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Modeling Coastal Vulnerability of the St. Johns River and Northeastern Florida Shorelines

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Thesis

Modeling Coastal Vulnerability of the St. Johns River and Northeastern Florida Shorelines

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Abstract

Coastal and riverine communities, with anthropogenic congestion and natural and economic resources, are vulnerable to climate change impacts including rising sea levels and increasing severity and frequency of storms. Coastal habitats are being increasingly recognized as natural infrastructure that provides resiliency against these stressors. However, few studies have analyzed coastal vulnerability at landscape scale with finely resolved spatial data that account for habitats and demographics. The purpose of this study is to map the coastal vulnerability of the St. Johns River and adjacent Northeastern Florida Atlantic shoreline within the St. Johns River Water Management District. Unique to this study is that natural habitats, different sea level rise scenarios, and human demographics are considered. Specifically, the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) 3.9.0 coastal vulnerability model with seven metrics (geomorphology, relief, natural habitats, sea level change, wave exposure, wind exposure, and surge potential) was used to create a coastal exposure index for shore points. Results showed vulnerability to erosion and flooding. Using three sea level rise scenarios (current, 2050 Intermediate-High, and 2100 Intermediate-High), it was found that (1) the coastal exposure indexes and habitat role values were spatially correlated; (2) rising sea levels increased the coastal exposure index and the role of habitats in providing protection; (3) vulnerability of population density and population below poverty density increased with higher sea levels and without habitats present; and (4) low vulnerability areas had high concentrations of mangroves. These results could be used to help prioritize which habitat types and where habitat protection and/or restoration is most needed for protecting shorelines and disadvantaged people. This type of coastal vulnerability study could aid resiliency planning efforts in

Northeastern Florida and could be expanded upon for other socioeconomic, infrastructure, or ecosystem queries.

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Abbreviations

ACS	American Community Survey
AOI	Area of Interest
CREST	Coastal Resilience Evaluation Siting Tool
CVA	Coastal Vulnerability Assessment
CVMA	Coastal Vulnerability Mapping Assessment
DEM	Digital Elevation Model
ENSO	El Niño/La Niña Southern Oscillations
ESI	Environmental Sensitivity Index
ESL	Extreme Sea Level
FDEP	Florida Department of Environmental Protection
FWC	Florida Fish and Wildlife Conservation Commission
FGDL	Florida Geographic Data Library
GEER	Geotechnical Extreme Events Reconnaissance
GMSLR	Global Mean Sea Level Rise
InVEST	Integrated Valuation of Ecosystem Services and Tradeoffs
IPCC	Intergovernmental Panel on Climate Change
MSL	Mean Sea Level
NAVD88	North American Vertical Datum of 1988
NED	National Elevation Dataset
NEFRC	Northeast Florida Regional Council
NFWF	National Fish and Wildlife Foundation
NOAA	National Oceanic and Atmospheric Administration

RSLR	Relative Sea Level Rise
SACS	South Atlantic Coastal Study
SHELDUS	Spatial Hazards Events and Losses Database for the United States
SJRWMD	St. Johns River Water Management District
SLIP	Sea Level Impact Projection
SLR	Sea Level Rise
TERI	Taylor Engineering Research Institute
UNF	University of North Florida
USACE	United States Army Corps of Engineers
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
WGS	World Geodetic System

Nomenclature

Coastal exposure: Also called **coastal exposure index** and **exposure**, is the coastal landscape's exposure to flooding and erosion when faced with extreme weather.

Vulnerability: Ability of a system or place to cope with hazards. For **coastal vulnerability,** hazards include erosion and flooding caused by accelerated SLR, climate change, and extreme storms.

Habitat role: Difference between exposure (with habitats) and exposure without habitats present.

High exposure: The top 25% of coastal exposure indexes (75^{th} percentile, the highest quartile) across all SLR and habitat scenarios.

Middle exposure: The values in between the high and low exposures.

Low exposure: The bottom 25% of coastal exposure indexes (25^{th} percentile, the lowest quartile).

1.0 Introduction

1.1 Coastal Communities and Ecosystems

The exposure to flooding and erosion, and consequently the vulnerability that coastal communities face, is escalating due to climate change, sea level rise (SLR), storm frequency and intensity, and concentrated populations and infrastructure (Cabral et al., 2017). Coastal flooding and erosion globally result billions of dollars of damage and impact people in the hundreds of millions annually (Arkema et al., 2017). Globally, approximately 323 million people live at 0-5 meters above mean sea level, approximately 1.1 billion people live at 0-20 meters above mean sea level, and approximately 2.5 billion people are located within 100 km of a coastline (Bukvic et al., 2020). In the upcoming decades, coastal regions will face increasing strains from urbanization, population growth, and economic development (Wong et al., 2014). As a result, people, assets, and habitats are being exposed to coastal risks at a rapidly increasing rate, which is only expected to continue.

Coastal ecosystems (including salt marshes, wetlands, sand beaches, and vegetated dunes) are paramount to protecting coastal communities and providing habitat for biota. Yet, their value at providing coastal protection is not as readily quantified or visualized (Mandle et al., 2017) when compared to traditional hard-engineered ('grey') systems such as armored revetments, bulkheads, seawalls, jetties, and breakwaters. These structures are expensive. They also may cause unintended environmental repercussions to biodiversity and intertidal zones such as beach loss due to hardened shorelines reflecting wave energy to adjacent shorelines, other coastal morphology changes and erosion increases, ecosystem degradation (Arkema et al., 2017; Hopper & Meixler, 2016; Langridge et al., 2014).

On the other hand, coastal ecosystems can provide a host of benefits for coastal protection and critical habitat for species, and they can be less costly (Langridge et al., 2014; Leo et al., 2019). In addition, coastal ecosystems often improve erosion protection and wave attenuation, absorbing stressors such as SLR, storm surge, and anthropogenic interference (Arkema et al., 2017; Hopper & Meixler, 2016). Unfortunately, coastal ecosystems are experiencing degradation from these same stressors that they protect against, including climate change-induced ocean changes such as SLR and anthropogenic influences such as human infrastructure and increases in population density over time (IPCC, 2019; Leo et al., 2019). In response to SLR, coastal ecosystems can expand laterally and vertically, dependent on the site, but they need the room to do so (IPCC, 2019; Leo et al., 2019). Anthropogenic pressures are the primary agent of changes to coastal wetlands, deltas, estuaries, lagoons, and aquifers (Wong et al., 2014). Human activity has caused habitat areas to fragment and has constrained them from moving landward, weakening their ability to provide coastal protection and adapt to climate change impacts (IPCC, 2019). While habitats need space as SLR increases, there is a recognized lack of case studies showing examples where coastal habitats were given room to migrate landward or vertically in response to SLR (Leo et al., 2019).

By 2100, hundreds of millions of people will be displaced because of land loss without adaptation (Wong et al., 2014). Considering socioeconomic and SLR circumstances in most developed nations, it is often not economically viable to mitigate erosion and flooding (Wong et al., 2014). Coastal adaptation is becoming a more common practice, with disaster risk reduction and management methods, integrated coastal management, and ecosystem-based adaptation (Wong et al., 2014). The risk and the cost of inaction versus potential adaptation and mitigation measures to address coastal vulnerability are pertinent procedures coastal communities need to

undertake to achieve resiliency. For natural habitats to be included in local and regional shoreline planning efforts, planners and decision-makers first need to understand where habitats can provide the most benefit for combating erosion and flooding exposure (Langridge et al., 2014). A tool to analyze such metrics is the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) coastal vulnerability model used in this study for Northeastern Florida. The InVEST coastal vulnerability model is a type of coastal vulnerability assessment (CVA) that includes habitat, SLR, and population (or other sociodemographic) analysis as inputs. Details are provided in the following sections.

1.2 Coastal Vulnerability Assessments

For the context of this study, it is important to understand the concept of vulnerability. Vulnerability can be defined as the ability of a system or place to cope with hazards (VanZomeren & Acevedo-Mackey, 2019). For coastal vulnerability, hazards include erosion and flooding caused by accelerated SLR, climate change, and extreme storms (Arkema et al., 2013). Risk, in the context of this study, is the potential impacts from erosion and flooding (Arkema et al., 2013), such as human fatalities, economic damage, and environmental damage. Vulnerability, even when incorporating the impacts of physical, geologic, and socioeconomic variables, is truly a reflection of human judgments of worthiness and risk. For instance, quality of life, infrastructure, habitat, natural resources, and cultural resources are different components humans see as valuable for providing different functions. Therefore, if these components are seen as being at risk of being damaged, they are considered vulnerable (VanZomeren & Acevedo-Mackey, 2019).

Climate, whether it be from anthropogenic caused climate change or natural variability, drives coastal hazards, which in turn poses risks to human and natural coastal systems (Wong et

al., 2014). To quantify the risks that coastal areas face, CVAs have increased in use for local communities and countries. VanZomeren and Acevedo-Mackey (2019) identified thirteen variables that were the most used across the CVAs and grouped these variables into three categories: geologic (erosion), physical (inundation), and socioeconomic (society). These categories are illustrated below:

- Geologic:
  - Shoreline change
  - Geomorphology
  - Coastal slope
  - Elevation
  - Geology
- Physical:
  - Mean tidal range
  - Relative SLR
  - Mean wave height
  - Significant wave height
- Socioeconomic:
  - Population
  - Land use
  - Infrastructure
  - Road/railway networks.

These variables are often expressed in quantitative terms, using scales of 1-5 (with 5 being highest and 1 being lowest) to signify the impact on coastal vulnerability (Rocha et al., 2020). The square root of the product mean is the most common method for evaluating coastal vulnerability that was used during previous studies (VanZomeren and Acevedo-Mackey, 2019). Usually, a Coastal Vulnerability Index (CVI) is defined as $CVI = \sqrt{(X_1 * X_2 * \ldots X_n)/n}$, for ‘n’ number of variables ‘X’. The CVI may include a product mean[1], the sum of products[2], or weighting variables of interest[3].

[1] $CVI = (X_1 * X_2 * \ldots X_n)/n$
[2] For example, $CVI = 4X_1 + 4X_2 + 2X_3 + X_4 + \cdots$
[3] For example, $CVI = (X_1 * R_1) + (X_2 * R_2) + \cdots (X_n * R_n)$ where R is a weight factor.

There are some recognized challenges with CVAs. Unfortunately, socioeconomic variables are commonly neglected (Bukvic et al., 2020). Reasons for this are multi-faceted and include poorly developed variables associated with human well-being, time constrained data, changing perceptions (VanZomeren & Acevedo-Mackey, 2019), and general unfamiliarity with social vulnerability (Bukvic et al., 2020).

Despite the general recognition that SLR affects flooding frequencies and ranges, the Federal Emergency Management Agency (FEMA) does not consider SLR in their Flood Insurance Rate Maps (FIRMs). Instead, their FIRMs focus on flooding from storm surge and rainfall that both cause upland inundation (Corbin et al., 2019). CVAs provide information for planners/managers to use for adaptive planning purposes and preventative management. However, there is often a disconnect between these assessments and their findings being utilized for restoration and protection (VanZomeren & Acevedo-Mackey, 2019) or policy changes (Bukvic et al., 2020). Bukvic et al. (2020) reviewed coastal vulnerability mapping assessments (CVMAs) across many studies and found that CVMAs are often conducted locally using various methods. CVMAs struggle with portraying the interconnection of physical and geological hazards with social vulnerability. Challenges associated with addressing slow inception events (e.g., SLR) with quick inception events (e.g., floods) tend to exacerbate these issues.

The InVEST coastal vulnerability model (referred to as the “model” in this paper), addressed many of these issues and was used throughout this study. The model is unique because it shows through mapping coastal exposure indexes how changes to the physical and biological environment (e.g., removal of natural habitat for coastal development) can impact a community’s exposure to storm-induced flooding (inundation), erosion, waves, and surge. It covers the variables that VanZomeren and Acevedo-Mackey (2019) identified in their comprehensive

review of CVAs from around the world (listed prior in this section) while adding on a crucial parameter, habitats. Additionally, the model allows for socioeconomic analysis, an important subject often neglected in CVAs, with a model input for population (or any other demographic variable of choice), showing where higher concentrated populations are more vulnerable. The model is also capable of examining several SLR scenarios. The model offers a lens to visualize the protection that natural habitats provide, with the ability to show the increased exposure when habitats are no longer present. More on how the InVEST coastal vulnerability model works is provided in the Methods section. Since SLR is one of the overarching threats to coastal areas, it is the focus of different scenarios in this study. Some background is provided below.

1.3 Sea Level Rise

SLR projections are often contradictory because many of these projections, including several used in the United States, do not follow guidelines instituted by the Intergovernmental Panel on Climate Change (IPCC) (Houston, 2021). For this study, metrics from the IPCC are delineated below and projections local to the study area from the National Oceanic and Atmospheric Association (NOAA).

SLR can be broken into three scenarios: global mean sea level rise (GMSLR), relative sea level rise (RSLR), and extreme sea levels (ESL). From 1901 to 2018, GMSLR rose by 0.2 m, with increasing rates of 1.3 mm/yr from 1901 to 1971, 1.9 mm/yr from 1971 to 2006, and 3.7 mm/yr from 2006 to 2018 (IPCC, 2021). Since at least 1971, the primary cause of the rising global mean sea level has been anthropogenic impacts (IPCC, 2021). GMSLR is attributed to the following from 1971 to 2018: thermal expansion at 50%, glacier ice loss at 22%, ice sheet loss at 20%, and land water storage changes at 8% (IPCC, 2021). GMSLR is certain to increase, but how much depends on the level of greenhouse gas emissions. Using emissions-based, conditional

probabilistic, global model projections, NOAA's 2017 report discretized GMSL into six scenarios, with associated GMSL in parentheses: Low (0.3 m), Intermediate-Low (0.5 m), Intermediate (1.0 m), Intermediate-High (1.5 m), High (2.0 m) and Extreme (2.5 m) (Sweet et al., 2017).

RSLR can be higher or lower than GMSLR due to regional and local climate and oceanic dynamic processes and factors. Climate variability in different regions of the world (e.g., the El Niño/La Niña Southern Oscillations [ENSO]) affects the interannual and interdecadal rate of rise (Wong et al., 2014). In addition, most coastlines are experiencing a rise in sea level, but those near glaciers and ice sheets (current and former) are experiencing a fall in sea level (Wong et al., 2014). Local RSLR can occur due to sediment compaction and loading, such as from deltas; tectonic movements; building loads; extraction of groundwater, etc. (Wong et al., 2014). For low-lying areas, RSLR leads to increased inundation (frequency and duration), accelerated erosion, contamination of freshwater and crops, stressing natural vegetation with saltier conditions, etc. (VanZomeren & Acevedo-Mackey, 2019).

Lastly, ESL can be caused by a combination of factors such as storm surges, tides, wind waves and swell, RSLR, and interannual sea level variability (Kopp et al., 2019). The effect of RSLR is felt by coastal communities, experiencing increasing frequencies of ESLs, meaning more flooding for coastal areas. Due to anthropogenic factors from the historical and present-day settlement, low-lying coastal communities are especially vulnerable. However, if local exposure and vulnerability spots are targeted, adaptation can be accomplished before being overwhelmed by SLR, even with the uncertainty of SLR levels and impacts (IPCC, 2019).

Locally, at the Mayport, Florida tide gauge, the sea level has risen 0.91 feet in 100 years, and the RSLR is 2.76 mm/year with a 95% confidence interval of ± 0.25 mm/yr (NOAA, 2020).

