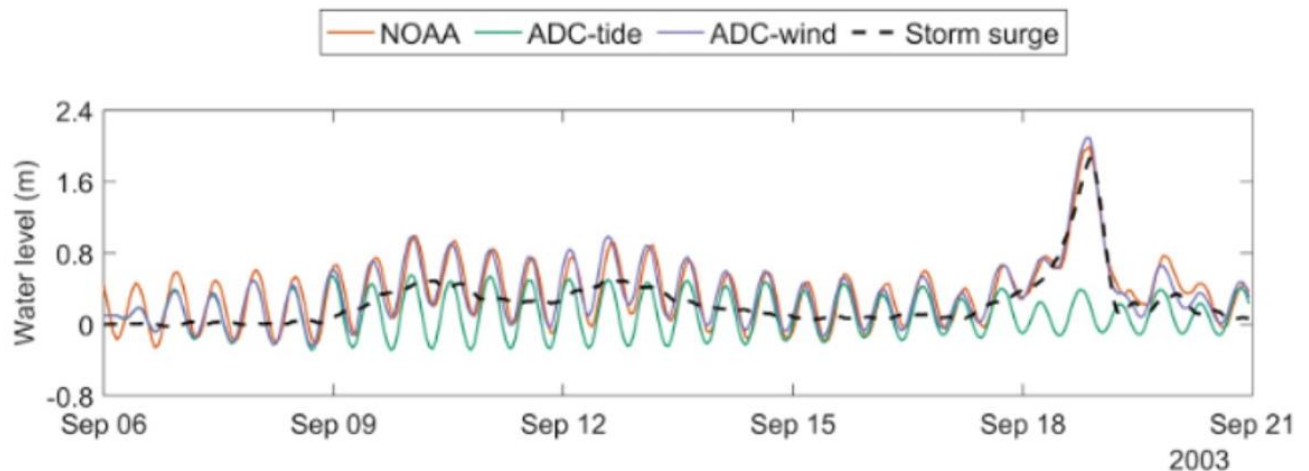


Fig. 3 Validation of ADCIRC model for the Norfolk domain against the NOAA tide gauge station at Sewells Point. This simulation had an average bias of 0.02m, an R^2 value of 0.86, and an RMSE of 0.14m

2.5 Future Climate Scenario Simulations

To assess potential future flood risks associated with climate change, the validated historic storm simulations were modified to represent projected future conditions. In general, ADCIRC future scenario simulations involved adjusting boundary conditions and forcing parameters to reflect anticipated changes in sea level and storm characteristics while maintaining the same underlying mesh and domain configuration (Hill et al., 2009).

To evaluate potential future storm flooding risks associated with climate change, three additional ADCIRC simulations were conducted, representing conditions 40 years after each of the historic storm events. In these future scenarios, the mean sea level was increased by 0.2 m, consistent with the local sea-level rise rate of approximately 5 mm yr^{-1} over a 40-year period. In addition, wind speeds were increased by 10% (a factor of 1.1) based on the observed long-term trend in wind speed over the past four decades at a nearby offshore wave buoy (Station ID: CHLV2) from NOAA's National Data Buoy Center.

These future simulations allow for comparison between historic and projected conditions, enabling the assessment of the combined effects of sea-level rise and increased storm intensity on storm surge extent and coastal flooding patterns in Norfolk and surrounding regions.

2.6 Applications of GIS

The resulting water level elevation output for both the historic storm events and corresponding future climate scenarios (six total simulations) were imported into ArcGIS to conduct the spatial analysis assessing the impact of sea level rise and increased storminess on flood risk. GIS has been used in previous studies as a link between ADCIRC and spatial analysis, providing a technique to estimate the flood inundation depths and extents of the storm simulations (Choi et al., 2019).

The first step of this process included preparing a floodplain map of Norfolk that delineates flood risk into high, moderate, and low-risk levels. The FEMA Flood Map Service Center (MSC) is a public source providing flood hazard information and flood risk products, including a coastal geodatabase containing GIS data for the delineation of flood zones based on the FIRM for the Norfolk area (FEMA, 2017). The flood zones delineated by the FIRM were reclassified into high, moderate, and low flood-risk zones based on the definitions of flood hazard zones provided by the Virginia Flood Risk Information System (VFRIS) and the Virginia Institute of Marine Science (VIMS) (Fig. 4 and Table 1).

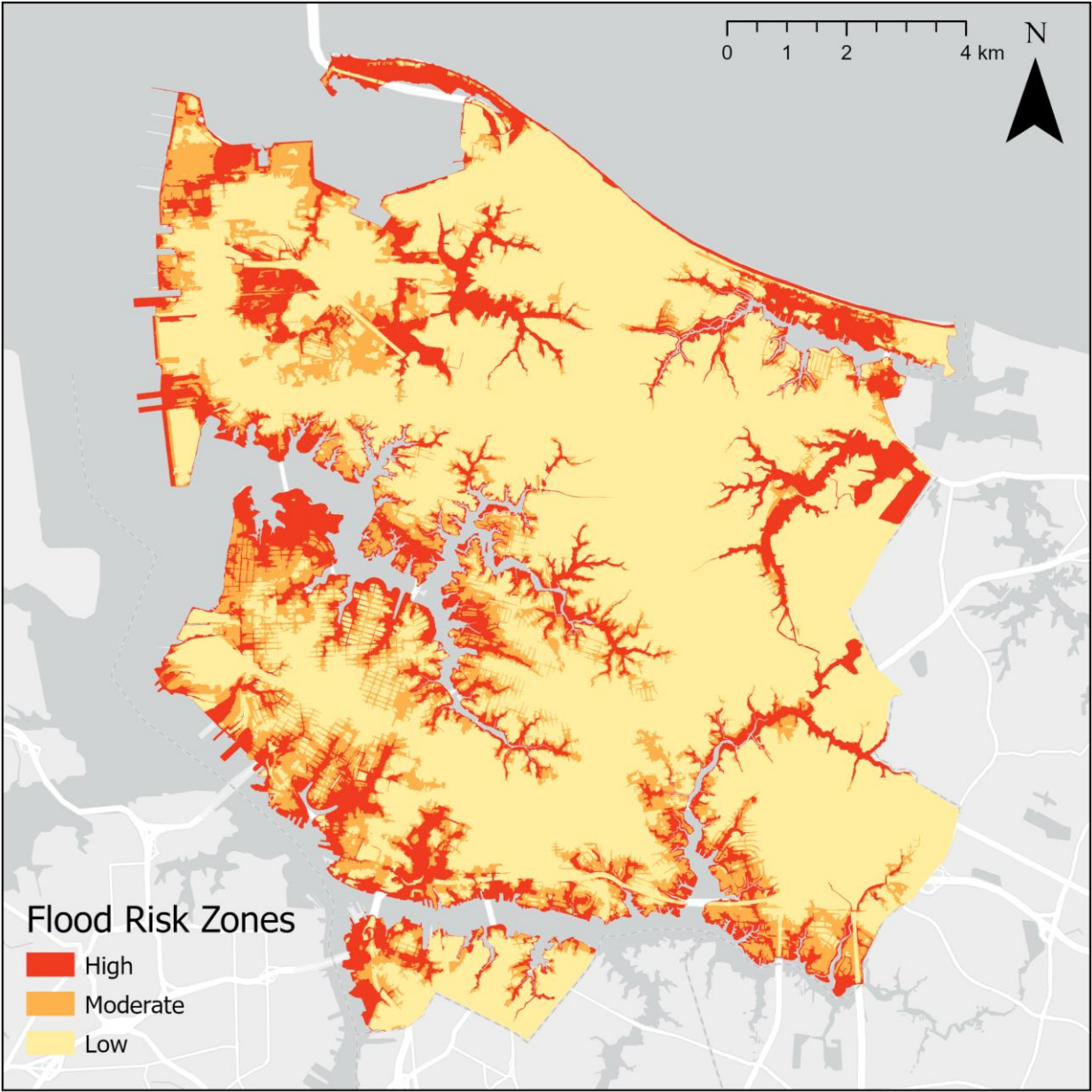


Fig. 4 Flood Risk Zones in Norfolk, Virginia. Reclassified from the FEMA’s Flood Insurance Rate Map (FIRM)

Table 1. Flood hazard zone definitions modified from the Virginia Institute of Marine Science (adapted from Virginia Institute of Marine Science “Find Your Property’s Flood Zone”)

Flood Hazard Classification	Area Designation	Definition	FIRM Zones
High Flood Risk Areas	Special Flood Hazard Area (SPHA)	The area that will be inundated by the flood event has a 1% chance of being equaled or exceeded in any given year. Also referred to as base flood or 100-year floodplain.	All A and V Zones

	Regulatory Floodway	The channel of a river or other watercourse and the adjacent land areas must be reserved to discharge base flood.	Within Zone AE
Moderate Flood Risk Areas	Area of Moderate Flood Hazard	The area between the limits of the 1% flood (SFHA) and the 0.2% of being equaled or exceeded in any given year. Also referred to as the 500-year floodplain.	Zone X (shaded) and Zone B
Low Flood Risk Areas	Area of Minimal Flood Hazard	The area is outside the SFHA and higher than the elevation of the 0.2% annual-chance flood.	Zone X (unshaded) and Zone C
Other Flood Risk Areas	Area of Undetermined Flood Hazard	The area with a possible, but undetermined flood risk, as no analysis of flood hazards has been conducted.	Zone D
	Area of Reduced Risk Due to Levee	The area protected by a levee, reducing the flood risk.	Zone X with reduced risk due to levee.