By 2100 under NOAA's 'intermediate' annual mean RSLR scenario, there will be over a meter of SLR from 2000 to 2100 at Mayport. Much of Northeastern Florida along the St. Johns River and Intracoastal areas has a land elevation of less than a meter with respect to the North American Vertical Datum of 1988 (NAVD88). SLR in Northeastern Florida will increase flood risk, salinity levels in the St. Johns River, and saltwater incursion into freshwater aquifers (Lahav, 2021).

1.4 Study Area

The area of interest for this study is the St. Johns River shoreline and adjacent Atlantic Ocean shoreline of Northeast Florida, USA, encompassed in the St. John's River Water Management District (SJRWMD), whose boundary and encompassed counties is shown in Figure 1. The coastline of Northeastern Florida is home to miles of sandy beach and dunes. The dunes serve as the first piece of critical protection against storms. Florida's eastern coastline is characterized as a barrier-island and tidal-inlet system (Hudyma et al., 2017). Florida's shallow bedrock is mostly limestone; however, the sand on the

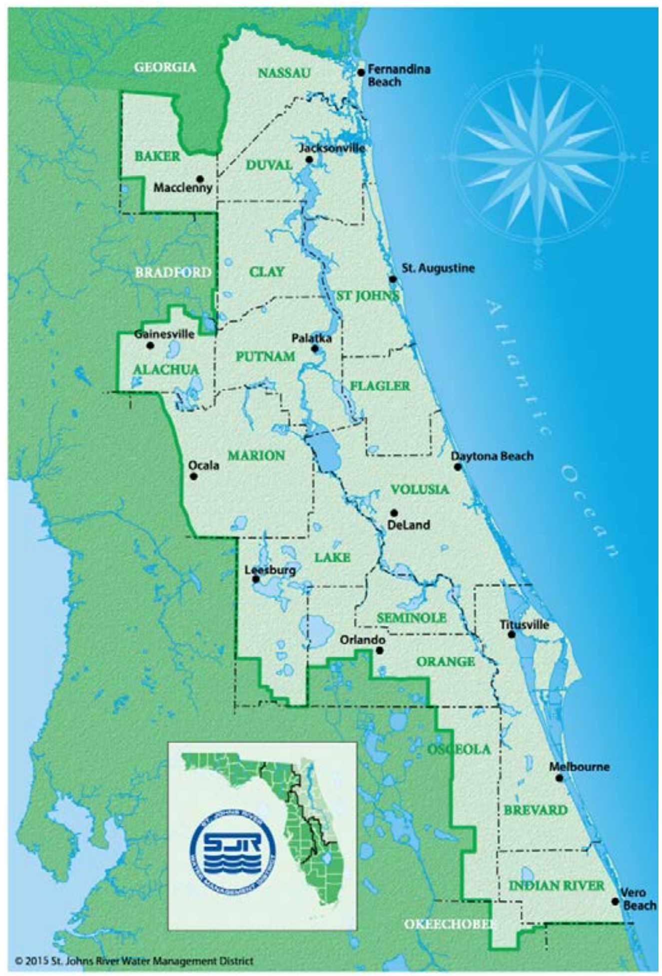

Figure 1. SJRWMD Boundary (SJRWMD, 2021)

Used by permission of the St. Johns River Water Management District

beaches is predominantly silica sands, likely from historic longshore transport from the Appalachian Mountains (Hudyma et al., 2017).

The mouth of the St. Johns River is located at 81.3947147°W 30.4004954°N. The St. Johns River runs from south to north. It is the longest river in Florida, flowing 310 miles from its marshy headwaters in Indian River County to its broad waterways through Jacksonville and into the Atlantic Ocean at Mayport (SJRWMD, 2021). The river is an ancient intracoastal lagoon system formed when sea levels lowered and barrier islands began trapping water in the flat valley (SJRWMD, 2021). The river has a very mild drop in elevation, with its headwaters less than 30 feet higher than its mouth (SJRWMD, 2021). Near the river's outlet, the river is dredged to a depth of 15 m so that large vessels can travel to the port of Jacksonville. Roughly 40 km upstream, the river returns to a natural depth of approximately 6 m (Henrie & Valle-Levinson, 2014).

The SJRWMD has jurisdiction over 12,283 square miles (7.8 million acres), has 1,400 lakes, has 148 springs, covers 18 counties, and as of 2020, has a population of 5.65 million people (SJRWMD, 2021). The river is divided into three basins: the upper basin comprises the river's marshy headwaters in the south in Indian River and Brevard counties; the middle basin in central Florida comprises where the river widens and includes Harney, Jesup, Monroe and George lakes; and lastly, the lower basin, furthest north, includes Putnam County from Lake George to the river's mouth at Mayport (SJRWMD, 2021).

The river is subject to tidal influence from the Atlantic Ocean far upstream, although there is some discrepancy as to how far. Sources vary between Lake George, 124 miles upstream from the mouth (Bacopoulos, 2017); Lake Monroe, 161 miles upstream from the river's mouth (SJRWMD, 2021); and up to 186 miles upstream (Henrie & Valle-Levinson, 2014). Storm

surges can travel as far as Lake George (Bacopoulos, 2017). When water levels are low, the river is subject to flow reversal twice a day (SJRWMD, 2021). Reversed flow can be held for multiple days if there are strong, constant northeasterly winds (SJRWMD, 2021).

1.5 Local Resiliency Efforts

Cities, regions, and nations are grappling with how to study and manage vulnerable coastal areas. For this study's area of interest, various sources have been used to help decision makers determine how best to protect vulnerable coastal regions. One of these sources is Crist et al. (2019), which included the St. Johns River. They identified large parcels of land that are beneficial as storm protection for humans and as a habitat for wildlife coined Resilience Hubs. The Crist et al. (2019) study uses different methods than this study, in part because this study centers on coastal shore points, not tracts of land. Sources in addition to this one include the following, although this is by no means a comprehensive list:

- City of Jacksonville Special Committee on Resiliency, Final Report (Lahav, 2021). The city is also currently working on a vulnerability assessment.
- Northeast Florida Regional Council (NEFRC) Resiliency Services provides grant funding, education, and coordination between agencies.
- South Atlantic Coastal Study (SACS) by the U.S. Army Corps of Engineers (USACE) (USACE, 2021b), of which the draft came out October 2021, including the Florida Appendix (USACE, 2021a).
- "Coastal Resilience Assessment of the Jacksonville and Lower St. Johns River Watersheds" (Crist et al., 2019): uses the National Fish and Wildlife Foundation (NFWF) Coastal Resilience Evaluation and Siting Tool (CREST) from Dobson et al. (2019) to

identify Resilience Hubs, defined as land areas that can provide vital habitat to fish and wildlife while also protecting humans from storms.

- City of Atlantic Beach Coastal Vulnerability Assessment (Corbin et al., 2019).
- City of St. Augustine 2016 Coastal Vulnerability Assessment, courtesy of the Florida Department of Economic Opportunity Community Resiliency Initiative: three pilot cities (one of which was St. Augustine) were chosen to study coastal flooding and identify resilient adaptations.
- "Planning for Sea Level Rise in the Matanzas Basin: Opportunities for Adaptation" by the University of Florida (Frank et al., 2015).
- Florida Department of Environmental Protection's (FDEP's) Beaches Programs, within the Office of Resilience and Coastal Protection produced the Strategic Beach Management Plan (SBMP) for Northeast Atlantic Coast Region in 2020.
- Florida's State Wildlife Action Plan by the Florida Fish and Wildlife Conservation Commission (FWC), 2019.
- Florida Coastal Mapping Program, an initiative of Florida and federal institutions to fill data gaps and accessibility of Florida seafloor data.
- St. John's River Water Management District Resiliency Work.
- NOAA's Sea Level Rise Viewer and Digital Coast.
- University of Florida's Geoplan Center Sea Level Scenario Sketch Planning Tool, which aids in the identification of transportation infrastructure that is vulnerable to SLR
- Florida Statutes Section 161.551 signed into law on June 29, 2020 and effective July 1, 2021, requires a sea level impact projection (SLIP) study before large construction projects financed by the state can begin (Schedel, 2021). FDEP is developing a mapping

tool to standardize SLR scenarios, coastal hazards, and adaptation options for SLIP studies (Schedel, 2021).

1.6 Objective

Few studies have analyzed coastal vulnerability with finely resolved spatial data at the landscape scale. Even fewer have done so with social vulnerability (besides just total population) (Arkema et al., 2017) or with the role of habitats. The purpose of this study is to map the coastal vulnerability of the St. Johns River and Northeastern Florida Atlantic Ocean shoreline within the SJRWMD, while including natural habitats, SLR, and demographics information in this analysis. The InVEST 3.9.0 coastal vulnerability model provides a visual mapped output of an exposure index to better understand the vulnerability of shorelines to storm-induced inundation (flooding), erosion, and the role of habitats on the exposure index. The model uses seven metrics (geomorphology, relief, natural habitats, wind exposure, wave exposure, surge potential, and sea level change) to create an exposure index for shorelines. SLR scenarios for current, 2050 Intermediate-High and 2100 Intermediate-High were analyzed using scenarios including habitats and no habitats scenarios. Results were juxtaposed against population density and population below poverty density. This study aims to fill a knowledge gap on the holistic vulnerability of the shorelines in Northeastern Florida, particularly with the role of habitats and some socioeconomic parameters, with the hopes of potentially becoming useful for future resiliency understanding and efforts in the region for natural-based coastal solutions that can adapt with SLR.

2.0 Methods

2.1 InVEST Coastal Vulnerability Model

The Natural Capital Project created InVEST, a suite of free, open-source software models. The coastal vulnerability model of InVEST 3.9.0 uses map inputs of natural habitat and geophysical parameters to produce map outputs of the coastal landscape's exposure to flooding and erosion when faced with extreme weather (Zaks, 2019). The model can be overlaid with human population density (or other socioeconomic parameters), allowing identification of where humans are more at risk. The model uses the spatial representation of the following bio-

Table 1. Rankings

Metric	Rank				
	1 (very low)	**2 (low)**	**3 (moderate)**	**4 (high)**	**5 (very high)**
Geomorphology[a]	Rocky shores; sheltered scarps	Solid man-made structures; wave cut platforms	Rip-rap; exposed scarps	Gravel beaches; marshes	Sand beaches; tidal/ mud/ sand flats
Relief	81 to 100 percentile	61 to 80 percentile	41 to 60 percentile	21 to 40 percentile	0 to 20 percentile
Natural Habitats[b]	Wetland hardwood, coniferous, and mixed forest; mangroves	Vegetated non-forested wetlands	Rangeland/ dunes (herbaceous, and shrub/ brushland)	Non-vegetated wetlands; seagrass	No habitat
Sea Level Change[c]	0 to 20 percentile	21 to 40 percentile	41 to 60 percentile	61 to 80 percentile	81 to 100 percentile
Wave Exposure	0 to 20 percentile	21 to 40 percentile	41 to 60 percentile	61 to 80 percentile	81 to 100 percentile
Wind Exposure	0 to 20 percentile	21 to 40 percentile	41 to 60 percentile	61 to 80 percentile	81 to 100 percentile
Surge Potential	0 to 20 percentile	21 to 40 percentile	41 to 60 percentile	61 to 80 percentile	81 to 100 percentile

[a] See Table 3 for more information.
[b] See Table 2 for more information.
[c] See Table 5 for more information.

geophysical variables: relief, natural habitats, wind exposure, wave exposure, surge potential depth contour, geomorphology, and sea level change. Each variable at each shore point is ranked from very low (rank = 1) to very high (rank = 5), and an overall exposure index is calculated (see Equation 1). The ranking system is modelled after ranking systems from Gornitz (1990) and Hammar-Klose and Thieler (2001). The ranking table used in this project is presented as Table 1; see Tables 2 and 3 for more information on the habitat and geomorphology rankings, respectively.

At each shoreline point, the exposure index (EI) is calculated as the geometric mean of the variable ranks, where R_i is the ranking of the i^{th} variable:

$$EI = \left(\prod_{i=1}^{n} R_i\right)^{1/n} \tag{1}$$

An overview of how each metric is ranked follows; further background information can be found in the InVEST User Guide for the coastal vulnerability model (Sharp et al., 2020).

The rankings for geomorphology and natural habitat were based on information provided in the InVEST User Guide, along with a literature review (see the Data Gathering section for more information). The habitat ranking calculation algorithm for each shore point is as follows: given the habitats in proximity to the shore point (based on each habitat's protective distance), the habitat with the lowest rank is weighted 1.5 times greater than the other habitats near that shore point. This provides a means to promote areas with multiple habitats in proximity as being more protected, vice areas with only one type of habitat.

The relief rankings are based on the mean elevation of the landmass, using the digital elevation model (DEM) data, within the user-defined elevation average radius of each shore

point, parceled into percentile bins (5 equal bins, 20% each) and ranked per Table 1. Areas at higher elevations above mean sea level (MSL) are less likely to be inundated.

The wind exposure rankings involve 16 equiangular sectors of a 360-degree compass. For each sector, the following values are multiplied: the fetch distance, the mean wind speed of the largest 10% wind speeds, and the percent of wind speeds that blew in that sector direction. These 16 values were summed and then ranked based on the percentile bins in Table 1. The result is each shore point's exposure to strong winds.

The wave exposure rankings are calculated as the maximum weighted average of local wind waves and oceanic waves. Both the local wind waves and oceanic waves are computed as the sum of 16 equiangular sectors. For oceanic waves, the weighted contribution is the multiplication of Heaviside step functions (where the value is one for positive arguments and zero for negative arguments) pertaining to the maximum fetch distance, highest 10% wave power values, and percentage of the time those highest 10% power waves were observed in that sector. This is similar for wind waves, except the wave power of the top 10% wind speeds is of interest instead of the top 10% wave power. For oceanic waves, the Heaviside step function is 0 if the fetch distance is less than the maximum fetch distance and 1 if otherwise. For local wind waves, this is reversed – i.e., local wind waves will only accumulate for fetch rays less than the maximum fetch ray. The average water depth from the bathymetry data is used in calculating the wave period (T) and height (H), which are used in computing the wave power ($P = \frac{1}{2}H^2T$). The maximum weighted average power of the local wind and oceanic waves is then parceled into percentile bins and ranked per Table 1 for each shore point. In general, waves with a longer period (such as swells generated by a storm) are more powerful, given the same wave height, than shorter period waves. Larger fetch distances also contribute to bigger waves. Thus,

coastlines facing the open ocean are typically subject to more powerful waves than sheltered areas and, consequently, more susceptible to erosion.

Surge potential is calculated from the distance of the shore point to the continental shelf contour and then ranked per percentile bins in Table 1. This is a proxy way of estimating storm surge elevation, which is more accurately defined as a function of wind direction and speed and the time wind blows over shallow water.

Sea level change for the model involves inputting a point vector with an attribute field for a SLR metric (such as net rise or rate). Then, the model takes weighted averages of the values at the two nearest SLR points to assign SLR values to each shore point, where the weights are the inverted distance from SLR point to shore point (Sharp et al., 2020). See the Data Gathering section for more information on this parameter.