267 The original ADCIRC output consisted of time series data displaying variations in water
 268 level at each model mesh throughout the storm event rather than spatial data. To obtain spatial
 269 data, the time of peak water level, or maximum storm-surge conditions, was identified for each
 270 of the storm events (Choi et al., 2019). At this peak time, spatial data, including the latitude,
 271 longitude, and water elevation relative to the mean sea level for each point on the model mesh,
 272 were extracted. This output was then imported into ArcGIS Pro as a .csv file. Point layers for
 273 each of the six simulations were generated to display inundation points on the model mesh.
 274 These point layers were then clipped to the study region and masked using a hydrology layer to
 275 exclude points over water, ensuring that only land inundation points were identified and
 276 displayed.

277 Further data processing was conducted in ArcGIS, including the substitution of NaN
 278 values with -9999, a standard GIS convention for missing data, to prevent confusion with valid
 279 elevation values (e.g., 0 meters). A definition query (water level elevation > -9999) was applied
 280 to exclude missing values from the inundation point layer.

Since ADCIRC output represents water elevation relative to mean sea level, it was necessary to subtract land elevation to determine inundation depth, which is defined in this study as the total water that occurs on normally dry ground resulting from storm surge. Elevation values were extracted from a Digital Elevation Model (DEM) of Norfolk (USGS, 2021) for each inundation point, adding an elevation field to the attribute table. Inundation depth was then calculated by subtracting land elevation from water elevation, where positive values indicate areas where water levels exceeded the land surface. A Wilcoxon Signed-Rank test for paired samples was conducted to determine whether there was a significant difference in inundation depth between the simulations for each storm event (Welsch & Neuhäuser, 2025).

To estimate the extent of inundation, a buffer was applied to each ADCIRC-generated inundation point. The initial approach was to base the buffer size on the average spacing between nodes in the ADCIRC model mesh for Norfolk. However, because the model mesh is not uniformly distributed—meaning node spacing varies across the domain—this method led to inconsistencies in the resulting inundation surface. A buffer size of 175 meters was selected through an iterative process, as it effectively minimized both gaps between buffer rings (which could underestimate inundation extent) and excessive overlap (which could overestimate it), resulting in a more spatially continuous and representative inundation area.

The boundaries of the buffers were then dissolved to create a single polygon layer representing the total inundation area for each storm event. A percent change analysis was conducted to determine how both inundation area and mean inundation depth may be increasing from historic to future storm events.

An intersection analysis was used to determine areas where flooding, as predicted by the ADCIRC simulations, overlapped with FEMA-designated flood zones. The inundation extent

map and the flood risk map were then combined, and the resulting inundation extent polygon layer was reclassified according to flood risk designations. Then, the total area of each flood zone was calculated within the inundation extent. This process was repeated for each flood zone and storm simulation.

The mean inundation depth for each flood zone was calculated using the same attribute selection process, which involved extracting and averaging the inundation depth within each flood zone classification.

2.7 Social Vulnerability Analysis

The 2022 Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry Social Vulnerability Index (hereafter referred to as the SVI) dataset was utilized for the demographic analysis. This dataset was developed to support efforts in mapping and identifying communities that are most likely to require assistance before, during, and after hazardous events. The SVI measures the relative vulnerability of each U.S. census tract based on sixteen social factors, such as unemployment, age, minority status, disability status, and housing type. Social vulnerability has several definitions, but in this study, it refers to ‘characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist, or recover from the impact of a hazard’ (Cutter et al., 2003).

A few studies have assessed social vulnerability to sea level rise and storm surge in the Hampton Roads region, particularly Norfolk. Kleinosky et al. (2006) used US Census data to build a social vulnerability index which was compared to current and future storm-surge risk zones produced from the SLOSH (Sea, Lake, and Overland Surges from Hurricanes) model. Liu et al. (2015) also used storm surge flooding zones from the SLOSH model in conjunction with household conditions (including storm preparedness, financial constraints, and health fragility) to

assess the vulnerability of populations in 12 coastal localities of Virginia. This study expands on prior work by incorporating simulated future flooding events to evaluate how both flood risk and social vulnerability may shift under projected climate conditions, and by examining how these future patterns correspond to current federal flood zone designations. Additionally, this study draws on a more extensive set of social vulnerability indicators, enabling a more comprehensive assessment of population risk across Norfolk.

In this study, sixteen variables were selected and placed into one of the four overarching themes of vulnerability: Socioeconomic Status, Household Characteristics, Racial & Ethnic Minority Status, and Housing Type & Transportation. The categorization of the sixteen variables into the four themes was already predetermined within the SVI dataset by the CDC/ASTDR (Table 2).

Table 2. *Social Vulnerability Index (SVI) Variables. Adapted from the Center for Disease Control (CDC) CDC/ATSDR Social Vulnerability Index*

Social Vulnerability Theme	Variable Name	Definition
Socioeconomic Status	POV150	Below 150% Poverty
	UNEMP	Unemployed
	HBURD	Housing Cost Burden
	NOHSDP	No High School Diploma
	UNINSUR	No Health Insurance
Household Characteristics	AGE65	Aged 65 & Older
	AGE17	Aged 17 & Younger
	SNGPNT	Single-Parent Households
	LIMENG	English Language Proficiency
	DISABL	Civilian with a Disability
Racial and Ethnic Minority Status	MINRTY	Hispanic or Latino (or any race) Black or African American, Not Hispanic or Latino Asian, Not Hispanic or Latino American Indian or Alaska Native, Not Hispanic or Latino Native Hawaiian or Pacific Islander, Not Hispanic or Latino

		Two or More Races, Not Hispanic or Latino
		Other Races, Not Hispanic or Latino
	MUNIT	Multi-Unit Structures
	MOBILE	Mobile Homes
	CROWD	Crowding
	GROUPQ	Group Quarters
	NOVEH	No Vehicle

Each variable reflects a dimension of social vulnerability that may affect a community's ability to prepare for, respond to, and recover from flood events. Low-income individuals, for example, often lack the financial resources needed for evacuation, floodproofing, insurance, or post-disaster recovery, increasing their risk during flood events (Cutter, 2003). Similarly, households experiencing housing cost burden may have limited disposable income for emergency preparedness or rebuilding efforts. A lack of health insurance can restrict access to medical care before, during, and after a flood, compounding both immediate and long-term health risks (Davlasheridze & Fan, 2025). Age is also a key factor, as individuals at both ends of the spectrum, children and older adults, tend to have greater physical vulnerability and dependence on caregivers, which can limit their ability to evacuate or respond effectively in emergencies (Fernandez et al., 2015). Individuals with disabilities may face a range of challenges during flood events (including mobility, communication, and healthcare access barriers) that increase their exposure and hinder timely evacuation or assistance (Morales, 2025). Minority populations are disproportionately affected by flooding due to a combination of systemic inequities in infrastructure investment, emergency response, and access to resources (Eghdami et al., 2023). Housing characteristics also play a role: residents in overcrowded households or multi-unit structures may face greater challenges in evacuation and recovery, including limited space, shared infrastructure, and constrained mobility (Fernandez et al., 2015). Lastly, households without access to a personal vehicle face significant barriers to evacuation,

particularly in areas where public transit is limited or unreliable, increasing their exposure during flood events (Morales, 2025).

The SVI dataset was joined to a census tract shapefile for the City of Norfolk using the Federal Information Processing Standards (FIPS) geographic identifier, which allowed for a spatial analysis to be performed to identify patterns between flooding and social vulnerability. The SVI dataset contains the variable “RPL_THEME”, which represents the percentile ranking for each specific social vulnerability theme, with “RPL_THEME1” for Socioeconomic Status, “RPL_THEME2” for Household Characteristics, “RPL_THEME3” for Racial and Ethnic Minority Status, and “RPL_THEME4” for Housing Type & Transportation. Percentile ranking values range from 0 to 1, with higher values indicating greater social vulnerability.

The Natural Breaks (Jenks) method was employed to reclassify the percentile ranking values for each of the four vulnerability themes into five risk classes (Papaioannou et al., 2015). This method is one of the most common methods for the classification of flood risk areas and divides the data into classes based on groups inherent in the data distribution, aiming to reduce variance within classes and maximize variance between classes (Jenks, 1967). In this study, the five classes of social vulnerability are very low, low, moderate, high, and very high (Fig. 5).

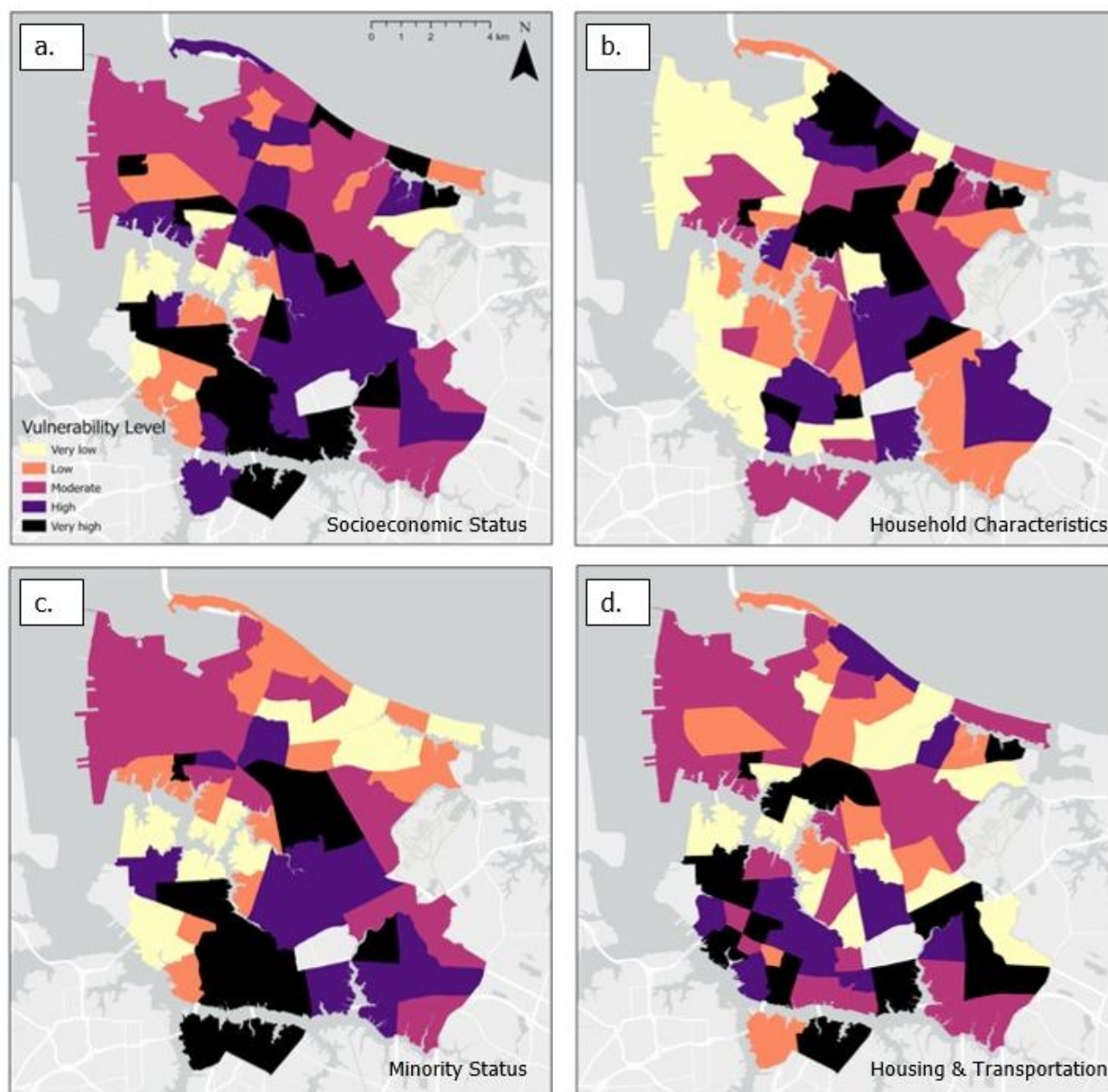


Fig. 5 Choropleth maps of the four social vulnerability themes: **a.** socioeconomic vulnerability, **b.** household characteristics, **c.** minority status, and **d.** housing & transportation type (CDC/ASTDR, 2022). Each vulnerability theme is broken into five classes, spanning from very low social vulnerability to very high

To identify where high social vulnerability coincides with flood risk within the flooding extent of the storm simulations, a hot spot analysis was conducted. First, the FIRM flood risk layer and the census tract layer with the corresponding SVI data were converted from polygon layers into rasters. Next, the rasters were reclassified so that the categorical variables have an

assigned numerical value. For example, the flood risk classes of “high,” “moderate,” and “low” were assigned values of 3, 2, and 1, respectively. For each of the four vulnerability themes, the field “RPL_THEME” was reclassified into five classes (“very low”, “low”, “moderate”, “high”, and “very high”) using the Jenks Natural Breaks method. Thus, flood risk has a range of 1 to 3, and social vulnerability has a scale of 1 to 5 (where “very low” was assigned a value of 1 and “very high” a value of 5).

Then, the flood risk scores were multiplied by the vulnerability scores, resulting in a product ranging from 1 to 15, which created a composite index (drawing from the methods of Kleinosky et al., 2006, which multiplied social vulnerability scores by flood risk scores to assess overall vulnerability). The resulting layers were then masked with the inundation layers from the historic and future simulations of Hurricane Isabel, which was selected for the social vulnerability analysis because it exhibited the largest increases in inundation area under future climate conditions. Hotspots were identified as areas having both high flood risk and high vulnerability (with a product of greater than 7). Following the creation of the composite index map, a series of matrices was produced to display the changes in inundation area under future climate conditions within each flood risk zone and social vulnerability class.

Because both flood risk zones and SVI levels were treated as static variables, using the same datasets for historic and future simulations, the spatial intersections between flood risk and social vulnerability remained unchanged in future scenarios. Instead, increased inundation in the future scenario exposed a greater extent of these pre-existing vulnerable areas.

Results

3.1 ADCIRC Water Levels

The resulting water levels for future ADCIRC simulations of each of the three hurricanes were approximately 0.2 m higher than the observed water levels during the historic storm event, suggesting a sea level rise of 20 cm in 40 years (Fig. 6). Even though the modeled sea level rose by 0.2 m, at the peak time during Hurricane Isabel, there was a 0.6 m increase in water levels (indicating an elevated storm surge).

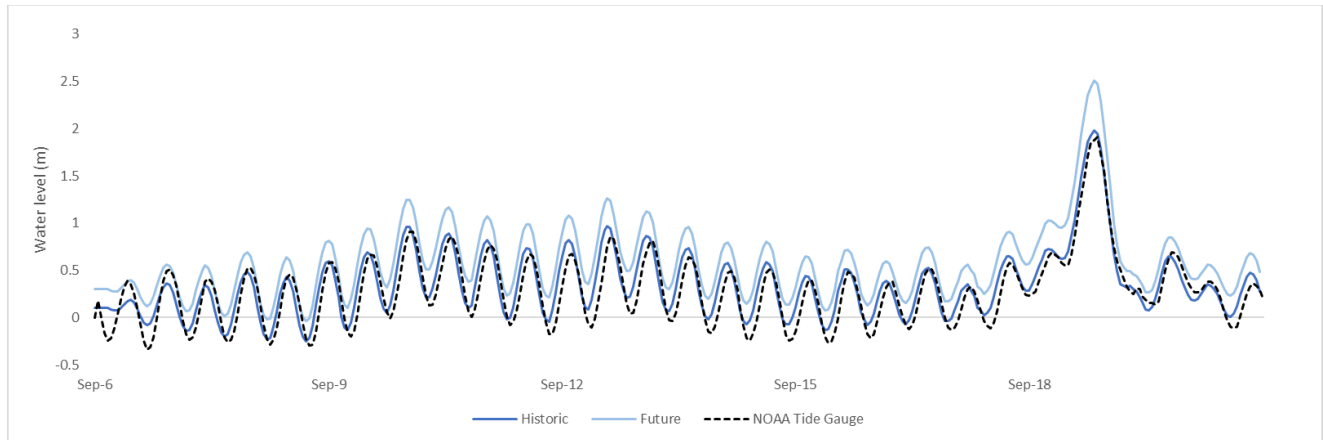
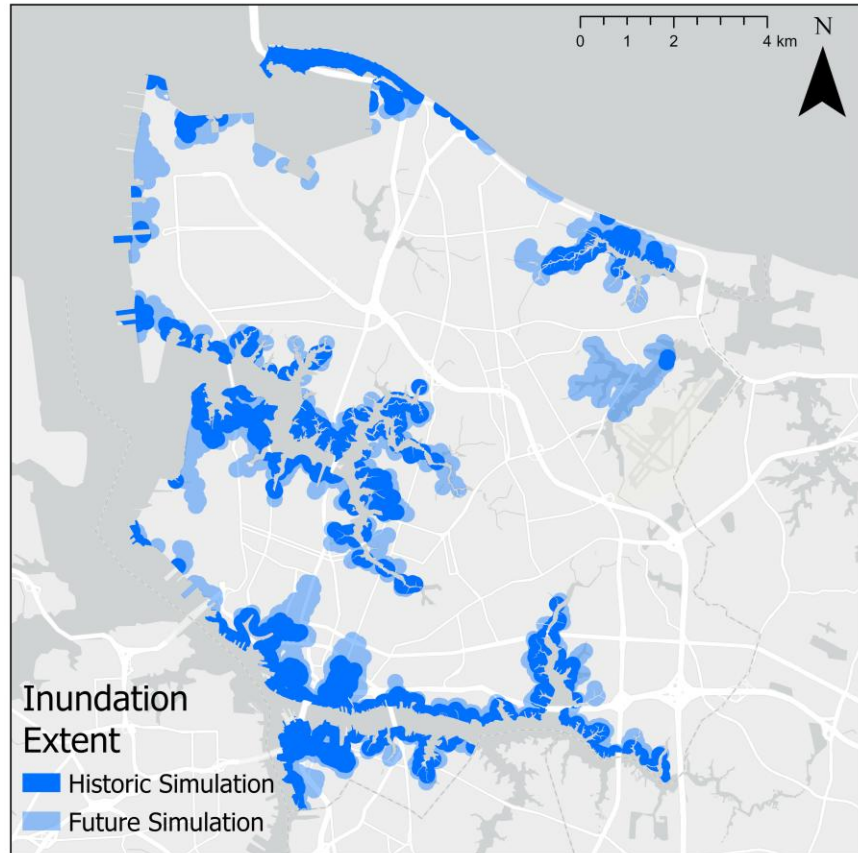


Fig. 6 Comparison of water levels (in meters) between the historic and future ADCIRC simulations of Hurricane Isabel along with the water levels measured by the NOAA tide gauge at Sewells Point throughout the duration of the storm event (1:00 AM 9/06/03 to 11:00 PM 9/21/03)