2.1.1 Limitations

The InVEST coastal vulnerability model is meant for coastlines, so including the St. Johns River shoreline, even though the river is connected to the ocean and influenced by tides far upstream, is using the model not in its fully intended capacity. For instance, the wave and wind data in WaveWatchIII provided by InVEST is oceanic. According to Bacopoulos et al. (2009), the water surface elevation of the St. Johns River depends on wind effects from the deep ocean as well as local wind. Hence, local wind data and an idealized model of waves would need to be added that reflects the subtidal pulses specific to the St. Johns River (Henrie & Valle-Levinson, 2014) to reflect wind and waves for the river accurately. The river is influenced far more by meteorological forcing and astronomic tides than freshwater river flows (Bacopoulos et al., 2009). This implies output from the InVEST coastal vulnerability model may be appropriate. But, since SLR for each shore point is computed as a weighted average from the point vector

input (e.g., tide gauge), the SLR values up the St. Johns River are likely not accurate as they do not consider bathymetry and distance upriver. In summary, the results for the St. Johns River shoreline should be viewed with more skepticism than the Northeastern Florida coastline.

In addition to the site-specific limitation mentioned above, there are some broader limitations to the InVEST coastal vulnerability model. One limitation is that while ranks of only 1-5 follow the traditional CVA precedent, the model may truncate detail that some planners would find valuable. In other words, expanding to ranks from 1-10 might provide more helpful information. Another limitation is that the model produces qualitative outputs associated with exposure to erosion and inundation (again, the nature of a CVA). However, quantitative inputs are used, and statistical analysis can be done on the qualitative outputs. Thirdly, the model is intended to be used on a large scale. The model does not account for regional nearshore characteristics such as large-scale sediment transport, nor does the model provide a prediction of the response of an area to specific storms. The model also does not account for the quality and quantity of habitats or attempt to enumerate how habitats reduce coastal hazards (Sharp et al., 2020). The model does not assign a monetary value to the role of habitats. By using the geometric mean of seven variables, the model oversimplifies dynamic local coastal processes. The model assumes that areas of the same geomorphic exposure class behave similarly and do not incorporate processes of sediment or hydrodynamic transport. The model does not predict changes in the shoreline configuration (Sharp et al., 2020).

The InVEST coastal vulnerability model also does not have the capability of accounting for interactions between different parameters. For instance, the modeled weight of relative wave and wind exposure will not change as a function of the site geomorphic conditions. Furthermore, the model assumes that habitats provide erosion protection independent of the geomorphology in

that area; this causes devaluation of the vulnerability of regions with low geomorphic rankings (e.g., high rocky cliffs) and exaggeration of the vulnerability of regions with high geomorphic rankings (e.g., mud flats) (Sharp et al., 2020).

The model also does not include nearshore wave field or storm surge modeling. Since InVEST provides default WaveWatchIII worldwide wind and wave data with the aim of being usable for most locations, input for wave and wind exposure is also relatively simplified. For example, each coastal segment is allotted a weighted average of the wave statistics of the closest three WaveWatchIII grid points to approximate the oceanic wave exposure. Thus, any 2D processes that may occur nearshore are not included. Furthermore, instead of using the full-time series of wind speeds from WaveWatchIII to compute storm wind speeds, the model uses the mean of wind speeds greater than the 90th percentile. Therefore, extreme events are not fully represented in InVEST (Sharp et al., 2020). Additionally, there is one maximum fetch distance entry instead of computation of maximum fetch distance per shore point.

2.2 Data Gathering

QGIS 3.16.6 and ArcGIS Pro 2.8.2 were used to format datasets to input them into InVEST per the coastal vulnerability model's specifications and visualize and analyze the model's spatial results. MATLAB was used for post model analysis as well. WaveWatchIII (Tolman, 2009) and the continental shelf contour were provided with the InVEST sample data; the rest of the spatial files were obtained from other sources. The data inputs are summarized below and reproduced in tabular form in Appendix B. The only requirement for coordinate systems for the InVEST coastal vulnerability model was for the area of interest to be in a projected coordinate system; Universal Transverse Mercator (UTM) Zone 17N was used. Global

data provided by InVEST was in the World Geodetic System (WGS) 1984 geographic coordinate system.

Area of Interest (AOI): The AOI is a polygon vector encompassing the St. Johns River and adjacent Atlantic Ocean coastal area. The model plots shore points on the coastline of the landmass within the AOI. The AOI polygon was created in-house to be within the water management district boundary obtained from the SJRWMD.

Model Resolution: The model resolution is a numeric value in meters for designating the spacing between shore points. A smaller value provides more shore points but a slower model computation speed. The default 1 km was used.

Landmass: The Florida Shoreline polygon vector from the FWC was used for the landmass.

WaveWatchIII: WaveWatchIII is a shapefile of model hindcast analysis of wind and wave data representing storm conditions at each grid point and is used to compute the wind, wave, and surge potential exposure rankings (Sharp et al., 2020). WaveWatchIII model results were provided by InVEST.

Maximum Fetch Distance: Fetch distance is the distance wave and wind energy can travel over water without being intercepted by land. The maximum fetch distance is a numeric value in meters used in the wind exposure ranking to avoid using fetch distances across a whole ocean. The default 12,000 m was used for this proposal; however, a sensitivity analysis was conducted to ensure doing so was satisfactory, as described in Section 3.1.

Bathymetry: As a raster dataset, bathymetry is used for average water depths in calculating wave periods and heights. The data was obtained from NOAA.

Digital Elevation Model (DEM): The DEM is a raster dataset of elevation data used for the relief rankings of the shoreline. Ten raster files from the United States Geological Survey (USGS) National Elevation Dataset (NED) at 1/3 arc-second resolution were merged into one file to cover the AOI.

Elevation Averaging Radius: The elevation averaging radius is a numeric value in meters to specify the distance around each shore point for an average elevation. The default 5,000 m was used.

Continental Shelf Contour: The continental shelf contour is a polyline vector, provided by InVEST, used in the surge potential rankings; typically, the further distance between the continental shelf and the coastline, the greater the storm surge (Sharp et al., 2020).

Habitats: A CSV table was made to specify to the model the habitat shapefiles, their rank, and their protective distance (the distance in meters that the habitat will provide coastal protection). All habitat data came from the SJRWMD 2014 Land Use and Cover dataset, obtained from Florida Geographic Data Library (FGDL), except for seagrass obtained from FWC. Note that there are no coral reefs in the AOI. Ranks and protective distances for the habitats were based on information provided in the InVEST User Guide (Sharp et al., 2020) as well as from a literature review of other studies that used the coastal vulnerability model (Arkema et al., 2013, 2017; Cabral et al., 2017; CZMAI, 2016; Hopper & Meixler, 2016; Langridge et al., 2014; Mandle et al., 2017; Ruckelshaus et al., 2016). Further information is provided below and in Table 2.

Coastal forests, including mangrove wetlands, provide protection by reducing current strength (wave and wind-generated currents), and lessening shallow water wave heights (Mandle et al., 2017; Sharp et al., 2020). Marshes and seagrass decrease wave energy, reduce sediment

movement and help nearshore beds grow (Sharp et al., 2020). Mangroves and saltmarshes are also documented to reduce annual flooding by over 20% and 15%, respectively (Leo et al., 2019). In addition to shoreline protection, these habitats can improve water quality, habitats for biota, and other ecosystem services (Langridge et al., 2014). Sand beaches without vegetation do not provide much shoreline protection for flooding and erosion. Since the mangroves and seagrass for the AOI are within estuaries (i.e., not fronting the coastline), they were given protection distances on the short end of the range of distances from the literature review.

For wetlands, the SJRWMD level 3 data types were used in this study; they include the following: bay swamps, cypress, emergent aquatic vegetation, freshwater marshes, hydric pine flatwoods, mangrove swamps, mixed wetland hardwoods, non-vegetated wetlands, pond pine, saltwater marshes, treeless hydric savanna, wet prairies, wetland forested mixed, and willow and elderberry. Generally, wetlands were ranked 1 if they were a hardwood or coniferous forest, ranked 2 if they were vegetated but not forested, and ranked 4 if non-vegetated. It was decided to parse out the wetlands at the finer level 3 to provide greater flexibility for rankings and protective distances.

The SJRWMD rangeland level 2 and level 3 were the same and included herbaceous (dry prairie), mixed rangeland (mixed upland non-forested), and shrub and brushland (wax myrtle or saw palmetto, occasionally scrub oak). Rangeland incorporated dunes for the Northeastern Atlantic coastline. All rangeland was ranked 3, but different protective distances were given.

For this study, SJRWMD level 1 for upland forests was sufficient and was ranked 1. Level 2 included tree plantations, upland coniferous forests, and upland hardwood forests. Level 3 consisted of the following: Australian pine, cabbage palm, coniferous plantations, forest regeneration areas, hardwood – coniferous mixed, longleaf pine – xeric oak, pine flatwoods, sand

pine, tree plantations, upland hardwood forests, upland hardwood forests, and xeric oak. These different types of forests are listed for reference, they were not delineated for the model, just upland forest habitat was sufficient.

Table 2. Habitat Rankings and Protective Distances

Habitat	Rank	Protective Distance (m)
Rangeland Herbaceous	3	75
Rangeland Mixed	3	75
Rangeland Shrub and Brushland	3	100
Seagrass	4	500
Upland Forests	1	500
Wetlands Bayswamps	1	300
Wetlands Cypress	1	200
Wetlands Emergent Aquatic Vegetation	2	125
Wetlands Forested Mixed	1	250
Wetlands Freshwater Marshes	2	125
Wetlands Hydric Pine Flatwoods	1	200
Wetlands Mangrove Swamps	1	500
Wetlands Mixed Hardwoods	1	300
Wetlands Non-vegetated	4	125
Wetlands Pond Pine	1	200
Wetlands Saltwater Marshes	2	125
Wetlands Treeless Hydric Savanna	2	125
Wetlands Wet Prairies	2	125
Wetlands Willow and Elderberry	1	300

Geomorphology: The geomorphology polyline vector identifies different shoreline types and assigns them a rank (a "rank column" was added to the attribute table). The data was primarily obtained from the FWC Environmental Sensitivity Index (ESI) Shoreline Classification Lines. In the vein of being conservative, the most sensitive code present for the shoreline segments was used; rankings for the different shoreline types are presented in Table 3. In addition, InVEST recommends including hard coastal structures (e.g., seawall, bulkheads, etc.)

with the geomorphology data. The ESI dataset already included rip-rap walls and other man-made structures, including the jetties at New Smyrna Beach, Fort Pierce Inlet, Indian River Lagoon, and Canaveral Barge. However, the jetties at Mayport and St. Augustine inlet had to be added manually.

Table 3. Geomorphology Shoreline Rankings

Shoreline Type[1]	Rank
1A: Exposed rocky shores; Exposed rocky banks	1
1B: Exposed, solid man-made structures	2
2A: Exposed wave-cut platforms in bedrock, mud or clay	2
2B: Exposed scarps and steep slopes in clay	3
3A: Fine- to medium- grained sand beaches	5
3B: Scarps and steep slopes in sand	5
4: Coarse-grained sand beaches	5
5: Mixed sand and gravel beaches	5
6A: Gravel beaches	4
6B: Exposed riprap	3
7: Exposed tidal flats; Sand flats	5
8A: Sheltered rocky shores and sheltered scarps in bedrock, mud or clay	1
8B: Sheltered solid man-made structures	2
8C: Sheltered riprap	3
9A: Sheltered tidal flats; Mud flats	5
9B: Vegetated low banks	4
9C: Hypersaline tidal flats	5
10A: Salt- and brackish- water marsh	4
10B: Freshwater marsh	4
10C: Swamps	4
10D: Scrub-shrub wetlands	4
[1]Most sensitive (MSTSENDES) code from the Florida Fish and Wildlife Conservation Commission, Environmental Sensitivity Index (ESI.) Shoreline Lines.	

Human Population: Data from the US Census Bureau 2015 Census Block Groups in Florida (with Selected Fields from the 2011-2015 American Community Survey (ACS)) via FGDL was used. The data was in a geodatabase and had to be converted to a raster for the InVEST model. Total population and population below the poverty level (population with

income in the past 12 months below poverty level) were trimmed to the extent of the SJRWMD (to save computation by not having the whole state).

Population Search Radius: The population search radius is used around each shore point to calculate the population density. The default 5,000 m was used.

Sea Level Rise: The model takes SLR as a point vector with an attribute field for a sea level change metric (rise, rate, etc.). Several CVA's use 1 ft SLR increments (or similar), including the NFWF CREST Targeted Watershed Assessment for Jacksonville and the Lower St. Johns (Crist et al., 2019), and the City of St. Augustine (2016) CVA, which increased sea level at half foot increments. NOAA's Technical Report NOS CO-OPS 83 "Global and Regional Sea Level Rise Scenarios for the United States", referenced as Sweet et al. (2017), recommends for long-term risk management to set an upper-bound and a mid-range scenario for SLR, which can provide a planning envelope. In their example for Miami, Sweet et al. (2017) use Intermediate (GMSLR of 1.0 m), Intermediate-High (GMSLR of 1.5 m) and Extreme (GMSLR of 2.5 m), with the first two as the envelope, and the Extreme for demonstrating worst-case possibility. Langridge et al. (2014) use SLR projections for the years 2050 and 2100, Mandle et al. (2017) for 2050, and Arkema et al. (2013) for 2100 (but for four climate related SLR scenarios). Corbin et al. (2019), the City of Atlantic Beach CVA, did 2044, 2069 and 2119 (for 25, 50 and 100-year timeframes, respectively), with 2017 NOAA Intermediate-High SLR projections. Frank et al. (2015) SLR planning report for the Matanzas Basin did a range of SLR scenarios but focused on 3 feet SLR by 2100. The Draft SACS uses the USACE Sea Level Calculator, which uses the older 2006 NOAA sea level change rate, not the newer 2017 NOAA rate. In SACS Appendix for Florida (USACE, 2021a), for their refined Tier 2 analyses, they use 2120 USACE Intermediate and High scenarios.

Given the examples above, this study used SLR data for the years 2050 and 2100 for Intermediate, Intermediate-High, and Extreme projections from the 2017 NOAA's Technical Report NOS CO-OPS 83, as listed in Table 4. This totals to seven SLR datasets, including current at 0 cm of SLR (which corresponds to the year 2000 from the 2017 NOAA report). The 2017 NOAA data consists of updated GMSL and associated RSL scenarios per future greenhouse gas emissions at a 1-degree spatial grid, with ocean-level change and vertical land motion for RSL. Tide gauges used, from north to south, as seen in Figure 2, are Fernandina Beach, Mayport, Daytona Beach, Trident Pier, and Virginia Key. Daytona Beach and Trident Pier have less than 40 years of data, and because of that, were excluded from the SACS. However, NOAA did calculate projections for these tide stations, and more data points are helpful for this large study area, so these tide stations were included in this study.

Table 4. NOAA SLR Data (Sweet et al., 2017)

Tide Gauge	**Latitude**	**Longitude**	**2050 Int. (cm)**	**2050 Int. High (cm)**	**2050 Ext. (cm)**	**2100 Int. (cm)**	**2100 Int. High (cm)**	**2100 Ext. (cm)**
Fernandina Beach	30.67	-81.47	43	60	92	114	184	319
Mayport	30.39	-81.43	43	60	93	115	185	320
Daytona Beach	29.23	-81	40	58	90	110	181	315
Trident Pier	28.41	-80.59	41	60	91	113	183	318
Virginia Key	25.73	-80.16	42	58	88	115	183	316
Note: Values are for the medium sub-scenario or 50^{th} percentile of the climate related sea level projections consistent with the GMSL scenario, and associated RSL changes projected at the grid locations and tide gauge.								

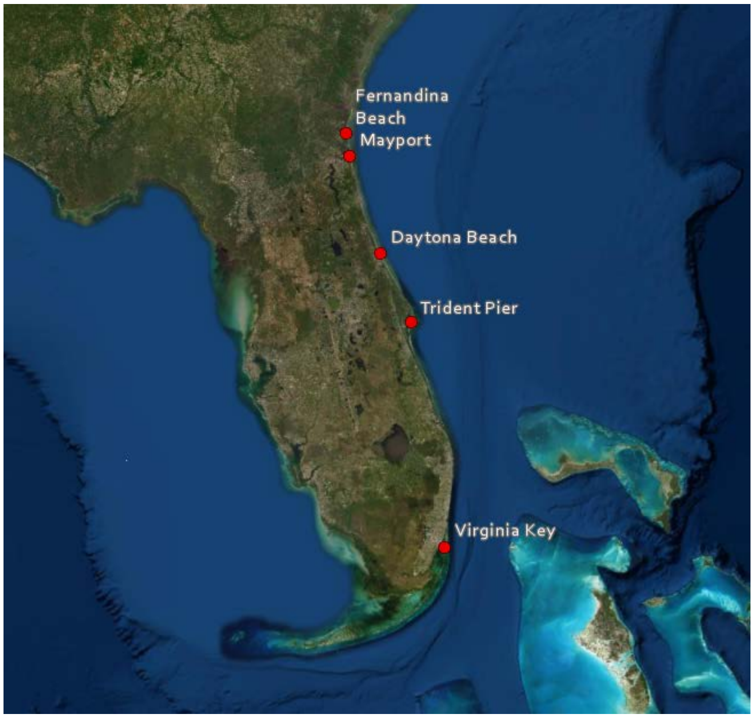

Figure 2. NOAA Tide Gauges Used

The InVEST coastal vulnerability model is designed to analyze variation over space, but for SLR, understanding time variation is also critical. There is some variation for SLR projections of the tide gauges along the eastern coast of Florida, but these differences are relatively small (± 5 cm). In the context of the model, if, for example, the 2050 Intermediate scenario is run, the SLR values between 40 cm and 43 cm (only 3 cm difference) will be binned into five percentile groups and ranked 1 through 5. This example spatially ranks a SLR scenario, but it would be better to examine SLR changes over time while maintaining some spatial uniqueness. Langridge et al. (2014) cited three SLR scenarios per projections from state guidance for 2000 (baseline), 2050 (moderate) and 2100 (high). They reflected these in the InVEST model by assigning them ranks 1, 3 and 5, respectively. In other words, they appeared to have lost any connection to the actual SLR values for their area. All seven SLR datasets were run in the model to incorporate the Florida SLR projections. Then, using Excel, the SLR values for

each shore point (the intermediate model output SLR values in cm before being ranked) were combined to get the five percentile groups across all scenarios (see Table 5).

Table 5. SLR Rankings

Rank	**1 (very low)**	**2 (low)**	**3 (moderate)**	**4 (high)**	**5 (very high)**
Percentile	0 to 20 Percentile	21 to 40 Percentile	41 to 60 Percentile	61 to 80 Percentile	81 to 100 Percentile
SLR (cm)	0 – 40.50537667	40.50537668 – 60	60.0000001 – 111. 4425571	111.4425572 – 182.1295189	182.1295189 – 319.5180566

With the revised ranks shown in Table 5, the current scenario is rank 1 throughout; the 2050 Intermediate-High is composed of ranks 2 and 3; and the 2100 Intermediate-High is composed of ranks 4 and 5 - these are the three scenarios analyzed for the rest of this study. In other words, 2050 Intermediate, 2050 Extreme, 2100 Intermediate, and 2100 Extreme scenarios aided in the distribution of SLR ranks but will not be analyzed as stand-alone scenarios since the previous three mentioned provide sufficient coverage of rank values. Also, by focusing on three scenarios instead of seven, this study was able to more thoroughly analyze other metrics such as habitat role and demographics. The SLR ranks in the ArcGIS Pro attribute tables for the current, 2050 Intermediate-High and 2100 Intermediate-High were therefore updated per the conditions in Table 5. The exposure index was recalculated using Equation 1. The exposure no habitats ranks were recalculated using Equation 1 but with habitat rankings all set to 5. Habitat role was recalculated as the difference between exposure (with habitats) and exposure no habitats.

2.3 Analysis Methods

Similarly to Hopper and Meixler (2016), ArcGIS Pro’s Spatial Autocorrelation (Global Moran’s I) geoprocessing tool and Hot Spot Analysis (Getis-Ord Gi*) spatial statistics tool were utilized for analysis. Before employing these tools, though, the *distance band or threshold*

distance was determined by using the Calculate Distance Band from Neighbor Count tool, with the recommended eight neighbor count (ESRI, n.d.).

The Moran I tool was used to test for significant clustering of coastal exposure values. *Fixed distance band* was used for the *conceptualization of spatial relationships* method in the tool since that method works well for point data and is also the appropriate method to use in the Hot Spot Analysis tool. The *distance method* used was *Euclidean*, as it measures the straight-line distance between points. It was more appropriate than the *Manhattan* method, which measures the distance between points along axes at right angles, intended for when distance is restricted to a street network. *Row standardization* was used to counteract the bias imposed by using an aggregation scheme to compute the exposure indexes of the shore points. The null hypothesis for the Moran I tool is that parameter values (in this case, the coastal exposure index) are randomly distributed (i.e., are not spatially correlated). The tool computes an Index value (between -1 and 1) compared to the Expected Index value. Along with the variance of the data and the total number of data points, the tool computes a z-score and a p-value, which can be used to infer whether there is statistical significance for spatial configuration of a field of a feature, i.e., if it is clustered, dispersed, or random.

The Hot Spot Analysis (Getis-Ord Gi*) spatial statistics tool pinpoints statistically significant hot spots and cold spots of given data. Based upon the input, the tool produces an output with a z-score, p-value, and confidence level bin. In this study, large positive z-scores and low p-values are hot spots and indicate highly vulnerable locations, whereas large negative z-scores and low p-values are cold spots and indicate areas of low coastal vulnerability.

In addition to these spatial statistics analysis methods, other analyses were conducted. One of which was a sensitivity analysis of the model to the maximum fetch distance. Another

was using MATLAB to calculate the high exposure index percentile (top 25%) of all scenarios to more readily compare to demographics (population and population below poverty), analogous to the technique employed by Arkema et al. (2013).

2.4 Areas of Focus

Since the study area is large, it is beneficial to zoom in on a few areas to get a closer look at the model results. Some areas impacted by Hurricane Matthew in 2016 and Hurricane Irma in 2017, which had immense impacts on Northeastern Florida, were chosen. Hurricane Matthew, a major Category Three hurricane, tracked northward along Florida's eastern coast. It hit Duval through Indian River Counties causing significant damages, including along beaches that were already critically eroded (FDEP, 2017). Hurricane Irma was a strong Category Four hurricane at landfall, which tracked northward up the Florida peninsula and impacted the entire east coast of Florida heavily (FDEP, 2018). In Northeastern Florida, the elevated storm tide along with stormwater runoff led to the lower St. Johns River to flood Jacksonville (FDEP, 2018). The St. Johns River rose approximately 0.75 m above the ground during Hurricane Irma because of rainfall and storm surge (Hudyma et al., 2017). The 2017 Geotechnical Extreme Events Reconnaissance (GEER) Report (Hudyma et al., 2017) documented geotechnical damage from Hurricane Irma in Central and Northeastern Florida. Some of the sites in the 2017 GEER report include the Jacksonville historic district (just south of downtown Jacksonville) and beaches along Northeastern Florida, as detailed in

Table 6; these will be the focus areas (callouts) for this study. Figures including these focus areas are in Appendix A.

Table 6. Focus Areas (Hudyma et al., 2017)

Site	Latitude	Longitude	Description
Jacksonville			
1. Donald Street Pocket Park	30° 18' 0.99" N	81° 41' 47.13" W	Local scour behind river bulkhead and private boat dock damage from Hurricane Irma.
2. Memorial Park	30° 18' 38.44" N	81° 41' 46.16" W	The park and adjacent streets flooded during Hurricane Irma, resulting in damage along the riverfront.
Northeast Florida Beaches			
3. Beverly Beach – Flagler County	29° 32' 36.21" N	81° 9' 30.17" W	Location of Beverly Beach Camptown RV Resort. Scour occurred at the concrete sea wall and staircase from Hurricane Irma.
4. Painters Hill – Flagler County	29° 32' 36.21" N	81° 9' 30.17" W	Dune erosion occurred here during Hurricane Matthew and Irma. Hudyma et al. (2017) had this as two locations separated by ~140 m, 3423 N. Ocean Shore Blvd and 3397 N. Ocean Shore Blvd; coordinates to the left are for the first address.
5. Marineland	29° 40' 18.47" N	81° 12' 50.97" W	Border of Flagler County to the south and St. Johns County to the north, located at 9600 N Ocean Shore Blvd, St. Augustine. Hudyma et al. (2017) investigated a breach site and an overwash site from Hurricane Irma just north of Marineland, located about 1.36 km apart.
6. St. Johns Ocean Pier	29° 51' 25.98" N	81° 15' 55.61" W	Located at 350 A1A Beach Blvd. Beach revetment did not withstand overwash from Hurricane Irma well.
7. Vilano Beach – St. Johns County	29° 56' 46.05" N	81° 18' 7.5" W	Regarded as the most damaged beach from Hurricane Irma. Coordinates to the left are from near the 3920 Coastal Highway, St. Augustine study location.

3.0 Results and Discussion

3.1 Sensitivity Analysis

To determine if using the default 12,000 m for the maximum fetch distance was appropriate, four additional model runs were conducted: +/- 10% of 12,000 m (10,800 m and 13,200 m), 20 km (to represent maximum fetch distance for the St. Johns River) and 40 km (to represent maximum fetch distance for the Indian River). These model runs were conducted without a SLR input. Considering computational expense with model run time, it was deemed appropriate to test one model input in this manner. As seen in Table 7, the exposure index mean and standard deviation did not change for different maximum fetch distances. The exposure index median is 0.03 higher for 12,000 m and 13,200 m fetch distances. This small variation in model output suggests that the default maximum fetch distance of 12,000 m is sufficiently long for this study. If of interest, one could have kept decreasing the maximum fetch distance input to find the minimum value that would be appropriate to use (i.e., find a cutoff value where below that value the model outputs change but above that value the model outputs are consistent). But this study was primarily concerned with ensuring that maximum fetch distance was sufficiently large, so this reduction analysis was not conducted.

Table 7. Maximum Fetch Distance Sensitivity Analysis

Maximum Fetch Distance	Exposure Index Mean	Exposure Index Median	Exposure Index Standard Deviation
10,800 m	2.57	2.5	0.55
12,000 m	2.57	2.53	0.55
13,200 m	2.57	2.53	0.55
20,000 m	2.57	2.5	0.55
40,000 m	2.57	2.5	0.55

3.2 Scenario Analysis

Histograms of various outputs from the InVEST model are presented in the following figures. Recall that rank = 1 is for very low exposure and rank = 5 is for very high exposure. Figure 3 includes the model outputs that are consistent between scenarios, albeit wind, wave, surge, and relief rankings were left out of the figure because these metrics are placed in five equal percentile bins, and thus are not as interesting to see. As seen in the top left histogram of Figure 3, habitats have strong rankings throughout the study area, whereas the rankings for geomorphology, the top right histogram, are moderate to highly vulnerable. The population output from InVEST is the average human population density (as seen in the bottom left histogram, average population below poverty density in the bottom right histogram) for each

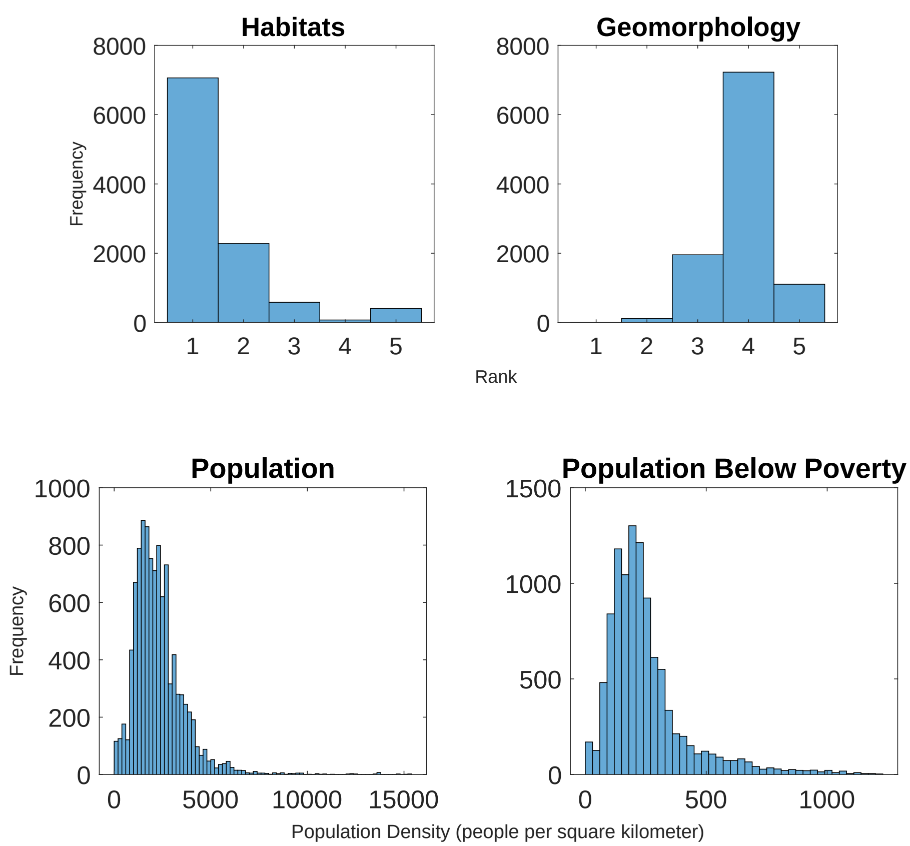

Figure 3. Model Outputs Consistent Across Scenarios

shore point (i.e., the people per square kilometer). Both histograms have distributions that are skewed to the left, meaning there are fewer areas with large populations densities. This result is somewhat intuitive for such a large AOI. The mean population density is 2,298 people per km^2. The mean population below poverty density is 250.98 people per km^2.