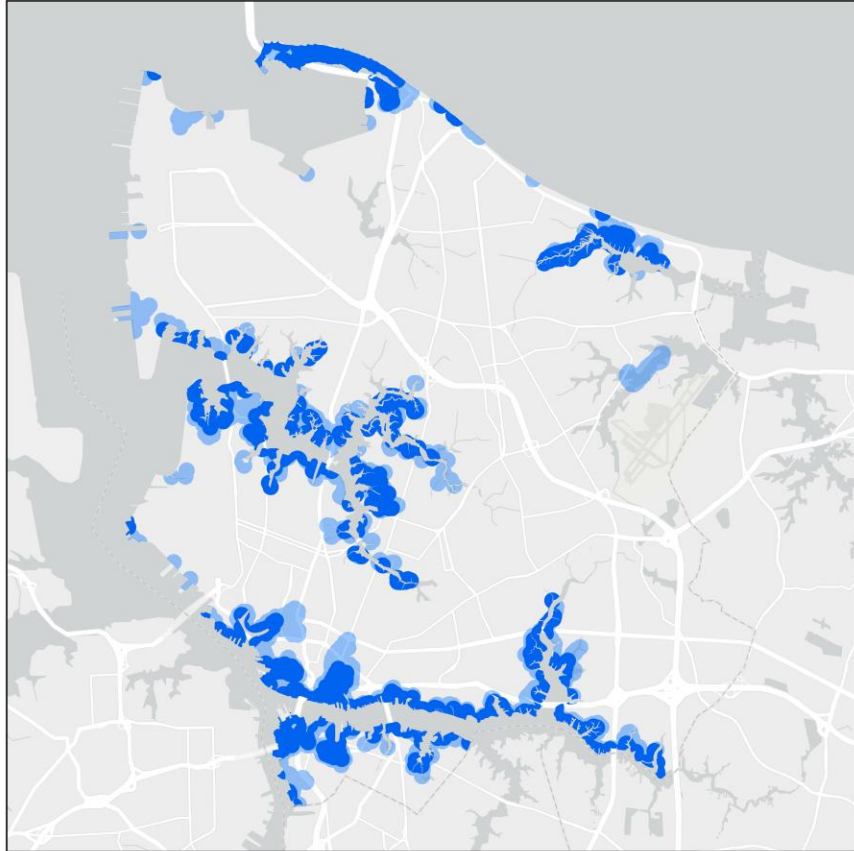
3.2 Projected Changes in Inundation Extent and Depth

Total flood inundation area increased substantially under future climate conditions for Hurricanes Isabel, Sandy, and Dorian, with increases of 80%, 65%, and 89%, respectively. This increased inundation area extends further inland (Fig. 7 and Table 3).



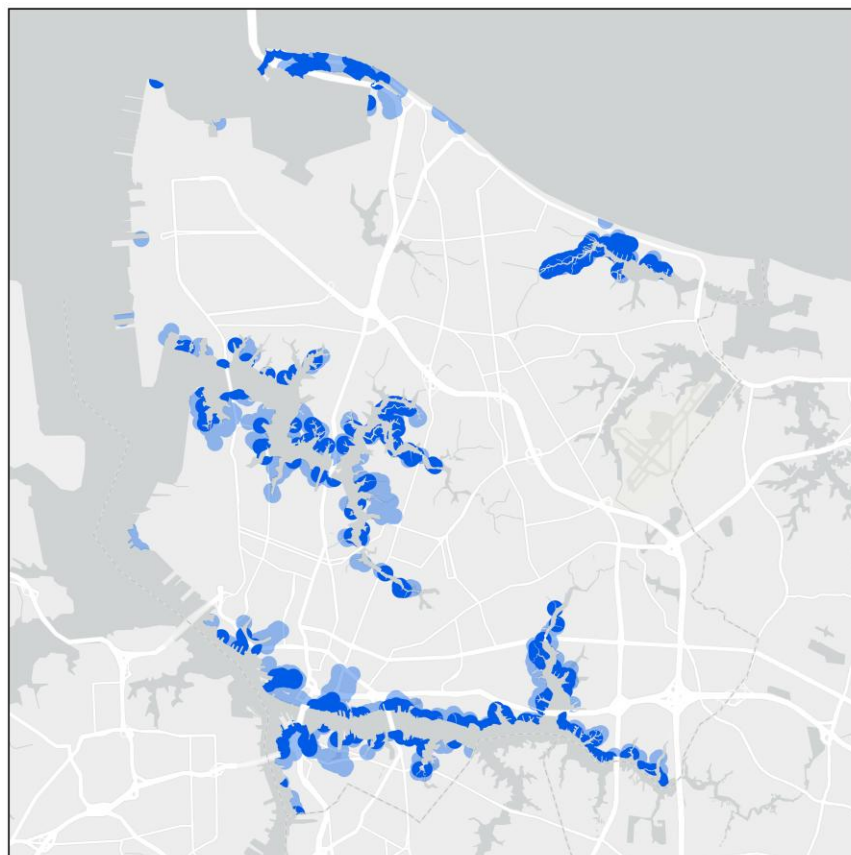
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Fig. 7 Changes in total inundation area from historic to future ADCIRC storm simulations across all three major storm events: **a.** Hurricane Isabel **b.** Hurricane Sandy **c.** Hurricane Dorian.

Table 3. Table summary of the inundation area (in km^2) for the historic and future simulations for each storm event, along with the percent change

Storm Event	Historic Inundation Area (km^2)	Future Inundation Area (km^2)	% Change
Isabel	19.0	34.2	80%
Sandy	14.3	23.7	65%
Dorian	8.6	16.2	89%

Although the mean inundation depth varied across each storm, it consistently increased between historic and future simulations for all three hurricanes, with increases of 23%, 14%, and 13%, respectively, for Isabel, Sandy, and Dorian (Table 4). The Wilcoxon Signed-Rank test for paired samples indicated a statistically significant difference in median inundation depth between historic and future simulations for each of the three storm events.

Table 4. Summary statistics for the inundation depth output from the ADCIRC storm simulations.
A () indicates statistical significance, where the p-value is less than the alpha value of 0.05*

Storm Event	Scenario	Median (m)	Mean (m)	Max (m)	p-value
Isabel	Historic	0.61	0.72	2.05	0.0247*
	Future	0.76	0.88	2.67	
Sandy	Historic	0.56	0.68	1.80	0.0225*
	Future	0.67	0.78	2.24	
Dorian	Historic	0.55	0.64	1.54	0.000513*
	Future	0.61	0.72	1.93	

Along with increased mean inundation depths, there were notable increases in the maximum inundation depths for each storm under future climate conditions: a 0.62 m increase for Hurricane Isabel, 0.5 m for Sandy, and 0.39 m for Hurricane Dorian.

3.4 Intersections of Projected Flooding and Flood Risk

All three flood risk zones (low, moderate, and high) experienced increases in inundation areas as predicted by the ADCIRC model (Fig. 8a and Table 5). For Hurricane Isabel, the historic simulation projected a total inundation area of 19.02 km², with 62% of that total inundation area falling within high flood risk areas, 22% within moderate risk areas, and 16% within low flood risk zones. Under future climate conditions, the total inundation area was predicted to increase to 34.21 km², with 49% of the total inundation area falling within high flood risk zones, 27% within moderate risk zones, and 24% within low-risk zones (Fig. 8b and 8c).

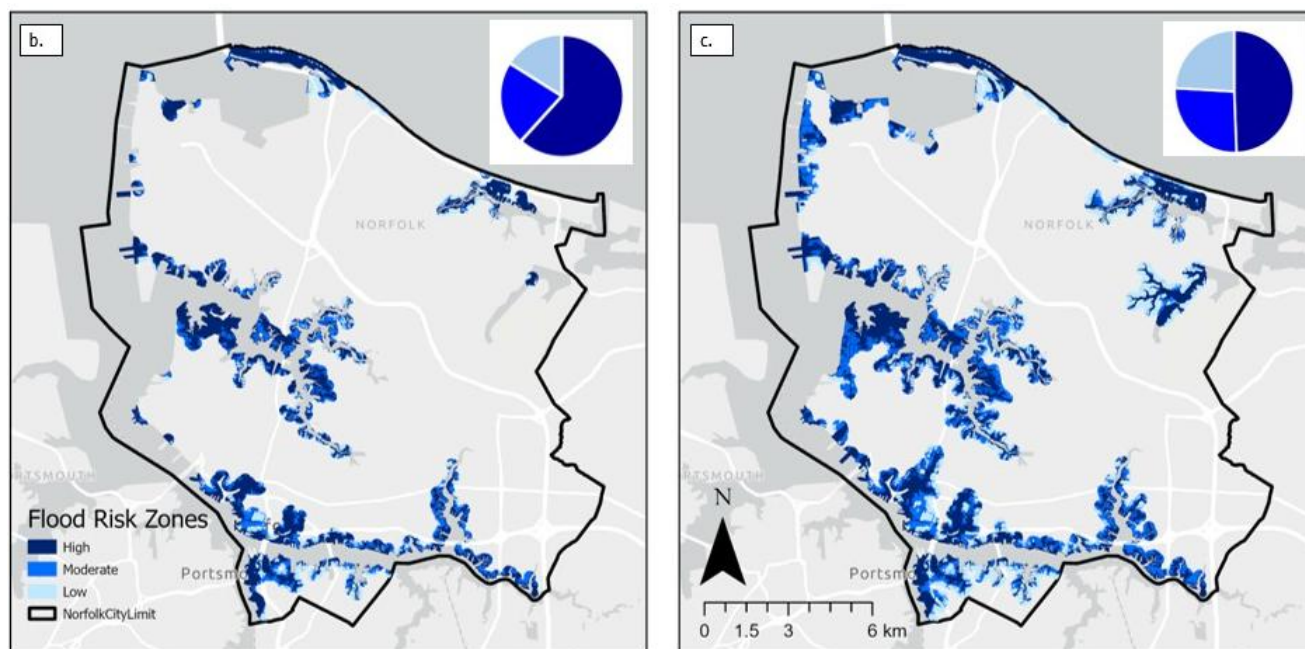
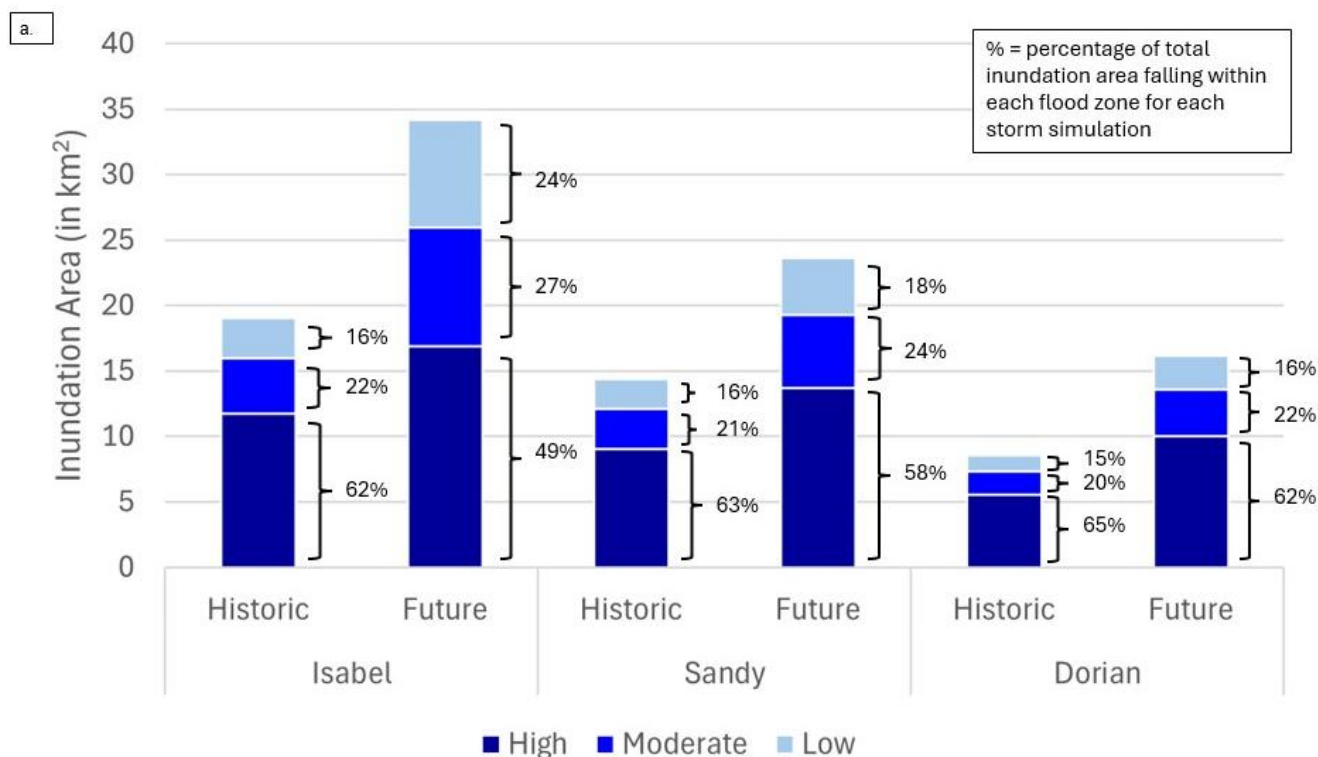


Fig. 8a Bar graph of the inundation area projected for each storm scenario (Isabel, Sandy, Dorian) and simulation (historic or future) classified by flood risk according to FEMA's Flood Insurance Rate Map for Norfolk, VA. **Fig. 8b & 8c** Overlay of flood inundation extent maps for historic (9a) and future (9b) simulations of Hurricane Isabel and flood risk

In the historic simulation of Hurricane Sandy, the total inundation area was projected to have been 14.38 km², with 63% of that area falling within high flood risk zones, 21% within

moderate risk zones, and 16% within low flood risk zones. In the future simulation of Hurricane Sandy, the total inundation area was predicted to be 23.67 km², with 58% of that total inundation area located in high flood risk areas, 24% in moderate risk areas, and 18% in low risk areas.

Lastly, Hurricane Dorian had a total inundation area of 8.56 km² in the historic simulation, with 65% of that area being in high flood risk areas, 20% in moderate risk areas, and 15% in low risk areas. In the future simulation of Dorian, the total inundation area was projected to increase to 16.16 km², with 62% of the inundation area located in high flood risk areas, 22% in moderate risk areas, and 16% in low-risk areas.

Table 5. Total inundation area for each of the six storm simulations, along with the proportion of the inundation area that falls into each of the flood risk zone classifications. The proportions were calculated by dividing the inundation area within each flood risk zone by the total inundation area

Storm Event	Simulation	Total Inundation Area (km ²)	Flood Risk Zone Classification					
			High		Moderate		Low	
			Area (km ²)	% of total inundation area	Area (km ²)	% of total inundation area	Area (km ²)	% of total inundation area
Isabel	Historic	19.02	11.74	62%	4.23	22%	3.05	16%
	Future	34.21	16.90	49%	9.06	27%	8.25	24%
Sandy	Historic	14.38	9.07	63%	3.06	21%	2.24	16%
	Future	23.67	13.68	58%	5.59	24%	4.40	18%
Dorian	Historic	8.56	5.56	65%	1.74	20%	1.25	15%
	Future	16.16	10.02	62%	3.59	22%	2.55	16%

Furthermore, mean inundation depths varied across the different flood zones of Norfolk, as delineated by the FIRMs, and differed between historic and future simulations for each hurricane (Fig. 9). Across all three storms, the mean inundation depth of floodwaters in high flood zones was projected to increase with storm intensity and sea level rise (37%, 15%, and 13% respectively for Hurricanes Isabel, Sandy, and Dorian). Within the moderate flood zones of

Norfolk, there was more variability in the changes of mean inundation depth between the historic and future simulations. While Hurricane Dorian exhibited an 11% increase, both Hurricanes Isabel and Sandy experienced a decrease (-58% and -12%, respectively). Lastly, for low flood risk areas, the mean inundation depth was also projected to increase: 18% for Hurricane Isabel, 60% for Sandy, and 134% for Dorian.

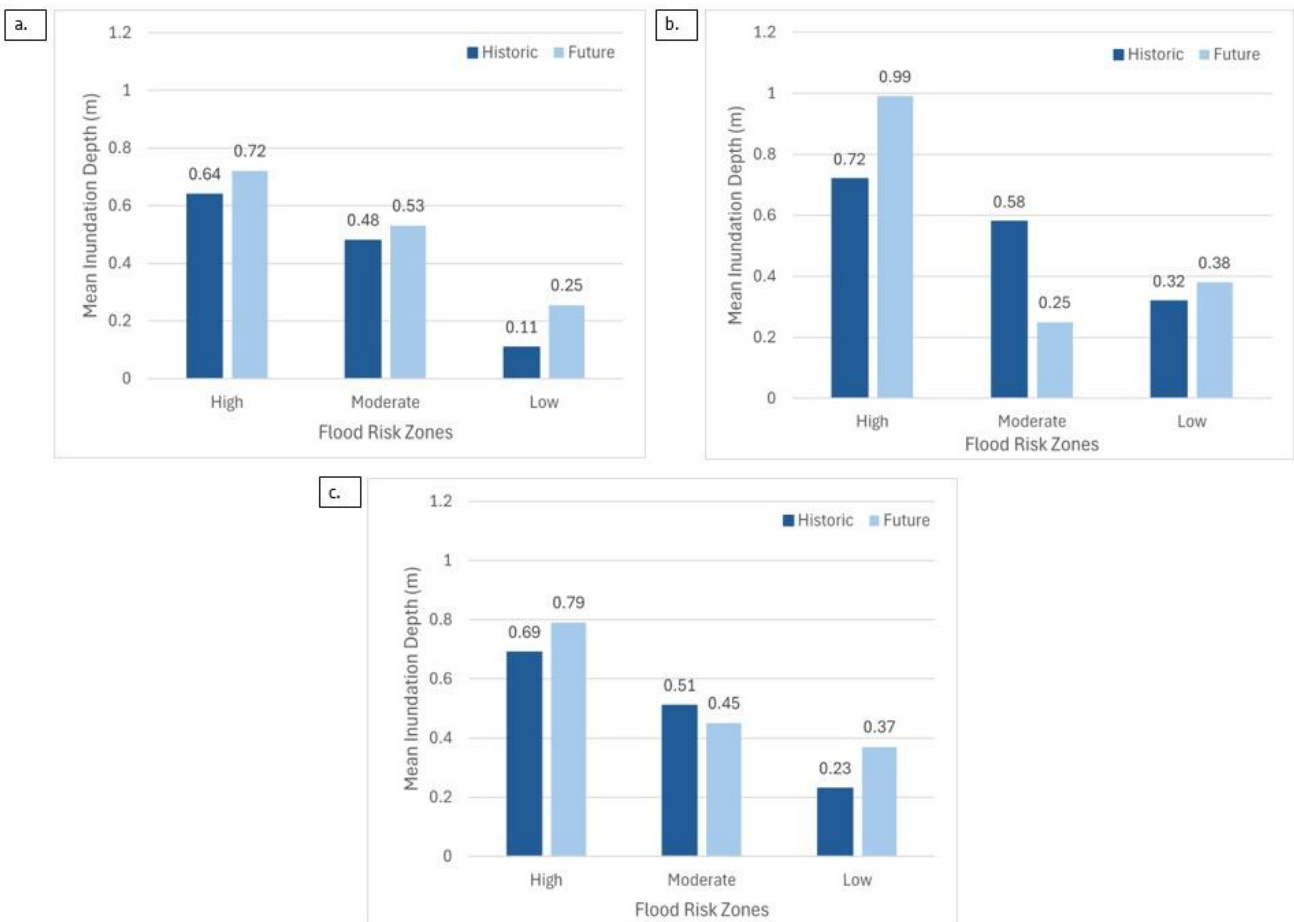


Fig. 9 Series of three bar graphs representing the change of mean inundation depth within each of the three flood risk zones (as delineated by FEMA's Flood Insurance Rate Map) between historic and future simulations of **a.** Hurricanes Isabel, **b.** Sandy, and **c.** Dorian

3.4 Social Vulnerability Analysis

Hurricane Isabel produced the largest expansion in flood extent under future climate conditions, resulting in the greatest increase in exposure within socially vulnerable areas. Because flood risk zones and SVI classifications were held constant across all simulations, the locations where flood risk intersected with social vulnerability were the same for all storm events. Differences among Hurricane Isabel, Sandy, and Dorian were therefore driven solely by the magnitude of inundation, not by changes in the spatial distribution of vulnerability. The increased exposure observed for Hurricane Isabel reflects greater flooding into areas that were already identified as high-risk and socially vulnerable, rather than the emergence of new vulnerability–risk intersections.