Model outputs different across three SLR scenarios (current, 2050 Intermediate-High, and 2100 Intermediate-High) are displayed as histograms in Figure 4. *Exposure* is the final coastal exposure index. *Habitat role* is the difference between *exposure* and *exposure no habitat*

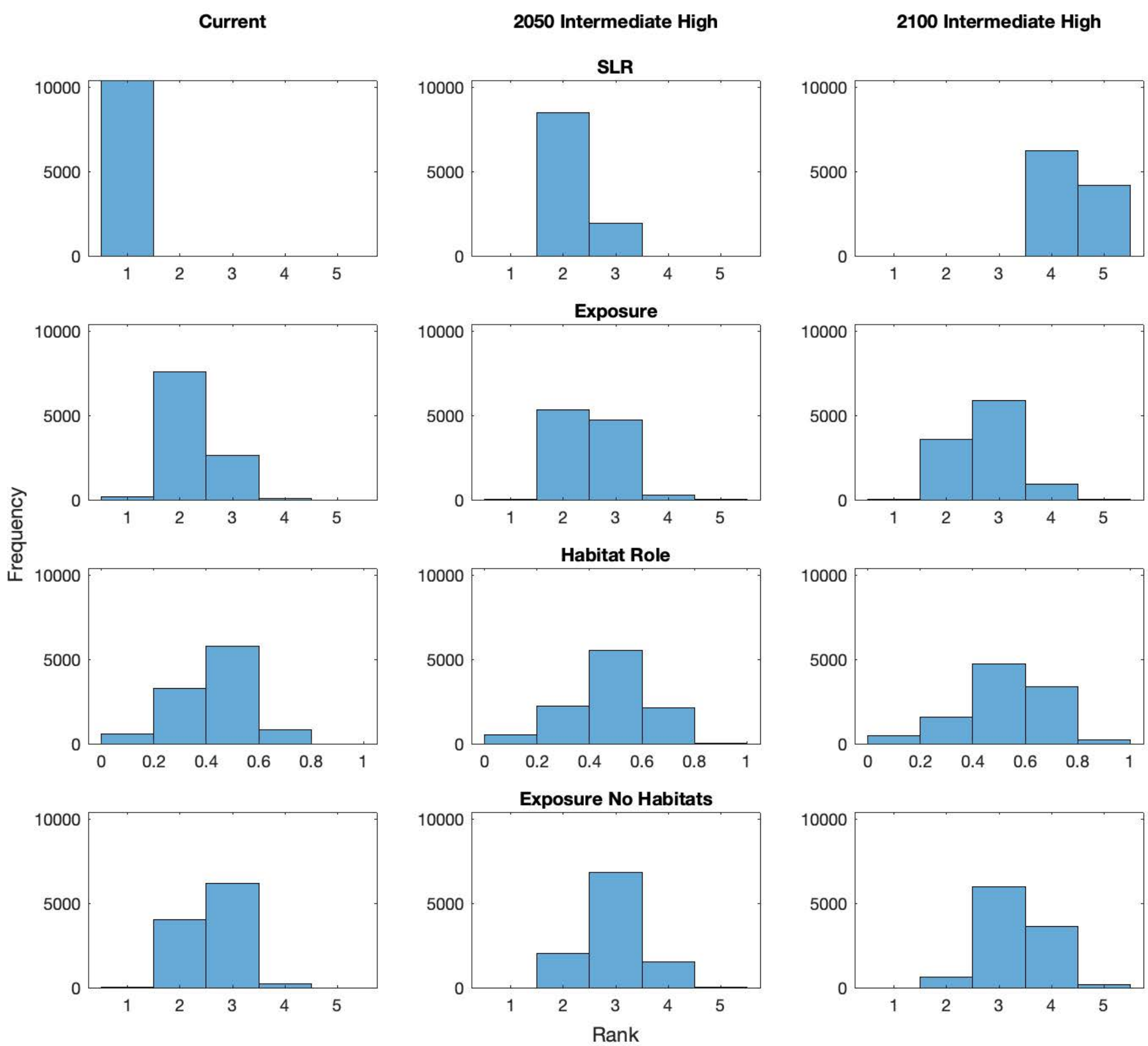

Figure 4. Model Outputs for Different SLR Scenarios

ranks. Exposure no habitat is computed with habitat rank as 5 everywhere (which corresponds to no habitat per the ranking scheme). The x-axis (rank) for habitat role has a shorter range than the other histograms to show more detail. In Figure 4 it is apparent how exposure, habitat role, and exposure no habitats increase in rank as SLR increases. Mean exposure increases from a rank of 2.24 to 2.50 to 2.77 for the SLR scenarios of current, 2050 and 2100, respectively; mean habitat role increases from 0.42 to 0.47 to 0.52, respectively; and mean exposure no habitats increases from 2.67, to 2.98, to 3.29, respectively. As SLR rises, the importance of habitats for protecting coastlines increases, because as shown here, the mean habitat role increases along with mean exposure no habitats.

To compare the different SLR and habitat scenarios (with and without habitats) for the different demographics scenarios (population and population below poverty), the exposure indexes for all of the SLR and habitat scenarios were conglomerated to find the top 25% of coastal exposure indexes (75th percentile), similar to the method deployed in Arkema et al. (2013) and Langridge et al. (2014). This highest quartile was rank greater than 3.12, termed *high* exposure. The lowest quartile, for the bottom 25% of coastal exposure indexes, was 2.3063, called *low* exposure. *Middle* exposure comprises the values in between the high and low quartile exposures. The charts in Figure 5 were created for the percent of the population (left chart) and percent of population below poverty (right chart) in these high exposure areas (rank > 3.12) for the different SLR and habitat scenarios.

As seen in Figure 5, for the high exposure areas, vulnerability is greater for *without habitats* than for *with habitats* for every SLR scenario for both total population and population below poverty. As SLR increases, so do people vulnerable to flooding and erosion. The values from Figure 5 are delineated in Table 8, with an additional calculation: *percent difference* of

percent of population (or population below poverty) in high exposure areas between without habitats scenario and with habitats scenario. Examining population (the first half of Table 8), the percent difference increases from 12.88% to 28.86% to 36.08%, for the current, 2050, and 2100 SLR scenarios, respectively. This shows that as SLR increases, habitats have greater agency shielding people out of high exposure areas. Similarly, for the population below poverty (the second half of Table 8), the percent difference increases from 12.02% to 28.94% to 37.78%, for the current, 2050, and 2100 SLR scenarios, respectively. There is no discernable difference between the percentages of the total population and the population below poverty being affected under the different scenarios. Since populations are expected to grow, this study likely underestimates the number of vulnerable people in future scenarios if resiliency efforts are not undertaken. This exercise demonstrates how the with habitats scenario provides more protection (than the without habitats scenario) to the total population and population below poverty for each SLR scenario. Furthermore, it shows that as SLR increases, the protective capacity of habitats increases, keeping more of the population and population below poverty out of high exposure areas.

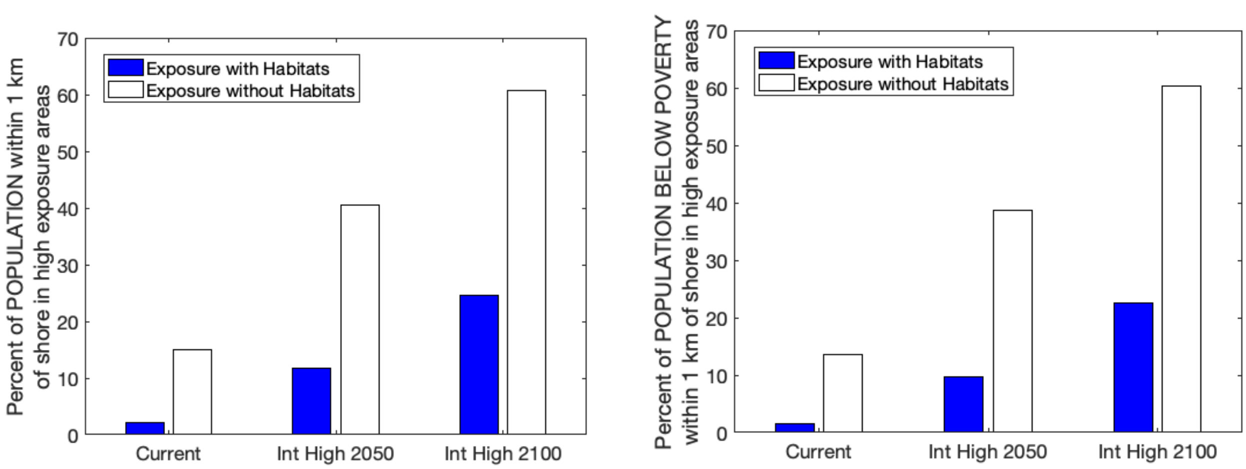

Figure 5. Demographics for SLR and Habitat Scenarios

Table 8. Habitat Protection Provided to Total Population and Population Below Poverty

Scenario	Current	2050 Intermediate-High	2100 Intermediate-High
Percent of *population* in high exposure areas			
With habitats	2.14%	11.76%	24.62%
Without habitats	15.02%	40.62%	60.70%
Percent difference*	12.88%	28.86%	36.08%
Percent of *population below poverty* in high exposure areas			
With habitats	1.61%	9.76%	22.57%
Without habitats	13.63%	38.7%	60.35%
Percent difference*	12.02%	28.94%	37.78%
*Difference between *without* habitats and *with* habitats scenario.			

3.3 Spatial Analysis

To visualize the exposure indexes in quartiles from the section above, Figure 6 was produced, where *low* exposure is ranked ≤ 2.3063 and shown as yellow, *high* exposure is rank > 3.1203 and shown as red, and *medium* exposure is the ranks in between the high and low quartile exposures and shown as orange. The figure shows that as SLR increases with time, coastal exposure increases. It also shows that coastal exposure is worse when habitats are not present, as evidenced by comparing the bottom row of images without habitats present to the top row of images where habitats are present. Figure 6 presents a strong case for the increased vulnerability of coastal communities in this study area to erosion and flooding as SLR increases and if habitats are not protected.

Appendix A includes larger figures that showcase the areas of focus from Section 2.4. Figure 9 in Appendix A includes the current scenario coastal exposure indexes with low, medium, and high quartiles, Figure 10 shows the same for the 2050 SLR scenario, and Figure 11 for the 2100 SLR scenario. Across these three images, it is apparent how exposure increases with increasing SLR for the whole AOI and for each area of focus. The focus area in downtown Jacksonville is primarily medium exposure for the current scenario and jumps to primarily high

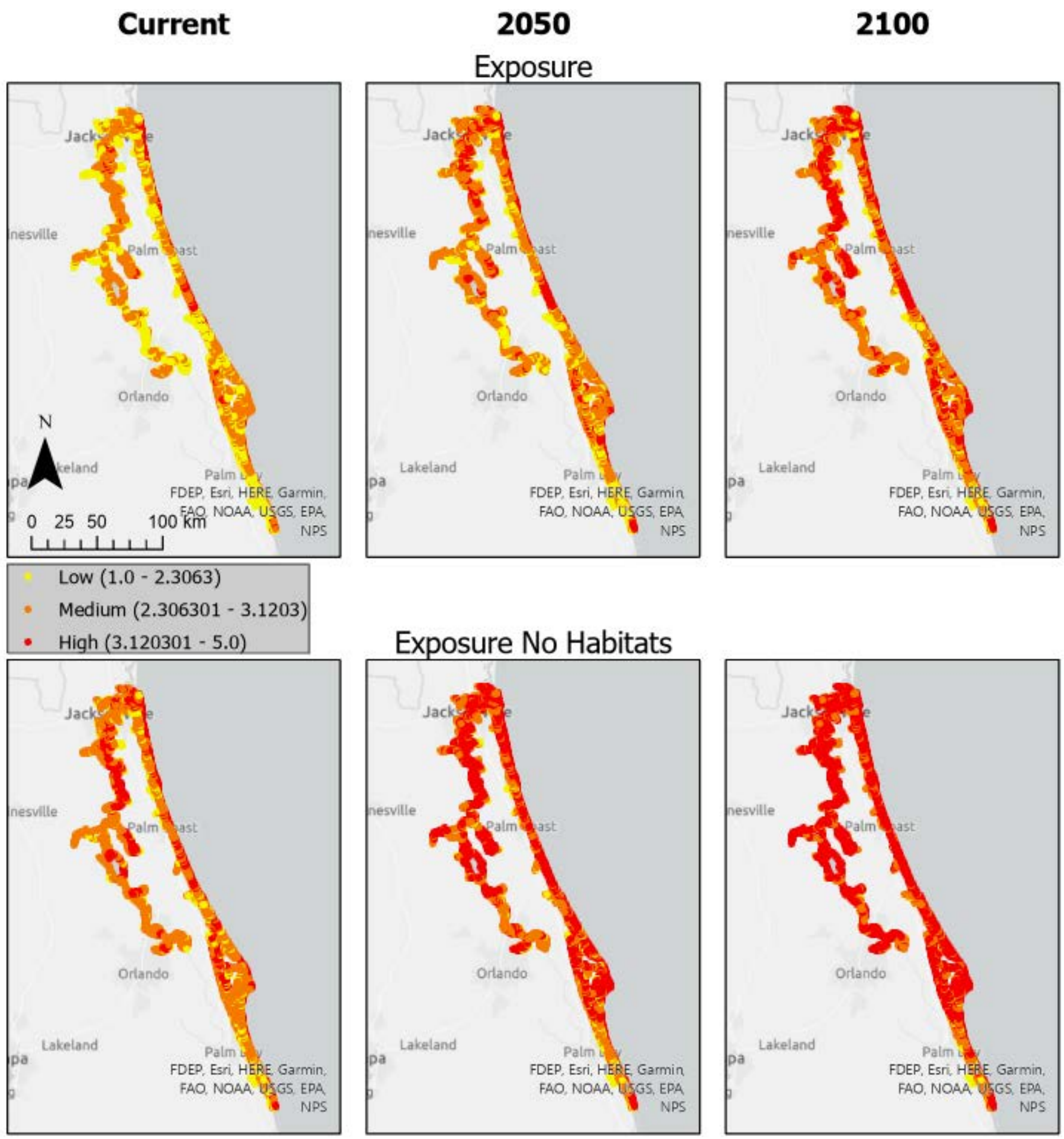

Figure 6. Coastal Exposure Scenarios

exposure by the 2050 scenario. For the other two focus areas along the Northeastern Florida beaches, the shorelines start with mostly high and some medium exposure, and they become all high exposure as SLR increases. For the Intracoastal waters in these focus areas, there is a more gradual increase in exposure.

In addition, spatial analysis using ArcGIS Pro tools was conducted. For the current scenario, the Calculate Distance Band from Neighbor Count tool was used to find the distances between each feature and its eighth nearest neighbor; it produced a maximum distance of 3,989.42 m and an average distance of 810.46 m. Using the maximum distance in the Moran I tool produced a memory warning; thus 3,000 m was used as the distance band. Note that this is greater than the default 1,751.56 m when the Moran I tool was run without specifying a distance band. For consistency, 3,000 m was used as the distance band for the other scenarios in the Moran I and Hot Spot Analysis tools, ensuring every feature had eight neighbors.

Using the Moran I spatial autocorrelation geoprocessing tool in ArcGIS Pro for the coastal exposure index and habitat role under all SLR scenarios, the p-value was statistically significant and the z-score was positive, seen in Table 9. Hence the null hypothesis was rejected, meaning the spatial distribution of the exposure index values and habitat role values are clustered. In other words, there is less than 1% probability that the clustered values are due to randomness.

Table 9. Spatial Autocorrelation (Global Moran's I) Statistics Results

Scenario	Coastal Exposure Index		Habitat Role	
	z-score	**p-value**	**z-score**	**p-value**
Current	201.15	< 0.0001	182.55	< 0.0001
2050 Intermediate-High	218.31	< 0.0001	180.51	< 0.0001
2100 Intermediate-High	211.81	< 0.0001	182.85	<0.0001

The following figures in this section were produced using the Hot Spot Analysis tool in ArcGIS Pro. Figure 7 shows hot spots for coastal exposure (top row of images) and hot spots for exposure without habitats (bottom row of images) for the current scenario, the 2050 Intermediate-High scenario, and the 2100 Intermediate-High scenario. Figure 8 shows hot spots for coastal exposure weighted by population (top row of images), and hot spots for coastal

exposure weighted by population below poverty (bottom row of images) for the three SLR scenarios. The images in Figure 8 are weighted as such because while the population density is computed for each shore point, it is not included in the coastal exposure index (or as part of any other rank). Overall, coastal exposure hot spot differences between the different SLR scenarios within Figure 7 and Figure 8 were small. As seen in Figure 7, the Lower St. Johns River and Northeastern Florida Beaches overwhelmingly have more coastal vulnerability hot spots than cold spots.