Across all four vulnerability themes, the total areas with high composite scores (high flood risk and high social vulnerability) for Hurricane Isabel increased substantially under future climate conditions (Fig. 10). Furthermore, the expansion of inundation area revealed additional intersections of high social vulnerability and flood risk appearing in areas previously outside the historic floodplain, especially in the Southern Norfolk region and along the Elizabeth and Lafayette rivers.

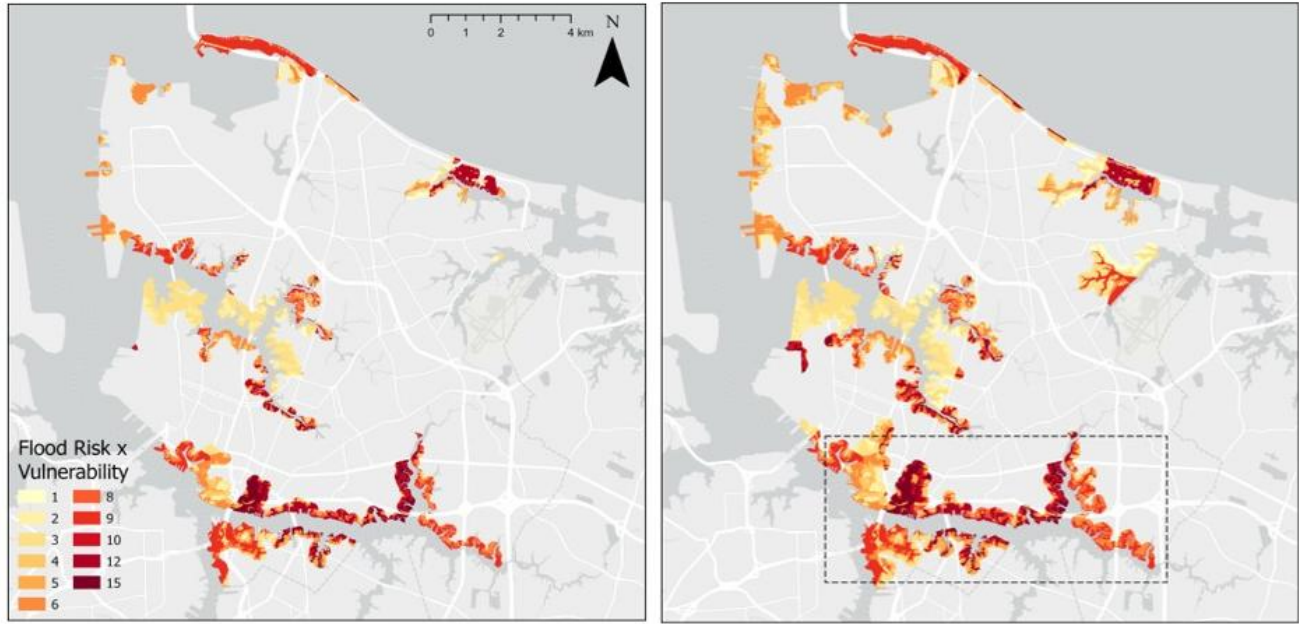


Fig. 10. Composite index map of flood risk $\times$ social vulnerability (for all vulnerability themes combined) for historic (left) and future (right) simulations of Hurricane Isabel. Darker colors indicate higher risk and vulnerability

Although the composite index highlighted spatial patterns of risk-vulnerability overlap, it could not distinguish whether the high composite scores are driven by flood risk, social vulnerability, or both. To isolate theme-specific contributions, the SVI was disaggregated into its four component themes (Socioeconomic Status, Household Characteristics, Minority Status, and Housing & Transportation Type), with each theme classified into five vulnerability levels ranging from “very low” to “very high.” Matrix-based analyses were then used to partition changes in inundation area by both flood risk category and vulnerability level (Table 6).

Table 6. Matrices of social vulnerability and flood risk. Values represent the absolute change in inundation area (km^2) between historic and future simulations within each combined vulnerability–flood risk class. Higher values indicate greater spatial expansion of flooding under future conditions.

Change in inundation area (in km^2) from historic to future simulation	
Theme 1 - Socioeconomic Status	Theme 2 - Household Characteristics
Flood Risk Classification	Flood Risk Classification

Vulnerability Level				Vulnerability Level			
	Low	Moderate	High		Low	Moderate	High
Very low	0.65	0.72	0.87	Very low	1.15	2.13	1.79
Low	0.45	0.47	0.44	Low	1.05	1.15	1.27
Moderate	1.85	1.94	2.06	Moderate	1.97	0.84	1.12
High	0.78	0.49	0.66	High	0.43	0.32	0.40
Very high	1.16	0.96	0.78	Very high	0.29	0.13	0.25

Theme 3 - Minority Status				Theme 4 - Housing and Transportation Type			
Vulnerability Class	Flood Risk Classification			Vulnerability Class	Flood Risk Classification		
	Low	Moderate	High		Low	Moderate	High
Very low	0.90	0.98	1.21	Very low	1.06	0.80	1.03
Low	1.07	0.79	0.87	Low	0.69	0.38	0.25
Moderate	1.24	1.28	1.44	Moderate	1.85	2.18	2.37
High	0.40	0.80	0.75	High	0.56	0.45	0.45
Very high	1.27	0.74	0.55	Very high	0.73	0.78	0.72

Across all four social vulnerability themes, exposure to flooding increased (which is denoted by a positive change in inundation area) within all five SVI levels and three flood risk zones, but the distribution of that growth varies. SVI levels 1 (very low), 3 (moderate), and 5 (very high) consistently experienced the largest expansions in inundation, though the dominant class shifted across themes.

For Theme 1 (Socioeconomic Status), moderately vulnerable census tracts, which are standardized subdivisions of a county, exhibited the greatest increases in inundation area, with values increasing from 1.85 km² under low flood risk to 2.06 km² under high flood risk. In contrast, very low and low vulnerability classes showed comparatively smaller changes across all flood risk categories. High and very high vulnerability classes displayed lower and more variable

increases compared to the moderate vulnerability level, with no clear trend across flood risk classifications.

For Theme 2 (Household Characteristics), the changes in the inundation area within very low and low vulnerability levels increased as flood risk increased from low to high risk. Very low vulnerability tracts showed a pronounced increase under moderate flood risk zones (2.13 km²). Moderately vulnerable tracts experienced their largest increase under low flood risk (1.97 km²), while highly and very highly vulnerable tracts exhibited smaller increases across all flood risk levels.

For Theme 3 (Household Characteristics), the largest increases in inundation area occurred in moderately vulnerable tracts, followed by tracts with very low vulnerability, where the values increased as flood risk increased for both levels. While the values were comparatively smaller for high vulnerability levels, they also increased as flood risk increased. Low and very high vulnerability levels experienced the greatest increases in inundation area within low flood risk areas, but these values decreased as flood risk increases.

For Theme 4 (Housing and Transportation Type), moderately vulnerable tracts experienced the largest increases in inundation area across all flood risk zones, with values increasing from 1.85 km² (low risk) to 2.37 km² (high risk). All other vulnerability levels showed substantially smaller changes.

Across all four vulnerability themes, the future climate scenario produced a consistent spatial expansion of areas where higher flood risk and elevated social vulnerability overlapped, as reflected in the composite maps. This pattern was mirrored in the matrices of social vulnerability and flood risk, where several mid- and high-vulnerability classes (most commonly levels 3 and 5) showed the largest increases in inundated areas across the moderate and high

flood-risk tiers. Although the specific SVI class with the greatest increase varied by theme, in general, projections of future coastal flooding enlarged the portion of each vulnerability theme exposed to flooding, including areas that were outside the historic inundation event.

3.5 Neighborhood-level Analysis

As portrayed in the composite maps (Fig. 10), the Southern Norfolk region exhibited a high concentration of elevated flood risk and social vulnerability. To get an understanding of the spatial patterns of inundation, flood risk, and vulnerability on a neighborhood-level scale, an intersection analysis between a layer delineating the civic leagues of Norfolk and the flood inundation layers resulting from the ADCIRC simulations was conducted. Several neighborhoods that were not inundated in the historic simulations became substantially inundated under future simulations (Fig. 11 and Table 7). For example, within the Southern Norfolk region, Calvert Square was 0% inundated in the historic simulation of Hurricane Isabel but was 81% inundated under the future simulation.