In Figure 8, the exposure hot spots weighted by population is relatively similar to the exposure hot spots weighted by population below poverty, although the latter displayed more cold spots just south of Port Orange. An interesting example is the Jacksonville Beach shoreline (south of the St. Johns River outlet at Mayport), which is very vulnerable. In comparison to the rest of the AOI, the population density by Jacksonville Beach is low. This signalizes that the hot spots here are so great that they pose a threat to a sparser population. By looking at the individual rankings of the shore points at Jacksonville Beach, the vulnerability is primarily due to the wind and wave rankings (all ranked as 5), from the surge and relief rankings (all ranked as 4), and from the geomorphology rankings (mostly ranked 5, with some 4's and 3.5's). Focusing on areas of concern to see the individual rankings for specific shore points provides insight into the factors contributing to a certain area's vulnerability; however, this tactic is tedious at a larger scale.

Figures 12 – 14 in Appendix A show the hot spots for coastal exposure for SLR scenarios enlarged to better see the focus areas. The downtown Jacksonville focus areas contained shore points that are hot spots with 99% confidence throughout the SLR scenarios. The focus areas for the Northeastern Florida beaches displayed increasing numbers of hot spots as SLR increased –

particularly focus areas 3 (Beverly Beach) and 4 (Painters Hill) in the 2100 scenario. Similar to the coastal exposure by quartiles figures (Figure 9-11), the Intracoastal waters generally contained fewer hot spots than the ocean facing coastline.

In the southern portion of the AOI resides the Indian River Lagoon which as seen in hot spot Figure 7 and Figures 12-14 has the greatest concentration of cold spots for two areas: (i) Port Orange going south for approximately 26.3 km with New Smyrna Beach in the middle, and (ii) south of Palm Bay for 57.5 km with Vero Beach near the end. What these two regions have in common is the density of wetland mangroves. Around New Smyrna Beach is the largest grouping of mangroves in the AOI, and the next largest concentration is by Vero Beach. There are mangroves in between these two areas by Cape Canaveral, but not as many. Mangroves have a strong ranking and protective distance because they lessen shallow water wave heights, reduce current strength, and reduce annual flooding (Leo et al., 2019; Mandle et al., 2017; Sharp et al., 2020). The low vulnerability is not only portrayed in the hot spot figures but also in coastal exposure Figures 9-11, which also show these Indian River Lagoon areas (the lagoon, not the coastline facing the open ocean) with mostly low exposure and some medium exposure as SLR increases.

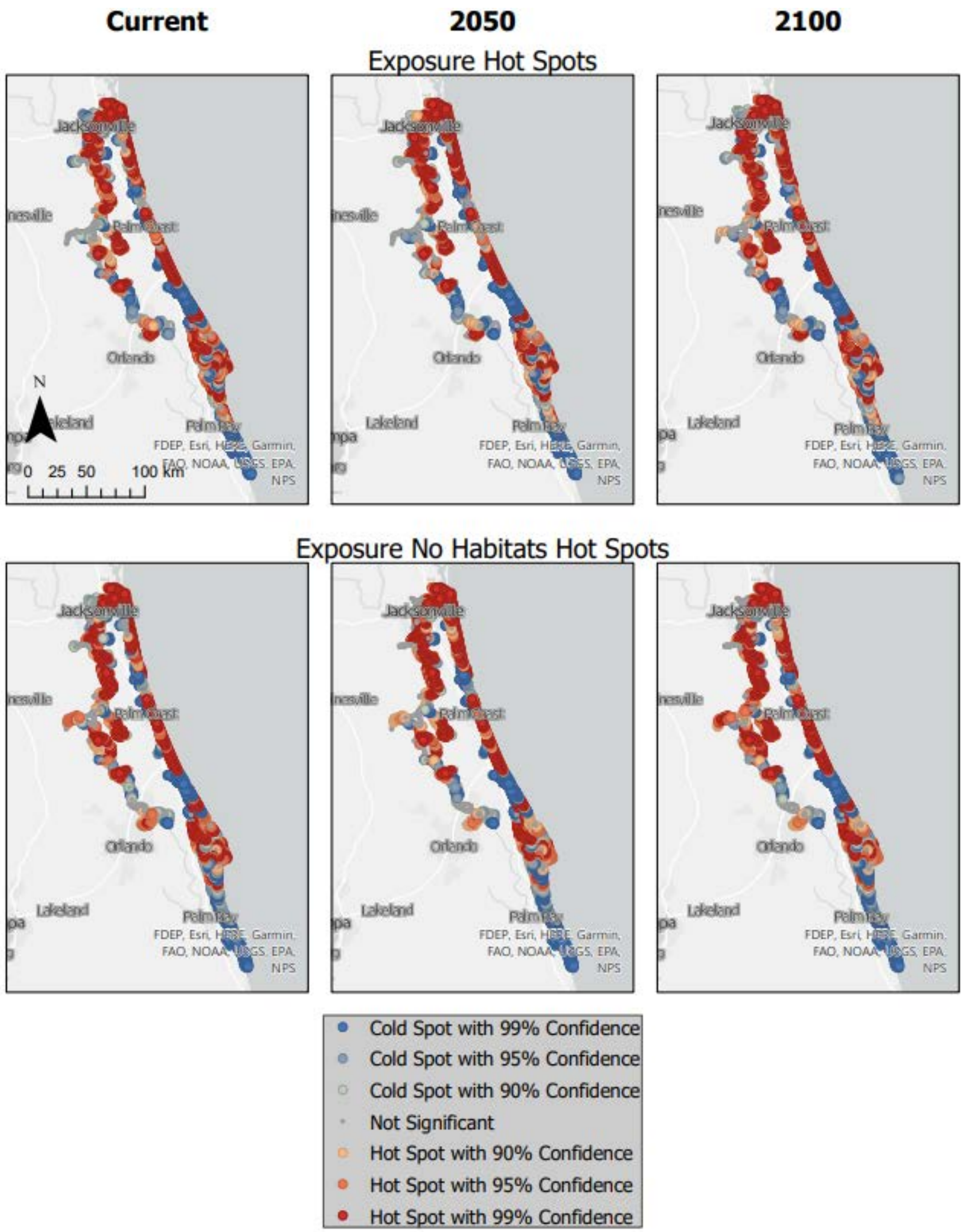

Figure 7. Hot Spots Scenarios for Exposure and Exposure No Habitats

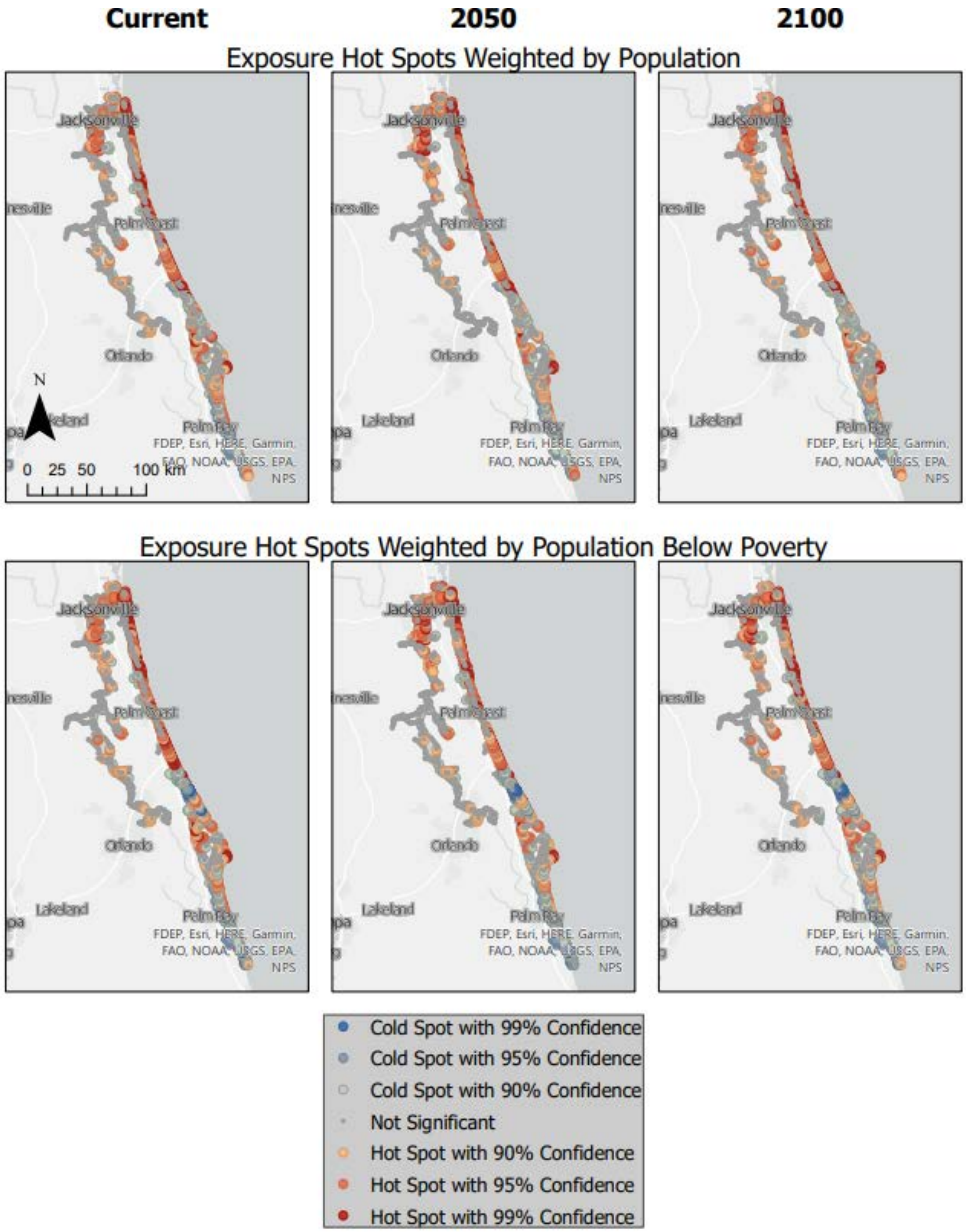

Figure 8. Hot Spots Scenarios with Demographics

3.4 Discussion

As SLR increased for the current, 2050 Intermediate-High, and 2100 Intermediate-High scenarios, the exposure, habitat role, and exposure no habitats ranks increased, as seen in Figure 4 and Figure 6. In other words, the coastal areas became more vulnerable and the importance of habitats for protection intensified with higher sea levels. For the highest quartile of exposure indexes across all SLR and habitat scenarios (rank > 3.12), the importance of habitats is again seen in the context of demographics in Figure 5 and Table 8. Comparing the without habitats scenarios to the with habitats scenarios shows that habitats increasingly keep more people and people below poverty out of high exposure areas as SLR increases. The vulnerability of population density and population below poverty density increased with rising sea levels and without habitats present.

For spatial analysis under all SLR scenarios, it was found that the spatial distribution of exposure indexes and habitat roles were significantly clustered. Comparison of the hot spot analysis figures (Figures 7-8 and 12-14) showed almost no visible discernable difference between the SLR scenarios. This implies that while SLR increases the role of habitats (as shown in the quartile exposure figures), SLR is not particularly affecting certain areas more or less in the study area, since the hot spots are generally consistent. Areas vulnerable now will continue to be vulnerable, and there will not be any major new vulnerability hot spots for the region. The exception to this generalization is focus areas 3 (Beverly Beach) and 4 (Painters Hill), which have a greater number of hot spots in the 2100 scenario. The reason for low variability in the hot spot figures is likely because SLR projections between the tide gauges in the study were relatively low (i.e., mostly homogenous SLR along the eastern Florida coast). The hot spot

figures however do illuminate an important finding: lower coastal vulnerability regions (cold spots) have high concentrations of mangroves, as seen for two areas of the Indian River Lagoon.

By including population below poverty as an input, this study investigates environmental injustice in hand with coastal vulnerability, a relatively novel field. Environmental injustice is the systematic placement of racialized and low-income populations in residential areas that are detrimental to their physical, social, and financial health (Vaz et al., 2017). Socioeconomically deprived communities are more often located by pollutant emitting facilities and major highways and less by natural/green areas than privileged communities. In this study, there were approximately equal percentages of people below poverty in high exposure areas as total population for the various scenarios as seen in Figure 5 and Table 8. In Figure 8, the exposure hot spots weighted by population are relatively similar to those weighted by population below poverty. This implies that the socioeconomic impact of a habitat restoration project may be greater in a poorer area because those households would have fewer financial resources in the event of losses from a storm (Arkema et al., 2017). Conversely, when examining coastal habitat restoration projects from a cost-benefit perspective, wealthier communities with higher property values would be weighted greater (Arkema et al., 2017). Since total population and population below poverty were the demographics examined in this study, additional demographics inputs could help answer more socioeconomic questions regarding the best benefit for coastal habitat restoration/protection projects with environmental injustice in mind. Mapping environmental injustice is gaining traction, however, there is much work to be done with mapping it in terms of coastal vulnerability and using the results to enact projects and policy changes.

Adapting to SLR with nature-based solutions, such as living shorelines, is a relatively new field (Leo et al., 2019). For habitats to be included in local and regional shoreline planning

efforts, planners and decision makers need some understanding of where habitats provide the most benefit for combating erosion and flooding exposure (Langridge et al., 2014) with rising sea levels, along with protecting people and socioeconomically disadvantaged people, such as this study shows. Habitats provide erosion protection and wave attenuation, absorbing stressors such as SLR, storm surge, and anthropogenic interference (Arkema et al., 2017; Hopper & Meixler, 2016). In addition to the risk reduction from coastal hazards, natural coastal infrastructure provides numerous critical biological functions and can be cost-effective compared to typical hard engineered structures or 'grey' infrastructure (Arkema et al., 2017; Langridge et al., 2014). Leo et al. (2019) encourage communities to consider managed retreat or removal of hard engineered coastal structures for replacement with living shorelines or a hybrid solution of natural and grey infrastructure. When removal is not feasible, management actions like land use code changes, land acquisition, easements, and buffers are other options.

This study fills a vulnerability knowledge gap for the region of Northeastern Florida by conglomerating geologic, physical, and socioeconomic variables to output a mapped coastal exposure index and the role of habitats. While there are limitations to the InVEST coastal vulnerability model, it is a powerful tool that computes coastal exposure to flooding and erosion without running complex wave models (Ruckelshaus et al., 2016). This CVA attempted to illuminate the interconnection of physical and geological hazards with social vulnerability (by using total population and population below poverty), a commonly neglected aspect of CVAs (Bukvic et al., 2020), and natural habitats, another component not typically included in CVAs (VanZomeren & Acevedo-Mackey, 2019). Results from exposure indexes such as from the InVEST coastal vulnerability model are valuable for a visual overview, and with statistical analysis can provide an estimate of where habitat restoration or other resiliency efforts will be

most beneficial for protecting shorelines and communities (Ruckelshaus et al., 2016). This study illustrates how habitats are crucial for lowering coastal vulnerability to erosion and flooding for people and people below poverty, and how as SLR increases, the protective role habitats play also increases. Quantifying and understanding that habitats play a vital role in coastal vulnerability is one of the first steps for resilience. The next step is to use results from a regional study such as this or Crist et al. (2019) to prioritize where habitats should be protected and/or restored within local confines, and lastly, implement these projects.

This study shows that as SLR increases, habitats provide more protection to total human population and population below poverty from high exposure areas to inundation and erosion. Other socioeconomic parameters could be analyzed in this model to further assist vulnerability understanding and local resilience planning. The risk and the cost of inaction versus potential adaptation and mitigation measures is a pertinent procedure that coastal communities need to undertake if they want to be resilient (Wong et al., 2014). This study can aid resiliency planning efforts for the region (some of which were identified in Section 1.5), including where habitat protection and/or restoration is vital for protecting shorelines and people, helping taxpayer dollars go where they will provide most benefit to this riverine and coastal community in the face of climate change, rising sea levels, and increasing severity and frequency of storms.

3.5 Future Work

Ocean acidification, precipitation changes, and temperature changes are other climate change ramifications that will affect people and habitats but are not within the scope of the model. The model does not predict the loss of habitats or change to the shoreline under SLR scenarios. In this vein, Hopper and Meixler (2016) clipped their habitat areas and changed their

landmass to correspond to loss of area from SLR, instead of inputting SLR as a metric into the model. Following a similar approach could be of interest for a study that furthers this research.

Some parameters in the model could likely be tuned. A sensitivity analysis was done in this study of the maximum fetch distance, and the default was found to be satisfactory. The model resolution, elevation averaging radius, population search radius, and habitat protective distances are other parameters that could be massaged. The SLR scenarios could be approached and set up differently. Using forecasted wind and wave data that corresponds to the future SLR scenarios could be worth exploring, and would result in more accurate wind, wave, and surge potential exposure rankings. In addition to SLR rise, habitats, population, and population below poverty, many other factors could be analyzed, such as proximity of agricultural land, transportation, utilities, urban and built-up, property value (or other economic parameters), other demographics, etc. to high exposure areas. These factors could also be analyzed with respect to environmental injustice questions.

In addition to the inputs and results from the InVEST coastal vulnerability model, other factors and efforts at play correspond to vulnerability in the region. One other such factor is dredging. There is a lack of understanding of how dredging the St. Johns River will impact exposure to the region. For instance, rainfall runoff was not included in the USACE model for the river dredging project (Lahav, 2021; St. Johns Riverkeeper, 2019). The higher maximum water levels from dredging will impact storm surge and likely cause habitat loss and saltwater intrusion. Dredging scenarios for the St. Johns River could be run in the model by doing different bathymetry scenarios.

Another continuation option for this study could be to do a model validation. Of the literature review of studies that used the InVEST coastal vulnerability model, it was rare that

model validation was attempted. However, one example that included some validation is presented by Cabral et al. (2017) who showed significance in comparing high coastal exposure index areas to climate change disaster events (e.g., cyclones and floods) that caused fatalities from the Desinventar Database. The Desinventar Database does not include the US. Another similar example is Arkema et al. (2013), who compared coastal hazard-related fatalities from the Spatial Hazards Events and Losses Database for the United States (SHELDUS) per state to people in the highest exposure areas. Both studies showed statistical validation from the independent databases. CZMAI (2016) references the Arkema et al. (2013) as continuation of their work (they did not do another model validation). It was attempted to use SHELDUS for model validation for this study using county data for coastal hazard fatalities; however, due to subscription issues and site maintenance, data was ultimately not obtained from SHELDUS. If SHELDUS recoups full functionality, or another suitable database for cross examination is identified, a model validation could be conducted for this study area.

3.5.1 City of Jacksonville

Results from this study could aid in resiliency efforts for the City of Jacksonville, one of which could be to modify land-use codes. Habitat types that provide strong erosion and flooding protection could be prioritized. For example, the least vulnerable areas in this study were revealed to have mangroves. Jacksonville was very vulnerable in the results of this study. While it may be challenging to construct green infrastructure projects within the confines of an area already built-up, it is worth considering the ability to implement such projects whenever feasible. Land use code modifications could also be aimed at helping socioeconomically deprived communities, which historically have been the areas to bear the brunt of biased policies (Vaz et al., 2017). Prioritizing natural infrastructure projects for these communities could be a start to

addressing environmental injustice and would tackle both the exposure to flooding and erosion, as well as provide much needed green space for improved health and livelihoods.

4.0 Conclusions

The exposure to flooding and erosion for the St. Johns River and Northeastern Florida shorelines increases as sea level rises, as shown in current, 2050 and 2100 SLR scenarios. In these scenarios it is also shown that habitats play a progressively important role as SLR increases for protecting human population and population below poverty from high exposure areas. It was also found that coastal exposure indexes and habitat role values were spatially correlated. The model outputs present a case for the importance of habitats (especially wetland mangroves), as coastal protection against storm-induced flooding and erosion and for SLR. These results could be used to help prioritize which habitat types and where habitat protection and/or restoration is most needed for protecting shorelines and people. This type of coastal vulnerability study could aid resiliency planning efforts in Northeastern Florida, and could be expanded upon for other socieconomic, infrastructure, or ecosystem queries.

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Appendix A – Additional Figures