Other key neighborhoods that experienced a substantial increase in inundation areas included Brambleton (rising from 32% to 70%), Glengariff (0% to 87%), The Gardens (21% to 88%), and Talbot Hall West (1% to 77%). While some of these neighborhoods were comprised mostly of high flood risk areas (such as Calvert Square, Glengariff, and Tidewater Gardens), several of the neighborhoods experiencing the greatest projected increases in flooding were comprised mostly of low and moderate flood risk areas. Examples included Beacon Light Berkley, where 54% of the neighborhood contains low flood risk areas, Cottage Line (60% low flood risk), East Lynne & Saratoga (88%), Lake Whitehurst West (92%), and Young Terrace (93%).

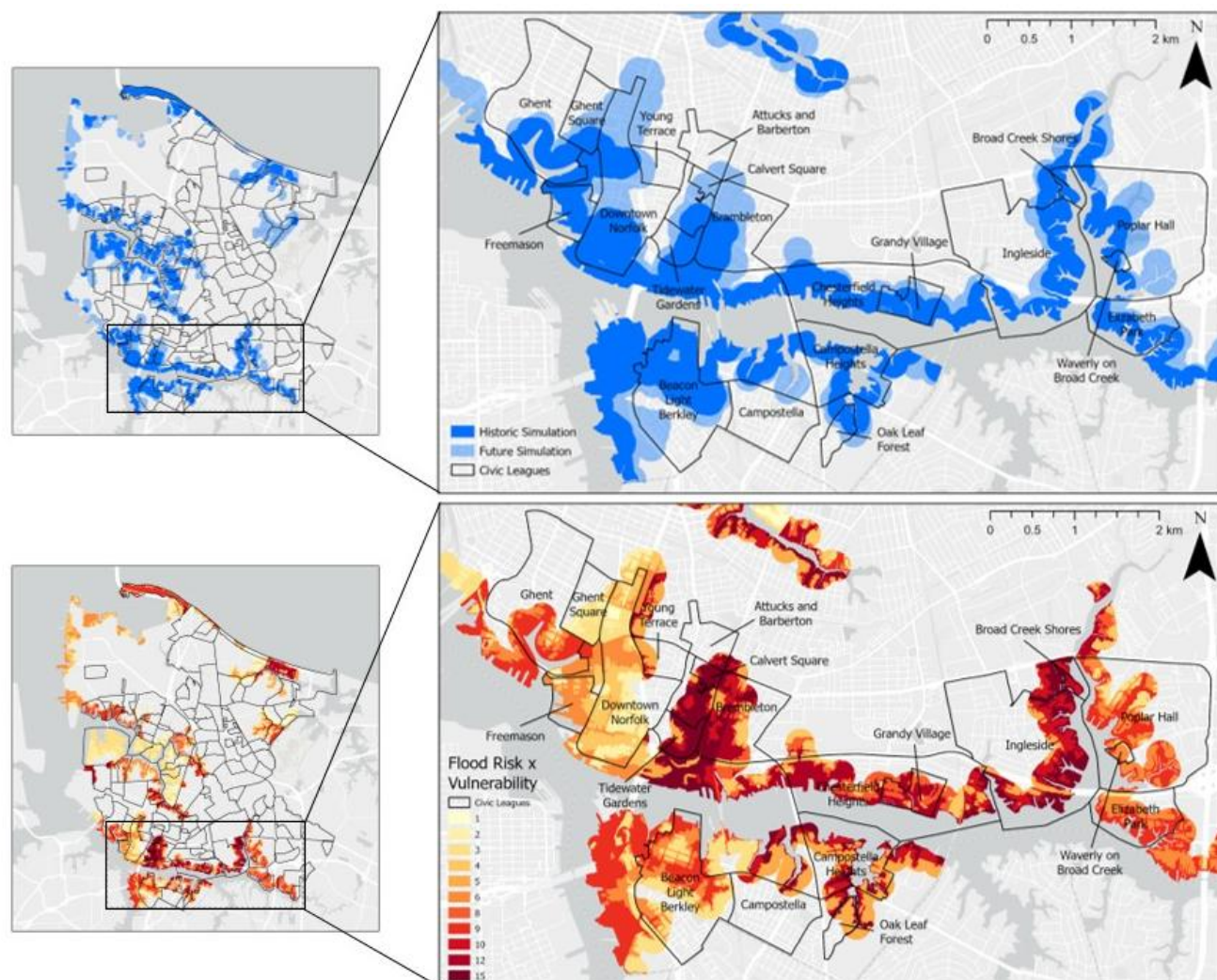


Fig 11. Inundation extent (top) and composite index map of flood extent, flood risk, and social vulnerability (bottom) for the Southern Norfolk region.

Table 7. Percentage of neighborhood inundated under historic and future climate conditions, along with the percentage of the neighborhood within each flood risk zone

Neighborhood	% of Neighborhood Inundated		% of neighborhood within each flood zone		
	Historic	Future	High	Moderate	Low
Beacon Light Berkley	48%	71%	21%	25%	54%
Broad Creek Shores	100%	100%	58%	42%	0%
Brambleton	32%	70%	36%	25%	39%
Calvert Square	0%	81%	74%	18%	8%
Campostella	1%	8%	3%	6%	91%
Campostella Heights	63%	82%	22%	22%	56%
Chesterfield Heights	50%	63%	34%	27%	39%

Cottage Line	4%	47%	33%	7%	60%
Downtown Norfolk Civic League	50%	84%	25%	38%	37%
East Lynne and Saratoga	0%	44%	9%	3%	88%
Elizabeth Park	55%	77%	45%	45%	10%
Freemason Street Area Association	85%	99%	71%	23%	6%
Ghent	27%	31%	31%	42%	27%
Ghent Square Community Association	22%	52%	43%	50%	7%
Glengariff	0%	87%	50%	16%	34%
Grandy Village	72%	91%	51%	42%	7%
Ingleside	30%	39%	24%	26%	50%
Lafayette and Winona	39%	72%	33%	37%	40%
Lake Whitehurst West	0%	26%	7%	2%	92%
Oak Leaf Forest	36%	52%	20%	2%	78%
Poplar Hall	19%	45%	24%	30%	46%
The Gardens	21%	88%	41%	11%	48%
Villa Heights	40%	80%	34%	42%	24%
Talbot Hall West	1%	77%	33%	51%	16%
Tidewater Gardens	57%	78%	58%	15%	27%
Waverly on Broad Creek	62%	86%	17%	74%	9%
Young Terrace	4%	32%	1%	6%	93%

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Discussion

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The main objectives of this research were to assess how projections of future storm surge flooding would alter flood risk in Norfolk, Virginia, and to evaluate the geospatial relationships among inundation extent, FEMA flood zone designations, and social vulnerability. Comparisons of water surface elevations from historic and future ADCIRC simulations for three major storm events revealed three overarching patterns: (1) total inundation area increases under scenarios of sea level rise and increased storm intensity, (2) the spatial footprint of flooding expands beyond boundaries currently classified by FEMA as high-risk, (3) flood exposure is shifting towards communities not traditionally classified as highly vulnerable.

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4.1 Inundation Depth and Extent

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This study found that the inundation area, the amount of land submerged by water during the hurricane simulations, was projected to increase substantially under elevated climate

conditions (SLR rate of 5 mm/yr and wind speeds increasing by 10%), with floodwaters predicted to reach farther inland than historically observed. This pattern aligns with observations from Danso et al. (2025), who demonstrated that sea level rise and tropical cyclone intensification can expand the inland extent of storm surge by redistributing water farther from the coastline, thereby increasing population exposure. As sea level rises, this increases the baseline at which storm surges form, allowing the storm-driven waves to propagate further inland (Morim et al., 2025). Moreover, the projected increases in storm winds can promote higher surges in addition to the baseline sea level rise. This notion is observed in our projected peak, or maximum, storm water levels being much higher than the 0.2 m SLR (Table 4).

The Wilcoxon Signed Rank test further indicated that inundation depth is significantly greater in the future simulations, with maximum depths increasing by an average of 0.5 meters. Similar findings were reported by Camelo et al. (2020), who observed that inundation volume increased during future storm surge simulations and suggested that it is reasonable to expect hurricanes to produce larger storm surge magnitudes. Collectively, these results indicate that sea level rise and greater storm intensity are not only widening the area exposed to storm surge flooding events but also amplifying the severity of the hazards.

4.2 Flooding and Flood Risk

While changes in inundation extent and depth follow a more direct path (increasing under future climate conditions), the spatial redistribution of floodwaters across flood zone designations produced nuanced results that should be seriously considered in future flood mitigation efforts. Although all flood risk zones (high, moderate, and low) experienced increases in inundation area under future climate scenarios, the largest relative gains occurred in low- and moderate-risk flood zones. That is, the starkest differences between historical and future

simulations were observed in non-high-risk zones, more than doubling the inundation area within these regions (Table 5 & Fig. 9). Additionally, flood depths increased in both high- and low-risk areas, eliciting two important inferences: First, future flooding events may become more severe in areas that are already highly vulnerable to flooding (high-risk zone). Second, future flooding may worsen in areas that do not typically expect extreme flooding to occur nor are prioritized in mitigation and response efforts (low-risk zones) (US Government Accountability Office, 2021).

4.3 Flooding and Social Vulnerability

The social vulnerability analysis explored how the physical changes in flooding under future climate scenarios overlap with community characteristics. The composite index map displayed a major inland expansion of risk-vulnerability intersections, such as Southern Norfolk and along river coastlines. Southern Norfolk, which has higher concentrations of greater socioeconomic vulnerability (Theme 1) and higher proportions of minority residents (Theme 3) compared to the rest of Norfolk, experienced substantial increases in flooding. This indicates that socially vulnerable communities may have an elevated exposure to future coastal flooding events. This notion is consistent with documented histories of marginalization and residential segregation in Norfolk (Martinich et al., 2013).