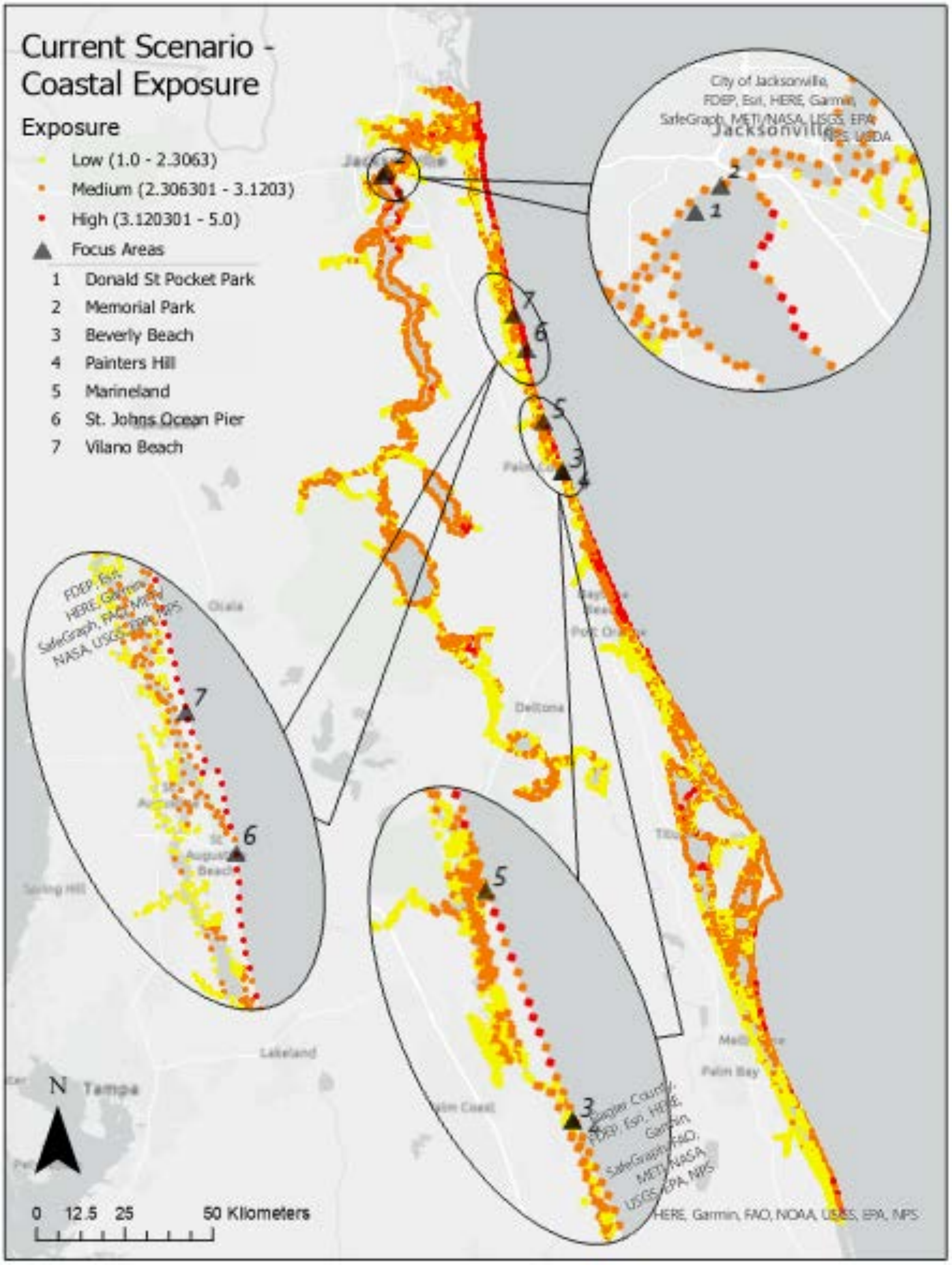

Figure 9. Current Scenario Coastal Exposure

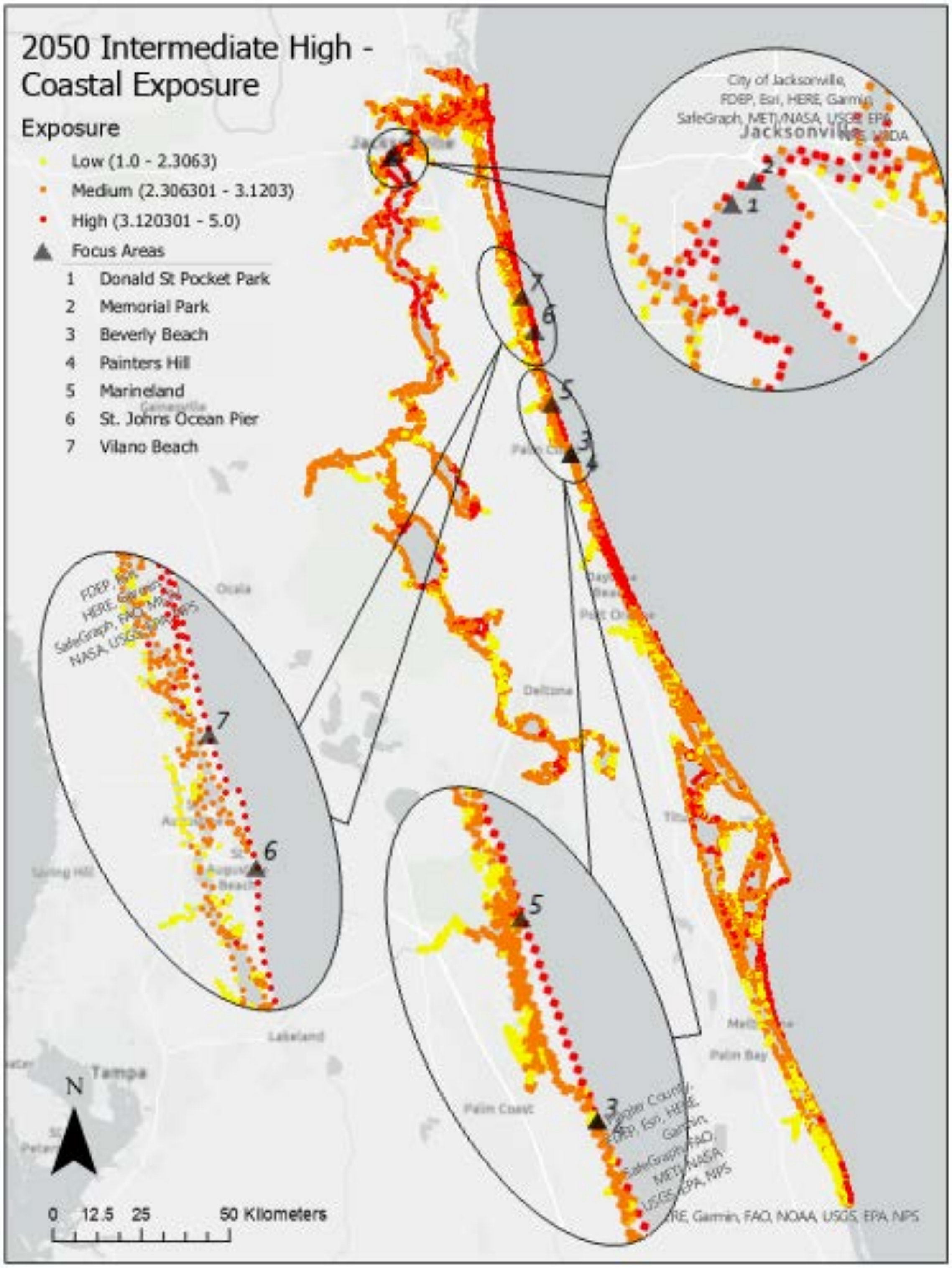

Figure 10. 2050 Scenario Coastal Exposure

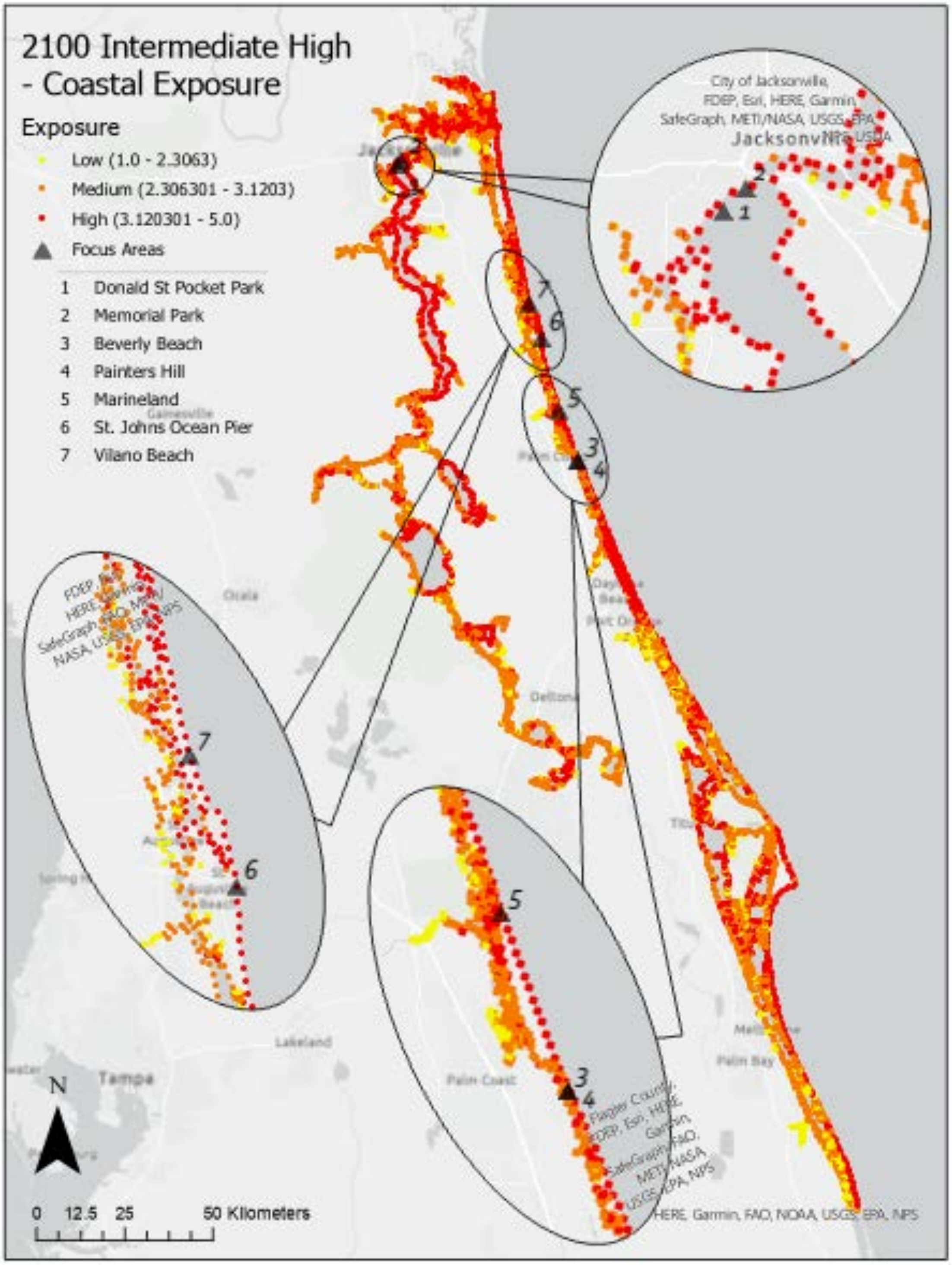

Figure 11. 2100 Scenario Coastal Exposure

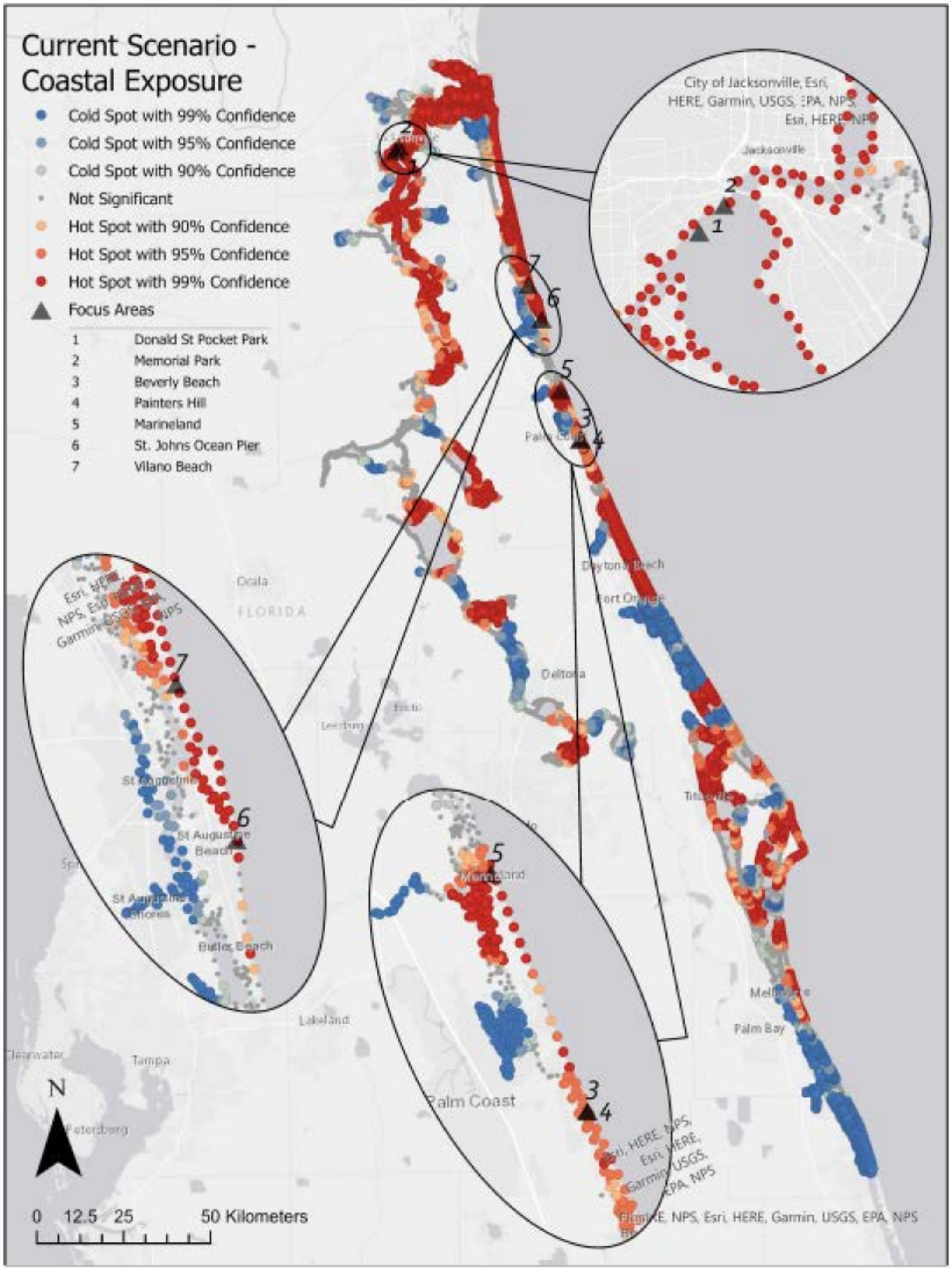

Figure 12. Current Scenario Coastal Exposure Hot Spots

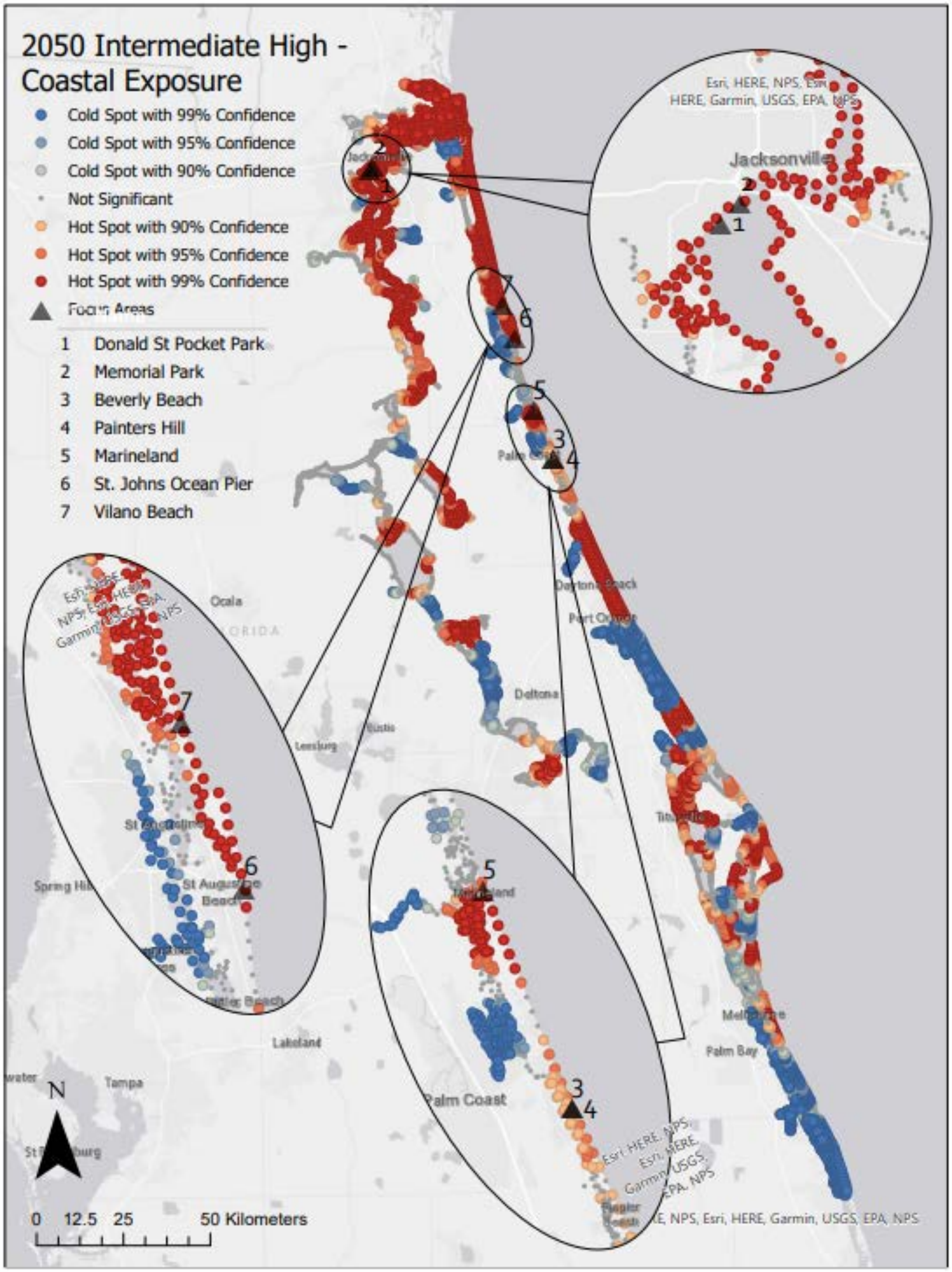

Figure 13. 2050 Scenario Coastal Exposure Hot Spots

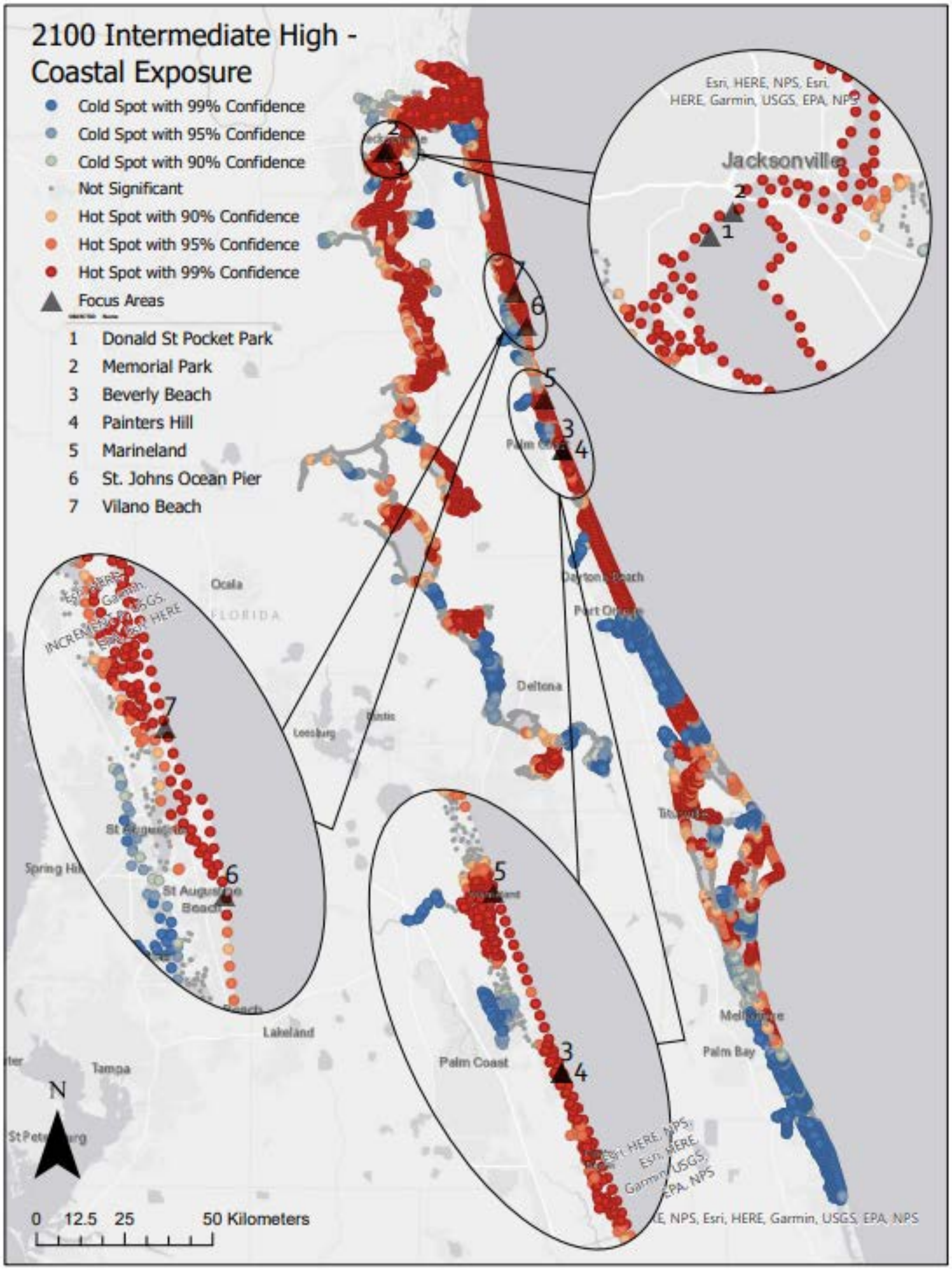

Figure 14. 2100 Scenario Coastal Exposure Hot Spots

Appendix B – Data Sources

Dataset	Purpose	File Type	Source Organization	Notes	Source Website
Water Management District Boundaries	AOI	Shapefile	SJRWMD via FGDL	Created the AOI in-house. These water management district boundaries were for guidance.	https://data-floridaswater.opendata.arcgis.com/datasets/floridaswater::water-management-district-boundaries/about
Florida Shoreline	Landmass	Shapefile	FWC		https://geodata.myfwc.com/datasets/myfwc::florida-shoreline-1-to-12000-scale/about
WaveWatch III	Waves & Wind	Shapefile	NOAA	InVEST default, came with sample download package.	N/A
	Bathym-etry	Raster	NOAA		From UNF records.
National Elevation Dataset (NED) 1/3 arc-second resolution	DEM	Raster	USGS	Merged together 10 raster files to cover entire AOI.	http://nationalmap.gov/elevation.html
Continental Shelf Polyline Global	Contin-ental Shelf Contour	Shapefile		InVEST default, came with sample download package.	N/A
Seagrass	Habitats	Shapefile	FWC via FGDL		https://www.fgdl.org/metadataexplorer/explorer.jsp
SJRWMD Land Use and Cover	Habitats	Shapefile	SJRWMD via FGDL	Used rangelands, wetlands (including mangroves), and upland forests.	https://www.fgdl.org/metadataexplorer/explorer.jsp
Environmental Sensitivity Index (ESI) Shoreline Lines	Geomorphology	Shapefile	FWC	Used the most sensitive codes present per shoreline segment for InVEST rankings. Added some jetties to the dataset manually.	https://geodata.myfwc.com/datasets/myfwc::esi-shoreline-classification-lines-florida/about

Dataset	Purpose	File Type	Source Organization	Notes	Source Website
2015 Census Block Groups in Florida (with Selected Fields from the 2011-2015 American Community Survey)	Human Population	Raster	US Census Bureau via FGDL	Converted gdb to tif, and extended to the SJRWMD boundary, for total population, population below poverty, and households below poverty.	https://www.fgdl.org/metadataexplorer/explorer.jsp
NOAA Technical Report NOS CO-OPS 83, Data: Global and Regional SLR Scenarios for the U.S. (CSV)	Sea Level Rise	CSV	NOAA	Data from tide gauges in the AOI was used to create a point vector file.	https://tidesandcurrents.noaa.gov/sltrends/sltrends.html