The matrices revealed that, across all themes, moderate vulnerability levels repeatedly experience the largest increases in inundation area, especially under moderate to high flood risk conditions (Table 6). Conversely, high and very high vulnerability classes often show smaller increases, which may reflect their existing location in already flood-prone areas where future expansion of inundation extent is spatially constrained. These results indicate that future flooding may increasingly affect areas that are not currently classified as the most socially vulnerable, potentially shifting flood exposure toward moderately vulnerable communities.

Further insights can be drawn from each vulnerability theme. In Theme 1 (Socioeconomic Status), it can be interpreted that future flooding is expanding most rapidly into areas that are socioeconomically constrained, but not the most disadvantaged. These areas may be underprioritized in adaptation and mitigation efforts, as they are neither affluent nor classified as “high vulnerability,” potentially widening future inequities. In Theme 2 (Household Characteristics), the misalignment between areas experiencing the greatest increases in inundation and those with high vulnerability indicates that future flooding may expose populations whose household-level sensitivities could intensify as demographic conditions change. Under Theme 3 (Minority Status), it was observed that while highly vulnerable tracts remained persistently exposed, the expansion of flooding into moderately vulnerable areas suggests a broadening spatial footprint of flood risk rather than a reduction in existing environmental inequities. Lastly, for Theme 4 (Housing & Transportation Type), very high vulnerability tracts had the greatest increase across all zones, highlighting elevated challenges related to evacuation, housing quality, and recovery for households with constrained mobility or older, multi-unit structures.

Overall, these results show that flood exposure is projected to expand across all levels of vulnerability, but mid- to very high-vulnerability classes (particularly levels 3 and 5) tend to absorb the greatest increases. These findings align with Kleinosky et al. (2006), who found that in the Hampton Roads metropolitan area (including Norfolk), socially vulnerable communities are most likely to experience flooding and face substantial risk due to limited capacity to respond to or adapt to natural hazards. The results of the social vulnerability analysis underscore the importance of forward-looking, equity-centered hazard mitigation strategies that anticipate not

only the intensification of existing coastal risk but the inland and demographic redistribution of future exposure.

4.4 Neighborhood-level Insights

A neighborhood-scale analysis reinforced these findings by demonstrating how projected changes may affect communities at finer spatial scales (Table 7). Several neighborhoods historically unaffected by storm surge, such as Calvert Square, experience dramatic increases in inundation under future scenarios, with Calvert Square shifting from no flooding to 81% inundation. Calvert Square is one of the many public housing communities within Norfolk that is projected to be impacted by future flooding, along with Grandy Village, Oakleaf Forest, and Young Terrace (Norfolk Redevelopment Housing Authority, 2026).

Many neighborhoods projected to experience increases in flooding were located predominantly in low-risk zones, emphasizing inconsistencies between current FEMA classifications and future hazard projections. These discrepancies underscore the need for proactive risk communication: communities not currently identified as high-risk may experience unexpectedly severe flooding despite being underserved in terms of mitigation resources.

4.5 Implications of this Study

Altogether, the results from this study have critical implications for coastal resilience efforts, equity-centered adaptation, and community response and preparedness in Norfolk. The projected inland expansion and deepening of storm surge flooding, particularly across areas currently mapped as moderate or low flood risk, indicate that planning, investment, and communication tools anchored to historical conditions will increasingly underestimate future hazards. In a statistical analysis conducted by the US Government Accountability Office (US GAO), it was found that FEMA's mapping investments were greater in areas of higher flood risk

and lower for areas with higher social vulnerability (US GAO, 2021). As shown in this study, flooding is projected to expand in lower flood risk zones, as well as socially vulnerable areas, underscoring the vital need for increased investment in flood planning and mitigation infrastructure and resources.

Communities such as those in Southern Norfolk, where inundation increases dramatically despite historically low exposure, may face disproportionately large and unexpected impacts while lacking the resources, insurance coverage, or infrastructure support typically directed toward high-risk zones. This underscores the need for climate-adjusted floodplain screening tools that incorporate forward-looking surge projections, as well as targeted outreach and mitigation programs for neighborhoods where social vulnerability and emerging flood risk intersect most strongly. Integrating these projections into hazard mitigation plans, infrastructural improvement strategies, and resilience investments would allow the city to anticipate shifting exposure patterns, reduce inequities in preparedness, and ensure that at-risk communities are informed and supported before conditions worsen.

4.6 Limitations and Areas for Future Work

This study has potential limitations. Due to the non-uniform spatial resolution of the ADCIRC model mesh, a 175-meter buffer was applied around inundation points to estimate flood extent. While necessary to achieve spatial continuity, the buffer-based approach introduces uncertainty, particularly in areas with complex topography or irregular mesh distribution. Future studies could refine this methodology by applying mesh-sensitive interpolation or exploring GRASS-GIS based downscaling tools. Additionally, the social vulnerability data is on a census-tract level, which may overlook fine-scale heterogeneity in vulnerability. Increasing the spatial

resolution would allow for more precise alignment between demographic characteristics and flood risk zones.

Future studies could integrate compound flooding effects from rainfall and riverine discharge by coupling ADCIRC with other hydrologic models, such as HEC-RAS or SWMM. While this study isolates the direct effects of increased storm intensity and sea level rise on storm surge flooding, there are several other causes of flooding whose inclusion could add to the results from this analysis. Similarly, storms across a range of return periods and different sea level rise scenarios could be compared to broaden the analyses in this study. Future work could also expand upon the social vulnerability analysis and connect demographic exposure to infrastructure-specific vulnerabilities, such as evacuation routes and public transit networks, providing additional guidance for resilience investments. Furthermore, to identify the nuances of a single variable, such as race or age, the methods in this study could be applied separately to each demographic variable.

Conclusion

This study evaluated projected changes in coastal flood risk in Norfolk, Virginia, by comparing historic and future storm simulations for Hurricanes Isabel, Sandy, and Dorian. Results indicated a marked increase in inundation area under projected future climate scenarios, with floodwaters extending further inland and increasingly affecting areas currently designated by FEMA as moderate or low flood risk. These shifts in flood exposure underscore the anticipated expansion of floodplains as sea levels rise and storm intensity escalates, emphasizing the need for forward-looking resources and mitigation strategies.

The findings raise critical concerns about the adequacy of current FEMA Flood Insurance Rate Maps (FIRMs) in reflecting future flood hazards. Given that FIRMs form the foundation of

floodplain management, land-use regulation, infrastructure planning, emergency response, and insurance pricing, their reliance on historical data may lead to an underestimation of future risk. In particular, the expansion of flooding into areas outside designated high-risk zones poses a threat to communities that may be underinsured, under-protected, and ill-equipped for future flood events. As both the spatial footprint and depth of flooding evolve, it becomes imperative that risk communication and mitigation tools integrate climate projections to remain effective and equitable.

The social vulnerability analysis furthered the evaluation of flood extent changes by correlating the growth to flood risk and social vulnerability levels, assessing the distribution of impacts, and drawing attention to areas that might require greater flood mitigation efforts and response. The composite index of flood risk and social vulnerability serves as a screening tool for identifying areas of elevated exposure to future flooding events.

Overall, this study demonstrates how hydrodynamic models such as ADCIRC can be leveraged not only for physical hazard modeling but also for interdisciplinary risk assessments that integrate social dimensions. This framework is transferable to other coastal cities; replication requires an area of interest, a set of major storm events, a high-resolution DEM, climate-driven adjustments to storm parameters, and demographic or vulnerability indicators.

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Contributions

R. Weghorst: conceptualization, methodology, investigation, data curation, formal analysis, visualization, writing—original draft, writing—review and editing. H. Christensen: conceptualization, methodology, writing—review and editing. Q. Zhu: model setup, run, and validation; writing—review and editing. M. Reidenbach: conceptualization, supervision, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Data Availability

The datasets used in this study are publicly available. ADCIRC output from the historic and future simulations of Hurricanes Isabel, Sandy, and Dorian can be accessed from the Environmental Data Initiative (EDI) database (<https://doi.org/10.6073/pasta/73c0fb5b68aaba3cedc137481189f7ab>). Water level data were obtained from NOAA tide gauge stations, including Wachapreague (ID 8631044), Kiptopeke (ID 8632200), and Sewells Point (ID 8638610) (<https://tidesandcurrents.noaa.gov/map/index.shtml>).

Hourly spatially varying wind and atmospheric pressure fields were obtained from the ERA5 reanalysis dataset provided by the Copernicus Climate Change Service (<https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=overview>). Meteorological data (including wind speed data used for determining future climate parameters) were obtained from NOAA's National Data Buoy Center (https://www.ndbc.noaa.gov/station_page.php?station=chlv2). The Flood Insurance Rate Map (FIRM) was obtained from FEMA's Flood Map Service Center (<https://msc.fema.gov/portal/home>). Social Vulnerability Index data were obtained from the Centers for Disease Control and Prevention/ Agency for Toxic Substances and Disease Registry/ Geospatial Research, Analysis, and Services Program (https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html). Norfolk-specific geospatial data, such as the "city limits" and "civic leagues" layer, were obtained from the City of Norfolk's Open GIS Site (<https://norfolkgisdata-orf.opendata.arcgis.com/>). The Digital Elevation Model for Norfolk was obtained from the USGS 3D Elevation Program (<https://portal.opentopography.org/datasetMetadata?otCollectionID=OT.012021.4269.3>).

Conflicts of Interest

The author declares no conflicts of interest.

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